LECTURE NOTES FOR ADVANCED CALCULUS

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introduction and motivations for these notes

There are many excellent texts on portions of this subject. However, the particular path I choose this semester is not quite in line with any particular text. I required the text on Advanced Calculus by Edwards because it contains all the major theorems that traditionally are covered in an Advanced Calculus course.

Linear algebra is not a prerequisite for this course. However, I will use linear algebra. Matrices, linear transformations and vector spaces are necessary ingredients for a proper discussion of advanced calculus. I believe an interested student can easily assimilate the needed tools as we go so I am not terribly worried if you have not had linear algebra previously. I will make a point to include some baby¹ linear exercises to make sure everyone who is working at this course keeps up with the story that unfolds.

Real analysis is also not a prerequisite for this course. However, I will present some proofs which properly fall in the category of real analysis. Some of these proofs involve a sophistication that is beyond the usual day-to-day business of the course. I include these thoughts for the sake of completeness. If I am to test them it's probably more on the question of were you paying attention as opposed to can you reconstruct the monster from scratch.

Certainly my main intent in this course is that you learn calculus more deeply. Yes we'll learn some new calculations, but I also hope that what we cover also gives you deeper insight into your previous experience with calculus. Towards that end, I am including a section or two on series and sequences and a discussion of pointwise verses uniform convergence. These discussions set-up the technique of exchanging derivatives and integrals which is a powerful technique seldom discussed in current calculus courses.

Doing the homework is doing the course. I cannot overemphasize the importance of thinking through the homework. I would be happy if you left this course with a working knowledge of:

- $\checkmark\,$ set-theoretic mapping langauge, fibers and images and how to picture relationships diagramatically.
- $\checkmark\,$ continuity in view of the metric topology in n-space.
- $\checkmark\,$ the concept and application of the derivative and differential of a mapping.
- \checkmark continuous differentiability
- $\checkmark\,$ inverse function theorem
- $\checkmark\,$ implicit function theorem
- $\checkmark\,$ tangent space and normal space via gradients or derivatives of parametrizations

¹if you view this as an insult then you haven't met the right babies yet. Baby exercises are cute.

- \checkmark extrema for multivariate functions, critical points and the Lagrange multiplier method
- $\checkmark~$ multivariate Taylor series.
- $\checkmark~$ quadratic forms
- \checkmark critical point analysis for multivariate functions
- $\checkmark\,$ dual space and the dual basis.
- $\checkmark\,$ multilinear algebra.
- $\checkmark\,$ metric dualities and Hodge duality.
- \checkmark the work and flux form mappings for \mathbb{R}^3 .
- \checkmark basic manifold theory (don't let me get too deep, please...)²
- $\checkmark\,$ vector fields as derivations.
- $\checkmark\,$ differential forms and the exterior derivative
- $\checkmark~$ integration of forms
- $\checkmark\,$ generalized Stokes's Theorem.
- \checkmark push-fowards and pull-backs
- \checkmark how differential forms and submanifolds naturally geometrize differential equations
- \checkmark elementary differential geometry of curves and surfaces via the method of moving frames
- \checkmark basic variational calculus (how to calculate the Euler-Lagrange equations for a given Lagrangian)

When I say *working knowledge* what I intend is that you have some sense of the problem and at least know where to start looking for a solution. Some of the topics above take a much longer time to understand deeply. I cover them to spark your interest and seed your intuition if all goes well.

Before we begin, I should warn you that I assume quite a few things from the reader. These notes are intended for someone who has already grappled with the problem of constructing proofs. I assume you know the difference between \Rightarrow and \Leftrightarrow . I assume the phrase "iff" is known to you. I assume you are ready and willing to do a proof by induction, strong or weak. I assume you know what \mathbb{R} , \mathbb{C} , \mathbb{Q} , \mathbb{N} and \mathbb{Z} denote. I assume you know what a subset of a set is. I assume you know how to prove two sets are equal. I assume you are familar with basic set operations such as union and intersection (although we don't use those much). More importantly, I assume you have started to appreciate that mathematics is more than just calculations. Calculations without context, without theory, are doomed to failure. At a minimum theory and proper mathematics allows you to communicate analytical concepts to other like-educated individuals.

Some of the most seemingly basic objects in mathematics are insidiously complex. We've been taught they're simple since our childhood, but as adults, mathematically-minded adults, we find the actual definitions of such objects as \mathbb{R} or \mathbb{C} are rather involved. I will not attempt to provide foundational arguments to build numbers from basic set theory. I believe it is possible, I think it's well-thought-out mathematics, but we take the existence of the real numbers as an axiom for these notes. We assume that \mathbb{R} exists and that the real numbers possess all their usual properties. In fact, I assume \mathbb{R} , \mathbb{C} , \mathbb{Q} , \mathbb{N} and \mathbb{Z} all exist complete with their standard properties. In short, I assume we have numbers to work with. We leave the rigorization of numbers to a different course.

I have avoided use of Einstein's implicit summation notation in the majority of these notes. This has introduced some clutter in calculations, but I hope the student finds the added detail helpful. Naturally if one goes on to study tensor calculations in physics then no such luxury is granted. In view of this, I left the more *physicsy* notation in the discussion of electromagnetism via differential forms.

This is the third time I have prepared an official offering of Advanced Calculus. The first offering was given to about 10 students, half engineering, half math, it was deliberately given with a computational focus. The second offering was intended for an audience of about 6 math students, all bailed except 1 and the course modified into a more serious, theoretically-focused introduction to manifolds (Spencer 2011). I have taught it off and on as an indpendent study to several students, Bobbi Beller, Jin Li.

This semester I hope to go further into the exposition of differential forms than I have previously. In past attempts, too much time was devoted to developing constructions in basic manifold theory we didn't really need. So, this time, I take a somewhat formal approach to manifolds. We'll see how differential forms allow great insight into the shape of surfaces and the geometrization of differential equations. Finally, at the end of the course I again spend several lectures on the calculus of variations.

note on editing: ran a little short on time this summer, sorry but only pages 1-224 ok for printing at moment. The remaining 225 and beyond are only about 80% finished. I will let you know once those are fixed. Thanks!

James Cook, August 18, 2013.

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Chapter 1

sets, functions and euclidean space

In this chapter we settle some basic terminology about sets and functions.

1.1 set theory

Let us denote sets by capital letters in as much as is possible. Often the lower-case letter of the same symbol will denote an element; $a \in A$ is to mean that the object a is in the set A. We can abbreviate $a_1 \in A$ and $a_2 \in A$ by simply writing $a_1, a_2 \in A$, this is a standard notation. The **union** of two sets A and B is denoted $A \cup B = \{x | x \in A \text{ or } x \in B\}$. The **intersection** of two sets is denoted $A \cap B = \{x | x \in A \text{ and } x \in B\}$. If a set S has no elements then we say S is the **empty set** and denote this by writing $S = \emptyset$. It sometimes convenient to use unions or intersections of several sets:

$$\bigcup_{\alpha \in \Lambda} U_{\alpha} = \{x \mid \text{there exists } \alpha \in \Lambda \text{ with } x \in U_{\alpha}\}$$
$$\bigcap_{\alpha \in \Lambda} U_{\alpha} = \{x \mid \text{for all } \alpha \in \Lambda \text{ we have } x \in U_{\alpha}\}$$

we say Λ is the **index set** in the definitions above. If Λ is a finite set then the union/intersection is said to be a finite union/interection. If Λ is a countable set then the union/intersection is said to be a countable union/interection¹. Suppose A and B are both sets then we say A is a **subset** of B and write $A \subseteq B$ iff $a \in A$ implies $a \in B$ for all $a \in A$. If $A \subseteq B$ then we also say B is a **superset** of A. If $A \subseteq B$ then we say $A \subset B$ iff $A \neq B$ and $A \neq \emptyset$. Recall, for sets A, B we define A = B iff $a \in A$ implies $a \in B$ for all $a \in A$ and conversely $b \in B$ implies $b \in A$ for all $b \in B$. This is equivalent to insisting A = B iff $A \subseteq B$ and $B \subseteq A$. The **difference** of two sets A and B is denoted A - B and is defined by $A - B = \{a \in A \mid \text{ such that } a \notin B\}^2$.

¹recall the term **countable** simply means there exists a bijection to the natural numbers. The cardinality of such a set is said to be \aleph_o

²other texts somtimes use $A - B = A \setminus B$

Real numbers can be constructed from set theory and about a semester of mathematics. We will accept the following as \mathbf{axioms}^3

Definition 1.1.1. real numbers

The set of real numbers is denoted \mathbb{R} and is defined by the following axioms: (A1) addition commutes; a + b = b + a for all $a, b \in \mathbb{R}$. (A2) addition is associative; (a + b) + c = a + (b + c) for all $a, b, c \in \mathbb{R}$. (A3) zero is additive identity; a + 0 = 0 + a = a for all $a \in \mathbb{R}$. (A4) additive inverses; for each $a \in \mathbb{R}$ there exists $-a \in \mathbb{R}$ and a + (-a) = 0. (A5) multiplication commutes; ab = ba for all $a, b \in \mathbb{R}$. (A6) multiplication is associative; (ab)c = a(bc) for all $a, b, c \in \mathbb{R}$. (A7) one is multiplicative identity; a1 = a for all $a \in \mathbb{R}$. (A8) multiplicative inverses for nonzero elements; for each $a \neq 0 \in \mathbb{R}$ there exists $\frac{1}{a} \in \mathbb{R}$ and $a\frac{1}{a} = 1$. (A9) distributive properties; a(b + c) = ab + ac and (a + b)c = ac + bc for all $a, b, c \in \mathbb{R}$. (A10) totally ordered field; for $a, b \in \mathbb{R}$: (i) antisymmetry; if $a \leq b$ and $b \leq c$ then a = b. (ii) transitivity; if $a \leq b$ and $b \leq c$ then $a \leq c$. (iii) transitivity; if $a \leq b$ or $b \leq a$

(A11) least upper bound property: every nonempty subset of \mathbb{R} that has an upper bound, has a least upper bound. This makes the real numbers **complete**.

Modulo A11 and some math jargon this should all be old news. An **upper bound** for a set $S \subseteq \mathbb{R}$ is a number $M \in \mathbb{R}$ such that M > s for all $s \in S$. Similarly a lower bound on S is a number $m \in \mathbb{R}$ such that m < s for all $s \in S$. If a set S is bounded above and below then the set is said to be **bounded**. For example, the open set (a, b) is bounded above by b and it is bounded below by a. In contrast, rays such as $(0, \infty)$ are not bounded above. Closed intervals contain their least upper bound and greatest lower bound. The bounds for an open interval are outside the set.

³an axiom is a basic belief which cannot be further reduced in the conversation at hand. If you'd like to see a construction of the real numbers from other math, see Ramanujan and Thomas' *Intermediate Analysis* which has the construction both from the so-called Dedekind cut technique and the Cauchy-class construction. Also, I've been informed, Terry Tao's Analysis I text has a very readable exposition of the construction from the Cauchy viewpoint.

We often make use of the following standard sets:

natural numbers (positive integers); $\mathbb{N} = \{1, 2, 3, ...\}$. natural numbers up to the number n; $\mathbb{N}_n = \{1, 2, 3, ..., n - 1, n\}$. integers; $\mathbb{Z} = \{\ldots, -2, -1, 0, 1, 2, \ldots\}$. Note, $\mathbb{Z}_{>0} = \mathbb{N}$. non-negative integers; $\mathbb{Z}_{\geq 0} = \{0, 1, 2, \ldots\} = \mathbb{N} \cup \{0\}$. negative integers; $\mathbb{Z}_{<0} = \{-1, -2, -3, \ldots\} = -\mathbb{N}$. rational numbers; $\mathbb{Q} = \{\frac{p}{q} \mid p, q \in \mathbb{Z}, q \neq 0\}$. irrational numbers; $\mathbb{J} = \{x \in \mathbb{R} \mid x \notin \mathbb{Q}\}$. open interval from a to b; $(a, b) = \{x \mid a < x < b\}$. half-open interval; $(a, b] = \{x \mid a < x \le b\}$ or $[a, b) = \{x \mid a \le x < b\}$. closed interval; $[a, b] = \{x \mid a \le x \le b\}$.

The final, and for us the most important, construction in set-theory is called the Cartesian product. Let A, B, C be sets, we define:

$$A \times B = \{(a, b) \mid a \in A \text{ and } b \in B\}$$

By a slight abuse of notation⁴ we also define:

$$A \times B \times C = \{(a, b, c) \mid a \in A \text{ and } b \in B \text{ and } c \in C\}$$

In the case the sets comprising the cartesian product are the same we use an exponential notation for the construction:

$$A^2 = A \times A, \qquad A^3 = A \times A \times A$$

We can extend to finitely many sets. Suppose A_i is a set for i = 1, 2, ..., n then we denote the Cartesian product by

$$A_1 \times A_2 \times \cdots \times A_n = \times_{i=1}^n A_i$$

and define $\vec{x} \in \times_{i=1}^{n} A_i$ iff $\vec{x} = (a_1, a_2, \dots, a_n)$ where $a_i \in A_i$ for each $i = 1, 2, \dots, n$. An element \vec{x} as above is often called an **n-tuple**.

We define $\mathbb{R}^2 = \{(x, y) \mid x, y \in \mathbb{R}\}$. I refer to \mathbb{R}^2 as "R-two" in conversational mathematics. Likewise, "R-three" is defined by $\mathbb{R}^3 = \{(x, y, z) \mid x, y, z \in \mathbb{R}\}$. We are ultimately interested in studying "R-n" where $\mathbb{R}^n = \{(x_1, x_2, \dots, x_n) \mid x_i \in \mathbb{R} \text{ for } i = 1, 2, \dots, n\}$. In this course if we consider \mathbb{R}^m

⁴technically $A \times (B \times C) \neq (A \times B) \times C$ since objects of the form (a, (b, c)) are not the same as ((a, b), c), we ignore these distinctions and map both of these to the triple (a, b, c) without ambiguity in what follows

it is assumed from the context that $m \in \mathbb{N}$.

In terms of cartesian products you can imagine the x-axis as the number line then if we paste another numberline at each x value the union of all such lines constructs the plane; this is the picture behind $\mathbb{R}^2 = \mathbb{R} \times \mathbb{R}$. Another interesting cartesian product is the **unit-square**; $[0,1]^2 =$ $[0,1] \times [0,1] = \{(x,y) \mid 0 \le x \le 1, 0 \le y \le 1\}$. Sometimes a rectangle in the plane with it's edges included can be written as $[x_1, x_2] \times [y_1, y_2]$. If we want to remove the edges use $(x_1, x_2) \times (y_1, y_2)$.

Moving to three dimensions we can construct the **unit-cube** as $[0,1]^3$. A generic rectangular solid can sometimes be represented as $[x_1, x_2] \times [y_1, y_2] \times [z_1, z_2]$ or if we delete the edges: $(x_1, x_2) \times (y_1, y_2) \times (z_1, z_2)$.

1.2 functions

Suppose A and B are sets, we say $f : A \to B$ is a **function** if for each $a \in A$ the function f assigns a single element $f(a) \in B$. Moreover, if $f : A \to B$ is a function we say it is a *B*-valued function of an *A*-variable and we say A = dom(f) whereas B = codomain(f). For example, if $f : \mathbb{R}^2 \to [0,1]$ then f is real-valued function of \mathbb{R}^2 . On the other hand, if $f : \mathbb{C} \to \mathbb{R}^2$ then we'd say f is a vector-valued function of a complex variable. The term mapping will be used interchangeably with function in these notes⁵. Suppose $f : U \to V$ and $U \subseteq S$ and $V \subseteq T$ then we may consisely express the same data via the notation $f : U \subseteq S \to V \subseteq T$.

Sometimes we can take two given functions and construct a new function.

- 1. if $f: U \to V$ and $g: V \to W$ then $g \circ f: U \to W$ is the composite of g with f.
- 2. if $f, g: U \to V$ and V is a set with an operation of addition then we define $f \pm g: U \to V$ pointwise by the natural assignment $(f \pm g)(x) = f(x) \pm g(x)$ for each $x \in U$. We say that $f \pm g$ is the sum(+) or difference(-) of f and g.
- 3. if $f: U \to V$ and $c \in S$ where there is an operation of scalar multiplication by S on V then $cf: U \to V$ is defined pointwise by (cf)(x) = cf(x) for each $x \in U$. We say that cf is scalar multiple of f by c.

Usually we have in mind $S = \mathbb{R}$ or $S = \mathbb{C}$ and often the addition is just that of vectors, however the definitions (2.) and (3.) apply equally well to matrix-valued functions or operators which is another term for function-valued functions. For example, in the first semester of calculus we study d/dx which is a function of functions; d/dx takes an input of f and gives the output df/dx. If we

⁵in my first set of advanced calculus notes (2010) I used the term function to mean the codomain was real numbers whereas mapping implied a codomain of vectors. I was following Edwards as he makes this convention in his text. I am not adopting that terminology any longer, I think it's better to use the term function as we did in Math 200 or 250. A function is an abstract construction which allows for a vast array of codomains.

write L = 3d/dx we have a new operator defined by (3d/dx)[f] = 3df/dx for each function f in the domain of d/dx.

Definition 1.2.1.

Suppose $f: U \to V$. We define the **image of** U_1 **under** f as follows:

 $f(U_1) = \{ y \in V \mid \text{there exists } x \in U_1 \text{ with } f(x) = y \}.$

The range of f is f(U). The inverse image of V_1 under f is defined as follows:

$$f^{-1}(V_1) = \{ x \in U \mid f(x) \in V_1 \}.$$

The inverse image of a single point in the codomain is called a **fiber**. Suppose $f: U \to V$. We say f is surjective or onto V_1 iff there exists $U_1 \subseteq U$ such that $f(U_1) = V_1$. If a function is onto its codomain then the **function is surjective**. If $f(x_1) = f(x_2)$ implies $x_1 = x_2$ for all $x_1, x_2 \in U_1 \subseteq U$ then we say **f** is injective on U_1 or 1 - 1 on U_1 . If a function is injective on its domain then we say the **function is injective**. If a function is both injective and surjective then the function is called a **bijection** or a **1-1 correspondance**.

Example 1.2.2. Suppose $f : \mathbb{R}^2 \to \mathbb{R}$ and f(x, y) = x for each $(x, y) \in \mathbb{R}^2$. The function is not injective since f(1, 2) = 1 and f(1, 3) = 1 and yet $(1, 2) \neq (1, 3)$. Notice that the fibers of f are simply vertical lines:

$$f^{-1}(x_o) = \{(x, y) \in dom(f) \mid f(x, y) = x_o\} = \{(x_o, y) \mid y \in \mathbb{R}\} = \{x_o\} \times \mathbb{R}$$

Example 1.2.3. Suppose $f : \mathbb{R} \to \mathbb{R}$ and $f(x) = \sqrt{x^2} + 1$ for each $x \in \mathbb{R}$. This function is not surjective because $0 \notin f(\mathbb{R})$. In contrast, if we construct $g : \mathbb{R} \to [1, \infty)$ with g(x) = f(x) for each $x \in \mathbb{R}$ then can argue that g is surjective. Neither f nor g is injective, the fiber of x_0 is $\{-x_0, x_0\}$ for each $x_0 \neq 0$. At all points except zero these maps are said to be **two-to-one**. This is an abbreviation of the observation that two points in the domain map to the same point in the range.

Definition 1.2.4.

Suppose $f: U \subseteq \mathbb{R}^p \to V \subseteq \mathbb{R}^n$ and suppose further that for each $x \in U$,

 $f(x) = (f_1(x), f_2(x), \dots, f_n(x)).$

Then we say that $f = (f_1, f_2, \ldots, f_n)$ and for each $j \in \mathbb{N}_p$ the functions $f_j : U \subseteq \mathbb{R}^p \to \mathbb{R}$ are called the **component functions** of f. Furthermore, we define the projection $\pi_j : \mathbb{R}^n \to \mathbb{R}$ to be the map $\pi_j(x) = x \cdot e_j$ for each $j = 1, 2, \ldots n$. This allows us to express each of the component functions as a composition $f_j = \pi_j \circ f$.

Example 1.2.5. Suppose $f : \mathbb{R}^3 \to \mathbb{R}^2$ and $f(x, y, z) = (x^2 + y^2, z)$ for each $(x, y, z) \in \mathbb{R}^3$. Identify that $f_1(x, y, z) = x^2 + y^2$ whereas $f_2(x, y, z) = z$. You can easily see that $range(f) = [0, \infty] \times \mathbb{R}$. Suppose $\mathbb{R}^2 \in [0, \infty)$ and $z_o \in \mathbb{R}$ then

$$f^{-1}(\{(R^2, z_o)\}) = S_1(R) \times \{z_o\}$$

where $S_1(R)$ denotes a circle of radius R. This result is a simple consequence of the observation that $f(x, y, z) = (R^2, z_o)$ implies $x^2 + y^2 = R^2$ and $z = z_o$.

Example 1.2.6. Let $a, b, c \in \mathbb{R}$ be particular constants. Suppose $f : \mathbb{R}^3 \to \mathbb{R}$ and f(x, y, z) = ax + by + cz for each $(x, y, z) \in \mathbb{R}^3$. Here there is just one component function so we could say that $f = f_1$ but we don't usually bother to make such an observation. If at least one of the constants a, b, c is nonzero then the fibers of this map are planes in three dimensional space with normal $\langle a, b, c \rangle$.

$$f^{-1}(\{d\}) = \{(x, y, z) \in \mathbb{R}^3 \mid ax + by + cz = d\}$$

If a = b = c = 0 then the fiber of f is simply all of \mathbb{R}^3 and the range $(f) = \{0\}$.

The definition below explains how to put together functions with a common domain. The codomain of the new function is the cartesian product of the old codomains.

Definition 1.2.7.

Let
$$f: U_1 \subseteq \mathbb{R}^n \to V_1 \subseteq \mathbb{R}^p$$
 and $g: U_1 \subseteq \mathbb{R}^n \to V_2 \subseteq \mathbb{R}^q$ be a mappings then (f,g) is a mapping from U_1 to $V_1 \times V_2$ defined by $(f,g)(x) = (f(x),g(x))$ for all $x \in U_1$.

There's more than meets the eye in the definition above. Let me expand it a bit here:

$$(f,g)(x) = (f_1(x), f_2(x), \dots, f_p(x), g_1(x), g_2(x), \dots, g_q(x))$$
 where $x = (x_1, x_2, \dots, x_n)$

You might notice that Edwards uses π for the identity mapping whereas I use Id. His notation is quite reasonable given that the identity is the cartesian product of all the projection maps:

$$\pi = (\pi_1, \pi_2, \dots, \pi_n)$$

I've had courses where we simply used the coordinate notation itself for projections, in that notation have formulas such as x(a, b, c) = a, $x_i(a) = a_i$ and $x_i(e_i) = \delta_{ii}$.

Another way to modify a given function is to adjust the domain of a given mapping by restriction and extension.

Definition 1.2.8.

Let $f: U \subseteq \mathbb{R}^n \to V \subseteq \mathbb{R}^m$ be a mapping. If $R \subset U$ then we define the **restriction of** fto R to be the mapping $f|_R: R \to V$ where $f|_R(x) = f(x)$ for all $x \in R$. If $U \subseteq S$ and $V \subset T$ then we say a mapping $g: S \to T$ is an **extension of** f iff $g|_{dom(f)} = f$.

When I say $g|_{dom(f)} = f$ this means that these functions have matching domains and they agree at each point in that domain; $g|_{dom(f)}(x) = f(x)$ for all $x \in dom(f)$. Once a particular subset is chosen the restriction to that subset is a unique function. Of course there are usually many subsets of dom(f) so you can imagine many different restrictions of a given function. The concept of extension is more vague, once you pick the enlarged domain and codomain it is not even necessarily the case that another extension to that same pair of sets will be the same mapping. To obtain uniqueness

for extensions one needs to add more stucture. This is one reason that complex variables are interesting, there are cases where the structure of the complex theory forces the extension of a complex-valued function of a complex variable to be unique. This is very surprising. Similarly a linear transformation is uniquely defined by its values on a basis, it extends uniquely from that finite set of vectors to the infinite number of points in the vector space. This is very restrictive on the possible ways we can construct linear mappings. Maybe you can find some other examples of extensions as you collect your own mathematical storybook.

Definition 1.2.9.

Let $f: U \subseteq \mathbb{R}^n \to V \subseteq \mathbb{R}^m$ be a mapping, if there exists a mapping $g: f(U) \to U$ such that $f \circ g = Id_{f(U)}$ and $g \circ f = Id_U$ then g is the inverse mapping of f and we denote $g = f^{-1}$.

If a mapping is injective then it can be shown that the inverse mapping is well defined. We define $f^{-1}(y) = x$ iff f(x) = y and the value x must be a single value if the function is one-one. When a function is not one-one then there may be more than one point which maps to a particular point in the range.

Notice that the inverse image of a set is well-defined even if there is no inverse mapping. Moreover, it can be shown that the fibers of a mapping are disjoint and their union covers the domain of the mapping:

$$f(y) \neq f(z) \quad \Rightarrow \quad f^{-1}\{y\} \cap f^{-1}\{z\} = \emptyset \qquad \qquad \bigcup_{y \in range(f)} f^{-1}\{y\} = dom(f)$$

This means that the fibers of a mapping *partition* the domain.

Example 1.2.10. Consider $f(x, y) = x^2 + y^2$ this describes a mapping from \mathbb{R}^2 to \mathbb{R} . Observe that $f^{-1}\{R^2\} = \{x^2 + y^2 = R^2 \mid (x, y) \in \mathbb{R}^2\}$. In words, the nonempty fibers of f are concentric circles about the origin and the origin itself.

Technically, the emptyset is always a fiber. It is the fiber over points in the codomain which are not found in the range. In the example above, $f^{-1}(-\infty, 0) = \emptyset$.

Definition 1.2.11.

Let $f: U \subseteq \mathbb{R}^n \to V \subseteq \mathbb{R}^m$ be a mapping. A **cross section** of the fiber partition is a subset $S \subseteq U$ for which $S \cap f^{-1}\{v\}$ contains a single element for every $v \in f(U)$.

How do we construct a cross section for a particular mapping? For particular examples the details of the formula for the mapping usually suggests some obvious choice. However, in general if you accept the **axiom of choice** then you can be comforted in the existence of a cross section even in the case that there are infinitely many fibers for the mapping.

Example 1.2.12. An easy cross-section for $f(x, y) = x^2 + y^2$ is given by any ray eminating from the origin. Notice that, if $ab \neq 0$ then $S = \{t(a, b) \mid t \in [0, \infty)\}$ interects the *a* circle of radius $R^2 = t^2(a^2 + b^2)$ at the point (ta, tb)

Proposition 1.2.13.

Let $f: U \subseteq \mathbb{R}^n \to V \subseteq \mathbb{R}^m$ be a mapping. The restriction of f to a cross section S of U is an injective function. The mapping $\tilde{f}: U \to f(U)$ is a surjection. The mapping $\tilde{f}|_S: S \to f(U)$ is a bijection.

The proposition above tells us that we can take any mapping and cut down the domain and/or codomain to reduce the function to an injection, surjection or bijection. If you look for it you'll see this result behind the scenes in other courses. For example, in linear algebra if we throw out the kernel of a linear mapping then we get an injection. The idea of a local inverse is also important to the study of calculus.

Example 1.2.14. Continuing with our example, $f : \mathbb{R}^2 \to \mathbb{R}$ with $f(x, y) = x^2 + y^2$ is neither surjective or injective. However, just to make a choice, $S = \{(t, 0) \mid t \in [0, \infty)\}$ then clearly $\tilde{f}: S \to [0, \infty)$ defined by $\tilde{f}(x, y) = f(x, y)$ for all $(x, y) \in S$ is a bijection.

Definition 1.2.15.

Let $f: U \subseteq \mathbb{R}^n \to V \subseteq \mathbb{R}^m$ be a mapping then we say a mapping g is a **local inverse** of f iff there exits $S \subseteq U$ such that $g = (f|_S)^{-1}$.

Usually we can find local inverses for functions in calculus. For example, $f(x) = \sin(x)$ is not 1-1 therefore it is not invertible. However, it does have a local inverse $g(y) = \sin^{-1}(y)$. If we were more pedantic we wouldn't write $\sin^{-1}(y)$. Instead we would write $g(y) = \left(\sin \left|_{\left[-\frac{\pi}{2}, \frac{\pi}{2}\right]}\right)^{-1}(y)\right)$ since the inverse sine is actually just a local inverse. To construct a local inverse for some mapping we must locate some subset of the domain upon which the mapping is injective. Then relative to that subset we can reverse the mapping. The inverse mapping theorem (which we'll study mid-course) will tell us more about the existence of local inverses for a given mapping.

1.3 vectors and geometry for *n*-dimensional space

Definition 1.3.1.

Let $n \in \mathbb{N}$, we define $\mathbb{R}^n = \{(x_1, x_2, \ldots, x_n) \mid x_j \in \mathbb{R} \text{ for } j = 1, 2, \ldots, n\}$. If $v \in \mathbb{R}^n$ then we say v is an **n-vector**. The numbers in the vector are called the **components**; $v = (v_1, v_2, \ldots, v_n)$ has *j*-th component v_j .

Notice, a consequence of the definition above and the construction of the Cartesian product⁶ is that two vectors v and w are equal iff $v_j = w_j$ for all $j \in \mathbb{N}_n$. Equality of two vectors is only true if all components are found to match. It is therefore logical to define addition and scalar multiplication in terms of the components of vectors as follows:

⁶see my Math 200 notes or ask me if interested, it's not entirely trivial

Definition 1.3.2.

Define functions $+ : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}^n$ and $\cdot : \mathbb{R} \times \mathbb{R}^n \to \mathbb{R}^n$ by the following rules: for each $v, w \in \mathbb{R}^n$ and $c \in \mathbb{R}$:

(1.) $(v+w)_j = v_j + w_j$ (2.) $(cv)_j = cv_j$

for all $j \in \{1, 2, ..., n\}$. The operation + is called **vector addition** and it takes two vectors $v, w \in \mathbb{R}^n$ and produces another vector $v + w \in \mathbb{R}^n$. The operation \cdot is called **scalar multiplication** and it takes a number $c \in \mathbb{R}$ and a vector $v \in \mathbb{R}^n$ and produces another vector $c \cdot v \in \mathbb{R}^n$. Often we simply denote $c \cdot v$ by juxtaposition cv.

If you are a gifted at visualization then perhaps you can add three-dimensional vectors in your mind. If you're mind is really unhinged maybe you can even add 4 or 5 dimensional vectors. The beauty of the definition above is that we have no need of pictures. Instead, algebra will do just fine. That said, let's draw a few pictures.



Notice these pictures go to show how you can break-down vectors into component vectors which point in the direction of the coordinate axis. Vectors of length one which point in the coordinate directions make up what is called the **standard basis**⁷ It is convenient to define special notation for the standard basis. First I define a useful shorthand,

Definition 1.3.3.

The symbol
$$\delta_{ij} = \begin{cases} 1 & , i = j \\ 0 & , i \neq j \end{cases}$$
 is called the **Kronecker delta**.

For example, $\delta_{22} = 1$ while $\delta_{12} = 0$.

⁷the term "basis" is carefully developed in the linear algebra course. In a nutshell we need two things: (1.) the basis has to be big enough that we can add together the basis elements to make any thing in the set (2.) the basis is minimal so no single element in the basis can be formed by adding together other basis elements

Definition 1.3.4.

Let $e_i \in \mathbb{R}^{n \times 1}$ be defined by $(e_i)_j = \delta_{ij}$. The size of the vector e_i is determined by context. We call e_i the *i*-th standard basis vector.

Example 1.3.5. Let me expand on what I mean by "context" in the definition above: In \mathbb{R} we have $e_1 = (1) = 1$ (by convention we drop the brackets in this case) In \mathbb{R}^2 we have $e_1 = (1,0)$ and $e_2 = (0,1)$. In \mathbb{R}^3 we have $e_1 = (1,0,0)$ and $e_2 = (0,1,0)$ and $e_3 = (0,0,1)$. In \mathbb{R}^4 we have $e_1 = (1,0,0,0)$ and $e_2 = (0,1,0,0)$ and $e_3 = (0,0,1,0)$ and $e_4 = (0,0,0,1)$.

A real linear combination of $\{v_1, v_2, \dots, v_n\}$ is simply a finite weighted-sum of the objects from the set; $c_1v_1 + c_2v_2 + \cdots + c_kv_k$ where $c_1, c_2, \cdots + c_k \in \mathbb{R}$. If we take coefficients $c_1, c_2, \cdots + c_k \in \mathbb{C}$ then is is said to be a **complex linear combination**. I invite the reader to verify that every vector in \mathbb{R}^n is a linear combination of e_1, e_2, \ldots, e_n^8 . It is not difficult to prove the following properties for vector addition and scalar multiplication: for all $x, y, z \in \mathbb{R}^n$ and $a, b \in \mathbb{R}$,

(i.) x+y=y+x,	(<i>ii</i> .) $(x+y) + z = x + (y+z)$
(iii.) x + 0 = x,	(iv.) x - x = 0
(v.) 1x = x,	(vi.) (ab)x = a(bx),
$(vii.) \ a(x+y) = ax + ay,$	$(viii.) \ (a+b)x = ax + bx$
$(ix.) x+y \in \mathbb{R}^n$	$(x.) \ cx \in \mathbb{R}^n$

These properties of \mathbb{R}^n are abstracted in linear algebra to form the definition of an abstract **vector space**. Naturally \mathbb{R}^n is a vector space, in fact it is the quintessial model for all other vector spaces. Fortunately \mathbb{R}^n also has a dot-product. The dot-product is a mapping from $\mathbb{R}^n \times \mathbb{R}^n$ to \mathbb{R} . We take in a pair of vectors and output a real number.

Definition 1.3.6. Let $x, y \in \mathbb{R}^n$ we define $x \cdot y \in \mathbb{R}$ by

$$x \cdot y = x_1 y_1 + x_2 y_2 + \dots + x_n y_n.$$

Example 1.3.7. Let v = (1, 2, 3, 4, 5) and w = (6, 7, 8, 9, 10)

$$v \cdot w = 6 + 14 + 24 + 36 + 50 = 130$$

Example 1.3.8. Suppose we are given a vector $v \in \mathbb{R}^n$. We can select the *j*-th component by taking the dot-product of v with e_j . Observe that $e_i \cdot e_j = \delta_{ij}$ and consider,

$$v \cdot e_j = \left(\sum_{i=1}^n v_i e_i\right) \cdot e_j = \sum_{i=1}^n v_i e_i \cdot e_j = \sum_{i=1}^n v_i \delta_{ij} = v_1 \delta_{1j} + \dots + v_j \delta_{jj} + \dots + \delta_{nj} v_n = v_j.$$

The dot-product with e_i has given us the length of the vector v in the j-th direction.

⁸the calculation is given explicitly in my linear notes

The length or norm of a vector and the angle between two vectors are induced from the dot-product:

Definition 1.3.9.

The **length** or **norm** of $x \in \mathbb{R}^n$ is a real number which is defined by $||x|| = \sqrt{x \cdot x}$. Furthermore, let x, y be nonzero vectors in \mathbb{R}^n we define the **angle** θ between x and y by $\cos^{-1}\left[\frac{x \cdot y}{||x|| ||y||}\right]$. \mathbb{R} together with these definitions of length and angle forms a **Euclidean Geometry**.



Technically, before we make this definition we should make sure that the formulas given above even make sense. I have not shown that $x \cdot x$ is nonnegative and how do we know that argument of the inverse cosine is within its domain of [-1, 1]? I now state the propositions which justify the preceding definition.(proofs of the propositions below are found in my linear algebra notes)

Proposition 1.3.10.

Suppose $x, y, z \in \mathbb{R}^n$ and $c \in \mathbb{R}$ then 1. $x \cdot y = y \cdot x$ 2. $x \cdot (y + z) = x \cdot y + x \cdot z$ 3. $c(x \cdot y) = (cx) \cdot y = x \cdot (cy)$ 4. $x \cdot x \ge 0$ and $x \cdot x = 0$ iff x = 0

The formula $\cos^{-1}\left[\frac{x \cdot y}{||x|| \cdot ||y||}\right]$ is harder to justify. The inequality that we need for it to be reasonable is $\left|\frac{x \cdot y}{||x|| \cdot ||y||}\right| \leq 1$, otherwise we would not have a number in the $dom(\cos^{-1}) = range(\cos) = [-1, 1]$. An equivalent inequality is $|x \cdot y| \leq ||x|| \cdot ||y||$ which is known as the **Cauchy-Schwarz** inequality.

Proposition 1.3.11.

If $x, y \in \mathbb{R}^n$ then $|x \cdot y| \le ||x|| ||y||$

Example 1.3.12. Let $v = [1, 2, 3, 4, 5]^T$ and $w = [6, 7, 8, 9, 10]^T$ find the angle between these vectors and calculate the unit vectors in the same directions as v and w. Recall that, $v \cdot w = 6 + 14 + 24 + 36 + 50 = 130$. Furthermore,

$$||v|| = \sqrt{1^2 + 2^2 + 3^2 + 4^2 + 5^2} = \sqrt{1 + 4 + 9 + 16 + 25} = \sqrt{55}$$
$$||w|| = \sqrt{6^2 + 7^2 + 8^2 + 9^2 + 10^2} = \sqrt{36 + 49 + 64 + 81 + 100} = \sqrt{330}$$

We find unit vectors via the standard trick, you just take the given vector and multiply it by the reciprocal of its length. This is called **normalizing** the vector,

 $\hat{v} = \frac{1}{\sqrt{55}} [1, 2, 3, 4, 5]^T \qquad \hat{w} = \frac{1}{\sqrt{330}} [6, 7, 8, 9, 10]^T$

The angle is calculated from the definition of angle,

$$\theta = \cos^{-1} \left(\frac{130}{\sqrt{55}\sqrt{330}} \right) = 15.21^{\circ}$$

It's good we have this definition, 5-dimensional protractors are very expensive.

Proposition 1.3.13.

Let
$$x, y \in \mathbb{R}^n$$
 and suppose $c \in \mathbb{R}$ then
1. $||cx|| = |c| ||x||$
2. $||x + y|| \le ||x|| + ||y||$ (triangle inequality)
3. $||x|| \ge 0$
4. $||x|| = 0$ iff $x = 0$

The four properties above make \mathbb{R}^n paired with $|| \cdot || : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$ a normed linear space. We'll see how differentiation can be defined given this structure. It turns out that we can define a reasonable concept of differentiation for other normed linear spaces. In this course we'll study how to differentiate functions to and from \mathbb{R}^n , matrix-valued functions and complex-valued functions of a real variable. Finally, if time permits, we'll study differentiation of functions of functions which is the central task of **variational calculus**. In each case the underlying linear structure along with the norm is used to define the limits which are necessary to set-up the derivatives. The focus of this course is the process and use of derivatives and integrals so I have not given proofs of the linear algebraic propositions in this chapter. The proofs and a deeper view of the meaning of these propositions is given at length in Math 321. If you haven't had linear then you'll just have to trust me on these propositions⁹

⁹or you could just read the linear notes if curious

Definition 1.3.14.

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The distance between a \in \mathbb{R}^n and b \in \mathbb{R}^n is defined to be d(a, b) \equiv ||b - a||.
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If we draw a picture this definition is very natural. Here we are thinking of the points a, b as vectors from the origin then b - a is the vector which points from a to b (this is algebraically clear since a + (b - a) = b). Then the distance between the points is the length of the vector that points from one point to the other. If you plug in two dimensional vectors you should recognize the distance formula from middle school math:

$$d((a_1, a_2), (b_1, b_2)) = \sqrt{(b_1 - a_1)^2 + (b_2 - a_2)^2}$$

Proposition 1.3.15.

Let $d : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$ be the distance function then 1. d(x, y) = d(y, x)2. $d(x, y) \ge 0$ 3. d(x, x) = 0 iff x = 04. $d(x, y) + d(y, z) \ge d(x, z)$

In real analysis one studies a set paired with a distance function. Abstractly speaking such a pair is called a **metric space**. A vector space with a norm is called a normed linear space. Because we can always induce a distance function from the norm via the formula d(a,b) = ||b-a|| every normed linear space is a metric space. The converse fails. Metric spaces need not be vector spaces, a metric space could just be formed from some subset of a vector space or something more exotic¹⁰. The absolute value function on \mathbb{R} defines distance function d(a,b) = |b-a|. In your real analysis course you will study the structure of the metric space ($\mathbb{R}, |\cdot| : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$) in great depth. I include these comments here to draw your attention to the connection between this course and the real analysis course. I primarily use the norm in what follows, but it should be noted that many things could be written in terms of the distance function.

1.3.1 vector algebra for three dimensions

Every nonzero vector can be written as a unit vector scalar multiplied by its magnitude.

 $v \in V^n$ such that $v \neq 0 \Rightarrow v = ||v||\hat{v}$ where $\hat{v} = \frac{1}{||v||}v$.

You should recall that we can write any vector in V^3 as

$$v = < a, b, c > = a < 1, 0, 0 > +b < 0, 1, 0 > +c < 0, 0, 1 > = a\hat{i} + b\hat{j} + c\hat{k}$$

 $^{^{10}}$ there are many texts to read on metric spaces, one nice treatment is Rosenlicht's *Introduction to Analysis*, it's a good read

where we defined the $\hat{i} = \langle 1, 0, 0 \rangle$, $\hat{j} = \langle 0, 1, 0 \rangle$, $\hat{k} = \langle 0, 0, 1 \rangle$. You can easily verify that distinct Cartesian unit-vectors are orthogonal. Sometimes we need to produce a vector which is orthogonal to a given pair of vectors, it turns out the cross-product is one of two ways to do that in V^3 . We will see much later that this is special to three dimensions.

Definition 1.3.16.

If $A = \langle A_1, A_2, A_3 \rangle$ and $B = \langle B_1, B_2, B_3 \rangle$ are vectors in V^3 then the **cross-product** of A and B is a **vector** $A \times B$ which is defined by:

$$\vec{A} \times \vec{B} = \langle A_2 B_3 - A_3 B_2, A_3 B_1 - A_1 B_3, A_1 B_2 - A_2 B_1 \rangle.$$

The magnitude of $\vec{A} \times \vec{B}$ can be shown to satisfy $||\vec{A} \times \vec{B}|| = ||\vec{A}|| ||\vec{B}|| \sin(\theta)$ and the direction can be deduced by **right-hand-rule**. The right hand rule for the unit vectors yields:

$$\hat{i} \times \hat{j} = \hat{k}, \quad \hat{k} \times \hat{i} = \hat{j}, \quad \hat{j} \times \hat{k} = \hat{i}$$

If I wish to discuss both the point and the vector to which it corresponds we may use the notation

$$P = (a_1, a_2, \dots, a_n) \iff \vec{P} = \langle a_1, a_2, \dots, a_n \rangle$$

With this notation we can easily define directed line-segments as the vector which points from one point to another, also the distance between points is simply the length of the vector which points from one point to the other:

Definition 1.3.17.

Let $P, Q \in \mathbb{R}^n$. The directed line segment from P to Q is $\overrightarrow{PQ} = \overrightarrow{Q} - \overrightarrow{P}$. This vector is drawn from tail Q to the tip P where we denote the direction by drawing an arrowhead. The **distance between** P and Q is $d(P,Q) = ||\overrightarrow{PQ}||$.

1.3.2 compact notations for vector arithmetic

I prefer the following notations over the hat-notation of the preceding section because this notation generalizes nicely to n-dimensions.

$$e_1 = <1, 0, 0>$$
 $e_2 = <0, 1, 0>$ $e_3 = <0, 0, 1>.$

Likewise the Kronecker delta and the Levi-Civita symbol are at times very convenient for abstract calculation:

$$\delta_{ij} = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} \quad \epsilon_{ijk} = \begin{cases} 1 & (i, j, k) \in \{(1, 2, 3), (3, 1, 2), (2, 3, 1)\} \\ -1 & (i, j, k) \in \{(3, 2, 1), (2, 1, 3), (1, 3, 2)\} \\ 0 & \text{if any index repeats} \end{cases}$$

An equivalent definition for the Levi-Civita symbol is simply that $\epsilon_{123} = 1$ and it is antisymmetric with respect to the interchange of any pair of indices;

$$\epsilon_{ijk} = \epsilon_{jki} = \epsilon_{kij} = -\epsilon_{kji} = -\epsilon_{ikj}.$$

Now let us restate some earlier results in terms of the Einstein repeated index conventions¹¹, let $\vec{A}, \vec{B} \in V^n$ and $c \in \mathbb{R}$ then

$\vec{A} = A_k e_k$	standard basis expansion
$e_i \cdot e_j = \delta_{ij}$	orthonormal basis
$(\vec{A} + \vec{B})_i = \vec{A}_i + \vec{B}_i$	vector addition
$(\vec{A} - \vec{B})_i = \vec{A}_i - \vec{B}_i$	vector subtraction
$(c\vec{A})_i = c\vec{A}_i$	scalar multiplication
$\vec{A} \cdot \vec{B} = A_k B_k$	dot product
$(\vec{A} \times \vec{B})_k = \epsilon_{ijk} A_i B_j$	cross product.

All but the last of the above are readily generalized to dimensions other than three by simply increasing the number of components. However, the cross product is special to three dimensions. I can't emphasize enough that the formulas given above for the dot and cross products can be utilized to yield great efficiency in abstract calculations.

Example 1.3.18. To prove the linearity of the cross-product in the second argument:

$$(\vec{A} \times (\vec{B} + \vec{C}))_k = \epsilon_{ijk} A_i (\vec{B} + \vec{C})_j$$

= $\epsilon_{ijk} A_i (B_j + C_j)$
= $\epsilon_{ijk} A_i B_j + \epsilon_{ijk} A_i C_j$
= $(\vec{A} \times \vec{B})_k + (\vec{A} \times \vec{C})_k$.

If you look at my grad, curl and div section in Chapter 7 of my Calculus III notes you'll see how this notation allows very elegant proofs of the basic identities of differential vector calculus.

¹¹I don't use the Einstein convention generally until the end of these notes, if in doubt, ask.

Chapter 2

linear algebra

Our goal in the first section of this chapter is to gain conceptual clarity on the meaning of the central terms from linear algebra. This is a birds-eye view of linear, my selection of topics here is centered around the goal of helping you to see the linear algebra in calculus. Once you see it then you can use the theory of linear algebra to help organize your thinking. Our ultimate goal is that organizational principle. Our goal here is not to learn all of linear algebra, rather we wish to use it as a tool for the right jobs as they arise this semester.

In the second section we summarize the tools of matrix computation. We will use matrix addition, multiplication and throughout this course. Inverse matrices and the noncommutive nature of matrix multiplication are illustrated. It is assumed that the reader has some previous experience in matrix computation, at least in highschool you should have spent some time.

In the third section the concept of a linear transformation is formalized. The formula for any linear transformation from \mathbb{R}^m to \mathbb{R}^m can be expressed as a matrix multiplication. We study this standard matrix in enough depth as to understand it's application in for differentiation. A number of examples to visualize the role of a linear transformation are offered for breadth. Finally, isomorphisms and coordinate maps are discussed.

In the fourth section we define norms for vector spaces. We study how the norm allows us to define limits for an abstract vector space. This is important since it allows us to quantify continuity for abstract linear transformations as well as ultimately to define differentiation on a normed vector space in the chapter that follows.

One important thing to remember, we do not typically use notation to denote domain. Sometimes x is a vector. Sometimes x is the first coordinate function. Therefore, if we just say "x" then it is ambiguous. We must state domains and context to engage in meaningful math here. Notation which encodes domain is convenient, but our interests are too varied to allow such abbreviated language.

2.1 vector spaces

Suppose we have a set V paired with an addition and scalar multiplication such that for all $x, y, z \in V$ and $a, b, c \in \mathbb{R}$:

then we say that V is a **vector space** over \mathbb{R} . To be a bit more precise, by (iii.) I mean to say that there exist some element $0 \in V$ such that x + 0 = x for each $x \in V$. Also, (iv.) should be understood to say that for each $x \in V$ there exists another element $-x \in V$ such that x + (-x) = 0.

Example 2.1.1. \mathbb{R}^n is a vector space with respect to the standard vector addition and scalar multiplication.

Example 2.1.2. $\mathbb{C} = \{a+ib \mid a, b \in \mathbb{R}\}$ is a vector space where the usual complex number addition provides the vector addition and multiplication by a real number c(a+ib) = ca+i(cb) clearly defines a scalar multiplication.

Example 2.1.3. The set of all $m \times n$ matrices is a vector space with respect to the usual matrix addition and scalar multiplication. We will elaborate on the details in an upcoming section.

Example 2.1.4. Suppose \mathcal{F} is the set of all functions from a set S to a vector space V then \mathcal{F} is naturally a vector space with respect to the function addition and multiplication by a scalar. Both of those operations are well-defined on the values of the function since we assumed the codomain of each function in \mathcal{F} is the vector space V.

There are many subspaces of function space which provide interesting examples of vector spaces. For example, the set of continuous functions:

Example 2.1.5. Let $C^0(\mathbb{R}^n, \mathbb{R}^m)$ be a set of continuous functions from \mathbb{R}^n to \mathbb{R}^m then $C^0(\mathbb{R}^n, \mathbb{R}^m)$ is a vector space with respect to function addition and the usual multiplication. This fact relies on the sum and scalar multiple of continuous functions is once more continuous.

Definition 2.1.6.

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We say a subset S of a vector space V is linearly independent (LI) iff for scalars c_1, c_2, \ldots, c_k,

c_1v_1 + c_2v_2 + \cdots + c_kv_k = 0 \implies c_1 = c_2 = \cdots = 0

for each finite subset \{v_1, v_2, \ldots, v_k\} of S.
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In the case that S is finite it suffices to show the implication for a linear combination of all the vectors in the set. Notice that if any vector in the set S can be written as a linear combination of the other vectors in S then that makes S fail the test for linear independence. Moreover, if a set S is not linearly independent then we say S is **linearly dependent**.

Example 2.1.7. The standard basis of \mathbb{R}^n is denoted $\{e_1, e_2, \ldots, e_n\}$. We can show linear independence easily via the dot-product: suppose that $c_1e_1 + c_2e_2 + \cdots + c_ne_n = 0$ and take the dot-product of both sides with e_i to obtain

 $(c_1e_1 + c_2e_2 + \dots + c_ne_n) \cdot e_j = 0 \cdot e_j \quad \Rightarrow \quad (c_1e_1 \cdot e_j + c_2e_2 \cdot e_j + \dots + c_ne_n \cdot e_j = 0 \quad \Rightarrow \quad c_j(1) = 0$

but, j was arbitrary hence it follows that $c_1 = c_2 = \cdots = c_n = 0$ which establishes the linear independence of the standard basis.

Example 2.1.8. Consider $S = \{1, i\} \subset \mathbb{C}$. We can argue S is LI as follows: suppose $c_1(1)+c_2(i) = 0$. Thus $c_1+ic_2 = 0$ for some real numbers c_1, c_2 . Recall that a basic property of complex numbers is that if $z_1 = z_2$ then $Re(z_1) = Re(z_2)$ and $Im(z_1) = Im(z_2)$ where $z_j = Re(z_j)+iIm(z_j)$. Therefore, the complex equation $c_1 + ic_2 = 0$ yields two real equations $c_1 = 0$ and $c_2 = 0$.

Example 2.1.9. Let $C^0(\mathbb{R})$ be the vector space of all continuous functions from \mathbb{R} to \mathbb{R} . Suppose S is the set of monic¹ monomials $S = \{1, t, t^2, t^3, \ldots\}$. This is an infinite set. We can argue LI as follows: suppose $c_1t^{p_1} + c_2t^{p_2} + \cdots + c_kt^{p_k} = 0$. For convenience relable the powers p_1, p_2, \ldots, p_k by $p_{i_1}, p_{i_2}, \ldots, p_{i_k}$ such that $1 < p_{i_1} < p_{i_2} < \cdots < p_{i_k}$. This notation just shuffles the terms in the finite sum around so that the first term has the lowest order: consider

$$c_{i_1}t_{i_1}^p + c_{i_1}t_{i_2}^p + \dots + c_{i_k}t_{i_k}^p = 0$$
 *

If $p_{i_1} = 0$ then evaluate \star at t = 0 to obtain $c_{i_1} = 0$. If $p_{i_1} > 0$ then differentiate $\star p_{i_1}$ times and denote this new equation by $D^{p_{i_1}}\star$. Evaluate $D^{p_{i_1}}\star$ at t = 0 to find

$$p_{i_1}(p_{i_1}-1)\cdots 3\cdot 2\cdot 1c_{i_1}=0$$

hence $c_{i_1} = 0$. Since we set-up $p_{i_1} < p_{i_2}$ it follows that after p_{i_1} -differentiations the second summand is still nontrivial in $D^{p_{i_1}} \star$. However, we can continue differentiating \star until we reach $D^{p_{i_2}} \star$ and then constant term is $p_{i_2}!c_{i_2}$ so evaluation will show $c_{i_2} = 0$. We continue in this fashion until we have shown that $c_{i_j} = 0$ for j = 1, 2, ..., k. It follows that S is a linearly independent set.

We spend considerable effort in linear algebra to understand LI from as many angles as possible. One equivalent formulation of LI is the ability to equate coefficients. In other words, a set of objects is LI iff whenever we have an equation with thos objects we can equate coefficients. In calculus when we equate coefficients we implicitly assume that the functions in question are LI. Generally speaking two functions are LI if their graphs have distinct shapes which cannot be related by a simple vertical stretch.

Example 2.1.10. Consider $S = \{2^t, 3(1/2)^{-t}\}$ as a subset the vector space $C^0(\mathbb{R})$. To show linear dependence we observe that $c_12^t + c_23(1/2)^{-t} = 0$ yields $(c_1 + 3c_2)2^t = 0$. Hence $c_1 + 3c_2 = 0$ which means nontrivial solutions exist. Take $c_2 = 1$ then $c_1 = -3$. Of course the heart of the matter is that $3(1/2)^{-t} = 3(2^t)$ so the second function is just a scalar multiple of the first function.

¹monic means that the leading coefficient is 1.

If you've taken differential equations then you should recognize the concept of LI from your study of solution sets to differential equations. Given an n-th order linear differential equation we always have a goal of calculating n-LI solutions. In that context LI is important because it helps us make sure we do not count the same solution twice. The general solution is formed from a linear combination of the LI solution set. Of course this is not a course in differential equations, I include this comment to make connections to the other course. One last example on LI should suffice to make certain you at least have a good idea of the concept:

Example 2.1.11. Consider \mathbb{R}^3 as a vector space and consider the set $S = \{\vec{v}, \hat{\mathbf{i}}, \hat{\mathbf{j}}, \hat{\mathbf{k}}\}$ where we could also denote $\hat{\mathbf{i}} = e_1, \hat{\mathbf{j}} = e_2, \hat{\mathbf{k}} = e_3$ but I'm aiming to make your mind connect with your calculus III background. This set is clearly linearly dependent since we can write any vector \vec{v} as a linear combination of the standard unit-vectors: moreover, we can use dot-products to select the x, y and z components as follows:

$$\vec{v} = (\vec{v} \cdot \hat{\mathbf{i}})\hat{\mathbf{i}} + (\vec{v} \cdot \hat{\mathbf{j}})\hat{\mathbf{j}} + (\vec{v} \cdot \hat{\mathbf{k}})\hat{\mathbf{k}}$$

Linear independence helps us quantify a type of redundancy for vectors in a given set. The next definition is equally important and it is sort of the other side of the coin; spanning is a criteria which helps us insure a set of vectors will cover a vector space without missing anything.

Definition 2.1.12.

We say a subset S of a vector space V is a **spanning set** for V iff for each $v \in V$ there exist scalars c_1, c_2, \ldots, c_k and vectors $v_1, v_2, \ldots, v_k \in V$ such that $v = c_1v_1 + c_2v_2 + \cdots + c_kv_k$. We denote $Span\{v_1, v_2, \ldots, v_k\} = \{c_1v_1 + c_2v_2 + \cdots + c_kv_k \mid c_1, c_2, \ldots, c_k \in \mathbb{R}\}.$

If $S \subset V$ and V is a vector space then it is immediately obvious that $Span(S) \subseteq V$. If S is a spanning set then it is obvious that $V \subseteq Span(S)$. It follows that when S is a spanning set for V we have Span(S) = V.

Example 2.1.13. It is easy to show that if $v \in \mathbb{R}^n$ then $v = v_1e_1 + v_2e_2 + \cdots + v_ne_n$. It follows that $\mathbb{R}^n = Span\{e_i\}_{i=1}^n$.

Example 2.1.14. Let $1, i \in \mathbb{C}$ where $i^2 = -1$. Clearly $\mathbb{C} = Span\{1, i\}$.

Example 2.1.15. Let P be the set of polynomials. Since the sum of any two polynomials and the scalar multiple of any polynomial is once more a polynomial we find P is a vector space with respect to function addition and multiplication of a function by a scalar. We can argue that the set of monic monomials $\{1, t, t^2, ...\}$ a spanning set for P. Why? Because if $f(t) \in P$ then that means there are scalars $a_0, a_1, ..., a_n$ such that $f(x) = a_0 + a_1t + a_2t^2 + \cdots + a_nt^n$

Definition 2.1.16.

We say a subset β of a vector space V is a **basis** for V iff β is a linearly independent spanning set for V. If β is a finite set then V is said to be finite dimensional and the number of vectors in β is called the **dimension** of V. That is, if $\beta = \{v_1, v_2, \ldots, v_n\}$ is a basis for V then dim(V) = n. If no finite basis exists for V then V is said to be **infinite dimensional**. The careful reader will question why this concept of dimension is well-defined. Why can we not have bases of differing dimension for a given vector space? I leave this question for linear algebra, the theorem which asserts the uniqueness of dimension is one of the deeper theorems in the course. However, like most everything in linear, at some level it just boils down to solving some particular set of equations. You might tell Dr. Sprano it's just algebra. In any event, it is common practice to use the term **dimension** in courses where linear algebra is not understood. For example, \mathbb{R}^2 is a two-dimensional space. Or we'll say that \mathbb{R}^3 is a three-dimensional space. This terminology agrees with the general observation of the next example.

Example 2.1.17. The standard basis $\{e_i\}_{i=1}^n$ for \mathbb{R}^n is a basis for \mathbb{R}^n and $dim(\mathbb{R}^n) = n$. This result holds for all $n \in \mathbb{N}$. The line is one-dimensional, the plane is two-dimensional, three-space is three-dimensional etc...

Example 2.1.18. The set $\{1, i\}$ is a basis for \mathbb{C} . It follows that $\dim(\mathbb{C}) = 2$. We say that the complex numbers form a two-dimensional real vector space.

Example 2.1.19. The set of polynomials is clearly infinite dimensional. Contradiction shows this without much effort. Suppose P had a finite basis β . Choose the polynomial of largest degree (say k) in β . Notice that $f(t) = t^{k+1}$ is a polynomial and yet clearly $f(t) \notin \text{Span}(\beta)$ hence β is not a spanning set. But this contradicts the assumption β is a basis. Hence, by contradiction, no finite basis exists and we conclude the set of polynomials is infinite dimensional.

There is a more general use of the term **dimension** which is beyond the context of linear algebra. For example, in calculus II or III you may have heard that a circle is one-dimensional or a surface is two-dimensional. Well, circles and surfaces are not usually vector spaces so the terminology is not taken from linear algebra. In fact, that use of the term dimension stems from manifold theory. I hope to discuss manifolds later in this course.

2.2 matrix calculation

An $m \times n$ matrix is an array of numbers with *m*-rows and *n*-columns. We define $\mathbb{R}^{m \times n}$ to be the set of all $m \times n$ matrices. The set of all *n*-dimensional column vectors is $\mathbb{R}^{n \times 1} = \mathbb{R}^{n^2}$. The set of all *n*-dimensional row vectors is $\mathbb{R}^{1 \times n}$. A given matrix $A \in \mathbb{R}^{m \times n}$ has *mn*-components A_{ij} . Notice that the components are numbers; $A_{ij} \in \mathbb{R}$ for all i, j such that $1 \leq i \leq m$ and $1 \leq j \leq n$. We should not write $A = A_{ij}$ because it is nonesense, however $A = [A_{ij}]$ is quite fine.

Suppose $A \in \mathbb{R}^{m \times n}$, note for $1 \leq j \leq n$ we have $col_j(A) \in \mathbb{R}^{m \times 1}$ whereas for $1 \leq i \leq m$ we find $row_i(A) \in \mathbb{R}^{1 \times n}$. In other words, an $m \times n$ matrix has n columns of length m and n rows of length m.

²We will use the convention that points in \mathbb{R}^n are column vectors. However, we will use the somewhat subtle notation $(x_1, x_2, \ldots, x_n) = [x_1, x_2, \ldots, x_n]^T$. This helps me write \mathbb{R}^n rather than $\mathbb{R}^{n \times 1}$ and I don't have to pepper transposes all over the place. If you've read my linear algebra notes you'll appreciate the wisdom of our convention.

Two matrices A and B are equal iff $A_{ij} = B_{ij}$ for all i, j. Given matrices A, B with components A_{ij}, B_{ij} and constant $c \in \mathbb{R}$ we define

$$(A+B)_{ij} = A_{ij} + B_{ij} \qquad (cA)_{ij} = cA_{ij} \qquad , \text{ for all } i, j.$$

The **zero matrix** in $\mathbb{R}^{m \times n}$ is denoted 0 and defined by $0_{ij} = 0$ for all i, j. The additive inverse of $A \in \mathbb{R}^{m \times n}$ is the matrix -A such that A + (-A) = 0. The components of the additive inverse matrix are given by $(-A)_{ij} = -A_{ij}$ for all i, j. Likewise, if $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times p}$ then the product $AB \in \mathbb{R}^{m \times p}$ is defined by³:

$$(AB)_{ij} = \sum_{k=1}^{n} A_{ik} B_{kj}$$

for each $1 \leq i \leq m$ and $1 \leq j \leq p$. In the case m = p = 1 the indices i, j are omitted in the equation since the matrix product is simply a number which needs no index. The identity matrix in $\mathbb{R}^{n \times n}$ is the $n \times n$ square matrix I whose components are the Kronecker delta; $I_{ij} = \delta_{ij} = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases}$. The notation I_n is sometimes used. For example, $I_2 = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$. If the size of the identity matrix needs emphasis otherwise the size of the matrix I is to be understood from the context.

Let $A \in \mathbb{R}^{n \times n}$. If there exists $B \in \mathbb{R}^{n \times n}$ such that AB = I and BA = I then we say that A is **invertible** and $A^{-1} = B$. Invertible matrices are also called **nonsingular**. If a matrix has no inverse then it is called a **noninvertible** or **singular** matrix.

Let $A \in \mathbb{R}^{m \times n}$ then $A^T \in \mathbb{R}^{n \times m}$ is called the **transpose** of A and is defined by $(A^T)_{ji} = A_{ij}$ for all $1 \leq i \leq m$ and $1 \leq j \leq n$. It is sometimes useful to know that $(AB)^T = B^T A^T$ and $(A^T)^{-1} = (A^{-1})^T$. It is also true that $(AB)^{-1} = B^{-1}A^{-1}$. Furthermore, note **dot-product** of $v, w \in V^n$ is given by $v \cdot w = v^T w$.

The *ij*-th standard basis matrix for $\mathbb{R}^{m \times n}$ is denoted E_{ij} for $1 \leq i \leq m$ and $1 \leq j \leq n$. The matrix E_{ij} is zero in all entries except for the (i, j)-th slot where it has a 1. In other words, we define $(E_{ij})_{kl} = \delta_{ik}\delta_{jl}$. I invite the reader to show that the term basis is justified in this context⁴. Given this basis we see that the vector space $\mathbb{R}^{m \times n}$ has $dim(\mathbb{R}^{m \times n}) = mn$.

 $^{^{3}}$ this product is defined so the matrix of the composite of a linear transformation is the product of the matrices of the composed transformations. This is illustrated later in this section and is proved in my linear algebra notes.

⁴the theorem stated below contains the needed results and then some, you can find the proof is given in my linear algebra notes. It would be wise to just work it out in the 2×2 case as a warm-up if you are interested

Theorem 2.2.1.

If
$$A \in \mathbb{R}^{m \times n}$$
 and $v \in \mathbb{R}$ then
(*i*.) $v = \sum_{i=1}^{n} v_n e_n$ (*ii*.) $A = \sum_{i=1}^{m} \sum_{j=1}^{n} A_{ij} E_{ij}$
(*iii*.) $[e_i^T A] = row_i(A)$ (*iv*.) $[Ae_i] = col_i(A)$
(*v*.) $E_{ij}E_{kl} = \delta_{jk}E_{il}$ (*vi*.) $E_{ij} = e_i e_j^T$ (*vii*.) $e_i^T e_j = e_i \cdot e_j = \delta_{ij}$.

You can look in my linear algebra notes for the details of the theorem. I'll just expand one point here: Let $A \in \mathbb{R}^{m \times n}$ then

$$A = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{mn} \end{bmatrix}$$
$$= A_{11} \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & 0 \\ 0 & 0 & \cdots & 0 \end{bmatrix} + A_{12} \begin{bmatrix} 0 & 1 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & 0 \\ 0 & 0 & \cdots & 0 \end{bmatrix} + \cdots + A_{mn} \begin{bmatrix} 0 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \cdots & 0 \\ 0 & 0 & \cdots & 1 \end{bmatrix}$$
$$= A_{11} E_{11} + A_{12} E_{12} + \cdots + A_{mn} E_{mn}.$$

The calculation above follows from repeated mn-applications of the definition of matrix addition and another mn-applications of the definition of scalar multiplication of a matrix.

Example 2.2.2. Suppose $A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}$. We see that A has 2 rows and 3 columns thus $A \in \mathbb{R}^{2 \times 3}$. Moreover, $A_{11} = 1$, $A_{12} = 2$, $A_{13} = 3$, $A_{21} = 4$, $A_{22} = 5$, and $A_{23} = 6$. It's not usually possible to find a formula for a generic element in the matrix, but this matrix satisfies $A_{ij} = 3(i-1) + j$ for all i, j^5 . The columns of A are,

$$col_1(A) = \begin{bmatrix} 1\\4 \end{bmatrix}$$
, $col_2(A) = \begin{bmatrix} 2\\5 \end{bmatrix}$, $col_3(A) = \begin{bmatrix} 3\\6 \end{bmatrix}$.

The rows of A are

 $row_1(A) = \begin{bmatrix} 1 & 2 & 3 \end{bmatrix}$, $row_2(A) = \begin{bmatrix} 4 & 5 & 6 \end{bmatrix}$

⁵In the statement "for all i, j" it is to be understood that those indices range over their allowed values. In the preceding example $1 \le i \le 2$ and $1 \le j \le 3$.

Example 2.2.3. Suppose $A = \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}$ then $A^T = \begin{bmatrix} 1 & 4 \\ 2 & 5 \\ 3 & 6 \end{bmatrix}$. Notice that

$$row_1(A) = col_1(A^T), \ row_2(A) = col_2(A^T)$$

and

$$col_1(A) = row_1(A^T), \ col_2(A) = row_2(A^T), \ col_3(A) = row_3(A^T)$$

Notice $(A^T)_{ij} = A_{ji} = 3(j-1) + i$ for all i, j; at the level of index calculations we just switch the indices to create the transpose.

Example 2.2.4. Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ and $B = \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix}$. We calculate

$$A + B = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} + \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix} = \begin{bmatrix} 6 & 8 \\ 10 & 12 \end{bmatrix}$$

Example 2.2.5. Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ and $B = \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix}$. We calculate

$$A - B = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} - \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix} = \begin{bmatrix} -4 & -4 \\ -4 & -4 \end{bmatrix}.$$

Now multiply A by the scalar 5,

$$5A = 5\begin{bmatrix} 1 & 2\\ 3 & 4 \end{bmatrix} = \begin{bmatrix} 5 & 10\\ 15 & 20 \end{bmatrix}$$

Example 2.2.6. Let $A, B \in \mathbb{R}^{m \times n}$ be defined by $A_{ij} = 3i + 5j$ and $B_{ij} = i^2$ for all i, j. Then we can calculate $(A + B)_{ij} = 3i + 5j + i^2$ for all i, j.

Example 2.2.7. Solve the following matrix equation,

$$0 = \begin{bmatrix} x & y \\ z & w \end{bmatrix} + \begin{bmatrix} -1 & -2 \\ -3 & -4 \end{bmatrix} \implies \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} x-1 & y-2 \\ z-3 & w-4 \end{bmatrix}$$

The definition of matrix equality means this single matrix equation reduces to 4 scalar equations: 0 = x - 1, 0 = y - 2, 0 = z - 3, 0 = w - 4. The solution is x = 1, y = 2, z = 3, w = 4.

The definition of matrix multiplication $((AB)_{ij} = \sum_{k=1}^{n} A_{ik}B_{kj})$ is very nice for general proofs, but pragmatically I usually think of matrix multiplication in terms of *dot-products*. It turns out we can view the matrix product as a collection of dot-products: suppose $A \in \mathbb{R}^{m \times n}$ and $B \in \mathbb{R}^{n \times p}$ then

$$AB = \begin{bmatrix} row_1(A) \cdot col_1(B) & row_1(A) \cdot col_2(B) & \cdots & row_1(A) \cdot col_p(B) \\ row_2(A) \cdot col_1(B) & row_2(A) \cdot col_2(B) & \cdots & row_2(A) \cdot col_p(B) \\ \vdots & \vdots & \ddots & \vdots \\ row_m(A) \cdot col_1(B) & row_m(A) \cdot col_2(B) & \cdots & row_m(A) \cdot col_p(B) \end{bmatrix}$$

Let me explain how this works. The formula above claims $(AB)_{ij} = row_i(A) \cdot col_j(B)$ for all i, j. Recall that $(row_i(A))_k = A_{ik}$ and $(col_j(B))_k = B_{kj}$ thus

$$(AB)_{ij} = \sum_{k=1}^{n} A_{ik} B_{kj} = \sum_{k=1}^{n} (row_i(A))_k (col_j(B))_k$$

Hence, using definition of the dot-product, $(AB)_{ij} = row_i(A) \cdot col_j(B)$. This argument holds for all i, j therefore the dot-product formula for matrix multiplication is valid.

Example 2.2.8. The product of a 3×2 and 2×3 is a 3×3

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix} = \begin{bmatrix} [1,0][4,7]^T & [1,0][5,8]^T & [1,0][6,9]^T \\ [0,1][4,7]^T & [0,1][5,8]^T & [0,1][6,9]^T \\ [0,0][4,7]^T & [0,0][5,8]^T & [0,0][6,9]^T \end{bmatrix} = \begin{bmatrix} 4 & 5 & 6 \\ 7 & 8 & 9 \\ 0 & 0 & 0 \end{bmatrix}$$

Example 2.2.9. The product of a 3×1 and 1×3 is a 3×3

$$\begin{bmatrix} 1\\2\\3 \end{bmatrix} \begin{bmatrix} 4 & 5 & 6 \end{bmatrix} = \begin{bmatrix} 4 \cdot 1 & 5 \cdot 1 & 6 \cdot 1\\4 \cdot 2 & 5 \cdot 2 & 6 \cdot 2\\4 \cdot 3 & 5 \cdot 3 & 6 \cdot 3 \end{bmatrix} = \begin{bmatrix} 4 & 5 & 6\\8 & 10 & 12\\12 & 15 & 18 \end{bmatrix}$$

Example 2.2.10. Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$ and $B = \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix}$. We calculate

$$AB = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix}$$
$$= \begin{bmatrix} [1,2][5,7]^T & [1,2][6,8]^T \\ [3,4][5,7]^T & [3,4][6,8]^T \end{bmatrix}$$
$$= \begin{bmatrix} 5+14 & 6+16 \\ 15+28 & 18+32 \end{bmatrix}$$
$$= \begin{bmatrix} 19 & 22 \\ 43 & 50 \end{bmatrix}$$

Notice the product of square matrices is square. For numbers $a, b \in \mathbb{R}$ it we know the product of a

and b is commutative (ab = ba). Let's calculate the product of A and B in the opposite order,

$$BA = \begin{bmatrix} 5 & 6 \\ 7 & 8 \end{bmatrix} \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$$
$$= \begin{bmatrix} [5,6][1,3]^T & [5,6][2,4]^T \\ [7,8][1,3]^T & [7,8][2,4]^T \end{bmatrix}$$
$$= \begin{bmatrix} 5+18 & 10+24 \\ 7+24 & 14+32 \end{bmatrix}$$
$$= \begin{bmatrix} 23 & 34 \\ 31 & 46 \end{bmatrix}$$

Clearly $AB \neq BA$ thus matrix multiplication is noncommutative or nonabelian.

When we say that matrix multiplication is noncommutive that indicates that the product of two matrices does not *generally* commute. However, there are special matrices which commute with other matrices.

Example 2.2.11. Let $I = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ and $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$. We calculate

$$IA = \left[\begin{array}{cc} 1 & 0 \\ 0 & 1 \end{array} \right] \left[\begin{array}{cc} a & b \\ c & d \end{array} \right] = \left[\begin{array}{cc} a & b \\ c & d \end{array} \right]$$

Likewise calculate,

$$AI = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

Since the matrix A was arbitrary we conclude that IA = AI for all $A \in \mathbb{R}^{2 \times 2}$.

Example 2.2.12. Consider A, v, w from Example ??.

$$v + w = \begin{bmatrix} 5\\7 \end{bmatrix} + \begin{bmatrix} 6\\8 \end{bmatrix} = \begin{bmatrix} 11\\15 \end{bmatrix}$$

Using the above we calculate,

$$A(v+w) = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} 11 \\ 15 \end{bmatrix} = \begin{bmatrix} 11+30 \\ 33+60 \end{bmatrix} = \begin{bmatrix} 41 \\ 93 \end{bmatrix}.$$

In constrast, we can add Av and Aw,

$$Av + Aw = \begin{bmatrix} 19\\43 \end{bmatrix} + \begin{bmatrix} 22\\50 \end{bmatrix} = \begin{bmatrix} 41\\93 \end{bmatrix}.$$

Behold, A(v+w) = Av + Aw for this example. It turns out this is true in general.

I collect all my favorite properties for matrix multiplication in the theorem below. To summarize, matrix math works as you would expect with the exception that matrix multiplication is not commutative. We must be careful about the order of letters in matrix expressions.
Theorem 2.2.13.

If $A, B, C \in \mathbb{R}^{m \times n}$, $X, Y \in \mathbb{R}^{n \times p}$, $Z \in \mathbb{R}^{p \times q}$ and $c_1, c_2 \in \mathbb{R}$ then 1. (A + B) + C = A + (B + C), 2. (AX)Z = A(XZ), 3. A + B = B + A, 4. $c_1(A + B) = c_1A + c_2B$, 5. $(c_1 + c_2)A = c_1A + c_2A$, 6. $(c_1c_2)A = c_1(c_2A)$, 7. $(c_1A)X = c_1(AX) = A(c_1X) = (AX)c_1$, 8. 1A = A, 9. $I_mA = A = AI_n$, 10. A(X + Y) = AX + AY, 11. $A(c_1X + c_2Y) = c_1AX + c_2AY$, 12. (A + B)X = AX + BX,

Proof: I will prove a couple of these primarily to give you a chance to test your understanding of the notation. Nearly all of these properties are proved by breaking the statement down to components then appealing to a property of real numbers. Just a reminder, we assume that it is known that \mathbb{R} is an ordered field. Multiplication of real numbers is commutative, associative and distributes across addition of real numbers. Likewise, addition of real numbers is commutative, associative, associative and obeys familar distributive laws when combined with addition.

Proof of (1.): assume A, B, C are given as in the statement of the Theorem. Observe that

$$\begin{array}{rcl} ((A+B)+C)_{ij} &= (A+B)_{ij}+C_{ij} & \text{defn. of matrix add.} \\ &= (A_{ij}+B_{ij})+C_{ij} & \text{defn. of matrix add.} \\ &= A_{ij}+(B_{ij}+C_{ij}) & \text{assoc. of real numbers} \\ &= A_{ij}+(B+C)_{ij} & \text{defn. of matrix add.} \\ &= (A+(B+C))_{ij} & \text{defn. of matrix add.} \end{array}$$

for all i, j. Therefore (A + B) + C = A + (B + C). \Box Proof of (6.): assume c_1, c_2, A are given as in the statement of the Theorem. Observe that

$$\begin{array}{ll} ((c_1c_2)A)_{ij} &= (c_1c_2)A_{ij} & \text{defn. scalar multiplication.} \\ &= c_1(c_2A_{ij}) & \text{assoc. of real numbers} \\ &= (c_1(c_2A))_{ij} & \text{defn. scalar multiplication.} \end{array}$$

for all i, j. Therefore $(c_1c_2)A = c_1(c_2A)$. \Box Proof of (10.): assume A, X, Y are given as in the statement of the Theorem. Observe that

$$\begin{array}{ll} ((A(X+Y))_{ij} &= \sum_k A_{ik}(X+Y)_{kj} & \text{defn. matrix multiplication,} \\ &= \sum_k A_{ik}(X_{kj}+Y_{kj}) & \text{defn. matrix addition,} \\ &= \sum_k (A_{ik}X_{kj}+A_{ik}Y_{kj}) & \text{dist. of real numbers,} \\ &= \sum_k A_{ik}X_{kj} + \sum_k A_{ik}Y_{kj}) & \text{prop. of finite sum,} \\ &= (AX)_{ij} + (AY)_{ij} & \text{defn. matrix multiplication}(\times 2), \\ &= (AX + AY)_{ij} & \text{defn. matrix addition,} \end{array}$$

for all i, j. Therefore A(X + Y) = AX + AY. \Box

The proofs of the other items are similar, we consider the i, j-th component of the identity and then apply the definition of the appropriate matrix operation's definition. This reduces the problem to a statement about real numbers so we can use the properties of real numbers at the level of components. Then we reverse the steps. Since the calculation works for arbitrary i, j it follows the the matrix equation holds true.

2.3 linear transformations

Definition 2.3.1.

Let V and W be vector spaces over \mathbb{R} . If a mapping $L: V \to W$ satisfies

1. L(x+y) = L(x) + L(y) for all $x, y \in V$; this is called **additivity**.

2. L(cx) = cL(x) for all $x \in V$ and $c \in \mathbb{R}$; this is called **homogeneity**.

then we say L is a linear transformation. If V = W then we may say that L is a linear transformation on V.

Proposition 2.3.2.

If $A \in \mathbb{R}^{m \times n}$ and $L : \mathbb{R}^n \to \mathbb{R}^m$ is defined by L(x) = Ax for each $x \in \mathbb{R}^n$ then L is a linear transformation.

Proof: Let $A \in \mathbb{R}^{m \times n}$ and define $L : \mathbb{R}^n \to \mathbb{R}^m$ by L(x) = Ax for each $x \in \mathbb{R}^n$. Let $x, y \in \mathbb{R}^n$ and $c \in \mathbb{R}$,

$$L(x + y) = A(x + y) = Ax + Ay = L(x) + L(y)$$

and

$$L(cx) = A(cx) = cAx = cL(x)$$

thus L is a linear transformation. \Box

Obviously this gives us a nice way to construct examples. The following proposition is really at the heart of all the geometry in this section.

Proposition 2.3.3.

Let $\mathcal{L} = \{p + tv \mid t \in [0, 1], p, v \in \mathbb{R}^n \text{ with } v \neq 0\}$ define a line segment from p to p + v in \mathbb{R}^n . If $T:\mathbb{R}^n\to\mathbb{R}^m$ is a linear transformation then $T(\mathcal{L})$ is a either a line-segment from T(p) to T(p+v) or a point.

Proof: suppose T and \mathcal{L} are as in the proposition. Let $y \in T(\mathcal{L})$ then by definition there exists $x \in \mathcal{L}$ such that T(x) = y. But this implies there exists $t \in [0,1]$ such that x = p + tv so T(p+tv) = y. Notice that

$$y = T(p + tv) = T(p) + T(tv) = T(p) + tT(v).$$

which implies $y \in \{T(p) + sT(v) \mid s \in [0,1]\} = \mathcal{L}_2$. Therefore, $T(\mathcal{L}) \subseteq \mathcal{L}_2$. Conversely, suppose $z \in \mathcal{L}_2$ then z = T(p) + sT(v) for some $s \in [0, 1]$ but this yields by linearity of T that z = T(p + sv)hence $z \in T(\mathcal{L})$. Since we have that $T(\mathcal{L}) \subseteq \mathcal{L}_2$ and $\mathcal{L}_2 \subseteq T(\mathcal{L})$ it follows that $T(\mathcal{L}) = \mathcal{L}_2$. Note that \mathcal{L}_2 is a line-segment provided that $T(v) \neq 0$, however if T(v) = 0 then $\mathcal{L}_2 = \{T(p)\}$ and the proposition follows. \Box

a gallery of linear transformations 2.3.1

My choice of mapping the unit square has no particular significance in the examples below. I merely wanted to keep it simple and draw your eye to the distinction between the examples. In each example we'll map the four corners of the square to see where the transformation takes the unit-square. Those corners are simply (0,0), (1,0), (1,1), (0,1) as we traverse the square in a counter-clockwise direction.

Example 2.3.4. Let $A = \begin{bmatrix} k & 0 \\ 0 & k \end{bmatrix}$ for some k > 0. Define L(v) = Av for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x,y) = A(x,y) = \begin{bmatrix} k & 0 \\ 0 & k \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} kx \\ ky \end{bmatrix}.$$

We find L(0,0) = (0,0), L(1,0) = (k,0), L(1,1) = (k,k), L(0,1) = (0,k). This mapping is called a dilation.



Example 2.3.5. Let $A = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}$. Define L(v) = Av for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x,y) = A(x,y) = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} -x \\ -y \end{bmatrix}.$$

We find L(0,0) = (0,0), L(1,0) = (-1,0), L(1,1) = (-1,-1), L(0,1) = (0,-1). This mapping is called an inversion.



Example 2.3.6. Let $A = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix}$. Define L(v) = Av for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x,y) = A(x,y) = \begin{bmatrix} 1 & 2 \\ 3 & 4 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x+2y \\ 3x+4y \end{bmatrix}$$

We find L(0,0) = (0,0), L(1,0) = (1,3), L(1,1) = (3,7), L(0,1) = (2,4). This mapping shall remain nameless, it is doubtless a combination of the other named mappings.



Example 2.3.7. Let $A = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$. Define L(v) = Av for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x,y) = A(x,y) = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \frac{1}{\sqrt{2}} \begin{bmatrix} x-y \\ x+y \end{bmatrix}.$$

We find $L(0,0) = (0,0), \ L(1,0) = \frac{1}{\sqrt{2}}(1,1), \ L(1,1) = \frac{1}{\sqrt{2}}(0,2), \ L(0,1) = \frac{1}{\sqrt{2}}(-1,1).$ This mapping is a rotation by $\pi/4$ radians.



Example 2.3.8. Let $A = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$. Define L(v) = Av for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x,y) = A(x,y) = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x-y \\ x+y \end{bmatrix}.$$

We find L(0,0) = (0,0), L(1,0) = (1,1), L(1,1) = (0,2), L(0,1) = (-1,1). This mapping is a rotation followed by a dilation by $k = \sqrt{2}$.



Example 2.3.9. Let $A = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix}$. Define L(v) = Av for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x,y) = A(x,y) = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x\cos(\theta) - y\sin(\theta) \\ x\sin(\theta) + y\cos(\theta) \end{bmatrix}$$

We find L(0,0) = (0,0), $L(1,0) = (\cos(\theta), \sin(\theta))$, $L(1,1) = (\cos(\theta) - \sin(\theta), \cos(\theta) + \sin(\theta)) L(0,1) = (\sin(\theta), \cos(\theta))$. This mapping is a rotation by θ in the counter-clockwise direction. Of course you could have derived the matrix A from the picture below.



Example 2.3.10. Let $A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$. Define L(v) = Av for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x,y) = A(x,y) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix}.$$

We find L(0,0) = (0,0), L(1,0) = (1,0), L(1,1) = (1,1), L(0,1) = (0,1). This mapping is a rotation by zero radians, or you could say it is a dilation by a factor of 1, ... usually we call this the identity mapping because the image is identical to the preimage.



Example 2.3.11. Let $A_1 = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$. Define $P_1(v) = A_1 v$ for all $v \in \mathbb{R}^2$. In particular this means,

$$P_1(x,y) = A_1(x,y) = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x \\ 0 \end{bmatrix}.$$

We find $P_1(0,0) = (0,0)$, $P_1(1,0) = (1,0)$, $P_1(1,1) = (1,0)$, $P_1(0,1) = (0,0)$. This mapping is a **projection** onto the first coordinate.

Let $A_2 = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$. Define $L(v) = A_2 v$ for all $v \in \mathbb{R}^2$. In particular this means, $P_2(x, y) = A_2(x, y) = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix}.$

We find
$$P_2(0,0) = (0,0)$$
, $P_2(1,0) = (0,0)$, $P_2(1,1) = (0,1)$, $P_2(0,1) = (0,1)$. This mapping is **projection** onto the second coordinate.

We can picture both of these mappings at once:



Example 2.3.12. Let $A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$. Define L(v) = Av for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x,y) = A(x,y) = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} x+y \\ x+y \end{bmatrix}.$$

We find L(0,0) = (0,0), L(1,0) = (1,1), L(1,1) = (2,2), L(0,1) = (1,1). This mapping is not a projection, but it does collapse the square to a line-segment.



Remark 2.3.13.

The examples here have focused on linear transformations from \mathbb{R}^2 to \mathbb{R}^2 . It turns out that higher dimensional mappings can largely be understood in terms of the geometric operations we've seen in this section.

Example 2.3.14. Let $A = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$. Define L(v) = Av for all $v \in \mathbb{R}^2$. In particular this means,

$$L(x,y) = A(x,y) = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ x \\ y \end{bmatrix}.$$

We find L(0,0) = (0,0,0), L(1,0) = (0,1,0), L(1,1) = (0,1,1), L(0,1) = (0,0,1). This mapping moves the xy-plane to the yz-plane. In particular, the horizontal unit square gets mapped to vertical unit square; $L([0,1] \times [0,1]) = \{0\} \times [0,1] \times [0,1]$. This mapping certainly is not surjective because no point with $x \neq 0$ is covered in the range.



Example 2.3.15. Let $A = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix}$. Define L(v) = Av for all $v \in \mathbb{R}^3$. In particular this means,

$$L(x,y,z) = A(x,y,z) = \begin{bmatrix} 1 & 1 & 0 \\ 1 & 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} x+y \\ x+y+z \end{bmatrix}.$$

Let's study how L maps the unit cube. We have $2^3 = 8$ corners on the unit cube,

$$L(0,0,0) = (0,0), \ L(1,0,0) = (1,1), \ L(1,1,0) = (2,2), \ L(0,1,0) = (1,1)$$

$$L(0,0,1) = (0,1), L(1,0,1) = (1,2), L(1,1,1) = (2,3), L(0,1,1) = (1,2).$$

This mapping squished the unit cube to a shape in the plane which contains the points (0,0), (0,1), (1,1), (1,2), (2,2), (2,3). Face by face analysis of the mapping reveals the image is a parallelogram. This mapping is certainly not injective since two different points get mapped to the same point. In particular, I have color-coded the mapping of top and base faces as they map to line segments. The vertical faces map to one of the two parallelograms that comprise the image.



I have used terms like "vertical" or "horizontal" in the standard manner we associate such terms with three dimensional geometry. Visualization and terminology for higher-dimensional examples is not as obvious. However, with a little imagination we can still draw pictures to capture important aspects of mappings.

Example 2.3.16. Let $A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix}$. Define L(v) = Av for all $v \in \mathbb{R}^4$. In particular this means,

$$L(x, y, z, t) = A(x, y, z, t) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix} \begin{vmatrix} x \\ y \\ z \\ t \end{vmatrix} = \begin{bmatrix} x \\ x \end{bmatrix}.$$

Let's study how L maps the unit hypercube $[0,1]^4 \subset \mathbb{R}^4$. We have $2^4 = 16$ corners on the unit hypercube, note L(1, a, b, c) = (1, 1) whereas L(0, a, b, c) = (0, 0) for all $a, b, c \in [0, 1]$. Therefore, the unit hypercube is squished to a line-segment from (0,0) to (1,1). This mapping is neither surjective nor injective. In the picture below the vertical axis represents the y, z, t-directions.



Example 2.3.17. Suppose $f(t,s) = (\sqrt{t}, s^2 + t)$ note that f(1,1) = (1,2) and f(4,4) = (2,20). Note that (4,4) = 4(1,1) thus we should see f(4,4) = f(4(1,1)) = 4f(1,1) but that fails to be true so f is not a linear transformation.

Example 2.3.18. Let $L(x,y) = x^2 + y^2$ define a mapping from \mathbb{R}^2 to \mathbb{R} . This is not a linear transformation since

$$L(c(x,y)) = L(cx,cy) = (cx)^{2} + (cy)^{2} = c^{2}(x^{2} + y^{2}) = c^{2}L(x,y).$$

We say L is a nonlinear transformation.

Example 2.3.19. Suppose $L : \mathbb{R} \to \mathbb{R}$ is defined by L(x) = mx + b for some constants $m, b \in \mathbb{R}$. Is this a linear transformation on \mathbb{R} ? Observe:

$$L(0) = m(0) + b = b$$

thus L is not a linear transformation if $b \neq 0$. On the other hand, if b = 0 then L is a linear transformation.

A mapping on \mathbb{R}^n which has the form T(x) = x + b is called a **translation**. If we have a mapping of the form F(x) = Ax + b for some $A \in \mathbb{R}^{n \times n}$ and $b \in \mathbb{R}$ then we say F is an **affine transformation** on \mathbb{R}^n . Technically, in general, the line y = mx + b is the graph of an affine function on \mathbb{R} . I invite the reader to prove that affine transformations also map line-segments to line-segments (or points).

2.3.2 standard matrices

Definition 2.3.20.

Let $L : \mathbb{R}^n \to \mathbb{R}^m$ be a linear transformation, the matrix $A \in \mathbb{R}^{m \times n}$ such that L(x) = Axfor all $x \in \mathbb{R}^n$ is called the **standard matrix** of L. We denote this by [L] = A or more compactly, $[L_A] = A$, we say that L_A is the linear transformation induced by A. Moreover, the components of the matrix A are found from $A_{ji} = (L(e_i))_j$.

Example 2.3.21. Given that $L([x, y, z]^T) = [x+2y, 3y+4z, 5x+6z]^T$ for $[x, y, z]^T \in \mathbb{R}^3$ find the the standard matrix of L. We wish to find a 3×3 matrix such that L(v) = Av for all $v = [x, y, z]^T \in \mathbb{R}^3$. Write L(v) then collect terms with each coordinate in the domain,

$$L\left(\left[\begin{array}{c}x\\y\\z\end{array}\right]\right) = \left[\begin{array}{c}x+2y\\3y+4z\\5x+6z\end{array}\right] = x\left[\begin{array}{c}1\\0\\5\end{array}\right] + y\left[\begin{array}{c}2\\3\\0\end{array}\right] + z\left[\begin{array}{c}0\\4\\6\end{array}\right]$$

It's not hard to see that,

$$L\left(\left[\begin{array}{c}x\\y\\z\end{array}\right]\right) = \left[\begin{array}{ccc}1&2&0\\0&3&4\\5&0&6\end{array}\right]\left[\begin{array}{c}x\\y\\z\end{array}\right] \quad \Rightarrow \quad A = [L] = \left[\begin{array}{cccc}1&2&0\\0&3&4\\5&0&6\end{array}\right]$$

Notice that the columns in A are just as you'd expect from the proof of theorem ??. $[L] = [L(e_1)|L(e_2)|L(e_3)]$. In future examples I will exploit this observation to save writing.

Example 2.3.22. Suppose that L((t, x, y, z)) = (t + x + y + z, z - x, 0, 3t - z), find [L].

$L(e_1) = L((1, 0, 0, 0)) = (1, 0, 0, 3)$		[1]	1	1	1 -	1
$L(e_2) = L((0, 1, 0, 0)) = (1, -1, 0, 0)$	[7]	0	-1	0	1	
$L(e_3) = L((0, 0, 1, 0)) = (1, 0, 0, 0) \implies$	[L] =	0	0	0	0	
$L(e_4) = L((0, 0, 0, 1)) = (1, 1, 0, -1)$		3	0	0	-1	

I invite the reader to check my answer here and see that L(v) = [L]v for all $v \in \mathbb{R}^4$ as claimed.

Proposition 2.3.23.

Suppose $T: \mathbb{R}^n \to \mathbb{R}^m$ and $S: \mathbb{R}^n \to \mathbb{R}^m$ are linear transformations then S+T and cT are linear transformations and

(1.)
$$[T+S] = [T] + [S],$$
 (2.) $[T-S] = [T] - [S],$ (3.) $[cT] = c[T].$

In words, the standard matrix of the sum, difference or scalar multiple of linear transformations is the sum, difference or scalar multiple of the standard matrices of the respsective linear transformations.

Example 2.3.24. Suppose T(x,y) = (x+y, x-y) and S(x,y) = (2x, 3y). It's easy to see that

$$[T] = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} \text{ and } [S] = \begin{bmatrix} 2 & 0 \\ 0 & 3 \end{bmatrix} \Rightarrow [T+S] = [T] + [S] = \begin{bmatrix} 3 & 1 \\ 1 & 2 \end{bmatrix}$$

Therefore, $(T+S)(x,y) = \begin{bmatrix} 3 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 3x+y \\ x+2y \end{bmatrix} = (3x+y,x+2y)$. Naturally this is the same formula that we would obtain through direct addition of the formulas of T and S.

Proposition 2.3.25.

 $L_1: \mathbb{R}^m \to \mathbb{R}^n$ and $L_2: \mathbb{R}^n \to \mathbb{R}^p$ are linear transformations then $L_2 \circ L_1: \mathbb{R}^m \to \mathbb{R}^p$ is a linear transformation with matrix $[L_2 \circ L_1]$ such that

$$[L_2 \circ L_1]_{ij} = \sum_{k=1}^n [L_2]_{ik} [L_1]_{kj}$$

for all i = 1, 2, ..., p and j = 1, 2, ..., m.

Example 2.3.26. Let $T : \mathbb{R}^{2 \times 1} \to \mathbb{R}^{2 \times 1}$ be defined by

$$T([x, y]^T) = [x + y, 2x - y]^T$$

for all $[x, y]^T \in \mathbb{R}^{2 \times 1}$. Also let $S : \mathbb{R}^{2 \times 1} \to \mathbb{R}^{3 \times 1}$ be defined by

$$S([x,y]^T) = [x, x, 3x + 4y]^T$$

for all $[x, y]^T \in \mathbb{R}^{2 \times 1}$. We calculate the composite as follows:

$$\begin{aligned} (S \circ T)([x, y]^T) &= S(T([x, y]^T)) \\ &= S([x + y, 2x - y]^T) \\ &= [x + y, x + y, 3(x + y) + 4(2x - y)]^T \\ &= [x + y, x + y, 11x - y]^T \end{aligned}$$

Notice we can write the formula above as a matrix multiplication,

$$(S \circ T)([x,y]^T) = \begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 11 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad \Rightarrow \quad [S \circ T] = \begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 11 & -1 \end{bmatrix}.$$

Notice that the standard matrices of S and T are:

$$[S] = \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 3 & 4 \end{bmatrix} \qquad [T] = \begin{bmatrix} 1 & 1 \\ 2 & -1 \end{bmatrix}$$

It's easy to see that $[S \circ T] = [S][T]$ (as we should expect since these are linear operators)

Notice that $T \circ S$ is not even defined since the dimensions of the codomain of S do not match the domain of T. Likewise, the matrix product [T][S] is not defined since there is a dimension mismatch; $(2 \times 2)(3 \times 2)$ is not a well-defined product of matrices.

2.3.3 coordinates and isomorphism

Let V be a finite dimensional vector space with basis $\beta = \{v_1, v_2, \dots, v_n\}$. The coordinate map $\Phi_{\beta}: V \to \mathbb{R}^n$ is defined by

$$\Phi_{\beta}(x_1v_1 + x_2v_2 + \dots + x_nv_n) = x_1e_1 + x_2e_2 + \dots + x_ne_n$$

for all $v = x_1v_1 + x_2v_2 + \cdots + x_nv_n \in V$. Sometimes we have to adjust the numbering a bit for double-indices. For example:

Example 2.3.27. Let $\Phi : \mathbb{R}^{m \times n} \to \mathbb{R}^{mn}$ be defined by

$$\Phi(\sum_{i,j} A_{ij} E_{ij}) = (A_{11}, \dots, A_{1n}, A_{21}, \dots, A_{2n}, \dots, A_{m1}, \dots, A_{mn})$$

This map simply takes the entries in the matrix and strings them out to a vector of length mn.

Example 2.3.28. Let $\Psi : \mathbb{C} \to \mathbb{R}^2$ be defined by $\Psi(x+iy) = (x, y)$. This is the coordinate map for the basis $\{1, i\}$.

Matrix multiplication is for vectors in \mathbb{R}^n . Direct matrix multiplication of an abstract vector makes no sense (how would you multiply a polynomial and a matrix?), however, since we can use the coordinate map to change the abstract vector to a vector in \mathbb{R}^n . The diagram below illustrates the idea for a linear transformation T from an abstract vector space V with basis β to another abstract vector space W with basis $\bar{\beta}$:



Let's walk through the formula $[T]_{\beta,\bar{\beta}} x = \Phi_{\bar{\beta}}(T(\Phi_{\beta}^{-1}(x)))$: we begin on the RHS with a column vector x, then Φ_{β}^{-1} lifts the column vector up to the abstract vector $\Phi_{\beta}^{-1}(x)$ in V. Next we operate by T which moves us over to the vector $T(\Phi_{\beta}^{-1}(x))$ which is in W. Finally the coordinate map $\Phi_{\bar{\beta}}$ pushes the abstract vector in W back to a column vector $\Phi_{\bar{\beta}}(T(\Phi_{\beta}^{-1}(x)))$ which is in $\mathbb{R}^{m \times 1}$. The same journey is accomplished by just multiplying x by the $m \times n$ matrix $[T]_{\beta,\bar{\beta}}$.

Example 2.3.29. Let $\beta = \{1, x, x^2\}$ be the basis for P_2 and consider the derivative mapping $D: P_2 \rightarrow P_2$. Find the matrix of D assuming that P_2 has coordinates with respect to β on both copies of P_2 . Define and observe

$$\Phi(x^n) = e_{n+1} \quad whereas \quad \Phi^{-1}(e_n) = x^{n-1}$$

for n = 0, 1, 2. Recall $D(ax^2 + bx + c) = 2ax + bx$.

$$col_1([D]_{\beta,\beta}) = \Phi_\beta(D(\Phi_\beta^{-1}(e_1))) = \Phi_\beta(D(1)) = \Phi_\beta(0) = 0$$

$$col_2([D]_{\beta,\beta}) = \Phi_\beta(D(\Phi_\beta^{-1}(e_2))) = \Phi_\beta(D(x)) = \Phi_\beta(1) = e_1$$

$$col_3([D]_{\beta,\beta}) = \Phi_\beta(D(\Phi_\beta^{-1}(e_3))) = \Phi_\beta(D(x^2)) = \Phi_\beta(2x) = 2e_2$$

Therefore we find,

$$[D]_{\beta,\beta} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix}$$

Calculate D^3 . Is this surprising?

A one-one correspondence is a map which is 1-1 and onto. If we can find such a mapping between two sets then it shows those sets have the same cardnality. Cardnality is a crude idea of size, it turns out that all finite dimensional vector spaces over \mathbb{R} have the same cardnality. On the other hand, not all vector spaces have the same dimension. Isomorphisms help us discern if two vector spaces have the same dimension.

Definition 2.3.30.

Let V, W be vector spaces then $\Phi : V \to W$ is an **isomorphism** if it is a 1-1 and onto mapping which is also a linear transformation. If there is an isomorphism between vector spaces V and W then we say those vector spaces are **isomorphic** and we denote this by $V \cong W$.

Other authors sometimes denote isomorphism by equality. But, I'll avoid that custom as I am reserving = to denote set equality. Details of the first two examples below can be found in my linear algebra notes.

Example 2.3.31. Let $V = \mathbb{R}^3$ and $W = P_2$. Define a mapping $\Phi : P_2 \to \mathbb{R}^3$ by

$$\Phi(ax^2 + bx + c) = (a, b, c)$$

for all $ax^2 + bx + c \in P_2$. As vector spaces, \mathbb{R}^3 and polynomials of upto quadratic order are the same.

Example 2.3.32. Let S_2 be the set of 2×2 symmetric matrices. Let $\Psi : \mathbb{R}^3 \to S_2$ be defined by

$$\Psi(x,y,z) = \left[\begin{array}{cc} x & y \\ y & z \end{array} \right].$$

Example 2.3.33. Let $L(\mathbb{R}^n, \mathbb{R}^m)$ denote the set of all linear transformations from \mathbb{R}^n to \mathbb{R}^m . $L(\mathbb{R}^n, \mathbb{R}^m)$ forms a vector space under function addition and scalar multiplication. There is a natural isomorphism to $m \times n$ matrices. Define $\Psi : L(\mathbb{R}^n, \mathbb{R}^m) \to \mathbb{R}^{m \times n}$ by $\Psi(T) = [T]$ for all linear transformations $T \in L(\mathbb{R}^n, \mathbb{R}^m)$. In other words, linear transformations and matrices are the same as vector spaces.

The quantification of "same" is a large theme in modern mathematics. In fact, the term *iso-morphism* as we use it here is more accurately phrased *vector space isomorphism*. The are other kinds of isomorphisms which preserve other interesting stuctures like Group, Ring or Lie Algebra isomorphism. But, I think we've said more than enough for this course.

Chapter 3

topology and limits

Topology is the study of continuity and open sets in general. A **topology** on a given set of points is a collection of all sets which are defined to be **open**. Of course, the subject of topology is more interesting than just picking which sets are open, that's just the start of it. Topology also looks to find criteria with which to classify spaces as *topologically distinct*. Two topologies are equivalent if there exists a **homeomorphism** from one space to the other. A **homeomorphism** is bijection which preserves the topological structure. Just as an isomorphism was a bijection which preserved linear structure in the last Chapter. The abstract study of topology is a nontrivial task which we do not undertake here, I merely make these comments for some context.

Our study of topology is very introductory. We merely need topology as a langauge to describe sets in which are theorems and calculations typically hold. Moreover, the topologies we consider are all **metric** topologies. This means the definition of our open sets is based on some natural concept of distance. In the context of \mathbb{R}^n it is simply Euclidean distance function. For a vector space with norm the distance is naturally induced from the norm. Typically, the theorems which interest us here can be shown true in the context of an abstract vector space with norm. Therefore, we give some proofs in that context. However, to be kind to the student we begin with a discussion of topology and limits in Euclidean space before we abstract to the arena of normed vector spaces. Continuity and limits in Euclidean spaces present new difficulties in two or more dimensions. Limits for finite dimensional vector spaces with a norm are not much different. In some sense, it's just the Euclidean case with some extra notational baggage. In particular, spaces of matrices provide an interesting class of examples which take us a bit beyond the context of Euclidean space.

Occasionally we need to quote a nontrivial topological result. For example, the fact that the real numbers are **complete** is an important base fact. However, discussing the justification of that fact is outside the scope (and interest) of this course. That said, we conclude this chapter by collecting a few basic theorems of a topological nature which we will not prove. I also recap all the interesting proofs from calculus I which we at times use in our study of advanced calculus. These are included for your edification and convenience, it is unlikely we devote much lecture time to the calculus I proofs.

3.1 elementary topology and limits

In this section we describe the *metric topology* for \mathbb{R}^n . In the study of functions of one real variable we often need to refer to open or closed intervals. The definition that follows generalizes those concepts to *n*-dimensions.

Definition 3.1.1.

An **open ball** of radius ϵ centered at $a \in \mathbb{R}^n$ is the subset all points in \mathbb{R}^n which are less than ϵ units from a, we denote this open ball by

$$B_{\epsilon}(a) = \{ x \in \mathbb{R}^n \mid ||x - a|| < \epsilon \}$$

The **closed ball** of radius ϵ centered at $a \in \mathbb{R}^n$ is likewise defined

$$B_{\epsilon}(a) = \{ x \in \mathbb{R}^n \mid ||x - a|| \le \epsilon \}$$

Notice that in the n = 1 case we observe an open ball is an open interval: let $a \in \mathbb{R}$,

$$B_{\epsilon}(a) = \{x \in \mathbb{R} \mid ||x - a|| < \epsilon\} = \{x \in \mathbb{R} \mid |x - a| < \epsilon\} = (a - \epsilon, a + \epsilon)$$

In the n = 2 case we observe that an open ball is an open disk: let $(a, b) \in \mathbb{R}^2$,

$$B_{\epsilon}((a,b)) = \{(x,y) \in \mathbb{R}^2 \mid || (x,y) - (a,b) || < \epsilon\} = \{(x,y) \in \mathbb{R}^2 \mid \sqrt{(x-a)^2 + (y-b)^2} < \epsilon\}$$

For n = 3 an open-ball is a sphere without the outer shell. In contrast, a closed ball in n = 3 is a solid sphere which includes the outer shell of the sphere.

Definition 3.1.2.

Let $D \subseteq \mathbb{R}^n$. We say $y \in D$ is an **interior point** of D iff there exists some open ball centered at y which is completely contained in D. We say $y \in \mathbb{R}^n$ is a **limit point** of D iff every open ball centered at y contains points in $D - \{y\}$. We say $y \in \mathbb{R}^n$ is a **boundary point** of D iff every open ball centered at y contains points not in D and other points which are in $D - \{y\}$. We say $y \in D$ is an **isolated point** of D if there exist open balls about y which do not contain other points in D. The set of all interior points of D is called the **interior of** D. Likewise the set of all boundary points for D is denoted ∂D . The **closure** of D is defined to be $\overline{D} = D \cup \{y \in \mathbb{R}^n \mid y \text{ a limit point}\}$

All the terms are aptly named. The term "limit point" is given because those points are the ones for which it is natural to define a limit. The picture below illustrates an interior point y_1 , a boundary point y_2 and an isolated poin y_3 . Also, the dotted-line around the hole indicates that edge is not part of the set. However, the closure of D would be formed by connecting those dots to give \overline{D} a solid edge.



The dotted circle around y_1 is meant to illustrate an open ball which is centered on y_1 and it contained within D, the existence of this open ball is what proves y_1 is an interior point.

Definition 3.1.3.

Let $A \subseteq \mathbb{R}^n$ is an **open set** iff for each $x \in A$ there exists $\epsilon > 0$ such that $x \in B_{\epsilon}(x)$ and $B_{\epsilon}(x) \subseteq A$. Let $B \subseteq \mathbb{R}^n$ is an **closed set** iff its complement $\mathbb{R}^n - B = \{x \in \mathbb{R}^n \mid x \notin B\}$ is an open set.

Notice that $\mathbb{R} - [a, b] = (\infty, a) \cup (b, \infty)$. It is not hard to prove that open intervals are open hence we find that a closed interval is a closed set. Likewise it is not hard to prove that open balls are open sets and closed balls are closed sets. In fact, it can be shown that a closed set contains all its limit points, that is $A \subseteq \mathbb{R}^n$ is closed iff $A = \overline{A}$.

Limits of vector-valued functions of several real variables are defined below:

Definition 3.1.4.

Let $f: U \subseteq \mathbb{R}^n \to V \subseteq \mathbb{R}^m$ be a mapping. We say that f has limit $b \in \mathbb{R}^m$ at limit point a of U iff for each $\epsilon > 0$ there exists a $\delta > 0$ such that $x \in \mathbb{R}^n$ with $0 < ||x - a|| < \delta$ implies $||f(x) - b|| < \epsilon$. In such a case we can denote the above by stating that

$$\lim_{x \to a} f(x) = b$$

In calculus I the limit of a function is defined in terms of deleted open intervals centered about the limit point. We just defined the limit of a mapping in terms of deleted open balls centered at the limit point. The term "deleted" refers to the fact that we assume 0 < ||x - a|| which means we do not consider x = a in the limiting process. In other words, the limit of a mapping considers values close to the limit point but not necessarily the limit point itself. The case that the function is defined at the limit point is special, when the limit and the mapping agree then we say the mapping is continuous at that point.

Example 3.1.5. Let $F : \mathbb{R}^n - \{a\} \to \mathbb{R}^n$ be defined by $F(x) = \frac{1}{||x-a||}(x-a)$. In this case, certainly a is a limit point of F but geometrically it is clear that $\lim_{x\to a} F(x)$ does not exist. Notice for n = 1, the discontinuity of F at a can be understood by seeing that left and right limits exist, but are not equal. On the other hand, $G(x) = \frac{||x-a||}{||x-a||}(x-a)$ clearly has $\lim_{x\to a} G(x) = 0$ and we could classify the discontinuity of G at x = a as removeable. Clearly $\tilde{G}(x) = x - a$ is a continuous extension of G to all of \mathbb{R}^n Multivariate limits are much trickier than single-variate limits because there are infinitely many ways to approach a limit point. In the single-variate case we can only approach from the left $x \to a^-$ or from the right $x \to a^+$. However, even in \mathbb{R}^2 there are infinitely many lines on which we can approach a limit point. But, perhaps, even more insidiously, there are infinitely many parabolas, cubics, exponentials etc... which intersect the limit point. It turns out that the method of approach matters. It is possible for the function to limit to the same value by all linear paths and yet parabolic paths yield different values.

Example 3.1.6. Suppose $f(x,y) = \begin{cases} \frac{2x^2y}{x^4+y^2} & (x,y) \neq (0,0) \\ 0 & (x,y) = (0,0) \end{cases}$. Notice that we can calculate the limit

for $(a, b) \neq (0, 0)$ with ease:

$$\lim_{(x,y)\to(a,b)} = \frac{2a^2b}{a^4 + b^2}$$

However, if we consider the limit at (0,0) it is indeterminant since we have an expression of type 0/0. Other calculation is required. Consider the path $\vec{r}(t) = (t, mt)$ then clearly this is continuous at t = 0 and $\vec{r}(0) = (0,0)$; in-fact, this is just the parametric equation of a line y = mx. Consider, for $m \neq 0$,

$$\lim_{t \to 0} f(\vec{r}(t)) = \lim_{t \to 0} \frac{2mt^4}{t^4 + m^2t^2} = \lim_{t \to 0} \frac{2mt^2}{t^2 + m^2} = \frac{2m(0)}{0 + m^2} = 0.$$

If $\vec{r}(t) = (t, 0)$ then for $t \neq 0$ we have $f(\vec{r}(t)) = f(t, 0) = 0$ thus the limit of the function restricted to any linear path is just zero. The three pictures on the right illustrate how differing linear paths yield the same limits. The red lines are the x, y axes.



What about parabolic paths? Those are easily constructed via $\vec{r}_2(t) = (t, kt^2)$ again $\vec{r}_2(0) = (0, 0)$ and $\lim_{t\to 0} \vec{r}_2(t) = (0, 0)$. Calculate, for $k \neq 0$,

$$\lim_{t \to 0} f(\vec{r}_2(t)) = \lim_{t \to 0} \frac{2kt^4}{t^4 + k^2t^4} = \lim_{t \to 0} \frac{2k}{1+k^2} = \frac{2k}{1+k^2}.$$

Clearly if we choose differing values for k we obtain different values for the limit hence the limit of f does not exist as $(x, y) \rightarrow (0, 0)$. Here's the graph of this function, maybe you can see the problem at the origin. The red plane is vertical through the origin. The three pictures on the right illustrate how differing parabolic paths yield differing limits. The red lines are the x, y axes.



See the limit of the blue path would be negative whereas the yellow path would give a positive limit.

Definition 3.1.7.

Let $f: U \subseteq \mathbb{R}^n \to V \subseteq \mathbb{R}^m$ be a function. If $a \in U$ is a limit point of f then we say that f is **continuous at** a iff

 $\lim_{x \to a} f(x) = f(a)$

If $a \in U$ is an isolated point then we also say that f is continous at a. The mapping f is continuous on S iff it is continuous at each point in S. The mapping f is continuous iff it is continuous on its domain.

Notice that in the m = n = 1 case we recover the definition of continuous functions from calc. I. Another funny consequence of this definition is that sequences are by default continuous functions since each point in their domain is isolated.

Proposition 3.1.8.

Let $f: U \subseteq \mathbb{R}^n \to V \subseteq \mathbb{R}^m$ be a mapping with component functions f_1, f_2, \dots, f_m hence $f = (f_1, f_2, \dots, f_m)$. If $a \in U$ is a limit point of f then $\lim_{x \to a} f(x) = b \quad \Leftrightarrow \quad \lim_{x \to a} f_j(x) = b_j$ for each $j = 1, 2, \dots, m$.

Proof: (\Rightarrow) Suppose $\lim_{x\to a} f(x) = b$. Then for each $\epsilon > 0$ choose $\delta > 0$ such that $0 < ||x-a|| < \delta$ implies $||f(x) - b|| < \epsilon$. This choice of δ suffices for our purposes as:

$$|f_j(x) - b_j| = \sqrt{(f_j(x) - b_j)^2} \le \sqrt{\sum_{j=1}^m (f_j(x) - b_j)^2} = ||f(x) - b|| < \epsilon.$$

Hence we have shown that $\lim_{x\to a} f_j(x) = b_j$ for all $j = 1, 2, \dots m$.

(\Leftarrow) Suppose $\lim_{x\to a} f_j(x) = b_j$ for all j = 1, 2, ..., m. Let $\epsilon > 0$. Note that $\epsilon/m > 0$ and therefore by the given limits we can choose $\delta_j > 0$ such that $0 < ||x - a|| < \delta$ implies $||f_j(x) - b_j|| < \sqrt{\epsilon/m}$. Choose $\delta = min\{\delta_1, \delta_2, ..., \delta_m\}$ clearly $\delta > 0$. Moreoever, notice $0 < ||x - a|| < \delta \leq \delta_j$ hence requiring $0 < ||x - a|| < \delta$ automatically induces $0 < ||x - a|| < \delta_j$ for all j. Suppose that $x \in \mathbb{R}^n$ and $0 < ||x - a|| < \delta$ it follows that

$$||f(x) - b|| = ||\sum_{j=1}^{m} (f_j(x) - b_j)e_j|| = \sqrt{\sum_{j=1}^{m} |f_j(x) - b_j|^2} < \sum_{j=1}^{m} (\sqrt{\epsilon/m})^2 < \sum_{j=1}^{m} \epsilon/m = \epsilon.$$

Therefore, $\lim_{x\to a} f(x) = b$ and the proposition follows. \Box

The beauty of the previous proposition is that it means we can analyze the limit of a vector-valued function by analyzing the limits of the component functions. However, this does not remove the fundamental difficulty of analyzing the multivariate limits of the component functions. It just means we can tackel the problem one-component at time. This is a relief, it would be annoying if the range was as intertwined as the domain in this analysis.

Proposition 3.1.9.

Suppose that $f: U \subseteq \mathbb{R}^n \to V \subseteq \mathbb{R}^m$ is a vector-valued function with component functions f_1, f_2, \ldots, f_m . Let $a \in U$ be a limit point of f then f is continuous at a iff f_j is continuous at a for $j = 1, 2, \ldots, m$. Moreover, f is continuous on S iff all the component functions of f are continuous on S. Finally, a vector-valued function f is continuous iff all of its component functions are continuous.

Proposition 3.1.10.

The projection functions are continuous. The identity mapping is continuous.

Proof: Let $\epsilon > 0$ and choose $\delta = \epsilon$. If $x \in \mathbb{R}^n$ such that $0 < ||x - a|| < \delta$ then it follows that $||x-a|| < \epsilon$. Therefore, $\lim_{x\to a} x = a$ which means that $\lim_{x\to a} Id(x) = Id(a)$ for all $a \in \mathbb{R}^n$. Hence Id is continuous on \mathbb{R}^n which means Id is continuous. Since the projection functions are component functions of the identity mapping it follows that the projection functions are also continuous (using the previous proposition). \Box

Definition 3.1.11.

The sum and product are functions from \mathbb{R}^2 to \mathbb{R} defined by

 $s(x,y) = x + y \qquad p(x,y) = xy$

Proposition 3.1.12.

The sum and product functions are continuous.

Preparing for the proof: Let the limit point be (a, b). Consider what we wish to show: given a point (x, y) such that $0 < ||(x, y) - (a, b)|| < \delta$ we wish to show that

$$|s(x,y) - (a+b)| < \epsilon$$
 or for the product $|p(x,y) - (ab)| < \epsilon$

follow for appropriate choices of δ . Think about the sum for a moment,

$$|s(x,y) - (a+b)| = |x+y-a-b| \le |x-a| + |y-b|$$

I just used the triangle inequality for the absolute value of real numbers. We see that if we could somehow get control of |x - a| and |y - b| then we'd be getting closer to the prize. We have control of $0 < ||(x, y) - (a, b)|| < \delta$ notice this reduces to

$$||(x-a,y-b)|| < \delta \quad \Rightarrow \quad \sqrt{(x-a)^2 + (y-b)^2} < \delta$$

it is clear that $(x-a)^2 < \delta^2$ since if it was otherwise the inequality above would be violated as adding a nonegative quantity $(y-b)^2$ only increases the radicand resulting in the squareroot to be larger than δ . Hence we may assume $(x-a)^2 < \delta^2$ and since $\delta > 0$ it follows $\boxed{|x-a| < \delta}$. Likewise, $\boxed{|y-b| < \delta}$. Thus $|s(x,y) - (a+b)| = |x+y-a-b| < |x-a| + |y-b| < 2\delta$. We see for the sum proof we can choose $\delta = \epsilon/2$ and it will work out nicely.

Proof: Let $\epsilon > 0$ and let $(a,b) \in \mathbb{R}^2$. Choose $\delta = \epsilon/2$ and suppose $(x,y) \in \mathbb{R}^2$ such that $||(x,y) - (a,b)|| < \delta$. Observe that

$$||(x,y) - (a,b)|| < \delta \implies ||(x-a,y-b)||^2 < \delta^2 \implies |x-a|^2 + |y-b|^2 < \delta^2$$

It follows $|x - a| < \delta$ and $|y - b| < \delta$. Thus

$$|s(x,y) - (a+b)| = |x+y-a-b| \le |x-a| + |y-b| < \delta + \delta = 2\delta = \epsilon.$$

Therefore, $\lim_{(x,y)\to(a,b)} s(x,y) = a+b$. and it follows that the sum function if continuous at (a,b). But, (a,b) is an arbitrary point thus s is continuous on \mathbb{R}^2 hence the sum function is continuous. \Box .

Preparing for the proof of continuity of the product function: I'll continue to use the same notation as above. We need to study $|p(x, y) - (ab)| = |xy - ab| < \epsilon$. Consider that

$$|xy - ab| = |xy - ya + ya - ab| = |y(x - a) + a(y - b)| \le |y||x - a| + |a||y - b|$$

We know that $|x-a| < \delta$ and $|y-b| < \delta$. There is one less obvious factor to bound in the expression. What should we do about |y|?. I leave it to the reader to show that:

$$|y-b| < \delta \qquad \Rightarrow \qquad |y| < |b| + \delta$$

Now put it all together and hopefully we'll be able to "solve" for ϵ .

$$|xy - ab| = \le |y||x - a| + |a||y - b| < (|b| + \delta)\delta + |a|\delta = \delta^2 + \delta(|a| + |b|) " = "\epsilon$$

I put solve in quotes because we have considerably more freedom in our quest for finding δ . We could just as well¹ find δ which makes the " = " become an <. That said let's pursue equality,

$$\delta^2 + \delta(|a| + |b|) - \epsilon = 0 \qquad \delta = \frac{-|a| - |b| \pm \sqrt{(|a| + |b|)^2 + 4\epsilon}}{2}$$

¹Minh Nguyen showed me a much shorter argument involving well-known inequalities for the geometric and arithmetic means, this argument can be improved!

Since ϵ , |a|, |b| > 0 it follows that $\sqrt{(|a| + |b|)^2 + 4\epsilon} < \sqrt{(|a| + |b|)^2} = |a| + |b|$ hence the (+) solution to the quadratic equation yields a positive δ namely: $\delta = \frac{-|a| - |b| + \sqrt{(|a| + |b|)^2 + 4\epsilon}}{2}$.

Proof: Let $\epsilon > 0$ and let $(a, b) \in \mathbb{R}^2$. By the calculations that prepared for the proof we know that the following quantity is positive, hence choose

$$\delta = \frac{-|a| - |b| + \sqrt{(|a| + |b|)^2 + 4\epsilon}}{2} > 0$$

Note that²,

$$\begin{aligned} |xy - ab| &= |xy - ya + ya - ab| &= |y(x - a) + a(y - b)| & \text{algebra} \\ &\leq |y||x - a| + |a||y - b| & \text{triangle inequality} \\ &< (|b| + \delta)\delta + |a|\delta & \text{by the boxed lemmas} \\ &= \delta^2 + \delta(|a| + |b|) & \text{algebra} \\ &= \epsilon \end{aligned}$$

where we know that last step follows due to the steps leading to the boxed equation in the proof preparation. Therefore, $\lim_{(x,y)\to(a,b)} p(x,y) = ab$. and it follows that the product function if continuous at (a, b). But, (a, b) is an arbitrary point thus p is continuous on \mathbb{R}^2 hence the product function is continuous. \Box .

Proposition 3.1.13.

Let $f: V \subseteq \mathbb{R}^p \to \mathbb{R}^m$ and $g: U \subseteq \mathbb{R}^n \to \mathbb{R}^p$ be mappings. Suppose that $\lim_{x \to a} g(x) = b$ and suppose that f is continuous at b then $\lim_{x \to a} (f \circ g)(x) = f(\lim_{x \to a} g(x)).$

The proof is on pages 46-47 of C.H. Edwards Advanced Calculus text. I will provide a proof in the setting of normed spaces later in this chapter. Notice that the proposition above immediately gives us the important result below:

Proposition 3.1.14.

Let f and g be mappings such that $f \circ g$ is well-defined. The composite function $f \circ g$ is continuous for points $a \in dom(f \circ g)$ such that the following two conditions hold:

1. g is continuous at a

2. f is continuous at g(a).

 $^{^{2}}$ my notation is that when we stack inequalities the inequality in a particular line refers only to the immediate vertical successor.

I make use of the earlier proposition that a mapping is continuous iff its component functions are continuous throughout the examples that follow. For example, I know (Id, Id) is continuous since Id was previously proved continuous.

Example 3.1.15. Note that if $f = p \circ (Id, Id)$ then $f(x) = (p \circ (Id, Id))(x) = p((Id, Id)(x)) = p(x, x) = x^2$. Therefore, the quadratic function $f(x) = x^2$ is continuous on \mathbb{R} as it is the composite of continuous functions.

Example 3.1.16. Note that if $f = p \circ (p \circ (Id, Id), Id)$ then $f(x) = p(x^2, x) = x^3$. Therefore, the cubic function $f(x) = x^3$ is continuous on \mathbb{R} as it is the composite of continuous functions.

Example 3.1.17. The power function is inductively defined by $x^1 = x$ and $x^n = xx^{n-1}$ for all $n \in \mathbb{N}$. We can prove $f(x) = x^n$ is continuous by induction on n. We proved the n = 1 case previously. Assume inductively that $f(x) = x^{n-1}$ is continuous. Notice that

$$x^{n} = xx^{n-1} = xf(x) = p(x, f(x)) = (p \circ (Id, f))(x).$$

Therefore, using the induction hypothesis, we see that $g(x) = x^n$ is the composite of continuous functions thus it is continuous. We conclude that $f(x) = x^n$ is continuous for all $n \in \mathbb{N}$.

We can play similar games with the sum function to prove that sums of power functions are continuous. In your homework you will prove constant functions are continuous. Putting all of these things together gives us the well-known result that polynomials are continuous on \mathbb{R} .

Proposition 3.1.18.

Let a be a limit point of mappings $f, g : U \subseteq \mathbb{R}^n \to V \subseteq \mathbb{R}$ and suppose $c \in \mathbb{R}$. If $\lim_{x\to a} f(x) = b_1 \in \mathbb{R}$ and $\lim_{x\to a} g(x) = b_2 \in \mathbb{R}$ then

1. $\lim_{x \to a} (f(x) + g(x)) = \lim_{x \to a} f(x) + \lim_{x \to a} g(x).$

2.
$$\lim_{x \to a} (f(x)g(x)) = (\lim_{x \to a} f(x)) (\lim_{x \to a} g(x))$$

3.
$$\lim_{x \to a} (cf(x)) = c \lim_{x \to a} f(x)$$

Moreover, if f, g are continuous then f + g, fg and cf are continuous.

Proof: Edwards proves (1.) carefully on pg. 48. I'll do (2.) here: we are given that If $\lim_{x\to a} f(x) = b_1 \in \mathbb{R}$ and $\lim_{x\to a} g(x) = b_2 \in \mathbb{R}$ thus by Proposition 3.1.8 we find $\lim_{x\to a} (f,g)(x) = (b_1,b_2)$. Consider then,

$$\begin{split} \lim_{x \to a} (f(x)g(x)) &= \lim_{x \to a} (p(f,g)) & \text{defn. of product function} \\ &= p(\lim_{x \to a} (f,g)) & \text{since } p \text{ is continuous} \\ &= p(b_1,b_2) & \text{by Proposition 3.1.8.} \\ &= b_1 b_2 & \text{definition of product function} \\ &= (\lim_{x \to a} f(x)) (\lim_{x \to a} g(x)). \end{split}$$

I leave it to the reader to show $\lim_{x\to a} c = c$ and hence item (3.) follows from (2.). \Box .

The proposition that follows does follow immediately from the proposition above, however I give a proof that again illustrates the idea we used in the examples. Reinterpreting a given function as a composite of more basic functions is a useful theoretical and calculational technique.

Proposition 3.1.19.

Assume $f, g: U \subseteq \mathbb{R}^n \to V \subseteq \mathbb{R}$ are continuous functions at $a \in U$ and suppose $c \in \mathbb{R}$.

1. f + g is continuous at a.

2. fg is continuous at a

3. cf is continuous at a.

Moreover, if f, g are continuous then f + g, fg and cf are continuous.

Proof: Observe that $(f + g)(x) = (s \circ (f, g))(x)$ and $(fg)(x) = (p \circ (f, g))(x)$. We're given that f, g are continuous at a and we know s, p are continuous on all of \mathbb{R}^2 thus the composite functions $s \circ (f, g)$ and $p \circ (f, g)$ are continuous at a and the proof of items (1.) and (2.) is complete. To prove (3.) I refer the reader to their homework where it was shown that h(x) = c for all $x \in U$ is a continuous function. We then find (3.) follows from (2.) by setting g = h (function multiplication commutes for real-valued functions). \Box .

We can use induction arguments to extend these results to arbitrarily many products and sums of power functions. To prove continuity of algebraic functions we'd need to do some more work with quotient and root functions. I'll stop here for the moment, perhaps I'll ask you to prove a few more fundamentals from calculus I. I haven't delved into the definition of exponential or log functions not to mention sine or cosine³ We will assume that the basic functions of calculus are continuous on the interior of their respective domains. Basically if the formula for a function can be evaluated at the limit point then the function is continuous.

It's not hard to see that the comments above extend to functions of several variables and mappings. If the formula for a mapping is comprised of finite sums and products of power functions then we can prove such a mapping is continuous using the techniques developed in this section. If we have a mapping with a more complicated formula built from elementary functions then that mapping will be continuous provided its component functions have formulas which are sensibly calculated at the limit point. In other words, if you are willing to believe me that $\sin(x), \cos(x), e^x, \ln(x), \cosh(x), \sinh(x), \sqrt{x}, \frac{1}{x^n}, \ldots$ are continuous on the interior of their domains

³sine, cosine and exponentials are all nicely defined in terms of power series arguments, if time permits we may sketch the development of these basic functions when we discuss series calculation

then it's not hard to prove:

$$f(x,y,z) = \left(\sin(x) + e^x + \sqrt{\cosh(x^2) + \sqrt{y + e^x}}, \ \cosh(xyz), \ xe^{\sqrt{x + \frac{1}{yz}}}\right)$$

is a continuous mapping at points where the radicands of the square root functions are nonnegative. It wouldn't be very fun to write explicitly but it is clear that this mapping is the Cartesian product of functions which are the sum, product and composite of continuous functions.

Definition 3.1.20.

A polynomial in *n*-variables has the form:

$$f(x_1, x_2, \dots, x_n) = \sum_{i_1, i_2, \dots, i_k=0}^{\infty} c_{i_1, i_2, \dots, i_n} x_1^{i_1} x_2^{i_2} \cdots x_n^{i_k}$$

where only finitely many coefficients $c_{i_1,i_2,\ldots,i_n} \neq 0$. We denote the set of multinomials in *n*-variables as $\mathbb{R}[x_1, x_2, \ldots, x_n]$.

Polynomials are $\mathbb{R}[x]$. Polynomials in two variables are $\mathbb{R}[x, y]$, for example,

f(x,y)	= ax + by	deg(f) = 1, linear function
f(x, y)	= ax + by + c	deg(f) = 1, affine function
f(x,y)	$= ax^2 + bxy + cy^2$	$\deg(f)=2$, quadratic form
f(x, y)	$= ax^2 + bxy + cy^2 + dx + ey + g$	$\deg(f)=2$

If all the terms in the polynomial have the same number of variables then it is said to be **homo-geneous**. In the list above only the linear function and the quadratic form were homogeneous.

3.2 normed vector spaces

Much of linear algebra is done without any regard to the length of vectors. In fact, if one begins linear algebra with both linear structure and the concept of vector length then many proofs can be made rather intuitive. If you wish to read linear algebra from such a viewpoint then you might find a copy of Gilbert Strang's linear algebra text as it makes use of geometry from the outset.

Definition 3.2.1.

Suppose V is a vector space. If $|| \cdot || : V \times V \to \mathbb{R}$ is a function such that for all $x, y \in V$ and $c \in \mathbb{R}$: 1. ||cx|| = |c| ||x||2. $||x + y|| \le ||x|| + ||y||$ (triangle inequality) 3. $||x|| \ge 0$ 4. ||x|| = 0 iff x = 0then we say $(V, || \cdot ||)$ is a normed vector space. When there is no danger of ambiguity we

also say that V is a normed vector space.

Notice that we did not assume V was finite-dimensional in the definition above. Our current focus is on finite-dimensional cases.

Example 3.2.2. \mathbb{R}^n can be given the Euclidean norm which is defined by $||x|| = \sqrt{x \cdot x}$ for each $x \in \mathbb{R}^n$.

Example 3.2.3. \mathbb{R}^n can also be given the 1-norm which is defined by $||x||_1 = |x_1| + |x_2| + \cdots + |x_n|$ for each $x \in \mathbb{R}^n$.

We use the Euclidean norm by default.

Example 3.2.4. Consider \mathbb{C} as a two dimensional real vector space. Let $a + ib \in \mathbb{C}$ and define $||a + ib|| = \sqrt{a^2 + b^2}$. This is a norm for \mathbb{C} .

Example 3.2.5. Let $A \in \mathbb{R}^{m \times n}$. For each $A = [A_{ij}]$ we define

$$||A|| = \sqrt{A_{11}^2 + A_{12}^2 + \dots + A_{mn}^2} = \sqrt{\sum_{i=1}^m \sum_{j=1}^n A_{ij}^2}.$$

This is the Frobenius norm for matrices.

Each of the norms above allows us to define a distance function and hence open sets and limits for functions as we discuss next.

3.2.1 open balls, limits and sequences in normed vector spaces

In what follows here I give a brief overview of how we define open sets and limits in a normed vector space. The answer is simply to replace Euclidean vector length with the appropriate norm.

Definition 3.2.6. Open sets and limit points for normed space V

An open ball in $(V, || \cdot ||_V)$ is defined

$$B_{\epsilon}(x_o) = \{ y \in V \mid ||y - x_o||_V < \epsilon \}.$$

We define the deleted open ball by removing the center from the open ball

$$B_{\epsilon}(x_{o})_{o} = B_{\epsilon}(x_{o}) - \{x_{o}\} = \{y \in V \mid 0 < ||y - x_{o}||_{V} < \epsilon\}.$$

We say x_o is a limit point of a function f iff there exists a deleted open ball which is contained in the dom(f). We say $U \subseteq V$ is an open set iff for each $u \in U$ there exists an open ball $B_{\epsilon}(u) \subseteq U$.

Limits and continuous functions are also defined in the same way as in \mathbb{R}^n .

Definition 3.2.7. *Limits and continuity in normed spaces.*

If $f: V \to W$ is a function from normed space $(V, ||\cdot||_V)$ to normed vector space $(W, ||\cdot||_W)$ then we say $\lim_{x\to x_o} f(x) = L$ iff for each $\epsilon > 0$ there exists $\delta > 0$ such that for all $x \in V$ subject to $0 < ||x - x_o||_V < \delta$ it follows $||f(x) - f(x_o)||_W < \epsilon$. If $\lim_{x\to x_o} f(x) = f(x_o)$ then we say that f is a continuous function at x_o .

Let $(V, || \cdot ||_V)$ be a normed vector space, a function from N to V is a called a **sequence**. Limits of sequences play an important role in analysis in normed linear spaces. The real analysis course makes great use of sequences to tackle questions which are more difficult with only $\epsilon - \delta$ arguments. In fact, we can reformulate limits in terms of sequences and subsequences. Perhaps one interesting feature of abstract topological spaces is the appearance of spaces in which sequential convergence is insufficient to capture the concept of limits. In general, one needs *nets* and *filters*. I digress. More important to our context, the criteria of **completeness**. Let us settle a few definitions to make the words meaningful.

Definition 3.2.8.

Suppose $\{a_n\}$ is a sequence then we say $\lim_{n\to\infty} a_n = L \in V$ iff for each $\epsilon > 0$ there exists $M \in \mathbb{N}$ such that $||a_n - L||_V < \epsilon$ for all $n \in \mathbb{N}$ with n > M. If $\lim_{n\to\infty} a_n = L \in V$ then we say $\{a_n\}$ is a **convergent sequence**.

We spent some effort attempting to understand the definition above and its application to the problem of infinite summations in calculus II. It is less likely you have thought much about the following:

Definition 3.2.9.

We say $\{a_n\}$ is a **Cauchy sequence** iff for each $\epsilon > 0$ there exists $M \in \mathbb{N}$ such that $||a_m - a_n||_V < \epsilon$ for all $m, n \in \mathbb{N}$ with m, n > M.

In other words, a sequence is Cauchy if the terms in the sequence get arbitarily close as we go sufficiently far out in the list. Many concepts we cover in calculus II are made clear with proofs built around the concept of a Cauchy sequence. The interesting thing about Cauchy is that for some spaces of numbers we can have a sequence which converges but is not Cauchy. For example, if you think about the rational numbers \mathbb{Q} we can construct a sequence of truncated decimal expansions of π :

 $\{a_n\} = \{3, 3.1, 3.14, 3.141, 3.1415\dots\}$

note that $a_n \in \mathbb{Q}$ for all $n \in \mathbb{N}$ and yet the $a_n \to \pi \notin \mathbb{Q}$. When spaces are missing their limit points they are in some sense incomplete.

Definition 3.2.10.

If every Cauchy sequence in a metric space converges to a point within the space then we say the metric space is **complete**. If a normed vector space V is complete then we say V is a **Banach space**.

A metric space need not be a vector space. In fact, we can take any open set of a normed vector space and construct a metric space. Metric spaces require less structure.

Fortunately all the main examples of this course are built on the real numbers which are complete, this induces completeness for \mathbb{C}, \mathbb{R}^n and $\mathbb{R}^{m \times n}$. The proof that $\mathbb{R}, \mathbb{C}, \mathbb{R}^n$ and $\mathbb{R}^{m \times n}$ are Banach spaces follow from arguments similar to those given in the example below.

Example 3.2.11. Claim: \mathbb{R} complete implies \mathbb{R}^2 is complete.

Proof: suppose (x_n, y_n) is a Cauchy sequence in \mathbb{R}^2 . Therefore, for each $\epsilon > 0$ there exists $N \in \mathbb{N}$ such that $m, n \in \mathbb{N}$ with N < m < n implies $||(x_m, y_m) - (x_n, y_n)|| < \epsilon$. Consider that:

$$||(x_m, y_m) - (x_n, y_n)|| = \sqrt{(x_m - x_n)^2 + (y_m - y_n)^2}$$

Therefore, as $|x_m - x_n| = \sqrt{(x_m - x_n)^2}$, it is clear that:

$$|x_m - x_n| \le ||(x_m, y_m) - (x_n, y_n)||$$

But, this proves that $\{x_n\}$ is a Cauchy sequence of real numbers since for each $\epsilon > 0$ we can choose N > 0 such that N < m < n implies $|x_m - x_n| < \epsilon$. The same holds true for the sequence $\{y_n\}$. By completeness of \mathbb{R} we have $x_n \to x$ and $y_n \to y$ as $n \to \infty$. We propose that $(x_n, y_n) \to (x, y)$. Let $\epsilon > 0$ once more and choose $N_x > 0$ such that $n > N_x$ implies $|x_n - x| < \epsilon/2$ and $N_y > 0$ such that $n > N_y$ implies $|y_n - y| < \epsilon/2$. Let $N = \max(N_x, N_y)$ and suppose n > N:

$$||(x_n, y_n) - (x, y)|| = ||x_n - x, 0| + (0, y_n - y)|| \le |x_n - x| + |y_n - y| < \epsilon/2 + \epsilon/2 = \epsilon.$$

The key point here is that components of a Cauchy sequence form Cauchy sequences in \mathbb{R} . That will also be true for sets of matrices and complex numbers. Moreover, this proof is almost identical to that which I gave to prove the limit of a sum was the sum of the limits. It is not an accident that the structure of sequential limits and continuum limits are so closely paired. However, I leave further analysis of that point to analysis. At the risk of killing that which is already dead⁴

Proposition 3.2.12.

Let V, W be normed vector spaces. Let a be a limit point of mappings $f, g: U \subseteq V \to W$ and suppose $c \in \mathbb{R}$. If $\lim_{x \to a} f(x) = b_1 \in W$ and $\lim_{x \to a} g(x) = b_2 \in W$ then

- 1. $\lim_{x \to a} (f(x) + g(x)) = \lim_{x \to a} f(x) + \lim_{x \to a} g(x).$
- 2. $\lim_{x \to a} (cf(x)) = c \lim_{x \to a} f(x).$

Moreover, if f, g are continuous then f + g and cf are continuous.

Proof: Let $\epsilon > 0$ and suppose $\lim_{x\to a} f(x) = b_1 \in W$ and $\lim_{x\to a} g(x) = b_2 \in W$. Choose $\delta_1, \delta_2 > 0$ such that $0 < ||x-a|| < \delta_1$ implies $||f(x)-b_1|| < \epsilon/2$ and $0 < ||x-a|| < \delta_2$ implies $||g(x)-b_2|| < \epsilon/2$. Choose $\delta = \min(\delta_1, \delta_2)$ and suppose $0 < ||x-a|| < \delta \le \delta_1, \delta_2$ hence

$$||(f+g)(x) - (b_1 + b_2)|| = ||f(x) - b_1 + g(x) - b_2|| \le ||f(x) - b_1|| + ||g(x) - b_2|| < \epsilon/2 + \epsilon/2 = \epsilon.$$

Item (2.) follows. To prove (2.) note that if c = 0 the result is clearly true so suppose $c \neq 0$. Suppose $\epsilon > 0$ and choose $\delta > 0$ such that $||f(x) - b_1|| < \epsilon/|c|$. Note that if $0 < ||x - a|| < \delta$ then

 $||(cf)(x) - cb_1|| = ||c(f(x) - b_1)|| = |c|||f(x) - b_1|| < |c|\epsilon/|c| = \epsilon.$

The claims about continuity follow immediately from the limit properties \Box .

Perhaps you recognize these arguments from calculus I. The logic used to prove the basic limit theorems on \mathbb{R} is essentially identical.

Proposition 3.2.13.

Suppose V_1, V_2, V_3 are normed vector spaces with norms $|| \cdot ||_1, || \cdot ||_2, || \cdot ||_3$ respective. Let $f : dom(f) \subseteq V_2 \to V_3$ and $g : dom(g) \subseteq V_1 \to V_2$ be mappings. Suppose that $\lim_{x \to x_o} g(x) = y_o$ and suppose that f is continuous at y_o then

$$\lim_{x \to x_o} (f \circ g)(x) = f\left(\lim_{x \to x_o} g(x)\right).$$

Proof: Let $\epsilon > 0$ and choose $\beta > 0$ such that $0 < ||y - b||_2 < \beta$ implies $||f(y) - f(y_o)||_3 < \epsilon$. We can choose such a β since Since f is continuous at y_o thus it follows that $\lim_{y \to y_o} f(y) = f(y_o)$. Next choose $\delta > 0$ such that $0 < ||x - x_o||_1 < \delta$ implies $||g(x) - y_o||_2 < \beta$. We can choose such

⁴turns out this is quite interesting television and cinema for what it's worth

a δ because we are given that $\lim_{x\to x_o} g(x) = y_o$. Suppose $0 < ||x - x_o||_1 < \delta$ and let y = g(x) note $||g(x) - y_o||_2 < \beta$ yields $||y - y_o||_2 < \beta$ and consequently $||f(y) - f(y_o)||_3 < \epsilon$. Therefore, $0 < ||x - x_o||_1 < \delta$ implies $||f(g(x)) - f(y_o)||_3 < \epsilon$. It follows that $\lim_{x\to x_o} (f(g(x)) = f(\lim_{x\to x_o} g(x))$. \Box

The squeeze theorem relies heavily on the order properties of \mathbb{R} . Generally a normed vector space has no natural ordering. For example, is 1 > i or is 1 < i in \mathbb{C} ? That said, we can state a squeeze theorem for functions whose domain reside in a normed vector space. This is a generalization of what we learned in calculus I. That said, the proof offered below is very similar to the typical proof which is not given in calculus I⁵

Proposition 3.2.14. squeeze theorem.

Suppose $f : dom(f) \subseteq V \to \mathbb{R}$, $g : dom(g) \subseteq V \to \mathbb{R}$, $h : dom(h) \subseteq V \to \mathbb{R}$ where V is a normed vector space with norm $|| \cdot ||$. Let $f(x) \leq g(x) \leq h(x)$ for all x on some $\delta > 0$ ball of⁶ $a \in V$ then we find that the limits at x_o follow the same ordering,

$$\lim_{x \to a} f(x) \le \lim_{x \to a} g(x) \le \lim_{x \to a} h(x).$$

Moreover, if $\lim_{x\to x_o} f(x) = \lim_{x\to x_o} h(x) = L \in \mathbb{R}$ then $\lim_{x\to x_o} f(x) = L$.

Proof: Suppose $f(x) \leq g(x)$ for all $x \in B_{\delta_1}(a)_o$ for some $\delta_1 > 0$ and also suppose $\lim_{x \to a} f(x) = L_f \in \mathbb{R}$ and $\lim_{x \to a} g(x) = L_g \in \mathbb{R}$. We wish to prove that $L_f \leq L_g$. Suppose otherwise towards a contradiction. That is, suppose $L_f > L_g$. Note that $\lim_{x \to a} [g(x) - f(x)] = L_g - L_f$ by the linearity of the limit. It follows that for $\epsilon = \frac{1}{2}(L_f - L_g) > 0$ there exists $\delta_2 > 0$ such that $x \in B_{\delta_2}(a)_o$ implies $|g(x) - f(x) - (L_g - L_f)| < \epsilon = \frac{1}{2}(L_f - L_g)$. Expanding this inequality we have

$$-\frac{1}{2}(L_f - L_g) < g(x) - f(x) - (L_g - L_f) < \frac{1}{2}(L_f - L_g)$$

adding $L_g - L_f$ yields,

$$-\frac{3}{2}(L_f - L_g) < g(x) - f(x) < -\frac{1}{2}(L_f - L_g) < 0.$$

Thus, f(x) > g(x) for all $x \in B_{\delta_2}(a)_o$. But, $f(x) \le g(x)$ for all $x \in B_{\delta_1}(a)_o$ so we find a contradiction for each $x \in B_{\delta}(a)$ where $\delta = \min(\delta_1, \delta_2)$. Hence $L_f \le L_g$. The same proof can be applied to g and h thus the first part of the theorem follows.

Next, we suppose that $\lim_{x\to a} f(x) = \lim_{x\to a} h(x) = L \in \mathbb{R}$ and $f(x) \leq g(x) \leq h(x)$ for all $x \in B_{\delta_1}(a)$ for some $\delta_1 > 0$. We seek to show that $\lim_{x\to a} f(x) = L$. Let $\epsilon > 0$ and choose $\delta_2 > 0$ such that $|f(x) - L| < \epsilon$ and $|h(x) - L| < \epsilon$ for all $x \in B_{\delta}(a)_o$. We are free to choose such a $\delta_2 > 0$ because the limits of f and h are given at x = a. Choose $\delta = \min(\delta_1, \delta_2)$ and note that if $x \in B_{\delta}(a)_o$ then

$$f(x) \le g(x) \le h(x)$$

⁵this is lifted word for word from my calculus I notes, however here the meaning of open ball is considerably more general and the linearity of the limit which is referenced is the one proven earlier in this section

hence,

$$f(x) - L \le g(x) - L \le h(x) - L$$

but $|f(x) - L| < \epsilon$ and $|h(x) - L| < \epsilon$ imply $-\epsilon < f(x) - L$ and $h(x) - L < \epsilon$ thus

$$-\epsilon < f(x) - L \le g(x) - L \le h(x) - L < \epsilon.$$

Therefore, for each $\epsilon > 0$ there exists $\delta > 0$ such that $x \in B_{\delta}(a)_o$ implies $|g(x) - L| < \epsilon$ so $\lim_{x \to a} g(x) = L$. \Box

Our typical use of the theorem above applies to equations of norms from a normed vector space. The norm takes us from V to \mathbb{R} so the theorem above is essential to analyze interesting limits. We shall make use of it in the next chapter.

Proposition 3.2.15. norm is continuous with respect to itself.

Suppose V has norm $|| \cdot ||$ then $f : V \to \mathbb{R}$ defined by f(x) = ||x|| is continuous.

Proof: Suppose $a \in V$ and let $\epsilon > 0$. Choose $\delta = \epsilon$ and consider $x \in V$ such that $0 < ||x - a|| < \delta$. Observe $||x|| = ||x - a + a|| \le ||x - a|| + ||a|| = \delta + ||a||$ and hence

$$|f(x) - f(a)| = |||x|| - ||a||| < |\delta + ||a|| - ||a||| = |\delta| = \epsilon.$$

Thus $f(x) \to f(a)$ as $x \to a$ and as $a \in V$ was arbitrary the proposition follows \Box .

Perhaps the most interesting feature of an abstract vector space is the loss of a canonical basis in general. One might worry that this ambiguity spoils the result of Proposition 3.1.8, however, this is not the case. Existence of limits for a set of component functions with respect to a particular basis implies existence for all others⁷

Theorem 3.2.16.

Let
$$V, W$$
 be normed vector spaces and suppose W has basis $\beta = \{w_j\}_{j=1}^m$. Let $a \in V$ then

$$\lim_{x \to a} F(x) = B = \sum_{j=1}^m B_j w_j \qquad \Leftrightarrow \qquad \lim_{x \to a} F_j(x) = B_j \text{ for all } j = 1, 2, \dots m.$$

Proof: Throughout this proof we should keep in mind the basis vector $w_j \neq 0$ implies $||w_j|| \neq 0$ hence we may form quotients by the length of any basis vector if the need arises.

⁷component functions with respect to different bases are related by multiplication by a constant nonsingular matrix, so this result is not too surprising.

Suppose $\lim_{x\to a} F(x) = B = \sum_{j=1}^{m} B_j w_j$. Also, let $F_j : V \to \mathbb{R}$ denote the *j*-th component function of F with respect to basis β ; that is suppose $F = \sum_{j=1}^{m} F_j w_j$. Consider that by the triangle inequality:

$$\left| \left| (F_j(x) - B_j)w_j \right| \right| \le \left| (F_1(x) - B_1)w_1 + \dots + (F_m(x) - B_m)w_m \right| = \left| |F(x) - B| \right|$$

Therefore, using the above in the last step, observe:

$$F_j(x) - B_j = \frac{||w_j||}{||w_j||} |F_j(x) - B_j| \le \frac{1}{||w_j||} ||(F_j(x) - B_j)w_j|| \le \frac{1}{||w_j||} ||F(x) - B||$$

Therefore, $|F_j(x) - B_j| \leq \frac{1}{||w_j||} ||F(x) - B||$. Let $\epsilon > 0$ and choose $\delta > 0$ such that $||F(x) - B|| < \epsilon ||w_j||$. If $x \in V$ such that $0 < ||x - a|| < \delta$ then note,

$$|F_j(x) - B_j| = \frac{1}{||w_j||} \le ||F(x) - B|| < \epsilon.$$

Thus $\lim_{x\to a} F_j(x) = B_j$ as $x \to a$ for all $j \in \mathbb{N}_n$.

Conversely, suppose $\lim_{x\to a} F_j(x) = B_j$ as $x \to a$ for all $j \in \mathbb{N}_n$. Let $\epsilon > 0$ and choose $\delta_j > 0$ such that $0 < ||x - a|| < \delta_j$ implies $||F_j(x) - B_j|| < \frac{\epsilon}{||w_j||m}$. We are free to choose such δ_j by the given limits as clearly $\frac{\epsilon}{||w_j||m} > 0$ for each j. Choose $\delta = \min(\delta_j \mid j \in \mathbb{N}_m)$ and suppose $x \in V$ such that $0 < ||x - a|| < \delta$. Using properties $||x + y|| \le ||x|| + ||y||$ and ||cx|| = |c|||x|| multiple times yield:

$$||F(x) - B|| = ||\sum_{j=1}^{m} (F_j(x) - B_j)w_j|| \le \sum_{j=1}^{m} |F_j(x) - B_j|||w_j|| < \sum_{j=1}^{m} \frac{\epsilon}{||w_j||m}||w_j|| = \sum_{j=1}^{m} \frac{\epsilon}{m} = \epsilon.$$

Therefore, $\lim_{x\to a} F(x) = B$ and this completes the proof \Box .

Remark 3.2.17.

There are other topologies possible for \mathbb{R}^n . For example, one can prove that

$$||v||_1 = |v_1| + |v_2| + \dots + |v_n|$$

gives a norm on \mathbb{R}^n and the theorems we proved transfer over almost without change by just trading $|| \cdot ||$ for $|| \cdot ||_1$. The unit "ball" becomes a diamond for the 1-norm. There are many other norms which can be constructed, infinitely many it turns out. However, it has been shown that the topology of all these different norms is equivalent. This means that open sets generated from different norms will be the same class of sets. For example, if you can fit an open disk around every point in a set then it's clear you can just as well fit an open diamond and vice-versa. One of the things that makes infinite dimensional linear algebra more fun is the fact that the topology generated by distinct norms need not be equivalent for infinite dimensions. There is a difference between the open sets generated by the Euclidean norm verses those generated by the 1-norm. Incidentally, my thesis work is mostly built over the 1-norm. It makes the supernumbers happy.

3.3 intuitive theorems of calculus

In this section we review some of the important theorems of calculus which justify analytical arguments via derivatives and continuity. Most of these you should have seen in Calculus I, but perhaps the proof was not given. I give the proofs here for your mathematical edification. I doubt we'll cover them in lecture. That said, the end of this section presents the Extreme Value Theorem's generalization to multivariate, real-valued functions and we will probably discuss that. One interesting thing to think about, which theorems in the next subsection generalize to functions whose domain is a Banach space and range if \mathbb{R} ?

3.3.1 theorems for single-variable calculus

Proposition 3.3.1.

Let f be continuous at c such that $f(c) \neq 0$ then there exists $\delta > 0$ such that either f(x) > 0or f(x) < 0 for all $x \in (c - \delta, c + \delta)$.

Proof: we are given that $\lim_{x\to c} f(x) = f(a) \neq 0$.

1.) Assume that f(a) > 0. Choose $\epsilon = \frac{f(a)}{2}$ and use existence of the limit $\lim_{x \to c} f(x) = f(a)$ to select $\delta > 0$ such that $0 < |x - c| < \delta$ implies $|f(x) - f(a)| < \frac{f(a)}{2}$ hence $-\frac{f(a)}{2} < f(x) - f(a) < \frac{f(a)}{2}$. Adding f(a) across the inequality yields $0 < \frac{f(a)}{2} < f(x) < \frac{3f(a)}{2}$.

2.) If f(a) < 0 then we can choose $\epsilon = -\frac{f(a)}{2} > 0$ and select $\delta > 0$ such that $0 < |x - c| < \delta$ implies $|f(x) - f(a)| < -\frac{f(a)}{2}$ hence $\frac{f(a)}{2} < f(x) - f(a) < -\frac{f(a)}{2}$. It follows that $\frac{3f(a)}{2} < f(x) < \frac{f(a)}{2} < 0$.

The proposition follows. \Box

Bolzano understood there was a gap in the arguments of the founders of calculus. Often, theorems like those stated in this section would merely be claimed without proof. The work of Bolzano and others like him ultimately gave rise to the careful rigorous study of the real numbers and more generally the study of *real analysis*⁸

Proposition 3.3.1 is clearly extended to sets which have boundary points. If we know a function is continuous on [a, b) and $f(a) \neq 0$ then we can find $\delta > 0$ such that $f([a, a + \delta)) > 0$. (*This is needed in the proof below in the special case that* c = a *and a similar comment applies to* c = b.)

⁸the Bolzano-Weierstrauss theorem is one of the central theorems of real analysis, in 1817 Bolzano used it to prove the IVT. It states every bounded sequence contains a convergent subsequence. Sequences can also be used to formulate limits and continuity. Sequential convergence is dealt with properly in Math 431 at LU.

Theorem 3.3.2. Bolzano's theorem

Let f be continuous on [a,b] such that f(a)f(b) < 0 then there exists $c \in (a,b)$ such that f(c) = 0.

Proof: suppose f(a) < f(b) then f(a)f(b) < 0 implies f(a) < 0 and f(b) > 0. We can use axiom A11 for the heart of this proof. Our goal is to find a nonempty subset $S \subseteq \mathbb{R}$ which has an upper bound. Axiom A11 will then provides the existence of the least upper bound. We should like to construct a set which has the property desired in this theorem. Define $S = \{x \in [a,b] \mid f(x) < 0\}$. Notice that $a \in S$ since f(a) < 0 thus $S \neq \emptyset$. Moreover, it is clear that $x \leq b$ for all $x \in S$ thus S is bounded above. Axiom A11 states that there exists a least upper bound $c \in S$. To say c is the least upper bound means that any other upperbound of S is larger than c.

We now seek to show that f(c) = 0. Consider that there exist three possibilities:

- 1. if f(c) < 0 then the continuous function f has $f(c) \neq 0$ so by prop. 3.3.1 there exists $\delta > 0$ such that $x \in (c - \delta, c + \delta) \cap [a, b]$ implies f(x) < 0. However, this implies there is a value $x \in [c, c + \delta)$ such that f(x) < 0 and x > c which means x is in S and is larger than the upper bound c. Therefore, c is not an upper bound of S. Obviously this is a contradiction therefore $f(c) \neq 0$.
- 2. if f(c) > 0 then the continuous function f has $f(c) \neq 0$ so by prop. 3.3.1 there exists $\delta > 0$ such that $x \in (c - \delta, c + \delta) \cap [a, b]$ implies f(x) > 0. However, this implies that all values $x \in (c - \delta, c]$ have f(x) > 0 and thus $x \notin S$ which means $x = c - \delta/2 < c$ is an upper bound of S which is smaller than the least upper bound c. Therefore, c is not the least upper bound of S. Obviously this is a contradiction therefore $f(c) \neq 0$.
- 3. if f(c) = 0 then no contradiction is found. The theorem follows. \Box

My proof here essentially follows Apostol's argument, however I suspect this argument in one form or another can be found in many serious calculus texts. With Bolzano's theorem settled we can prove the IVT without much difficulty.

Proposition 3.3.3. Intermediate Value Theorem .

Suppose that f is continuous on an interval [a, b] with $f(a) \neq f(b)$ and let N be a number such that N is between f(a) and f(b) then there exists $c \in (a, b)$ such that f(c) = N.

Proof: let N be as described above and define g(x) = f(x) - N. Note that g is clearly continuous. Suppose that f(a) < f(b) then we must have f(a) < N < f(b) which gives $f(a) - N \le 0 \le f(b) - N$ hence g(a) < 0 < g(b). Applying Bolzano's theorem to g gives $c \in (a, b)$ such that g(c) = 0. But, g(c) = f(c) - N = 0 therefore f(c) = N. If f(a) > f(b) then a similar argument applies. \Box .

Proposition 3.3.4. Extreme value theorem.

Suppose that f is a function which is continuous on [a, b] then f attains its absolute maximum f(c) on [a, b] and its absolute minimum f(d) on [a, b] for some $c, d \in [a, b]$.

It's easy to see why the requirement of continuity is essential. If the function had a vertical asymptote on [a, b] then the function gets arbitrarily large or negative so there is no biggest or most negative value the function takes on the closed interval. Of course, if we had a vertical asymptote then the function is not continuous at the asymptote. The proof of this theorem is technical and beyond the scope of this course. See Apostol pages 150-151 for a nice proof.

Definition 3.3.5. critical numbers.

We say $c \in \mathbb{R}$ is a **critical number** of a function f if either f'(c) = 0 or f'(c) does not exist. If $c \in dom(f)$ is a critical number then (c, f(c)) is a **critical point** of f.

Notice that a critical number need not be in the domain of a given function. For example, f(x) = 1/x has $f'(x) = -1/x^2$ and thus c = 0 is a critical numbers as f'(0) does not exist in \mathbb{R} . Clearly $0 \notin dom(f)$ either. It is usually the case that a vertical asymptote of the function will likewise be a vertical asymptote of the derivative function.

Proposition 3.3.6. Fermat's theorem.

If f has a local extreme value of f(c) and f'(c) exists then f'(c) = 0.

Proof: suppose f(c) is a local maximum. Then there exists $\delta_1 > 0$ such that $f(c+h) \leq f(c)$ for all $h \in B_{\delta_1}(0)$. Furthermore, since $f'(c) \in \mathbb{R}$ we have $\lim_{h\to 0} \frac{f(c+h)-f(c)}{h} = f'(c) \in \mathbb{R}$. If h > 0 and $h \in B_{\delta_1}(0)$ then $f(c+h) - f(c) \leq 0$ hence,

$$\frac{f(c+h) - f(c)}{h} \le 0$$

Using the squeeze theorem we find $f'(c) = \lim_{h \to 0^+} \frac{f(c+h) - f(c)}{h} \leq \lim_{h \to 0} (0) = 0$. Likewise, if h < 0 and $h \in B_{\delta_1}(0)$ then $f(c+h) - f(c) \leq 0$ hence,

$$\frac{f(c+h) - f(c)}{h} \ge 0$$

Using the squeeze theorem we find $f'(c) = \lim_{h\to 0^-} \frac{f(c+h)-f(c)}{h} \ge \lim_{h\to 0} (0) = 0$. Consequently, $f'(c) \le 0$ and $f'(c) \ge 0$ therefore f'(c) = 0. The proof in the case that f(c) is a local minimum is similar. \Box

Remember, if f'(c) does not exist then c is a critical point by definition. Therefore, if f(c) is a local extrema then c must be a critical point for one of two general reasons:

1. f'(c) exists so Fermat's theorem proves f'(c) = 0 so c is a critical point.

2. f'(c) does not exist so by definition c is a critical point.

Sometimes Fermat's Theorem is simply stated as "local extrema happen at critical points".

The converse of this Theorem is not true. We can have a critical number c such that f(c) is **not** a local maximum or minimum. For example, $f(x) = x^3$ has critical number c = 0 yet f(0) = 0 which is neither a local max. nor min. value of $f(x) = x^3$. It turns out that (0,0) is actually an *inflection point* as we'll discuss soon. Another example of a critical point which yields something funny is a constant function; if g(x) = k then g'(x) = 0 for each and every $x \in dom(g)$. Technically, y = k is both the minimum and maximum value of g. Constant functions are a sort of exceptional case in this game we are playing.

Proposition 3.3.7. Rolle's theorem.

Suppose that f is a function such that

1. f is continuous on [a, b],

2. f is differentiable on (a, b),

3. f(a) = f(b).

Then there exists $c \in (a, b)$ such that f'(c) = 0.

Proof: If f(x) = k for all $x \in [a, b]$ then every point is a critical point and the theorem is trivially satisfied. Suppose f is not constant, apply the Extreme Value Theorem to show there exists $c, d \in [a, b]$ such that $f(c) \geq f(x)$ for all $x \in [a, b]$ and $f(d) \leq f(x)$ for all $x \in [a, b]$. Since $f(x_0) \neq f(a)$ for at least one $x_0 \in (a, b)$ it follows that $f(x_0) > f(a)$ or $f(x_0) < f(a)$. If $x_0 \in (a, b)$ and $f(x_0) > f(a)$ then f(a) is not the absolute maximum therefore we deduce $c \in (a, b)$ is the absolute maximum. Likewise, if $x_0 \in (a, b)$ and $f(x_0) < f(a)$ then f(a) is not the absolute minimum therefore we deduce $d \in (a, b)$ is the absolute maximum. In all cases there is an absolute extremum in the open set (a, b) hence there exists a critical point in the interior of the set. Moreover, since f is differentiable on (a, b) it follows that either f'(c) = 0 or f'(d) = 0 and Rolle's theorem follows. \Box

Proposition 3.3.8. Mean Value Theorem (MVT).

Suppose that f is a function such that

- 1. f is continuous on [a, b],
- 2. f is differentiable on (a, b),

Then there exists $c \in (a, b)$ such that $f'(c) = \frac{f(b) - f(a)}{b - a}$. That is, there exists $c \in (a, b)$ such that f(b) - f(a) = f'(c)(b - a).

Proof:(essentially borrowed from Stewart's Calculus, this proof is common to a host of calculus texts). The equation of the secant line to y = f(x) on the interval [a, b] is y = s(x) where s(x) is
defined via the standard formula for a line going from (a, f(a) to (b, f(b)))

$$s(x) = f(a) + \frac{f(b) - f(a)}{b - a}(x - a).$$

The Mean Value Theorem proposes that there is some point on the interval [a, b] such that the slope of the tangent line is equal to the slope of the secant line y = s(x). Consider a new function defined to be the difference of the secant line and the given function, call it h:

$$h(x) = f(x) - s(x) = f(x) - f(a) - \frac{f(b) - f(a)}{b - a}(x - a)$$

Observe that h(a) = h(b) = 0 and h is clearly continuous on [a, b] because f is continuous and besides that the function is constructed from a sum of a polynomial with f. Additionally, it is clear that h is differentiable on (a, b) since polynomials are differentiable everywhere and f was assumed to be differentiable on (a, b). Thus Rolle's Theorem applies to h so there exists a $c \in (a, b)$ such that h'(c) = 0 which yields

$$h'(c) = f'(c) - \frac{f(b) - f(a)}{b - a} = 0 \implies f'(c) = \frac{f(b) - f(a)}{b - a}.$$

Proposition 3.3.9. sign of the derivative function f' indicates strict increase or decrease of f.

Suppose that f is a function and J is a connected subset of dom(f)1. if f'(x) > 0 for all $x \in J$ then f is strictly increasing on J2. if f'(x) < 0 for all $x \in J$ then f is strictly decreasing on J.

Proof: suppose f'(x) > 0 for all $x \in J$. Let $[a, b] \subseteq J$ and note f is continuous on [a, b] since it is given to be differentiable on a superset of [a, b]. The MVT applied to f with respect to [a, b] implies there exists $c \in [a, b]$ such that

$$\frac{f(b) - f(a)}{b - a} = f'(c).$$

Notice that f(b) - f(a) = (b-a)f'(c) but b-a > 0 and f'(c) > 0 hence f(b) - f(a) > 0. Therefore, for each pair $a, b \in J$ with a < b we find f(a) < f(b) which means f is strictly increasing on J. Likewise, if f'(c) < 0 then almost the same argument applies to show a < b implies f(a) > f(b). \Box

3.3.2 theorems for multivariate calculus

To begin, we need to define⁹ compact sets in \mathbb{R}^n .

Definition 3.3.10.

We say C is a **bounded** subset of \mathbb{R}^n if there exists an open ball which contains C. A subset $C \subseteq \mathbb{R}^n$ is **compact** iff it is both closed and bounded.

In the one-dimensional case, clearly closed intervals [a, b] are compact sets. In higher dimensions it's not hard to see that spheres, cubes, disks, ellipses, ellipsoids and more generally finite shapes with solid edges are compact. In particular, if there is some maximum distance between points then it is clear we can place a slightly larger ball around the set so it's bounded. Also, if the edges are solid then the set should be closed.

Definition 3.3.11.

Let $S \subset \mathbb{R}$. We say $u \in \mathbb{R}$ is an **upper bound** of S if $u \ge s$ for all $s \in S$. We say $l \in \mathbb{R}$ is an **lower bound** of S if $l \le s$ for all $s \in S$. Define the **least upper bound** to be $sup(S) \in \mathbb{R}$ for which $sup(S) \le u$ for all upper bounds u of S. Similarly, define the **greatest lower bound** to be $inf(S) \in \mathbb{R}$ for which $inf(S) \ge l$ for all lower bounds l of S.

The **completeness** of the real numbers can be expressed by the statement that every set which is bounded above has a suprememum sup(S). This is a clever way¹⁰ to capture the idea that every Cauchy sequence of real numbers converges to a real number.

Finally we reach the punchline of this section. The following theorem generalizes the **Extreme** Value Theorem for \mathbb{R} to the *n*-dimensional case.

Theorem 3.3.12.

Let C be a compact subset of \mathbb{R}^n and suppose $f: C \to \mathbb{R}$ is a continuous function. Then $sup(f(C)), inf(f(C)) \in \mathbb{R}$. The values of f attain a minimum and maximum over C.

Even in the one-dimensional case the proof of this theorem is non-trivial. Take a look at Apostol pages 150-151. Note that pages 49-55 of C.H. Edwards' *Advanced Calculus of Several Variables* discuss compactness in greater depth and list several theorems which are related to the Extreme Value Theorem given here. I think my comments here suffice for our purposes.

⁹the real definition of compactness says that C is compact if every open cover of C admits a finite subcover then this definition is a theorem which can be proved in the context of \mathbb{R}^n . See the Heine Borel theorem and related discussion in a good real analysis text

¹⁰some mathematicians construct the real numbers by simply adjoining these limit points to the rational numbers.

Chapter 4

differentiation

Our goal in this chapter is to describe differentiation for functions to and from normed linear spaces. It turns out this is actually quite simple given the background of the preceding chapter. The differential at a point is a linear transformation which best approximates the change in a function at a particular point. We can quantify "best" by a limiting process which is naturally defined in view of the fact there is a norm on the spaces we consider.

The most important example is of course the case $f : \mathbb{R}^n \to \mathbb{R}^m$. In this context it is natural to write the differential as a matrix multiplication. The matrix of the differential is what Edwards calls the *derivative*. Partial derivatives are also defined in terms of directional derivatives. The directional derivative is sometimes defined where the differential fails to exist. We will discuss how the criteria of continuous differentiability allows us to build the differential from the directional derivatives. We'll see how the Cauchy-Riemann equations of complex analysis are really just an algebraic result if we already have the theorem for continuously differentiability. We will see how this general concept of differentiation recovers all the derivatives you've seen previously in calculus and much more.

On the other hand, I postpone implicit differentiation for a future chapter where we have the existence theorems for implicit and inverse functions. I also postpone discussion of the geometry of the differential. In short, existence of the differential and the tangent space are essentially two sides of the same problem. In fact, the approach of this chapter is radically different than my first set of notes on advanced calculus. In those notes I followed Edwards a bit more and built up to the definition of the differential on the basis of the directional derivative and geometry. I don't think students appreciate geometry or directional differentiation well enough to make that approach successful. Consquently, I begin with the unjustified definition of the derivative and then spend the rest of the chapter working out precise implications and examples that flow from the definition. I essentially ignore the question of motivating the definition here. If you want motivation, think backward with this chapter or perhaps read Edwards or my old notes.

4.1 the Frechet differential

The definition¹ below says that $\Delta F = F(a+h) - F(a) \approx dF_a(h)$ when h is close to zero.

Definition 4.1.1.

Let $(V, || \cdot ||_V)$ and $(W, || \cdot ||_W)$ be normed vector spaces. Suppose that U is open and $F: U \subseteq V \to W$ is a function the we say that F is **differentiable** at $a \in U$ iff there exists a linear mapping $L: V \to W$ such that

$$\lim_{h \to 0} \left[\frac{F(a+h) - F(a) - L(h)}{||h||_V} \right] = 0.$$

In such a case we call the linear mapping L the **differential at** a and we denote $L = dF_a$. In the case $V = \mathbb{R}^m$ and $W = \mathbb{R}^n$ are given the standard euclidean norms, the matrix of the differential is called the **derivative of** F **at** a and we denote $[dF_a] = F'(a) \in \mathbb{R}^{m \times n}$ which means that $dF_a(v) = F'(a)v$ for all $v \in \mathbb{R}^n$.

Notice this definition gives an equation which implicitly defines dF_a . For the moment the only way we have to calculate dF_a is educated guessing. We simply use brute-force calculation to suggest a guess for L which forces the Frechet quotient to vanish. In the next section we'll discover a systematic calculational method for functions on euclidean spaces. The purpose of this section is to understand the definition of the differential and to connect it to some previous concepts of basic calculus. Efficient calculational schemes are discussed later in this chapter.

Example 4.1.2. Suppose $T: V \to W$ is a linear transformation of normed vector spaces V and W. I propose L = T. In other words, I think we can show the best linear approximation to the change in a linear function is simply the function itself. Clearly L is linear since T is linear. Consider the difference quotient:

$$\frac{T(a+h) - T(a) - L(h)}{||h||_V} = \frac{T(a) + T(h) - T(a) - T(h)}{||h||_V} = \frac{0}{||h||_V}.$$

Note $h \neq 0$ implies $||h||_V \neq 0$ by the definition of the norm. Hence the limit of the difference quotient vanishes since it is identically zero for every nonzero value of h. We conclude that $dT_a = T$.

Example 4.1.3. Let $T: V \to W$ where V and W are normed vector spaces and define $T(v) = w_o$ for all $v \in V$. I claim the differential is the zero transformation. Linearity of L(v) = 0 is trivially verified. Consider the difference quotient:

$$\frac{T(a+h) - T(a) - L(h)}{||h||_V} = \frac{w_o - w_o - 0}{||h||_V} = \frac{0}{||h||_V}.$$

Using the arguments to the preceding example, we find $dT_a = 0$.

¹Some authors might put a norm in the numerator of the quotient. That is an equivalent condition since a function $g: V \to W$ has $\lim_{h\to 0} g(h) = 0$ iff $\lim_{h\to 0} ||g(h)||_W = 0$

Typically the difference quotient is not identically zero. The pair of examples above are very special cases. Now that we've seen a sample pair of abstract examples now we turn to the question of how this general definition recovers the concept of differentiation we studied in introductory calculus.

Example 4.1.4. Suppose $f : dom(f) \subseteq \mathbb{R} \to \mathbb{R}$ is differentiable at x. It follows that there exists a linear function $df_x : \mathbb{R} \to \mathbb{R}$ such that²

$$\lim_{h \to 0} \frac{f(x+h) - f(x) - df_x(h)}{|h|} = 0.$$

Note that

$$\lim_{h \to 0} \frac{f(x+h) - f(x) - df_x(h)}{|h|} = 0 \quad \Leftrightarrow \quad \lim_{h \to 0^{\pm}} \frac{f(x+h) - f(x) - df_x(h)}{|h|} = 0$$

In the left limit $h \to 0^-$ we have h < 0 hence |h| = -h. On the other hand, in the right limit $h \to 0^+$ we have h > 0 hence |h| = h. Thus, differentiability suggests that $\lim_{h\to 0^-} \frac{f(x+h)-f(x)-df_x(h)}{\pm h} = 0$. But we can pull the minus out of the left limit to obtain $\lim_{h\to 0^-} \frac{f(x+h)-f(x)-df_x(h)}{h} = 0$. Therefore, after an algebra step, we find:

$$\lim_{h \to 0} \left[\frac{f(x+h) - f(x)}{h} - \frac{df_x(h)}{h} \right] = 0.$$

Linearity of $df_x : \mathbb{R} \to \mathbb{R}$ implies there exists $m \in \mathbb{R}^{1 \times 1} = \mathbb{R}$ such that $df_x(h) = mh$. Observe that

$$\lim_{h \to 0} \frac{df_x(h)}{h} = \lim_{h \to 0} \frac{mh}{h} = m$$

It is a simple exercise to show that if $\lim(A - B) = 0$ and $\lim(B)$ exists then $\lim(A)$ exists and $\lim(A) = \lim(B)$. Identify $A = \frac{f(x+h) - f(x)}{h}$ and $B = \frac{df_x(h)}{h}$. Therefore,

$$m = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

Consequently, we find the 1×1 matrix m of the differential is precisely f'(x) as we defined it via a difference quotient in first semester calculus. In summary, we find $df_x(h) = f'(x)h$. In other words, if a function is differentiable in the sense we defined at the beginning of this chapter then it is differentiable in the terminology we used in calculus I. Moreover, the derivative at x is precisely the matrix of the differential.

Remark 4.1.5.

Incidentally, I should mention that df_x is the differential of f at the point x. The differential of f would be the mapping $x \mapsto df_x$. Technically, the differential df is a function from \mathbb{R} to the set of linear transformations on \mathbb{R} . You can contrast this view with that of first semester calculus. There we say the mapping $x \mapsto f'(x)$ defines the derivative f' as a function from \mathbb{R} to \mathbb{R} . This simplification in perspective is only possible because calculus in one-dimension is so special. More on this later. This distinction is especially important to understand if you begin to look at questions of higher derivatives.

²unless we state otherwise, \mathbb{R}^n is assumed to have the euclidean norm, in this case $||x||_{\mathbb{R}} = \sqrt{x^2} = |x|$.

Example 4.1.6. Suppose $F : \mathbb{R}^2 \to \mathbb{R}^3$ is defined by $F(x, y) = (xy, x^2, x + 3y)$ for all $(x, y) \in \mathbb{R}^2$. Consider the difference function $\triangle F$ at (x, y):

$$\triangle F = F((x, y) + (h, k)) - F(x, y) = F(x + h, y + k) - F(x, y)$$

Calculate,

$$\Delta F = \left((x+h)(y+k), \ (x+h)^2, \ x+h+3(y+k) \right) - \left(xy, \ x^2, \ x+3y \right)$$

Simplify by cancelling terms which cancel with F(x, y):

$$\triangle F = \left(xk + hy + hk, \ 2xh + h^2, \ h + 3k\right)$$

Identify the linear part of $\triangle F$ as a good candidate for the differential. I claim that:

$$L(h,k) = (xk + hy, 2xh, h + 3k).$$

is the differential for f at (x,y). Observe first that we can write

$$L(h,k) = \begin{bmatrix} y & x \\ 2x & 0 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} h \\ k \end{bmatrix}.$$

therefore $L: \mathbb{R}^2 \to \mathbb{R}^3$ is manifestly linear. Use the algebra above to simplify the difference quotient below:

$$\lim_{(h,k)\to(0,0)} \left[\begin{array}{c} \underline{\Delta F - L(h,k)} \\ ||(h,k)|| \end{array} \right] = \lim_{(h,k)\to(0,0)} \left[\frac{(hk,h^2,0)}{||(h,k)||} \right]$$

Note $||(h,k)|| = \sqrt{h^2 + k^2}$ therefore we fact the task of showing that $\frac{1}{\sqrt{h^2 + k^2}}(hk, h^2, 0) \rightarrow (0,0,0)$ as $(h,k) \rightarrow (0,0)$. Notice that:

$$||(hk, h^2, 0)|| = |h|\sqrt{h^2 + k^2}$$

Therefore, as $(h,k) \rightarrow 0$ we find

$$\left\|\frac{1}{\sqrt{h^2+k^2}}(hk, h^2, 0)\right\| = |h| \to 0.$$

However, if $||v|| \to 0$ it follows $v \to 0$ so we derive the desired limit. Therefore,

$$df_{(x,y)}(h,k) = \begin{bmatrix} y & x \\ 2x & 0 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} h \\ k \end{bmatrix}$$

Computation of less trivial multivariate limits is an art we'd like to avoid if possible. It turns out that we can actually avoid these calculations by computing partial derivatives. However, we still need a certain multivariate limit to exist for the partial derivative functions so in some sense it's unavoidable. The limits are there whether we like to calculate them or not.

Calculation of the differential simplifies considerably when the domain is one-dimensional. We already worked out the case of $f : \mathbb{R} \to \mathbb{R}$ in Example 4.1.4 and the following pair of examples work out the concrete case of $F : \mathbb{R} \to \mathbb{C}$ and then the general case $F : \mathbb{R} \to V$ for an arbitrary finite dimensional normed linear space V.

Example 4.1.7. Suppose F(t) = U(t) + iV(t) for all $t \in dom(f)$ and both U and V are differentiable functions on dom(F). By the arguments given in Example 4.1.4 it suffices to find $L : \mathbb{R} \to \mathbb{C}$ such that

$$\lim_{h \to 0} \left[\frac{F(t+h) - F(t) - L(h)}{h} \right] = 0.$$

I propose that on the basis of analogy to Example 4.1.4 we ought to have $dF_t(h) = (U'(t) + iV'(t))h$. Let L(h) = (U'(t) + iV'(t))h. Observe that, using properties of \mathbb{C} :

$$L(h_1 + ch_2) = (U'(t) + iV'(t))(h_1 + ch_2)$$

= $(U'(t) + iV'(t))h_1 + c(U'(t) + iV'(t))h_2$
= $L(h_1) + cL(h_2).$

for all $h_1, h_2 \in \mathbb{R}$ and $c \in \mathbb{R}$. Hence $L : \mathbb{R} \to \mathbb{C}$ is linear. Moreover,

$$\frac{F(t+h)-F(t)-L(h)}{h} = \frac{1}{h} \left(U(t+h) + iV(t+h) - U(t) + iV(t) - (U'(t) + iV'(t))h \right)$$
$$= \frac{1}{h} \left(U(t+h) - U(t) - U'(t)h \right) + i\frac{1}{h} \left(V(t+h) - V(t) - V'(t)h \right)$$

Consider the problem of calculating $\lim_{h\to 0} \frac{F(t+h)-F(t)-L(h)}{h}$. We observe that a complex function converges to zero iff the real and imaginary parts of the function separately converge to zero (this is covered by Theorem 3.2.16). By differentiability of U and V we find again using Example 4.1.4

$$\lim_{h \to 0} \frac{1}{h} \left(U(t+h) - U(t) - U'(t)h \right) = 0 \qquad \lim_{h \to 0} \frac{1}{h} \left(V(t+h) - V(t) - V'(t)h \right) = 0.$$

Therefore, $dF_t(h) = (U'(t) + iV'(t))h$. Note that the quantity U'(t) + iV'(t) is not a real matrix in this case. To write the derivative in terms of a real matrix multiplication we need to construct some further notation which makes use of the isomorphism between \mathbb{C} and \mathbb{R}^2 . Actually, it's pretty easy if you agree that a + ib = (a, b) then $dF_t(h) = (U'(t), V'(t))h$ so the matrix of the differential is $(U'(t), V'(t)) \in \mathbb{R}^{1 \times 2}$ which makes since as $F : \mathbb{C} \approx \mathbb{R}^2 \to \mathbb{R}$. **Example 4.1.8.** Suppose V is a normed vector space with basis $\beta = \{f_1, f_2, \dots, f_n\}$. Futhermore, let $G : I \subseteq \mathbb{R} \to V$ be defined by

$$G(t) = \sum_{i=1}^{n} G_i(t) f_i$$

where $G_i: I \to \mathbb{R}$ is differentiable on I for i = 1, 2, ..., n. Recall Theorem 3.2.16 revealed that $T = \sum_{j=1}^{n} T_j f_j : \mathbb{R} \to V$ then $\lim_{t\to 0} T(t) = \sum_{j=1}^{n} l_j f_j$ iff $\lim_{t\to 0} T_j(t) = l_j$ for all j = 1, 2, ..., n. In words, the limit of a vector-valued function can be parsed into a vector of limits. With this in mind consider (again we can trade |h| for h as we explained in-depth in Example 4.1.4) the difference quotient $\lim_{h\to 0} \left[\frac{G(t+h)-G(t)-h\sum_{i=1}^{n} \frac{dG_i}{dt}f_i}{h} \right]$, factoring out the basis yields:

$$\lim_{h \to 0} \left[\frac{\sum_{i=1}^{n} [G_i(t+h) - G_i(t) - h\frac{dG_i}{dt}]f_i}{h} \right] = \sum_{i=1}^{n} \left[\lim_{h \to 0} \frac{G_i(t+h) - G_i(t) - h\frac{dG_i}{dt}}{h} \right] f_i = 0$$

where the zero above follows from the supposed differentiability of each component function. It follows that:

$$dG_t(h) = h \sum_{i=1}^n \frac{dG_i}{dt} f_i$$

The example above encompasses a number of cases at once:

- 1. $V = \mathbb{R}$, functions on \mathbb{R} , $f : \mathbb{R} \to \mathbb{R}$
- 2. $V = \mathbb{R}^n$, space curves in $\mathbb{R}, \vec{r} : \mathbb{R} \to \mathbb{R}^n$
- 3. $V = \mathbb{C}$, complex-valued functions of a real variable, $f = u + iv : \mathbb{R} \to \mathbb{C}$
- 4. $V = \mathbb{R}^{m \times n}$, matrix-valued functions of a real variable, $F : \mathbb{R} \to \mathbb{R}^{m \times n}$.

In short, when we differentiate a function which has a real domain then we can define the derivative of such a function by component-wise differentiation. It gets more interesting when the domain has several independent variables as Examples 4.1.6 and 4.1.9 illustrate.

Example 4.1.9. Suppose $F : \mathbb{R}^{n \times n} \to \mathbb{R}^{n \times n}$ is defined by $F(X) = X^2$. Notice

$$\triangle F = F(X + H) - F(X) = (X + H)(X + H) - X^{2} = XH + HX + H^{2}$$

I propose that F is differentiable at X and L(H) = XH + HX. Let's check linearity,

$$L(H_1 + cH_2) = X(H_1 + cH_2) + (H_1 + cH_2)X = XH_1 + H_1X + c(XH_2 + H_2X)$$

Hence $L : \mathbb{R}^{n \times n} \to \mathbb{R}^{n \times n}$ is a linear transformation. By construction of L the linear terms in the numerator cancel leaving just the quadratic term,

$$\lim_{H \to 0} \frac{F(X+H) - F(X) - L(H)}{||H||} = \lim_{H \to 0} \frac{H^2}{||H||}$$

It suffices to show that $\lim_{H\to 0} \frac{||H^2||}{||H||} = 0$ since $\lim(||g||) = 0$ iff $\lim(g) = 0$ in a normed vector space. Fortunately the normed vector space $\mathbb{R}^{n \times n}$ is actually a **Banach algebra**. A vector space with a multiplication operation is called an algebra. In the current context the multiplication is simply matrix multiplication. A Banach algebra is a normed vector space with a multiplication that satisfies $||XY|| \leq ||X|| ||Y||$. Thanks to this inequality³ we can calculate our limit via the squeeze theorem. Observe $0 \leq \frac{||H^2||}{||H||} \leq ||H||$. As $H \to 0$ it follows $||H|| \to 0$ hence $\lim_{H\to 0} \frac{||H^2||}{||H||} = 0$. We find $dF_X(H) = XH + HX$.

Generally constructing the matrix for a function $f: V \to W$ where $V, W \neq \mathbb{R}$ involves a fair number of relatively ad-hoc conventions because the constructions necessarily involving choosing coordinates. The situation is similar in linear algebra. Writing abstract linear transformations in terms of matrix multiplication takes a little thinking. If you look back you'll notice that I did not bother to try to write a matrix for the differential in Examples 4.1.2 or 4.1.3.

Remark 4.1.10.

I have deliberately defined the derivative in slightly more generality than we need for this course. It's probably not much trouble to continue to develop the theory of differentiation for a normed vector space, however I will for the most part stop here modulo an example here or there.

If you understand many of the theorems that follow from here on out for \mathbb{R}^n then it is a simple matter to transfer arguments to the setting of a Banach space by using an appropriate isomorphism. Traditionally this type of course only covers continuous differentiability, inverse and implicit function theorems in the context of mappings from \mathbb{R}^n to \mathbb{R}^m .

For the reader interested in generalizing these results to the context of an abstract normed vector space feel free to discuss it with me sometime. Also, if you want to read a master on these topics you could look at the text by Shlomo Sternberg on Advanced Calculus. He develops many things for normed spaces. Or, take a look at Dieudonne's Modern Analysis which pays special attention to reaping infinite dimensional results from our finite-dimensional arguments. Both of those texts would be good to read to follow-up my course with something deeper.

³it does take a bit of effort to prove this inequality holds for the matrix norm, I omit it since it would be distracting here

4.2 partial derivatives and the Jacobian matrix

In the preceding section we calculated the differential at a point via educated guessing. We should like to find better method to derive differentials. It turns out that we can systematically calculate the differential from partial derivatives of the component functions. However, certain topological conditions are required for us to properly paste together the partial derivatives of the component functions. The story is given near the end of the Chapter in Section 4.7. There we describe how the criteria of continuous differentiability achieves this goal. The difference between what we do here and calculus III is that the derivative is no longer a number or a vector, instead as we shall see soon, it is a matrix. Even this is a convenience, the better view is that the differential is primary. Thus the better concept for the derivative is that of linear transformations. Dieudonne said it best: this is the introduction to his chapter on differentiation in *Modern Analysis* Chapter VIII.

The subject matter of this Chapter is nothing else but the elementary theorems of Calculus, which however are presented in a way which will probably be new to most students. That presentation, which throughout adheres strictly to our general "geometric" outlook on Analysis, aims at keeping as close as possible to the fundamental idea of Calculus, namely the "local" approximation of functions by *linear* functions. In the classical teaching of Calculus, the idea is immediately obscured by the accidental fact that, on a one-dimensional vector space, there is a one-to-one correspondence between *linear* forms and numbers, and therefore the derivative at a point is defined as a *number* instead of a *linear form*. This slavish subservience to the shibboleth⁴ of numerical interpretation at any cost becomes much worse when dealing with functions of several variables...

Dieudonne's then spends the next half page continuing this thought with explicit examples of how this custom of our calculus presentation injures the conceptual generalization. If you want to see differentiation written for mathematicians, that is the place to look. He proves many results for infinite dimensions because, well, why not?

4.2.1 directional derivatives

The directional derivative of a mapping F at a point $a \in dom(F)$ along v is defined to be the derivative of the curve $\gamma(t) = F(a + tv)$. In other words, the directional derivative gives you the instantaneous vector-rate of change in the mapping F at the point a along v.

⁴from wikipedia: is a word, sound, or custom that a person unfamiliar with its significance may not pronounce or perform correctly relative to those who are familiar with it. It is used to identify foreigners or those who do not belong to a particular class or group of people. It also refers to features of language, and particularly to a word or phrase whose pronunciation identifies a speaker as belonging to a particular group.

Definition 4.2.1.

Let $F : dom(F) \subseteq \mathbb{R}^n \to \mathbb{R}^m$ and suppose the limit below exists for $a \in dom(F)$ and $v \in \mathbb{R}^n$ then we define the **directional derivative of** F at a along v to be $D_v F(a) \in \mathbb{R}^m$ where

$$D_v F(a) = \lim_{h \to 0} \frac{F(a+hv) - F(a)}{h}$$

One great contrast we should pause to note is that the definition of the directional derivative is explicit whereas the definition of the differential was implicit. The picture below might help motivate the definition we just offered.



In the case that m = 1 then $F : dom(F) \subseteq \mathbb{R}^n \to \mathbb{R}$ and the directional derivative gives the instantaneous rate of change of the function F at the point a along v. You probably insisted that ||v|| = 1 in calculus III but we make no such demand here. We define the directional derivative for mappings and vectors of non-unit length.

Proposition 4.2.2.

If $F: U \subseteq \mathbb{R}^n \to \mathbb{R}^m$ is differentiable at $a \in U$ then the directional derivative $D_v F(a)$ exists for each $v \in \mathbb{R}^n$ and $D_v F(a) = dF_a(v)$.

Proof: Suppose $a \in U$ such that dF_a is well-defined then we are given that

$$\lim_{h \to 0} \frac{F(a+h) - F(a) - dF_a(h)}{||h||} = 0$$

This is a limit in \mathbb{R}^n , when it exists it follows that the limits that approach the origin along particular paths also exist and are zero. In particular we can consider the path $t \mapsto tv$ for $v \neq 0$ and t > 0, we find

$$\lim_{tv\to 0,\ t>0} \frac{F(a+tv) - F(a) - dF_a(tv)}{||tv||} = \frac{1}{||v||} \lim_{t\to 0^+} \frac{F(a+tv) - F(a) - tdF_a(v)}{|t|} = 0.$$

Hence, as |t| = t for t > 0 we find

$$\lim_{t \to 0^+} \frac{F(a+tv) - F(a)}{t} = \lim_{t \to 0} \frac{tdF_a(v)}{t} = dF_a(v).$$

Likewise we can consider the path $t \mapsto tv$ for $v \neq 0$ and t < 0

$$\lim_{tv\to 0, t<0} \frac{F(a+tv) - F(a) - dF_a(tv)}{||tv||} = \frac{1}{||v||} \lim_{t\to 0^-} \frac{F(a+tv) - F(a) - tdF_a(v)}{|t|} = 0$$

Note |t| = -t thus the limit above yields

$$\lim_{t \to 0^{-}} \frac{F(a+tv) - F(a)}{-t} = \lim_{t \to 0^{-}} \frac{tdF_a(v)}{-t} \quad \Rightarrow \quad \lim_{t \to 0^{-}} \frac{F(a+tv) - F(a)}{t} = dF_a(v).$$

Therefore,

$$\lim_{t \to 0} \frac{F(a+tv) - F(a)}{t} = dF_a(v)$$

and we conclude that $D_v F(a) = dF_a(v)$ for all $v \in \mathbb{R}^n$ since the v = 0 case follows trivially. \Box

Let's think about the problem we face. We want to find a nice formula for the differential. We now know that if it exists then the directional derivatives allow us to calculate the values of the differential in particular directions. The natural thing to do is to calculate the standard matrix for the differential using the preceding proposition. Recall that if $L : \mathbb{R}^n \to \mathbb{R}^m$ then the standard matrix was simply

$$[L] = [L(e_1)|L(e_2)|\cdots|L(e_n)]$$

and thus the action of L is expressed nicely as a matrix multiplication; L(v) = [L]v. Similarly, $df_a : \mathbb{R}^n \to \mathbb{R}^m$ is linear transformation and thus $df_a(v) = [df_a]v$ where

$$[df_a] = [df_a(e_1)|df_a(e_2)|\cdots|df_a(e_n)].$$

Moreover, by the preceding proposition we can calculate $df_a(e_j) = D_{e_j}f(a)$ for j = 1, 2, ..., n. Clearly the directional derivatives in the coordinate directions are of great importance. For this reason we make the following definition:

Definition 4.2.3. Partial derivatives are directional derivatives in coordinate directions.

Suppose that $F: U \subseteq \mathbb{R}^n \to \mathbb{R}^m$ is a mapping the we say that F is **has partial derivative** $\frac{\partial F}{\partial x_i}(a)$ at $a \in U$ iff the directional derivative in the e_i direction exists at a. In this case we denote.

$$\frac{\partial F}{\partial x_i}(a) = D_{e_i}F(a).$$

Also, the notation $D_{e_i}F(a) = D_iF(a)$ or $\partial_i F = \frac{\partial F}{\partial x_i}$ is convenient. We construct the **partial** derivative function $\partial_i F : V \subseteq \mathbb{R}^n \to \mathbb{R}^m$ as the function defined pointwise for each $v \in V$ where $\partial_i F(v)$ exists.

Let's expand this definition a bit. Note that if $F = (F_1, F_2, \ldots, F_m)$ then

~ ---

$$D_{e_i}F(a) = \lim_{h \to 0} \frac{F(a+he_i) - F(a)}{h} \quad \Rightarrow \quad [D_{e_i}F(a)] \cdot e_j = \lim_{h \to 0} \frac{F_j(a+he_i) - F_j(a)}{h}$$

for each j = 1, 2, ..., m. But then the limit of the component function F_j is precisely the directional derivative at a along e_i hence we find the result

$$\frac{\partial F}{\partial x_i} \cdot e_j = \frac{\partial F_j}{\partial x_i} \quad \text{in other words,} \quad \boxed{\partial_i F = (\partial_i F_1, \partial_i F_2, \dots, \partial_i F_m).}$$

In the particular case $f: \mathbb{R}^2 \to \mathbb{R}$ the partial derivatives with respect to x and y at (x_o, y_o) are related to the graph z = f(x, y) as illustrated below:



Similar pictures can be imagined for partial derivatives of more variables, even for vector-valued maps, but direct visualization is not possible (at least for me).

The proposition below shows how the differential of a m-vector-valued function of n-real variables is connected to a matrix of partial derivatives.

Proposition 4.2.4.

If $F : U \subseteq \mathbb{R}^n \to \mathbb{R}^m$ is differentiable at $a \in U$ then the differential dF_a has derivative matrix F'(a) and it has components which are expressed in terms of partial derivatives of the component functions:

$$[dF_a]_{ij} = \partial_j F_i$$

for $1 \leq i \leq m$ and $1 \leq j \leq n$.

Perhaps it is helpful to expand the derivative matrix explicitly for future reference:

$$F'(a) = \begin{bmatrix} \partial_1 F_1(a) & \partial_2 F_1(a) & \cdots & \partial_n F_1(a) \\ \partial_1 F_2(a) & \partial_2 F_2(a) & \cdots & \partial_n F_2(a) \\ \vdots & \vdots & \vdots & \vdots \\ \partial_1 F_m(a) & \partial_2 F_m(a) & \cdots & \partial_n F_m(a) \end{bmatrix}$$

Let's write the operation of the differential for a differentiable mapping at some point $a \in \mathbb{R}$ in terms of the explicit matrix multiplication by F'(a). Let $v = (v_1, v_2, \dots, v_n) \in \mathbb{R}^n$,

$$dF_{a}(v) = F'(a)v = \begin{bmatrix} \partial_{1}F_{1}(a) & \partial_{2}F_{1}(a) & \cdots & \partial_{n}F_{1}(a) \\ \partial_{1}F_{2}(a) & \partial_{2}F_{2}(a) & \cdots & \partial_{n}F_{2}(a) \\ \vdots & \vdots & \vdots & \vdots \\ \partial_{1}F_{m}(a) & \partial_{2}F_{m}(a) & \cdots & \partial_{n}F_{m}(a) \end{bmatrix} \begin{bmatrix} v_{1} \\ v_{2} \\ \vdots \\ v_{n} \end{bmatrix}$$

You may recall the notation from calculus III at this point, omitting the a-dependence,

$$\nabla F_j = grad(F_j) = \left[\partial_1 F_j, \ \partial_2 F_j, \ \cdots, \ \partial_n F_j \right]^T$$

So if the derivative exists we can write it in terms of a stack of gradient vectors of the component functions: (I used a transpose to write the stack side-ways),

$$F' = \left[\nabla F_1 | \nabla F_2 | \cdots | \nabla F_m\right]^T$$

Finally, just to collect everything together,

F' =	$\begin{bmatrix} \partial_1 F_1 \\ \partial_1 F_2 \\ \vdots \end{bmatrix}$	$\partial_2 F_1 \\ \partial_2 F_2 \\ \vdots$	···· ···	$ \begin{array}{c} \partial_n F_1 \\ \partial_n F_2 \\ \vdots \end{array} $	$= \left[\partial_1 F \mid \partial_2 F \mid \cdots \mid \partial_n F\right] =$	$ \begin{bmatrix} (\nabla F_1)^T \\ (\nabla F_2)^T \\ \vdots \end{bmatrix} $
		$\partial_1 F_m$	$\partial_2 F_m$	••••	$\partial_n F_m$	

Example 4.2.5. Recall that in Example 4.1.6 we showed that $F : \mathbb{R}^2 \to \mathbb{R}^3$ defined by $F(x, y) = (xy, x^2, x + 3y)$ for all $(x, y) \in \mathbb{R}^2$ was differentiable. In fact we calculated that

$$dF_{(x,y)}(h,k) = \begin{bmatrix} y & x \\ 2x & 0 \\ 1 & 3 \end{bmatrix} \begin{bmatrix} h \\ k \end{bmatrix}.$$

If you recall from calculus III the mechanics of partial differentiation it's simple to see that

$$\frac{\partial F}{\partial x} = \frac{\partial}{\partial x}(xy, \ x^2, \ x+3y) = (y, \ 2x, 1) = \begin{bmatrix} y \\ 2x \\ 1 \end{bmatrix}$$
$$\frac{\partial F}{\partial y} = \frac{\partial}{\partial y}(xy, \ x^2, \ x+3y) = (x, \ 0, 3) = \begin{bmatrix} x \\ 0 \\ 3 \end{bmatrix}$$

Thus $[dF] = [\partial_x F | \partial_y F]$ (as we expect given the derivations in this section!)

Directional derivatives and partial derivatives are of secondary importance in this course. They are merely the substructure of what is truly of interest: the differential. That said, it is useful to know how to construct directional derivatives via partial derivative formulas. In fact, in careless calculus texts it sometimes presented as the definition.

Proposition 4.2.6.

If $F: U \subseteq \mathbb{R}^n \to \mathbb{R}^m$ is differentiable at $a \in U$ then the directional derivative $D_v F(a)$ can be expressed as a sum of partial derivative maps for each $v = \langle v_1, v_2, \ldots, v_n \rangle \in \mathbb{R}^n$:

$$D_v F(a) = \sum_{j=1}^n v_j \partial_j F(a)$$

Proof: since F is differentiable at a the differential dF_a exists and $D_vF(a) = dF_a(v)$ for all $v \in \mathbb{R}^n$. Use linearity of the differential to calculate that

$$D_v F(a) = dF_a(v_1 e_1 + \dots + v_n e_n) = v_1 dF_a(e_1) + \dots + v_n dF_a(e_n).$$

Note $dF_a(e_j) = D_{e_j}F(a) = \partial_j F(a)$ and the prop. follows. \Box

Example 4.2.7. Suppose $f : \mathbb{R}^3 \to \mathbb{R}$ then $\nabla f = [\partial_x f, \partial_y f, \partial_z f]^T$ and we can write the directional derivative in terms of

$$D_v f = [\partial_x f, \partial_y f, \partial_z f]^T v = \nabla f \cdot v$$

if we insist that ||v|| = 1 then we recover the standard directional derivative we discuss in calculus III. Naturally the $||\nabla f(a)||$ yields the maximum value for the directional derivative at a if we limit the inputs to vectors of unit-length. If we did not limit the vectors to unit length then the directional derivative at a can become arbitrarily large as $D_v f(a)$ is proportional to the magnitude of v. Since our primary motivation in calculus III was describing rates of change along certain directions for some multivariate function it made sense to specialize the directional derivative to vectors of unitlength. The definition used in these notes better serves the theoretical discussion.⁵

In Section 4.4 we give many explicit examples.

⁵If you read my calculus III notes you'll find a derivation of how the directional derivative in Stewart's calculus arises from the general definition of the derivative as a linear mapping. Look up page 305g.

4.3 derivatives of sum and scalar product

Suppose $F_1 : U \subseteq \mathbb{R}^n \to \mathbb{R}^m$ and $F_2 : U \subseteq \mathbb{R}^n \to \mathbb{R}^m$. Furthermore, suppose both of these are differentiable at $a \in \mathbb{R}^n$. It follows that $(dF_1)_a = L_1$ and $(dF_2)_a = L_2$ are linear operators from \mathbb{R}^n to \mathbb{R}^m which approximate the change in F_1 and F_2 near a, in particular,

$$\lim_{h \to 0} \frac{F_1(a+h) - F_1(a) - L_1(h)}{||h||} = 0 \qquad \lim_{h \to 0} \frac{F_2(a+h) - F_2(a) - L_2(h)}{||h||} = 0$$

To prove that $H = F_1 + F_2$ is differentiable at $a \in \mathbb{R}^n$ we need to find a differential at a for H. Naturally, we expect $dH_a = d(F_1 + F_2)_a = (dF_1)_a + (dF_2)_a$. Let $L = (dF_1)_a + (dF_2)_a$ and consider,

$$\begin{split} \lim_{h \to 0} \frac{H(a+h) - H(a) - L(h)}{||h||} &= \lim_{h \to 0} \frac{F_1(a+h) + F_2(a+h) - F_1(a) - F_2(a) - L_1(h) - L_2(h)}{||h||} \\ &= \lim_{h \to 0} \frac{F_1(a+h) - F_1(a) - L_1(h)}{||h||} + \lim_{h \to 0} \frac{F_2(a+h) - F_2(a) - L_2(h)}{||h||} \\ &= 0 + 0 \\ &= 0 \end{split}$$

Note that breaking up the limit was legal because we knew the subsequent limits existed and were zero by the assumption of differentiability of F_1 and F_2 at a. Finally, since $L = L_1 + L_2$ we know L is a linear transformation since the sum of linear transformations is a linear transformation. Moreover, the matrix of L is the sum of the matrices for L_1 and L_2 . Let $c \in \mathbb{R}$ and suppose $G = cF_1$ then we can also show that $dG_a = d(cF_1)_a = c(dF_1)_a$, the calculation is very similar except we just pull the constant c out of the limit. I'll let you write it out. Collecting our observations:

Proposition 4.3.1.

Suppose $F_1 : U \subseteq \mathbb{R}^n \to \mathbb{R}^m$ and $F_2 : U \subseteq \mathbb{R}^n \to \mathbb{R}^m$ are differentiable at $a \in U$ then $F_1 + F_2$ is differentiable at a and $d(F_1 + F_2)_a = (dF_1)_a + (dF_2)_a$ or $(F_1 + F_2)'(a) = F'_1(a) + F'_2(a)$ Likewise, if $c \in \mathbb{R}$ then $d(cF_1)_a = c(dF_1)_a$ or $(cF_1)'(a) = c(F'_1(a))$

These results suggest that the differential of a function is a new object which has a vector space structure. Of course, from a calculational view, these also say that the Jacobian matrix of a sum or scalar product is simply the sum or scalar product of the Jacobian matrices.

4.4 a gallery of explicit derivatives

Our goal here is simply to exhibit the Jacobian matrix and partial derivatives for a few mappings. At the base of all these calculations is the observation that partial differentiation is just ordinary differentiation where we treat all the independent variable not being differentiated as constants. The criteria of independence is important. We'll study the case where variables are not independent in a later section (see implicit differentiation).

Example 4.4.1. Let $f(t) = (t, t^2, t^3)$ then $f'(t) = (1, 2t, 3t^2)$. In this case we have

$$f'(t) = [df_t] = \begin{bmatrix} 1\\ 2t\\ 3t^2 \end{bmatrix}$$

Example 4.4.2. Let $f(\vec{x}, \vec{y}) = \vec{x} \cdot \vec{y}$ be a mapping from $\mathbb{R}^3 \times \mathbb{R}^3 \to \mathbb{R}$. I'll denote the coordinates in the domain by $(x_1, x_2, x_3, y_1, y_2, y_3)$ thus $f(\vec{x}, \vec{y}) = x_1y_1 + x_2y_2 + x_3y_3$. Calculate,

$$[df_{(\vec{x},\vec{y})}] = \nabla f(\vec{x},\vec{y})^T = [y_1, y_2, y_3, x_1, x_2, x_3]$$

Example 4.4.3. Let $f(\vec{x}, \vec{y}) = \vec{x} \cdot \vec{y}$ be a mapping from $\mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$. I'll denote the coordinates in the domain by $(x_1, \ldots, x_n, y_1, \ldots, y_n)$ thus $f(\vec{x}, \vec{y}) = \sum_{i=1}^n x_i y_i$. Calculate,

$$\frac{\partial}{x_j} \left[\sum_{i=1}^n x_i y_i \right] = \sum_{i=1}^n \frac{\partial x_i}{x_j} y_i = \sum_{i=1}^n \delta_{ij} y_i = y_j$$

Likewise,

$$\frac{\partial}{y_j} \left[\sum_{i=1}^n x_i y_i \right] = \sum_{i=1}^n x_i \frac{\partial y_i}{y_j} = \sum_{i=1}^n x_i \delta_{ij} = x_j$$

Therefore, noting that $\nabla f = (\partial_{x_1} f, \dots, \partial_{x_n} f, \partial_{y_1} f, \dots, \partial_{y_n} f),$

$$[df_{(\vec{x},\vec{y})}]^T = (\nabla f)(\vec{x},\vec{y}) = \vec{y} \times \vec{x} = (y_1, \dots, y_n, x_1, \dots, x_n)$$

Example 4.4.4. Suppose F(x, y, z) = (xyz, y, z) we calculate,

$$\frac{\partial F}{\partial x} = (yz, 0, 0)$$
 $\frac{\partial F}{\partial y} = (xz, 1, 0)$ $\frac{\partial F}{\partial z} = (xy, 0, 1)$

Remember these are actually column vectors in my sneaky notation; $(v_1, \ldots, v_n) = [v_1, \ldots, v_n]^T$. This means the **derivative** or **Jacobian matrix** of F at (x, y, z) is

$$F'(x, y, z) = [dF_{(x,y,z)}] = \begin{bmatrix} yz & xz & xy \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Example 4.4.5. Suppose $F(x, y, z) = (x^2 + z^2, yz)$ we calculate,

$$\frac{\partial F}{\partial x} = (2x, 0)$$
 $\frac{\partial F}{\partial y} = (0, z)$ $\frac{\partial F}{\partial z} = (2z, y)$

The derivative is a 2×3 matrix in this example,

$$F'(x, y, z) = [dF_{(x, y, z)}] = \begin{bmatrix} 2x & 0 & 2z \\ 0 & z & y \end{bmatrix}$$

Example 4.4.6. Suppose $F(x,y) = (x^2 + y^2, xy, x + y)$ we calculate,

$$\frac{\partial F}{\partial x} = (2x, y, 1)$$
 $\frac{\partial F}{\partial y} = (2y, x, 1)$

The derivative is a 3×2 matrix in this example,

$$F'(x,y) = [dF_{(x,y)}] = \begin{bmatrix} 2x & 2y \\ y & x \\ 1 & 1 \end{bmatrix}$$

Example 4.4.7. Suppose $P(x, v, m) = (P_o, P_1) = (\frac{1}{2}mv^2 + \frac{1}{2}kx^2, mv)$ for some constant k. Let's calculate the derivative via gradients this time,

$$\nabla P_o = (\partial P_o / \partial x, \partial P_o / \partial v, \partial P_o / \partial m) = (kx, mv, \frac{1}{2}v^2)$$
$$\nabla P_1 = (\partial P_1 / \partial x, \partial P_1 / \partial v, \partial P_1 / \partial m) = (0, m, v)$$

Therefore,

$$P'(x,v,m) = \left[\begin{array}{ccc} kx & mv & \frac{1}{2}v^2\\ 0 & m & v\end{array}\right]$$

Example 4.4.8. Let $F(r, \theta) = (r \cos \theta, r \sin \theta)$. We calculate,

$$\partial_r F = (\cos \theta, \sin \theta)$$
 and $\partial_\theta F = (-r \sin \theta, r \cos \theta)$

Hence,

$$F'(r,\theta) = \begin{bmatrix} \cos\theta & -r\sin\theta\\ \sin\theta & r\cos\theta \end{bmatrix}$$

Example 4.4.9. Let $G(x, y) = (\sqrt{x^2 + y^2}, \tan^{-1}(y/x))$. We calculate,

$$\partial_x G = \left(\frac{x}{\sqrt{x^2 + y^2}}, \frac{-y}{x^2 + y^2}\right)$$
 and $\partial_y G = \left(\frac{y}{\sqrt{x^2 + y^2}}, \frac{x}{x^2 + y^2}\right)$

Hence,

$$G'(x,y) = \begin{bmatrix} \frac{x}{\sqrt{x^2 + y^2}} & \frac{y}{\sqrt{x^2 + y^2}} \\ \frac{-y}{x^2 + y^2} & \frac{x}{x^2 + y^2} \end{bmatrix} = \begin{bmatrix} \frac{x}{r} & \frac{y}{r} \\ \frac{-y}{r^2} & \frac{x}{r^2} \end{bmatrix} \quad (using \ r = \sqrt{x^2 + y^2} \)$$

Example 4.4.10. Let $F(x,y) = (x, y, \sqrt{R^2 - x^2 - y^2})$ for a constant R. We calculate,

$$\nabla \sqrt{R^2 - x^2 - y^2} = \left(\frac{-x}{\sqrt{R^2 - x^2 - y^2}}, \frac{-y}{\sqrt{R^2 - x^2 - y^2}} \right)$$

Also, $\nabla x = (1,0)$ and $\nabla y = (0,1)$ thus

$$F'(x,y) = \begin{bmatrix} 1 & 0\\ 0 & 1\\ \frac{-x}{\sqrt{R^2 - x^2 - y^2}} & \frac{-y}{\sqrt{R^2 - x^2 - y^2}} \end{bmatrix}$$

Example 4.4.11. Let $F(x, y, z) = (x, y, z, \sqrt{R^2 - x^2 - y^2 - z^2})$ for a constant *R*. We calculate,

$$\nabla\sqrt{R^2 - x^2 - y^2 - z^2} = \left(\frac{-x}{\sqrt{R^2 - x^2 - y^2 - z^2}}, \frac{-y}{\sqrt{R^2 - x^2 - y^2 - z^2}}, \frac{-z}{\sqrt{R^2 - x^2 - y^2 - z^2}} \right)$$

Also, $\nabla x = (1,0,0), \ \nabla y = (0,1,0) \ and \ \nabla z = (0,0,1) \ thus$

$$F'(x,y,z) = \begin{bmatrix} 1 & 0 & 0\\ 0 & 1 & 0\\ 0 & 0 & 1\\ \frac{-x}{\sqrt{R^2 - x^2 - y^2 - z^2}} & \frac{-y}{\sqrt{R^2 - x^2 - y^2 - z^2}} & \frac{-z}{\sqrt{R^2 - x^2 - y^2 - z^2}} \end{bmatrix}$$

Example 4.4.12. Let f(x, y, z) = (x + y, y + z, x + z, xyz). You can calculate,

$$[df_{(x,y,z)}] = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \\ yz & xz & xy \end{bmatrix}$$

Example 4.4.13. Let f(x, y, z) = xyz. You can calculate,

$$[df_{(x,y,z)}] = \left[\begin{array}{ccc} yz & xz & xy \end{array} \right]$$

Example 4.4.14. Let f(x, y, z) = (xyz, 1 - x - y). You can calculate,

$$[df_{(x,y,z)}] = \left[\begin{array}{ccc} yz & xz & xy \\ -1 & -1 & 0 \end{array} \right]$$

Example 4.4.15. Let $f : \mathbb{R}^3 \times \mathbb{R}^3$ be defined by $f(x) = x \times v$ for a fixed vector $v \neq 0$. We denote $x = (x_1, x_2, x_3)$ and calculate,

$$\frac{\partial}{\partial x_a}(x \times v) = \frac{\partial}{\partial x_a} \Big(\sum_{i,j,k} \epsilon_{ijk} x_i v_j e_k \Big) = \sum_{i,j,k} \epsilon_{ijk} \frac{\partial x_i}{\partial x_a} v_j e_k = \sum_{i,j,k} \epsilon_{ijk} \delta_{ia} v_j e_k = \sum_{j,k} \epsilon_{ajk} v_j e_k$$

It follows,

$$\frac{\partial}{\partial x_1}(x \times v) = \sum_{j,k} \epsilon_{1jk} v_j e_k = v_2 e_3 - v_3 e_2 = (0, -v_3, v_2)$$
$$\frac{\partial}{\partial x_2}(x \times v) = \sum_{j,k} \epsilon_{2jk} v_j e_k = v_3 e_1 - v_1 e_3 = (v_3, 0, -v_1)$$
$$\frac{\partial}{\partial x_3}(x \times v) = \sum_{j,k} \epsilon_{3jk} v_j e_k = v_1 e_2 - v_2 e_1 = (-v_2, v_1, 0)$$

Thus the Jacobian is simply,

$$[df_{(x,y)}] = \begin{bmatrix} 0 & v_3 & -v_2 \\ -v_3 & 0 & -v_1 \\ v_2 & v_1 & 0 \end{bmatrix}$$

In fact, $df_p(h) = f(h) = h \times v$ for each $p \in \mathbb{R}^3$. The given mapping is linear so the differential of the mapping is precisely the mapping itself (we could short-cut much of this calculation and simply quote Example 4.1.2 where we proved dT = T for linear T).

Example 4.4.16. Let f(x, y) = (x, y, 1 - x - y). You can calculate,

$$[df_{(x,y,z)}] = \begin{bmatrix} 1 & 0\\ 0 & 1\\ -1 & -1 \end{bmatrix}$$

Example 4.4.17. Let X(u, v) = (x, y, z) where x, y, z denote functions of u, v and I prefer to omit the explicit dependence to reduce clutter in the equations to follow.

$$\frac{\partial X}{\partial u} = X_u = (x_u, y_u, z_u) \quad and \quad \frac{\partial X}{\partial v} = X_v = (x_v, y_v, z_v)$$

Then the Jacobian is the 3×2 matrix

$$\begin{bmatrix} dX_{(u,v)} \end{bmatrix} = \begin{bmatrix} x_u & x_v \\ y_u & y_v \\ z_u & z_v \end{bmatrix}$$

Remark 4.4.18.

I return to these examples in the next chapter and we'll explore the geometric content of these formulas as they support the application of certain theorems. More on that later, for the remainder of this chapter we continue to focus on properties of differentiation.

4.5 chain rule

The proof in Edwards is on 77-78. I'll give a heuristic proof here which captures the essence of the argument. The simplicity of this rule continues to amaze me.

Proposition 4.5.1.

If $F : U \subseteq \mathbb{R}^n \to \mathbb{R}^p$ is differentiable at a and $G : V \subseteq \mathbb{R}^p \to \mathbb{R}^m$ is differentiable at $F(a) \in V$ then $G \circ F$ is differentiable at a and $d(G \circ F)_a = (dG)_{F(a)} \circ dF_a$ or, in matrix notation, $(G \circ F)'(a) = G'(F(a))F'(a)$

Proof Sketch: (please forgive my lazy formatting, if only the summer was a year)

$$F(a+h) \approx F(a) + dF_a(h) = F(a) + F(a)h$$

$$G(3+k) \approx G(3) + dG_{3'}(k) = G(3) + G'(3)k$$
Consider then,

$$(G \circ F)(a+h) = G(F(a+h))$$

$$\approx G(F(a) + F'(a)h) : let 3 = F(a) and$$

$$k = F'(a)h, note$$

$$= G(3 + k) \qquad h small \Rightarrow k small$$

$$\approx G(3) + G'(3)k \qquad hence this reasonable$$

$$= G(F(a)) + G'(F(a))F'(a)h \Rightarrow d(G \circ F) = dG \circ dF$$
Thus $\Delta(G \circ F) \approx G'(F(a))F'(a)h \Rightarrow d(G \circ F) = dG \circ dF$

In calculus III you may have learned how to calculate partial derivatives in terms of tree-diagrams and intermediate variable etc... We now have a way of understanding those rules and all the other chain rules in terms of one over-arching calculation: matrix multiplication of the constituent Jacobians in the composite function. Of course once we have this rule for the composite of two functions we can generalize to *n*-functions by a simple induction argument. For example, for three suitably defined mappings F, G, H,

$$(F \circ G \circ H)'(a) = F'(G(H(a)))G'(H(a))H'(a)$$

Example 4.5.2. .

Recall,
$$x = x(u, yw)$$
, $y = y(u, yw)$, $f = f(x, y)$ then,
 $\frac{\partial f}{\partial u} = \frac{\partial x}{\partial u} \frac{\partial f}{\partial x} + \frac{\partial y}{\partial u} \frac{\partial f}{\partial y}$
note we derive these
 v_{1a} matrix multiplication
 $\frac{\partial f}{\partial y} = \frac{\partial x}{\partial y} \frac{\partial f}{\partial x} + \frac{\partial y}{\partial y} \frac{\partial f}{\partial y}$
in example below p
 $\frac{\partial f}{\partial w} = \frac{\partial x}{\partial w} \frac{\partial f}{\partial x} + \frac{\partial y}{\partial y} \frac{\partial f}{\partial y}$

Example 4.5.3. .

$$f = f(x,y) \longrightarrow f' = (\nabla f)^{T} = \begin{bmatrix} \frac{2f}{2x}, \frac{2f}{2y} \end{bmatrix}$$

$$f : \mathbb{R}^{2} \longrightarrow \mathbb{R}$$

$$\vec{r} (u,v,w) = \begin{bmatrix} \times (w,v,w), \forall (u,v,w) \end{bmatrix}^{T} \longrightarrow \vec{r}' = \begin{bmatrix} \frac{2f}{2x} & \frac{2f}{2w} \end{bmatrix}$$

$$\vec{r} : \mathbb{R}^{3} \longrightarrow \mathbb{R}^{2} \longrightarrow \mathbb{R}$$

$$f \circ \vec{r} : \mathbb{R}^{3} \longrightarrow \mathbb{R}^{2} \longrightarrow \mathbb{R}$$

$$f \circ \vec{r} : \mathbb{R}^{3} \longrightarrow \mathbb{R}^{2} \longrightarrow \mathbb{R}$$

$$(f \circ \vec{r})^{I} = f' \vec{r}'$$

$$= \begin{bmatrix} \frac{2f}{2x}, \frac{2f}{2y} \end{bmatrix} \begin{bmatrix} \frac{2x}{2x} & \frac{2x}{2y} & \frac{2x}{2y} \\ \frac{2y}{2y} & \frac{2y}{2y} & \frac{2y}{2y} \\ \frac{2y}{2y} & \frac{2y}{2y} & \frac{2y}{2y} \\ \frac{2f}{2y} & \frac{2f}{2y} & \frac{2f}{2y} \\ \frac{2f}{2y} & \frac{2f}{2y} & \frac{2f}{2y} \\ \frac{2f}{2y} & \frac{2f}{2y} & \frac{2f}{2y} \\ \frac{2f}{$$

Example 4.5.4. .

$$\begin{aligned} \underbrace{f:\mathbb{R} \to \mathbb{R}^{n}}_{\frac{df}{dt}} &= \begin{bmatrix} \frac{df_{1}}{dt}, \frac{df_{2}}{dt}, \frac{df_{m}}{dt} \end{bmatrix}^{T} \quad \text{and} \quad \Im : \begin{bmatrix} n^{n} \to R \\ - \to R \end{bmatrix} \\ (\Im \circ f)'(t) &= \begin{bmatrix} \frac{df_{1}}{dt}, \frac{df_{2}}{dt}, \frac{df_{m}}{dt} \end{bmatrix}^{T} \quad \text{and} \quad \Im : (\nabla g)(x)^{T} = \begin{bmatrix} \frac{\partial g}{\partial x_{1}}, \dots, \frac{\partial g}{\partial x_{m}} \end{bmatrix} \\ \begin{pmatrix} g \circ f \end{pmatrix}'(t) &= \Im'(f(t))f'(t) = \begin{bmatrix} \frac{\partial g}{\partial x_{1}}, \dots, \frac{\partial g}{\partial x_{m}} \end{bmatrix} \begin{bmatrix} \frac{df_{1}}{dt} \\ \vdots \\ \frac{df_{m}}{dt} \end{bmatrix} \\ \frac{df}{dt} \begin{bmatrix} g(f(t)) \end{bmatrix} = \frac{\partial g}{\partial x_{1}} \frac{df_{1}}{dt} + \frac{\partial g}{\partial x_{2}} \frac{df_{2}}{dt} + \dots + \frac{\partial g}{\partial x_{m}} \frac{df_{m}}{dt} \end{bmatrix} \end{aligned}$$

Example 4.5.5. .

Let
$$f(x,y) = x^2y^2$$
 and $g(t) = (t, t^2)$
We have $f: \mathbb{R}^2 \to \mathbb{R}$ and $g: \mathbb{R} \to \mathbb{R}^2$ note,
 $f'(x,y) = [2xy^2, 2x^2y]$ and $g'(t) = \begin{bmatrix} 1\\ 2t \end{bmatrix}$
Note $f \circ g: \mathbb{R} \to \mathbb{R}^2 \to \mathbb{R}$ has
 $(f \circ g)'(t) = f'(g(t))g'(t) = f'(t,t^2)g'(t) = [2t^5, 2t^4]\begin{bmatrix} 1\\ 2t \end{bmatrix} = 6t^5$.
Note that $(f \circ g)(t) = f(t,t^2) = t^2t^4 = t^6$ so this result is not
surprising!

Example 4.5.6. .

$$T(r, \Theta) = (r\cos\Theta, r\sin\Theta) = (X, Y)$$

$$T' = \begin{pmatrix} \frac{\partial X}{\partial r} & \frac{\partial Y}{\partial \Phi} \\ \frac{\partial Y}{\partial r} & \frac{\partial Y}{\partial \Theta} \end{pmatrix} = \begin{pmatrix} \cos\Theta & -r\sin\Theta \\ \sin\Theta & r\cos\Theta \end{pmatrix}$$
If $w = f(X, Y)$ then $W = \frac{\partial}{\partial Y}(r, \Theta) = \frac{f}{r}(T(r, \Theta))$

$$f rewritten in polarr.$$

$$\left[\frac{\partial S}{\partial r}, \frac{\partial \Theta}{\partial \Theta}\right] = \left[\frac{\partial f}{\partial X}, \frac{\partial f}{\partial Y}\right] \begin{bmatrix} \cos\Theta - r\sin\Theta \\ \sin\Theta & r\cos\Theta \end{bmatrix} = \left[\frac{\cos\Theta \frac{\partial f}{\partial X} + r\cos\Theta \frac{\partial f}{\partial Y}}{\sin\Theta & r\cos\Theta}\right]$$

With the proper understanding we have derived,

$$\frac{\partial}{\partial r} = (os 0 \frac{\partial}{\partial x} + sin 0 \frac{\partial}{\partial y})$$
$$\frac{\partial}{\partial \theta} = -rsin\theta \frac{\partial}{\partial x} + rcos\theta \frac{\partial}{\partial y}$$

You can invest these,
$$r = -\frac{1}{2x^2 + y^2} \neq 0 = \tan^{-1}(\frac{y}{x})$$

 $\frac{3}{3x} = \frac{3r}{3x} \frac{2}{3r} + \frac{20}{3x} \frac{2}{30} = \frac{x}{7} \frac{2}{3r} - \frac{y}{7} \frac{2}{30} = \cos \frac{2}{3r} - \frac{5ng}{7} \frac{2}{30}$
 $\frac{3}{3y} = \frac{3r}{3y} \frac{2}{3r} + \frac{20}{3y} \frac{2}{30} = \frac{y}{7} \frac{2}{3r} + \frac{x}{7} \frac{2}{30} = \sin \frac{3}{3r} + \frac{\cos \frac{3}{7}}{7} \frac{2}{30}$

You can use these to change coordinates. For example

$$\nabla^{2} f = \frac{2^{2} f}{2x^{2}} + \frac{2^{2} f}{2y^{2}} = \left(\cos \theta \frac{2}{2r} - \frac{\sin \theta}{r} \frac{2}{2\theta}\right) \left(\cos \theta \frac{2f}{2r} - \frac{\sin \theta}{r} \frac{2f}{2\theta}\right)$$

$$+ \left(\sin \theta \frac{2}{2r} + \frac{\cos \theta}{2\theta}\right) \left(\sin \theta \frac{2f}{2r} + \frac{\cos \theta}{r} \frac{2f}{2\theta}\right)$$

$$+ \left(\sin \theta \frac{2}{2r} + \frac{\cos \theta}{2\theta}\right) \left(\sin \theta \frac{2f}{2r} + \frac{\cos \theta}{r} \frac{2f}{2\theta}\right)$$

$$+ \left(\sin \theta \frac{2}{2r} + \frac{\cos \theta}{r} \frac{2f}{r} \frac{2f}{r}\right) - \frac{\sin \theta}{r} \frac{2}{2\theta} \left(\cos \theta \frac{2f}{2r}\right) + \frac{\sin \theta}{r^{2}} \frac{2}{2\theta} \left(\sin \theta \frac{2f}{2\theta}\right)$$

$$+ \sin^{2} \theta \frac{2^{2} f}{2r^{2}} + \sin \theta \cos \theta \frac{2f}{2r} \left[r \frac{2f}{r} \frac{2f}{r}\right] + \frac{\cos \theta}{r^{2}} \frac{2}{2\theta} \left[\sin \theta \frac{2f}{2r}\right] + \frac{\cos \theta}{r^{2}} \frac{2}{2\theta} \left[\cos \theta \frac{2f}{2\theta}\right]$$

$$= \frac{2^{2} f}{2r^{2}} + \frac{\sin^{2} \theta}{r^{2}} \frac{2f}{2r} + \frac{\cos^{2} \theta}{r^{2}} \frac{2f}{2\theta} + \frac{\sin^{2} \theta}{r^{2}} \frac{2f}{2\theta} + \frac{\cos^{2} \theta}{r^{2}} \frac{2^{2} f}{2\theta^{2}} + \frac{2}{r^{2}} \frac{2}{2\theta}$$

$$= \frac{2^{2} f}{r^{2}} + \frac{2^{2} f}{r^{2}} = \frac{2^{2} f}{r^{2}} + \frac{1}{r} \frac{2f}{2r} + \frac{1}{r^{2}} \frac{2^{2} f}{2\theta^{2}}$$

4.6 common product rules

What sort of product can we expect to find among mappings? Remember two mappings have vector outputs and there is no way to multiply vectors in general. Of course, in the case we have two mappings that have equal-dimensional outputs we could take their dot-product. There is a product rule for that case: if $\vec{A}, \vec{B} : \mathbb{R}^n \to \mathbb{R}^m$ then

$$\partial_j (\vec{A} \cdot \vec{B}) = (\partial_j \vec{A}) \cdot \vec{B}) + \vec{A} \cdot (\partial_j \vec{B})$$

Or in the special case of m = 3 we could even take their cross-product and there is another product rule in that case:

$$\partial_j(\vec{A} \times \vec{B}) = (\partial_j \vec{A}) \times \vec{B} + \vec{A} \times (\partial_j \vec{B})$$

What other case can we "multiply" vectors? One very important case is $\mathbb{R}^2 = \mathbb{C}$ where is is customary to use the notation (x, y) = x + iy and f = u + iv. If our range is complex numbers then we again have a product rule: if $f : \mathbb{R}^n \to \mathbb{C}$ and $g : \mathbb{R}^n \to \mathbb{C}$ then

$$\partial_j (fg) = (\partial_j f)g + f(\partial_j g)$$

I have relegated the proof of most of these product rules to the end of this section. One other object worth differentiating is a matrix-valued function of \mathbb{R}^n . If we **define** the partial derivative of a matrix to be the matrix of partial derivatives then partial differentiation will respect the sum and product of matrices (we may return to this in depth if need be later on):

$$\partial_j(A+B) = \partial_j B + \partial_j B$$
 $\partial_j(AB) = (\partial_j A)B + A(\partial_j B)$

Moral of this story? If you have a pair mappings whose ranges allow some sort of product then it is entirely likely that there is a corresponding product rule 6 .

4.6.1 scalar-vector product rule

There is one product rule which we can state for arbitrary mappings, note that we can always sensibly multiply a mapping by a function. Suppose then that $G: U \subseteq \mathbb{R}^n \to \mathbb{R}^m$ and $f: U \subseteq \mathbb{R}^n \to \mathbb{R}$ are differentiable at $a \in U$. It follows that there exist linear transformations $L_G: \mathbb{R}^n \to \mathbb{R}^m$ and $L_f: \mathbb{R}^n \to \mathbb{R}$ where

$$\lim_{h \to 0} \frac{G(a+h) - G(a) - L_G(h)}{||h||} = 0 \qquad \lim_{h \to 0} \frac{f(a+h) - f(a) - L_f(h)}{h} = 0$$

Since $G(a+h) \approx G(a) + L_G(h)$ and $f(a+h) \approx f(a) + L_f(h)$ we expect

$$\begin{split} fG(a+h) &\approx (f(a) + L_f(h))(G(a) + L_G(h)) \\ &\approx (fG)(a) + \underbrace{G(a)L_f(h) + f(a)L_G(h)}_{\text{linear in }h} + \underbrace{L_f(h)L_G(h)}_{2^{nd} \text{ order in }h} \end{split}$$

⁶In my research I consider functions on supernumbers, these also can be multiplied. Naturally there is a product rule for super functions, the catch is that super numbers z, w do not necessarily commute. However, if they're homogeneneous $zw = (-1)^{\epsilon_w \epsilon_z} wz$. Because of this the super product rule is $\partial_M (fg) = (\partial_M f)g + (-1)^{\epsilon_f \epsilon_M} f(\partial_M g)$

Thus we propose: $L(h) = G(a)L_f(h) + f(a)L_G(h)$ is the best linear approximation of fG.

$$\begin{split} \lim_{h \to 0} \frac{(fG)(a+h) - (fG)(a) - L(h)}{||h||} &= \\ &= \lim_{h \to 0} \frac{f(a+h)G(a+h) - f(a)G(a) - G(a)L_f(h) - f(a)L_G(h)}{||h||} \\ &= \lim_{h \to 0} \frac{f(a+h)G(a+h) - f(a)G(a) - G(a)L_f(h) - f(a)L_G(h)}{||h||} + \\ &+ \lim_{h \to 0} \frac{f(a)G(a+h) - G(a+h)f(a)}{||h||} \\ &+ \lim_{h \to 0} \frac{f(a)G(a) - G(a)f(a+h)}{||h||} \\ &+ \lim_{h \to 0} \frac{f(a)G(a) - G(a)f(a)}{||h||} \\ &= \lim_{h \to 0} \left[f(a)\frac{G(a+h) - G(a) - L_G(h)}{||h||} + \frac{f(a+h) - f(a) - L_f(h)}{||h||}G(a) + \\ &+ \left(f(a+h) - f(a) \right)\frac{G(a+h) - G(a)}{||h||} \right] \\ &= f(a) \left[\lim_{h \to 0} \frac{G(a+h) - G(a) - L_G(h)}{||h||} + \left[\lim_{h \to 0} \frac{f(a+h) - f(a) - L_f(h)}{||h||} \right] G(a) \\ &= 0 \end{split}$$

Where we have made use of the differentiability and the consequent continuity of both f and G at a. Furthermore, note

$$L(h + ck) = G(a)L_f(h + ck) + f(a)L_G(h + ck)$$

= $G(a)(L_f(h) + cL_f(k)) + f(a)(L_G(h) + cL_G(k))$
= $G(a)L_f(h) + f(a)(L_G(h) + c(G(a)L_f(k) + f(a)L_G(k)))$
= $L(h) + cL(k)$

for all $h, k \in \mathbb{R}^n$ and $c \in \mathbb{R}$ hence $L = G(a)L_f + f(a)L_G$ is a linear transformation. We have proved (most of) the following proposition:

Proposition 4.6.1.

If
$$G : U \subseteq \mathbb{R}^n \to \mathbb{R}^m$$
 and $f : U \subseteq \mathbb{R}^n \to \mathbb{R}$ are differentiable at $a \in U$ then fG is
differentiable at a and
 $d(fG)_a = (df)_a G(a) + f(a) dG_a \qquad (fG)'(a) = f'(a) G(a) + f(a) G'(a)$

The argument above covers the ordinary product rule and a host of other less common rules. Note again that G(a) and G'(a) are vectors.

4.6.2 calculus of paths in \mathbb{R}^3

A **path** is a mapping from \mathbb{R} to \mathbb{R}^m . We use such mappings to model position, velocity and acceleration of particles in the case m = 3. Some of these things were proved in previous sections of this chapter but I intend for this section to be self-contained so that you can read it without digging through the rest of this chapter.

Proposition 4.6.2.

If $F, G: U \subseteq \mathbb{R} \to \mathbb{R}^m$ are differentiable vector-valued functions and $\phi: U \subseteq \mathbb{R} \to \mathbb{R}$ is a differentiable real-valued function then for each $t \in U$,

1.
$$(F+G)'(t) = F'(t) + G'(t)$$

- 2. (cF)'(t) = cF'(t).
- 3. $(\phi F)'(t) = \phi'(t)F(t) + \phi(t)F'(t).$

4.
$$(F \cdot G)'(t) = F'(t) \cdot G(t) + F(t) \cdot G'(t).$$

- 5. provided m = 3, $(F \times G)'(t) = F'(t) \times G(t) + F(t) \times G'(t)$.
- 6. provided $\phi(U) \subset dom(F'), (F \circ \phi)'(t) = \phi'(t)F(\phi(t)).$

We have to insist that m = 3 for the statement with cross-products since we only have a standard cross-product in \mathbb{R}^3 . We prepare for the proof of the proposition with a useful lemma. Notice this lemma tells us how to actually calculate the derivative of paths in examples. The derivative of component functions is nothing more than calculus I and one of our goals is to reduce things to those sort of calculations whenever possible.

Lemma 4.6.3.

If
$$F: U \subseteq \mathbb{R} \to \mathbb{R}^m$$
 is differentiable vector-valued function then for all $t \in U$,
 $F'(t) = (F'_1(t), F'_2(t), \dots, F'_m(t))$

We are given that the following vector limit exists and is equal to F'(t),

$$F'(t) = \lim_{h \to 0} \frac{F(t+h) - F(t)}{h}$$

then by Proposition 3.1.8 the limit of a vector is related to the limits of its components as follows:

$$F'(t) \cdot e_j = \lim_{h \to 0} \frac{F_j(t+h) - F_j(t)}{h}.$$

Thus $(F'(t))_j = F'_j(t)$ and the lemma follows⁷. ∇

 $^{^{7}}$ this notation I first saw in a text by Marsden, it means the proof is partially completed but you should read on to finish the proof

Proof of proposition: We use the notation $F = \sum F_j e_j = (F_1, \ldots, F_m)$ and $G = \sum_i G_i e_i = (G_1, \ldots, G_m)$ throughout the proofs below. The \sum is understood to range over $1, 2, \ldots m$. Begin with (1.),

$$[(F+G)']_j = \frac{d}{dt}[(F+G)_j]$$
 using the lemma
$$= \frac{d}{dt}[F_j + G_j]$$
 using def. $(F+G)_j = F_j + G_j$
$$= \frac{d}{dt}[F_j] + \frac{d}{dt}[G_j]$$
 by calculus I, $(f+g)' = f' + g'$.
$$= [F'+G']_j$$
 def. of vector addition for F' and G'

Hence $(F \times G)' = F' \times G + F \times G'$. The proofs of 2,3,5 and 6 are similar. I'll prove (5.),

$$[(F \times G)']_{k} = \frac{d}{dt}[(F \times G)_{k}]$$
 using the lemma

$$= \frac{d}{dt}[\sum \epsilon_{ijk}F_{i}G_{j}]$$
 using def. $F \times G$

$$= \sum \epsilon_{ijk}\frac{d}{dt}[F_{i}G_{j}]$$
 repeatedly using, $(f+g)' = f'+g'$

$$= \sum \epsilon_{ijk}[\frac{dF_{i}}{dt}G_{j} + F_{i}\frac{dG_{j}}{dt}]$$
 repeatedly using, $(fg)' = f'g + fg'$

$$= \sum \epsilon_{ijk}\frac{dF_{i}}{dt}G_{j}\sum \epsilon_{ijk}F_{i}\frac{dG_{j}}{dt}]$$
 property of finite sum \sum

$$= (\frac{dF}{dt} \times G)_{k} + (F \times \frac{dG}{dt})_{k}$$
 def. of vector addition

Notice that the calculus step really just involves calculus I applied to the components. The ordinary product rule was the crucial factor to prove the product rule for cross-products. We'll see the same for the dot product of mappings. Prove (4.)

$$(F \cdot G)'(t) = \frac{d}{dt} \left[\sum F_k G_k \right]$$
 using def. $F \cdot G$
$$= \sum \frac{d}{dt} \left[F_k G_k \right]$$
 repeatedly using, $(f+g)' = f' + g'$
$$= \sum \left[\frac{dF_k}{dt} G_k + F_k \frac{dG_k}{dt} \right]$$
 repeatedly using, $(fg)' = f'g + fg'$
$$= \frac{dF}{dt} \cdot G + F \cdot \frac{dG}{dt}.$$
 def. of dot product

The proof of (3.) follows from applying the product rule to each component of $\phi(t)F(t)$. The proof of (2.) follow from (3.) in the case that $\phi(t) = c$ so $\phi'(t) = 0$. Finally the proof of (6.) follows from applying the chain-rule to each component. \Box

4.6.3 calculus of matrix-valued functions of a real variable

Definition 4.6.4.

A matrix-valued function of a real variable is a function from $I \subseteq \mathbb{R}$ to $\mathbb{R}^{m \times n}$. Suppose $A : I \subseteq \mathbb{R} \to \mathbb{R}^{m \times n}$ is such that $A_{ij} : I \subseteq \mathbb{R} \to \mathbb{R}$ is differentiable for each i, j then we define

$$\frac{dA}{dt} = \left[\frac{dA_{ij}}{dt}\right]$$

which can also be denoted $(A')_{ij} = A'_{ij}$. We likewise define $\int Adt = [\int A_{ij}dt]$ for A with integrable components. Definite integrals and higher derivatives are also defined component-wise.

Example 4.6.5. Suppose $A(t) = \begin{bmatrix} 2t & 3t^2 \\ 4t^3 & 5t^4 \end{bmatrix}$. I'll calculate a few items just to illustrate the definition above. calculate; to differentiate a matrix we differentiate each component one at a time:

$$A'(t) = \begin{bmatrix} 2 & 6t \\ 12t^2 & 20t^3 \end{bmatrix} \qquad A''(t) = \begin{bmatrix} 0 & 6 \\ 24t & 60t^2 \end{bmatrix} \qquad A'(0) = \begin{bmatrix} 2 & 0 \\ 0 & 0 \end{bmatrix}$$

Integrate by integrating each component:

$$\int A(t)dt = \begin{bmatrix} t^2 + c_1 & t^3 + c_2 \\ t^4 + c_3 & t^5 + c_4 \end{bmatrix} \qquad \int_0^2 A(t)dt = \begin{bmatrix} t^2 \Big|_0^2 & t^3 \Big|_0^2 \\ t^4 \Big|_0^2 & t^5 \Big|_0^2 \end{bmatrix} = \begin{bmatrix} 4 & 8 \\ 16 & 32 \end{bmatrix}$$

Proposition 4.6.6.

Suppose A, B are matrix-valued functions of a real variable, f is a function of a real variable, c is a constant, and C is a constant matrix then

- 1. (AB)' = A'B + AB' (product rule for matrices)
- 2. (AC)' = A'C
- 3. (CA)' = CA'
- 4. (fA)' = f'A + fA'
- 5. (cA)' = cA'
- 6. (A+B)' = A' + B'

where each of the functions is evaluated at the same time t and I assume that the functions and matrices are differentiable at that value of t and of course the matrices A, B, C are such that the multiplications are well-defined. **Proof:** Suppose $A(t) \in \mathbb{R}^{m \times n}$ and $B(t) \in \mathbb{R}^{n \times p}$ consider,

$$\begin{aligned} (AB)'_{ij} &= \frac{d}{dt} ((AB)_{ij}) & \text{defn. derivative of matrix} \\ &= \frac{d}{dt} (\sum_k A_{ik} B_{kj}) & \text{defn. of matrix multiplication} \\ &= \sum_k \frac{d}{dt} (A_{ik} B_{kj}) & \text{linearity of derivative} \\ &= \sum_k \left[\frac{dA_{ik}}{dt} B_{kj} + A_{ik} \frac{dB_{kj}}{dt} \right] & \text{ordinary product rules} \\ &= \sum_k \frac{dA_{ik}}{dt} B_{kj} + \sum_k A_{ik} \frac{dB_{kj}}{dt} & \text{algebra} \\ &= (A'B)_{ij} + (AB')_{ij} & \text{defn. of matrix multiplication} \\ &= (A'B + AB')_{ij} & \text{defn. matrix addition} \end{aligned}$$

this proves (1.) as i, j were arbitrary in the calculation above. The proof of (2.) and (3.) follow quickly from (1.) since C constant means C' = 0. Proof of (4.) is similar to (1.):

$$(fA)'_{ij} = \frac{d}{dt}((fA)_{ij})$$
 defn. derivative of matrix

$$= \frac{d}{dt}(fA_{ij})$$
 defn. of scalar multiplication

$$= \frac{df}{dt}A_{ij} + f\frac{dA_{ij}}{dt}$$
 ordinary product rule

$$= (\frac{df}{dt}A + f\frac{dA}{dt})_{ij}$$
 defn. matrix addition

$$= (\frac{df}{dt}A + f\frac{dA}{dt})_{ij}$$
 defn. scalar multiplication.

The proof of (5.) follows from taking f(t) = c which has f' = 0. I leave the proof of (6.) as an exercise for the reader. \Box .

To summarize: the calculus of matrices is the same as the calculus of functions with the small qualifier that we must respect the rules of matrix algebra. The noncommutativity of matrix multiplication is the main distinguishing feature.

4.6.4 calculus of complex-valued functions of a real variable

Differentiation of functions from \mathbb{R} to \mathbb{C} is defined by splitting a given function into its real and imaginary parts then we just differentiate with respect to the real variable one component at a time. For example:

$$\frac{d}{dt}(e^{2t}\cos(t) + ie^{2t}\sin(t)) = \frac{d}{dt}(e^{2t}\cos(t)) + i\frac{d}{dt}(e^{2t}\sin(t))
= (2e^{2t}\cos(t) - e^{2t}\sin(t)) + i(2e^{2t}\sin(t) + e^{2t}\cos(t))
= e^{2t}(2+i)(\cos(t) + i\sin(t))
= (2+i)e^{(2+i)t}$$
(4.1)

where I have made use of the identity⁸ $e^{x+iy} = e^x(\cos(y) + i\sin(y))$. We just saw that $\frac{d}{dt}e^{\lambda t} = \lambda e^{\lambda t}$ which seems obvious enough until you appreciate that we just proved it for $\lambda = 2 + i$.

 $^{^{8}\}mathrm{or}$ definition, depending on how you choose to set-up the complex exponential, I take this as the definition in calculus II

4.7 continuous differentiability

We have noted that differentiablility on some set U implies all sorts of nice formulas in terms of the partial derivatives. Curiously the converse is not quite so simple. It is possible for the partial derivatives to exist on some set and yet the mapping may fail to be differentiable. We need an extra topological condition on the partial derivatives if we are to avoid certain pathological⁹ examples.

Example 4.7.1. I found this example in Hubbard's advanced calculus text(see Ex. 1.9.4, pg. 123). It is a source of endless odd examples, notation and bizarre quotes. Let f(x) = 0 and

$$f(x) = \frac{x}{2} + x^2 \sin \frac{1}{x}$$

for all $x \neq 0$. I can be shown that the derivative f'(0) = 1/2. Moreover, we can show that f'(x) exists for all $x \neq 0$, we can calculate:

$$f'(x) = \frac{1}{2} + 2x\sin\frac{1}{x} - \cos\frac{1}{x}$$

Notice that $dom(f') = \mathbb{R}$. Note then that the tangent line at (0,0) is y = x/2.



You might be tempted to say then that this function is increasing at a rate of 1/2 for x near zero. But this claim would be false since you can see that f'(x) oscillates wildly without end near zero. We have a tangent line at (0,0) with positive slope for a function which is not increasing at (0,0)(recall that increasing is a concept we must define in a open interval to be careful). This sort of thing cannot happen if the derivative is continuous near the point in question.

The one-dimensional case is really quite special, even though we had discontinuity of the derivative we still had a well-defined tangent line to the point. However, many interesting theorems in calculus of one-variable require the function to be continuously differentiable near the point of interest. For example, to apply the 2nd-derivative test we need to find a point where the first derivative is zero and the second derivative exists. We cannot hope to compute $f''(x_o)$ unless f' is continuous at x_o . The next example is *sick*.

⁹"pathological" as in, "your clothes are so pathological, where'd you get them?"

Example 4.7.2. Let us define f(0,0) = 0 and

$$f(x,y) = \frac{x^2y}{x^2 + y^2}$$

for all $(x, y) \neq (0, 0)$ in \mathbb{R}^2 . It can be shown that f is continuous at (0, 0). Moreover, since f(x, 0) = f(0, y) = 0 for all x and all y it follows that f vanishes identically along the coordinate axis. Thus the rate of change in the e_1 or e_2 directions is zero. We can calculate that

$$\frac{\partial f}{\partial x} = \frac{2xy^3}{(x^2 + y^2)^2} \qquad and \qquad \frac{\partial f}{\partial y} = \frac{x^4 - x^2y^2}{(x^2 + y^2)^2}$$

If you examine the plot of z = f(x, y) you can see why the tangent plane does not exist at (0, 0, 0).



Notice the sides of the box in the picture are parallel to the x and y axes so the path considered below would fall on a diagonal slice of these boxes¹⁰. Consider the path to the origin $t \mapsto (t,t)$ gives $f_x(t,t) = 2t^4/(t^2+t^2)^2 = 1/2$ hence $f_x(x,y) \to 1/2$ along the path $t \mapsto (t,t)$, but $f_x(0,0) = 0$ hence the partial derivative f_x is not continuous at (0,0). In this example, the discontinuity of the partial derivatives makes the tangent plane fail to exist.

One might be tempted to suppose that if a function is continuous at a given point and if all the possible directional derivatives exist then differentiability should follow. It turns out this is not sufficient since continuity of the function does not imply some continuity along the partial derivatives. For example:

Example 4.7.3. Let us define $f : \mathbb{R}^2 \to \mathbb{R}$ by f(x, y) = 0 for $y \neq x^2$ and $f(x, x^2) = x$. I invite the reader to verify that this function is continuous at the origin. Moreover, consider the directional derivatives at (0,0). We calculate, if $v = \langle a, b \rangle$

$$D_v f(0,0) = \lim_{h \to 0} \frac{f(0+hv) - f(0)}{h} = \lim_{h \to 0} \frac{f(ah,bh)}{h} = \lim_{h \to 0} \frac{0}{h} = 0.$$

¹⁰the argument to follow stands alone, you don't need to understand the picture to understand the math here, but it's nice if you do

To see why f(ah, bh) = 0, consider the intersection of $\vec{r}(h) = (ha, hb)$ and $y = x^2$ the intersection is found at $hb = (ha)^2$ hence, noting h = 0 is not of interest in the limit, $b = ha^2$. If a = 0then clearly (ah, bh) only falls on $y = x^2$ at (0, 0). If $a \neq 0$ then the solution $h = b/a^2$ gives f(ha, hb) = ha a nontrivial value. However, as $h \to 0$ we eventually reach values close enough to (0, 0) that f(ah, bh) = 0. Hence we find **all** directional derivatives exist and are zero at (0, 0). Let's examine the graph of this example to see how this happened. The pictures below graph the xy-plane as red and the nontrivial values of f as a blue curve. The union of these forms the graph z = f(x, y).



Clearly, f is continuous at (0,0) as I invited you to prove. Moreover, clearly z = f(x,y) cannot be well-approximated by a tangent plane at (0,0,0). If we capture the xy-plane then we lose the blue curve of the graph. On the other hand, if we use a tilted plane then we lose the xy-plane part of the graph.

The moral of the story in the last two examples is simply that derivatives at a point, or even all directional derivatives at a point do not necessarily tell you much about the function near the point. This much is clear: something else is required if the differential is to have meaning which extends beyond one point in a nice way. Therefore, we consider the following:

Definition 4.7.4.

A mapping $F : U \subseteq \mathbb{R}^n \to \mathbb{R}^m$ is **continuously differentiable** at $a \in U$ iff the partial derivative mappings $D_j F$ exist on an open set containing a and are continuous at a.

Technically, the term **continuously differentiable** would seem to indicate that the mapping $x \to dF_x$ is a continuous mapping at x = a. If dF_x is the **differential** at x then surely continuous differentiability ought to indicate that the linear transformations dF_x (thinking of x as varying) are glued together in some continuous fashion. That is correct, however, it is beyond our techniques at the present to discuss continuity of an *operator-valued* function. Further techniques must be developed to properly address the continuity in question. That said, once we do those things¹¹

¹¹see C.H. Edwards pages 172-180 and Proposition 2.4 in particular if you are so impatient as to not wait for me

then we'll find that this much more abstract idea of continuity indicates that the partial derivatives of the Jacobian are continuous at x = a. Therefore, the definition above is not at odds with the natural definition¹²

The import of the theorem below is that we can build the tangent plane from the Jacobian matrix provided the partial derivatives exist near the point of tangency and are continuous at the point of tangency. This is a very nice result because the concept of the linear mapping is quite abstract but partial differentiation of a given mapping is often easy. The proof that follows here is found in many texts, in particular see C.H. Edwards *Advanced Calculus of Several Variables* on pages 72-73.

Theorem 4.7.5.

If $F: \mathbb{R}^n \to \mathbb{R}$ is continuously differentiable at a then F is differentiable at a

Proof: Consider a+h sufficiently close to a that all the partial derivatives of F exist. Furthermore, consider going from a to a+h by traversing a hyper-parallel-piped travelling n-perpendicular paths:

$$\underbrace{a}_{p_o} \to \underbrace{a+h_1e_1}_{p_1} \to \underbrace{a+h_1e_1+h_2e_2}_{p_2} \to \cdots \underbrace{a+h_1e_1+\dots+h_ne_n}_{p_n} = a+h_1e_1+\dots+h_ne_n$$

Let us denote $p_j = a + b_j$ where clearly b_j ranges from $b_o = 0$ to $b_n = h$ and $b_j = \sum_{i=1}^j h_i e_i$. Notice that the difference between p_j and p_{j-1} is given by:

$$p_j - p_{j-1} = a + \sum_{i=1}^j h_i e_i - a - \sum_{i=1}^{j-1} h_i e_i = h_j e_j$$

Consider then the following identity,

$$F(a+h) - F(a) = F(p_n) - F(p_{n-1}) + F(p_{n-1}) - F(p_{n-2}) + \dots + F(p_1) - F(p_o)$$

This is to say the change in F from $p_o = a$ to $p_n = a + h$ can be expressed as a sum of the changes along the *n*-steps. Furthermore, if we consider the difference $F(p_j) - F(p_{j-1})$ you can see that only the *j*-th component of the argument of F changes. Since the *j*-th partial derivative exists on the interval for h_j considered by construction we can apply the mean value theorem to locate c_j such that:

$$h_j \partial_j F(p_{j-1} + c_j e_j) = F(p_j) - F(p_{j-1})$$

Therefore, using the mean value theorem for each interval, we select $c_1, \ldots c_n$ with:

$$F(a+h) - F(a) = \sum_{j=1}^{n} h_j \partial_j F(p_{j-1} + c_j e_j)$$

 $^{^{12}}$ Obviously, the reason this is given as the definition of continuously differentiable here and in most textbooks is to avoid the discussion about continuity of operators.

It follows we should propose L to satisfy the definition of Frechet differentiation as follows:

$$L(h) = \sum_{j=1}^{n} h_j \partial_j F(a)$$

It is clear that L is linear (in fact, perhaps you recognize this as $L(h) = (\nabla F)(a) \cdot h$). Let us prepare to study the Frechet quotient,

$$F(a+h) - F(a) - L(h) = \sum_{j=1}^{n} h_j \partial_j F(p_{j-1} + c_j e_j) - \sum_{j=1}^{n} h_j \partial_j F(a)$$
$$= \sum_{j=1}^{n} h_j \left[\underbrace{\partial_j F(p_{j-1} + c_j e_j) - \partial_j F(a)}_{g_j(h)} \right]$$

Observe that $p_{j-1} + c_j e_j \to a$ as $h \to 0$. Thus, $g_j(h) \to 0$ by the continuity of the partial derivatives at x = a. Finally, consider the Frechet quotient:

$$\lim_{h \to 0} \frac{F(a+h) - F(a) - L(h)}{||h||} = \lim_{h \to 0} \frac{\sum_j h_j g_j(h)}{||h||} = \lim_{h \to 0} \sum_j \frac{h_j}{||h||} g_j(h)$$

Notice $|h_j| \leq ||h||$ hence $\left|\frac{h_j}{||h||}\right| \leq 1$ and

$$0 \le \left| \frac{h_j}{||h||} g_j(h) \right| \le |g_j(h)|$$

Apply the squeeze theorem to deduce each term in the sum \star limits to zero. Consquently, L(h) satisfies the Frechet quotient and we have shown that F is differentiable at x = a and the differential is expressed in terms of partial derivatives as expected; $dF_x(h) = \sum_{j=1}^n h_j \partial_j F(a) \square$.

Given the result above it is a simple matter to extend the proof to $F : \mathbb{R}^n \to \mathbb{R}^m$.

Theorem 4.7.6.

If $F : \mathbb{R}^n \to \mathbb{R}^m$ is continuously differentiable at a then F is differentiable at a

Proof: If F is continuously differentiable at a then clearly each component function $F^j : \mathbb{R}^n \to \mathbb{R}$ is continuously differentiable at a. Thus, by Theorem 4.7.5 we have F^j differentiable at a hence

$$\lim_{h \to 0} \frac{F^{j}(a+h) - F^{j}(a) - dF^{j}_{a}(h)}{||h||} = 0 \text{ for all } j \in \mathbb{N}_{m} \Rightarrow \lim_{h \to 0} \frac{F(a+h) - F(a) - dF_{a}(h)}{||h||} = 0$$

by Proposition 3.1.8. This proves F is differentiable at $a \square$.

4.8 on why partial derivatives commute

The goal of this section is to prove the partial derivatives commute for nice functions. Of course some of the results we discuss on the way to that goal are interesting in their own right as well.

Definition 4.8.1.

We say $U \subseteq \mathbb{R}^n$ is **path connected** iff any two points in U can be connected by a path which is contained within the set.

For example, \mathbb{R}^n is connected since given any two points $a, b \in \mathbb{R}^n$ we can construct the path $\phi(t) = a + t(b - a)$ from a to b and naturally the path is within the set. You can easily verify that open and closed balls are also path connected. Even a donut is path connected. However, a pair donuts is not path connected unless it's one of those artsy figure-8 deals.



Proposition 4.8.2.

If U is a connected open subset of \mathbb{R}^n then a differentiable mapping $F: U \to \mathbb{R}^m$ is constant iff F'(u) = 0 for all $u \in U$.

Let A, B $\in U$ and <u>connect</u> these points with a smooth path $V: [a,b] \longrightarrow U$. (perhaps we should insist path connected \Rightarrow <u>smooth</u> paths exist inside U...) (onsider, $F(Y(H)) = \Im(H)$. If F is constant then $\Im(H)$ is constant hence $F'(Y(H)) \Upsilon(H) = 0$ but Υ smooth $\Rightarrow \Im'(H) \neq o$ hence $F'(Y(a)) = F'(a) = 0 \Rightarrow F'(a) = 0 \quad \forall a \in U$. <u>Conversely</u> if $F'(u) = 0 \quad \forall u \in U \Rightarrow \frac{d}{H} (\Im(H)) = F'(\Upsilon(H)) \Upsilon'(H) = 0$ Thus $\Im(a) = \Im(b) \Rightarrow F(\Upsilon(a)) = F(\Upsilon(b)) \qquad zero$ $\Rightarrow F(A) = F(B) \quad \forall A, B \in U := F \text{ constant on } U$

Proposition 4.8.3.

If U is a connected open subset of \mathbb{R}^n and the differentiable mappings $F, G : U \to \mathbb{R}$ such that F'(x) = G'(x) for all $x \in U$ then there exists a constant vector $c \in \mathbb{R}^m$ such that F(x) = G(x) + c for all $x \in U$.

Construct H(x) = F(x) - G(x) and note H'(x) = F'(x) - G'(x) = 0 $\forall x \in V$. By the previous prop. H(x) = C $\forall x \in V$ hence F(x) = G(x) + C $\forall x \in V$. There is no mean value theorem for mappings since counter-examples exist. For example, Exercise 1.12 on page 63 shows the mean value theorem fails for the helix. In particular, you can find average velocity vector over a particular time interval such that the velocity vector never matches the average velocity over that time period. Fortunately, if we restrict our attention to mappings with one-dimensional codomains we still have a nice theorem:

Proposition 4.8.4. (Mean Value Theorem)

Suppose that $f: U \to \mathbb{R}$ is a differentiable function and U is an open set. Furthermore, suppose U contains the line segment from a to b in U;

$$L_{a,b} = \{a + t(b - a) \mid t \in [0, 1]\} \subset U$$

It follows that there exists some point $c \in L_{a,b}$ such that f(b) - f(a) = f'(c)(b - a).

The proof follows from the construction of a function on R to which the elementary mean value Th^m is applied, let $\Im(t) = f(a + t(b-a))$ for $0 \le t \le 1$. Or if you prefer, construct $\P(t) = a + t(b-a)$ which parametrises the line segment from a to b. Clearly $\P'(t) = b - a$ and by the chain-rule, $\Im'(t) = f'(\P(t)) \P'(t)$ Note $\Im: [o, i] \xrightarrow{\P} \Im \xrightarrow{T} \inf R$ is differentiable on [o, i]thus the MVT gives $c_0 \in [o, i]$ such that $\Im(i) - \Im(o) = \Im'(c_0)$. Thus, $f(b) - f(a) = \Im(i) - \Im(o) = \Im'(c_0) = f'(\P(c_0)) \P'(G) = f'(c_0) \cdot (b-a)$. $f(c) = \P(c_0)$.

Definition 4.8.5. (higher derivatives)

We define nested directional derivatives in the natural way:

$$D_k D_h f(x) = D_k (D_h f(x)) = \lim_{t \to 0} \frac{D_h f(x+tk) - D_h f(x)}{t}$$

Furthermore, the **second difference** is defined by

$$\Delta^2 f_a(h,k) = f(a+h+k) - f(a+h) - f(a+k) + f(a)$$


This is Lemma 3.5 on page 86 of Edwards.

Proposition 4.8.6.

Suppose U us an open set and $f: U \to \mathbb{R}$ which is differentiable on U with likewise differentiable directional derivative function on U. Suppose that a, a + h, a + k, a + h + kare all in U then there exist $\alpha, \beta \in (0, 1)$ such that $\Delta^2 f_a(h, k) = D_k D_h f(a + \alpha h + \beta k)$.

The proof is rather neat. The α and β stem from two applications of the MVT, once for the function then once for its directional derivative.

$$\begin{aligned} \int eb \quad \Im(x) &= f(x+k) - f(x) \text{ then } d\Im_{x} = \partial f_{x+k} - \partial f_{x}^{2} - \\ & \text{Furthumore, using } \Delta^{2} f_{k}(h,k) = f(a+h+k) - f(a+h) - f(a+h) + f(a) \text{ note,} \\ & \text{Furthumore, using } \Delta^{2} f_{k}(h,k) = \Im(a+h) - \Im(a) \\ &= \Im(a+\alpha h) + i \text{ by } MVT \ni \alpha \in (0,1). \\ &= (D_{h} \Im)(a+\alpha h) + i \text{ diff} \Rightarrow \text{ directional derivative exist.} \\ &= d\Im_{a+\alpha h}(h) \\ &= d\Im_{a+\alpha h}(h) \\ &= d\Im_{a+\alpha h+k}(h) - df_{a+\alpha h}(h) \\ &= D_{h} f(a+\alpha h+k) - D_{h} f(a+\alpha h) \\ &= (D_{h} \Im)(a+\alpha h+\beta h)(k) \quad \text{fur some } \beta \in (0,1) \text{ by } MVT \text{ again.} \\ &= (D_{h} \Omega_{h} f)(a+\alpha h+\beta k) \quad : \text{ uncaveling notation.} \end{aligned}$$

Proposition 4.8.7.

Let U be an open subset of \mathbb{R}^n . If $f: U \to \mathbb{R}$ is a function with continuous first and second partial derivatives on U then for all i, j = 1, 2, ..., n we have $D_i D_j f = D_j D_i f$ on U;

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i}$$

$$\Delta^{2} f_{a} (he_{i}, ke_{j}) = D_{ke_{j}} D_{he_{i}} f(a + \alpha, he_{i} + \beta ke_{j})$$

$$\Delta^{2} f_{a} (he_{j}, he_{j}) = D_{he_{i}} D_{he_{i}} (a + \alpha, he_{i} + \beta ke_{j})$$

$$\Delta^{2} f_{a} (he_{j}, he_{i}) = D_{he_{i}} D_{he_{j}} (a + \alpha, he_{j} + \beta, ke_{j})$$

$$\Delta^{2} f_{a} (he_{j}, he_{i}) = D_{he_{i}} D_{he_{j}} (a + \alpha, he_{j} + \beta, ke_{j})$$

$$\Delta^{2} f_{a} (he_{i}, ke_{j}) = \Delta^{2} f_{a} (he_{j}, he_{i})$$

$$\Longrightarrow D_{j} D_{j} f(a) = D_{j} D_{j} f(a)$$

Pull out h, k using homogeneity of $D_{cv}f = cD_vf$ and take limit $(h, k) \to 0$ to drop the h, k inside the $Df(\cdots)$ terms. This is possible thanks to the continuity of the partial derivatives near a.

4.9 complex analysis in a nutshell

Differentiation with respect to a real variable can be reduced to the slogan that we differentiate componentwise. Differentiation with respect to a complex variable requires additional structure. They key distinguishing ingredient is complex linearity:

Definition 4.9.1.

If we have some function $T : \mathbb{C} \to \mathbb{C}$ such that (1.) T(v+w) = T(v) + T(w) for all $v, w \in \mathbb{C}$ (2.) T(cv) = cT(v) for all $c, v \in \mathbb{C}$ then we would say that T is **complex-linear**.

Condition (1.) is **additivity** whereas condition (2.) is **homogeneity**. Note that complex linearity implies real linearity however the converse is not true.

Example 4.9.2. Suppose $T(z) = \overline{z}$ where if z = x + iy for $x, y \in \mathbb{R}$ then $\overline{z} = x - iy$ is the complex conjugate of z. Consider for c = a + ib where $a, b \in \mathbb{R}$,

$$T(cz) = T((a+ib)(x+iy))$$

= $T(ax - by + i(ay + bx))$
= $ax - by - i(ay + bx)$
= $(a - ib)(x - iy)$
= $\bar{c} T(z)$

hence this map is not complex linear. On the other hand, if we study multiplication by just $a \in \mathbb{R}$,

T(az) = T(a(x+iy)) = T(ax+iay) = ax - iay = a(x-iy) = aT(x+iy) = aT(z)

thus T is homogeneous with respect to real-number multiplication and it is also additive hence T is real linear.

Suppose that L is a linear mapping from \mathbb{R}^2 to \mathbb{R}^2 . It is known from linear algebra that there exists a matrix $A = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$ such that L(v) = Av for all $v \in \mathbb{R}^2$. In this section we use the notation a + ib = (a, b) and

$$(a,b) * (c,d) = (a+ib)(c+id) = ac - bd + i(ad + bc) = (ac - bd, ad + bc).$$

This construction is due to Gauss in the early nineteenth century, the idea is to use two component vectors to *construct* complex numbers. There are other ways to construct complex numbers¹³. Notice that $L(x + iy) = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = (ax + by, cx + dy) = ax + by + i(cx + dy)$ defines a real linear mapping on \mathbb{C} for any choice of the real constants a, b, c, d. In contrast, complex linearity puts strict conditions on these constants:

¹³the same is true for real numbers, you can construct them in more than one way, however all constructions agree on the basic properties and as such it is the properties of real or complex numbers which truly defined them. That said, we choose Gauss' representation for convenience.

Theorem 4.9.3.

The linear mapping L(v) = Av is complex linear iff the matrix A will have the special form below:

 $\begin{pmatrix} a & b \\ -b & a \end{pmatrix}$

To be clear, we mean to identify \mathbb{R}^2 with \mathbb{C} as before. Thus the condition of complex homogeneity reads L((a,b)*(x,y)) = (a,b)*L(x,y)

Proof: assume L is complex linear. Define the matrix of L as before:

$$L(x,y) = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix}$$

This yields,

$$L(x+iy) = ax + by + i(cx + dy)$$

We can gain conditions on the matrix by examining the special points 1 = (1, 0) and i = (0, 1)

L(1,0) = (a,c) L(0,1) = (b,d)

Note that $(c_1, c_2) * (1, 0) = (c_1, c_2)$ hence $L((c_1 + ic_2)1) = (c_1 + ic_2)L(1)$ yields

$$(ac_1 + bc_2) + i(cc_1 + dc_2) = (c_1 + ic_2)(a + ic) = c_1a - c_2c + i(c_1c + c_2a)$$

We find two equations by equating the real and imaginary parts:

$$ac_1 + bc_2 = c_1a - c_2c$$
 $cc_1 + dc_2 = c_1c + c_2a$

Therefore, $bc_2 = -c_2c$ and $dc_2 = c_2a$ for all $(c_1, c_2) \in \mathbb{C}$. Suppose $c_1 = 0$ and $c_2 = 1$. We find b = -c and d = a. We leave the converse proof to the reader. The proposition follows. \Box

In analogy with the real case we define f'(z) as follows:

Definition 4.9.4.

Suppose $f : dom(f) \subseteq \mathbb{C} \to \mathbb{C}$ and $z \in dom(f)$ then we define f'(z) by the limit below: $f'(z) = \lim_{h \to 0} \frac{f(z+h) - f(z)}{h}.$

The derivative function f' is defined pointwise for all such $z \in dom(f)$ that the limit above exists.

Note that $f'(z) = \lim_{h \to 0} \frac{f'(z)h}{h}$ hence

$$\lim_{h \to 0} \frac{f'(z)h}{h} = \lim_{h \to 0} \frac{f(z+h) - f(z)}{h} \quad \Rightarrow \quad \lim_{h \to 0} \frac{f(z+h) - f(z) - f'(z)h}{h} = 0$$

Note that the limit above simply says that L(v) = f'(z)v gives the is the best **complex-linear** approximation of $\Delta f = f(z+h) - f(z)$.

Proposition 4.9.5.

If f is a complex differentiable at z_o then linearization $L(h) = f'(z_o)h$ is a complex linear mapping.

Proof: let $c, h \in \mathbb{C}$ and note $L(ch) = f'(z_o)(ch) = cf'(z_o)h = cL(h)$. \Box

It turns out that complex differentiability automatically induces real differentiability:

Proposition 4.9.6.

If f is a complex differentiable at z_o then f is (real) differentiable at z_o with $L(h) = f'(z_o)h$.

Proof: note that $\lim_{h\to 0} \frac{f(z+h)-f(z)-f'(z)h}{h} = 0$ implies

$$\lim_{h \to 0} \frac{f(z+h) - f(z) - f'(z)h}{|h|} = 0$$

but then |h| = ||h|| and we know $L(h) = f'(z_o)h$ is real-linear hence L is the best linear approximation to Δf at z_o and the proposition follows. \Box

Let's summarize what we've learned: if $f : dom(f) \to \mathbb{C}$ is complex differentiable at z_o and f = u + iv then,

- 1. $L(h) = f'(z_o)h$ is complex linear.
- 2. $L(h) = f'(z_0)h$ is the best real linear approximation to f viewed as a mapping on \mathbb{R}^2 .

The Jacobian matrix for f = (u, v) has the form

$$J_f(p_o) = \left[\begin{array}{cc} u_x(p_o) & u_y(p_o) \\ v_x(p_o) & v_y(p_o) \end{array} \right]$$

Theorem 4.9.3 applies to $J_f(p_o)$ since L is a complex linear mapping. Therefore we find the Cauchy Riemann equations: $u_x = v_y$ and $u_y = -v_x$. We have proved the following theorem:

Theorem 4.9.7.

If f = u + iv is a complex function which is **complex-differentiable** at z_o then the partial derivatives of u and v exist at z_o and satisfy the Cauchy-Riemann equations at z_o

$$\frac{\partial u}{\partial x} = \frac{\partial v}{\partial y} \qquad \frac{\partial u}{\partial y} = -\frac{\partial v}{\partial x}$$

Example 4.9.8. Let $f(z) = e^z$ where the definition of the complex exponential function is given by the following, for each $x, y \in \mathbb{R}$ and z = x + iy

$$f(x + iy) = e^{x + iy} = e^x(\cos(y) + i\sin(y)) = e^x\cos(y) + ie^x\sin(y)$$

Identify for f = u + iv we have $u(x, y) = e^x \cos(y)$ and $v(x, y) = e^x \sin(y)$. Calculate:

$$\frac{\partial u}{\partial x} = \frac{\partial}{\partial x} \left[e^x \cos(y) \right] = e^x \cos(y) \qquad \& \qquad \frac{\partial u}{\partial y} = \frac{\partial}{\partial y} \left[e^x \cos(y) \right] = -e^x \sin(y)$$
$$\frac{\partial v}{\partial x} = \frac{\partial}{\partial x} \left[e^x \sin(y) \right] = e^x \sin(y) \qquad \& \qquad \frac{\partial v}{\partial x} = \frac{\partial}{\partial y} \left[e^x \sin(y) \right] = e^x \cos(y).$$

Thus f satisfies the CR-equations $\frac{\partial u}{\partial x} = \frac{\partial v}{\partial y}$ and $\frac{\partial u}{\partial y} = -\frac{\partial v}{\partial x}$. The complex exponential function is complex differentiable.

The converse of Theorem 4.9.7 is not true in general. It is possible to have functions $u, v : U \subseteq \mathbb{R}^2 \to \mathbb{R}$ that satisfy the CR-equations at $z_o \in U$ and yet f = u + iv fails to be complex differentiable at z_o .

Example 4.9.9. Counter-example to converse of Theorem 4.9.7. Suppose $f(x+iy) = \begin{cases} 0 & \text{if } xy \neq 0 \\ 1 & \text{if } xy = 0 \end{cases}$

Clearly f has constant value 1 on the coordinate axes thus along the x-axes we can calculate the partial derivatives for u and v and they are both zero.



Likewise, along the y-axis we find u_y and v_y exist and are zero. At the origin we find u_x, u_y, v_x, v_y all exist and are zero. Therefore, the Cauchy-Riemann equations hold true at the origin. However, this function is not even continuous at the origin, thus it is not real differentiable!

The example above equally well serves as an example for a point where a function has partial derivatives which exist at all orders and yet the differential fails to exist. It's not a problem of complex variables in my opinion, it's a problem of advanced calculus. The key concept to reverse the theorem is continuous differentiability.

Theorem 4.9.10.

If
$$u, v, u_x, u_y, v_x, v_y$$
 are continuous functions in some open disk of z_o and $u_x(z_o) = v_y(z_o)$
and $u_y(z_o) = -v_x(z_o)$ then $f = u + iv$ is complex differentiable at z_o .

Proof: we are given that a function $f : D_{\epsilon}(z_o) \subset \mathbb{R}^2 \to \mathbb{R}^2$ is continuous with continuous partial derivatives of its component functions u and v. Therefore, by Theorem 4.7.6 we know f is (real) differentiable at z_o . Therefore, we have a best linear approximation to the change in f near z_o which can be induced via multiplication of the Jacobian matrix:

$$L(v_1, v_2) = \begin{bmatrix} u_x(z_o) & u_y(z_o) \\ v_x(z_o) & v_y(z_o) \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}.$$

Note then that the given CR-equations show the matrix of L has the form

$$[L] = \left[\begin{array}{cc} a & b \\ -b & a \end{array} \right]$$

where $a = u_x(z_o)$ and $b = v_x(z_o)$. Consequently we find L is complex linear and it follows that f is complex differentiable at z_o since we have a complex linear map L such that

$$\lim_{h \to 0} \frac{f(z+h) - f(z) - L(h)}{||h||} = 0$$

note that the limit with h in the denominator is equivalent to the limit above which followed directly from the (real) differentiability at z_o . (the following is not needed for the proof of the theorem, but perhaps it is interesting anyway) Moreover, we can write

$$L(h_1, h_2) = \begin{bmatrix} u_x & u_y \\ -u_y & u_x \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \end{bmatrix}$$
$$= \begin{bmatrix} u_x h_1 + u_y h_2 \\ -u_y h_1 + u_x h_2 \end{bmatrix}$$
$$= u_x h_1 + u_y h_2 + i(-u_y h_1 + u_x h_2)$$
$$= (u_x - iu_y)(h_1 + ih_2)$$

Therefore we find $f'(z_o) = u_x - iu_y$ gives $L(h) = f'(z_o)z$. \Box

In the preceding section we found necessary and sufficient conditions for the component functions u, v to construct an complex differentiable function f = u + iv. The definition that follows is the next logical step: we say a function is analytic¹⁴ at z_o if it is complex differentiable at each point in some open disk about z_o .

Definition 4.9.11.

Let f = u + iv be a complex function. If there exists $\epsilon > 0$ such that f is complex differentiable for each $z \in D_{\epsilon}(z_o)$ then we say that f is **analytic** at z_o . If f is analytic for each $z_o \in U$ then we say f is analytic on U. If f is not analytic at z_o then we say that z_o is a **singular point**. Singular points may be outside the domain of the function. If f is analytic on the entire complex plane then we say f is entire. Analytic functions are also called holomorphic functions

If you look in my complex variables notes you can find proof of the following theorem (well, partial proof perhaps, but this result is shown in every good complex variables text)

¹⁴you may recall that a function on \mathbb{R} was analyic at x_o if its Talyor series at x_o converged to the function in some neighborhood of x_o . This terminology is consistent but I leave the details for your complex analysis course

Theorem 4.9.12.

If $f : \mathbb{R} \to \mathbb{R} \subset \mathbb{C}$ is a function and $\tilde{f} : \mathbb{C} \to \mathbb{C}$ is an extension of f which is analytic then \tilde{f} is unique. In particular, if there is an analytic extension of sine, cosine, hyperbolic sine or hyperbolic cosine then those extensions are unique.

This means if we demand analyticity then we actually had no freedom in our choice of the exponential. If we find a complex function which matches the exponential function on a line-segment (*in particular a closed interval in* \mathbb{R} *viewed as a subset of* \mathbb{C} *is a line-segment*) then there is just one complex function which agrees with the real exponential and is complex differentiable everywhere.

 $f(x) = e^x$ extends uniquely to $\tilde{f}(z) = e^{Re(z)}(\cos(Im(z)) + i\sin(Im(z))).$

Note $\tilde{f}(x+0i) = e^x(\cos(0) + i\sin(0)) = e^x$ thus $\tilde{f}|_{\mathbb{R}} = f$. Naturally, analyticity is a desireable property for the complex-extension of known functions so this concept of analytic continuation is very nice. Existence aside, we should first construct sine, cosine etc... then we have to check they are both analytic and also that they actually agree with the real sine or cosine etc... If a function on \mathbb{R} has vertical asymptotes, points of discontinuity or points where it is not smooth then the story is more complicated.

4.9.1 harmonic functions

We've discussed in some depth how to determine if a given function f = u + iv is in fact analytic. In this section we study another angle on the story. We learn that the component functions u, v of an analytic function f = u + iv are harmonic conjugates and they satisfy the phyically significant Laplace's equation $\nabla^2 \phi = 0$ where $\nabla^2 = \partial^2 / \partial x^2 + \partial^2 / \partial y^2$. In addition we'll learn that if we have one solution of Laplace's equation then we can consider it to be the "u" of some yet undetermined analytic function f = u + iv. The remaining function v is then constructed through some integration guided by the CR-equations. The construction is similar to the problem of construction of a potential function for a given conservative force in calculus III.

Proposition 4.9.13.

If f = u + iv is analytic on some domain $D \subseteq \mathbb{C}$ then u and v are solutions of Laplace's equation $\phi_{xx} + \phi_{yy} = 0$ on D.

Proof: since f = u + iv is analytic we know the CR-equations hold true; $u_x = v_y$ and $u_y = -v_x$. Moreover, f is continuously differentiable so we may commute partial derivatives by a theorem from multivariate calculus. Consider

$$u_{xx} + u_{yy} = (u_x)_x + (u_y)_y = (v_y)_x + (-v_x)_y = v_{yx} - v_{xy} = 0$$

Likewise,

$$v_{xx} + v_{yy} = (v_x)_x + (v_y)_y = (-u_y)_x + (u_x)_y = -u_{yx} + u_{xy} = 0$$

Of course these relations hold for all points inside D and the proposition follows. \Box

Example 4.9.14. Note $f(z) = z^2$ is analytic with $u = x^2 - y^2$ and v = 2xy. We calculate,

$$u_{xx} = 2, \quad u_{yy} = -2 \quad \Rightarrow \quad u_{xx} + u_{yy} = 0$$

Note $v_{xx} = v_{yy} = 0$ so v is also a solution to Laplace's equation.

Now let's see if we can reverse this idea.

Example 4.9.15. Let $u(x, y) = x + c_1$ notice that u solves Laplace's equation. We seek to find a harmonic conjugate of u. We need to find v such that,

$$\frac{\partial v}{\partial y} = \frac{\partial u}{\partial x} = 1$$
 $\frac{\partial v}{\partial x} = -\frac{\partial u}{\partial y} = 0$

Integrate these equations to deduce $v(x, y) = y + c_2$ for some constant $c_2 \in \mathbb{R}$. We thus construct an analytic function $f(x, y) = x + c_1 + i(y + c_2) = x + iy + c_1 + ic_2$. This is just f(z) = z + c for $c = c_1 + ic_2$.

Example 4.9.16. Suppose $u(x, y) = e^x \cos(y)$. Note that $u_{xx} = u$ whereas $u_{yy} = -u$ hence $u_{xx} + u_{yy} = 0$. We seek to find v such that

$$\frac{\partial v}{\partial y} = \frac{\partial u}{\partial x} = e^x \cos(y)$$
 $\frac{\partial v}{\partial x} = -\frac{\partial u}{\partial y} = e^x \sin(y)$

Integrating $v_y = e^x \cos(y)$ with respect to y and $v_x = e^x \sin(y)$ with respect to x yields $v(x, y) = e^x \sin(y)$. We thus construct an analytic function $f(x, y) = e^x \cos(y) + ie^x \sin(y)$. Of course we should recognize the function we just constructed, it's just the complex exponential $f(z) = e^z$.

Notice we cannot just construct an analytic function from any given function of two variables. We have to start with a solution to Laplace's equation. This condition is rather restrictive. There is much more to say about harmonic functions, especially where applications are concerned. My goal here was just to give another perspective on analytic functions. Geometrically one thing we could see without further work at this point is that for an analytic function f = u + iv the families of level curves $u(x,y) = c_1$ and $v(x,y) = c_2$ are orthogonal. Note $grad(u) = \langle u_x, u_y \rangle$ and $grad(v) = \langle v_x, v_y \rangle$ have

$$grad(u) \cdot grad(v) = u_x v_x + u_y v_y = -u_x u_y + u_y u_x = 0$$

This means the normal lines to the level curves for u and v are orthogonal. Hence the level curves of u and v are orthogonal. Another way to twist this, if you want to obtain orthogonal families of curves then analytic functions provide an easy way to create examples.

Remark 4.9.17.

This section covers a few lectures of the complex analysis course. I include it here in part to make connections. I always encourage students to understand math outside the comfort zone of isolated course components. Whenever we can understand material from several courses as part of a larger framework it is a step in the right direction.

Chapter 5

inverse and implicit function theorems

It is tempting to give a complete and rigourous proof of these theorems at the outset, but I will resist the temptation in lecture. I'm actually more interested that the student understand what the theorem claims before I show the real proof. I will sketch the proof and show many applications. A nearly complete proof is found in Edwards where he uses an iterative approximation technique founded on the contraction mapping principle, we will go through that a bit later in the course. I probably will not have typed notes on that material this semester, but Edward's is fairly readable and I think we'll profit from working through those sections. That said, we develop an intuition for just what these theorems are all about to start. That is the point of this chapter: to grasp what the linear algebra of the Jacobian suggests about the local behaviour of functions and equations.

5.1 inverse function theorem

Consider the problem of finding a **local** inverse for $f : dom(f) \subseteq \mathbb{R} \to \mathbb{R}$. If we are given a point $p \in dom(f)$ such that there exists an open interval I containing p with $f|_I$ a one-one function then we can reasonably construct an inverse function by the simple rule $f^{-1}(y) = x$ iff f(x) = y for $x \in I$ and $y \in f(I)$. A sufficient condition to insure the existence of a local inverse is that the derivative function is either strictly positive or strictly negative on some neighborhood of p. If we are give a continuously differentiable function at p then it has a derivative which is continuous on some neighborhood of p. For such a function if $f'(p) \neq 0$ then there exists some interval centered at p for which the derivative is strictly positive or negative. It follows that such a function is strictly monotonic and is hence one-one thus there is a local inverse at p. We should all learn in calculus I that the derivative informs us about the local invertibility of a function. Natural question to ask for us here: does this extend to higher dimensions? If so, how?

The arguments I just made are supported by theorems that are developed in calculus I. Let me shift gears a bit and give a direct calculational explaination based on the linearization approximation.

If $x \approx p$ then $f(x) \approx f(p) + f'(p)(x-p)$. To find the formula for the inverse we solve y = f(x) for x:

$$y \approx f(p) + f'(p)(x-p) \Rightarrow x \approx p + \frac{1}{f'(p)} [y - f(p)]$$

Therefore, $f^{-1}(y) \approx p + \frac{1}{f'(p)} [y - f(p)]$ for y near f(p).

Example 5.1.1. Just to help you believe me, consider f(x) = 3x - 2 then f'(x) = 3 for all x. Suppose we want to find the inverse function near p = 2 then the discussion preceding this example suggests,

$$f^{-1}(y) = 2 + \frac{1}{3}(y - 4).$$

I invite the reader to check that $f(f^{-1}(y)) = y$ and $f^{-1}(f(x)) = x$ for all $x, y \in \mathbb{R}$.

In the example above we found a global inverse exactly, but this is thanks to the linearity of the function in the example. Generally, inverting the linearization just gives the first approximation to the inverse.

Consider $F : dom(F) \subseteq \mathbb{R}^n \to \mathbb{R}^n$. If F is differentiable at $p \in \mathbb{R}^n$ then we can write $F(x) \approx F(p) + F'(p)(x-p)$ for $x \approx p$. Set y = F(x) and solve for x via matrix algebra. This time we need to assume F'(p) is an invertible matrix in order to isolate x,

$$y \approx F(p) + F'(p)(x-p) \Rightarrow x \approx p + (F'(p))^{-1} [y - f(p)]$$

Therefore, $F^{-1}(y) \approx p + (F'(p))^{-1}[y - f(p)]$ for y near F(p). Apparently the condition to find a local inverse for a mapping on \mathbb{R}^n is that the derivative matrix is nonsingular¹ in some neighborhood of the point. Experience has taught us from the one-dimensional case that we must insist the derivative is continuous near the point in order to maintain the validity of the approximation.

Recall from calculus II that as we attempt to approximate a function with a power series it takes an infinite series of power functions to recapture the formula exactly. Well, something similar is true here. However, the method of approximation is through an iterative approximation procedure which is built off the idea of Newton's method. The product of this iteration is a nested sequence of composite functions. To prove the theorem below one must actually provide proof the recursively generated sequence of functions converges. See pages 160-187 of Edwards for an in-depth exposition of the iterative approximation procedure. Then see pages 404-411 of Edwards for some material on uniform convergence² The main analytical tool which is used to prove the convergence is called the **contraction mapping principle**. The proof of the principle is relatively easy to follow and interestingly the main non-trivial step is an application of the geometric series. For

¹nonsingular matrices are also called invertible matrices and a convenient test is that A is invertible iff $det(A) \neq 0$.

²actually that later chapter is part of why I chose Edwards' text, he makes a point of proving things in \mathbb{R}^n in such a way that the proof naturally generalizes to function space. This is done by arguing with properties rather than formulas. The properties offen extend to infinite dimensions whereas the formulas usually do not.

the student of analysis this is an important topic which you should spend considerable time really trying to absorb as deeply as possible. The contraction mapping is at the base of a number of interesting and nontrivial theorems. Read Rosenlicht's *Introduction to Analysis* for a broader and better organized exposition of this analysis. In contrast, Edwards' uses analysis as a tool to obtain results for advanced calculus but his central goal is not a broad or well-framed treatment of analysis. Consequently, if analysis is your interest then you really need to read something else in parallel to get a better ideas about sequences of functions and uniform convergence. I have some notes from a series of conversations with a student about Rosenlicht, I'll post those for the interested student. These notes focus on the part of the material I require for this course. This is Theorem 3.3 on page 185 of Edwards' text:

Theorem 5.1.2. (inverse function theorem)

Suppose $F : \mathbb{R}^n \to \mathbb{R}^n$ is continuously differentiable in an open set W containing a and the derivative matrix F'(a) is invertible. Then F is locally invertible at a. This means that there exists an open set $U \subseteq W$ containing a and V a open set containing b = F(a) and a one-one, continuously differentiable mapping $G : V \to W$ such that G(F(x)) = x for all $x \in U$ and F(G(y)) = y for all $y \in V$. Moreover, the local inverse G can be obtained as the limit of the sequence of successive approximations defined by

$$G_o(y) = a$$
 and $G_{n+1}(y) = G_n(y) - [F'(a)]^{-1}[F(G_n(y)) - y]$ for all $y \in V$.

The qualifier local is important to note. If we seek a global inverse then other ideas are needed. If the function is everywhere injective then logically F(x) = y defines $F^{-1}(y) = x$ and F^{-1} so constructed in single-valued by virtue of the injectivity of F. However, for differentiable mappings, one might wonder how can the criteria of global injectivity be tested via the differential. Even in the one-dimensional case a vanishing derivative does not indicate a lack of injectivity; $f(x) = x^3$ has $f^{-1}(y) = \sqrt[3]{y}$ and yet f'(0) = 0 (therefore f'(0) is not invertible). One the other hand, we'll see in the examples that follow that even if the derivative is invertible over a set it is possible for the values of the mapping to double-up and once that happens we cannot find a single-valued inverse function³

Remark 5.1.3. James R. Munkres' Analysis on Manifolds good for a different proof.

Another good place to read the inverse function theorem is in James R. Munkres *Analysis* on *Manifolds*. That text is careful and has rather complete arguments which are not entirely the same as the ones given in Edwards. Munkres' text does not use the contraction mapping principle, instead the arguments are more topological in nature.

³there are scientists and engineers who work with multiply-valued functions with great success, however, as a point of style if nothing else, we try to use functions in math.

To give some idea of what I mean by topological let be give an example of such an argument. Suppose $F : \mathbb{R}^n \to \mathbb{R}^n$ is continuously differentiable and F'(p) is invertible. Here's a sketch of the argument that F'(x) is invertible for all x near p as follows:

- 1. the function $g : \mathbb{R}^n \to \mathbb{R}$ defined by g(x) = det(F'(x)) is formed by a multinomial in the component functions of F'(x). This function is clearly continuous since we are given that the partial derivatives of the component functions of F are all continuous.
- 2. note we are given F'(p) is invertible and hence $det(F'(p)) \neq 0$ thus the continuous function g is nonzero at p. It follows there is some open set U containing p for which $0 \notin g(U)$
- 3. we have $det(F'(x)) \neq 0$ for all $x \in U$ hence F'(x) is invertible on U.

I would argue this is a topological argument because the key idea here is the continuity of g. Topology is the study of continuity in general.

Remark 5.1.4. James J. Callahan's Advanced Calculus: a Geometric View, good reading.

James J. Callahan's Advanced Calculus: a Geometric View has great merit in both visualization and well-thought use of linear algebraic techniques. In addition, many student will enjoy his staggered proofs where he first shows the proof for a simple low dimensional case and then proceeds to the general case.

Example 5.1.5. Suppose $F(x, y) = (\sin(y) + 1, \sin(x) + 2)$ for $(x, y) \in \mathbb{R}^2$. Clearly F is continuously differentiable as all its component functions have continuous partial derivatives. Observe,

$$F'(x,y) = \left[\begin{array}{cc} \partial_x F \mid \partial_y F \end{array}\right] = \left[\begin{array}{cc} 0 & \cos(y) \\ \cos(x) & 0 \end{array}\right]$$

Hence F'(x,y) is invertible at points (x,y) such that $det(F'(x,y)) = -\cos(x)\cos(y) \neq 0$. This means we **may** not be able to find local inverses at points (x,y) with $x = \frac{1}{2}(2n+1)\pi$ or $y = \frac{1}{2}(2m+1)\pi$ for some $m, n \in \mathbb{Z}$. Points where F'(x,y) are singular are points where one or both of $\sin(y)$ and $\sin(x)$ reach extreme values thus the points where the Jacobian matrix are singular are in fact points where we cannot find a local inverse. Why? Because the function is clearly not 1-1 on any set which contains the points of singularity for dF. Continuing, recall from precalculus that sine has a standard inverse on $[-\pi/2, \pi/2]$. Suppose $(x, y) \in [-\pi/2, \pi/2]^2$ and seek to solve F(x, y) = (a, b) for (x, y):

$$F(x,y) = \begin{bmatrix} \sin(y)+1\\ \sin(x)+2 \end{bmatrix} = \begin{bmatrix} a\\ b \end{bmatrix} \Rightarrow \begin{cases} \sin(y)+1=a\\ \sin(x)+2=b \end{cases} \Rightarrow \begin{cases} y=\sin^{-1}(a-1)\\ x=\sin^{-1}(b-2) \end{cases}$$

It follows that $F^{-1}(a, b) = (\sin^{-1}(b-2), \sin^{-1}(a-1))$ for $(a, b) \in [0, 2] \times [1, 3]$ where you should note $F([-\pi/2, \pi/2]^2) = [0, 2] \times [1, 3]$. We've found a local inverse for F on the region $[-\pi/2, \pi/2]^2$. In other words, we just found a global inverse for the restriction of F to $[-\pi/2, \pi/2]^2$. Technically we ought not write F^{-1} , to be more precise we should write:

$$(F|_{[-\pi/2,\pi/2]^2})^{-1}(a,b) = (\sin^{-1}(b-2), \sin^{-1}(a-1)).$$

It is customary to avoid such detail in many contexts. Inverse functions for sine, cosine, tangent etc... are good examples of this slight of language.

A coordinate system on \mathbb{R}^n is an invertible mapping of \mathbb{R}^n to \mathbb{R}^n . However, in practice the term coordinate system is used with less rigor. Often a coordinate system has various degeneracies. For example, in polar coordinates you could say $\theta = \pi/4$ or $\theta = 9\pi/4$ or generally $\theta = 2\pi k + \pi/4$ for any $k \in \mathbb{Z}$. Let's examine polar coordinates in view of the inverse function theorem.

Example 5.1.6. Let $T(r,\theta) = (r\cos(\theta), r\sin(\theta))$ for $(r,\theta) \in [0,\infty) \times (-\pi/2,\pi/2)$. Clearly T is continuously differentiable as all its component functions have continuous partial derivatives. To find the inverse we seek to solve $T(r,\theta) = (x,y)$ for (r,θ) . Hence, consider $x = r\cos(\theta)$ and $y = r\sin(\theta)$. Note that

$$x^{2} + y^{2} = r^{2}\cos^{2}(\theta) + r^{2}\sin^{2}(\theta) = r^{2}(\cos^{2}(\theta) + \sin^{2}(\theta)) = r^{2}$$

and

$$\frac{y}{x} = \frac{r\sin(\theta)}{r\cos(\theta)} = \tan(\theta).$$

It follows that $r = \sqrt{x^2 + y^2}$ and $\theta = \tan^{-1}(y/x)$ for $(x, y) \in (0, \infty) \times \mathbb{R}$. We find

$$T^{-1}(x,y) = \left(\sqrt{x^2 + y^2}, \tan^{-1}(y/x)\right).$$

Let's see how the derivative fits with our results. Calcuate,

$$T'(r,\theta) = \left[\begin{array}{cc} \partial_r T \mid \partial_\theta T \end{array}\right] = \left[\begin{array}{cc} \cos(\theta) & -r\sin(\theta) \\ \sin(\theta) & r\cos(\theta) \end{array}\right]$$

note that $det(T'(r,\theta)) = r$ hence we the inverse function theorem provides the existence of a local inverse around any point except the origin. Notice the derivative does not detect the defect in the angular coordinate. Challenge, find the inverse function for $T(r,\theta) = (r\cos(\theta), r\sin(\theta))$ with $dom(T) = [0,\infty) \times (\pi/2, 3\pi/2)$. Or, find the inverse for polar coordinates in a neighborhood of (0,-1).

Example 5.1.7. Suppose $T : \mathbb{R}^3 \to \mathbb{R}^3$ is defined by T(x, y, z) = (ax, by, cz) for constants $a, b, c \in \mathbb{R}$ where $abc \neq 0$. Clearly T is continuously differentiable as all its component functions have continuous partial derivatives. We calculate $T'(x, y, z) = [\partial_x T | \partial_y T | \partial_z T] = [ae_1 | be_2 | ce_3]$. Thus $det(T'(x, y, z)) = abc \neq 0$ for all $(x, y, z) \in \mathbb{R}^3$ hence this function is locally invertible everywhere. Moreover, we calculate the inverse mapping by solving T(x, y, z) = (u, v, w) for (x, y, z):

$$(ax, by, cz) = (u, v, w) \quad \Rightarrow \quad (x, y, z) = (u/a, v/b, w/c) \quad \Rightarrow \quad \boxed{T^{-1}(u, v, w) = (u/a, v/b, w/c)}.$$

Example 5.1.8. Suppose $F : \mathbb{R}^n \to \mathbb{R}^n$ is defined by F(x) = Ax + b for some matrix $A \in \mathbb{R}^{n \times n}$ and vector $b \in \mathbb{R}^n$. Under what conditions is such a function invertible ?. Since the formula for this function gives each component function as a polynomial in the n-variables we can conclude the

function is continuously differentiable. You can calculate that F'(x) = A. It follows that a sufficient condition for local inversion is $det(A) \neq 0$. It turns out that this is also a necessary condition as det(A) = 0 implies the matrix A has nontrivial solutions for Av = 0. We say $v \in Null(A)$ iff Av = 0. Note if $v \in Null(A)$ then F(v) = Av + b = b. This is not a problem when $det(A) \neq 0$ for in that case the null space is contains just zero; $Null(A) = \{0\}$. However, when det(A) = 0 we learn in linear algebra that Null(A) contains infinitely many vectors so F is far from injective. For example, suppose $Null(A) = span\{e_1\}$ then you can show that $F(a_1, a_2, \ldots, a_n) = F(x, a_2, \ldots, a_n)$ for all $x \in \mathbb{R}$. Hence any point will have other points nearby which output the same value under F. Suppose $det(A) \neq 0$, to calculate the inverse mapping formula we should solve F(x) = y for x,

$$y = Ax + b \Rightarrow x = A^{-1}(y - b) \Rightarrow F^{-1}(y) = A^{-1}(y - b).$$

Remark 5.1.9. inverse function theorem holds for higher derivatives.

In Munkres the inverse function theorem is given for r-times differentiable functions. In short, a C^r function with invertible differential at a point has a C^r inverse function local to the point. Edwards also has arguments for r > 1, see page 202 and arguments and surrounding arguments.

5.2 implicit function theorem

Consider the problem of solving $x^2 + y^2 = 1$ for y as a function of x.

$$x^{2} + y^{2} = 1 \Rightarrow y^{2} = 1 - x^{2} \Rightarrow y = \pm \sqrt{1 - x^{2}}.$$

A function cannot have two outputs for a single input, when we write \pm in the expression above it simply indicates our ignorance as to which is chosen. Once further information is given then we may be able to choose a + or a -. For example:

- 1. if $x^2 + y^2 = 1$ and we want to solve for y near (0, 1) then $y = \sqrt{1 x^2}$ is the correct choice since y > 0 at the point of interest.
- 2. if $x^2 + y^2 = 1$ and we want to solve for y near (0, -1) then $y = -\sqrt{1 x^2}$ is the correct choice since y < 0 at the point of interest.
- 3. if $x^2 + y^2 = 1$ and we want to solve for y near (1,0) then it's impossible to find a single function which reproduces $x^2 + y^2 = 1$ on an **open disk** centered at (1,0).

What is the defect of case (3.)? The trouble is that no matter how close we zoom in to the point there are always two *y*-values for each given *x*-value. Geometrically, this suggests either we have a discontinuity, a kink, or a vertical tangent in the graph. The given problem has a vertical tangent and hopefully you can picture this with ease since its just the unit-circle. In calculus I we studied implicit differentiation, our starting point was to assume y = y(x) and then we differentiated equations to work out implicit formulas for dy/dx. Take the unit-circle and differentiate both sides,

$$x^2 + y^2 = 1 \Rightarrow 2x + 2y \frac{dy}{dx} = 0 \Rightarrow \frac{dy}{dx} = -\frac{x}{y}.$$

Note $\frac{dy}{dx}$ is not defined for y = 0. It's no accident that those two points (-1,0) and (1,0) are precisely the points at which we cannot solve for y as a function of x. Apparently, the singularity in the derivative indicates where we may have trouble solving an equation for one variable as a function of the remaining variable.

We wish to study this problem in general. Given *n*-equations in (m+n)-unknowns when can we solve for the last *n*-variables as functions of the first *m*-variables? Given a continuously differentiable mapping $G = (G_1, G_2, \ldots, G_n) : \mathbb{R}^m \times \mathbb{R}^n \to \mathbb{R}^n$ study the level set: (here k_1, k_2, \ldots, k_n are constants)

$$G_1(x_1, \dots, x_m, y_1, \dots, y_n) = k_1$$
$$G_2(x_1, \dots, x_m, y_1, \dots, y_n) = k_2$$
$$\vdots$$
$$G_n(x_1, \dots, x_m, y_1, \dots, y_n) = k_n$$

We wish to locally solve for y_1, \ldots, y_n as functions of x_1, \ldots, x_m . That is, find a mapping $h : \mathbb{R}^m \to \mathbb{R}^n$ such that G(x, y) = k iff y = h(x) near some point $(a, b) \in \mathbb{R}^m \times \mathbb{R}^n$ such that G(a, b) = k. In this section we use the notation $x = (x_1, x_2, \ldots, x_m)$ and $y = (y_1, y_2, \ldots, y_n)$.

Before we turn to the general problem let's analyze the unit-circle problem in this notation. We are given $G(x, y) = x^2 + y^2$ and we wish to find f(x) such that y = f(x) solves G(x, y) = 1. Differentiate with respect to x and use the chain-rule:

$$\frac{\partial G}{\partial x}\frac{dx}{dx} + \frac{\partial G}{\partial y}\frac{dy}{dx} = 0$$

We find that $dy/dx = -G_x/G_y = -x/y$. Given this analysis we should suspect that if we are given some level curve G(x, y) = k then we may be able to solve for y as a function of x near p if G(p) = k and $G_y(p) \neq 0$. This suspicion is valid and it is one of the many consequences of the implicit function theorem.

We again turn to the linearization approximation. Suppose G(x, y) = k where $x \in \mathbb{R}^m$ and $y \in \mathbb{R}^n$ and suppose $G : \mathbb{R}^m \times \mathbb{R}^n \to \mathbb{R}^n$ is continuously differentiable. Suppose $(a, b) \in \mathbb{R}^m \times \mathbb{R}^n$ has G(a, b) = k. Replace G with its linearization based at (a, b):

$$G(x,y) \approx k + G'(a,b)(x-a,y-b)$$

here we have the matrix multiplication of the $n \times (m+n)$ matrix G'(a,b) with the $(m+n) \times 1$ column vector (x-a, y-b) to yield an *n*-component column vector. It is convenient to define partial derivatives with respect to a whole vector of variables,

$$\frac{\partial G}{\partial x} = \begin{bmatrix} \frac{\partial G_1}{\partial x_1} & \cdots & \frac{\partial G_1}{\partial x_m} \\ \vdots & & \vdots \\ \frac{\partial G_n}{\partial x_1} & \cdots & \frac{\partial G_n}{\partial x_m} \end{bmatrix} \qquad \frac{\partial G}{\partial y} = \begin{bmatrix} \frac{\partial G_1}{\partial y_1} & \cdots & \frac{\partial G_1}{\partial y_n} \\ \vdots & & \vdots \\ \frac{\partial G_n}{\partial y_1} & \cdots & \frac{\partial G_n}{\partial y_n} \end{bmatrix}$$

In this notation we can write the $n \times (m+n)$ matrix G'(a,b) as the concatenation of the $n \times m$ matrix $\frac{\partial G}{\partial x}(a,b)$ and the $n \times n$ matrix $\frac{\partial G}{\partial y}(a,b)$

$$G'(a,b) = \left[\frac{\partial G}{\partial x}(a,b) \middle| \frac{\partial G}{\partial y}(a,b) \right]$$

Therefore, for points close to (a, b) we have:

$$G(x,y) \approx k + \frac{\partial G}{\partial x}(a,b)(x-a) + \frac{\partial G}{\partial y}(a,b)(y-b)$$

The nonlinear problem G(x, y) = k has been (locally) replaced by the linear problem of solving what follows for y:

$$k \approx k + \frac{\partial G}{\partial x}(a,b)(x-a) + \frac{\partial G}{\partial y}(a,b)(y-b)$$
(5.1)

Suppose the square matrix $\frac{\partial G}{\partial y}(a, b)$ is invertible at (a, b) then we find the following approximation for the implicit solution of G(x, y) = k for y as a function of x:

$$y = b - \left[\frac{\partial G}{\partial y}(a,b)\right]^{-1} \left[\frac{\partial G}{\partial x}(a,b)(x-a)\right].$$

Of course this is not a formal proof, but it does suggest that $det\left[\frac{\partial G}{\partial y}(a,b)\right] \neq 0$ is a necessary condition for solving for the y variables.

As before suppose $G : \mathbb{R}^m \times \mathbb{R}^n \to \mathbb{R}^n$. Suppose we have a continuously differentiable function $h : \mathbb{R}^m \to \mathbb{R}^n$ such that h(a) = b and G(x, h(x)) = k. We seek to find the derivative of h in terms of the derivative of G. This is a generalization of the implicit differentiation calculation we perform in calculus I. I'm including this to help you understand the notation a bit more before I state the implicit function theorem. Differentiate with respect to x_l for $l \in \mathbb{N}_m$:

$$\frac{\partial}{\partial x_l} \left[G(x, h(x)) \right] = \sum_{i=1}^m \frac{\partial G}{\partial x_i} \frac{\partial x_i}{\partial x_l} + \sum_{j=1}^n \frac{\partial G}{\partial y_j} \frac{\partial h_j}{\partial x_l} = \frac{\partial G}{\partial x_l} + \sum_{j=1}^n \frac{\partial G}{\partial y_j} \frac{\partial h_j}{\partial x_l} = 0$$

we made use of the identity $\frac{\partial x_i}{\partial x_k} = \delta_{ik}$ to squash the sum of *i* to the single nontrivial term and the zero on the r.h.s follows from the fact that $\frac{\partial}{\partial x_l}(k) = 0$. Concatenate these derivatives from k = 1

up to k = m:

$$\left[\frac{\partial G}{\partial x_1} + \sum_{j=1}^n \frac{\partial G}{\partial y_j} \frac{\partial h_j}{\partial x_1} \middle| \frac{\partial G}{\partial x_2} + \sum_{j=1}^n \frac{\partial G}{\partial y_j} \frac{\partial h_j}{\partial x_2} \middle| \cdots \middle| \frac{\partial G}{\partial x_m} + \sum_{j=1}^n \frac{\partial G}{\partial y_j} \frac{\partial h_j}{\partial x_m} \right] = [0|0|\cdots|0]$$

Properties of matrix addition allow us to parse the expression above as follows:

$$\left[\frac{\partial G}{\partial x_1}\left|\frac{\partial G}{\partial x_2}\right|\cdots\left|\frac{\partial G}{\partial x_m}\right] + \left[\sum_{j=1}^n \frac{\partial G}{\partial y_j}\frac{\partial h_j}{\partial x_1}\right|\sum_{j=1}^n \frac{\partial G}{\partial y_j}\frac{\partial h_j}{\partial x_2}\right|\cdots\left|\sum_{j=1}^n \frac{\partial G}{\partial y_j}\frac{\partial h_j}{\partial x_m}\right] = [0|0|\cdots|0]$$

But, this reduces to

$$\frac{\partial G}{\partial x} + \left[\frac{\partial G}{\partial y}\frac{\partial h}{\partial x_1} \left|\frac{\partial G}{\partial y}\frac{\partial h}{\partial x_2}\right| \cdots \left|\frac{\partial G}{\partial y}\frac{\partial h}{\partial x_m}\right] = 0 \in \mathbb{R}^{m \times n}$$

The concatenation property of matrix multiplication states $[Ab_1|Ab_2|\cdots|Ab_m] = A[b_1|b_2|\cdots|b_m]$ we use this to write the expression once more,

$$\frac{\partial G}{\partial x} + \frac{\partial G}{\partial y} \left[\frac{\partial h}{\partial x_1} \middle| \frac{\partial h}{\partial x_2} \middle| \cdots \middle| \frac{\partial h}{\partial x_m} \right] = 0 \quad \Rightarrow \quad \frac{\partial G}{\partial x} + \frac{\partial G}{\partial y} \frac{\partial h}{\partial x} = 0 \quad \Rightarrow \quad \left| \frac{\partial h}{\partial x} = -\frac{\partial G}{\partial y} \right|^{-1} \frac{\partial G}{\partial x}$$

where in the last implication we made use of the assumption that $\frac{\partial G}{\partial u}$ is invertible.

Theorem 5.2.1. (Theorem 3.4 in Edwards's Text see pg 190)

Let $G : dom(G) \subseteq \mathbb{R}^m \times \mathbb{R}^n \to \mathbb{R}^n$ be continuously differentiable in a open ball about the point (a, b) where G(a, b) = k (a constant vector in \mathbb{R}^n). If the matrix $\frac{\partial G}{\partial y}(a, b)$ is invertible then there exists an open ball U containing a in \mathbb{R}^m and an open ball W containing (a, b) in $\mathbb{R}^m \times \mathbb{R}^n$ and a continuously differentiable mapping $h : U \to \mathbb{R}^n$ such that G(x, y) = k iff y = h(x) for all $(x, y) \in W$. Moreover, the mapping h is the limit of the sequence of successive approximations defined inductively below

$$h_o(x) = b$$
, $h_{n+1} = h_n(x) - \left[\frac{\partial G}{\partial y}(a,b)\right]^{-1} G(x,h_n(x))$ for all $x \in U$.

We will not attempt a proof of the last sentence for the same reasons we did not pursue the details in the inverse function theorem. However, we have already derived the first step in the iteration in our study of the linearization solution.

Proof: Let $G : dom(G) \subseteq \mathbb{R}^m \times \mathbb{R}^n \to \mathbb{R}^n$ be continuously differentiable in a open ball B about the point (a, b) where G(a, b) = k ($k \in \mathbb{R}^n$ a constant). Furthermore, assume the matrix $\frac{\partial G}{\partial y}(a, b)$ is invertible. We seek to use the inverse function theorem to prove the implicit function theorem. Towards that end consider $F : \mathbb{R}^m \times \mathbb{R}^n \to \mathbb{R}^m \times \mathbb{R}^n$ defined by F(x, y) = (x, G(x, y)). To begin, observe that F is continuously differentiable in the open ball B which is centered at (a, b) since G and x have continuous partials of their components in B. Next, calculate the derivative of F = (x, G),

$$F'(x,y) = [\partial_x F | \partial_y F] = \begin{bmatrix} \frac{\partial_x x \mid \partial_y x}{\partial_x G \mid \partial_y G} \end{bmatrix} = \begin{bmatrix} I_m \mid 0_{m \times n} \\ \frac{\partial_x G \mid \partial_y G}{\partial_y G} \end{bmatrix}$$

The determinant of the matrix above is the product of the determinant of the blocks I_m and $\partial_y G$; $det(F'(x,y) = det(I_m)det(\partial_y G) = \partial_y G$. We are given that $\frac{\partial G}{\partial y}(a,b)$ is invertible and hence $det(\frac{\partial G}{\partial y}(a,b)) \neq 0$ thus $det(F'(x,y) \neq 0$ and we find F'(a,b) is invertible. Consequently, the inverse function theorem applies to the function F at (a,b). Therefore, there exists $F^{-1}: V \subseteq \mathbb{R}^m \times \mathbb{R}^n \to U \subseteq \mathbb{R}^m \times \mathbb{R}^n$ such that F^{-1} is continuously differentiable. Note $(a,b) \in U$ and V contains the point F(a,b) = (a,G(a,b)) = (a,k).

Our goal is to find the implicit solution of G(x, y) = k. We know that

$$F^{-1}(F(x,y)) = (x,y)$$
 and $F(F^{-1}(u,v)) = (u,v)$

for all $(x, y) \in U$ and $(u, v) \in V$. As usual to find the formula for the inverse we can solve F(x, y) = (u, v) for (x, y) this means we wish to solve (x, G(x, y)) = (u, v) hence x = u. The formula for v is more elusive, but we know it exists by the inverse function theorem. Let's say y = H(u, v) where $H: V \to \mathbb{R}^n$ and thus $F^{-1}(u, v) = (u, H(u, v))$. Consider then,

$$(u, v) = F(F^{-1}(u, v)) = F(u, H(u, v)) = (u, G(u, H(u, v)))$$

Let v = k thus (u, k) = (u, G(u, H(u, k)) for all $(u, v) \in V$. Finally, define h(u) = H(u, k) for all $(u, k) \in V$ and note that k = G(u, h(u)). In particular, $(a, k) \in V$ and at that point we find h(a) = H(a, k) = b by construction. It follows that y = h(x) provides a continuously differentiable solution of G(x, y) = k near (a, b).

Uniqueness of the solution follows from the uniqueness for the limit of the sequence of functions described in Edwards' text on page 192. However, other arguments for uniqueness can be offered, independent of the iterative method, for instance: see page 75 of Munkres Analysis on Manifolds. \Box

Remark 5.2.2. notation and the implementation of the implicit function theorem.

We assumed the variables y were to be written as functions of x variables to make explicit a local solution to the equation G(x, y) = k. This ordering of the variables is convenient to argue the proof, however the real theorem is far more general. We can select any subset of ninput variables to make up the "y" so long as $\frac{\partial G}{\partial y}$ is invertible. I will use this generalization of the formal theorem in the applications that follow. Moreover, the notations x and y are unlikely to maintain the same interpretation as in the previous pages. Finally, we will for convenience make use of the notation y = y(x) to express the existence of a function f such that y = f(x) when appropriate. Also, z = z(x, y) means there is some function h for which z = h(x, y). If this notation confuses then invent names for the functions in your problem. **Example 5.2.3.** Suppose $G(x, y, z) = x^2 + y^2 + z^2$. Suppose we are given a point (a, b, c) such that $G(a, b, c) = R^2$ for a constant R. Problem: For which variable can we solve? What, if any, influence does the given point have on our answer? Solution: to begin, we have one equation and three unknowns so we should expect to find one of the variables as functions of the remaining two variables. The implicit function theorem applies as G is continuously differentiable.

- 1. if we wish to solve z = z(x, y) then we need $G_z(a, b, c) = 2c \neq 0$.
- 2. if we wish to solve y = y(x, z) then we need $G_y(a, b, c) = 2b \neq 0$.
- 3. if we wish to solve x = x(y, z) then we need $G_x(a, b, c) = 2a \neq 0$.

The point has no local solution for z if it is a point on the intersection of the xy-plane and the sphere $G(x, y, z) = R^2$. Likewise, we cannot solve for y = y(x, z) on the y = 0 slice of the sphere and we cannot solve for x = x(y, z) on the x = 0 slice of the sphere.

Notice, algebra verifies the conclusions we reached via the implicit function theorem:

$$z = \pm \sqrt{R^2 - x^2 - y^2}$$
 $y = \pm \sqrt{R^2 - x^2 - z^2}$ $x = \pm \sqrt{R^2 - y^2 - z^2}$

When we are at zero for one of the coordinates then we cannot choose + or - since we need both on an open ball intersected with the sphere centered at such a point⁴. Remember, when I talk about local solutions I mean solutions which exist over the intersection of the solution set and an open ball in the ambient space (\mathbb{R}^3 in this context). The preceding example is the natural extension of the unit-circle example to \mathbb{R}^3 . A similar result is available for the *n*-sphere in \mathbb{R}^n . I hope you get the point of the example, if we have one equation then if we wish to solve for a particular variable in terms of the remaining variables then all we need is continuous differentiability of the level function and a nonzero partial derivative at the point where we wish to find the solution. Now, the implicit function theorem doesn't find the solution for us, but it does provide the existence. In the section on implicit differentiation, existence is really all we need since focus our attention on rates of change rather than actually solutions to the level set equation.

Example 5.2.4. Consider the equation $e^{xy} + z^3 - xyz = 2$. Can we solve this equation for z = z(x, y) near (0, 0, 1)? Let $G(x, y, z) = e^{xy} + z^3 - xyz$ and note $G(0, 0, 1) = e^0 + 1 + 0 = 2$ hence (0, 0, 1) is a point on the solution set G(x, y, z) = 2. Note G is clearly continuously differentiable and

$$G_z(x, y, z) = 3z^2 - xy \Rightarrow G_z(0, 0, 1) = 3 \neq 0$$

therefore, there exists a continuously differentiable function $h : dom(h) \subseteq \mathbb{R}^2 \to \mathbb{R}$ which solves G(x, y, h(x, y)) = 2 for (x, y) near (0, 0) and h(0, 0) = 1.

I'll not attempt an explicit solution for the last example.

⁴if you consider $G(x, y, z) = R^2$ as a space then the open sets on the space are taken to be the intersection with the space and open balls in \mathbb{R}^3 . This is called the subspace topology in topology courses.

Example 5.2.5. Let $(x, y, z) \in S$ iff x + y + z = 2 and y + z = 1. **Problem: For which** variable(s) can we solve? Solution: define G(x, y, z) = (x + y + z, y + z) we wish to study G(x, y, z) = (2, 1). Notice the solution set is not empty since G(1, 0, 1) = (1 + 0 + 1, 0 + 1) = (2, 1)Moreover, G is continuously differentiable. In this case we have two equations and three unknowns so we expect two variables can be written in terms of the remaining free variable. Let's examine the derivative of G:

$$G'(x,y,z) = \left[\begin{array}{rrr} 1 & 1 & 1 \\ 0 & 1 & 1 \end{array}\right]$$

Suppose we wish to solve x = x(z) and y = y(z) then we should check invertibility of⁵

$$\frac{\partial G}{\partial(x,y)} = \left[\begin{array}{cc} 1 & 1\\ 0 & 1 \end{array} \right].$$

The matrix above is invertible hence the implicit function theorem applies and we can solve for xand y as functions of z. On the other hand, if we tried to solve for y = y(x) and z = z(x) then we'll get no help from the implicit function theorem as the matrix

$$\frac{\partial G}{\partial(y,z)} = \left[\begin{array}{cc} 1 & 1 \\ 1 & 1 \end{array} \right].$$

is not invertible. Geometrically, we can understand these results from noting that G(x, y, z) = (2, 1)is the intersection of the plane x + y + z = 2 and y + z = 1. Substituting y + z = 1 into x + y + z = 2yields x + 1 = 2 hence x = 1 on the line of intersection. We can hardly use x as a free variable for the solution when the problem fixes x from the outset.

The method I just used to analyze the equations in the preceding example was a bit adhoc. In linear algebra we do much better for systems of linear equations. A procedure called Gaussian elimination naturally reduces a system of equations to a form in which it is manifestly obvious how to eliminate redundant variables in terms of a minimal set of basic free variables. The "y" of the implicit function proof discussions plays the role of the so-called **pivotal variables** whereas the "x" plays the role of the remaining **free variables**. These variables are generally intermingled in the list of total variables so to reproduce the pattern assumed for the implicit function theorem we would need to relabel variables from the outset of a calculation. In the following example, I show how reordering the variables allows us to solve for various pairs. In short, put the dependent variable first and the independent variables second so the Gaussian elimination shows the solution with minimal effort. Here's how:

⁵this notation should not be confused with $\frac{\partial(x,y)}{\partial(u,v)}$ which is used to denote a particular determinant associated with coordinate change of integrals, or pull-back of a differential form as explained on page 100 of H.M Edward's Advanced Calculus: A differential Forms Approach, we should discuss it in a later chapter.

Example 5.2.6. Consider G(x, y, u, v) = (3x + 2y - u, 2x + y - v) = (-1, 3). We have two equations with four variables. Let's investigate which pairs of variables can be taken as independent or dependent variables. The most efficient method to dispatch these questions is probably Gaussian elimination. I leave it to the reader to verify that:

$$rref \begin{bmatrix} 3 & 2 & -1 & 0 & | & -1 \\ 2 & 1 & 0 & -1 & | & 3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 1 & -2 & | & 7 \\ 0 & 1 & -2 & 3 & | & -11 \end{bmatrix}$$

We can immediately read from the result above that x, y can be taken to depend on u, v via the formulas:

$$x = -u + 2v + 7, \qquad y = 2u - 3v - 11$$

On the other hand, if we order the variables (u, v, x, y) then Gaussian elimination gives:

$$rref \begin{bmatrix} -1 & 0 & 3 & 2 & | & -1 \\ 0 & -1 & 2 & 1 & | & 3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & -3 & -2 & | & 1 \\ 0 & 1 & -2 & -1 & | & -3 \end{bmatrix}$$

Therefore, we find u(x, y) and v(x, y) as follows:

$$u = 3x + 2y + 1,$$
 $v = 2x + y - 3.$

To solve for x, u as functions of y, v consider:

$$rref \left[\begin{array}{cccc|c} 3 & -1 & 2 & 0 \\ 2 & 0 & 1 & -1 \end{array} \right| \left. \begin{array}{cccc|c} -1 \\ 3 \end{array} \right] = \left[\begin{array}{cccc|c} 1 & 0 & 1/2 & -1/2 \\ 0 & 1 & -1/2 & -3/2 \end{array} \right| \left. \begin{array}{cccc|c} 3/2 \\ 11/2 \end{array} \right]$$

From which we can read,

$$x = -y/2 + v/2 + 3/2,$$
 $u = y/2 + 3v/2 + 11/2$

I could solve the problem below in the efficient style above, but I will instead follow the method in which we discussed in the paragraphs surrounding Equation 5.1. In contrast to the general case, because the problem is linear the solution of Equation 5.1 is also a solution of the actual problem.

Example 5.2.7. Solve the following system of equations near (1, 2, 3, 4, 5).

$$G(x, y, z, a, b) = \begin{bmatrix} x + y + z + 2a + 2b \\ x + 0 + 2z + 2a + 3b \\ 3x + 2y + z + 3a + 4b \end{bmatrix} = \begin{bmatrix} 24 \\ 30 \\ 42 \end{bmatrix}$$

Differentiate to find the Jacobian:

$$G'(x, y, z, a, b) = \begin{bmatrix} 1 & 1 & 1 & 2 & 2 \\ 1 & 0 & 2 & 2 & 3 \\ 3 & 2 & 1 & 3 & 4 \end{bmatrix}$$

Let us solve G(x, y, z, a, b) = (24, 30, 42) for x(a, b), y(a, b), z(a, b) by the method of Equation 5.1. I'll omit the point-dependence of the Jacobian since it clearly has none.

$$G(x, y, z, a, b) = \begin{bmatrix} 24\\ 30\\ 42 \end{bmatrix} + \frac{\partial G}{\partial(x, y, z)} \begin{bmatrix} x-1\\ y-2\\ z-3 \end{bmatrix} + \frac{\partial G}{\partial(a, b)} \begin{bmatrix} a-4\\ b-5 \end{bmatrix}$$

Let me make the notational chimera above explicit:

$$G(x, y, z, a, b) = \begin{bmatrix} 24\\ 30\\ 42 \end{bmatrix} + \begin{bmatrix} 1 & 1 & 1\\ 1 & 0 & 2\\ 3 & 2 & 1 \end{bmatrix} \begin{bmatrix} x-1\\ y-2\\ z-3 \end{bmatrix} + \begin{bmatrix} 2 & 2\\ 2 & 3\\ 3 & 4 \end{bmatrix} \begin{bmatrix} a-4\\ b-5 \end{bmatrix}$$

To solve G(x, y, z, a, b) = (24, 30, 42) for (x, y, z) we may use the expression above. After a little calculation one finds:

$$\begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 2 \\ 3 & 2 & 1 \end{bmatrix}^{-1} = \frac{1}{3} \begin{bmatrix} -4 & 1 & 2 \\ 5 & -2 & -1 \\ 2 & 1 & -1 \end{bmatrix}$$

The constant term cancels and we find:

$$\begin{bmatrix} x-1\\y-2\\z-3 \end{bmatrix} = -\frac{1}{3} \begin{bmatrix} -4 & 1 & 2\\5 & -2 & -1\\2 & 1 & -1 \end{bmatrix} \begin{bmatrix} 2 & 2\\2 & 3\\3 & 4 \end{bmatrix} \begin{bmatrix} a-4\\b-5 \end{bmatrix}$$

Multiplying the matrices gives:

$$\begin{bmatrix} x-1\\y-2\\z-3 \end{bmatrix} = -\frac{1}{3} \begin{bmatrix} 0 & 3\\3 & 0\\3 & 3 \end{bmatrix} \begin{bmatrix} a-4\\b-5 \end{bmatrix} = \begin{bmatrix} 0 & -1\\-1 & 0\\-1 & -1 \end{bmatrix} \begin{bmatrix} a-4\\b-5 \end{bmatrix} = \begin{bmatrix} 5-b\\4-a\\9-a-b \end{bmatrix}$$

Therefore,

$$x = 6 - b$$
, $y = 6 - a$, $z = 12 - a - b$.

Is it possible to solve for any triple of the variables x, y, z, a, b for the given system? In fact, no. Let me explain by linear algebra. We can calculate: the augmented coefficient matrix for G(x, y, z, a, b) = (24, 30, 42) Gaussian eliminates as follows:

$$rref \left[\begin{array}{rrr} 1 & 1 & 1 & 2 & 2 & 24 \\ 1 & 0 & 2 & 2 & 3 & 30 \\ 3 & 2 & 1 & 3 & 4 & 42 \end{array} \right] = \left[\begin{array}{rrr} 1 & 0 & 0 & 0 & 1 & 6 \\ 0 & 1 & 0 & 1 & 0 & 6 \\ 0 & 0 & 1 & 1 & 1 & 12 \end{array} \right].$$

First, note this is consistent with the answer we derived above. Second, examine the columns of rref[G']. You can ignore the 6-th column in the interest of this thought extending to nonlinear systems. The question of the suitability of a triple amounts to the invertibility of the submatrix of G' which corresponds to the triple. Examine:

$$\frac{\partial G}{\partial (y,z,a)} = \begin{bmatrix} 1 & 1 & 2\\ 0 & 2 & 2\\ 2 & 1 & 3 \end{bmatrix}, \qquad \frac{\partial G}{\partial (x,z,b)} = \begin{bmatrix} 1 & 1 & 2\\ 1 & 2 & 3\\ 3 & 1 & 4 \end{bmatrix}$$

both of these are clearly singular since the third column is the sum of the first two columns. Alternatively, you can calculate the determinant of each of the matrices above is zero. In contrast,

$$\frac{\partial G}{\partial(z,a,b)} = \begin{bmatrix} 1 & 2 & 2\\ 2 & 2 & 2\\ 1 & 3 & 4 \end{bmatrix}$$

is non-singular. How to I know there is no linear dependence? Well, we could calculate the determinant is $1(8-6) - 2(8-2) + 2(6-2) = -2 \neq 0$. Or, we could examine the row reduction above. The column correspondance property⁶ states that linear dependences amongst columns of a matrix are preserved under row reduction. This means we can easily deduce dependence (if there is any) from the reduced matrix. Observe that column 4 is clearly the sum of columns 2 and 3. Likewise, column 5 is the sum of columns 1 and 3. On the other hand, columns 3,4,5 admit no linear dependence. In general, more calculation would be required to "see" the independence of the far right columns. One reorders the columns and performs a new reduction to ascertain dependence. No such calculation is needed here since the problem is not that complicated.

I find calculating the determinant of sub-Jacobian matrices is the simplest way for most students to quickly understand. I'll showcase this method in a series of examples attached to a later section. I have made use of some matrix theory in this section. If you didn't learn it in linear (or haven't taken linear yet) it's worth learning. These are nice tools to keep for later problems in life.

Remark 5.2.8. independent constraints

Gaussian elimination on a system of linear equations may produce a row of zeros. For example, x + y = 0 and 2x + 2y = 0 gives $\operatorname{rref} \begin{bmatrix} 1 & 1 & 0 \\ 2 & 2 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$. The reason for this is quite obvious: the equations consider are not indpendent. In fact the second equation is a scalar multiple of the first. Generally, if there is some linear-dependence in a set of equations then we can expect this will happen. Although, if the equations are inhomogenous the last column might not be trivial because the system could be inconsistent (for example x + y = 1 and 2x + 2y = 5).

Consider $G : \mathbb{R}^n \times \mathbb{R}^p \to \mathbb{R}^n$. As we linearize G = k we arrive at a homogeneous system which can be written briefly as $G'\vec{r} = 0$ (think about Equation 5.1 with the k's cancelled). We should **define** $G(\vec{r}) = k$ is a **system of** *n* **independent equations at** $\vec{r_o}$ iff $G(\vec{r_o}) = k$ and $\operatorname{rref}[G'(\vec{r_o})]$ has zero row. In other terminology, we could say the system of (possibly nonlinear) equations $G(\vec{r}) = k$ is built from *n*-independent equations near $\vec{r_o}$ iff the Jacobian matrix has **full-rank** at $\vec{r_o}$. If this full-rank condition is met then we can solve for *n* of the variables in terms of the remaining *p* variables. In general there will be many choices of how to do this, and some choices will be forbidden as we have seen in the examples already.

⁶I like to call it the CCP in my linear notes

5.3 implicit differentiation

Enough theory, let's calculate. In this section I apply previous theoretical constructions to specific problems. I also introduce standard notation for "constrained" partial differentiation which is also sometimes called "partial differentiation with a side condition". The typical problem is the following: given equations:

$$G_1(x_1, \dots, x_m, y_1, \dots, y_n) = k_1$$
$$G_2(x_1, \dots, x_m, y_1, \dots, y_n) = k_2$$
$$\vdots$$
$$G_n(x_1, \dots, x_m, y_1, \dots, y_n) = k_n$$

calculate partial derivative of dependent variables with respect to independent variables. Continuing with the notation of the implicit function discussion we'll assume that y will be dependent on x. I want to recast some of our arguments via differentials⁷. Take the total differential of each equation above,

$$dG_1(x_1, \dots, x_m, y_1, \dots, y_n) = 0$$

$$dG_2(x_1, \dots, x_m, y_1, \dots, y_n) = 0$$

$$\vdots$$

$$dG_n(x_1, \dots, x_m, y_1, \dots, y_n) = 0$$

Hence,

$$\partial_{x_1}G_1dx_1 + \dots + \partial_{x_m}G_1dx_m + \partial_{y_1}G_1dy_1 + \dots + \partial_{y_n}G_1dy_n = 0$$

$$\partial_{x_1}G_2dx_1 + \dots + \partial_{x_m}G_2dx_m + \partial_{y_1}G_2dy_1 + \dots + \partial_{y_n}G_2dy_n = 0$$

$$\vdots$$

$$\partial_{x_1}G_ndx_1 + \dots + \partial_{x_m}G_ndx_m + \partial_{y_1}G_ndy_1 + \dots + \partial_{y_n}G_ndy_n = 0$$

Notice, this can be nicely written in column vector notation as:

$$\partial_{x_1}Gdx_1 + \dots + \partial_{x_m}Gdx_m + \partial_{y_1}Gdy_1 + \dots + \partial_{y_n}Gdy_n = 0$$

Or, in matrix notation:

$$\left[\partial_{x_1}G|\cdots|\partial_{x_m}G\right]\left[\begin{array}{c}dx_1\\\vdots\\dx_m\end{array}\right]+\left[\partial_{y_1}G|\cdots|\partial_{y_n}G\right]\left[\begin{array}{c}dy_1\\\vdots\\dy_n\end{array}\right]=0$$

⁷in contrast, In the previous section we mostly used derivative notation

Finally, solve for dy, we assume $[\partial_{y_1}G|\cdots|\partial_{y_n}G]^{-1}$ exists,

$$\begin{bmatrix} dy_1 \\ \vdots \\ dy_n \end{bmatrix} = -[\partial_{y_1}G|\cdots|\partial_{y_n}G]^{-1}[\partial_{x_1}G|\cdots|\partial_{x_m}G] \begin{bmatrix} dx_1 \\ \vdots \\ dx_m \end{bmatrix}$$

Given all of this we can calculate $\frac{\partial y_i}{\partial x_j}$ by simply reading the coefficient dx_j in the *i*-th row. I will make this idea quite explicit in the examples that follow.

Example 5.3.1. Let's return to a common calculus III problem. Suppose F(x, y, z) = k for some constant k. Find partial derivatives of x, y or z with repsect to the remaining variables. Solution: I'll use the method of differentials once more:

$$dF = F_x dx + F_y dy + F_z dz = 0$$

We can solve for dx, dy or dz provided F_x, F_y or F_z is nonzero respective and these differential expressions reveal various partial derivatives of interest:

$$dx = -\frac{F_y}{F_x}dy - \frac{F_z}{F_x}dz \qquad \Rightarrow \qquad \frac{\partial x}{\partial y} = -\frac{F_y}{F_x} \& \quad \frac{\partial x}{\partial z} = -\frac{F_z}{F_x}$$
$$dy = -\frac{F_x}{F_y}dx - \frac{F_z}{F_y}dz \qquad \Rightarrow \qquad \frac{\partial y}{\partial x} = -\frac{F_x}{F_y} \& \quad \frac{\partial y}{\partial z} = -\frac{F_z}{F_y}$$
$$dz = -\frac{F_x}{F_z}dx - \frac{F_y}{F_z}dy \qquad \Rightarrow \qquad \frac{\partial z}{\partial x} = -\frac{F_x}{F_z} \& \quad \frac{\partial z}{\partial y} = -\frac{F_y}{F_z}$$

In each case above, the implicit function theorem allows us to solve for one variable in terms of the remaining two. If the partial derivative of F in the denominator are zero then the implicit function theorem does not apply and other thoughts are required. Often calculus text give the following as a homework problem:

$$\frac{\partial x}{\partial y}\frac{\partial y}{\partial z}\frac{\partial z}{\partial x} = -\frac{F_y}{F_x}\frac{F_z}{F_y}\frac{F_x}{F_z} = -1.$$

In the equation above we have x appear as a dependent variable on y, z and also as an independent variable for the dependent variable z. These mixed expressions are actually of interest to engineering and physics. The less mbiguous notation below helps better handle such expressions:

$$\left(\frac{\partial x}{\partial y}\right)_z \left(\frac{\partial y}{\partial z}\right)_x \left(\frac{\partial z}{\partial x}\right)_y = -1.$$

In each part of the expression we have clearly denoted which variables are taken to depend on the others and in turn what sort of partial derivative we mean to indicate. Partial derivatives are not taken alone, they must be done in concert with an understanding of the totality of the indpendent variables for the problem. We hold all the remaining indpendent variables fixed as we take a partial derivative.

The explicit independent variable notation is more important for problems where we can choose more than one set of indpendent variables for a given dependent variables. In the example that follows we study w = w(x, y) but we could just as well consider w = w(x, z). Generally it will not be the case that $\left(\frac{\partial w}{\partial x}\right)_y$ is the same as $\left(\frac{\partial w}{\partial x}\right)_z$. In calculation of $\left(\frac{\partial w}{\partial x}\right)_y$ we hold y constant as we vary x whereas in $\left(\frac{\partial w}{\partial x}\right)_z$ we hold z constant as we vary x. There is no reason these ought to be the same⁸.

Example 5.3.2. Suppose x+y+z+w = 3 and $x^2-2xyz+w^3 = 5$. Calculate partial derivatives of z and w with respect to the independent variables x, y. Solution: we begin by calculation of the differentials of both equations:

$$dx + dy + dz + dw = 0$$

(2x - 2yz)dx - 2xzdy - 2xydz + 3w²dw = 0

We can solve for (dz, dw). In this calculation we can treat the differentials as formal variables.

$$dz + dw = -dx - dy$$

-2xydz + 3w²dw = -(2x - 2yz)dx + 2xzdy

I find matrix notation is often helpful,

$$\begin{bmatrix} 1 & 1 \\ -2xy & 3w^2 \end{bmatrix} \begin{bmatrix} dz \\ dw \end{bmatrix} = \begin{bmatrix} -dx - dy \\ -(2x - 2yz)dx + 2xzdy \end{bmatrix}$$

Use Kramer's rule, multiplication by inverse, substitution, adding/subtracting equations etc... whatever technique of solving linear equations you prefer. Our goal is to solve for dz and dw in terms of dx and dy. I'll use Kramer's rule this time:

$$dz = \frac{\det \begin{bmatrix} -dx - dy & | & 1 \\ -(2x - 2yz)dx + 2xzdy & | & 3w^2 \end{bmatrix}}{\det \begin{bmatrix} 1 & 1 \\ -2xy & 3w^2 \end{bmatrix}} = \frac{3w^2(-dx - dy) + (2x - 2yz)dx - 2xzdy}{3w^2 + 2xy}$$

Collecting terms,

$$dz = \left(\frac{-3w^2 + 2x - 2yz}{3w^2 + 2xy}\right)dx + \left(\frac{-3w^2 - 2xz}{3w^2 + 2xy}\right)dy$$

From the expression above we can read various implicit derivatives,

$$\left(\frac{\partial z}{\partial x}\right)_y = \frac{-3w^2 + 2x - 2yz}{3w^2 + 2xy} \qquad \& \qquad \left(\frac{\partial z}{\partial y}\right)_x = \frac{-3w^2 - 2xz}{3w^2 + 2xy}$$

The notation above indicates that z is understood to be a function of independent variables x, y. $\left(\frac{\partial z}{\partial x}\right)_y$ means we take the derivative of z with respect to x while holding y fixed. The appearance

⁸a good exercise would be to do the example over but instead aim to calculate partial derivatives for y, w with respect to independent variables x, z

of the dependent variable w can be removed by using the equations G(x, y, z, w) = (3, 5). Similar ambiguities exist for implicit differentiation in calculus I. Apply Kramer's rule once more to solve for dw:

$$dw = \frac{\det \begin{bmatrix} 1 & -dx - dy \\ -2xy & -(2x - 2yz)dx + 2xzdy \end{bmatrix}}{\det \begin{bmatrix} 1 & 1 \\ -2xy & 3w^2 \end{bmatrix}} = \frac{-(2x - 2yz)dx + 2xzdy - 2xy(dx + dy)}{3w^2 + 2xy}$$

Collecting terms,

$$dw = \left(\frac{-2x + 2yz - 2xy}{3w^2 + 2xy}\right)dx + \left(\frac{2xzdy - 2xydy}{3w^2 + 2xy}\right)dy$$

We can read the following from the differential above:

$$\left[\left(\frac{\partial w}{\partial x}\right)_y = \frac{-2x + 2yz - 2xy}{3w^2 + 2xy} \qquad \& \qquad \left(\frac{\partial w}{\partial y}\right)_x = \frac{2xzdy - 2xydy}{3w^2 + 2xy}$$

You should ask: where did we use the implicit function theorem in the preceding example? Notice our underlying hope is that we can solve for z = z(x, y) and w = w(x, y). The implicit function theorem states this is possible precisely when $\frac{\partial G}{\partial(z,w)} = \begin{bmatrix} 1 & 1 \\ -2xy & 3w^2 \end{bmatrix}$ is non-singular. Interestingly this is the same matrix we must consider to isolate dz and dw. The calculations of the example are only meaningful if the $det \begin{bmatrix} 1 & 1 \\ -2xy & 3w^2 \end{bmatrix} \neq 0$. In such a case the implicit function theorem applies and it is reasonable to suppose z, w can be written as functions of x, y.

5.3.1 computational techniques for partial differentiation with side conditions

In this section I show you how I teach this to calculus III. In other words, we set-aside the explicit mention of the implicit function theorem and work out some typical calculations. If one desires rigor then the answer is found from the implicit function theorems careful application, that is how to justify what follows. These notes are taken from my calculus III notes, but I thought it wise to include them here since most calculus texts do not bother to show these calculations (which is sad since they actually matter to the application of multivariate analysis to many real world applications) To begin, we define⁹ the total differential.

Definition 5.3.3.

If
$$f = f(x_1, x_2, \dots, x_n)$$
 then $df = \frac{\partial f}{\partial x_1} dx_1 + \frac{\partial f}{\partial x_2} dx_2 + \dots + \frac{\partial f}{\partial x_n} dx_n$.

 $^{{}^{9}}$ I invite the reader to verify the notation "defined" in this section is in fact totally sympatico with our previous definitions

Example 5.3.4. Suppose $E = pv + t^2$ then dE = vdp + pdv + 2tdt. In this example the dependent variable is E whereas the independent variables are p, v and t.

Example 5.3.5. Problem: what are $\partial F/\partial x$ and $\partial F/\partial y$ if we know that F = F(x, y) and $dF = (x^2 + y)dx - \cos(xy)dy$.

Solution: if F = F(x, y) then the total differential has the form $dF = F_x dx + F_y dy$. We simply compare the general form to the given $dF = (x^2 + y)dx - \cos(xy)dy$ to obtain:

$$\frac{\partial F}{\partial x} = x^2 + y, \qquad \frac{\partial F}{\partial y} = -\cos(xy)$$

Example 5.3.6. Suppose w = xyz then dw = yzdx + xzdy + xydz. On the other hand, we can solve for z = z(x, y, w)

$$z = \frac{w}{xy}$$
 \Rightarrow $dz = -\frac{w}{x^2y}dx - \frac{w}{xy^2}dy + \frac{1}{xy}dw.$ \star

If we solve dw = yzdx + xzdy + xydz directly for dz we obtain:

m

$$dz = -\frac{z}{x}dx - \frac{z}{y}dy + \frac{1}{xy}dw \quad \star \star.$$

Are \star and $\star\star$ consistent? Well, yes. Note $\frac{w}{x^2y} = \frac{xyz}{x^2y} = \frac{z}{x}$ and $\frac{w}{xy^2} = \frac{xyz}{xy^2} = \frac{z}{y}$.

Which variables are independent/dependent in the example above? It depends. In this initial portion of the example we treated x, y, z as independent whereas w was dependent. But, in the last half we treated x, y, w as independent and z was the dependent variable. Consider this, if I ask you what the value of $\frac{\partial z}{\partial x}$ is in the example above then this question is ambiguous!

$$\frac{\partial z}{\partial x} = 0$$
 verses
$$\frac{\partial z}{\partial x} = \frac{-z}{x}$$

z indpendent of *x z* depends on *x*

Obviously this sort of ambiguity is rather unpleasant. A natural solution to this trouble is simply to write a bit more when variables are used in multiple contexts. In particular,

$$\frac{\partial z}{\partial x}\Big|_{y,z} = 0 \qquad \text{is different than} \qquad \underbrace{\frac{\partial z}{\partial x}\Big|_{y,w}}_{means x,y,z \text{ independent}} = \frac{-z}{x}$$

The key concept is that all the other independent variables are held fixed as an indpendent variable is partial differentiated. Holding y, z fixed as x varies means z does not change hence $\frac{\partial z}{\partial x}\Big|_{y,z} = 0$. On the other hand, if we hold y, w fixed as x varies then the change in z need not be trivial; $\frac{\partial z}{\partial x}\Big|_{y,w} = \frac{-z}{x}$. Let me expand on how this notation interfaces with the total differential.

Definition 5.3.7.

If w, x, y, z are variables then $dw = \frac{\partial w}{\partial x}\Big|_{y,z} dx + \frac{\partial w}{\partial y}\Big|_{x,z} dy + \frac{\partial w}{\partial z}\Big|_{x,y} dz.$ Alternatively, $dx = \frac{\partial x}{\partial w}\Big|_{y,z} dw + \frac{\partial x}{\partial y}\Big|_{w,z} dy + \frac{\partial x}{\partial z}\Big|_{w,y} dz.$

The larger idea here is that we can identify partial derivatives from the coefficients in equations of differentials. I'd say a differential equation but you might get the wrong idea... Incidentally, there is a whole theory of solving differential equations by clever use of differentials, I have books if you are interested.

Example 5.3.8. Suppose w = x + y + z and x + y = wz then calculate $\frac{\partial w}{\partial x}\Big|_{y}$ and $\frac{\partial w}{\partial x}\Big|_{z}$. Notice we must choose dependent and independent variables to make sense of partial derivatives in question.

1. suppose w, z both depend on x, y. Calculate,

$$\frac{\partial w}{\partial x}\Big|_{y} = \frac{\partial}{\partial x}\Big|_{y}(x+y+z) = \frac{\partial x}{\partial x}\Big|_{y} + \frac{\partial y}{\partial x}\Big|_{y} + \frac{\partial z}{\partial x}\Big|_{y} = 1 + 0 + \frac{\partial z}{\partial x}\Big|_{y} \quad \star$$

To calculate further we need to eliminate w by substituting w = x + y + z into x + y = wz; thus x + y = (x + y + z)z hence dx + dy = (dx + dy + dz)z + (x + y + z)dz

$$(2z + x + y)dz = (1 - z)dx + (1 - z)dy \quad \star \star$$

Therefore,

$$dz = \frac{1-z}{2z+x+y}dx + \frac{1-z}{2z+x+y}dy = \frac{\partial z}{\partial x}\Big|_y dx + \frac{\partial z}{\partial y}\Big|_x dy \quad \Rightarrow \quad \frac{\partial z}{\partial x}\Big|_y = \frac{1-z}{2z+x+y}dy dx + \frac{\partial z}{\partial x}\Big|_y dx + \frac{\partial z}{\partial y}\Big|_x dy \quad \Rightarrow \quad \frac{\partial z}{\partial x}\Big|_y = \frac{1-z}{2z+x+y}dy dx + \frac{\partial z}{\partial x}\Big|_y dx + \frac{\partial z}{\partial y}\Big|_x dy \quad \Rightarrow \quad \frac{\partial z}{\partial x}\Big|_y = \frac{1-z}{2z+x+y}dy dx + \frac{\partial z}{\partial x}\Big|_y dx + \frac{\partial z}{\partial y}\Big|_x dy \quad \Rightarrow \quad \frac{\partial z}{\partial x}\Big|_y dx + \frac{\partial z}{\partial x}\Big|_y d$$

Returning to \star we derive

$$\left[\frac{\partial w}{\partial x} \right|_y = 1 + \frac{1-z}{2z+x+y}.$$

2. suppose w, y both depend on x, z. Calculate,

$$\frac{\partial w}{\partial x}\Big|_{z} = \frac{\partial}{\partial x}\Big|_{z}(x+y+z) = \frac{\partial x}{\partial x}\Big|_{z} + \frac{\partial y}{\partial x}\Big|_{z} + \frac{\partial z}{\partial x}\Big|_{z} = 1 + \frac{\partial y}{\partial x}\Big|_{z} + 0$$

To complete this calculation we need to eliminate w as before, using $\star\star$,

$$(1-z)dy = (1-z)dx - (2z+x+y)dz \Rightarrow \frac{\partial y}{\partial x}\Big|_z = 1.$$

Therefore,

$$\left| \frac{\partial w}{\partial x} \right|_z = 2.$$

I hope you can begin to see how the game is played. Basically the example above generalizes the idea of implicit differentiation to several equations of many variables. This is actually a pretty important type of calculation for engineering. The study of thermodynamics is full of variables which are intermittently used as either dependent or independent variables. The so-called equation of state can be given in terms of about a dozen distinct sets of state variables.

Example 5.3.9. The ideal gas law states that for a fixed number of particles n the pressure P, volume V and temperature T are related by PV = nRT where R is a constant. Calculate,

$$\begin{split} \frac{\partial P}{\partial V} \bigg|_T &= \frac{\partial}{\partial V} \bigg[\frac{nRT}{V} \bigg] \bigg|_T = -\frac{nRT}{V^2}, \\ \frac{\partial V}{\partial T} \bigg|_P &= \frac{\partial}{\partial T} \bigg[\frac{nRT}{P} \bigg] \bigg|_T = \frac{nR}{P}, \\ \frac{\partial T}{\partial P} \bigg|_V &= \frac{\partial}{\partial P} \bigg[\frac{PV}{nR} \bigg] \bigg|_T = \frac{V}{nR}. \end{split}$$

You might expect that $\frac{\partial P}{\partial V}\Big|_T \frac{\partial V}{\partial T}\Big|_P \frac{\partial T}{\partial P}\Big|_V = 1$. Is it true?

$$\frac{\partial P}{\partial V}\bigg|_{T}\frac{\partial V}{\partial T}\bigg|_{P}\frac{\partial T}{\partial P}\bigg|_{V} = -\frac{nRT}{V^{2}}\cdot\frac{nR}{P}\cdot\frac{V}{nR} = \frac{-nRT}{PV} = -1.$$

This is an example where naive cancellation of partials fails.

Example 5.3.10. Suppose F(x, y) = 0 then $dF = F_x dx + F_y dy = 0$ and it follows that $dx = -\frac{F_y}{F_x} dy$ or $dy = -\frac{F_x}{F_y} dx$. Hence, $\frac{\partial x}{\partial y} = -\frac{F_y}{F_x}$ and $\frac{\partial y}{\partial x} = -\frac{F_x}{F_y}$. Therefore,

$$\frac{\partial x}{\partial y}\frac{\partial y}{\partial x} = \frac{F_y}{F_x} \cdot \frac{F_x}{F_y} = 1$$

for (x, y) such that $F_x \neq 0$ and $F_y \neq 0$. The condition $F_x \neq 0$ suggests we can solve for y = y(x)whereas the condition $F_y \neq 0$ suggests we can solve for x = x(y).

5.4 the constant rank theorem

The implicit function theorem required we work with independent constraints. However, one does not always have that luxury. There is a theorem which deals with the slightly more general case. The base idea is that if the Jacobian has rank k then it locally injects a k-dimensional image into the codomain. If we are using a map as a parametrization then the rank k condition suggests the mapping does parametrize a k-fold, at least locally. On the other hand, if we are using the map to

define a space as a level set then $F : \mathbb{R}^n \to \mathbb{R}^p$ has $F^{-1}(C)$ as a (n-k)-fold. Previously, we would have insisted k = p. I've run out of time for 2013 notes so sadly I have no reference for this claim. However, the troubing Section 10.7.2 quotes the Theorem we desire in a somewhat unfortunate language for our current purposes. In any event, theorems aside, I think the red comments are worth some discussion.

Remark 5.4.1.

I have put remarks about the rank of the derivative in red for the examples below.

Example 5.4.2. Let $f(t) = (t, t^2, t^3)$ then $f'(t) = (1, 2t, 3t^2)$. In this case we have

$$f'(t) = [df_t] = \begin{bmatrix} 1\\ 2t\\ 3t^2 \end{bmatrix}$$

The Jacobian here is a single column vector. It has rank 1 provided the vector is nonzero. We see that $f'(t) \neq (0,0,0)$ for all $t \in \mathbb{R}$. This corresponds to the fact that this space curve has a well-defined tangent line for each point on the path.

Example 5.4.3. Let $f(\vec{x}, \vec{y}) = \vec{x} \cdot \vec{y}$ be a mapping from $\mathbb{R}^3 \times \mathbb{R}^3 \to \mathbb{R}$. I'll denote the coordinates in the domain by $(x_1, x_2, x_3, y_1, y_2, y_3)$ thus $f(\vec{x}, \vec{y}) = x_1y_1 + x_2y_2 + x_3y_3$. Calculate,

$$[df_{(\vec{x},\vec{y})}] = \nabla f(\vec{x},\vec{y})^T = [y_1, y_2, y_3, x_1, x_2, x_3]$$

The Jacobian here is a single row vector. It has rank 6 provided all entries of the input vectors are nonzero.

Example 5.4.4. Let $f(\vec{x}, \vec{y}) = \vec{x} \cdot \vec{y}$ be a mapping from $\mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$. I'll denote the coordinates in the domain by $(x_1, \ldots, x_n, y_1, \ldots, y_n)$ thus $f(\vec{x}, \vec{y}) = \sum_{i=1}^n x_i y_i$. Calculate,

$$\frac{\partial}{x_j} \left[\sum_{i=1}^n x_i y_i \right] = \sum_{i=1}^n \frac{\partial x_i}{x_j} y_i = \sum_{i=1}^n \delta_{ij} y_i = y_j$$

Likewise,

$$\frac{\partial}{y_j} \left[\sum_{i=1}^n x_i y_i \right] = \sum_{i=1}^n x_i \frac{\partial y_i}{y_j} = \sum_{i=1}^n x_i \delta_{ij} = x_j$$

Therefore, noting that $\nabla f = (\partial_{x_1} f, \dots, \partial_{x_n} f, \partial_{y_1} f, \dots, \partial_{y_n} f)$,

$$[df_{(\vec{x},\vec{y})}]^T = (\nabla f)(\vec{x},\vec{y}) = \vec{y} \times \vec{x} = (y_1,\ldots,y_n,x_1,\ldots,x_n)$$

The Jacobian here is a single row vector. It has rank 2n provided all entries of the input vectors are nonzero.

Example 5.4.5. Suppose F(x, y, z) = (xyz, y, z) we calculate,

$$\frac{\partial F}{\partial x} = (yz, 0, 0)$$
 $\frac{\partial F}{\partial y} = (xz, 1, 0)$ $\frac{\partial F}{\partial z} = (xy, 0, 1)$

Remember these are actually column vectors in my sneaky notation; $(v_1, \ldots, v_n) = [v_1, \ldots, v_n]^T$. This means the **derivative** or **Jacobian matrix** of F at (x, y, z) is

$$F'(x, y, z) = [dF_{(x,y,z)}] = \begin{bmatrix} yz & xz & xy \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Note, rank(F'(x, y, z)) = 3 for all $(x, y, z) \in \mathbb{R}^3$ such that $y, z \neq 0$. There are a variety of ways to see that claim, one way is to observe det[F'(x, y, z)] = yz and this determinant is nonzero so long as neither y nor z is zero. In linear algebra we learn that a square matrix is invertible iff it has nonzero determinant iff it has linearly indpendent column vectors.

Example 5.4.6. Suppose $F(x, y, z) = (x^2 + z^2, yz)$ we calculate,

$$\frac{\partial F}{\partial x} = (2x, 0)$$
 $\frac{\partial F}{\partial y} = (0, z)$ $\frac{\partial F}{\partial z} = (2z, y)$

The derivative is a 2×3 matrix in this example,

$$F'(x, y, z) = [dF_{(x,y,z)}] = \begin{bmatrix} 2x & 0 & 2z \\ 0 & z & y \end{bmatrix}$$

The maximum rank for F' is 2 at a particular point (x, y, z) because there are at most two linearly independent vectors in \mathbb{R}^2 . You can consider the three square submatrices to analyze the rank for a given point. If any one of these is nonzero then the rank (dimension of the column space) is two.

$$M_1 = \begin{bmatrix} 2x & 0 \\ 0 & z \end{bmatrix} \qquad M_2 = \begin{bmatrix} 2x & 2z \\ 0 & y \end{bmatrix} \qquad M_3 = \begin{bmatrix} 0 & 2z \\ z & y \end{bmatrix}$$

We'll need either $det(M_1) = 2xz \neq 0$ or $det(M_2) = 2xy \neq 0$ or $det(M_3) = -2z^2 \neq 0$. I believe the only point where all three of these fail to be true simulataneously is when x = y = z = 0. This mapping has maximal rank at all points except the origin.

Example 5.4.7. Suppose $F(x, y) = (x^2 + y^2, xy, x + y)$ we calculate,

$$\frac{\partial F}{\partial x} = (2x, y, 1)$$
 $\frac{\partial F}{\partial y} = (2y, x, 1)$

The derivative is a 3×2 matrix in this example,

$$F'(x,y) = [dF_{(x,y)}] = \begin{bmatrix} 2x & 2y \\ y & x \\ 1 & 1 \end{bmatrix}$$

The maximum rank is again 2, this time because we only have two columns. The rank will be two if the columns are not linearly dependent. We can analyze the question of rank a number of ways but I find determinants of submatrices a comforting tool in these sort of questions. If the columns are linearly dependent then all three sub-square-matrices of F' will be zero. Conversely, if even one of them is nonvanishing then it follows the columns must be linearly independent. The submatrices for this problem are:

$$M_1 = \begin{bmatrix} 2x & 2y \\ y & x \end{bmatrix} \qquad M_2 = \begin{bmatrix} 2x & 2y \\ 1 & 1 \end{bmatrix} \qquad M_3 = \begin{bmatrix} y & x \\ 1 & 1 \end{bmatrix}$$

You can see $det(M_1) = 2(x^2 - y^2)$, $det(M_2) = 2(x - y)$ and $det(M_3) = y - x$. Apparently we have rank(F'(x, y, z)) = 2 for all $(x, y) \in \mathbb{R}^2$ with $y \neq x$. In retrospect this is not surprising.

Example 5.4.8. Let $F(x,y) = (x, y, \sqrt{R^2 - x^2 - y^2})$ for a constant R. We calculate,

$$\nabla\sqrt{R^2 - x^2 - y^2} = \left(\begin{array}{c} \frac{-x}{\sqrt{R^2 - x^2 - y^2}}, & \frac{-y}{\sqrt{R^2 - x^2 - y^2}} \end{array}\right)$$

Also, $\nabla x = (1,0)$ and $\nabla y = (0,1)$ thus

$$F'(x,y) = \begin{bmatrix} 1 & 0\\ 0 & 1\\ \frac{-x}{\sqrt{R^2 - x^2 - y^2}} & \frac{-y}{\sqrt{R^2 - x^2 - y^2}} \end{bmatrix}$$

This matrix clearly has rank 2 where is is well-defined. Note that we need $R^2 - x^2 - y^2 > 0$ for the derivative to exist. Moreover, we could define $G(y, z) = (\sqrt{R^2 - y^2 - z^2}, y, z)$ and calculate,

$$G'(y,z) = \begin{bmatrix} 1 & 0\\ \frac{-y}{\sqrt{R^2 - y^2 - z^2}} & \frac{-z}{\sqrt{R^2 - y^2 - z^2}}\\ 0 & 1 \end{bmatrix}$$

Observe that G'(y,z) exists when $R^2 - y^2 - z^2 > 0$. Geometrically, F parametrizes the sphere above the equator at z = 0 whereas G parametrizes the right-half of the sphere with x > 0. These parametrizations overlap in the first octant where both x and z are positive. In particular, $dom(F') \cap dom(G') = \{(x,y) \in \mathbb{R}^2 \mid x, y > 0 \text{ and } x^2 + y^2 < R^2\}$

Example 5.4.9. Let $F(x, y, z) = (x, y, z, \sqrt{R^2 - x^2 - y^2 - z^2})$ for a constant *R*. We calculate,

$$\nabla\sqrt{R^2 - x^2 - y^2 - z^2} = \left(\frac{-x}{\sqrt{R^2 - x^2 - y^2 - z^2}}, \frac{-y}{\sqrt{R^2 - x^2 - y^2 - z^2}}, \frac{-z}{\sqrt{R^2 - x^2 - y^2 - z^2}} \right)$$

Also, $\nabla x = (1, 0, 0)$, $\nabla y = (0, 1, 0)$ and $\nabla z = (0, 0, 1)$ thus

$$F'(x,y,z) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ \frac{-x}{\sqrt{R^2 - x^2 - y^2 - z^2}} & \frac{-y}{\sqrt{R^2 - x^2 - y^2 - z^2}} & \frac{-z}{\sqrt{R^2 - x^2 - y^2 - z^2}} \end{bmatrix}$$

This matrix clearly has rank 3 where is is well-defined. Note that we need $R^2 - x^2 - y^2 - z^2 > 0$ for the derivative to exist. This mapping gives us a parametrization of the 3-sphere $x^2 + y^2 + z^2 + w^2 = R^2$ for w > 0. (drawing this is a little trickier)

Example 5.4.10. Let f(x, y, z) = (x + y, y + z, x + z, xyz). You can calculate,

$$[df_{(x,y,z)}] = \begin{bmatrix} 1 & 1 & 0\\ 0 & 1 & 1\\ 1 & 0 & 1\\ yz & xz & xy \end{bmatrix}$$

This matrix clearly has rank 3 and is well-defined for all of \mathbb{R}^3 .

Example 5.4.11. Let f(x, y, z) = xyz. You can calculate,

$$[df_{(x,y,z)}] = \begin{bmatrix} yz & xz & xy \end{bmatrix}$$

This matrix fails to have rank 3 if x, y or z are zero. In other words, f'(x, y, z) has rank 3 in \mathbb{R}^3 provided we are at a point which is not on some coordinate plane. (the coordinate planes are x = 0, y = 0 and z = 0 for the yz, zx and xy coordinate planes respective)

Example 5.4.12. Let f(x, y, z) = (xyz, 1 - x - y). You can calculate,

$$[df_{(x,y,z)}] = \left[\begin{array}{ccc} yz & xz & xy \\ -1 & -1 & 0 \end{array} \right]$$

This matrix has rank 3 if either $xy \neq 0$ or $(x - y)z \neq 0$. In contrast to the preceding example, the derivative does have rank 3 on certain points of the coordinate planes. For example, f'(1,1,0) and f'(0,1,1) both give rank(f') = 3.

Example 5.4.13. Let X(u, v) = (x, y, z) where x, y, z denote functions of u, v and I prefer to omit the explicit dependence to reduce clutter in the equations to follow.

$$\frac{\partial X}{\partial u} = X_u = (x_u, y_u, z_u) \quad and \quad \frac{\partial X}{\partial v} = X_v = (x_v, y_v, z_v)$$

Then the Jacobian is the 3×2 matrix

$$\begin{bmatrix} dX_{(u,v)} \end{bmatrix} = \begin{bmatrix} x_u & x_v \\ y_u & y_v \\ z_u & z_v \end{bmatrix}$$

The matrix $[dX_{(u,v)}]$ has rank 2 if at least one of the determinants below is nonzero,

$$det \left[\begin{array}{cc} x_u & x_v \\ y_u & y_v \end{array} \right] \quad det \left[\begin{array}{cc} x_u & x_v \\ z_u & z_v \end{array} \right] \quad det \left[\begin{array}{cc} y_u & y_v \\ z_u & z_v \end{array} \right]$$

Chapter 6

two views of manifolds in \mathbb{R}^n

In this chapter we describe spaces inside \mathbb{R}^n which are k-dimensional ¹. Technically, to make this precise we would need to study manifolds with boundary. Careful discussion of manifolds with boundary in euclidean space can be found in Munkres Analysis on Manifolds. In the interest of focusing on examples, I'll be a bit fuzzy about the definition of a k-dimensional subspace S of euclidean space. This much we can say: there are two ways to envision the geometry of S:

(1.) **Parametrically**: provide a **patch** R such that $R : U \subseteq \mathbb{R}^k \to S \subseteq \mathbb{R}^n$. Here U is called the **parameter space** and R^{-1} is called a **coordinate chart**. The cannonical example:

$$R(x_1,\ldots,x_k) = (x_1,\ldots,x_k,0,\ldots,0).$$

(2.) **Implicitly**: provide a **level function** $G : \mathbb{R}^k \times \mathbb{R}^p \to \mathbb{R}^p$ such that $S = G^{-1}\{c\} = S$. This viewpoint casts S as points in $x \in \mathbb{R}^k \times \mathbb{R}^p$ for which G(x) = k. The cannonical example:

$$G(x_1, \dots, x_{k+p}) = (x_{k+1}, \dots, x_{k+p}) = (0, \dots, 0)$$

The canonical examples of (1.) and (2.) are both the $x_1 \dots x_k$ -coordinate plane embedded in \mathbb{R}^n . Just to take it down a notch. If n = 3 then we could look at the *xy*-plane in either view as follows:

(1.)
$$R(x,y) = (x,y,0)$$
 (2.) $G(x,y,z) = z = 0.$

Which viewpoint should we adopt? What is the dimension of a given space S? How should we find tangent space to S? How should we find the normal space to S? These are the questions we set-out to answer in this chapter.

Orthogonal complements help us to understand how all of this fits together. This is possible since we deal with embedded manifolds for which the euclidean dot-product of \mathbb{R}^n is available to sort out the geometry. Finally, we use this geometry and a few simple lemmas to justify the method of Lagrange multipliers. Lagrange's technique paired with the theory of multivariate Taylor polynomials form

¹I'll try to stick with this notation for this chapter, $n \ge k$ and n = p + k

the basis for analyzing extrema for multivariate functions. In this chapter we deal with the question of extrema on the edges of a set. The second half of the story is found in the next chapter where we deal with the interior points via the theory of quadratic forms applied to the second-order approximation to a function of several variables.

6.1 definition of level set

A level set is the solution set of some equation or system of equations. We confine our interest to level sets of \mathbb{R}^n . For example, the set of all (x, y) that satisfy

$$G(x,y) = c$$

is called a **level curve** in \mathbb{R}^2 . Often we can use k to label the curve. You should also recall **level** surfaces in \mathbb{R}^3 are defined by an equation of the form

$$G(x, y, z) = c.$$

The set of all $(x_1, x_2, x_3, x_4) \in \mathbb{R}^4$ which solve $G(x_1, x_2, x_3, x_4) = c$ is a **level volume** in \mathbb{R}^4 . We can obtain lower dimensional objects by simultaneously imposing several equations at once. For example, suppose $G_1(x, y, z) = z = 1$ and $G_2(x, y, z) = x^2 + y^2 + z^2 = 5$, points (x, y, z) which solve both of these equations are on the intersection of the plane z = 1 and the sphere $x^2 + y^2 + z^2 = 5$. Let $G = (G_1, G_2)$, note that G(x, y, z) = (1, 5) describes a circle in \mathbb{R}^3 . More generally:

Definition 6.1.1.

Suppose $G: dom(G) \subseteq \mathbb{R}^k \times \mathbb{R}^p \to \mathbb{R}^p$. Let *c* be a vector of constants in \mathbb{R}^p and suppose $S = \{x \in \mathbb{R}^k \times \mathbb{R}^p \mid G(x) = c\}$ is non-empty and *G* is continuously differentiable on an open set containing *S*. We say *S* is an *k*-dimensional level set iff G'(x) has *p* linearly independent rows at each $x \in S$.

The condition of linear independence of the rows is give to eliminate possible redundancy in the system of equations. In the case that p = 1 the criteria reduces to $G'(x) \neq 0$ over the level set of dimension n - 1. Intuitively we think of each equation in G(x) = c as removing one of the dimensions of the ambient space $\mathbb{R}^n = \mathbb{R}^k \times \mathbb{R}^p$. It is worthwhile to cite a useful result from linear algebra at this point:

Proposition 6.1.2.

Let $A \in \mathbb{R}^{m \times n}$. The number of linearly independent columns in A is the same as the number of linearly independent rows in A. This invariant of A is called the **rank** of A.

Given the wisdom of linear algebra we see that we should require a k-dimensional level set $S = G^{-1}(c)$ to have a level function $G : \mathbb{R}^n \to \mathbb{R}^p$ whose derivative is of rank n - k = p over all of S. We can either analyze linear independence of columns or rows.
Example 6.1.3. Consider $G(x, y, z) = x^2 + y^2 - z^2$ and suppose $S = G^{-1}\{0\}$. Calculate,

$$G'(x, y, z) = [2x, 2y, -2z]$$

Notice that $(0,0,0) \in S$ and G'(0,0,0) = [0,0,0] hence G' is not rank one at the origin. At all other points in S we have $G'(x,y,z) \neq 0$ which means this is almost a 3-1 = 2-dimensional level set. However, almost is not good enough in math. Under our definition the cone S is not a 2-dimensional level set since it fails to meet the full-rank criteria at the point of the cone.

A *p*-dimensional level set is an example of a *p*-dimensional manifold. The example above with the origin included is a manifold paired with a singular point, such spaces are known as **orbifolds**. The study of orbifolds has attracted considerable effort in recent years as the singularities of such orbifolds can be used to do physics in string theory. I digress. Let us examine another level set:

Example 6.1.4. Let G(x, y, z) = (x, y) and define $S = G^{-1}(a, b)$ for some fixed pair of constants $a, b \in \mathbb{R}$. We calculate that $G'(x, y, z) = I_2 \in \mathbb{R}^{2 \times 2}$. We clearly have rank two at all points in S hence S is a 3-2 = 1-dimensional level set. Perhaps you realize S is the vertical line which passes through (a, b, 0) in the xy-plane.

6.2 tangents and normals to a level set

There are many ways to define a tangent space for some subset of \mathbb{R}^n . One natural definition is that the tangent space to $p \in S$ is simply the set of all tangent vectors to curves on S which pass through the point p. In this section we study the geometry of curves on a level-set. We'll see how the tangent space is naturally a vector space in the particular context of level-sets in \mathbb{R}^n .

Throughout this section we assume that S is a k-dimensional level set defined by $G : \mathbb{R}^k \times \mathbb{R}^p \to \mathbb{R}^p$ where $G^{-1}(c) = S$. This means that we can apply the implicit function theorem to S and for any given point $p = (p_x, p_y) \in S$ where $p_x \in \mathbb{R}^k$ and $p_y \in \mathbb{R}^p$. There exists a local continuously differentiable solution $h : U \subseteq \mathbb{R}^k \to \mathbb{R}^p$ such that $h(p_x) = p_y$ and for all $x \in U$ we have G(x, h(x)) =c. We can view G(x, y) = c for x near p as the graph of y = h(x) for $x \in U$. With the set-up above in mind, suppose that $\gamma : \mathbb{R} \to U \subseteq S$. If we write $\gamma = (\gamma_x, \gamma_y)$ then it follows $\gamma = (\gamma_x, h \circ \gamma_x)$ over the subset $U \times h(U)$ of S. More explicitly, for all $t \in \mathbb{R}$ such that $\gamma(t) \in U \times h(U)$ we have

$$\gamma(t) = (\gamma_x(t), h(\gamma_x(t))).$$

Therefore, if $\gamma(0) = p$ then $\gamma(0) = (p_x, h(p_x))$. Differentiate, use the chain-rule in the second factor to obtain:

$$\gamma'(t) = (\gamma'_x(t), h'(\gamma_x(t))\gamma'_x(t)).$$

We find that the tangent vector to $p \in S$ of γ has a rather special form which was forced on us by the implicit function theorem:

$$\gamma'(0) = (\gamma'_x(0), h'(p_x)\gamma'_x(0)),$$

Or to cut through the notation a bit, if $\gamma'(0) = v = (v_x, v_y)$ then $v = (v_x, h'(p_x)v_x)$. The second component of the vector is not free of the first, it essentially redundant. This makes us suspect that the tangent space to S at p is k-dimensional.

Theorem 6.2.1.

Let $G : \mathbb{R}^k \times \mathbb{R}^p \to \mathbb{R}^p$ be a level-mapping which defines a k-dimensional level set S by $G^{-1}(c) = S$. Suppose $\gamma_1, \gamma_2 : \mathbb{R} \to S$ are differentiable curves with $\gamma'_1(0) = v_1$ and $\gamma'_2(0) = v_2$ then there exists a differentiable curve $\gamma : \mathbb{R} \to S$ such that $\gamma'(0) = v_1 + v_2$ and $\gamma(0) = p$. Moreover, there exists a differentiable curve $\beta : \mathbb{R} \to S$ such that $\beta'(0) = cv_1$ and $\beta(0) = p$.

Proof: It is convenient to define a map which gives a **local parametrization** of S at p. Since we have a description of S locally as a graph y = h(x) (near p) it is simple to construct the parameterization. Define $\Phi : U \subseteq \mathbb{R}^k \to S$ by $\Phi(x) = (x, h(x))$. Clearly $\Phi(U) = U \times h(U)$ and there is an inverse mapping $\Phi^{-1}(x, y) = x$ is well-defined since y = h(x) for each $(x, y) \in U \times h(U)$. Let $w \in \mathbb{R}^k$ and observe that

$$\psi(t) = \Phi(\Phi^{-1}(p) + tw) = \Phi(p_x + tw) = (p_x + tw, h(p_x + tw))$$

is a curve from \mathbb{R} to $U \subseteq S$ such that $\psi(0) = (p_x, h(p_x)) = (p_x, p_y) = p$ and using the chain rule on the final form of $\psi(t)$:

$$\psi'(0) = (w, h'(p_x)w).$$

The construction above shows that any vector of the form $(v_x, h'(p_x)v_x)$ is the tangent vector of a particular differentiable curve in the level set (differentiability of ψ follows from the differentiability of h and the other maps which we used to construct ψ). In particular we can apply this to the case $w = v_{1x} + v_{2x}$ and we find $\gamma(t) = \Phi(\Phi^{-1}(p) + t(v_{1x} + v_{2x}))$ has $\gamma'(0) = v_1 + v_2$ and $\gamma(0) = p$. Likewise, apply the construction to the case $w = cv_{1x}$ to write $\beta(t) = \Phi(\Phi^{-1}(p) + t(cv_{1x}))$ with $\beta'(0) = cv_1$ and $\beta(0) = p$. \Box

The idea of the proof is encapsulated in the picture below. This idea of mapping lines in a flat domain to obtain standard curves in a curved domain is an idea which plays over and over as you study manifold theory. The particular redundancy of the x and y sub-vectors is special to the discussion level-sets, however anytime we have a local parametrization we'll be able to construct curves with tangents of our choosing by essentially the same construction. In fact, there are infinitely many curves which produce a particular tangent vector in the tangent space of a manifold.

picture.

Theorem 6.2.1 shows that the definition given below is logical. In particular, it is not at all obvious that the sum of two tangent vectors ought to again be a tangent vector. However, that is just what the Theorem 6.2.1 told us for level-sets².

²technically, there is another logical gap which I currently ignore. I wonder if you can find it.

Definition 6.2.2.

Suppose S is a k-dimensional level-set defined by $S = G^{-1}\{c\}$ for $G : \mathbb{R}^k \times \mathbb{R}^p \to \mathbb{R}^p$. We define the **tangent space at** $p \in S$ to be the set of pairs:

 $T_p S = \{(p, v) \mid \text{there exists differentiable } \gamma : \mathbb{R} \to S \text{ and } \gamma(0) = p \text{ where } v = \gamma'(0) \}$

Moreover, we define (i.) addition and (ii.) scalar multiplication of vectors by the rules

(*i*.)
$$(p, v_1) + (p, v_2) = (p, v_1 + v_2)$$
 (*ii*.) $c(p, v_1) = (p, cv_1)$

for all $(p, v_1), (p, v_2) \in T_p S$ and $c \in \mathbb{R}$.

When I picture T_pS in my mind I think of vectors pointing out from the base-point p. To make an explicit connection between the pairs of the above definition and the classical geometric form of the tangent space we simply take the image of T_pS under the mapping $\Psi(x,y) = x + y$ thus $\Psi(T_pS) = \{p + v \mid (p,v) \in T_pS\}$. I often picture T_pS as $\psi(T_pS)^3$

We could set out to calculate tangent spaces in view of the definition above, but we are actually interested in more than just the tangent space for a level-set. In particular. we want a concrete description of all the vectors which are not in the tangent space.

Definition 6.2.3.

Suppose S is a k-dimensional level-set defined by $S = G^{-1}\{c\}$ for $G : \mathbb{R}^k \times \mathbb{R}^p \to \mathbb{R}^p$ and T_pS is the tangent space at p. Note that $T_pS \leq V_p$ where $V_p = \{p\} \times \mathbb{R}^k \times \mathbb{R}^p$ is given the natural vector space structure which we already exhibited on the subspace T_pS . We define the **inner product** on V_p as follows: for all $(p, v), (p, w) \in V_p$,

$$(p,v)\cdot(p,w)=v\cdot w.$$

The length of a vector (p, v) is naturally defined by ||(p, v)|| = ||v||. Moreover, we say two vectors $(p, v), (p, w) \in V_p$ are **orthogonal** iff $v \cdot w = 0$. Given a set of vectors $R \subseteq V_p$ we define the **orthogonal complement** by

$$R^{\perp} = \{ (p, v) \in V_p \mid (p, v) \cdot (p, r) \text{ for all } (p, r) \in R \}.$$

Suppose $W_1, W_2 \subseteq V_p$ then we say W_1 is **orthogonal** to W_2 iff $w_1 \cdot w_2 = 0$ for all $w_1 \in W_1$ and $w_2 \in W_2$. We denote orthogonality by writing $W_1 \perp W_2$. If every $v \in V_p$ can be written as $v = w_1 + w_2$ for a pair of $w_1 \in W_1$ and $w_2 \in W_2$ where $W_1 \perp W_2$ then we say that V_p is the **direct sum** of W_1 and W_2 which is denoted by $V_p = W_1 \oplus W_2$.

There is much more to say about orthogonality, however, our focus is not in that vein. We just need the langauge to properly define the normal space. The calculation below is probably the most

³In truth, as you continue to study manifold theory you'll find at least three seemingly distinct objects which are all called "tangent vectors"; equivalence classes of curves, derivations, contravariant tensors.

important calculation to understand for a level-set. Suppose we have a curve $\gamma : \mathbb{R} \to S$ where $S = G^{-1}(c)$ is a k-dimensional level-set in $\mathbb{R}^k \times \mathbb{R}^p$. Observe that for all $t \in \mathbb{R}$,

$$G(\gamma(t)) = c \Rightarrow G'(\gamma(t))\gamma'(t) = 0.$$

In particular, suppose for t = 0 we have $\gamma(0) = p$ and $v = \gamma'(0)$ which makes $(p, v) \in T_pS$ with

$$G'(p)v = 0.$$

Recall $G : \mathbb{R}^k \times \mathbb{R}^p \to \mathbb{R}^p$ has an $p \times n$ derivative matrix where the *j*-th row is the gradient vector of the *j*-th component function. The equation G'(p)v = 0 gives us *p*-independent equations as we examine it componentwise. In particular, it reveals that (p, v) is orthogonal to $\nabla G_j(p)$ for $j = 1, 2, \ldots, p$. We have derived the following theorem:

Theorem 6.2.4.

Let $G : \mathbb{R}^k \times \mathbb{R}^p \to \mathbb{R}^p$ be a level-mapping which defines a k-dimensional level set S by $G^{-1}(c) = S$. The gradient vectors $\nabla G_j(p)$ are perpendicular to the tangent space at p; for each $j \in \mathbb{N}_p$

$$(p, \nabla(G_j(p))^T) \in (T_p S)^\perp$$

It's time to do some counting. Observe that the mapping $\phi : \mathbb{R}^k \to T_p S$ defined by $\phi(v) = (p, v)$ is an isomorphism of vector spaces hence $\dim(T_p S) = k$. But, by the same isomorphism we can see that $V_p = \phi(\mathbb{R}^k \times \mathbb{R}^p)$ hence $\dim(V_p) = p + k$. In linear algebra we learn that if we have a k-dimensional subspace W of an n-dimensional vector space V then the orthogonal complement W^{\perp} is a subspace of V with **codimension** k. The term **codimension** is used to indicate a loss of dimension from the ambient space, in particular $\dim(W^{\perp}) = n - k$. We should note that the direct sum of W and W^{\perp} covers the whole space; $W \oplus W^{\perp} = V$. In the case of the tangent space, the codimension of $T_p S \leq V_p$ is found to be p + k - k = p. Thus $\dim(T_p S)^{\perp} = p$. Any basis for this space must consist of p linearly independent vectors which are all orthogonal to the tangent space. Naturally, the subset of vectors $\{(p, (\nabla G_j(p))^T)_{j=1}^p \text{ forms just such a basis since it is given$ to be linearly independent by the <math>rank(G'(p)) = p condition. It follows that:

$$(T_pS)^\perp \approx Row(G'(p))$$

where equality can be obtained by the slightly tedious equation $(T_pS)^{\perp} = \phi(Col(G'(p)^T))$. That equation simply does the following:

- 1. transpose G'(p) to swap rows to columns
- 2. construct column space by taking span of columns in $G'(p)^T$
- 3. adjoin p to make pairs of vectors which live in V_p

many wiser authors wouldn't bother. The comments above are primarily about notation. Certainly hiding these details would make this section prettier, however, would it make it better? Finally, I once more refer the reader to linear algebra where we learn that $(Row(A))^{\perp} = Null(A^T)$. Let me walk you through the proof: let $A \in \mathbb{R}^{m \times n}$. Observe $v \in Null(A^T)$ iff $A^T v = 0$ for $v \in \mathbb{R}^m$ iff $v^T A = 0$ iff $v^T col_j(A) = 0$ for j = 1, 2, ..., n iff $v \cdot col_j(A) = 0$ for j = 1, 2, ..., n iff $v \in Col(A)^{\perp}$. Another useful identity for the "perp" is that $(A^{\perp})^{\perp} = A$. With those two gems in mind consider that:

$$(T_pS)^{\perp} \approx Row(G'(p)) \Rightarrow T_pS \approx Row(G'(p))^{\perp} = Null(G'(p)^T)$$

Let me once more replace \approx by a more tedious, but explicit, procedure:

$$T_pS = \phi(Null(G'(p)^T))$$

Theorem 6.2.5.

vector and a normal vector.

Let $G : \mathbb{R}^k \times \mathbb{R}^p \to \mathbb{R}^p$ be a level-mapping which defines a k-dimensional level set S by $G^{-1}(c) = S$. The **tangent space** T_pS and the **normal space** N_pS at $p \in S$ are given by $T_pS = \{p\} \times Null(G'(p)^T)$ & $N_pS = \{p\} \times Col(G'(p)^T)$. Moreover, $V_p = T_pS \oplus N_pS$. Every vector can be uniquely written as the sum of a tangent

The fact that there are only tangents and normals is the key to the method of Lagrange multipliers. It forces two seemingly distinct objects to be in the same direction as one another.

Example 6.2.6. Let $g: \mathbb{R}^4 \to \mathbb{R}$ be defined by $g(x, y, z, t) = t + x^2 + y^2 - 2z^2$ note that g(x, y, z, t) = 0 gives a three dimensional subset of \mathbb{R}^4 , let's call it M. Notice $\nabla g = \langle 2x, 2y, -4z, 1 \rangle$ is nonzero everywhere. Let's focus on the point (2, 2, 1, 0) note that g(2, 2, 1, 0) = 0 thus the point is on M. The tangent plane at (2, 2, 1, 0) is formed from the union of all tangent vectors to g = 0 at the point (2, 2, 1, 0). To find the equation of the tangent plane we suppose $\gamma : \mathbb{R} \to M$ is a curve with $\gamma' \neq 0$ and $\gamma(0) = (2, 2, 1, 0)$. By assumption $g(\gamma(s)) = 0$ since $\gamma(s) \in M$ for all $s \in \mathbb{R}$. Define $\gamma'(0) = \langle a, b, c, d \rangle$, we find a condition from the chain-rule applied to $g \circ \gamma = 0$ at s = 0,

$$\frac{d}{ds} (g \circ \gamma(s)) = (\nabla g)(\gamma(s)) \cdot \gamma'(s) = 0 \qquad \Rightarrow \qquad \nabla g(2, 2, 1, 0) \cdot \langle a, b, c, d \rangle = 0$$
$$\Rightarrow \qquad \langle 4, 4, -4, 1 \rangle \cdot \langle a, b, c, d \rangle = 0$$
$$\Rightarrow \qquad 4a + 4b - 4c + d = 0$$

Thus the equation of the tangent plane is 4(x-2) + 4(y-2) - 4(z-1) + t = 0. In invite the reader to find a vector in the tangent plane and check it is orthogonal to $\nabla g(2,2,1,0)$. However, this should not be surprising, the condition the chain rule just gave us is just the statement that $\langle a, b, c, d \rangle \in Null(\nabla g(2,2,1,0)^T)$ and that is precisely the set of vector orthogonal to $\nabla g(2,2,1,0)$.

Example 6.2.7. Let $G : \mathbb{R}^4 \to \mathbb{R}^2$ be defined by $G(x, y, z, t) = (z + x^2 + y^2 - 2, z + y^2 + t^2 - 2)$. In this case G(x, y, z, t) = (0, 0) gives a two-dimensional manifold in \mathbb{R}^4 let's call it M. Notice that $G_1 = 0$ gives $z + x^2 + y^2 = 2$ and $G_2 = 0$ gives $z + y^2 + t^2 = 2$ thus G = 0 gives the intersection of both of these three dimensional manifolds in \mathbb{R}^4 (no I can't "see" it either). Note,

$$\nabla G_1 = \langle 2x, 2y, 1, 0 \rangle$$
 $\nabla G_2 = \langle 0, 2y, 1, 2t \rangle$

It turns out that the inverse mapping theorem says G = 0 describes a manifold of dimension 2 if the gradient vectors above form a linearly independent set of vectors. For the example considered here the gradient vectors are linearly dependent at the origin since $\nabla G_1(0) = \nabla G_2(0) = (0,0,1,0)$. In fact, these gradient vectors are collinear along along the plane x = t = 0 since $\nabla G_1(0, y, z, 0) =$ $\nabla G_2(0, y, z, 0) = \langle 0, 2y, 1, 0 \rangle$. We again seek to contrast the tangent plane and its normal at some particular point. Choose (1,1,0,1) which is in M since G(1,1,0,1) = (0+1+1-2,0+1+1-2) = (0,0). Suppose that $\gamma : \mathbb{R} \to M$ is a path in M which has $\gamma(0) = (1,1,0,1)$ whereas $\gamma'(0) = \langle a, b, c, d \rangle$. Note that $\nabla G_1(1,1,0,1) = \langle 2, 2, 1, 0 \rangle$ and $\nabla G_2(1,1,0,1) = \langle 0, 2, 1, 1 \rangle$. Applying the chain rule to both G_1 and G_2 yields:

$$(G_1 \circ \gamma)'(0) = \nabla G_1(\gamma(0)) \cdot \langle a, b, c, d \rangle = 0 \qquad \Rightarrow \qquad \langle 2, 2, 1, 0 \rangle \cdot \langle a, b, c, d \rangle = 0 (G_2 \circ \gamma)'(0) = \nabla G_2(\gamma(0)) \cdot \langle a, b, c, d \rangle = 0 \qquad \Rightarrow \qquad \langle 0, 2, 1, 1 \rangle \cdot \langle a, b, c, d \rangle = 0$$

This is two equations and four unknowns, we can solve it and write the vector in terms of two free variables correspondent to the fact the tangent space is two-dimensional. Perhaps it's easier to use matrix techiques to organize the calculation:

$$\begin{bmatrix} 2 & 2 & 1 & 0 \\ 0 & 2 & 1 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

We calculate, $rref\begin{bmatrix} 2 & 2 & 1 & 0 \\ 0 & 2 & 1 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & -1/2 \\ 0 & 1 & 1/2 & 1/2 \end{bmatrix}$. It's natural to chose c, d as free variables then we can read that a = d/2 and b = -c/2 - d/2 hence

$$< a, b, c, d > = < d/2, -c/2 - d/2, c, d > = \frac{c}{2} < 0, -1, 2, 0 > +\frac{d}{2} < 1, -1, 0, 2 >$$

We can see a basis for the tangent space. In fact, I can give parametric equations for the tangent space as follows:

$$X(u, v) = (1, 1, 0, 1) + u < 0, -1, 2, 0 > +v < 1, -1, 0, 2 > 0$$

Not surprisingly the basis vectors of the tangent space are perpendicular to the gradient vectors $\nabla G_1(1,1,0,1) = \langle 2,2,1,0 \rangle$ and $\nabla G_2(1,1,0,1) = \langle 0,2,1,1 \rangle$ which span the **normal plane** N_p to the tangent plane T_p at p = (1,1,0,1). We find that T_p is orthogonal to N_p . In summary $T_p^{\perp} = N_p$ and $T_p \oplus N_p = \mathbb{R}^4$. This is just a fancy way of saying that the normal and the tangent plane only intersect at zero and they together span the entire ambient space.

6.3 tangent and normal space from patches

I use the term **parametrization** in courses more basic than this, however, perhaps the term **patch** would be better. It's certainly easier to say and in our current context has the same meaning. I suppose the term **parametrization** is used in a bit less technical sense, so it fits calculus III better. In any event, we should make a definition of patched k-dimensional surface for the sake of concrete discussion in this section.

Definition 6.3.1.

Suppose $R : dom(R) \subseteq \mathbb{R}^k \to S \subseteq \mathbb{R}^n$. We say S is an k-dimensional patch iff R'(t) has rank k for each $t \in dom(R)$. We also call S a k-dimensional parametrized subspace of \mathbb{R}^n .

The condition R'(t) is just a slick way to say that the k-tangent vectors to S obtained by partial differentiation with respect to t_1, \ldots, t_k are linearly independent at $t = (t_1, \ldots, t_k)$. I spent considerable effort justifying the formulae for the level-set case. I believe what follows should be intuitively clear given our previous efforts. Or, if that leaves you unsatisfied then read on to the examples. It's really not that complicated. This theorem is dual to Theorem 6.2.5.

Theorem 6.3.2.

Suppose $R: dom(R) \subseteq \mathbb{R}^k \to S \subseteq \mathbb{R}^n$ defines a k-dimensional patch of S. The tangent space T_pS and the normal space at $p = R(t) \in S$ are given by

$$T_p S = \{p\} \times Col(R'(t)) \qquad \& \qquad N_p S = \{p\} \times Null(R'(t)^T)$$

Moreover, $V_p = T_p S \oplus N_p S$. Every vector can be uniquely written as the sum of a tangent vector and a normal vector.

Once again, the vector space structure of T_pS and N_pS is given by the addition of vectors based at p. Let us begin with a reasonably simple example.

Example 6.3.3. Let $R : \mathbb{R}^2 \to \mathbb{R}^3$ with R(x, y) = (x, y, xy) define $S \subset \mathbb{R}^3$. We calculate,

$$R'(x,y) = [\partial_x R | \partial_y R] = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ y & x \end{bmatrix}$$

If $p = (a, b, ab) \in S$ then $T_pS = \{(a, b, ab)\} \times span\{(1, 0, b), (0, 1, a)\}$. The normal space is found from $Null(R'(a, b)^T)$. A short calculation shows that

$$Null \left[\begin{array}{ccc} 1 & 0 & b \\ 0 & 1 & a \end{array} \right] = span\{(-b, -a, 1)\}$$

As a quick check, note $(1,0,b) \cdot (-b,-a,1) = 0$ and $(0,1,a) \cdot (-b,-a,1) = 0$. We conclude, for p = (a, b, ab) the normal space is simply:

$$N_p S = \{(a, b, ab)\} \times span\{(-b, -a, 1)\}.$$

In the previous example, we could rightly call T_pS the tangent plane at p and N_pS the normal line through p. Moreover, we could have used three-dimensional vector analysis to find the normal line from the cross-product. However, that will not be possible in what follows:

Example 6.3.4. Let $R : \mathbb{R}^2 \to \mathbb{R}^4$ with $R(s,t) = (s^2, t^2, t, s)$ define $S \subset \mathbb{R}^4$. We calculate,

$$R'(s,t) = [\partial_s R | \partial_t R] = \begin{bmatrix} 2s & 0 \\ 0 & 2t \\ 0 & 1 \\ 1 & 0 \end{bmatrix}$$

If $p = (1, 9, 3, 1) \in S$ then $T_p S = \{(1, 9, 3, 1)\} \times span\{(2, 0, 0, 1), (0, 6, 3, 0)\}$. The normal space is found from $Null(R'(1, 3)^T)$. A short calculation shows that

$$Null \begin{bmatrix} 2 & 0 & 0 & 1 \\ 0 & 6 & 3 & 0 \end{bmatrix} = span\{(-1, 0, 0, 2), (0, -3, 6, 0)\}$$

We conclude, for p = (1, 9, 3, 1) the normal space is simply:

$$N_p S = \{(1,9,3,1)\} \times span\{(-1,0,0,2), (0,-3,6,0)\}.$$

6.4 summary of tangent and normal spaces

Let me briefly draw together what we did thus far in this chapter: the notation below given in I is also used in II. and III.

- (I.) a set S has dimension k if
 - (a) $\{\partial_1 R(t), \ldots, \partial_k R(t)\}$ is pointwise linearly independent at each $t \in U$ where $R: U \to S$ is a patch.
 - (b) $\operatorname{rank}(F'(x)) = p$ for all $x \in \tilde{S}$ where \tilde{S} is open and contains $S = F^{-1}\{c\}$ for continuously differentiable $F : \mathbb{R}^k \times \mathbb{R}^p \to \mathbb{R}^p$
- (II.) the tangent space at x_o for the k-dimensional set S is found from:
 - (a) attaching the span of the vectors $\{\partial_1 R(t_o), \ldots, \partial_k R(t_o)\}$ to $x_o = R(t_o) \in S$.
 - (b) attaching the $Row(F'(x_o))^{\perp}$ to $x_o \in S$.
- (III.) the normal space to a k-dimensional set S (embedded in \mathbb{R}^n) is found from:
 - (a) attaching $\{\partial_1 R(t_o), \ldots, \partial_k R(t_o)\}^{\perp}$ to $x_o = R(t_o)$.
 - (b) attaching $Row(F'(x_o))$ to $x_o \in S$.

6.5 method of Lagrange mulitpliers

Let us begin with a statement of the problem we wish to solve.

Problem: given an objective function $f : \mathbb{R}^n \to \mathbb{R}$ and continuously differentiable constraint function $G : \mathbb{R}^n \to \mathbb{R}^p$, find extreme values for the objective function f relative to the constraint G(x) = c.

Note that G(x) = c is a vector notation for *p*-scalar equations. If we suppose rank(G'(x)) = p then the constraint surface G(x) = c will form an (n - p)-dimensional level set. Let us make that supposition throughout the remainder of this section.

In order to solve a problem it is sometimes helpful to find necessary conditions by assuming an answer exists. Let us do that here. Suppose x_o maps to the local extrema of $f(x_o)$ on $S = G^{-1}\{c\}$. This means there exists an open ball around x_o for which $f(x_o)$ is either an upper or lower bound of all the values of f over the ball intersected with S. One clear implication of this data is that if we take any continuously differentiable curve on S which passes through x_o , say $\gamma : \mathbb{R} \to \mathbb{R}^n$ with $\gamma(0) = x_o$ and $G(\gamma(t)) = c$ for all t, then the composite $f \circ \gamma$ is a function on \mathbb{R} which takes an extreme value at t = 0. Fermat's theorem from calculus I applies and as $f \circ \gamma$ is differentiable near t = 0 we find $(f \circ \gamma)'(0) = 0$ is a necessary condition. But, this means we have two necessary conditions on γ :

1. $G(\gamma(t)) = c$

2.
$$(f \circ \gamma)'(0) = 0$$

Let us expand a bit on both of these conditions:

$$1. \ G'(x_o)\gamma'(0) = 0$$

2.
$$f'(x_o)\gamma'(0) = 0$$

The first of these conditions places $\gamma'(0) \in T_{x_o}S$ but then the second condition says that $f'(x_o) = (\nabla f)(x_o)^T$ is orthogonal to $\gamma'(0)$ hence $(\nabla f)(x_o)^T \in N_{x_o}$. Now, recall from the last section that the gradient vectors of the component functions to G span the normal space, this means any vector in N_{x_o} can be written as a linear combination of the gradient vectors. In particular, this means there exist constants $\lambda_1, \lambda_2, \ldots, \lambda_p$ such that

$$(\nabla f)(x_o)^T = \lambda_1 (\nabla G_1)(x_o)^T + \lambda_2 (\nabla G_2)(x_o)^T + \dots + \lambda_p (\nabla G_p)(x_o)^T$$

We may summarize the method of Lagrange multipliers as follows:

- 1. choose *n*-variables which aptly describe your problem.
- 2. identify your objective function and write all constraints as level surfaces.
- **3.** solve $\nabla f = \lambda_1 \nabla G_1 + \lambda_2 \nabla G_2 + \dots + \lambda_p \nabla G_p$ subject to the constraint G(x) = c.
- 4. test the validity of your proposed extremal points.

The obvious gap in the method is the supposition that an extrema exists for the restriction $f|_S$. Well examine a few examples before I reveal a sufficient condition. We'll also see how absence of that sufficient condition does allow the method to fail.

Example 6.5.1. Suppose we wish to find maximum and minimum distance to the origin for points on the curve $x^2 - y^2 = 1$. In this case we can use the distance-squared function as our objective $f(x,y) = x^2 + y^2$ and the single constraint function is $g(x,y) = x^2 - y^2$. Observe that $\nabla f = \langle 2x, 2y \rangle$ whereas $\nabla g = \langle 2x, -2y \rangle$. We seek solutions of $\nabla f = \lambda \nabla g$ which gives us $\langle 2x, 2y \rangle =$ $\lambda \langle 2x, -2y \rangle$. Hence $2x = 2\lambda x$ and $2y = -2\lambda y$. We must solve these equations subject to the condition $x^2 - y^2 = 1$. Observe that x = 0 is not a solution since $0 - y^2 = 1$ has no real solution. On the other hand, y = 0 does fit the constraint and $x^2 - 0 = 1$ has solutions $x = \pm 1$. Consider then

$$2x = 2\lambda x$$
 and $2y = -2\lambda y$ \Rightarrow $x(1-\lambda) = 0$ and $y(1+\lambda) = 0$

Since $x \neq 0$ on the constraint curve it follows that $1 - \lambda = 0$ hence $\lambda = 1$ and we learn that y(1+1) = 0 hence y = 0. Consequently, (1, 0 and (-1, 0) are the two point where we expect to find extreme-values of f. In this case, the method of Lagrange multipliers served it's purpose, as you can see in the graph. Below the green curves are level curves of the objective function whereas the particular red curve is the given constraint curve.



The picture below is a screen-shot of the Java applet created by David Lippman and Konrad Polthier to explore 2D and 3D graphs. Especially nice is the feature of adding vector fields to given objects, many other plotters require much more effort for similar visualization. See more at the website: http://dlippman.imathas.com/g1/GrapherLaunch.html.



Note how the gradient vectors to the objective function and constraint function line-up nicely at those points.

In the previous example, we actually got lucky. There are examples of this sort where we could get false maxima due to the nature of the constraint function.

Example 6.5.2. Suppose we wish to find the points on the unit circle $g(x, y) = x^2 + y^2 = 1$ which give extreme values for the objective function $f(x, y) = x^2 - y^2$. Apply the method of Lagrange multipliers and seek solutions to $\nabla f = \lambda \nabla g$:

$$<2x,-2y>=\lambda<2x,2y>$$

We must solve $2x = 2x\lambda$ which is better cast as $(1 - \lambda)x = 0$ and $-2y = 2\lambda y$ which is nicely written as $(1 + \lambda)y = 0$. On the basis of these equations alone we have several options:

- 1. if $\lambda = 1$ then (1+1)y = 0 hence y = 0
- 2. if $\lambda = -1$ then (1 (1))x = 0 hence x = 0

But, we also must fit the constraint $x^2 + y^2 = 1$ hence we find four solutions:

- 1. if $\lambda = 1$ then y = 0 thus $x^2 = 1 \implies x = \pm 1 \implies (\pm 1, 0)$
- 2. if $\lambda = -1$ then x = 0 thus $y^2 = 1 \Rightarrow y = \pm 1 \Rightarrow (0, \pm 1)$

We test the objective function at these points to ascertain which type of extrema we've located:

$$f(0,\pm 1) = 0^2 - (\pm 1)^2 = -1$$
 & $f(\pm 1,0) = (\pm 1)^2 - 0^2 = 1$

When constrained to the unit circle we find the objective function attains a maximum value of 1 at the points (1,0) and (-1,0) and a minimum value of -1 at (0,1) and (0,-1). Let's illustrate the answers as well as a few non-answers to get perspective. Below the green curves are level curves of the objective function whereas the particular red curve is the given constraint curve.



The success of the last example was no accident. The fact that the constraint curve was a circle which is a closed and bounded subset of \mathbb{R}^2 means that is is a **compact** subset of \mathbb{R}^2 . A well-known theorem of analysis states that any real-valued continuous function on a compact domain attains both maximum and minimum values. The objective function is continuous and the domain is compact hence the theorem applies and the method of Lagrange multipliers succeeds. In contrast, the constraint curve of the preceding example was a hyperbola which is not compact. We have no assurance of the existence of any extrema. Indeed, we only found minima but no maxima in Example 6.5.1.

The generality of the method of Lagrange multipliers is naturally limited to smooth constraint curves and smooth objective functions. We must insist the gradient vectors exist at all points of inquiry. Otherwise, the method breaks down. If we had a constraint curve which has sharp corners then the method of Lagrange breaks down at those corners. In addition, if there are points of discontinuity in the constraint then the method need not apply. This is not terribly surprising, even in calculus I the main attack to analyze extrema of function on \mathbb{R} assumed continuity, differentiability and sometimes twice differentiability. Points of discontinuity require special attention in whatever context you meet them.

At this point it is doubtless the case that some of you are, to misquote an ex-student of mine, "notimpressed". Perhaps the following examples better illustrate the dangers of non-compact constraint curves.

Example 6.5.3. Suppose we wish to find extrema of f(x,y) = x when constrained to xy = 1. Identify g(x,y) = xy = 1 and apply the method of Lagrange multipliers and seek solutions to $\nabla f = \lambda \nabla g$:

$$< 1, 0 >= \lambda < y, x > \Rightarrow 1 = \lambda y and 0 = \lambda x$$

If $\lambda = 0$ then $1 = \lambda y$ is impossible to solve hence $\lambda \neq 0$ and we find x = 0. But, if x = 0 then xy = 1 is not solvable. Therefore, we find no solutions. Well, I suppose we have succeeded here

in a way. We just learned there is no extreme value of x on the hyperbola xy = 1. Below the green curves are level curves of the objective function whereas the particular red curve is the given constraint curve.



Example 6.5.4. Suppose we wish to find extrema of f(x, y) = x when constrained to $x^2 - y^2 = 1$. Identify $g(x, y) = x^2 - y^2 = 1$ and apply the method of Lagrange multipliers and seek solutions to $\nabla f = \lambda \nabla g$:

 $<1,0>=\lambda<2x,-2y>$ \Rightarrow $1=2\lambda x$ and $0=-2\lambda y$

If $\lambda = 0$ then $1 = 2\lambda x$ is impossible to solve hence $\lambda \neq 0$ and we find y = 0. If y = 0 and $x^2 - y^2 = 1$ then we must solve $x^2 = 1$ whence $x = \pm 1$. We are tempted to conclude that:

- 1. the objective function f(x,y) = x attains a maximum on $x^2 y^2 = 1$ at (1,0) since f(1,0) = 1
- 2. the objective function f(x, y) = x attains a minimum on $x^2 y^2 = 1$ at (-1, 0) since f(1, 0) = -1

But, both conclusions are false. Note $\sqrt{2}^2 - 1^2 = 1$ hence $(\pm\sqrt{2}, 1)$ are points on the constraint curve and $f(\sqrt{2}, 1) = \sqrt{2}$ and $f(-\sqrt{2}, 1) = -\sqrt{2}$. The error of the method of Lagrange multipliers in this context is the supposition that there exists extrema to find, in this case there are no such points. It is possible for the gradient vectors to line-up at points where there are no extrema. Below the green curves are level curves of the objective function whereas the particular red curve is the given constraint curve.



Incidentally, if you want additional discussion of Lagrange multipliers for two-dimensional problems one very nice source I certainly profitted from was the YouTube video by Edward Frenkel of Berkley. See his website http://math.berkeley.edu/ frenkel/ for links.

Example 6.5.5. Find points on the circle $x^2 + y^2 = 1$ which are closest to the parabola $y^2 = 2(4-x)$.

$$\begin{aligned} \int_{ab} f(x,y,u,v) &= (x-u)^{2} + (y-v)^{2} \quad \text{and} \quad and \quad an$$

Example 6.5.6. Find points on $x^2 + y^2 + z^2 = 1$ and plane x + y + z = 3 which are closest.

9,
$$(x, y, z) = (1 - x^{2} - y^{2} - 3^{2}) = 0$$
 give sphere. as $y_{1}^{-1} dy_{2}^{2}$
 $g_{2}(u, v, w) = 3 - 4 - V - W = 0$ give plane as $y_{2}^{-1} dy_{2}^{2}$.
Consider $f(\vec{x}, \vec{u}) = ||\vec{x} - \vec{u}||^{2}$. We'd like to find purphases
for f subject the unstraints
 $G(\vec{x}, \vec{u}) = \langle \vartheta, (\vec{x})_{3} \vartheta_{3}(\vec{u}) \rangle = \langle 0, 0 \rangle$.
To sung $G = 0$ is to place \vec{x} on the sphere and
 \vec{u} on the plane. Let $G_{1}(\vec{x}, \vec{u}) = \vartheta_{1}(\vec{x})$ and
 $G_{2}(\vec{x}, \vec{u}) = \vartheta_{2}(\vec{u})$ then
 $\nabla G_{1} = \langle \nabla \vartheta_{1}, \sigma \rangle = \langle \vartheta_{1} w, \vartheta_{1} \vartheta, \vartheta_{2}, 0, 0, v \rangle$
 $\nabla G_{2} = \langle 0, \nabla \vartheta_{2} \rangle = \langle 0, 0, \vartheta_{2} \vartheta, \vartheta_{2} \psi, \vartheta_{3} \psi, \vartheta_{3} \psi$
Linewise, $f(\vec{x}, \vec{u}) = \sum_{2^{n+1}}^{n} (x_{2} - u_{2}^{2})^{2} = (x - w)^{2} + (z - w)^{2}$
Then $\nabla f = \lambda_{1} \nabla G_{1} + \lambda_{2} \nabla G_{2}$ widds,
 $2(x - u) = \lambda_{1} \vartheta_{12} = -2\lambda_{1} Z$
 $-2(x - w) = \lambda_{1} \vartheta_{12} = -2\lambda_{1} Z$
 $-2(x - w) = \lambda_{1} \vartheta_{12} = -2\lambda_{1} Z$
 $-2(x - w) = \lambda_{1} \vartheta_{12} = -\lambda_{1} Z$
 $-2(x - w) = \lambda_{1} \vartheta_{12} = -\lambda_{2}$
 $-2(x - w) = \lambda_{2} \vartheta_{12} = -\lambda_$

Notice that on page 116 of Edwards he derives this as a mere special case of the fascinatingly general Example 10 of that section.

Chapter 7

critical point analysis for several variables

In the typical calculus sequence you learn the first and second derivative tests in calculus I. Then in calculus II you learn about power series and Taylor's Theorem. Finally, in calculus III, in many popular texts, you learn an essentially ad-hoc procedure for judging the nature of critical points as minimum, maximum or saddle. These topics are easily seen as disconnected events. In this chapter, we connect them. We learn that the geometry of quadratic forms is ellegantly revealed by eigenvectors and more than that this geometry is precisely what elucidates the proper classifications of critical points of multivariate functions with real values.

7.1 multivariate power series

We set aside the issue of convergence for now. We will suppose the series discussed in this section exist on and converge on some domain, but we do not seek to treat that topic here. Our focus is computational. How should we calculate the Taylor series for f(x, y) at (a, b)? Or, what about f(x) at $x_o \in \mathbb{R}^n$?.

7.1.1 taylor's polynomial for one-variable

If $f: U \subseteq \mathbb{R} \to \mathbb{R}$ is analytic at $x_o \in U$ then we can write

$$f(x) = f(x_o) + f'(x_o)(x - x_o) + \frac{1}{2}f''(x_o)(x - x_o)^2 + \dots = \sum_{n=0}^{\infty} \frac{f^{(n)}(x_o)}{n!}(x - x_o)^n$$

We could write this in terms of the operator $D = \frac{d}{dt}$ and the evaluation of $t = x_o$

$$f(x) = \left[\sum_{n=0}^{\infty} \frac{1}{n!} (x-t)^n D^n f(t)\right]_{t=x_o} =$$

I remind the reader that a function is called **entire** if it is analytic on all of \mathbb{R} , for example e^x , $\cos(x)$ and $\sin(x)$ are all entire. In particular, you should know that:

$$e^{x} = 1 + x + \frac{1}{2}x^{2} + \dots = \sum_{n=0}^{\infty} \frac{1}{n!}x^{n}$$
$$\cos(x) = 1 - \frac{1}{2}x^{2} + \frac{1}{4!}x^{4} \dots = \sum_{n=0}^{\infty} \frac{(-1)^{n}}{(2n)!}x^{2n}$$
$$\sin(x) = x - \frac{1}{3!}x^{3} + \frac{1}{5!}x^{5} \dots = \sum_{n=0}^{\infty} \frac{(-1)^{n}}{(2n+1)!}x^{2n+1}$$

Since $e^x = \cosh(x) + \sinh(x)$ it also follows that

$$\cosh(x) = 1 + \frac{1}{2}x^2 + \frac{1}{4!}x^4 \dots = \sum_{n=0}^{\infty} \frac{1}{(2n)!}x^{2n}$$
$$\sinh(x) = x + \frac{1}{3!}x^3 + \frac{1}{5!}x^5 \dots = \sum_{n=0}^{\infty} \frac{1}{(2n+1)!}x^{2n+1}$$

The geometric series is often useful, for $a, r \in \mathbb{R}$ with |r| < 1 it is known

$$a + ar + ar^{2} + \dots = \sum_{n=0}^{\infty} ar^{n} = \frac{a}{1-r}$$

This generates a whole host of examples, for instance:

$$\frac{1}{1+x^2} = 1 - x^2 + x^4 - x^6 + \cdots$$
$$\frac{1}{1-x^3} = 1 + x^3 + x^6 + x^9 + \cdots$$
$$\frac{x^3}{1-2x} = x^3(1+2x+(2x)^2+\cdots) = x^3 + 2x^4 + 4x^5 + \cdots$$

Moreover, the term-by-term integration and differentiation theorems yield additional results in conjuction with the geometric series:

$$\tan^{-1}(x) = \int \frac{dx}{1+x^2} = \int \sum_{n=0}^{\infty} (-1)^n x^{2n} dx = \sum_{n=0}^{\infty} \frac{(-1)^n}{2n+1} x^{2n+1} = x - \frac{1}{3}x^3 + \frac{1}{5}x^5 + \cdots$$
$$\ln(1-x) = \int \frac{d}{dx} \ln(1-x) dx = \int \frac{-1}{1-x} dx = -\int \sum_{n=0}^{\infty} x^n dx = \sum_{n=0}^{\infty} \frac{-1}{n+1} x^{n+1}$$

Of course, these are just the basic building blocks. We also can twist things and make the student use algebra,

$$e^{x+2} = e^x e^2 = e^2 (1 + x + \frac{1}{2}x^2 + \dots)$$

or trigonmetric identities,

$$\sin(x) = \sin(x - 2 + 2) = \sin(x - 2)\cos(2) + \cos(x - 2)\sin(2)$$

$$\Rightarrow \quad \sin(x) = \cos(2)\sum_{n=0}^{\infty} \frac{(-1)^n}{(2n+1)!} (x - 2)^{2n+1} + \sin(2)\sum_{n=0}^{\infty} \frac{(-1)^n}{(2n)!} (x - 2)^{2n}.$$

Feel free to peruse my most recent calculus II materials to see a host of similarly sneaky calculations.

7.1.2 taylor's multinomial for two-variables

Suppose we wish to find the taylor polynomial centered at (0,0) for $f(x,y) = e^x \sin(y)$. It is a simple as this:

$$f(x,y) = \left(1 + x + \frac{1}{2}x^2 + \dots\right)\left(y - \frac{1}{6}y^3 + \dots\right) = y + xy + \frac{1}{2}x^2y - \frac{1}{6}y^3 + \dots$$

the resulting expression is called a multinomial since it is a polynomial in multiple variables. If all functions f(x, y) could be written as f(x, y) = F(x)G(y) then multiplication of series known from calculus II would often suffice. However, many functions do not possess this very special form. For example, how should we expand $f(x, y) = \cos(xy)$ about (0, 0)?. We need to derive the two-dimensional Taylor's theorem.

We already know Taylor's theorem for functions on \mathbb{R} ,

$$g(x) = g(a) + g'(a)(x-a) + \frac{1}{2}g''(a)(x-a)^2 + \dots + \frac{1}{k!}g^{(k)}(a)(x-a)^k + R_k$$

and... If the remainder term vanishes as $k \to \infty$ then the function g is represented by the Taylor series given above and we write:

$$g(x) = \sum_{k=0}^{\infty} \frac{1}{k!} g^{(k)}(a) (x-a)^k.$$

Consider the function of two variables $f : U \subseteq \mathbb{R}^2 \to \mathbb{R}$ which is smooth with smooth partial derivatives of all orders. Furthermore, let $(a, b) \in U$ and construct a line through (a, b) with direction vector (h_1, h_2) as usual:

$$\phi(t) = (a, b) + t(h_1, h_2) = (a + th_1, b + th_2)$$

for $t \in \mathbb{R}$. Note $\phi(0) = (a, b)$ and $\phi'(t) = (h_1, h_2) = \phi'(0)$. Construct $g = f \circ \phi : \mathbb{R} \to \mathbb{R}$ and choose dom(g) such that $\phi(t) \in U$ for $t \in dom(g)$. This function g is a real-valued function of a

real variable and we will be able to apply Taylor's theorem from calculus II on g. However, to differentiate g we'll need tools from calculus III to sort out the derivatives. In particular, as we differentiate g, note we use the chain rule for functions of several variables:

$$g'(t) = (f \circ \phi)'(t) = f'(\phi(t))\phi'(t)$$

= $\nabla f(\phi(t)) \cdot (h_1, h_2)$
= $h_1 f_x(a + th_1, b + th_2) + h_2 f_y(a + th_1, b + th_2)$

Note $g'(0) = h_1 f_x(a, b) + h_2 f_y(a, b)$. Differentiate again (I omit $(\phi(t))$ dependence in the last steps),

$$g''(t) = h_1 f'_x(a + th_1, b + th_2) + h_2 f'_y(a + th_1, b + th_2)$$

= $h_1 \nabla f_x(\phi(t)) \cdot (h_1, h_2) + h_2 \nabla f_y(\phi(t)) \cdot (h_1, h_2)$
= $h_1^2 f_{xx} + h_1 h_2 f_{yx} + h_2 h_1 f_{xy} + h_2^2 f_{yy}$
= $h_1^2 f_{xx} + 2h_1 h_2 f_{xy} + h_2^2 f_{yy}$

Thus, making explicit the point dependence, $g''(0) = h_1^2 f_{xx}(a,b) + 2h_1 h_2 f_{xy}(a,b) + h_2^2 f_{yy}(a,b)$. We may construct the Taylor series for g up to quadratic terms:

$$g(0+t) = g(0) + tg'(0) + \frac{1}{2}g''(0) + \cdots$$

= $f(a,b) + t[h_1f_x(a,b) + h_2f_y(a,b)] + \frac{t^2}{2}[h_1^2f_{xx}(a,b) + 2h_1h_2f_{xy}(a,b) + h_2^2f_{yy}(a,b)] + \cdots$

Note that $g(t) = f(a + th_1, b + th_2)$ hence $g(1) = f(a + h_1, b + h_2)$ and consequently,

$$f(a+h_1,b+h_2) = f(a,b) + h_1 f_x(a,b) + h_2 f_y(a,b) + \frac{1}{2} \left[h_1^2 f_{xx}(a,b) + 2h_1 h_2 f_{xy}(a,b) + h_2^2 f_{yy}(a,b) \right] + \cdots$$

Omitting point dependence on the 2^{nd} derivatives,

$$f(a+h_1,b+h_2) = f(a,b) + h_1 f_x(a,b) + h_2 f_y(a,b) + \frac{1}{2} \left[h_1^2 f_{xx} + 2h_1 h_2 f_{xy} + h_2^2 f_{yy} \right] + \cdots$$

Sometimes we'd rather have an expansion about (x, y). To obtain that formula simply substitute $x - a = h_1$ and $y - b = h_2$. Note that the point (a, b) is fixed in this discussion so the derivatives are not modified in this substitution,

$$f(x,y) = f(a,b) + (x-a)f_x(a,b) + (y-b)f_y(a,b) + \frac{1}{2} \left[(x-a)^2 f_{xx}(a,b) + 2(x-a)(y-b)f_{xy}(a,b) + (y-b)^2 f_{yy}(a,b) \right] + \cdots$$

At this point we ought to recognize the first three terms give the tangent plane to z = f(z, y) at (a, b, f(a, b)). The higher order terms are nonlinear corrections to the linearization, these quadratic

terms form a *quadratic form*. If we computed third, fourth or higher order terms we will find that, using $a = a_1$ and $b = a_2$ as well as $x = x_1$ and $y = x_2$,

$$f(x,y) = \sum_{n=0}^{\infty} \sum_{i_1=0}^{2} \sum_{i_2=0}^{2} \cdots \sum_{i_n=0}^{2} \frac{1}{n!} \frac{\partial^{(n)} f(a_1, a_2)}{\partial x_{i_1} \partial x_{i_2} \cdots \partial x_{i_n}} (x_{i_1} - a_{i_1}) (x_{i_2} - a_{i_2}) \cdots (x_{i_n} - a_{i_n})$$

Example 7.1.1. Expand $f(x, y) = \cos(xy)$ about (0, 0). We calculate derivatives,

$$f_{xx} = -y\sin(xy) \qquad f_{y} = -x\sin(xy)$$

$$f_{xx} = -y^{2}\cos(xy) \qquad f_{xy} = -\sin(xy) - xy\cos(xy) \qquad f_{yy} = -x^{2}\cos(xy)$$

$$f_{xxx} = y^{3}\sin(xy) \qquad f_{xxy} = -y\cos(xy) - y\cos(xy) + xy^{2}\sin(xy)$$

$$f_{xyy} = -x\cos(xy) - x\cos(xy) + x^{2}y\sin(xy) \qquad f_{yyy} = x^{3}\sin(xy)$$

Next, evaluate at x = 0 and y = 0 to find $f(x, y) = 1 + \cdots$ to third order in x, y about (0, 0). We can understand why these derivatives are all zero by approaching the expansion a different route: simply expand cosine directly in the variable (xy),

$$f(x,y) = 1 - \frac{1}{2}(xy)^2 + \frac{1}{4!}(xy)^4 + \dots = 1 - \frac{1}{2}x^2y^2 + \frac{1}{4!}x^4y^4 + \dots$$

Apparently the given function only has nontrivial derivatives at (0,0) at orders 0,4,8,... We can deduce that $f_{xxxxy}(0,0) = 0$ without further calculation.

This is actually a very interesting function, I think it defies our analysis in the later portion of this chapter. The second order part of the expansion reveals nothing about the nature of the critical point (0,0). Of course, any student of trigonometry should recognize that f(0,0) = 1 is likely a local maximum, it's certainly not a local minimum. The graph reveals that f(0,0) is a local maximum for f restricted to certain rays from the origin whereas it is constant on several special directions (the coordinate axes).



And, if you were wondering, yes, we could also derive this from subsitution of u = xy into the standard expansion for $\cos(u) = 1 - \frac{1}{2}u^2 + \frac{1}{4!}u^4 + \cdots$. Often such subsitutions are the quickest way to generate interesting examples.

7.1.3 taylor's multinomial for many-variables

Suppose $f: dom(f) \subseteq \mathbb{R}^n \to \mathbb{R}$ is a function of *n*-variables and we seek to derive the Taylor series centered at $a = (a_1, a_2, \ldots, a_n)$. Once more consider the composition of f with a line in dom(f). In particular, let $\phi: \mathbb{R} \to \mathbb{R}^n$ be defined by $\phi(t) = a + th$ where $h = (h_1, h_2, \ldots, h_n)$ gives the direction of the line and clearly $\phi'(t) = h$. Let $g: dom(g) \subseteq \mathbb{R} \to \mathbb{R}$ be defined by $g(t) = f(\phi(t))$ for all $t \in \mathbb{R}$ such that $\phi(t) \in dom(f)$. Differentiate, use the multivariate chain rule, recall here that $\nabla = e_1 \frac{\partial}{\partial x_1} + e_2 \frac{\partial}{\partial x_2} + \cdots + e_n \frac{\partial}{\partial x_n} = \sum_{i=1}^n e_i \partial_i$,

$$g'(t) = \nabla f(\phi(t)) \cdot \phi'(t) = \nabla f(\phi(t)) \cdot h = \sum_{i=1}^{n} h_i(\partial_i f)(\phi(t))$$

If we omit the explicit dependence on $\phi(t)$ then we find the simple formula $g'(t) = \sum_{i=1}^{n} h_i \partial_i f$. Differentiate a second time,

$$g''(t) = \frac{d}{dt} \left[\sum_{i=1}^n h_i \partial_i f(\phi(t)) \right] = \sum_{i=1}^n h_i \frac{d}{dt} \left[\left(\partial_i f \right)(\phi(t)) \right] = \sum_{i=1}^n h_i \left(\nabla \partial_i f \right)(\phi(t)) \cdot \phi'(t)$$

Omitting the $\phi(t)$ dependence and once more using $\phi'(t) = h$ we find

$$g''(t) = \sum_{i=1}^{n} h_i \nabla \partial_i f \cdot h$$

Recall that $\nabla = \sum_{j=1}^{n} e_j \partial_j$ and expand the expression above,

$$g''(t) = \sum_{i=1}^{n} h_i \left(\sum_{j=1}^{n} e_j \partial_j \partial_i f \right) \cdot h = \sum_{i=1}^{n} \sum_{j=1}^{n} h_i h_j \partial_j \partial_i f$$

where we should remember $\partial_j \partial_i f$ depends on $\phi(t)$. It should be clear that if we continue and take k-derivatives then we will obtain:

$$g^{(k)}(t) = \sum_{i_1=1}^n \sum_{i_2=1}^n \cdots \sum_{i_k=1}^n h_{i_1} h_{i_2} \cdots h_{i_k} \partial_{i_1} \partial_{i_2} \cdots \partial_{i_k} f$$

More explicitly,

$$g^{(k)}(t) = \sum_{i_1=1}^{n} \sum_{i_2=1}^{n} \cdots \sum_{i_k=1}^{n} h_{i_1} h_{i_2} \cdots h_{i_k} (\partial_{i_1} \partial_{i_2} \cdots \partial_{i_k} f)(\phi(t))$$

Hence, by Taylor's theorem, provided we are sufficiently close to t = 0 as to bound the remainder¹

$$g(t) = \sum_{k=0}^{\infty} \frac{1}{k!} \left(\sum_{i_1=1}^{n} \sum_{i_2=1}^{n} \cdots \sum_{i_k=1}^{n} h_{i_1} h_{i_2} \cdots h_{i_k} (\partial_{i_1} \partial_{i_2} \cdots \partial_{i_k} f)(\phi(t)) \right) t^k$$

¹there exist smooth examples for which no neighborhood is small enough, the bump function in one-variable has higher-dimensional analogues, we focus our attention to functions for which it is possible for the series below to converge

Recall that $g(t) = f(\phi(t)) = f(a + th)$. Put² t = 1 and bring in the $\frac{1}{k!}$ to derive

$$f(a+h) = \sum_{k=0}^{\infty} \sum_{i_1=1}^{n} \sum_{i_2=1}^{n} \cdots \sum_{i_k=1}^{n} \frac{1}{k!} (\partial_{i_1} \partial_{i_2} \cdots \partial_{i_k} f)(a) \ h_{i_1} h_{i_2} \cdots h_{i_k}.$$

Naturally, we sometimes prefer to write the series expansion about a as an expression in x = a + h. With this substitution we have h = x - a and $h_{i_j} = (x - a)_{i_j} = x_{i_j} - a_{i_j}$ thus

$$f(x) = \sum_{k=0}^{\infty} \sum_{i_1=1}^{n} \sum_{i_2=1}^{n} \cdots \sum_{i_k=1}^{n} \frac{1}{k!} (\partial_{i_1} \partial_{i_2} \cdots \partial_{i_k} f)(a) \ (x_{i_1} - a_{i_1})(x_{i_2} - a_{i_2}) \cdots (x_{i_k} - a_{i_k}).$$

Example 7.1.2. Suppose $f : \mathbb{R}^3 \to \mathbb{R}$ let's unravel the Taylor series centered at (0,0,0) from the general formula boxed above. Utilize the notation $x = x_1, y = x_2$ and $z = x_3$ in this example.

$$f(x) = \sum_{k=0}^{\infty} \sum_{i_1=1}^{3} \sum_{i_2=1}^{3} \cdots \sum_{i_k=1}^{3} \frac{1}{k!} (\partial_{i_1} \partial_{i_2} \cdots \partial_{i_k} f)(0) \ x_{i_1} x_{i_2} \cdots x_{i_k}.$$

The terms to order 2 are as follows:

$$\begin{aligned} f(x) &= f(0) + f_x(0)x + f_y(0)y + f_z(0)z \\ &+ \frac{1}{2} \left(\begin{array}{c} f_{xx}(0)x^2 + f_{yy}(0)y^2 + f_{zz}(0)z^2 + \\ &+ f_{xy}(0)xy + f_{xz}(0)xz + f_{yz}(0)yz + f_{yx}(0)yx + f_{zx}(0)zx + f_{zy}(0)zy \end{array} \right) + \cdots \end{aligned}$$

Partial derivatives commute for smooth functions hence,

$$\begin{aligned} f(x) &= f(0) + f_x(0)x + f_y(0)y + f_z(0)z \\ &+ \frac{1}{2} \left(\begin{array}{c} f_{xx}(0)x^2 + f_{yy}(0)y^2 + f_{zz}(0)z^2 + 2f_{xy}(0)xy + 2f_{xz}(0)xz + 2f_{yz}(0)yz \end{array} \right) \\ &+ \frac{1}{3!} \left(\begin{array}{c} f_{xxx}(0)x^3 + f_{yyy}(0)y^3 + f_{zzz}(0)z^3 + 3f_{xxy}(0)x^2y + 3f_{xxz}(0)x^2z \\ &+ 3f_{yyz}(0)y^2z + 3f_{xyy}(0)xy^2 + 3f_{xzz}(0)xz^2 + 3f_{yzz}(0)yz^2 + 6f_{xyz}(0)xyz \end{array} \right) + \cdots \end{aligned}$$

Example 7.1.3. Suppose $f(x, y, z) = e^{xyz}$. Find a quadratic approximation to f near (0, 1, 2). Observe:

$$\begin{aligned} f_x &= yze^{xyz} \qquad f_y = xze^{xyz} \qquad f_z = xye^{xyz} \\ f_{xx} &= (yz)^2 e^{xyz} \qquad f_{yy} = (xz)^2 e^{xyz} \qquad f_{zz} = (xy)^2 e^{xyz} \\ f_{xy} &= ze^{xyz} + xyz^2 e^{xyz} \qquad f_{yz} = xe^{xyz} + x^2 yze^{xyz} \qquad f_{xz} = ye^{xyz} + xy^2 ze^{xyz} \end{aligned}$$

² if t = 1 is not in the domain of g then we should rescale the vector h so that t = 1 places $\phi(1)$ in dom(f), if f is smooth on some neighborhood of a then this is possible

Evaluating at x = 0, y = 1 and z = 2,

$$f_x(0,1,2) = 2 \qquad f_y(0,1,2) = 0 \qquad f_z(0,1,2) = 0$$
$$f_{xx}(0,1,2) = 4 \qquad f_{yy}(0,1,2) = 0 \qquad f_{zz}(0,1,2) = 0$$

$$f_{xy}(0,1,2) = 2$$
 $f_{yz}(0,1,2) = 0$ $f_{xz}(0,1,2) = 1$

Hence, as $f(0, 1, 2) = e^0 = 1$ *we find*

$$f(x, y, z) = 1 + 2x + 2x^{2} + 2x(y - 1) + 2x(z - 2) + \cdots$$

Another way to calculate this expansion is to make use of the adding zero trick,

$$f(x, y, z) = e^{x(y-1+1)(z-2+2)} = 1 + x(y-1+1)(z-2+2) + \frac{1}{2} [x(y-1+1)(z-2+2)]^2 + \cdots$$

Keeping only terms with two or less of x, (y-1) and (z-2) variables,

$$f(x, y, z) = 1 + 2x + x(y - 1)(2) + x(1)(z - 2) + \frac{1}{2}x^{2}(1)^{2}(2)^{2} + \cdots$$

Which simplifies once more to $f(x, y, z) = 1 + 2x + 2x(y - 1) + x(z - 2) + 2x^2 + \cdots$

7.2 a brief introduction to the theory of quadratic forms

Definition 7.2.1.

Generally, a **quadratic form** Q is a function $Q : \mathbb{R}^n \to \mathbb{R}$ whose formula can be written $Q(\vec{x}) = \vec{x}^T A \vec{x}$ for all $\vec{x} \in \mathbb{R}^n$ where $A \in \mathbb{R}^{n \times n}$ such that $A^T = A$. In particular, if $\vec{x} = (x, y)$ and $A = \begin{bmatrix} a & b \\ b & c \end{bmatrix}$ then $Q(\vec{x}) = \vec{x}^T A \vec{x} = ax^2 + bxy + byx + cy^2 = ax^2 + 2bxy + y^2$. The n = 3 case is similar, denote $A = [A_{ij}]$ and $\vec{x} = (x, y, z)$ so that $Q(\vec{x}) = \vec{x}^T A \vec{x} = A_{11}x^2 + 2A_{12}xy + 2A_{13}xz + A_{22}y^2 + 2A_{23}yz + A_{33}z^2$. Generally, if $[A_{ij}] \in \mathbb{R}^{n \times n}$ and $\vec{x} = [x_i]^T$ then the associated quadratic form is $Q(\vec{x}) = \vec{x}^T A \vec{x} = \sum_{i,j} A_{ij} x_i x_j = \sum_{i=1}^n A_{ii} x_i^2 + \sum_{i < j} 2A_{ij} x_i x_j$.

In case you wondering, yes you could write a given quadratic form with a different matrix which is not symmetric, but we will find it convenient to insist that our matrix is symmetric since that choice is always possible for a given quadratic form.

It is at times useful to use the dot-product to express a given quadratic form:

$$\vec{x}^T A \vec{x} = \vec{x} \cdot (A \vec{x}) = (A \vec{x}) \cdot \vec{x} = \vec{x}^T A^T \vec{x}$$

Some texts actually use the middle equality above to define a symmetric matrix.

Example 7.2.2.

$$2x^{2} + 2xy + 2y^{2} = \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Example 7.2.3.

$$2x^{2} + 2xy + 3xz - 2y^{2} - z^{2} = \begin{bmatrix} x & y & z \end{bmatrix} \begin{bmatrix} 2 & 1 & 3/2 \\ 1 & -2 & 0 \\ 3/2 & 0 & -1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

Proposition 7.2.4.

The values of a quadratic form on $\mathbb{R}^n - \{0\}$ is completely determined by it's values on the (n-1)-sphere $S_{n-1} = \{\vec{x} \in \mathbb{R}^n \mid ||\vec{x}|| = 1\}$. In particular, $Q(\vec{x}) = ||\vec{x}||^2 Q(\hat{x})$ where $\hat{x} = \frac{1}{||\vec{x}||} \vec{x}$.

Proof: Let $Q(\vec{x}) = \vec{x}^T A \vec{x}$. Notice that we can write any nonzero vector as the product of its magnitude ||x|| and its direction $\hat{x} = \frac{1}{||\vec{x}||} \vec{x}$,

$$Q(\vec{x}) = Q(||\vec{x}||\hat{x}) = (||\vec{x}||\hat{x})^T A ||\vec{x}||\hat{x} = ||\vec{x}||^2 \hat{x}^T A \hat{x} = ||x||^2 Q(\hat{x}).$$

Therefore $Q(\vec{x})$ is simply proportional to $Q(\hat{x})$ with proportionality constant $||\vec{x}||^2$. \Box

The proposition above is very interesting. It says that if we know how Q works on unit-vectors then we can extrapolate its action on the remainder of \mathbb{R}^n . If $f: S \to \mathbb{R}$ then we could say f(S) > 0iff f(s) > 0 for all $s \in S$. Likewise, f(S) < 0 iff f(s) < 0 for all $s \in S$. The proposition below follows from the proposition above since $||\vec{x}||^2$ ranges over all nonzero positive real numbers in the equations above.

Proposition 7.2.5.

If Q is a quadratic form on \mathbb{R}^n and we denote $\mathbb{R}^n_* = \mathbb{R}^n - \{0\}$ 1.(negative definite) $Q(\mathbb{R}^n_*) < 0$ iff $Q(S_{n-1}) < 0$ 2.(positive definite) $Q(\mathbb{R}^n_*) > 0$ iff $Q(S_{n-1}) > 0$ 3.(non-definite) $Q(\mathbb{R}^n_*) = \mathbb{R} - \{0\}$ iff $Q(S_{n-1})$ has both positive and negative values.

Before I get too carried away with the theory let's look at a couple examples.

Example 7.2.6. Consider the quadric form $Q(x, y) = x^2 + y^2$. You can check for yourself that z = Q(x, y) is a cone and Q has positive outputs for all inputs except (0, 0). Notice that $Q(v) = ||v||^2$ so it is clear that $Q(S_1) = 1$. We find agreement with the preceding proposition. Next, think about the application of Q(x, y) to level curves; $x^2 + y^2 = k$ is simply a circle of radius \sqrt{k} or just the origin. Here's a graph of z = Q(x, y):



Notice that Q(0,0) = 0 is the absolute minimum for Q. Finally, let's take a moment to write $Q(x,y) = [x,y] \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$ in this case the matrix is diagonal and we note that the e-values are $\lambda_1 = \lambda_2 = 1$.

Example 7.2.7. Consider the quadric form $Q(x, y) = x^2 - 2y^2$. You can check for yourself that z = Q(x, y) is a hyperboloid and Q has non-definite outputs since sometimes the x^2 term dominates whereas other points have $-2y^2$ as the dominent term. Notice that Q(1,0) = 1 whereas Q(0,1) = -2 hence we find $Q(S_1)$ contains both positive and negative values and consequently we find agreement with the preceding proposition. Next, think about the application of Q(x, y) to level curves; $x^2 - 2y^2 = k$ yields either hyperbolas which open vertically (k > 0) or horizontally (k < 0) or a pair of lines $y = \pm \frac{x}{2}$ in the k = 0 case. Here's a graph of z = Q(x, y):



The origin is a saddle point. Finally, let's take a moment to write $Q(x, y) = [x, y] \begin{bmatrix} 1 & 0 \\ 0 & -2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$ in this case the matrix is diagonal and we note that the e-values are $\lambda_1 = 1$ and $\lambda_2 = -2$.

Example 7.2.8. Consider the quadric form $Q(x, y) = 3x^2$. You can check for yourself that z = Q(x, y) is parabola-shaped trough along the y-axis. In this case Q has positive outputs for all inputs except (0, y), we would call this form **positive semi-definite**. A short calculation reveals that $Q(S_1) = [0,3]$ thus we again find agreement with the preceding proposition (case 3). Next, think about the application of Q(x, y) to level curves; $3x^2 = k$ is a pair of vertical lines: $x = \pm \sqrt{k/3}$ or just the y-axis. Here's a graph of z = Q(x, y):



Finally, let's take a moment to write $Q(x,y) = [x,y] \begin{bmatrix} 3 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$ in this case the matrix is diagonal and we note that the e-values are $\lambda_1 = 3$ and $\lambda_2 = 0$.

Example 7.2.9. Consider the quadric form $Q(x, y, z) = x^2 + 2y^2 + 3z^2$. Think about the application of Q(x, y, z) to level surfaces; $x^2 + 2y^2 + 3z^2 = k$ is an ellipsoid. I can't graph a function of three variables, however, we can look at level surfaces of the function. I use Mathematica to plot several below:



Finally, let's take a moment to write $Q(x, y, z) = [x, y, z] \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$ in this case the matrix is diagonal and we note that the e-values are $\lambda_1 = 1$ and $\lambda_2 = 2$ and $\lambda_3 = 3$.

7.2.1 diagonalizing forms via eigenvectors

The examples given thus far are the simplest cases. We don't really need linear algebra to understand them. In contrast, e-vectors and e-values will prove a useful tool to unravel the later examples³

Definition 7.2.10.

Let $A \in \mathbb{R}^{n \times n}$. If $v \in \mathbb{R}^{n \times 1}$ is **nonzero** and $Av = \lambda v$ for some $\lambda \in \mathbb{C}$ then we say v is an **eigenvector** with **eigenvalue** λ of the matrix A.

Proposition 7.2.11.

Let $A \in \mathbb{R}^{n \times n}$ then λ is an eigenvalue of A iff $det(A - \lambda I) = 0$. We say $P(\lambda) = det(A - \lambda I)$ the **characteristic polynomial** and $det(A - \lambda I) = 0$ is the **characteristic equation**.

Proof: Suppose λ is an eigenvalue of A then there exists a nonzero vector v such that $Av = \lambda v$ which is equivalent to $Av - \lambda v = 0$ which is precisely $(A - \lambda I)v = 0$. Notice that $(A - \lambda I)0 = 0$

³this is the one place in this course where we need eigenvalues and eigenvector calculations, I include these to illustrate the structure of quadratic forms in general, however, as linear algebra is not a prerequisite you may find some things in this section mysterious. The homework and study guide will elaborate on what is required this semester

thus the matrix $(A - \lambda I)$ is singular as the equation $(A - \lambda I)x = 0$ has more than one solution. Consequently $det(A - \lambda I) = 0$.

Conversely, suppose $det(A - \lambda I) = 0$. It follows that $(A - \lambda I)$ is singular. Clearly the system $(A - \lambda I)x = 0$ is consistent as x = 0 is a solution hence we know there are infinitely many solutions. In particular there exists at least one vector $v \neq 0$ such that $(A - \lambda I)v = 0$ which means the vector v satisfies $Av = \lambda v$. Thus v is an eigenvector with eigenvalue λ for A. \Box

Example 7.2.12. Let $A = \begin{bmatrix} 3 & 1 \\ 3 & 1 \end{bmatrix}$ find the e-values and e-vectors of A.

$$det(A - \lambda I) = det \begin{bmatrix} 3 - \lambda & 1\\ 3 & 1 - \lambda \end{bmatrix} = (3 - \lambda)(1 - \lambda) - 3 = \lambda^2 - 4\lambda = \lambda(\lambda - 4) = 0$$

We find $\lambda_1 = 0$ and $\lambda_2 = 4$. Now find the e-vector with e-value $\lambda_1 = 0$, let $u_1 = [u, v]^T$ denote the e-vector we wish to find. Calculate,

$$(A - 0I)u_1 = \begin{bmatrix} 3 & 1 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 3u + v \\ 3u + v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Obviously the equations above are redundant and we have infinitely many solutions of the form 3u + v = 0 which means v = -3u so we can write, $u_1 = \begin{bmatrix} u \\ -3u \end{bmatrix} = u \begin{bmatrix} 1 \\ -3 \end{bmatrix}$. In applications we often make a choice to select a particular e-vector. Most modern graphing calculators can calculate e-vectors. It is customary for the e-vectors to be chosen to have length one. That is a useful choice for certain applications as we will later discuss. If you use a calculator it would likely give $u_1 = \frac{1}{\sqrt{10}} \begin{bmatrix} 1 \\ -3 \end{bmatrix}$ although the $\sqrt{10}$ would likely be approximated unless your calculator is smart.

Continuing we wish to find eigenvectors $u_2 = [u, v]^T$ such that $(A - 4I)u_2 = 0$. Notice that u, v are disposable variables in this context, I do not mean to connect the formulas from the $\lambda = 0$ case with the case considered now.

$$(A-4I)u_1 = \begin{bmatrix} -1 & 1 \\ 3 & -3 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} -u+v \\ 3u-3v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Again the equations are redundant and we have infinitely many solutions of the form v = u. Hence, $u_2 = \begin{bmatrix} u \\ u \end{bmatrix} = u \begin{bmatrix} 1 \\ 1 \end{bmatrix}$ is an eigenvector for any $u \in \mathbb{R}$ such that $u \neq 0$.

Theorem 7.2.13.

A matrix $A \in \mathbb{R}^{n \times n}$ is symmetric iff there exists an orthonormal eigenbasis for A.

There is a geometric proof of this theorem in Edwards⁴ (see Theorem 8.6 pgs 146-147). I prove half of this theorem in my linear algebra notes by a non-geometric argument (full proof is in Appendix C of Insel, Spence and Friedberg). It might be very interesting to understand the connection between the geometric verse algebraic arguments. We'll content ourselves with an example here:

Example 7.2.14. Let $A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 2 \\ 0 & 2 & 1 \end{bmatrix}$. Observe that $det(A - \lambda I) = -\lambda(\lambda + 1)(\lambda - 3)$ thus $\lambda_1 = 0, \lambda_2 = -1, \lambda_3 = 3$. We can calculate orthonormal e-vectors of $v_1 = [1, 0, 0]^T$, $v_2 = \frac{1}{\sqrt{2}}[0, 1, -1]^T$

and $v_3 = \frac{1}{\sqrt{2}} [0, 1, 1]^T$. I invite the reader to check the validity of the following equation:

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{2}} & \frac{-1}{\sqrt{2}} \\ 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 2 \\ 0 & 2 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ 0 & \frac{-1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 3 \end{bmatrix}$$

Its really neat that to find the inverse of a matrix of orthonormal e-vectors we need only take the $\begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$

transpose; note	$\begin{bmatrix} 1\\0\\0 \end{bmatrix}$	$\begin{array}{c} 0\\ \frac{1}{\sqrt{2}}\\ \frac{1}{\sqrt{2}} \end{array}$	$\begin{array}{c} 0\\ \underline{-1}\\ \sqrt{2}\\ \underline{1}\\ \sqrt{2} \end{array}$	$\begin{bmatrix} 1\\0\\0 \end{bmatrix}$	$\begin{array}{c} 0\\ \frac{1}{\sqrt{2}}\\ \frac{-1}{\sqrt{2}} \end{array}$	$\begin{array}{c} 0\\ \frac{1}{\sqrt{2}}\\ \frac{1}{\sqrt{2}} \end{array}$	=	$\left[\begin{array}{c}1\\0\\0\end{array}\right]$	$\begin{array}{c} 0 \\ 1 \\ 0 \end{array}$	$\begin{array}{c} 0\\ 0\\ 1\end{array}$	
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Proposition 7.2.15.

If Q is a quadratic form on \mathbb{R}^n with matrix A and e-values $\lambda_1, \lambda_2, \ldots, \lambda_n$ with orthonormal e-vectors v_1, v_2, \ldots, v_n then $Q(v_i) = \lambda_i^2$ for $i = 1, 2, \ldots, n$. Moreover, if $P = [v_1 | v_2 | \cdots | v_n]$ then $Q(\vec{x}) = (P^T \vec{x})^T P^T A P P^T \vec{x} = \lambda_1 y_1^2 + \lambda_2 y_2^2 + \dots + \lambda_n y_n^2$ where we defined $\vec{y} = P^T \vec{x}$.

Let me restate the proposition above in simple terms: we can transform a given quadratic form to a diagonal form by finding orthonormalized e-vectors and performing the appropriate coordinate transformation. Since P is formed from orthonormal e-vectors we know that P will be either a rotation or reflection. This proposition says we can remove "cross-terms" by transforming the quadratic forms with an appropriate rotation.

Example 7.2.16. Consider the quadric form $Q(x,y) = 2x^2 + 2xy + 2y^2$. It's not immediately obvious (to me) what the level curves Q(x,y) = k look like. We'll make use of the preceding proposition to understand those graphs. Notice $Q(x,y) = [x,y] \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$. Denote the matrix

⁴think about it, there is a 1-1 correspondence between symmetric matrices and quadratic forms

of the form by A and calculate the e-values/vectors:

$$det(A - \lambda I) = det \begin{bmatrix} 2-\lambda & 1\\ 1 & 2-\lambda \end{bmatrix} = (\lambda - 2)^2 - 1 = \lambda^2 - 4\lambda + 3 = (\lambda - 1)(\lambda - 3) = 0$$

Therefore, the e-values are $\lambda_1 = 1$ and $\lambda_2 = 3$.

$$(A-I)\vec{u}_1 = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \Rightarrow \quad \vec{u}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

I just solved u + v = 0 to give v = -u choose u = 1 then normalize to get the vector above. Next,

$$(A - 3I)\vec{u}_2 = \begin{bmatrix} -1 & 1\\ 1 & -1 \end{bmatrix} \begin{bmatrix} u\\ v \end{bmatrix} = \begin{bmatrix} 0\\ 0 \end{bmatrix} \quad \Rightarrow \quad \vec{u}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1\\ 1 \end{bmatrix}$$

I just solved u - v = 0 to give v = u choose u = 1 then normalize to get the vector above. Let $P = [\vec{u}_1 | \vec{u}_2]$ and introduce new coordinates $\vec{y} = [\vec{x}, \vec{y}]^T$ defined by $\vec{y} = P^T \vec{x}$. Note these can be inverted by multiplication by P to give $\vec{x} = P\vec{y}$. Observe that

$$P = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \Rightarrow \begin{array}{c} x &= \frac{1}{2}(\bar{x} + \bar{y}) \\ y &= \frac{1}{2}(-\bar{x} + \bar{y}) \end{array} or \begin{array}{c} \bar{x} &= \frac{1}{2}(x - y) \\ \bar{y} &= \frac{1}{2}(x + y) \end{array}$$

The proposition preceding this example shows that substitution of the formulas above into Q yield⁵:

$$\tilde{Q}(\bar{x},\bar{y}) = \bar{x}^2 + 3\bar{y}^2$$

It is clear that in the barred coordinate system the level curve Q(x, y) = k is an ellipse. If we draw the barred coordinate system superposed over the xy-coordinate system then you'll see that the graph of $Q(x, y) = 2x^2 + 2xy + 2y^2 = k$ is an ellipse rotated by 45 degrees. Or, if you like, we can plot z = Q(x, y):



⁵technically $\tilde{Q}(\bar{x}, \bar{y})$ is $Q(x(\bar{x}, \bar{y}), y(\bar{x}, \bar{y}))$

Example 7.2.17. Consider the quadric form $Q(x, y) = x^2 + 2xy + y^2$. It's not immediately obvious (to me) what the level curves Q(x, y) = k look like. We'll make use of the preceding proposition to understand those graphs. Notice $Q(x, y) = [x, y] \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$. Denote the matrix of the form by A and calculate the e-values/vectors:

$$det(A - \lambda I) = det \begin{bmatrix} 1 - \lambda & 1\\ 1 & 1 - \lambda \end{bmatrix} = (\lambda - 1)^2 - 1 = \lambda^2 - 2\lambda = \lambda(\lambda - 2) = 0$$

Therefore, the e-values are $\lambda_1 = 0$ and $\lambda_2 = 2$.

$$(A-0)\vec{u}_1 = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \Rightarrow \quad \vec{u}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

I just solved u + v = 0 to give v = -u choose u = 1 then normalize to get the vector above. Next,

$$(A-2I)\vec{u}_2 = \begin{bmatrix} -1 & 1\\ 1 & -1 \end{bmatrix} \begin{bmatrix} u\\ v \end{bmatrix} = \begin{bmatrix} 0\\ 0 \end{bmatrix} \implies \vec{u}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1\\ 1 \end{bmatrix}$$

I just solved u - v = 0 to give v = u choose u = 1 then normalize to get the vector above. Let $P = [\vec{u}_1 | \vec{u}_2]$ and introduce new coordinates $\vec{y} = [\vec{x}, \vec{y}]^T$ defined by $\vec{y} = P^T \vec{x}$. Note these can be inverted by multiplication by P to give $\vec{x} = P\vec{y}$. Observe that

$$P = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \Rightarrow \begin{array}{c} x &= \frac{1}{2}(\bar{x} + \bar{y}) \\ y &= \frac{1}{2}(-\bar{x} + \bar{y}) \end{array} or \begin{array}{c} \bar{x} &= \frac{1}{2}(x - y) \\ \bar{y} &= \frac{1}{2}(x + y) \end{array}$$

The proposition preceding this example shows that substitution of the formulas above into Q yield:

$$\tilde{Q}(\bar{x},\bar{y}) = 2\bar{y}^2$$

It is clear that in the barred coordinate system the level curve Q(x,y) = k is a pair of paralell lines. If we draw the barred coordinate system superposed over the xy-coordinate system then you'll see that the graph of $Q(x,y) = x^2 + 2xy + y^2 = k$ is a line with slope -1. Indeed, with a little algebraic insight we could have anticipated this result since $Q(x,y) = (x+y)^2$ so Q(x,y) = k implies $x + y = \sqrt{k}$ thus $y = \sqrt{k} - x$. Here's a plot which again verifies what we've already found:



Example 7.2.18. Consider the quadric form Q(x, y) = 4xy. It's not immediately obvious (to me) what the level curves Q(x, y) = k look like. We'll make use of the preceding proposition to understand those graphs. Notice $Q(x, y) = [x, y] \begin{bmatrix} 0 & 2 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$. Denote the matrix of the form by A and calculate the e-values/vectors:

$$det(A - \lambda I) = det \begin{bmatrix} -\lambda & 2\\ 2 & -\lambda \end{bmatrix} = \lambda^2 - 4 = (\lambda + 2)(\lambda - 2) = 0$$

Therefore, the e-values are $\lambda_1 = -2$ and $\lambda_2 = 2$.

$$(A+2I)\vec{u}_1 = \begin{bmatrix} 2 & 2\\ 2 & 2 \end{bmatrix} \begin{bmatrix} u\\ v \end{bmatrix} = \begin{bmatrix} 0\\ 0 \end{bmatrix} \implies \vec{u}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1\\ -1 \end{bmatrix}$$

I just solved u + v = 0 to give v = -u choose u = 1 then normalize to get the vector above. Next,

$$(A-2I)\vec{u}_2 = \begin{bmatrix} -2 & 2\\ 2 & -2 \end{bmatrix} \begin{bmatrix} u\\ v \end{bmatrix} = \begin{bmatrix} 0\\ 0 \end{bmatrix} \quad \Rightarrow \quad \vec{u}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1\\ 1 \end{bmatrix}$$

I just solved u - v = 0 to give v = u choose u = 1 then normalize to get the vector above. Let $P = [\vec{u}_1 | \vec{u}_2]$ and introduce new coordinates $\vec{y} = [\vec{x}, \vec{y}]^T$ defined by $\vec{y} = P^T \vec{x}$. Note these can be inverted by multiplication by P to give $\vec{x} = P\vec{y}$. Observe that

$$P = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix} \Rightarrow \begin{array}{c} x &= \frac{1}{2}(\bar{x} + \bar{y}) \\ y &= \frac{1}{2}(-\bar{x} + \bar{y}) \end{array} or \begin{array}{c} \bar{x} &= \frac{1}{2}(x - y) \\ \bar{y} &= \frac{1}{2}(x + y) \end{array}$$

The proposition preceding this example shows that substitution of the formulas above into Q yield:

$$\tilde{Q}(\bar{x},\bar{y}) = -2\bar{x}^2 + 2\bar{y}^2$$

It is clear that in the barred coordinate system the level curve Q(x, y) = k is a hyperbola. If we draw the barred coordinate system superposed over the xy-coordinate system then you'll see that the graph of Q(x, y) = 4xy = k is a hyperbola rotated by 45 degrees. The graph z = 4xy is thus a hyperbolic paraboloid:



The fascinating thing about the mathematics here is that if you don't want to graph z = Q(x, y), but you do want to know the general shape then you can determine which type of quadraic surface you're dealing with by simply calculating the eigenvalues of the form.

Remark 7.2.19.

I made the preceding triple of examples all involved the same rotation. This is purely for my lecturing convenience. In practice the rotation could be by all sorts of angles. In addition, you might notice that a different ordering of the e-values would result in a redefinition of the barred coordinates. 6

We ought to do at least one 3-dimensional example.

Example 7.2.20. Consider the quadric form Q defined below:

$$Q(x, y, z) = [x, y, z] \begin{bmatrix} 6 & -2 & 0 \\ -2 & 6 & 0 \\ 0 & 0 & 5 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

Denote the matrix of the form by A and calculate the e-values/vectors:

$$det(A - \lambda I) = det \begin{bmatrix} 6 - \lambda & -2 & 0 \\ -2 & 6 - \lambda & 0 \\ 0 & 0 & 5 - \lambda \end{bmatrix}$$
$$= [(\lambda - 6)^2 - 4](5 - \lambda)$$
$$= (5 - \lambda)[\lambda^2 - 12\lambda + 32](5 - \lambda)$$
$$= (\lambda - 4)(\lambda - 8)(5 - \lambda)$$

Therefore, the e-values are $\lambda_1 = 4$, $\lambda_2 = 8$ and $\lambda_3 = 5$. After some calculation we find the following orthonormal e-vectors for A:

$$\vec{u}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1\\1\\0 \end{bmatrix} \qquad \vec{u}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1\\-1\\0 \end{bmatrix} \qquad \vec{u}_3 = \begin{bmatrix} 0\\0\\1 \end{bmatrix}$$

Let $P = [\vec{u}_1 | \vec{u}_2 | \vec{u}_3]$ and introduce new coordinates $\vec{y} = [\bar{x}, \bar{y}, \bar{z}]^T$ defined by $\vec{y} = P^T \vec{x}$. Note these can be inverted by multiplication by P to give $\vec{x} = P\vec{y}$. Observe that

$$P = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 & 0\\ -1 & 1 & 0\\ 0 & 0 & \sqrt{2} \end{bmatrix} \Rightarrow \begin{array}{ccc} x & = \frac{1}{2}(\bar{x} + \bar{y}) & \bar{x} & = \frac{1}{2}(x - y)\\ y & = \frac{1}{2}(-\bar{x} + \bar{y}) & or & \bar{y} & = \frac{1}{2}(x + y)\\ z & = \bar{z} & \bar{z} & z & z \end{array}$$

The proposition preceding this example shows that substitution of the formulas above into Q yield:

$$\tilde{Q}(\bar{x}, \bar{y}, \bar{z}) = 4\bar{x}^2 + 8\bar{y}^2 + 5\bar{z}^2$$

It is clear that in the barred coordinate system the level surface Q(x, y, z) = k is an ellipsoid. If we draw the barred coordinate system superposed over the xyz-coordinate system then you'll see that the graph of Q(x, y, z) = k is an ellipsoid rotated by 45 degrees around the z – axis. Plotted below are a few representative ellipsoids:



In summary, the behaviour of a quadratic form $Q(x) = x^T A x$ is governed by it's set of eigenvalues⁷ $\{\lambda_1, \lambda_2, \ldots, \lambda_k\}$. Moreover, the form can be written as $Q(y) = \lambda_1 y_1^2 + \lambda_2 y_2^2 + \cdots + \lambda_k y_k^2$ by choosing the coordinate system which is built from the orthonormal eigenbasis of col(A). In this coordinate system the shape of the level-sets of Q becomes manifest from the signs of the e-values.)

Remark 7.2.21.

If you would like to read more about conic sections or quadric surfaces and their connection to e-values/vectors I reccommend sections 9.6 and 9.7 of Anton's linear algebra text. I have yet to add examples on how to include translations in the analysis. It's not much more trouble but I decided it would just be an uncessary complication this semester. Also, section 7.1,7.2 and 7.3 in Lay's linear algebra text show a bit more about how to use this math to solve concrete applied problems. You might also take a look in Gilbert Strang's linear algebra text, his discussion of tests for positive-definite matrices is much more complete than I will give here.

7.3 second derivative test in many-variables

There is a connection between the shape of level curves $Q(x_1, x_2, ..., x_n) = k$ and the graph $x_{n+1} = f(x_1, x_2, ..., x_n)$ of f. I'll discuss n = 2 but these comments equally well apply to w = f(x, y, z) or higher dimensional examples. Consider a critical point (a, b) for f(x, y) then the Taylor expansion about (a, b) has the form

$$f(a+h,b+k) = f(a,b) + Q(h,k)$$

where $Q(h,k) = \frac{1}{2}h^2 f_{xx}(a,b) + hk f_{xy}(a,b) + \frac{1}{2}h^2 f_{yy}(a,b) = [h,k][Q](h,k)$. Since $[Q]^T = [Q]$ we can find orthonormal e-vectors \vec{u}_1, \vec{u}_2 for [Q] with e-values λ_1 and λ_2 respective. Using $U = [\vec{u}_1 | \vec{u}_2]$ we

⁷this set is called the spectrum of the matrix

can introduce rotated coordinates $(\bar{h}, \bar{k}) = U(h, k)$. These will give

$$Q(\bar{h},\bar{k}) = \lambda_1 \bar{h}^2 + \lambda_2 \bar{k}^2$$

Clearly if $\lambda_1 > 0$ and $\lambda_2 > 0$ then f(a, b) yields the local minimum whereas if $\lambda_1 < 0$ and $\lambda_2 < 0$ then f(a, b) yields the local maximum. Edwards discusses these matters on pgs. 148-153. In short, supposing $f \approx f(p) + Q$, if all the e-values of Q are positive then f has a local minimum of f(p) at p whereas if all the e-values of Q are negative then f reaches a local maximum of f(p) at p. Otherwise Q has both positive and negative e-values and we say Q is non-definite and the function has a saddle point. If all the e-values of Q are positive then Q is said to be **positive-definite** whereas if all the e-values of Q are negative then Q is said to be **positive-definite**. Edwards gives a few nice tests for ascertaining if a matrix is positive definite without explicit computation of e-values. Finally, if one of the e-values is zero then the graph will be like a trough.

Example 7.3.1. Suppose $f(x, y) = exp(-x^2 - y^2 + 2y - 1)$ expand f about the point (0, 1):

$$f(x,y) = exp(-x^2)exp(-y^2 + 2y - 1) = exp(-x^2)exp(-(y-1)^2)$$

expanding,

$$f(x,y) = (1 - x^2 + \dots)(1 - (y - 1)^2 + \dots) = 1 - x^2 - (y - 1)^2 + \dots$$

Recenter about the point (0,1) by setting x = h and y = 1 + k so

$$f(h, 1+k) = 1 - h^2 - k^2 + \cdots$$

If (h, k) is near (0, 0) then the dominant terms are simply those we've written above hence the graph is like that of a quadraic surface with a pair of negative e-values. It follows that f(0, 1) is a local maximum. In fact, it happens to be a global maximum for this function.

Example 7.3.2. Suppose $f(x, y) = 4 - (x-1)^2 + (y-2)^2 + Aexp(-(x-1)^2 - (y-2)^2) + 2B(x-1)(y-2)$ for some constants A, B. Analyze what values for A, B will make (1, 2) a local maximum, minimum or neither. Expanding about (1, 2) we set x = 1 + h and y = 2 + k in order to see clearly the local behaviour of f at (1, 2),

$$f(1+h, 2+k) = 4 - h^2 - k^2 + Aexp(-h^2 - k^2) + 2Bhk$$

= 4 - h^2 - k^2 + A(1 - h^2 - k^2) + 2Bhk \cdots
= 4 + A - (A + 1)h² + 2Bhk - (A + 1)k² + ...

There is no nonzero linear term in the expansion at (1,2) which indicates that f(1,2) = 4 + Amay be a local extremum. In this case the quadratic terms are nontrivial which means the graph of this function is well-approximated by a quadratic surface near (1,2). The quadratic form Q(h,k) = $-(A+1)h^2 + 2Bhk - (A+1)k^2$ has matrix

$$[Q] = \begin{bmatrix} -(A+1) & B \\ B & -(A+1)^2 \end{bmatrix}.$$
The characteristic equation for Q is

$$det([Q] - \lambda I) = det \begin{bmatrix} -(A+1) - \lambda & B \\ B & -(A+1)^2 - \lambda \end{bmatrix} = (\lambda + A + 1)^2 - B^2 = 0$$

We find solutions $\lambda_1 = -A - 1 + B$ and $\lambda_2 = -A - 1 - B$. The possibilities break down as follows:

- 1. if $\lambda_1, \lambda_2 > 0$ then f(1, 2) is local minimum.
- 2. if $\lambda_1, \lambda_2 < 0$ then f(1,2) is local maximum.
- 3. if just one of λ_1, λ_2 is zero then f is constant along one direction and min/max along another so technically it is a local extremum.
- 4. if $\lambda_1 \lambda_2 < 0$ then f(1,2) is not a local etremum, however it is a saddle point.

In particular, the following choices for A, B will match the choices above

- 1. Let A = -3 and B = 1 so $\lambda_1 = 3$ and $\lambda_2 = 1$;
- 2. Let A = 3 and B = 1 so $\lambda_1 = -3$ and $\lambda_2 = -5$
- 3. Let A = -3 and B = -2 so $\lambda_1 = 0$ and $\lambda_2 = 4$
- 4. Let A = 1 and B = 3 so $\lambda_1 = 1$ and $\lambda_2 = -5$

Here are the graphs of the cases above, note the analysis for case 3 is more subtle for Taylor approximations as opposed to simple quadraic surfaces. In this example, case 3 was also a local minimum. In contrast, in Example 7.2.17 the graph was like a trough. The behaviour of f away from the critical point includes higher order terms whose influence turns the trough into a local minimum.



Example 7.3.3. Suppose $f(x, y) = \sin(x)\cos(y)$ to find the Taylor series centered at (0, 0) we can simply multiply the one-dimensional result $\sin(x) = x - \frac{1}{3!}x^3 + \frac{1}{5!}x^5 + \cdots$ and $\cos(y) = 1 - \frac{1}{2!}y^2 + \frac{1}{4!}y^4 + \cdots$ as follows:

$$f(x,y) = (x - \frac{1}{3!}x^3 + \frac{1}{5!}x^5 + \dots)(1 - \frac{1}{2!}y^2 + \frac{1}{4!}y^4 + \dots)$$

= $x - \frac{1}{2}xy^2 + \frac{1}{24}xy^4 - \frac{1}{6}x^3 - \frac{1}{12}x^3y^2 + \dots$
= $x + \dots$

The origin (0,0) is a critical point since $f_x(0,0) = 0$ and $f_y(0,0) = 0$, however, this particular critical point escapes the analysis via the quadratic form term since Q = 0 in the Taylor series for this function at (0,0). This is analogous to the inconclusive case of the 2nd derivative test in calculus III.

Example 7.3.4. Suppose f(x, y, z) = xyz. Calculate the multivariate Taylor expansion about the point (1, 2, 3). I'll actually calculate this one via differentiation, I have used tricks and/or calculus II results to shortcut any differentiation in the previous examples. Calculate first derivatives

$$f_x = yz$$
 $f_y = xz$ $f_z = xy$,

and second derivatives,

$$f_{xx} = 0 \qquad f_{xy} = z \qquad f_{xz} = y$$
$$f_{yx} = z \qquad f_{yy} = 0 \qquad f_{yz} = x$$
$$f_{zx} = y \qquad f_{zy} = x \qquad f_{zz} = 0,$$

and the nonzero third derivatives,

$$f_{xyz} = f_{yzx} = f_{zxy} = f_{zyx} = f_{yxz} = f_{xzy} = 1.$$

It follows,

$$\begin{aligned} f(a+h,b+k,c+l) &= \\ &= f(a,b,c) + f_x(a,b,c)h + f_y(a,b,c)k + f_z(a,b,c)l + \\ &= \frac{1}{2}(f_{xx}hh + f_{xy}hk + f_{xz}hl + f_{yx}kh + f_{yy}kk + f_{yz}kl + f_{zx}lh + f_{zy}lk + f_{zz}ll) + \cdots \end{aligned}$$

Of course certain terms can be combined since $f_{xy} = f_{yx}$ etc... for smooth functions (we assume smooth in this section, moreover the given function here is clearly smooth). In total,

$$f(1+h,2+k,3+l) = 6 + 6h + 3k + 2l + \frac{1}{2}(3hk + 2hl + 3kh + kl + 2lh + lk) + \frac{1}{3!}(6)hkl$$

Of course, we could also obtain this from simple algebra:

$$f(1+h, 2+k, 3+l) = (1+h)(2+k)(3+l) = 6+6h+3k+l+3hk+2hl+kl+hkl$$

Example 7.3.5. Find the extreme values of w = x + y subject to the condition $x^2 + y^2 + z^2 \le 1$.

Notice
$$f(x,y,z) = x+3$$
 has $\forall f = \langle 1, 0, 1 \rangle$ thus f has
no critical pts. It follows f must obtain max/min on boundary
 $g(x,y,z) = x^2 + y^2 + 3^2 - 1 = 0$. Use method of Superace,
 $\forall f = 2 \forall 9$ where $\vartheta = 0$
 $\langle 1, 0, \mathbf{n} \rangle = 2 \langle 3x, 3y, 3z \rangle$
 $1 = 22 \times 1 = 2 \langle 3x, 3y, 3z \rangle$
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Chapter 8

convergence and estimation

- 8.1 sequences of functions
- 8.2 power series
- 8.3 matrix exponential
- 8.4 uniform convergence
- 8.5 differentiating under the integral
- 8.6 contraction mappings and Newton's method
- 8.7 multivariate mean value theorem
- 8.8 proof of the inverse function theorem

Chapter 9

multilinear algebra

The principle aim of this chapter is to introduce how to calculate with \otimes and \wedge . We take a very concrete approach where the tensor and wedge product are understood in terms of multilinear mappings for which they form a basis. That said, there is a universal algebraic approach to construct the tensor and wedge products, I encourage the reader to study Dummit and Foote's *Abstract Algebra* Part III on *Modules and Vector Spaces* where these constructions are explained in a much broader algebraic context.

Beyond the basic definitions, we also study how wedge products capture determinants and give a natural language to ask certain questions of linear dependence. We also study metrics with particular attention to four dimensional Minkowski space with signature (-1, 1, 1, 1). Hodge duality is detailed for three dimensional Euclidean space and four dimensional Minkowski space. However, there is sufficient detail that one ought to be able to extrapolate to euclidean spaces of other dimension. Moreover, the Hodge duality is reduced to a few tables for computational convenience. I encourage the reader to see David Bleeker's text for a broader discussion of Hodge duality with a physical bent.

When I lecture this material I'll probably just give examples to drive home the computational aspects. Also, it should be noted this Chapter can be studied without delving deeply into Sections 9.4 and 9.6. However, Chapter 12 requires some understanding of both of those sections.

9.1 dual space

Definition 9.1.1.

Suppose V is a vector space over \mathbb{R} . We define the **dual space** to V to be the set of all linear functions from V to \mathbb{R} . In particular, we denote:

$$V^* = \{ f : V \to \mathbb{R} \mid f(x+y) = f(x) + f(y) \text{ and } f(cx) = cf(x) \quad \forall x, y \in V \text{ and } c \in \mathbb{R} \}$$

If $\alpha \in V^*$ then we say α is a **dual vector**.

I offer several abstract examples to begin, however the majority of this section concerns \mathbb{R}^n .

Example 9.1.2. Suppose \mathcal{F} denotes the set of continuous functions on \mathbb{R} . Define $\alpha(f) = \int_0^1 f(t) dt$. The mapping $\alpha : \mathcal{F} \to \mathbb{R}$ is linear by properties of definite integrals therefore we identify the definite integral defines a dual-vector to the vector space of continuous functions.

Example 9.1.3. Suppose $V = \mathcal{F}(W, \mathbb{R})$ denotes a set of functions from a vector space W to \mathbb{R} . Note that V is a vector space with respect to point-wise defined addition and scalar multiplication of functions. Let $w_o \in W$ and define $\alpha(f) = f(w_o)$. The mapping $\alpha : V \to \mathbb{R}$ is linear since $\alpha(cf + g) = (cf + g)(w_o) = cf(w_o) + g(w_o) = c\alpha(f) + \alpha(g)$ for all $f, g \in V$ and $c \in \mathbb{R}$. We find that the **evaluation** map defines a dual-vector $\alpha \in V^*$.

Example 9.1.4. The determinant is a mapping from $\mathbb{R}^{n \times n}$ to \mathbb{R} but it does not define a dual-vector to the vector space of square matrices since $det(A + B) \neq det(A) + det(B)$.

Example 9.1.5. Suppose $\alpha(x) = x \cdot v$ for a particular vector $v \in \mathbb{R}^n$. We argue $\alpha \in V^*$ where we recall $V = \mathbb{R}^n$ is a vector space. Additivity follows from a property of the dot-product on \mathbb{R}^n ,

$$\alpha(x+y) = (x+y) \cdot v = x \cdot v + y \cdot v = \alpha(x) + \alpha(y)$$

for all $x, y \in \mathbb{R}^n$. Likewise, homogeneity follows from another property of the dot-product: observe

$$\alpha(cx) = (cx) \cdot v = c(x \cdot v) = c\alpha(x)$$

for all $x \in \mathbb{R}^n$ and $c \in \mathbb{R}$.

Example 9.1.6. Let $\alpha(x,y) = 2x + 5y$ define a function $\alpha : \mathbb{R}^2 \to \mathbb{R}$. Note that

$$\alpha(x,y) = (x,y) \cdot (2,5)$$

hence by the preceding example we find $\alpha \in (\mathbb{R}^2)^*$.

The preceding example is no accident. It turns out there is a one-one correspondence between row vectors and dual vectors on \mathbb{R}^n . Let $v \in \mathbb{R}^n$ then we define $\alpha_v(x) = x \cdot v$. We proved in Example 9.1.5 that $\alpha_v \in (\mathbb{R}^n)^*$. Suppose $\alpha \in (\mathbb{R}^n)^*$ we see to find $v \in \mathbb{R}^n$ such that $\alpha = \alpha_v$. Recall that a linear function is uniquely defined by its values on a basis; the values of α on the standard basis will show us how to choose v. This is a standard technique. Consider: $v \in \mathbb{R}^n$ with $v = \sum_{i=1}^n v^i e_i$

$$\alpha(x) = \underbrace{\alpha(\sum_{j=1}^{n} x^{j}e_{j}) = \sum_{j=1}^{n} \alpha(x^{j}e_{j}) = \sum_{j=1}^{n} x^{j}\alpha(e_{j})}_{additivity} = x \cdot v$$

where we define $v = (\alpha(e_1), \alpha(e_2), \ldots, \alpha(e_n)) \in \mathbb{R}^n$. The vector which corresponds naturally² to α is simply the vector of the values of α on the standard basis.

¹the super-index is not a power in this context, it is just a notation to emphasize v^{j} is the component of a vector.

²some authors will say $\mathbb{R}^{n \times 1}$ is dual to $\mathbb{R}^{1 \times n}$ since $\alpha_v(x) = v^T x$ and v^T is a row vector, I will avoid that langauge in these notes.

The dual space to \mathbb{R}^n is a vector space and the correspondance $v \to \alpha_v$ gives an isomorphism of \mathbb{R}^n and $(\mathbb{R}^n)^*$. The image of a basis under an isomorphism is once more a basis. Define $\Phi : \mathbb{R}^n \to (\mathbb{R})^*$ by $\Phi(v) = \alpha_v$ to give the correspondance an explicit label. The image of the standard basis under Φ is called the **standard dual basis** for $(\mathbb{R}^n)^*$. Consider $\Phi(e_i)$, let $x \in \mathbb{R}^n$ and calculate

$$\Phi(e_j)(x) = \alpha_{e_j}(x) = x \cdot e_j$$

In particular, notice that when $x = e_i$ then $\Phi(e_j)(e_i) = e_i \cdot e_j = \delta_{ij}$. Dual vectors are linear transformations therefore we can define the dual basis by its values on the standard basis.

Definition 9.1.7.

The standard dual basis of $(\mathbb{R}^n)^*$ is denoted $\{e^1, e^2, \ldots, e^n\}$ where we define $e^j : \mathbb{R}^n \to \mathbb{R}$ to be the linear transformation such that $e^j(e_i) = \delta_{ij}$ for all $i, j \in \mathbb{N}_n$. Generally, given a vector space V with basis $\beta = \{f_1, f_2, \ldots, f_m\}$ we say the basis $\beta^* = \{f^1, f^2, \ldots, f^n\}$ is dual to β iff $f^j(f_i) = \delta_{ij}$ for all $i, j \in \mathbb{N}_n$.

The term *basis* indicates that $\{e^1, e^2, \ldots, e^n\}$ is linearly independent³ and $span\{e^1, e^2, \ldots, e^n\} = (\mathbb{R}^n)^*$. The following calculation is often useful: if $x \in \mathbb{R}^n$ with $x = \sum_{j=1}^n x^j e_j$ then

$$e^{i}(x) = e^{i}\left(\sum_{j=1}^{n} x^{j} e_{j}\right) = \sum_{j=1}^{n} x^{j} e^{i}(e_{j}) = \sum_{j=1}^{n} x^{j} \delta_{ij} = x^{i} \quad \Rightarrow \quad \boxed{e^{i}(x) = x^{i}}.$$

The calculation above is a prototype for many that follow in this chapter. Next, suppose $\alpha \in (\mathbb{R}^n)^*$ and suppose $x \in \mathbb{R}^n$ with $x = \sum_{j=1}^n x^j e_j$. Calculate,

$$\alpha(x) = \alpha\left(\sum_{i=1}^{n} x^{i} e_{i}\right) = \sum_{i=1}^{n} \alpha(e_{i}) e^{i}(x) \quad \Rightarrow \quad \left| \alpha = \sum_{i=1}^{n} \alpha(e_{i}) e^{i} \right|$$

this shows every dual vector is in the span of the dual basis $\{e^{j}\}_{j=1}^{n}$.

9.2 multilinearity and the tensor product

A multilinear mapping is a function of a Cartesian product of vector spaces which is linear with respect to each "slot". The goal of this section is to explain what that means. It turns out the set of all multilinear mappings on a particular set of vector spaces forms a vector space and we'll show how the tensor product can be used to construct an explicit basis by tensoring a bases which are dual to the bases in the domain. We also examine the concepts of symmetric and antisymmetric multilinear mappings, these form interesting subspaces of the set of all multilinear mappings. Our approach in this section is to treat the case of bilinearity in depth then transition to the case of multilinearity. Naturally this whole discussion demands a familarity with the preceding section.

³direct proof of LI is left to the reader

9.2.1 bilinear maps

Definition 9.2.1.

Suppose V_1, V_2 are vector spaces then $b: V_1 \times V_2 \to \mathbb{R}$ is a **binear mapping** on $V_1 \times V_2$ iff for all $x, y \in V_1, z, w \in V_2$ and $c \in \mathbb{R}$: (1.) b(cx + y, z) = cb(x, z) + b(y, z) (linearity in the first slot) (2.) b(x, cz + w) = cb(x, z) + b(x, w) (linearity in the second slot).

bilinear maps on $V \times V$

When $V_1 = V_2 = V$ we simply say that $b: V \times V \to \mathbb{R}$ is a **bilinear mapping on** V. The **set of all bilinear maps of** V **is denoted** $T_0^2 V$. You can show that $T_0^2 V$ forms a vector space under the usual point-wise defined operations of function addition and scalar multiplication⁴. Hopefully you are familar with the example below.

Example 9.2.2. Define $b : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$ by $b(x, y) = x \cdot y$ for all $x, y \in \mathbb{R}^n$. Linearity in each slot follows easily from properties of dot-products:

$$b(cx + y, z) = (cx + y) \cdot z = cx \cdot z + y \cdot z = cb(x, z) + b(y, z)$$
$$b(x, cy + z) = x \cdot (cy + z) = cx \cdot y + x \cdot z = cb(x, y) + b(x, z).$$

We can use matrix multiplication to generate a large class of examples with ease.

Example 9.2.3. Suppose $A \in \mathbb{R}^{n \times n}$ and define $b : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$ by $b(x, y) = x^T A y$ for all $x, y \in \mathbb{R}^n$. Observe that, by properties of matrix multiplication,

$$b(cx + y, z) = (cx + y)^T A z = (cx^T + y^T) A z = cx^T A z + y^T A z = cb(x, z) + b(y, z)$$
$$b(x, cy + z) = x^T A (cy + z) = cx^T A y + x^T A z = cb(x, y) + b(x, z)$$

for all $x, y, z \in \mathbb{R}^n$ and $c \in \mathbb{R}$. It follows that b is bilinear on \mathbb{R}^n .

Suppose $b: V \times V \to \mathbb{R}$ is bilinear and suppose $\beta = \{e_1, e_2, \dots, e_n\}$ is a basis for V whereas

⁴sounds like homework

 $\beta^* = \{e^1, e^2, \dots, e^n\}$ is a basis of V^* with $e^j(e_i) = \delta_{ij}$

$$b(x,y) = b\left(\sum_{i=1}^{n} x^{i}e_{i}, \sum_{j=1}^{n} y^{j}e_{j}\right)$$

$$= \sum_{i,j=1}^{n} b(x^{i}e_{i}, y^{j}e_{j})$$

$$= \sum_{i,j=1}^{n} x^{i}y^{j}b(e_{i}, e_{j})$$

$$= \sum_{i,j=1}^{n} b(e_{i}, e_{j})e^{i}(x)^{j}(y)$$
(9.1)
(9.1)

Therefore, if we define $b_{ij} = b(e_i, e_j)$ then we may compute $b(x, y) = \sum_{i,j=1}^n b_{ij} x^i y^j$. The calculation above also indicates that b is a linear combination of certain basic bilinear mappings. In particular, b can be written a linear combination of a tensor product of dual vectors on V.

Definition 9.2.4.

Suppose V is a vector space with dual space V^* . If $\alpha, \beta \in V^*$ then we define $\alpha \otimes \beta : V \times V \to \mathbb{R}$ by $(\alpha \otimes \beta)(x, y) = \alpha(x)\beta(y)$ for all $x, y \in V$.

Given the notation⁵ preceding this definition, we note $(e^i \otimes e^j)(x,y) = e^i(x)e^j(y)$ hence for all $x, y \in V$ we find:

$$b(x,y) = \sum_{i,j=1}^{n} b(e_i, e_j)(e^i \otimes e^j)(x,y) \text{ therefore, } \left| b = \sum_{i,j=1}^{n} b(e_i, e_j)e^i \otimes e^j \right|$$

We find⁶ that $T_0^2 V = span\{e^i \otimes e^j\}_{i,j=1}^n$. Moreover, it can be argued⁷ that $\{e^i \otimes e^j\}_{i,j=1}^n$ is a linearly independent set, therefore $\{e^i \otimes e^j\}_{i,j=1}^n$ forms a basis for $T_0^2 V$. We can count there are n^2 vectors in $\{e^i \otimes e^j\}_{i,j=1}^n$ hence $dim(T_0^2 V) = n^2$.

If $V = \mathbb{R}^n$ and if $\{e^i\}_{i=1}^n$ denotes the standard dual basis, then there is a standard notation for the set of coefficients found in the summation for b. In particular, we denote B = [b] where $B_{ij} = b(e_i, e_j)$ hence, following Equation 9.1,

$$b(x,y) = \sum_{i,j=1}^{n} x^{i} y^{j} b(e_{i}, e_{j}) = \sum_{i=1}^{n} \sum_{j=1}^{n} x^{i} B_{ij} y^{j} = x^{T} B y$$

⁵perhaps you would rather write $(e^i \otimes e^j)(x, y)$ as $e^i \otimes e^j(x, y)$, that is also fine.

⁶ with the help of your homework where you will show $\{e^i \otimes e^j\}_{i,j=1}^n \subseteq T_0^2 V$

⁷yes, again, in your homework

Definition 9.2.5.

Suppose $b: V \times V \to \mathbb{R}$ is a bilinear mapping then we say:

- 1. b is symmetric iff b(x, y) = b(y, x) for all $x, y \in V$
- 2. *b* is **antisymmetric** iff b(x, y) = -b(y, x) for all $x, y \in V$

Any bilinear mapping on V can be written as the sum of a symmetric and antisymmetric bilinear mapping, this claim follows easily from the calculation below:

$$b(x,y) = \underbrace{\frac{1}{2} \left(b(x,y) + b(y,x) \right)}_{symmetric} + \underbrace{\frac{1}{2} \left(b(x,y) - b(y,x) \right)}_{antisymmetric}.$$

We say S_{ij} is **symmetric** in i, j iff $S_{ij} = S_{ji}$ for all i, j. Likewise, we say A_{ij} is **antisymmetric** in i, j iff $A_{ij} = -A_{ji}$ for all i, j. If S is a symmetric bilinear mapping and A is an antisymmetric bilinear mapping then the components of S are symmetric and the components of A are antisymmetric. Why? Simply note:

$$S(e_i, e_j) = S(e_j, e_i) \quad \Rightarrow \quad S_{ij} = S_{ji}$$

and

$$A(e_i, e_j) = -A(e_j, e_i) \quad \Rightarrow \quad A_{ij} = -A_{ji}.$$

You can prove that the sum or scalar multiple of an (anti)symmetric bilinear mapping is once more (anti)symmetric therefore the set of antisymmetric bilinear maps $\Lambda^2(V)$ and the set of symmetric bilinear maps ST_2^0V are subspaces of T_2^0V . The notation $\Lambda^2(V)$ is part of a larger discussion on the wedge product, we will return to it in a later section.

Finally, if we consider the special case of $V = \mathbb{R}^n$ once more we find that a bilinear mapping $b : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$ has a symmetric matrix $[b]^T = [b]$ iff b is symmetric whereas it has an antisymmetric matric $[b]^T = -[b]$ iff b is antisymmetric.

bilinear maps on $V^* \times V^*$

Suppose $h: V^* \times V^* \to \mathbb{R}$ is bilinear then we say $h \in T_0^2 V$. In addition, suppose $\beta = \{e_1, e_2, \ldots, e_n\}$ is a basis for V whereas $\beta^* = \{e^1, e^2, \ldots, e^n\}$ is a basis of V^* with $e^j(e_i) = \delta_{ij}$. Let $\alpha, \beta \in V^*$

$$h(\alpha, \beta) = h\left(\sum_{i=1}^{n} \alpha_i e^i, \sum_{j=1}^{n} \beta_j e^j\right)$$

$$= \sum_{i,j=1}^{n} h(\alpha_i e^i, \beta_j e^j)$$

$$= \sum_{i,j=1}^{n} \alpha_i \beta_j h(e^i, e^j)$$

$$= \sum_{i,j=1}^{n} h(e^i, e^j) \alpha(e_i) \beta(e_j)$$
(9.2)

Therefore, if we define $h^{ij} = h(e^i, e^j)$ then we find the nice formula $h(\alpha, \beta) = \sum_{i,j=1}^n h^{ij} \alpha_i \beta_j$. To further refine the formula above we need a new concept.

The dual of the dual is called the double-dual and it is denoted V^{**} . For a finite dimensional vector space there is a cannonical isomorphism of V and V^{**} . In particular, $\Phi : V \to V^{**}$ is defined by $\Phi(v)(\alpha) = \alpha(v)$ for all $\alpha \in V^*$. It is customary to replace V with V^{**} wherever the context allows. For example, to define the tensor product of two vectors $x, y \in V$ as follows:

Definition 9.2.6.

Suppose V is a vector space with dual space V^* . We define the tensor product of vectors x, y as the mapping $x \otimes y : V^* \times V^* \to \mathbb{R}$ by $(x \otimes y)(\alpha, \beta) = \alpha(x)\beta(y)$ for all $x, y \in V$.

We could just as well have defined $x \otimes y = \Phi(x) \otimes \Phi(y)$ where Φ is once more the canonical isomorphism of V and V^{**} . It's called *canonical* because it has no particular dependendence on the coordinates used on V. In contrast, the isomorphism of \mathbb{R}^n and $(\mathbb{R}^n)^*$ was built around the dot-product and the standard basis.

All of this said, note that $\alpha(e_i)\beta(e_j) = e_i \otimes e_j(\alpha, \beta)$ thus,

$$h(\alpha,\beta) = \sum_{i,j=1}^{n} h(e^{i},e^{j})e_{i} \otimes e_{j}(\alpha,\beta) \quad \Rightarrow \quad \left| h = \sum_{i,j=1}^{n} h(e^{i},e^{j})e_{i} \otimes e_{j} \right|$$

We argue that $\{e_i \otimes e_j\}_{i,j=1}^n$ is a basis⁸

Definition 9.2.7.

 $\overline{{}^{8}T_{0}^{2}V}$ is a vector space and we've shown $\overline{T_{0}^{2}}(V) \subseteq span\{e_{i} \otimes e_{j}\}_{i,j=1}^{n}$ but we should also show $e_{i} \otimes e_{j} \in T_{0}^{2}$ and check for LI of $\{e_{i} \otimes e_{j}\}_{i,j=1}^{n}$.

The discussion of the preceding subsection transfers to this context, we simply have to switch some vectors to dual vectors and move some indices up or down. I leave this to the reader.

bilinear maps on $V \times V^*$

Suppose $H: V \times V^* \to \mathbb{R}$ is bilinear, we say $H \in T_1^1 V$ (or, if the context demands this detail $H \in T_1^{-1} V$). We define $\alpha \otimes x \in T_1^{-1} (V)$ by the natural rule; $(\alpha \otimes x)(y,\beta) = \alpha(x)\beta(x)$ for all $(y,\beta) \in V \times V^*$. We find, by calculations similar to those already given in this section,

$$H(y,\beta) = \sum_{i,j=1}^{n} H_i^{-j} y^i \beta_j \quad \text{and} \quad H = \sum_{i,j=1}^{n} H_i^{-j} e^i \otimes e_j$$

where we defined $H_i^{\ j} = H(e_i, e^j)$.

bilinear maps on $V^* \times V$

Suppose $G: V^* \times V \to \mathbb{R}$ is bilinear, we say $G \in T_1^1 V$ (or, if the context demands this detail $G \in T_1^1 V$). We define $x \otimes \alpha \in T_1^1 V$ by the natural rule; $(x \otimes \alpha)(\beta, y) = \beta(x)\alpha(y)$ for all $(\beta, y) \in V^* \times V$. We find, by calculations similar to those already given in this section,

$$G(\beta, y) = \sum_{i,j=1}^{n} G^{i}_{\ j} \beta_{i} y^{j} \quad \text{and} \quad G = \sum_{i,j=1}^{n} G^{i}_{\ j} e_{i} \otimes e^{j}$$

where we defined $G^{i}_{j} = G(e^{i}, e_{j}).$

9.2.2 trilinear maps

Definition 9.2.8.

Suppose V_1, V_2, V_3 are vector spaces then $T: V_1 \times V_2 \times V_3 \to \mathbb{R}$ is a **trilinear mapping** on $V_1 \times V_2 \times V_3$ iff for all $u, v \in V_1, w, x \in V_2$. $y, z \in V_3$ and $c \in \mathbb{R}$: (1.) T(cu + v, w, y) = cT(u, w, y) + T(v, w, y) (linearity in the first slot) (2.) T(u, cw + x, y) = cT(u, w, y) + T(u, x, y) (linearity in the second slot).

(3.)
$$T(u, w, cy + z) = cT(u, w, y) + T(u, w, z)$$
 (linearity in the third slot).

If $T: V \times V \times V \to \mathbb{R}$ is trilinear on $V \times V \times V$ then we say T is a trilinear mapping on V and we denote the set of all such mappings $T_3^0 V$. The tensor product of three dual vectors is defined much in the same way as it was for two,

$$(\alpha \otimes \beta \otimes \gamma)(x, y, z) = \alpha(x)\beta(y)\gamma(z)$$

Let $\{e_i\}_{i=1}^n$ is a basis for V with dual basis $\{e^i\}_{i=1}^n$ for V^{*}. If T is trilinear on V it follows

$$T(x, y, z) = \sum_{i,j,k=1}^{n} T_{ijk} x^{i} y^{j} z^{k} \quad \text{and} \quad T = \sum_{i,j,k=1}^{n} T_{ijk} e^{i} \otimes e^{j} \otimes e^{k}$$

where we defined $T_{ijk} = T(e_i, e_j, e_k)$ for all $i, j, k \in \mathbb{N}_n$.

Generally suppose that V_1, V_2, V_3 are possibly distinct vector spaces. Moreover, suppose V_1 has basis $\{e_i\}_{i=1}^{n_1}$, V_2 has basis $\{f_j\}_{j=1}^{n_2}$ and V_3 has basis $\{g_k\}_{k=1}^{n_3}$. Denote the dual bases for V_1^*, V_2^*, V_3^* in the usual fashion: $\{e^i\}_{i=1}^{n_1}, \{f^j\}_{j=1}^{n_1}, \{g^k\}_{k=1}^{n_1}$. With this notation, we can write a trilinear mapping on $V_1 \times V_2 \times V_3$ as follows: (where we define $T_{ijk} = T(e_i, f_j, g_k)$)

$$T(x,y,z) = \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \sum_{k=1}^{n_3} T_{ijk} x^i y^j z^k \quad \text{and} \quad T = \sum_{i=1}^{n_1} \sum_{j=1}^{n_2} \sum_{k=1}^{n_3} T_{ijk} e^i \otimes f^j \otimes g^k$$

However, if V_1, V_2, V_3 happen to be related by duality then it is customary to use up/down indices. For example, if $T: V \times V \times V^* \to \mathbb{R}$ is trilinear then we write⁹

$$T = \sum_{i,j,k=1}^{n} T_{ij}^{\ k} e^{i} \otimes e^{j} \otimes e_{k}$$

and say $T \in T_2^{-1}V$. On the other hand, if $S: V^* \times V^* \times V$ is trilinear then we'd write

$$T = \sum_{i,j,k=1}^{n} S^{ij}{}_{k} e_{i} \otimes e_{j} \otimes e^{k}$$

and say $T \in T_1^2 V$. I'm not sure that I've ever seen this notation elsewhere, but perhaps it could be useful to denote the set of trinlinear maps $T: V \times V^* \times V \to \mathbb{R}$ as $T_1^{1} V$. Hopefully we will not need such silly notation in what we consider this semester.

There was a natural correspondence between bilinear maps on \mathbb{R}^n and square matrices. For a trilinear map we would need a three-dimensional array of components. In some sense you could picture $T : \mathbb{R}^n \times \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$ as multiplication by a cube of numbers. Don't think too hard about these silly comments, we actually already wrote the useful formulae for dealing with trilinear objects. Let's stop to look at an example.

⁹we identify e_k with its double-dual hence this tensor product is already defined, but to be safe let me write it out in this context $e^i \otimes e^j \otimes e_k(x, y, \alpha) = e^i(x)e^j(y)\alpha(e_k)$.

Example 9.2.9. Define $T : \mathbb{R}^3 \times \mathbb{R}^3 \times \mathbb{R}^3 \to \mathbb{R}$ by T(x, y, z) = det(x|y|z). You may not have learned this in your linear algebra course¹⁰ but a nice formula¹¹ for the determinant is given by the Levi-Civita symbol,

$$det(A) = \sum_{i,j,k=1}^{3} \epsilon_{ijk} A_{i1} A_{j2} A_{k3}$$

note that $col_1(A) = [A_{i1}], col_2(A) = [A_{i2}]$ and $col_3(A) = [A_{i3}]$. It follows that

$$T(x, y, z) = \sum_{i, j, k=1}^{3} \epsilon_{ijk} x^{i} y^{j} z^{k}$$

Multilinearity follows easily from this formula. For example, linearity in the third slot:

$$T(x, y, cz + w) = \sum_{i,j,k=1}^{3} \epsilon_{ijk} x^{i} y^{j} (cz + w)^{k}$$
(9.3)

$$=\sum_{i,j,k=1}^{3} \epsilon_{ijk} x^{i} y^{j} (cz^{k} + w^{k})$$
(9.4)

$$= c \sum_{i,j,k=1}^{3} \epsilon_{ijk} x^{i} y^{j} z^{k} + \sum_{i,j,k=1}^{3} \epsilon_{ijk} x^{i} y^{j} w^{k}$$
(9.5)

$$= cT(x, y, z) + T(x, y, w).$$
(9.6)

Observe that by properties of determinants, or the Levi-Civita symbol if you prefer, swapping a pair of inputs generates a minus sign, hence:

$$T(x, y, z) = -T(y, x, z) = T(y, z, x) = -T(z, y, x) = T(z, x, y) = -T(x, z, y).$$

If $T: V \times V \times V \to \mathbb{R}$ is a trilinear mapping such that

$$T(x, y, z) = -T(y, x, z) = T(y, z, x) = -T(z, y, x) = T(z, x, y) = -T(x, z, y)$$

for all $x, y, z \in V$ then we say T is antisymmetric. Likewise, if $S: V \times V \times V \to \mathbb{R}$ is a trilinear mapping such that

$$S(x,y,z) = -S(y,x,z) = S(y,z,x) = -S(z,y,x) = S(z,x,y) = -S(x,z,y).$$

for all $x, y, z \in V$ then we say T is symmetric. Clearly the mapping defined by the determinant is antisymmetric. In fact, many authors define the determinant of an $n \times n$ matrix as the antisymmetric *n*-linear mapping which sends the identity matrix to 1. It turns out these criteria unquely

¹⁰maybe you haven't even taken linear yet!

¹¹actually, I take this as the definition in linear algebra, it does take considerable effort to recover the expansion by minors formula which I use for concrete examples

define the determinant. That is the motivation behind my Levi-Civita symbol definition. That formula is just the nuts and bolts of complete antisymmetry.

You might wonder, can every trilinear mapping can be written as a the sum of a symmetric and antisymmetric mapping? The answer is no. Consider $T: V \times V \times V \to \mathbb{R}$ defined by $T = e^1 \otimes e^2 \otimes e^3$. Is it possible to find constants a, b such that:

$$e^1 \otimes e^2 \otimes e^3 = ae^{[1} \otimes e^2 \otimes e^{3]} + be^{(1} \otimes e^2 \otimes e^{3)}$$

where $[\ldots]$ denotes complete antisymmetrization of 1, 2, 3 and (\ldots) complete symmetrization:

$$e^{[1} \otimes e^2 \otimes e^{3]} = \frac{1}{6} \left[e^{123} + e^{231} + e^{312} - e^{321} - e^{213} - e^{132} \right]$$

For the symmetrization we also have to include all possible permutations of (1, 2, 3) but all with +:

$$e^{(1} \otimes e^2 \otimes e^{3)} = \frac{1}{6} \left[e^{123} + e^{231} + e^{312} + e^{321} + e^{213} + e^{132} \right]$$

As you can see:

$$ae^{[1} \otimes e^{2} \otimes e^{3]} + be^{(1} \otimes e^{2} \otimes e^{3)} = \frac{a+b}{6}(e^{123} + e^{231} + e^{312}) + \frac{b-a}{6}(e^{321} + e^{213} + e^{132})$$

There is no way for these to give back only $e^1 \otimes e^2 \otimes e^3$. I leave it to the reader to fill the gaps in this argument. Generally, the decomposition of a multilinear mapping into more basic types is a problem which requires much more thought than we intend here. Representation theory does address this problem: how can we decompose a tensor product into irreducible pieces. Their idea of tensor product is not precisely the same as ours, however algebraically the problems are quite intertwined. I'll leave it at that unless you'd like to do an independent study on representation theory. Ideally you'd already have linear algebra and abstract algebra complete before you attempt that study.

9.2.3 multilinear maps

Definition 9.2.10.

Suppose V_1, V_2, \ldots, V_k are vector spaces then $T: V_1 \times V_2 \times \cdots \times V_k \to \mathbb{R}$ is a *k*-multilinear mapping on $V_1 \times V_2 \times \cdots \times V_k$ iff for each $c \in \mathbb{R}$ and $x_1, y_1 \in V_1, x_2, y_2 \in V_2, \ldots, x_k, y_k \in V_k$

$$T(x_1, \ldots, cx_j + y_j, \ldots, x_k) = cT(x_1, \ldots, x_j, \ldots, x_k) + T(x_1, \ldots, y_j, \ldots, x_k)$$

for j = 1, 2, ..., k. In other words, we assume T is linear in each of its k-slots. If T is multilinear on $V^r \times (V^*)^s$ then we say that $T \in T_r^s V$ and we say T is a type (r, s) tensor on V.

The definition above makes a dual vector a type (1,0) tensor whereas a double dual of a vector a type (0,1) tensor, a bilinear mapping on V is a type (2,0) tensor and a bilinear mapping on V^{*} is

a type (0,2) tensor with respect to V.

We are free to define tensor products in this context in the same manner as we have previously. Suppose $\alpha_1 \in V_1^*, \alpha_2 \in V_2^*, \ldots, \alpha_k \in V_k^*$ and $v_1 \in V_1, v_2 \in V_2, \ldots, v_k \in V_k$ then

$$\alpha_1 \otimes \alpha_2 \otimes \cdots \otimes \alpha_k(v_1, v_2, \dots, v_k) = \alpha_1(v_1)\alpha_2(v_2) \cdots \alpha_k(v_k)$$

It is easy to show the tensor produce of k-dual vectors as defined above is indeed a k-multilinear mapping. Moreover, the set of all k-multilinear mappings on $V_1 \times V_2 \times \cdots \times V_k$ clearly forms a vector space of dimension $dim(V_1)dim(V_2)\cdots dim(V_k)$ since it naturally takes the tensor product of the dual bases for $V_1^*, V_2^*, \ldots, V_k^*$ as its basis. In particular, suppose for $j = 1, 2, \ldots, k$ that V_j has basis $\{E_{ji}\}_{i=1}^{n_j}$ which is dual to $\{E_j^i\}_{i=1}^{n_j}$ the basis for V_j^* . Then we can derive that a k-multilinear mapping can be written as

$$T = \sum_{i_1=1}^{n_1} \sum_{i_2=1}^{n_2} \cdots \sum_{i_k=1}^{n_k} T_{i_1 i_2 \dots i_k} E_1^{i_1} \otimes E_2^{i_2} \otimes E_k^{i_k}$$

If T is a type (r, s) tensor on V then there is no need for the ugly double indexing on the basis since we need only tensor a basis $\{e_i\}_{i=1}^n$ for V and its dual $\{e^i\}_{i=1}^n$ for V^{*} in what follows:

$$T = \sum_{i_1,\dots,i_r=1}^n \sum_{j_1,\dots,j_s=1}^n T^{j_1j_2\dots j_s}_{i_1i_2\dots i_r} e^{i_1} \otimes e^{i_2} \otimes \dots \otimes e^{i_r} \otimes e_{j_1} \otimes e_{j_2} \otimes \dots \otimes e_{j_s}.$$

permutations

Before I define symmetric and antisymmetric for k-linear mappings on V I think it is best to discuss briefly some ideas from the theory of permutations.

Definition 9.2.11.

A permutation on $\{1, 2, \ldots p\}$ is a bijection on $\{1, 2, \ldots p\}$. We define the set of permutations on $\{1, 2, \ldots p\}$ to be Σ_p . Further, define the sign of a permutation to be $sgn(\sigma) = 1$ if σ is the product of an even number of transpositions whereas $sgn(\sigma) = -1$ if σ is the product of a odd number transpositions.

Let us consider the set of permutations on $\{1, 2, 3, ..., n\}$, this is called S_n the symmetric group, its order is n! if you were wondering. Let me remind¹² you how the cycle notation works since it allows us to explicitly present the number of transpositions contained in a permutation,

$$\sigma = \begin{pmatrix} 1 & 2 & 3 & 4 & 5 & 6 \\ 2 & 1 & 5 & 4 & 6 & 3 \end{pmatrix} \quad \Longleftrightarrow \quad \sigma = (12)(356) = (12)(36)(35) \tag{9.7}$$

recall the cycle notation is to be read right to left. If we think about inputing 5 we can read from the matrix notation that we ought to find $5 \mapsto 6$. Clearly that is the case for the first version of

¹²or perhaps, more likely, introduce you to this notation

 σ written in cycle notation; (356) indicates that $5 \mapsto 6$ and nothing else messes with 6 after that. Then consider feeding 5 into the version of σ written with just two-cycles (a.k.a. transpositions), first we note (35) indicates $5 \mapsto 3$, then that 3 hits (36) which means $3 \mapsto 6$, finally the cycle (12) doesn't care about 6 so we again have that $\sigma(5) = 6$. Finally we note that $sgn(\sigma) = -1$ since it is made of 3 transpositions.

It is always possible to write any permutation as a product of transpositions, such a decomposition is not unique. However, if the number of transpositions is even then it will remain so no matter how we rewrite the permutation. Likewise if the permutation is an product of an odd number of transpositions then any other decomposition into transpositions is also comprised of an odd number of transpositions. This is why we can **define** an **even** permutation is a permutation comprised by an even number of transpositions and an **odd** permutation is one comprised of an odd number of transpositions.

Example 9.2.12. Sample cycle calculations: we rewrite as product of transpositions to determin if the given permutation is even or odd,

$$\begin{aligned} \sigma &= (12)(134)(152) = (12)(14)(13)(12)(15) \implies sgn(\sigma) = -1 \\ \lambda &= (1243)(3521) = (13)(14)(12)(31)(32)(35) \implies sgn(\lambda) = 1 \\ \gamma &= (123)(45678) = (13)(12)(48)(47)(46)(45) \implies sgn(\gamma) = 1 \end{aligned}$$

We will not actually write down permutations in the calculations the follow this part of the notes. I merely include this material as to give a logically complete account of antisymmetry. In practice, if you understood the terms as the apply to the bilinear and trilinear case it will usually suffice for concrete examples. Now we are ready to define symmetric and antisymmetric.

Definition 9.2.13.

A k-linear mapping
$$L: V \times V \times \cdots \times V \to \mathbb{R}$$
 is completely symmetric if
 $L(x_1, \dots, x, \dots, y, \dots, x_k) = L(x_1, \dots, y, \dots, x, \dots, x_k)$

for all possible $x, y \in V$. Conversely, if a k-linear mapping on V has

$$L(x_1,\ldots,x,\ldots,y,\ldots,x_p) = -L(x_1,\ldots,y,\ldots,x,\ldots,x_p)$$

for all possible pairs $x, y \in V$ then it is said to be **completely antisymmetric or alternating**. Equivalently a k-linear mapping L is alternating if for all $\pi \in \Sigma_k$

$$L(x_{\pi_1}, x_{\pi_2}, \dots, x_{\pi_k}) = sgn(\pi)L(x_1, x_2, \dots, x_k)$$

The set of alternating multilinear mappings on V is denoted ΛV , the set of k-linear alternating maps on V is denoted $\Lambda^k V$. Often an alternating k-linear map is called a k-form. Moreover, we say the **degree** of a k-form is k. Similar terminology applies to the components of tensors. We say $T_{i_1i_2...i_k}$ is completely symmetric in $i_1, i_2, ..., i_k$ iff $T_{i_1i_2...i_k} = T_{i_{\sigma(1)}i_{\sigma(2)}...i_{\sigma(k)}}$ for all $\sigma \in \Sigma_k$. On the other hand, $T_{i_1i_2...i_k}$ is completely antisymmetric in $i_1, i_2, ..., i_k$ iff $T_{i_1i_2...i_k} = sgn(\sigma)T_{i_{\sigma(1)}i_{\sigma(2)}...i_{\sigma(k)}}$ for all $\sigma \in \Sigma_k$. It is a simple exercise to show that a completely (anti)symmetric tensor¹³ has completely (anti)symmetric components.

The tensor product is an interesting construction to discuss at length. To summarize, it is associative and distributive across addition. Scalars factor out and it is not generally commutative. For a given vector space V we can in principle generate by tensor products multilinear mappings of arbitrarily high order. This tensor algebra is infinite dimensional. In contrast, the space ΛV of forms on V is a finite-dimensional subspace of the tensor algebra. We discuss this next.

9.3 wedge product

We assume V is a vector space with basis $\{e_i\}_{i=1}^n$ throughout this section. The dual basis is denoted $\{e^i\}_{i=1}^n$ as is our usual custom. Our goal is to find a basis for the alternating maps on V and explore the structure implicit within its construction. This will lead us to call ΛV the **exterior algebra** of V after the discussion below is complete.

9.3.1 wedge product of dual basis generates basis for ΛV

Suppose $b: V \times V \to \mathbb{R}$ is antisymmetric and $b = \sum_{i,j=1}^{n} b_{ij} e^i \otimes e^j$, it follows that $b_{ij} = -b_{ji}$ for all $i, j \in \mathbb{N}_n$. Notice this implies that $b_{ii} = 0$ for i = 1, 2, ..., n. For a given pair of indices i, j either i < j or j < i or i = j hence,

$$b = \sum_{i < j} b_{ij} e^i \otimes e^j + \sum_{j < i} b_{ij} e^i \otimes e^j + \sum_{i = j} b_{ij} e^i \otimes e^j$$

$$= \sum_{i < j} b_{ij} e^i \otimes e^j + \sum_{j < i} b_{ij} e^i \otimes e^j$$

$$= \sum_{i < j} b_{ij} e^i \otimes e^j - \sum_{j < i} b_{ji} e^i \otimes e^j$$

$$= \sum_{k < l} b_{kl} e^k \otimes e^l - \sum_{k < l} b_{kl} e^l \otimes e^k$$

$$= \sum_{k < l} b_{kl} (e^k \otimes e^l - e^l \otimes e^k).$$
(9.8)

Therefore, $\{e^k \otimes e^l - e^l \otimes e^k | l, k \in \mathbb{N}_n \text{ and } l < k\}$ spans the set of antisymmetric bilinear maps on V. Moreover, you can show this set is linearly independent hence it is a basis fo $\Lambda^2 V$. We define

¹³in this context a tensor is simply a multilinear mapping, in physics there is more attached to the term

the wedge product of $e^k \wedge e^l = e^k \otimes e^l - e^l \otimes e^k$. With this notation we find that the alternating bilinear form b can be written as

$$b = \sum_{k < l} b_{kl} e^k \wedge e^l = \sum_{i,j=1}^n \frac{1}{2} b_{ij} e^i \wedge e^j$$

where the summation on the r.h.s. is over all indices¹⁴. Notice that $e^i \wedge e^j$ is an antisymmetric bilinear mapping because $e^i \wedge e^j(x,y) = -e^i \wedge e^j(y,x)$, however, there is more structure here than just that. It is also true that $e^i \wedge e^j = -e^j \wedge e^i$. This is a conceptually different antisymmetry, it is the antisymmetry of the wedge produce \wedge .

Suppose $b: V \times V \times V \to \mathbb{R}$ is antisymmetric and $b = \sum_{i,j,k=1}^{n} b_{ijk} e^i \otimes e^j \otimes e^k$, it follows that $b_{ijk} = b_{jki} = b_{kij}$ and $b_{ijk} = -b_{kji} = -b_{jik} = b_{ikj}$ for all $i, j, k \in \mathbb{N}_n$. Notice this implies that $b_{iii} = 0$ for i = 1, 2, ..., n. A calculation similar to the one just offered for the case of a bilinear map reveals that we can write b as follows:

$$b = \sum_{i < j < k} b_{ijk} \left(e^i \otimes e^j \otimes e^k + e^j \otimes e^k \otimes e^i + e^k \otimes e^i \otimes e^j - e^k \otimes e^j \otimes e^i - e^j \otimes e^i \otimes e^k - e^i \otimes e^k \otimes e^j \right)$$
(9.9)

Define $e^i \wedge e^j \wedge e^k = e^i \otimes e^j \otimes e^k + e^j \otimes e^k \otimes e^i + e^k \otimes e^j \otimes e^j - e^k \otimes e^j \otimes e^i - e^j \otimes e^i \otimes e^k - e^i \otimes e^k \otimes e^j$ thus

$$b = \sum_{i < j < k} b_{ijk} e^i \wedge e^j \wedge e^k = \sum_{i,j,k=1}^n \frac{1}{3!} b_{ijk} e^i \wedge e^j \wedge e^k$$
(9.10)

and it is clear that $\{e^i \wedge e^j \wedge e^k \mid i, j, k \in \mathbb{N}_n \text{ and } i < j < k\}$ forms a basis for the set of alternating trilinear maps on V.

Following the patterns above, we define the wedge product of p dual basis vectors,

$$e^{i_1} \wedge e^{i_2} \wedge \dots \wedge e^{i_p} = \sum_{\pi \in \Sigma_p} sgn(\pi) e^{i_{\pi(1)}} \otimes e^{i_{\pi(2)}} \otimes \dots \otimes e^{i_{\pi(p)}}$$
(9.11)

If $x, y \in V$ we would like to show that

$$e^{i_1} \wedge e^{i_2} \wedge \dots \wedge e^{i_p}(\dots, x, \dots, y, \dots) = -e^{i_1} \wedge e^{i_2} \wedge \dots \wedge e^{i_p}(\dots, y, \dots, x, \dots)$$
(9.12)

follows from the complete antisymmetrization in the definition of the wedge product. Before we give the general argument, let's see how this works in the trilinear case. Consider, $e^i \wedge e^j \wedge e^k =$

$$=e^i\otimes e^j\otimes e^k+e^j\otimes e^k\otimes e^i+e^k\otimes e^i\otimes e^j-e^k\otimes e^j\otimes e^i-e^j\otimes e^i\otimes e^k-e^i\otimes e^k\otimes e^j$$

¹⁴yes there is something to work out here, probably in your homework

Calculate, noting that $e^i \otimes e^j \otimes e^k(x,y,z) = e^i(x)e^j(y)e^k(z) = x^iy^jz^k$ hence

$$e^{i} \wedge e^{j} \wedge e^{k}(x, y, z) = x^{i}y^{j}z^{k} + x^{j}y^{k}z^{i} + x^{k}y^{i}z^{j} - x^{k}y^{j}z^{i} - x^{j}y^{i}z^{k} - x^{i}y^{k}z^{j}$$

Thus,

 $e^i \wedge e^j \wedge e^k(x,z,y) = x^i z^j y^k + x^j z^k y^i + x^k z^i y^j - x^k z^j y^i - x^j z^i y^k - x^i z^k y^j$

and you can check that $e^i \wedge e^j \wedge e^k(x, y, z) = -e^i \wedge e^j \wedge e^k(x, z, y)$. Similar tedious calculations prove antisymmetry of the the interchange of the first and second or the first and third slots. Therefore, $e^i \wedge e^j \wedge e^k$ is an alternating trilinear map as it is clearly trilinear since it is built from the sum of tensor products which we know are likewise trilinear.

The multilinear case follows essentially the same argument, note

$$e^{i_1} \wedge e^{i_2} \wedge \dots \wedge e^{i_p}(\dots, x_j, \dots, x_k, \dots) = \sum_{\pi \in \Sigma_p} sgn(\pi) x_1^{i_{\pi(1)}} \cdots x_j^{i_{\pi(j)}} \cdots x_k^{i_{\pi(k)}} \cdots x_p^{i_{\pi(p)}}$$
(9.13)

whereas,

$$e^{i_1} \wedge e^{i_2} \wedge \dots \wedge e^{i_p}(\dots, x_k, \dots, x_j, \dots) = \sum_{\sigma \in \Sigma_p} sgn(\sigma) x_1^{i_{\sigma(1)}} \cdots x_k^{i_{\sigma(k)}} \cdots x_j^{i_{\sigma(j)}} \cdots x_p^{i_{\sigma(p)}}.$$
 (9.14)

Suppose we take each permutation σ and subsitute $\delta \in \Sigma_p$ such that $\sigma(j) = \delta(k)$ and $\sigma(k) = \delta(j)$ and otherwise δ and σ agree. In cycle notation, $\delta(jk) = \sigma$. Substitution δ into Equation 9.14:

$$e^{i_1} \wedge e^{i_2} \wedge \dots \wedge e^{i_p} (\dots, x_k, \dots, x_j, \dots)$$

$$= \sum_{\delta \in \Sigma_p} sgn(\delta(jk)) x_1^{i_{\delta(1)}} \cdots x_k^{i_{\delta(j)}} \cdots x_j^{i_{\delta(k)}} \cdots x_p^{i_{\delta(p)}}$$

$$= -\sum_{\delta \in \Sigma_p} sgn(\delta) x_1^{i_{\delta(1)}} \cdots x_j^{i_{\delta(k)}} \cdots x_k^{i_{\delta(j)}} \cdots x_p^{i_{\delta(p)}}$$

$$= -e^{i_1} \wedge e^{i_2} \wedge \dots \wedge e^{i_p} (\dots, x_j, \dots, x_k, \dots)$$
(9.15)

Here the sgn of a permutation σ is $(-1)^N$ where N is the number of cycles in σ . We observed that $\delta(jk)$ has one more cycle than δ hence $sgn(\delta(jk)) = -sgn(\delta)$. Therefore, we have shown that $e^{i_1} \wedge e^{i_2} \wedge \cdots \wedge e^{i_p} \in \Lambda^p V$.

Recall that $e^i \wedge e^j = -e^j \wedge e^i$ in the p = 2 case. There is a generalization of that result to the p > 2 case. In words, the wedge product is antisymetric with respect the interchange of any two dual vectors. For p = 3 we have the following identities for the wedge product:

$$e^{i} \wedge e^{j} \wedge e^{k} = -\underbrace{e^{j} \wedge e^{i}}_{swapped} \wedge e^{k} = e^{j} \wedge \underbrace{e^{k} \wedge e^{i}}_{swapped} = -\underbrace{e^{k} \wedge e^{j}}_{swapped} \wedge e^{i} = e^{k} \wedge \underbrace{e^{i} \wedge e^{j}}_{swapped} = -\underbrace{e^{i} \wedge e^{k}}_{swapped} \wedge e^{j}$$

I've indicated how these signs are consistent with the p = 2 antisymmetry. Any permutation of the dual vectors can be thought of as a combination of several transpositions. In any event, it is sometimes useful to just know that the wedge product of three elements is invariant under **cyclic** permutations of the dual vectors,

$$e^i \wedge e^j \wedge e^k = e^j \wedge e^k \wedge e^i = e^k \wedge e^i \wedge e^j$$

and changes by a sign for **anticyclic** permutations of the given object,

$$e^i \wedge e^j \wedge e^k = -e^j \wedge e^i \wedge e^k = -e^k \wedge e^j \wedge e^i = -e^i \wedge e^k \wedge e^j$$

Generally we can argue that, for any permutation $\pi \in \Sigma_p$:

$$e^{i_1} \wedge e^{i_2} \wedge \dots \wedge e^{i_p} = sgn(\pi)e^{i_{\pi(1)}} \wedge e^{i_{\pi(2)}} \wedge \dots \wedge e^{i_{\pi(p)}}$$

This is just a slick formula which says the wedge product generates a minus whenever you flip two dual vectors which are wedged.

9.3.2 the exterior algebra

The careful reader will realize we have yet to define wedge products of anything except for the dual basis. But, naturally you must wonder if we can take the wedge product of other dual vectors or morer generally alternating tensors. The answer is yes. Let us define the general wedge product:

Definition 9.3.1. Suppose $\alpha \in \Lambda^p V$ and $\beta \in \Lambda^q V$. We define \mathcal{I}_p to be the set of all increasing lists of p-indices, this set can be empty if $\dim(V)$ is not sufficiently large. Moreover, if $I = (i_1, i_2, \ldots, i_p)$ then introduce notation $e^I = e^{i_1} \wedge e^{i_2} \wedge \cdots \wedge e^{i_p}$ hence:

$$\alpha = \sum_{i_1, i_2, \dots, i_p=1}^n \frac{1}{p!} \alpha_{i_1 i_2 \dots i_p} e^{i_1} \wedge e^{i_2} \wedge \dots \wedge e^{i_p} = \sum_I \frac{1}{p!} \alpha_I e^I = \sum_{I \in \mathcal{I}_p} \alpha_I e^I$$

and

$$\beta = \sum_{j_1, j_2, \dots, j_q=1}^n \frac{1}{q!} \beta_{j_1 j_2 \dots j_q} e^{j_1} \wedge e^{j_2} \wedge \dots \wedge e^{j_q} = \sum_J \frac{1}{q!} \beta_J e^J = \sum_{J \in \mathcal{I}_q} \beta_J e^J$$

Naturally, $e^{I} \wedge e^{J} = e^{i_{1}} \wedge e^{i_{2}} \wedge \cdots \wedge e^{i_{p}} \wedge e^{j_{1}} \wedge e^{j_{2}} \wedge \cdots \wedge e^{j_{q}}$ and we defined this carefully in the preceding subsection. Define $\alpha \wedge \beta \in \Lambda^{p+q}V$ as follows:

$$\alpha \wedge \beta = \sum_{I} \sum_{J} \frac{1}{p! q!} \alpha_{I} \beta_{J} e^{I} \wedge e^{J}$$

Again, but with less slick notation:

$$\alpha \wedge \beta = \sum_{i_1, i_2, \dots, i_p=1}^n \sum_{j_1, j_2, \dots, j_q=1}^n \frac{1}{p! q!} \alpha_{i_1 i_2 \dots i_p} \beta_{j_1 j_2 \dots j_q} e^{i_1} \wedge e^{i_2} \wedge \dots \wedge e^{i_p} \wedge e^{j_1} \wedge e^{j_2} \wedge \dots \wedge e^{j_q}$$

All the definition above really says is that we extend the wedge product on the basis to distribute over the addition of dual vectors. What this means calculationally is that the wedge product obeys the usual laws of addition and scalar multiplication. The one feature that is perhaps foreign is the antisymmetry of the wedge product. We must take care to maintain the order of expressions since the wedge product is not generally commutative.

Proposition 9.3.2.

	be forms on V and $c \in \mathbb{R}$ then	Let α, β, γ
distributes across vector addition	$(\alpha+\beta)\wedge\gamma=\alpha\wedge\gamma+\beta\wedge\gamma$	(i)
distributes across vector addition	$\alpha \wedge (\beta + \gamma) = \alpha \wedge \beta + \alpha \wedge \gamma$	(ii)
scalars factor out	$(c\alpha) \land \beta = \alpha \land (c\beta) = c (\alpha \land \beta)$	(iii)
associativity	$\alpha \wedge (\beta \wedge \gamma) = (\alpha \wedge \beta) \wedge \gamma$	(iv)

I leave the proof of this proposition to the reader.

Proposition 9.3.3. graded commutivity of homogeneous forms.

Let α, β be forms on V of degree p and q respectively then $\alpha \wedge \beta = -(-1)^{pq}\beta \wedge \alpha$

Proof: suppose $\alpha = \sum_{I} \frac{1}{p!} e^{I}$ is a *p*-form on *V* and $\beta = \sum_{J} \frac{1}{q!} e^{J}$ is a *q*-form on *V*. Calculate:

$$\begin{aligned} \alpha \wedge \beta &= \sum_{I} \sum_{J} \frac{1}{p! q!} \alpha_{I} \beta_{J} e^{I} \wedge e^{J} & \text{by defn. of } \wedge, \\ &= \sum_{I} \sum_{J} \frac{1}{p! q!} \beta_{J} \alpha_{I} e^{I} \wedge e^{J} & \text{coefficients are scalars,} \\ &= (-1)^{pq} \sum_{I} \sum_{J} \frac{1}{p! q!} \beta_{J} \alpha_{I} e^{J} \wedge e^{I} & (\text{details on sign given below}) \\ &= (-1)^{pq} \beta \wedge \alpha \end{aligned}$$

Let's expand in detail why $e^J \wedge e^I = (-1)^{pq} e^I \wedge e^J$. Suppose $I = (i_1, i_2, \ldots, i_p)$ and $J = (j_1, j_2, \ldots, j_q)$, the key is that every swap of dual vectors generates a sign:

$$e^{I} \wedge e^{J} = e^{i_{1}} \wedge e^{i_{2}} \wedge \dots \wedge e^{i_{p}} \wedge e^{j_{1}} \wedge e^{j_{2}} \wedge \dots \wedge e^{j_{q}}$$

$$= (-1)^{q} e^{i_{1}} \wedge e^{i_{2}} \wedge \dots \wedge e^{i_{p-1}} \wedge e^{j_{1}} \wedge e^{j_{2}} \wedge \dots \wedge e^{j_{q}} \wedge e^{i_{p}}$$

$$= (-1)^{q} (-1)^{q} e^{i_{1}} \wedge e^{i_{2}} \wedge \dots \wedge e^{i_{p-2}} \wedge e^{j_{1}} \wedge e^{j_{2}} \wedge \dots \wedge e^{j_{q}} \wedge e^{i_{p-1}} \wedge e^{i_{p}}$$

$$\vdots \qquad \vdots \qquad \vdots$$

$$= \underbrace{(-1)^{q} (-1)^{q} \cdots (-1)^{q}}_{p-factors} e^{j_{1}} \wedge e^{j_{2}} \wedge \dots \wedge e^{j_{q}} \wedge e^{i_{1}} \wedge e^{j_{2}} \wedge \dots \wedge e^{i_{p}}$$

$$= (-1)^{pq} e^{J} \wedge e^{I}.$$

Example 9.3.4. Let α be a 2-form defined by

$$\alpha = ae^1 \wedge e^2 + be^2 \wedge e^3$$

9.3. WEDGE PRODUCT

And let β be a 1-form defined by

$$\beta = 3e^1$$

Consider then,

$$\alpha \wedge \beta = (ae^1 \wedge e^2 + be^2 \wedge e^3) \wedge (3e^1)$$

= $(3ae^1 \wedge e^2 \wedge e^1 + 3be^2 \wedge e^3 \wedge e^1$
= $3be^1 \wedge e^2 \wedge e^3.$ (9.16)

whereas,

$$\wedge \alpha = 3e^1 \wedge (ae^1 \wedge e^2 + be^2 \wedge e^3)$$

= $(3ae^1 \wedge e^1 \wedge e^2 + 3be^1 \wedge e^2 \wedge e^3$
= $3be^1 \wedge e^2 \wedge e^3.$ (9.17)

so this agrees with the proposition, $(-1)^{pq} = (-1)^2 = 1$ so we should have found that $\alpha \wedge \beta = \beta \wedge \alpha$. This illustrates that although the wedge product is antisymmetric on the basis, it is not always antisymmetric, in particular it is commutative for even forms.

The graded commutivity rule $\alpha \wedge \beta = -(-1)^{pq}\beta \wedge \alpha$ has some suprising implications. This rule is ultimately the reason ΛV is finite dimensional. Let's see how that happens.

Proposition 9.3.5. *linear dependent one-forms wedge to zero:*

β

If $\alpha, \beta \in V^*$ and $\alpha = c\beta$ for some $c \in \mathbb{R}$ then $\alpha \wedge \beta = 0$.

Proof: to begin, note that $\beta \wedge \beta = -\beta \wedge \beta$ hence $2\beta \wedge \beta = 0$ and it follows that $\beta \wedge \beta = 0$. Note:

 $\alpha \wedge \beta = c\beta \wedge \beta = c(0) = 0$

therefore the proposition is true. \Box

Proposition 9.3.6.

Suppose that
$$\alpha_1, \alpha_2, \ldots, \alpha_p$$
 are linearly dependent 1-forms then
 $\alpha_1 \wedge \alpha_2 \wedge \cdots \wedge \alpha_p = 0.$

Proof: by assumption of linear dependence there exist constants c_1, c_2, \ldots, c_p not all zero such that

$$c_1\alpha_1 + c_2\alpha_2 + \cdots + c_p\alpha_p = 0.$$

Suppose that c_k is a nonzero constant in the sum above, then we may divide by it and consequently we can write α_k in terms of all the other 1-forms,

$$\alpha_k = \frac{-1}{c_k} \left(c_1 \alpha_1 + \dots + c_{k-1} \alpha_{k-1} + c_{k+1} \alpha_{k+1} + \dots + c_p \alpha_p \right)$$

Insert this sum into the wedge product in question,

$$\begin{aligned}
\alpha_1 \wedge \alpha_2 \wedge \ldots \wedge \alpha_p &= \alpha_1 \wedge \alpha_2 \wedge \cdots \wedge \alpha_k \wedge \cdots \wedge \alpha_p \\
&= (-c_1/c_k)\alpha_1 \wedge \alpha_2 \wedge \cdots \wedge \alpha_1 \wedge \cdots \wedge \alpha_p \\
&+ (-c_2/c_k)\alpha_1 \wedge \alpha_2 \wedge \cdots \wedge \alpha_2 \wedge \cdots \wedge \alpha_p + \cdots \\
&+ (-c_{k-1}/c_k)\alpha_1 \wedge \alpha_2 \wedge \cdots \wedge \alpha_{k-1} \wedge \cdots \wedge \alpha_p \\
&+ (-c_p/c_k)\alpha_1 \wedge \alpha_2 \wedge \cdots \wedge \alpha_p \wedge \cdots \wedge \alpha_p \\
&= 0.
\end{aligned}$$
(9.18)

We know all the wedge products are zero in the above because in each there is at least one 1-form repeated, we simply permute the wedge products till they are adjacent and by the previous proposition the term vanishes. The proposition follows. \Box

Let us pause to reflect on the meaning of the proposition above for a *n*-dimensional vector space V. The dual space V^* is likewise *n*-dimensional, this is a general result which applies to all finitedimensional vector spaces¹⁵. Thus, any set of more than *n* dual vectors is necessarily linearly dependent. Consequently, using the proposition above, we find the wedge product of more than *n* one-forms is trivial. Therefore, while it is possible to construct $\Lambda^k V$ for k > n we should understand that this space only contains zero. The highest degree of a nontrivial form over a vector space of dimension *n* is an *n*-form.

Moreover, we can use the proposition to deduce the dimension of a basis for $\Lambda^p V$, it must consist of the wedge product of distinct linearly independent one-forms. The number of ways to choose pdistinct objects from a list of n distinct objects is precisely "n choose p",

$$\binom{n}{p} = \frac{n!}{(n-p)!p!} \quad \text{for } 0 \le p \le n.$$

$$(9.19)$$

Proposition 9.3.7.

If V is an n-dimensional vector space then $\Lambda^k V$ is an $\binom{n}{p}$ -dimensional vector space of pforms. Moreover, the direct sum of all forms over V has the structure

 $\Lambda V = \mathbb{R} \oplus \Lambda^1 V \oplus \cdots \Lambda^{n-1} V \oplus \Lambda^n V$

and is a vector space of dimension 2^n

Proof: define $\Lambda^0 V = \mathbb{R}$ then it is clear $\Lambda^k V$ forms a vector space for k = 0, 1, ..., n. Moreover, $\Lambda^j V \cap \Lambda^k V = \{0\}$ for $j \neq k$ hence the term "direct sum" is appropriate. It remains to show $dim(\Lambda V) = 2^n$ where dim(V) = n. A natural basis β for ΛV is found from taking the union of the bases for each subspace of k-forms,

$$\beta = \{1, e^{i_1}, e^{i_1} \land e^{i_2}, \dots, e^{i_1} \land e^{i_2} \land \dots \land e^{i_n} \mid 1 \le i_1 < i_2 < \dots < i_n \le n\}$$

¹⁵however, in infinite dimensions, the story is not so simple

But, we can count the number of vectors N in the set above as follows:

$$N = 1 + n + \binom{n}{2} + \dots + \binom{n}{n-1} + \binom{n}{n}$$

Recall the binomial theorem states

$$(a+b)^{n} = \sum_{k=0}^{n} \binom{n}{k} a^{n-k} b^{k} = a^{n} + na^{n-1}b + \dots + nab^{n-1} + b^{n}.$$

Recognize that $N = (1+1)^n$ and the proposition follows. \Box

We should note that in the basis above the space of *n*-forms is one-dimensional because there is only one way to choose a strictly increasing list of *n* integers in \mathbb{N}_n . In particular, it is useful to note $\Lambda^n V = span\{e^1 \wedge e^2 \wedge \cdots \wedge e^n\}$. The form $e^1 \wedge e^2 \wedge \cdots \wedge e^n$ is sometimes called the the top-form¹⁶.

Example 9.3.8. exterior algebra of \mathbb{R}^2 Let us begin with the standard dual basis $\{e^1, e^2\}$. By definition we take the p = 0 case to be the field itself; $\Lambda^0 V \equiv \mathbb{R}$, it has basis 1. Next, $\Lambda^1 V = span(e^1, e^2) = V^*$ and $\Lambda^2 V = span(e^1 \wedge e^2)$ is all we can do here. This makes ΛV a $2^2 = 4$ -dimensional vector space with basis

$$\{1, e^1, e^2, e^1 \wedge e^2\}.$$

Example 9.3.9. exterior algebra of \mathbb{R}^3 Let us begin with the standard dual basis $\{e^1, e^2, e^3\}$. By definition we take the p = 0 case to be the field itself; $\Lambda^0 V \equiv \mathbb{R}$, it has basis 1. Next, $\Lambda^1 V = span(e^1, e^2, e^3) = V^*$. Now for something a little more interesting,

$$\Lambda^2 V = span(e^1 \wedge e^2, e^1 \wedge e^3, e^2 \wedge e^3)$$

and finally,

$$\Lambda^3 V = span(e^1 \wedge e^2 \wedge e^3).$$

This makes $\Lambda V \ a \ 2^3 = 8$ -dimensional vector space with basis

$$\{1,e^1,e^2,e^3,e^1\wedge e^2,e^1\wedge e^3,e^2\wedge e^3,e^1\wedge e^2\wedge e^3\}$$

it is curious that the number of independent one-forms and 2-forms are equal.

Example 9.3.10. exterior algebra of \mathbb{R}^4 Let us begin with the standard dual basis $\{e^1, e^2, e^3, e^4\}$. By definition we take the p = 0 case to be the field itself; $\Lambda^0 V \equiv \mathbb{R}$, it has basis 1. Next, $\Lambda^1 V = span(e^1, e^2, e^3, e^4) = V^*$. Now for something a little more interesting,

$$\Lambda^2 V = span(e^1 \wedge e^2, e^1 \wedge e^3, e^1 \wedge e^4, e^2 \wedge e^3, e^2 \wedge e^4, e^3 \wedge e^4)$$

and three forms,

$$\Lambda^3 V = span(e^1 \wedge e^2 \wedge e^3, e^1 \wedge e^2 \wedge e^4, e^1 \wedge e^3 \wedge e^4, e^2 \wedge e^3 \wedge e^4).$$

and $\Lambda^3 V = span(e^1 \wedge e^2 \wedge e^3)$. Thus ΛV a $2^4 = 16$ -dimensional vector space. Note that, in contrast to \mathbb{R}^3 , we do not have the same number of independent one-forms and two-forms over \mathbb{R}^4 .

¹⁶or volume form for reasons we will explain later, other authors begin the discussion of forms from the consideration of volume, see Chapter 4 in Bernard Schutz' Geometrical methods of mathematical physics

Let's explore how this algebra fits with calculations we already know about determinants.

Example 9.3.11. Suppose $A = [A_1|A_2]$. I propose the determinant of A is given by the top-form on \mathbb{R}^2 via the formula $det(A) = (e^1 \wedge e^2)(A_1, A_2)$. Suppose $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$ then $A_1 = (a, c)$ and $A_2 = (b, d)$. Thus,

$$det \begin{bmatrix} a & b \\ c & d \end{bmatrix} = (e^{1} \wedge e^{2})(A_{1}, A_{2})$$
$$= (e^{1} \otimes e^{2} - e^{2} \otimes e^{1})((a, c), (b, d))$$
$$= e^{1}(a, c)e^{2}(b, d) - e^{2}(a, c)e^{1}(b, d)$$
$$= ad - bc.$$

I hope this is not surprising!

Example 9.3.12. Suppose $A = [A_1|A_2|A_3]$. I propose the determinant of A is given by the topform on \mathbb{R}^3 via the formula $det(A) = (e^1 \wedge e^2 \wedge e^3)(A_1, A_2, A_3)$. Let's see if we can find the expansion by cofactors. By the definition we have $e^1 \wedge e^2 \wedge e^3 =$

$$\begin{split} &= e^1 \otimes e^2 \otimes e^3 + e^2 \otimes e^3 \otimes e^1 + e^3 \otimes e^1 \otimes e^2 - e^3 \otimes e^2 \otimes e^1 - e^2 \otimes e^1 \otimes e^3 - e^1 \otimes e^3 \otimes e^2 \\ &= e^1 \otimes (e^2 \otimes e^3 - e^3 \otimes e^2) - e^2 \otimes (e^1 \otimes e^3 - e^3 \otimes e^1) + e^3 \otimes (e^1 \otimes e^2 - e^2 \otimes e^1) \\ &= e^1 \otimes (e^2 \wedge e^3) - e^2 \otimes (e^1 \wedge e^3) + e^3 \otimes (e^1 \wedge e^2). \end{split}$$

I submit to the reader that this is precisely the cofactor expansion formula with respect to the first column of A. Suppose $A = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$ then $A_1 = (a, d, g), A_2 = (b, e, h)$ and $A_3 = (c, f, i).$

Calculate.

$$det(A) = e^{1}(A_{1})(e^{2} \wedge e^{3})(A_{2}, A_{3}) - e^{2}(A_{1})(e^{1} \wedge e^{3})(A_{2}, A_{3}) + e^{3}(A_{1})(e^{1} \wedge w^{2})(A_{2}, A_{3})$$

= $a(e^{2} \wedge e^{3})(A_{2}, A_{3}) - d(e^{1} \wedge e^{3})(A_{2}, A_{3}) + g(e^{1} \wedge w^{2})(A_{2}, A_{3})$
= $a(ei - fh) - d(bi - ch) + g(bf - ce)$

which is precisely my claim.

connecting vectors and forms in \mathbb{R}^3 9.3.3

There are a couple ways to connect vectors and forms in \mathbb{R}^3 . Mainly we need the following maps:

Definition 9.3.13.

Given $v = \langle a, b, c \rangle \in \mathbb{R}^3$ we can construct a corresponding one-form $\omega_v = ae^1 + be^2 + ce^3$ or we can construct a corresponding two-form $\Phi_v = ae^2 \wedge e^3 + be^3 \wedge e^1 + ce^1 \wedge e^2$

Recall that $dim(\Lambda^1 \mathbb{R}^3) = dim(\Lambda^2 \mathbb{R}^3) = 3$ hence the space of vectors, one-forms, and also twoforms are isomorphic as vector spaces. It is not difficult to show that $\omega_{v_1+cv_2} = \omega_{v_1} + c\omega_{v_2}$ and $\Phi_{v_1+cv_2} = \Phi_{v_1} + c\Phi_{v_2}$ for all $v_1, v_2 \in \mathbb{R}^3$ and $c \in \mathbb{R}$. Moreover, $\omega_v = 0$ iff v = 0 and $\Phi_v = 0$ iff v = 0 hence $ker(\omega) = \{0\}$ and $ker(\Phi) = \{0\}$ but this means that ω and Φ are injective and since the dimensions of the domain and codomain are 3 and these are linear transformations¹⁷ it follows ω and Φ are isomorphisms.

It appears we have two ways to represent vectors with forms in \mathbb{R}^3 . We'll see why this is important as we study integration of forms. It turns out the two-forms go with surfaces whereas the oneforms attach to curves. This corresponds to the fact in calculus III we have two ways to integrate a vector-field, we can either calculate flux or work. Partly for this reason the mapping ω is called the **work-form correspondence** and Φ is called the **flux-form correspondence**. Integration has to wait a bit, for now we focus on algebra.

Example 9.3.14. Suppose $v = < 2, 0, 3 > and w = < 0, 1, 2 > then \omega_v = 2e^1 + 3e^3$ and $\omega_w = e^2 + 2e^3$. Calculate the wedge product,

$$\omega_v \wedge \omega_w = (2e^1 + 3e^3) \wedge (e^2 + 2e^3)
= 2e^1 \wedge (e^2 + 2e^3) + 3e^3 \wedge (e^2 + 2e^3)
= 2e^1 \wedge e^2 + 4e^1 \wedge e^3 + 3e^3 \wedge e^2 + 6e^3 \wedge e^3
= -3e^2 \wedge e^3 - 4e^3 \wedge e^1 + 2e^1 \wedge e^2
= \Phi_{<-3,-4,2>}
= \Phi_{v \times w}$$
(9.20)

Coincidence? Nope.

Proposition 9.3.15.

Suppose $v, w \in \mathbb{R}^3$ then $\omega_v \wedge \omega_w = \Phi_{v \times w}$ where $v \times w$ denotes the cross-product which is defined by $v \times w = \sum_{i,j,k=1}^3 \epsilon_{ijk} v_i w_j e_k$.

Proof: Suppose $v = \sum_{i=1}^{3} v_i e_i$ and $w = \sum_{j=1}^{3} w_j e_j$ then $\omega_v = \sum_{i=1}^{3} v_i e^i$ and $\omega_w = \sum_{j=1}^{3} w_j e^j$. Calculate,

$$\omega_v \wedge \omega_w = \left(\sum_{i=1}^3 v_i e^i\right) \wedge \left(\sum_{j=1}^3 w_j e^j\right) = \sum_{i=1}^3 \sum_{j=1}^3 v_i w_j e^i \wedge e^j$$

In invite the reader to show $e^i \wedge e^j = \Phi(\sum_{k=1}^3 \epsilon_{ijk} e_k)$ where I'm using $\Phi_v = \Phi(v)$ to make the argument of the flux-form mapping easier to read, hence,

$$\omega_v \wedge \omega_w = \underbrace{\sum_{i=1}^3 \sum_{j=1}^3 v_i w_j \Phi(\sum_{k=1}^3 \epsilon_{ijk} e_k)}_{linearity of \Phi} = \Phi(\sum_{i,j,k=1}^3 v_i w_j \epsilon_{ijk} e_k) = \Phi(v \times w) = \Phi_{v \times w}$$

¹⁷this is not generally true, note $f(x) = x^2$ has f(x) = 0 iff x = 0 and yet f is not injective. The linearity is key.

Of course, if you don't like my proof you could just work it out like the example that precedes this proposition. I gave the proof to show off the mappings a bit more. \Box

Is the wedge product just the cross-product generalized? Well, not really. I think they're quite different animals. The wedge product is an associative product which makes sense in any vector space. The cross-product only matches the wedge product after we interpret it through a pair of isomorphisms (ω and ϕ) which are special to \mathbb{R}^3 . However, there is debate, largely the question comes down to what you think makes the cross-product the cross-product. If you think it must pick a unique perpendicular direction to a pair of given directions then that is only going to work in \mathbb{R}^3 since even in \mathbb{R}^4 there is a whole plane of perpendicular vectors to a given pair. On the other hand, if you think the cross-product in \mathbb{R}^4 should be pick the unique perpendicular to a given triple of vectors then you could set something up. You could define $v \times w \times x = \omega^{-1}(\psi(\omega_v \wedge \omega_w \wedge \omega_x))$ where $\psi : \Lambda^3 \mathbb{R}^4 \to \Lambda^1 \mathbb{R}^4$ is an isomorphism we'll describe in a upcoming section. But, you see it's no longer a product of two vectors, it's not a binary operation, it's a tertiary operation. In any event, you can read a lot more on this if you wish. We have all the tools we need for this course. The wedge product provides the natural antisymmetric algebra for *n*-dimensiona and the work and flux-form maps naturally connect us to the special world of three-dimensional mathematics.

There is more algebra for forms on \mathbb{R}^3 however we defer it to a later section where we have a few more tools. Chief among those is the Hodge dual. But, before we can discuss Hodge duality we need to generalize our idea of a dot-product just a little.

9.4 bilinear forms and geometry, metric duality

The concept of a metric goes beyond the familar case of the dot-product. If you want a more strict generalization of the dot-product then you should think about an *inner-product*. In contrast to the definition below, the inner-product replaces non-degeneracy with the stricter condition of positive-definite which would read g(x, x) > 0 for $x \neq 0$. I included a discussion of inner products at the end of this section for the interested reader although we are probably not going to need all of that material.

9.4.1 metric geometry

A **geometry** is a vector space paired with a metric. For example, if we pair \mathbb{R}^n with the dotproduct you get Euclidean space. However, if we pair \mathbb{R}^4 with the Minkowski metric then we obtain Minkowski space.

Definition 9.4.1.

- If V is a vector space and $g: V \times V \to \mathbb{R}$ is
 - 1. bilinear: $g \in T_2^0 V$,
 - 2. symmetric: g(x, y) = g(y, x) for all $x, y \in V$,
 - 3. nondegenerate: g(x, y) = 0 for all $x \in V$ implies y = 0.

the we call g a **metric** on V.

If $V = \mathbb{R}^n$ then we can write $g(x, y) = x^T G y$ where [g] = G. Moreover, g(x, y) = g(y, x) implies $G^T = G$. Nondegenerate means that g(x, y) = 0 for all $y \in \mathbb{R}^n$ iff x = 0. It follows that Gy = 0 has no non-trivial solutions hence G^{-1} exists.

Example 9.4.2. Suppose $g(x, y) = x^T y$ for all $x, y \in \mathbb{R}^n$. This defines a metric for \mathbb{R}^n , it is just the dot-product. Note that $g(x, y) = x^T y = x^T I y$ hence we see [g] = I where I denotes the identity matrix in $\mathbb{R}^{n \times n}$.

Example 9.4.3. Suppose $v = (v^0, v^1, v^2, v^3), w = (w^0, w^1, w^2, w^3) \in \mathbb{R}^4$ then define the Minkowski product of v and w as follows:

$$g(v,w) = -v^0 w^0 + v^1 w^1 + v^2 w^2 + v^3 w^3$$

It is useful to write the Minkowski product in terms of a matrix multiplication. Observe that for $x, y \in \mathbb{R}^4$,

$$g(x,y) = -x^{0}y^{0} + x^{1}y^{1} + x^{2}y^{2} + x^{3}y^{3} = \begin{pmatrix} x^{0} & x^{1} & x^{2} & x^{3} \end{pmatrix} \begin{pmatrix} -1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} y^{0} \\ y^{1} \\ y^{2} \\ y^{3} \end{pmatrix} \equiv x^{t}\eta y$$

where we have introduced η the matrix of the Minkowski product. Notice that $\eta^T = \eta$ and $det(\eta) = -1 \neq 0$ hence $g(x, y) = x^t \eta y$ makes g a symmetric, nondegenerate bilinear form on \mathbb{R}^4 . The formula is clearly related to the dot-product. Suppose $\bar{v} = (v^0, \bar{v})$ and $\bar{w} = (w^0, \bar{w})$ then note

$$g(v,w) = -v^0 w^0 + \vec{v} \cdot \vec{w}$$

For vectors with zero in the zeroth slot this Minkowski product reduces to the dot-product. However, for vectors which have nonzero entries in both the zeroth and later slots much differs. Recall that any vector's dot-product with itself gives the square of the vectors length. Of course this means that $\vec{x} \cdot \vec{x} = 0$ iff $\vec{x} = 0$. Contrast that with the following: if v = (1, 1, 0, 0) then

$$g(v, v) = -1 + 1 = 0$$

Yet $v \neq 0$. Why study such a strange generalization of length? The answer lies in physics. I'll give you a brief account by defining a few terms: Let $v = (v^0, v^1, v^2, v^3) \in \mathbb{R}^4$ then we say

- 1. v is a timelike vector if $\langle v, v \rangle \langle 0$
- 2. v is a lightlike vector if $\langle v, v \rangle = 0$
- 3. v is a spacelike vector if $\langle v, v \rangle > 0$

If we consider the trajectory of a massive particle in \mathbb{R}^4 that begins at the origin then at any later time the trajectory will be located at a timelike vector. If we consider a light beam emitted from the origin then at any future time it will located at the tip of a lightlike vector. Finally, spacelike vectors point to points in \mathbb{R}^4 which cannot be reached by the motion of physical particles that pass throughout the origin. We say that massive particles are confined within their light cones, this means that they are always located at timelike vectors relative to their current position in space time. If you'd like to know more I can recommend a few books.

At this point you might wonder if there are other types of metrics beyond these two examples. Surprisingly, in a certain sense, no. A rather old theorem of linear algebra due to Sylvester states that we can change coordinates so that the metric more or less resembles either the dot-product or something like it with some sign-flips. We'll return to this in a later section.

9.4.2 metric duality for tensors

Throughout this section we consider a vector space V paired with a metric $g: V \times V \to \mathbb{R}$. Moreover, the vector space V has basis $\{e_i\}_{i=1}^n$ which has a g-dual basis $\{e^i\}_{i=1}^n$. Up to this point we always have used a g-dual basis where the duality was offered by the dot-product. In the context of Minkowski geometry that sort of duality is no longer natural. Instead we must follow the definition below:

Definition 9.4.4.

If V is a vector space with metric g and basis $\{e_i\}_{i=1}^n$ then we say the basis $\{e^i\}_{i=1}^n$ is g-dual iff

Suppose $e^i(e_j) = \delta_{ij}$ and consider $g = \sum_{i,j=1}^n g_{ij} e^i \otimes e^j$. Furthermore, suppose g^{ij} are the components of the inverse matrix to (g_{ij}) this means that $\sum_{k=1}^n g_{ik}g^{kj} = \delta_{ij}$. We use the components of the metric and its inverse to raise and lower indices on tensors. Here are the basic conventions: given an object A^j which has the *contravariant* index j we can lower it to be covariant by contracting against the metric components as follows:

$$A_i = \sum_j g_{ij} A^j$$

On the other hand, given an object B_j which has a *covariant* index j we can raise it to be contravariant by contracting against the inverse components of the metric:

$$B^i = \sum_j g^{ij} B_j$$

I like to think of this as some sort of conservation of indices. Strict adherence to the notation drives us to write things such as $\sum_{k=1}^{n} g_{ik}g^{kj} = \delta_i^j$ just to keep up the up/down index pattern. I should mention that these formulas are much more beautiful in the physics literature, you can look at my old Math 430 notes from NCSU if you'd like a healthy dose of that notation¹⁸. I use Einstein's implicit summation notation throughout those notes and I discuss this index calculation more in the way a physicist typically approaches it. Here I am trying to be careful enough that these equations are useful to mathematicians. Let me show you some examples:

Example 9.4.5. Specialize for this example to $V = \mathbb{R}^4$ with $g(x, y) = x^T \eta y$. Suppose $x = \sum_{\mu=0}^4 x^{\mu} e_{\mu}$ the components x^{μ} are called **contravariant components**. The metric allows us to define **covariant components** by

$$x_{\nu} = \sum_{\mu=0}^{4} \eta_{\nu\mu} x^{\mu}.$$

For the minkowski metric this just adjoins a minus to the zeroth component: if $(x^{\mu}) = (a, b, c, d)$ then $x_{\mu} = (-a, b, c, d)$.

Example 9.4.6. Suppose we are working on \mathbb{R}^n with the Euclidean metric $g_{ij} = \delta_{ij}$ and it follows that $g^{ij} = \delta_{ij}$ or to be a purist for a moment $\sum_k g_{ik}g^{kj} = \delta_i^j$. In this case $v^i = \sum_j g^{ij}v_j = \sum_j \delta_{ij}v_j = v_i$. The covariant and contravariant components are the same. This is why is was ok to ignore up/down indices when we work with a dot-product exclusively.

What if we raise an index and the lower it back down once more? Do we really get back where we started? Given x^{μ} we lower the index by $x_{\nu} = \sum_{\mu} g_{\nu\mu} x^{\mu}$ then we raise it once more by

$$x^{\alpha} = \sum_{\nu} g^{\alpha\nu} x_{\nu} = \sum_{\nu} g^{\alpha\nu} \sum_{\mu} g_{\nu\mu} x^{\mu} = \sum_{\mu,\nu} g^{\alpha\nu} g_{\nu\mu} x^{\mu} = \sum_{\mu} \delta^{\alpha}_{\mu} x^{\mu}$$

and the last summation squishes down to x^{α} once more. It would seem this procedure of raising and lowering indices is at least consistent.

Example 9.4.7. Suppose we raise the index on the basis $\{e_i\}$ and formally obtain $\{e^j = \sum_k g^{jk} e_k\}$ on the other hand suppose we lower the index on the dual basis $\{e^l\}$ to formally obtain $\{e_m = \sum_l g_{ml} e^l\}$. I'm curious, are these consistent? We should get $e^j(e_m) = \delta_m^j$, I'll be nice an look at $e_m(e^j)$ in the following sense:

$$\sum_{l} g_{ml} e^l \left(\sum_{k} g^{jk} e_k \right) = \sum_{l,k} g_{ml} g^{jk} e^l (e_k) = \sum_{l,k} g_{ml} g^{jk} \delta^l_k = \sum_{k} g_{mk} g^{jk} = \delta^j_m$$

Interesting, but what does it mean?

¹⁸ just a taste: $v_{\mu} = \eta_{\mu\nu}v^{\nu}$ or $v^{\mu} = \eta^{\mu\nu}v_{\nu}$ or $v^{\mu}v_{\mu} = \eta^{\mu\nu}v_{\nu}v_{\mu} = \eta_{\mu\nu}v^{\mu}v^{\nu}$

I used the term *formal* in the preceding example to mean that the example makes sense in as much as you accept the equations which are written. If you think harder about it then you'll find it was rather meaningless. That said, this index notation is rather forgiving.

Ok, but what are we doing? Recall that I insisted on using lower indices for forms and upper indices for vectors? The index conventions I'm toying with above are the reason for this strange notation. When we lower an index we might be changing a vector to a dual vector, or vice-versa when we raise an index we might be changing a dual vector into a vector. Let me be explicit.

- 1. given $v \in V$ we create $\alpha_v \in V^*$ by the rule $\alpha_v(x) = g(x, v)$.
- 2. given $\alpha \in V^*$ we create $v_{\alpha} \in V^{**}$ by the rule $v_{\alpha}(\beta) = g^{-1}(\alpha, \beta)$ where $g^{-1}(\alpha, \beta) = \sum_{ij} \alpha_i \beta_j g^{ij}$.

Recall we at times identify V and V^{**}. Let's work out the component structure of α_v and see how it relates to v,

$$\alpha_v(e_i) = g(v, e_i) = g(\sum_j v^j e_j, e_i) = \sum_j v^j g(e_j, e_i) = \sum_j v^j g_{ji}$$

Thus, $\alpha_v = \sum_i v_i e^i$ where $v_i = \sum_j v^j g_{ji}$. When we lower the index we're actually using an isomorphism which is provided by the metric to map vectors to forms. The process of raising the index is just the inverse of this isomorphism.

$$v_{\alpha}(e^{i}) = g^{-1}(\alpha, e^{i}) = g^{-1}(\sum_{j} \alpha_{j}e^{j}, e^{i}) = \sum_{j} \alpha_{j}g^{ji}$$

thus $v_{\alpha} = \sum_{i} \alpha^{i} e_{i}$ where $\alpha^{i} = \sum_{j} \alpha_{j} g^{ji}$.

Suppose we want to change a type (0,2) tensor to a type (2,0) tensor. We're given $T: V^* \times V^*$ where $T = \sum_{ij} T^{ij} e_i \otimes e_j$. Define $\tilde{T}: V \times V \to \mathbb{R}$ as follows:

$$\tilde{T}(v,w) = T(\alpha_v, \alpha_w)$$

What does this look like in components? Note $\alpha_{e_i}(e_j) = g(e_i, e_j) = g_{ij}$ hence $\alpha_{e_i} = \sum_j g_{ij} e^j$ and

$$\tilde{T}(e_i, e_j) = T(\alpha_{e_i}, \alpha_{e_j}) = T\left(\sum_k g_{ik}e^k, \sum_l g_{jl}e^l\right) = \sum_{k,l} g_{ki}g_{lj}T(e^k, e^l) = \sum_{k,l} g_{ki}g_{lj}T^{kl}$$

Or, as is often customary, we could write $T_{ij} = \sum_{k,l} g_{ik} g_{jl} T^{kl}$. However, this is an abuse of notation since T_{ij} are not technically components for T. If we have a metric we can recover either T from \tilde{T} or vice-versa. Generally, if we are given two tensors, say T_1 of rank (r, s) and the T_2 of rank (r', s'), then these might be equivalent if r + s = r' + s'. It may be that through raising and lowering indices (a.k.a. appropriately composing with the vector \leftrightarrow dual vector isomorphisms) we can convert T_1 to T_2 . If you read *Gravitation* by Misner, Thorne and Wheeler you'll find many more thoughts on this equivalence. Challenge: can you find the explicit formulas like $\tilde{T}(v, w) = T(\alpha_v, \alpha_w)$ which back up the index calculations below?

$$T_{ij}^{\ \ k} = \sum_{a,b} g_{ia}g_{jb}T^{abk} \qquad \text{or} \qquad S^{ij} = \sum_{a,b} g^{ia}g^{jb}S_{ab}$$

I hope I've given you enough to chew on in this section to put these together.

9.4.3 inner products and induced norm

There are generalized dot-products on many abstract vector spaces, we call them **inner-products**.

Definition 9.4.8.

Suppose V is a vector space. If $\langle , \rangle : V \times V \to \mathbb{R}$ is a function such that for all $x, y, z \in V$ and $c \in \mathbb{R}$: 1. $\langle x, y \rangle = \langle y, x \rangle$ (symmetric) 2. $\langle x + y, z \rangle = \langle x, z \rangle + \langle y, z \rangle$ (additive in the first slot) 3. $\langle cx, y \rangle = c \langle x, y \rangle$ (homogeneity in the first slot) 4. $\langle x, x \rangle \geq 0$ and $\langle x, x \rangle = 0$ iff x = 0then we say (V, \langle , \rangle) is an **inner-product space** with inner product \langle , \rangle .

Given an inner-product space (V, <, >) we can easily induce a norm for V by the formula $||x|| = \sqrt{\langle x, x \rangle}$ for all $x \in V$. Properties (1.), (3.) and (4.) in the definition of the norm are fairly obvious for the induced norm. Let's think throught the triangle inequality for the induced norm:

$$\begin{split} ||x+y||^2 &= \langle x+y, x+y \rangle & \text{def. of induced norm} \\ &= \langle x, x+y \rangle + \langle y, x+y \rangle & \text{additive prop. of inner prod.} \\ &= \langle x, x \rangle + \langle x, y \rangle + \langle x, y \rangle + \langle y, y \rangle & \text{additive prop. of inner prod.} \\ &= ||x||^2 + 2 \langle x, y \rangle + ||y||^2 \end{split}$$

At this point we're stuck. A nontrivial identity¹⁹ called the **Cauchy-Schwarz** identity helps us proceed; $\langle x, y \rangle \leq ||x|| ||y||$. It follows that $||x + y||^2 \leq ||x||^2 + 2||x||||y|| + ||y||^2 = (||x|| + ||y||)^2$. However, the induced norm is clearly positive²⁰ so we find $||x + y|| \leq ||x|| + ||y||$.

Most linear algebra texts have a whole chapter on inner-products and their applications, you can look at my notes for a start if you're curious. That said, this is a bit of a digression for this course.

 $^{^{19}}$ I prove this for the dot-product in my linear notes, however, the proof is written in such a way it equally well applies to a general inner-product

²⁰note: if you have $(-5)^2 < (-7)^2$ it does not follow that -5 < -7, in order to take the squareroot of the inequality we need positive terms squared

9.5 hodge duality

We can prove that $\binom{n}{p} = \binom{n}{n-p}$. This follows from explicit computation of the formula for $\binom{n}{p}$ or from the symmetry of Pascal's triangle if you prefer. In any event, this equality suggests there is some isomorphism between p and (n-p)-forms. When we are given a metric g on a vector space V (and the notation of the preceding section) it is fairly simple to construct the isomorphism. Suppose we are given $\alpha \in \Lambda^p V$ and following our usual notation:

$$\alpha = \sum_{i_1, i_2, \dots, i_p=1}^n \frac{1}{p!} \alpha_{i_1 i_2 \dots i_p} e^{i_1} \wedge e^{i_2} \wedge \dots \wedge e^{i_p}$$

Then, define $*\alpha$ the **hodge dual** to be the (n-p)-form given below:

$$*\alpha = \sum_{i_1, i_2, \dots, i_n = 1}^n \frac{1}{p!(n-p)!} \alpha^{i_1 i_2 \dots i_p} \epsilon_{i_1 i_2 \dots i_p j_1 j_2 \dots j_{n-p}} e^{j_1} \wedge e^{j_2} \wedge \dots \wedge e^{j_{n-p}}$$

I should admit, to prove this is a reasonable definition we'd need to do some work. It's clearly a linear transformation, but bijectivity and coordinate invariance of this definition might take a little work. I intend to omit those details and instead focus on how this works for \mathbb{R}^3 or \mathbb{R}^4 . My advisor taught a course on fiber bundles and there is a much more general and elegant presentation of the hodge dual over a manifold. Ask if interested, I think I have a pdf.

9.5.1 hodge duality in euclidean space \mathbb{R}^3

To begin, consider a scalar 1, this is a 0-form so we expect the hodge dual to give a 3-form:

$$*1 = \sum_{i,j,k} \frac{1}{0!3!} \epsilon_{ijk} e^i \wedge e^j \wedge e^k = e^1 \wedge e^2 \wedge e^3$$

Interesting, the hodge dual of 1 is the top-form on \mathbb{R}^3 . Conversely, calculate the dual of the top-form, note $e^1 \wedge e^2 \wedge e^3 = \sum_{ijk} \frac{1}{6} \epsilon_{ijk} e^i \wedge e^j \wedge e^k$ reveals the components of the top-form are precisely ϵ_{ijk} thus:

$$*(e^{1} \wedge e^{2} \wedge e^{3}) = \sum_{i,j,k=1}^{3} \frac{1}{3!(3-3)!} \epsilon^{ijk} \epsilon_{ijk} = \frac{1}{6} (1+1+1+(-1)^{2}+(-1)^{2}+(-1)^{2}) = 1.$$

Next, consider e^1 , note that $e^1 = \sum_k \delta_{k1} e^k$ hence the components are δ_{k1} . Thus,

$$*e^{1} = \sum_{i,j,k} \frac{1}{1!2!} \epsilon_{ijk} \delta^{k1} e^{i} \wedge e^{j} = \frac{1}{2} \sum_{i,j} \epsilon_{ij1} e^{i} \wedge e^{j} = \frac{1}{2} (\epsilon_{231} e^{2} \wedge e^{3} + \epsilon_{321} e^{3} \wedge e^{2}) = e^{2} \wedge e^{3}$$

Similar calculations reveal $*e^2 = e^3 \wedge e^1$ and $*e^3 = e^1 \wedge e^2$. What about the duals of the two-forms? Begin with $\alpha = e^1 \wedge e^2$ note that $e^1 \wedge e^2 = e^1 \otimes e^2 - e^2 \otimes e^1$ thus we can see the components are
$$\alpha_{ij} = \delta_{i1}\delta_{j2} - \delta_{i2}\delta_{j1}$$
. Thus,

$$*(e^{1} \wedge e^{2}) = \sum_{i,j,k} \frac{1}{2!1!} \epsilon_{ijk} (\delta_{i1}\delta_{j2} - \delta_{i2}\delta_{j1}) e^{k} = \frac{1}{2} \left(\sum_{k} \epsilon_{12k} e^{k} - \sum_{k} \epsilon_{21k} e^{k} \right) = \frac{1}{2} (e^{3} - (-e^{3})) = e^{3}.$$

Similar calculations show that $*(e^2 \wedge e^3) = e^1$ and $*(e^3 \wedge e^1) = e^2$. Put all of this together and we find that

$$*(ae^{1} + be^{2} + ce^{3}) = ae^{2} \wedge e^{3} + be^{3} \wedge e^{1} + ce^{1} \wedge e^{2}$$

and

$$*(ae^{2} \wedge e^{3} + be^{3} \wedge e^{1} + ce^{1} \wedge e^{2}) = ae^{1} + be^{2} + ce^{3}$$

Which means that $[*\omega_v = \Phi_v]$ and $[*\Phi_v = \omega_v]$. Hodge duality links the two different form-representations of vectors in a natural manner. Moveover, for \mathbb{R}^3 we should also note that $**\alpha = \alpha$ for all $\alpha \in \Lambda \mathbb{R}^3$. In general, for other metrics, we can have a change of signs which depends on the degree of α .

We can summarize hodge duality for three-dimensional Euclidean space as follows:

$^*1 = e^1 \wedge e^2 \wedge e^3$	$^*(e^1 \wedge e^2 \wedge e^3) = 1$
$*e^1 = e^2 \wedge e^3$	$*(e^2 \wedge e^3) = e^1$
$^*e^2 = e^3 \wedge e^1$	$^*(e^3 \wedge e^1) = e^2$
$^*e^3 = e^1 \wedge e^2$	$^*(e^1 \wedge e^2) = e^3$

A simple rule to calculate the hodge dual of a basis form is as follows

- 1. begin with the top-form $e^1 \wedge e^2 \wedge e^3$
- 2. permute the forms until the basis form you wish to hodge dual is to the left of the expression, whatever remains to the right is the hodge dual.

For example, to calculate the dual of $e^2 \wedge e^3$ note

$$e^1 \wedge e^2 \wedge e^3 = \underbrace{e^2 \wedge e^3}_{to \ be \ dualed} \wedge \underbrace{e^1}_{the \ dual} \Rightarrow *(e^2 \wedge e^3) = e^1.$$

Consider what happens if we calculate $* * \alpha$, since the dual is a linear operation it suffices to think about the basis forms. Let me sketch the process of $* * e^{I}$ where I is a multi-index:

- 1. begin with $e^1 \wedge e^2 \wedge e^3$
- 2. write $e^1 \wedge e^2 \wedge e^3 = (-1)^N e^I \wedge e^J$ and identify $*e^I = (-1)^N e^J$.
- 3. then to calculate the second dual once more begin with $e^1 \wedge e^2 \wedge e^3$ and note

$$e^1 \wedge e^2 \wedge e^3 = (-1)^N e^J \wedge e^I$$

since the same N transpositions are required to push e^{I} to the left or e^{J} to the right.

4. It follows that $**e^I = e^I$ for any multi-index hence $[**\alpha = \alpha]$ for all $\alpha \in \Lambda \mathbb{R}^3$.

I hope that once you get past the index calculation you can see the hodge dual is not a terribly complicated construction. Some of the index calculation in this section was probably gratutious, but I would like you to be aware of such techniques. Brute-force calculation has it's place, but a well-thought index notation can bring far more insight with much less effort.

9.5.2 hodge duality in minkowski space \mathbb{R}^4

The logic here follows fairly close to the last section, however the wrinkle is that the metric here demands more attention. We must take care to raise the indices on the forms when we Hodge dual them. First let's list the basis forms, we have to add time to the mix (again c = 1 so $x^0 = ct = t$ if you worried about it) Remember that the Greek indices are defined to range over 0, 1, 2, 3. Here

Name	Degree	Typical Element	Basis for $\Lambda^p \mathbb{R}^4$
function	p = 0	f	1
one-form	p = 1	$\alpha = \sum_{\mu} \alpha_{\mu} e^{\mu}$	$e^{0}, e^{1}, e^{2}, e^{3}$
two-form	p = 2	$eta = \sum_{\mu, u} rac{1}{2} eta_{\mu u} e^{\mu} \wedge e^{ u}$	$e^2 \wedge e^3, \ e^3 \wedge e^1, \ e^1 \wedge e^2$
		<i>p</i> -,- - ·	$e^0 \wedge e^1, \ e^0 \wedge e^2, \ e^0 \wedge e^3$
three-form	p = 3	$\gamma = \sum_{\mu,\nu,\alpha} \frac{1}{3!} \gamma_{\mu\nu\alpha} e^{\mu} \wedge e^{\nu} e^{\alpha}$	$e^1 \wedge e^2 \wedge e^3, e^0 \wedge e^2 \wedge e^3$
			$e^0 \wedge e^1 \wedge e^3, e^0 \wedge e^1 \wedge e^2$
four-form	p = 4	$ge^0 \wedge e^1 \wedge e^2 \wedge e^3$	$e^0 \wedge e^1 \wedge e^2 \wedge e^3$

the top form is degree four since in four dimensions we can have at most four dual-basis vectors without a repeat. Wedge products work the same as they have before, just now we have e^0 to play with. Hodge duality may offer some surprises though.

Definition 9.5.1. The antisymmetric symbol in flat \mathbb{R}^4 is denoted $\epsilon_{\mu\nu\alpha\beta}$ and it is defined by the value

 $\epsilon_{0123} = 1$

plus the demand that it be completely antisymmetric.

We must not assume that this symbol is invariant under a cyclic exhange of indices. Consider,

 $\epsilon_{0123} = -\epsilon_{1023} \qquad \text{flipped (01)} \\ = +\epsilon_{1203} \qquad \text{flipped (02)} \\ = -\epsilon_{1230} \qquad \text{flipped (03).}$ (9.21)

In four dimensions we'll use antisymmetry directly and forego the cyclicity shortcut. Its not a big deal if you notice it before it confuses you.

Example 9.5.2. Find the Hodge dual of $\gamma = e^1$ with respect to the Minkowski metric $\eta_{\mu\nu}$, to begin notice that dx has components $\gamma_{\mu} = \delta^1_{\mu}$ as is readily verified by the equation $e^1 = \sum_{\mu} \delta^1_{\mu} e^{\mu}$. Lets

raise the index using η as we learned previously,

$$\gamma^{\mu} = \sum_{\nu} \eta^{\mu\nu} \gamma_{\nu} = \sum_{\nu} \eta^{\mu\nu} \delta^{1}_{\nu} = \eta^{1\mu} = \delta^{1\mu}$$

Starting with the definition of Hodge duality we calculate

the difference between the three and four dimensional Hodge dual arises from two sources, for one we are using the Minkowski metric so indices up or down makes a difference, and second the antisymmetric symbol has more possibilities than before because the Greek indices take four values.

I suspect we can calculate the hodge dual by the following pattern: suppose we wish to find the dual of α where α is a basis form for $\Lambda \mathbb{R}^4$ with the Minkowski metric

- 1. begin with the top-form $e^0 \wedge e^1 \wedge e^2 \wedge e^3$
- 2. permute factors as needed to place α to the left,
- 3. the form which remains to the right will be the hodge dual of α if no e^0 is in α otherwise the form to the right multiplied by -1 is $*\alpha$.

Note this works for the previous example as follows:

- 1. begin with $e^0 \wedge e^1 \wedge e^2 \wedge e^3$
- 2. note $e^0 \wedge e^1 \wedge e^2 \wedge e^3 = -e^1 \wedge e^0 \wedge e^2 \wedge e^3 = e^1 \wedge (-e^0 \wedge e^2 \wedge e^3)$
- 3. identify $*e^1 = -e^0 \wedge e^2 \wedge e^3$ (no extra sign since no e^0 appears in e^1)

Follow the algorithm for finding the dual of e^0 ,

- 1. begin with $e^0 \wedge e^1 \wedge e^2 \wedge e^3$
- 2. note $e^0 \wedge e^1 \wedge e^2 \wedge e^3 = e^0 \wedge (e^1 \wedge e^2 \wedge e^3)$

3. identify $*e^0 = -e^1 \wedge e^2 \wedge e^3$ (added sign since e^0 appears in form being hodge dualed)

Let's check from the definition if my algorithm worked out right.

Example 9.5.3. Find the Hodge dual of $\gamma = e^0$ with respect to the Minkowski metric $\eta_{\mu\nu}$, to begin notice that e^0 has components $\gamma_{\mu} = \delta^0_{\mu}$ as is readily verified by the equation $e^0 = \sum_{\mu} \delta^0_{\mu} e^{\mu}$. Lets raise the index using η as we learned previously,

$$\gamma^{\mu} = \sum_{\nu} \eta^{\mu\nu} \gamma_{\nu} = \sum_{\nu} \eta^{\mu\nu} \delta^{0}_{\nu} = \eta^{\mu 0} = -\delta^{0\mu}$$

the minus sign is due to the Minkowski metric. Starting with the definition of Hodge duality we calculate

Notice I am using the convention that Greek indices sum over 0, 1, 2, 3 whereas Latin indices sum over 1, 2, 3.

Example 9.5.4. Find the Hodge dual of $\gamma = e^0 \wedge e^1$ with respect to the Minkowski metric $\eta_{\mu\nu}$, to begin notice the following identity, it will help us find the components of γ

$$e^0 \wedge e^1 = \sum_{\mu,\nu} \frac{1}{2} 2 \delta^0_\mu \delta^1_\nu e^\mu \wedge e^\nu$$

now we antisymmetrize to get the components of the form,

$$e^0 \wedge e^1 = \sum_{\mu,\nu} \frac{1}{2} \delta^0_{[\mu} \delta^1_{\nu]} dx^\mu \wedge dx^\nu$$

where $\delta^0_{[\mu}\delta^1_{\nu]} = \delta^0_{\mu}\delta^1_{\nu} - \delta^0_{\nu}\delta^1_{\mu}$ and the factor of two is used up in the antisymmetrization. Lets raise the index using η as we learned previously,

$$\gamma^{\alpha\beta} = \sum_{\mu,\nu} \eta^{\alpha\mu} \eta^{\beta\nu} \gamma_{\mu\nu} = \sum_{\mu,\nu} \eta^{\alpha\mu} \eta^{\beta\nu} \delta^0_{[\mu} \delta^1_{\nu]} = -\eta^{\alpha0} \eta^{\beta1} + \eta^{\beta0} \eta^{\alpha1} = -\delta^{[\alpha0} \delta^{\beta]1}$$

the minus sign is due to the Minkowski metric. Starting with the definition of Hodge duality we

calculate

$$(e^{0} \wedge e^{1}) = \frac{1}{p!} \frac{1}{(n-p)!} \gamma^{\alpha\beta} \epsilon_{\alpha\beta\mu\nu} e^{\mu} \wedge e^{\nu}$$

$$= (1/4) (-\delta^{[\alpha 0} \delta^{\beta]1}) \epsilon_{\alpha\beta\mu\nu} e^{\mu} \wedge e^{\nu}$$

$$= -(1/4) (\epsilon_{01\mu\nu} e^{\mu} \wedge e^{\nu} - \epsilon_{10\mu\nu} e^{\mu} \wedge e^{\nu})$$

$$= -(1/2) \epsilon_{01\mu\nu} e^{\mu} \wedge e^{\nu}$$

$$= -(1/2) [\epsilon_{0123} e^{2} \wedge e^{3} + \epsilon_{0132} e^{3} \wedge e^{2}]$$

$$= -e^{2} \wedge e^{3}$$

(9.24)

Note, the algorithm works out the same,

*

$$e^0 \wedge e^1 \wedge e^2 \wedge e^3 = \underbrace{e^0 \wedge e^1}_{has \ e^0} \wedge (e^2 \wedge e^3) \quad \Rightarrow \quad *(e^0 \wedge e^1) = -e^2 \wedge e^3$$

The other Hodge duals of the basic two-forms calculate by almost the same calculation. Let us make a table of all the basic Hodge dualities in Minkowski space, I have grouped the terms to emphasize

$1 = e^0 \wedge e^1 \wedge e^2 \wedge e^3$	$^*(e^0 \wedge e^1 \wedge e^2 \wedge e^3) = -1$
$(e^1 \wedge e^2 \wedge e^3) = -e^0$	${}^*e^0 = -e^1 \wedge e^2 \wedge e^3$
$ *(e^0 \wedge e^2 \wedge e^3) = -e^1$	${}^*e^1 = -e^2 \wedge e^3 \wedge e^0$
$*(e^0 \wedge e^3 \wedge e^1) = -e^2$	${}^*e^2 = -e^3 \wedge e^1 \wedge e^0$
$*(e^0 \wedge e^1 \wedge e^2) = -e^3$	${}^*e^3 = -e^1 \wedge e^2 \wedge e^0$
$*(e^3 \wedge e^0) = e^1 \wedge e^2$	$^*(e^1 \wedge e^2) = -e^3 \wedge e^0$
$*(e^1 \wedge e^0) = e^2 \wedge e^3$	$^*(e^2 \wedge e^3) = -e^1 \wedge e^0$
$(e^2 \wedge e^0) = e^3 \wedge e^1$	$^*(e^3 \wedge e^1) = -e^2 \wedge e^0$

the isomorphisms between the one-dimensional $\Lambda^0 \mathbb{R}^4$ and $\Lambda^4 \mathbb{R}^4$, the four-dimensional $\Lambda^1 \mathbb{R}^4$ and $\Lambda^3 \mathbb{R}^4$, the six-dimensional $\Lambda^2 \mathbb{R}^4$ and itself. Notice that the dimension of $\Lambda \mathbb{R}^4$ is 16 which we have explained in depth in the previous section. Finally, it is useful to point out the three-dimensional work and flux form mappings to provide some useful identities in this 1 + 3-dimensional setting.

$$*\omega_{\vec{v}} = -e^0 \wedge \Phi_{\vec{v}} \qquad *\Phi_{\vec{v}} = e^0 \wedge \omega_{\vec{v}} \qquad *\left(e^0 \wedge \Phi_{\vec{v}}\right) = \omega_{\vec{v}}$$

I leave verification of these formulas to the reader (use the table). Finally let us analyze the process of taking two hodge duals in succession. In the context of \mathbb{R}^3 we found that $**\alpha = \alpha$, we seek to discern if a similar formula is available in the context of \mathbb{R}^4 with the minkows important. We can calculate one type of example with the identities above:

$$*\omega_{\vec{v}} = -e^0 \wedge \Phi_{\vec{v}} \implies **\omega_{\vec{v}} = -*(e^0 \wedge \Phi_{\vec{v}}) = -\omega_{\vec{v}} \implies **\omega_{\vec{v}} = -\omega_{\vec{v}}$$

Perhaps this is true in general?

If we accept my algorithm then it's not too hard to sort through using multi-index notation: since hodge duality is linear it suffices to consider a basis element e^{I} where I is a multi-index,

- 1. transpose dual vectors so that $e^0 \wedge e^1 \wedge e^2 \wedge e^3 = (-1)^N e^I \wedge e^J$
- 2. if $0 \notin I$ then $*e^I = (-1)^N e^J$ and $0 \in J$ since $I \cup J = \{0, 1, 2, 3\}$. Take a second dual by writing $e^0 \wedge e^1 \wedge e^2 \wedge e^3 = (-1)^N e^J \wedge e^I$ but note $*((-1)^N e^J) = -e^I$ since $0 \in J$. We find $* *e^I = -e^I$ for all I not containing the 0-index.
- 3. if $0 \in I$ then $*e^I = -(-1)^N e^J$ and $0 \notin J$ since $I \cup J = \{0, 1, 2, 3\}$. Take a second dual by writing $e^0 \wedge e^1 \wedge e^2 \wedge e^3 = -(-1)^N e^J \wedge (-e^I)$ and hence $*(-(-1)^N e^J) = -e^I$ since $0 \notin J$. We find $**e^I = -e^I$ for all I containing the 0-index.
- 4. it follows that $\boxed{\ast \ast \alpha = -\alpha}$ for all $\alpha \in \Lambda \mathbb{R}^4$ with the minkowski metric.

To conclude, I would warn the reader that the results in this section pertain to our choice of notation for \mathbb{R}^4 . Some other texts use a metric which is $-\eta$ relative to our notation. This modifies many signs in this section. See Misner, Thorne and Wheeler's *Gravitation* or Bertlmann's *Anomalies in Field Theory* for future reading on Hodge duality and a more systematic explaination of how and when these signs arise from the metric.

9.6 coordinate change

Suppose V has two bases $\bar{\beta} = \{\bar{f}_1, \bar{f}_2, \dots, \bar{f}_n\}$ and $\beta = \{f_1, f_2, \dots, f_n\}$. If $v \in V$ then we can write v in as a linear combination of the $\bar{\beta}$ basis or the β basis:

$$v = x^1 f_1 + x^2 f_2 + \dots + x^n f_n$$
 and $v = \bar{x}^1 \bar{f}_1 + \bar{x}^2 \bar{f}_2 + \dots + \bar{x}^n \bar{f}_n$

given the notation above, we define **coordinate maps** as follows:

$$\Phi_{\beta}(v) = (x^1, x^2, \dots, x^n) = x$$
 and $\Phi_{\bar{\beta}}(v) = (\bar{x}^1, \bar{x}^2, \dots, \bar{x}^n) = \bar{x}$

We sometimes use the notation $\Phi_{\beta}(v) = [v]_{\beta} = x$ whereas $\Phi_{\bar{\beta}}(v) = [v]_{\bar{\beta}} = \bar{x}$. A coordinate map takes an abstract vector v and maps it to a particular representative in \mathbb{R}^n . A natural question to ask is how do different representatives compare? How do x and \bar{x} compare in our current notation? Because the coordinate maps are isomorphisms it follows that $\Phi_{\beta} \circ \Phi_{\bar{\beta}}^{-1} : \mathbb{R}^n \to \mathbb{R}^n$ is an isomorphism and given the domain and codomain we can write its formula via matrix multiplication:

$$\Phi_{\beta} \circ \Phi_{\bar{\beta}}^{-1}(u) = Pu \quad \Rightarrow \quad \Phi_{\beta} \circ \Phi_{\bar{\beta}}^{-1}(\bar{x}) = P\bar{x}$$

However, $\Phi_{\bar{\beta}}^{-1}(\bar{x}) = v$ hence $\Phi_{\beta}(v) = P\bar{x}$ and consequently, $x = P\bar{x}$. Conversely, to switch to barred coordinates we multiply the coordinate vectors by P^{-1} ; $\bar{x} = P^{-1}x$.

Continuing this discussion we turn to the dual space. Suppose $\bar{\beta}^* = \{\bar{f}^j\}_{j=1}^n$ is dual to $\bar{\beta} = \{\bar{f}_j\}_{j=1}^n$ and $\beta^* = \{f^j\}_{j=1}^n$ is dual to $\beta = \{f_j\}_{j=1}^n$. By definition we are given that $f^j(f_i) = \delta_{ij}$ and $\bar{f}^j(\bar{f}_i) = \delta_{ij}$ for all $i, j \in \mathbb{N}_n$. Suppose $\alpha \in V^*$ is a dual vector with components α_j with respect to the β^* basis and components $\bar{\alpha}_j$ with respect to the $\bar{\beta}^*$ basis. In particular this means we can either write $\alpha = \sum_{j=1}^n \alpha_j f^j$ or $\alpha = \sum_{j=1}^n \bar{\alpha}_j \bar{f}^j$. Likewise, given a vector $v \in V$ we can either write $v = \sum_{i=1}^n x^i f_i$ or $v = \sum_{i=1}^n \bar{x}^i \bar{f}_i$. With these notations in mind calculate:

$$\alpha(v) = \left(\sum_{j=1}^{n} \alpha_j f^j\right) \left(\sum_{i=1}^{n} x^i f_i\right) = \sum_{i,j=1}^{n} \alpha_j x^i f^j(f_i) = \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_j x^i \delta_{ij} = \sum_{i=1}^{n} \alpha_i x^i \delta_{ij}$$

and by the same calculation in the barred coordinates we find, $\alpha(v) = \sum_{i=1}^{n} \bar{\alpha}_i \bar{x}^i$. Therefore,

$$\sum_{i=1}^{n} \alpha_i x^i = \sum_{i=1}^{n} \bar{\alpha}_i \bar{x}^i.$$

Recall, $x = P\bar{x}$. In components, $x^i = \sum_{k=1}^n P_k^i \bar{x}^k$. Substituting,

$$\sum_{i=1}^n \sum_{k=1}^n \alpha_i P_k^i \bar{x}^k = \sum_{i=1}^n \bar{\alpha}_i \bar{x}^i.$$

But, this formula holds for all possible vectors v and hence all possible coordinate vectors \bar{x} . If we consider $v = \bar{f}_j$ then $\bar{x}^i = \delta_{ij}$ hence $\sum_{i=1}^n \bar{\alpha}_i \bar{x}^i = \sum_{i=1}^n \bar{\alpha}_i \delta_{ij} = \bar{\alpha}_j$. Moreover, $\sum_{i=1}^n \sum_{k=1}^n \alpha_i P_k^i \bar{x}^k = \sum_{i=1}^n \sum_{k=1}^n \alpha_i P_k^i \delta_{kj} = \sum_{i=1}^n \alpha_i P_j^i$. Thus, $\bar{\alpha}_j = \sum_{i=1}^n P_j^i \alpha_i$. Compare how vectors and dual vectors transform:

$$\bar{\alpha}_j = \sum_{i=1}^n P_j^i \alpha_i$$
 verses $\bar{x}^j = \sum_{i=1}^n (P^{-1})_i^j x^i.$

It is customary to use lower-indices on the components of dual-vectors and upper-indices on the components of vectors: we say $x = \sum_{i=1}^{n} x^i e_i \in \mathbb{R}^n$ has **contravariant components** whereas $\alpha = \sum_{j=1}^{n} \alpha_j e^j \in (\mathbb{R}^n)^*$ has **covariant components**. These terms arise from the coordinate change properties we derived in this section. The convenience of the up/down index notation will be more apparent as we continue our study to more complicated objects. It is interesting to note the basis elements tranform inversely:

$$\bar{f}^{j} = \sum_{i=1}^{n} (P^{-1})^{j}_{i} f^{i}$$
 verses $\bar{f}_{j} = \sum_{i=1}^{n} P^{i}_{j} f_{i}.$

The formulas above can be derived by arguments similar to those we already gave in this section,

however I think it may be more instructive to see how these rules work in concert:

$$x = \sum_{i=1}^{n} \bar{x}^{i} \bar{f}_{i} = \sum_{i=1}^{n} \sum_{j=1}^{n} (P^{-1})^{i}_{j} x^{j} \bar{f}_{i}$$

$$= \sum_{i=1}^{n} \sum_{j=1}^{n} (P^{-1})^{i}_{j} x^{j} \sum_{k=1}^{n} P^{k}_{i} f_{k}$$

$$= \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} (P^{-1})^{i}_{j} P^{k}_{i} x^{j} f_{k}$$

$$= \sum_{j=1}^{n} \sum_{k=1}^{n} \delta^{k}_{j} x^{j} f_{k}$$

$$= \sum_{k=1}^{n} x^{k} f_{k}.$$
(9.25)

9.6.1 coordinate change for $T_2^0(V)$

For an abstract vector space, or for \mathbb{R}^n with a nonstandard basis, we have to replace v, w with their coordinate vectors. If V has basis $\bar{\beta} = \{\bar{f}_1, \bar{f}_2, \dots, \bar{f}_n\}$ with dual basis $\beta^* = \{\bar{f}^1, \bar{f}^2, \dots, \bar{f}^n\}$ and v, w have coordinate vectors \bar{x}, \bar{y} (which means $v = \sum_{i=1}^n \bar{x}^i \bar{f}_i$ and $w = \sum_{i=1}^n \bar{y}^i \bar{f}_i$) then,

$$b(v,w) = \sum_{i,j=1}^{n} \bar{x}^i \bar{y}^j \bar{B}_{ij} = \bar{x}^T \bar{B} \bar{y}$$

where $\bar{B}_{ij} = b(\bar{f}_i, \bar{f}_j)$. If $\beta = \{f_1, f_2, \dots, f_n\}$ is another basis on V with dual basis β^* then we define $B_{ij} = b(f_i, f_j)$ and we have

$$b(v,w) = \sum_{i,j=1}^{n} x^{i} y^{j} B_{ij} = x^{T} B y.$$

Recall that $\bar{f}_i = \sum_{k=1}^n P_i^k f_k$. With this in mind calculate:

$$\bar{B}_{ij} = b(\bar{f}_i, \bar{f}_j) = b\left(\sum_{k=1}^n P_i^k f_k, \sum_{l=1}^n P_j^l f_l\right) = \sum_{k,l=1}^n P_i^k P_j^l b(f_k, f_l) = \sum_{k,l=1}^n P_i^k P_j^l B_{kl}$$

We find the components of a bilinear map transform as follows:

$$\bar{B}_{ij} = \sum_{k,l=1}^{n} P_i^k P_j^l B_{kl}$$

Chapter 10

calculus with differential forms

A manifold is an abtract space which allows for local calculus. We discuss how coordinate charts cover the a manifold and how we use them to define smoothness in the abstract. For example, a function is smooth if all its local coordinate representations are smooth. The local coordinate representative is a function from \mathbb{R}^m to \mathbb{R}^n thus we may quantify its smoothness in terms of ordinary partial derivatives of the component functions. On the other hand, while the concept of a coordinate chart is at first glance abstract the usual theorems of advanced calculus all lift naturally to the abstract manifold. For example, we see how partial derivatives with respect to manifold coordinates hold to all the usual linearity, product and chain-rules hold in \mathbb{R}^n . We prove a number of these results in considerably more detail than Lecture will bear.

The differential gains a deeper meaning than we found in advanced calculus. In the manifold context, the differential acts on tangent space which is **not** identified as some subset of the manifold itself. So, in a sense we lose the direct approximating concept for the differential. One could always return to the best linear approximation ideal as needed, but the path ahead is quite removed from pure numerical approximation. First step towards this abstract picture of tangent space is the realization that tangent vectors themselves should be identified as **derivations**. We show how partial derivatives give derivations and we sketch a technical result which also provides a converse in the smooth category¹ Once we've settled how to study the tangent space to a manifold we find the natural extension of the differential as the **push-forward** induced from a smooth map. It turns out that you have probably already calculated a few push-forwards in multivariate calculus. We attempt to obtain some intuition for this abstract push-forward. We also pause to note how the push-forward might allow us to create new vectors fields from old (or not).

The cotangent space is the dual space to the tangent space. The basis which is dual to the partial derivative basis is naturally identified with the differentials of the coordinate maps themselves. We then have a basis and dual basis for the tangent and cotangent space at each point on the manifold.

¹it's actually false for C^k manifolds which have an infinite-dimensional space of derivations. The tangent space to a *n*-dimensional manifold is an *n*-dimensional vector space so we need an *n*-dimensional space of derivations to make the identification.

We use these to build vector fields and differential forms just as we used f_i and f^i in the previous chapter. Multilinear algebra transfers over point by point on the manifold. However, something new happens. Differential forms permit a differentiation called the **exterior derivative**. This natural operation takes a *p*-form and generates a new (p + 1)-form. We examine how the exterior derivative recovers **all** the interesting vector-calculus derivatives from vector calculus on \mathbb{R}^3 . Of course, it goes much deeper as the exterior derivative provides part of the machinery to write cohomology on spaces of arbitrarily high dimension. Ultimately, this theory of cohomology detects topological aspects of the space. A basic example of this is the Poincare Lemma.

To understand the Poincare Lemma as well as a number of other interesting calculations we find it necessary to introduce a dual operation to the push-foward; the **pull-back** gives us a natural method to take differential forms in the range of a mapping and transport them back to the domain of the map. Moreover, this pull-back operation plays nicely with the wedge product and the exterior derivative. Several pages are devotes towards understanding some intuitive method of calculating the pull-back. We are indebted to Harold M. Edwards' Advanced Calculus: A Differential Form Approach which encouraged us to search for intuition. I also attempted to translate a differential forms version of the implict mapping theorem from the same text, I'm fairly certain there is some conceptual error in that section as it stands. It is a work in progress.

The abstract calculus of forms is interesting in it's own right, but we are happy to find how it reduces to the familar calculus on \mathbb{R}^3 . We state² the Generalized Stokes Theorem and see how the **flux-form** and **work-form** mappings produce the usual theorems of vector calculus as corollaries to the Generalized Stokes Theorem. The definition of integrals of differential forms is accomplished by pulling-back the forms to euclidean space where an ordinary integral quantifies the result. In some sense, this discussion may help answer the question *what is a differential form?*. We spend some effort attempting to understand how the form integration interfaces with ordinary surface or line integration of vector fields.

Finally, the fact that $d^2 = 0$ paired with the nice properties of the pull-back and wedge product proves to give a technique for study of exact differential equations and partial differential equations. This final section opens a door to the vast topic of exterior differential systems. In this study, solutions to PDEs are manifolds and the PDE itself is formulated in terms of wedge products and differential forms. Here I borrow wisdom from *Cartan for Beginners* by Ivey and Landsberg as well as *Equivalence, Invariance, and Symmetry* by Olver. Please keep in mind, we're just dipping are toes in the pond here.

 $^{^{2}\}mathrm{the}$ proof is found in Edwards and many other places

10.1 an informal introduction to manifolds

A manifold \mathcal{M} is space which locally resembles \mathbb{R}^n . This requirement is implemented by the existence of coordinate charts (χ, U) which cover \mathcal{M} and allow us to do calculus locally. Let me sketch the idea with a picture:



The charts (χ_j, U_j) have to cover the manifold \mathcal{M} and their **transition functions** θ_{ij} must be smooth mappings on \mathbb{R}^n . Rather going on about the proper definition³, I'll show a few examples.

Example 10.1.1. Let $\mathcal{M} = \{(x, y) \in \mathbb{R}^2 \mid x^2 + y^2 = 1\}$. The usual chart on the unit-circle is the angle-chart $\chi = \theta$. Given $(\cos t, \sin t) = p \in \mathcal{M}$ we define $\theta(p) = t$. If x > 0 and $x^2 + y^2 = 1$ then $(x, y) \in \mathcal{M}$ and we have $\theta(x, y) = \tan^{-1}(y/x)$.

Example 10.1.2. Let $\mathcal{M} = \mathbb{R}^2$. The usual chart is simply the cartesian coordinate system $\chi_1 = (x, y)$ with $U_1 = \mathbb{R}^2$. If $(a, b) \in \mathbb{R}^2$ then x(a, b) = a and y(a, b) = b. In practice the symbols x, y are used both as maps and variables so one must pay attention to context. A second coordinate system on \mathcal{M} is given by the polar coordinate chart $\chi_2 = (r, \theta)$ with domain $U_2 = (0, \infty) \times \mathbb{R}$. I'll just take their domain to be the right half-plane for the sake of having a nice formula: $(r, \theta)(a, b) = (\sqrt{a^2 + b^2}, \tan^{-1}(b/a))$. You can extend these to most of the plane, but you have to delete the origin and you must lose a ray since the angle-chart is not injective if we go full-circle. That said, the coordinate systems ($\chi_1 = (x, y), U_1$) and ($\chi_2 = (r, \theta), U_2$) are **compatible** because they have smooth transition functions. One can calculate $\chi_1 \circ \chi_2^{-1}$ is a smooth mapping on \mathbb{R}^2 . Explicitly:

$$\chi_1 \circ \chi_2^{-1}(u, v) = \chi_1(\chi_2^{-1}(u, v)) = \chi_1(u \cos v, u \sin v) = (u \cos(v), u \sin(v))$$

Technically, the use of the term **coordinate system** in calculus III is less strict than the concept which appears in manifold theory. Departure from injectivity in a geometrically tractible setting is manageable, but for the abstract setting, injectivity of the coordinate charts is important to many arguments.

³see my 2011 notes, or better yet study Loring Tu's An Introduction to Manifolds

Example 10.1.3. Define $\chi_{spherical}(x, y, z) = (r, \theta, \phi)$ implicitly by the coordinate transformations

 $x = r\cos(\theta)\sin(\phi), \quad y = r\sin(\theta)\sin(\phi), \quad z = r\cos(\phi)$

These can be inverted,

$$r = \sqrt{x^2 + y^2 + z^2}, \quad \theta = \tan^{-1} \left[\frac{y}{x} \right], \quad \phi = \cos^{-1} \left[\frac{z}{\sqrt{x^2 + y^2 + z^2}} \right]$$

To show compatibility with the standard Cartesian coordinates we would need to select a subset of \mathbb{R}^3 for which $\chi_{spherical}$ is 1-1 and the since $\chi_{Cartesian} = Id$ the transition functions are just $\chi_{spherical}^{-1}$.

Example 10.1.4. Define $\chi_{cylindrical}(x, y, z) = (s, \theta, z)$ implicitly by the coordinate transformations

 $x = s\cos(\theta), \quad y = s\sin(\theta), \quad z = z$

These can be inverted,

$$s = \sqrt{x^2 + y^2}, \quad \theta = \tan^{-1} \left[\frac{y}{x} \right], \quad z = z$$

You can take
$$dom(\chi_{cylindrical}) = \{(x, y, z) \mid 0 < \theta < 2\pi, \} - \{(0, 0, 0)\}$$

Example 10.1.5. Let $\mathcal{M} = V$ where V is an n-dimensional vector space over \mathbb{R} . If β_1 is a basis for V then $\Phi_{\beta_1} : V \to \mathbb{R}^n$ gives a global coordinate chart. Moreover, if β_2 is another basis for Vthen $\Phi_{\beta_2} : V \to \mathbb{R}^n$ also gives a global coordinate chart. The transition function $\theta_{12} = \Phi_{\beta_2} \circ \Phi_{\beta_1}^{-1}$ is linear hence it is clearly smooth. In short, an n-dimensional vector space is an n-dimensional manifold. We could put non-linear charts on V if we wished, that freedom is new here, in linear algebra all the coordinate systems considered are linear.

Example 10.1.6. Let $\mathcal{M} = \{(x, y) \in \mathbb{R}^2 \mid x^2 + y^2 = 1\}.$

- 1. Let $V_+ = \{(x, y) \in \mathcal{M} \mid y > 0\} = dom(\chi_+)$ and define $\chi_+(x, y) = x$
- 2. Let $V_{-} = \{(x, y) \in \mathcal{M} \mid y < 0\} = dom(\chi_{-}) \text{ and define } \chi_{-}(x, y) = x$
- 3. Let $V_R = \{(x, y) \in \mathcal{M} \mid x > 0\} = dom(\chi_R)$ and define $\chi_R(x, y) = y$
- 4. Let $V_L = \{(x, y) \in \mathcal{M} \mid x < 0\} = dom(\chi_L)$ and define $\chi_L(x, y) = y$

The set of charts $\mathcal{A} = \{(V_+, \chi_+), (V_-, \chi_-), (V_R, \chi_R), (V_L, \chi_L)\}$ forms an atlas on \mathcal{M} which gives the circle a differentiable structure⁴. It is not hard to show the transition functions are smooth on the image of the intersection of their respect domains. For example, $V_+ \cap V_R = W_{+R} = \{(x, y) \in \mathcal{M} \mid x, y > 0\}$, it's easy to calculate that $\chi_+^{-1}(x) = (x, \sqrt{1-x^2})$ hence

$$(\chi_R \circ \chi_+^{-1})(x) = \chi_R(x, \sqrt{1-x^2}) = \sqrt{1-x^2}$$

for each $x \in \chi_R(W_{+R})$. Note $x \in \chi_R(W_{+R})$ implies 0 < x < 1 hence it is clear the transition function is smooth.

 $^{^4}$ meaning that if we adjoin the infinity of likewise compatible charts that defines a differentiable structure on $\mathcal M$



Similar calculations hold for all the other overlapping charts. This manifold is usually denoted $\mathcal{M} = S_1$.

A cylinder is the Cartesian product of a line and a circle. In other words, we can create a cylinder by gluing a copy of a circle at each point along a line. If all these copies line up and don't twist around then we get a cylinder. The example that follows here illustrates a more general pattern, we can take a given manifold an paste a copy at each point along another manifold by using a Cartesian product.

Example 10.1.7. Let $\mathcal{P} = \{(x, y, z) \in \mathbb{R}^3 \mid x^2 + y^2 = 1\}.$

1. Let
$$V_+ = \{(x, y, z) \in \mathcal{P} \mid y > 0\} = dom(\chi_+)$$
 and define $\chi_+(x, y, z) = (x, z)$

- 2. Let $V_{-} = \{(x, y, z) \in \mathcal{P} \mid y < 0\} = dom(\chi_{-})$ and define $\chi_{-}(x, y, z) = (x, z)$
- 3. Let $V_R = \{(x, y, z) \in \mathcal{P} \mid x > 0\} = dom(\chi_R)$ and define $\chi_R(x, y, z) = (y, z)$
- 4. Let $V_L = \{(x, y, z) \in \mathcal{P} \mid x < 0\} = dom(\chi_L)$ and define $\chi_L(x, y, z) = (y, z)$

The set of charts $\mathcal{A} = \{(V_+, \chi_+), (V_-, \chi_-), (V_R, \chi_R), (V_L, \chi_L)\}$ forms an atlas on \mathcal{P} which gives the cylinder a differentiable structure. It is not hard to show the transition functions are smooth on the image of the intersection of their respective domains. For example, $V_+ \cap V_R = W_{+R} = \{(x, y, z) \in \mathcal{P} \mid x, y > 0\}$, it's easy to calculate that $\chi_+^{-1}(x, z) = (x, \sqrt{1 - x^2}, z)$ hence

$$(\chi_R \circ \chi_+^{-1})(x,z) = \chi_R(x,\sqrt{1-x^2},z) = (\sqrt{1-x^2},z)$$

for each $(x,z) \in \chi_R(W_{+R})$. Note $(x,z) \in \chi_R(W_{+R})$ implies 0 < x < 1 hence it is clear the transition function is smooth. Similar calculations hold for all the other overlapping charts.

Generally, given two manifolds \mathcal{M} and \mathcal{N} we can construct $\mathcal{M} \times \mathcal{N}$ by taking the Cartesian product of the charts. Suppose $\chi_{\mathcal{M}} : V \subseteq \mathcal{M} \to U \subseteq \mathbb{R}^m$ and $\chi_{\mathcal{N}} : V' \subseteq \mathcal{N} \to U' \subseteq \mathbb{R}^n$ then you can define the product chart $\chi : V \times V' \to U \times U'$ as $\chi = \chi_{\mathcal{M}} \times \chi_{\mathcal{N}}$. The Cartesian product $\mathcal{M} \times \mathcal{N}$ together with all such product charts naturally is given the structure of an (m + n)-dimensional manifold. For example, in the preceding example we took $\mathcal{M} = S_1$ and $\mathcal{N} = \mathbb{R}$ to construct $\mathcal{P} = S_1 \times \mathbb{R}$. **Example 10.1.8.** The 2-torus, or donut, is constructed as $T_2 = S_1 \times S_1$. The n-torus is constructed by taking the product of n-circles:

$$T_n = \underbrace{S_1 \times S_1 \times \dots \times S_1}_{n \text{ copies}}$$

The atlas on this space can be obtained by simply taking the product of the S_1 charts n-times.

Recall from our study of linear algebra that vector space structure is greatly elucidated by the study of linear transformations. In our current context, the analogous objects are smooth maps. These are natural mappings between manifolds. In particular, suppose \mathcal{M} is an *m*-fold and \mathcal{N} is an *n*-fold with $f: U \subseteq \mathcal{M} \to \mathcal{N}$ is a function. Then, we say f is **smooth** iff all local coordinate representatives of f are smooth mappings from \mathbb{R}^m to \mathbb{R}^n . See the diagram below:



This definition allows us to discuss smooth curves on manifolds. A curve $\gamma : I \subseteq \mathbb{R} \to \mathcal{M}$ is smooth iff $\chi \circ \gamma : I \to \mathbb{R}^n$ is a smooth curve in \mathbb{R}^n .



Finally, just for your information, if a bijection between manifolds is smooth with smooth inverse then the manifolds are said to be **diffeomorphic**. One fascinating result of recent mathematics is

that \mathbb{R}^4 permits distinct differentiable structures in the sense that there does not exist a diffeomorphism between certain atlases⁵. Curiously, up to diffeomorphism, there is just one differentiable structure on \mathbb{R}^n for $n \neq 4$. Classifying possible differentiable structures for a given point set is an interesting and ongoing problem.

10.2 vectors as derivations

To begin, let us define the set of locally smooth functions at $p \in \mathcal{M}$:

 $C^{\infty}(p) = \{ f : \mathcal{M} \to \mathbb{R} \mid f \text{ is smooth on an open set containing } p \}$

In particular, we suppose $f \in C^{\infty}(p)$ to mean there exists a patch $\phi : U \to V \subseteq \mathcal{M}$ such that f is smooth on V. Since we use Cartesian coordinates on \mathbb{R} by convention it follows that $f : V \to \mathbb{R}$ smooth indicates the local coordinate representative $f \circ \phi : U \to \mathbb{R}$ is smooth (it has continuous partial derivatives of all orders).

Definition 10.2.1.

Suppose $X_p : C^{\infty}(p) \to \mathbb{R}$ is a linear transformation which satisfies the Leibniz rule then we say X_p is a **derivation** on $C^{\infty}(p)$. Moreover, we denote $X_p \in \mathcal{D}_p\mathcal{M}$ iff $X_p(f+cg) = X_p(f) + cX_p(g)$ and $X_p(fg) = f(p)X_p(g) + X_p(f)g(p)$ for all $f, g \in C^{\infty}(p)$ and $c \in \mathbb{R}$.

Example 10.2.2. Let $\mathcal{M} = \mathbb{R}$ and consider $X_{t_o} = d/dt|_{t_o}$. Clearly X is a derivation on smooth functions near t_o .

Example 10.2.3. Consider $\mathcal{M} = \mathbb{R}^2$. Pick $p = (x_o, y_o)$ and define $X_p = \frac{\partial}{\partial x}\Big|_p$ and $Y_p = \frac{\partial}{\partial y}\Big|_p$. Once more it is clear that $X_p, Y_p \in \mathcal{D}(p)\mathbb{R}^2$. These derivations action is accomplished by partial differentiation followed by evaluation at p.

Example 10.2.4. Suppose $\mathcal{M} = \mathbb{R}^m$. Pick $p \in \mathbb{R}^m$ and define $X = \frac{\partial}{\partial x^j}\Big|_p$. Clearly this is a derivation for any $j \in \mathbb{N}_m$.

Are the other types of derivations? Is the only thing a derivation is is a partial derivative operator? Before we can explore this question we need to define partial differentiation on a manifold. We should hope the definition is consistent with the langauge we already used in multivariate calculus (and the preceding pair of examples) and yet is also general enough to be stated on any abstract smooth manifold.

⁵there is even a whole book devoted to this exotic chapter of mathematics, see the *The Wild World of 4-Manifolds* by Alexandru Scorpan. This is on my list of books I "need" to buy.

Definition 10.2.5.

Let \mathcal{M} be a smooth *m*-dimensional manifold and let $\phi : U \to V$ be a local parametrization with $p \in V$. The *j*-th coordinate function $x^j : V \to \mathbb{R}$ is the *j*-component function of $\phi^{-1} : V \to U$. In other words:

$$\phi^{-1}(p) = x(p) = (x^1(p), x^2(p), \dots, x^m(p))$$

These x^j are **manifold coordinates**. In constrast, we will denote the standard Cartesian coordinates in $U \subseteq \mathbb{R}^m$ via u^j so a typical point has the form (u^1, u^2, \ldots, u^m) and viewed as functions $u^j : \mathbb{R}^m \to \mathbb{R}$ where $u^j(v) = e^j(v) = v^j$. We define the **partial derivative** with respect to x^j at p for $f \in C^{\infty}(p)$ as follows:

$$\frac{\partial f}{\partial x^{j}}(p) = \frac{\partial}{\partial u^{j}} \left[(f \circ \phi)(u) \right] \Big|_{u=\phi^{-1}(p)} = \frac{\partial}{\partial u^{j}} \left[f \circ x^{-1} \right] \Big|_{x(p)}$$

The idea of the definition is simply to take the function f with domain in \mathcal{M} then pull it back to a function $f \circ x^{-1} : U \subseteq \mathbb{R}^m \to V \to \mathbb{R}$ on \mathbb{R}^m . Then we can take partial derivatives of $f \circ x^{-1}$ in the same way we did in multivariate calculus. In particular, the partial derivative w.r.t. u^j is calculated by:

$$\frac{\partial f}{\partial x^{j}}(p) = \frac{d}{dt} \left[\left(f \circ \phi \right) (x(p) + te_{j}) \right]_{t=0}$$

which is precisely the directional derivative of $f \circ x^{-1}$ in the *j*-direction at x(p). In fact, Note

$$(f \circ \phi)(x(p) + te_j) = f(x^{-1}(x(p) + te_j)).$$

The curve $t \to x^{-1}(x(p) + te_j)$ is the curve on \mathcal{M} through p where all coordinates are fixed except the *j*-coordinate. It is a *coordinate curve* on \mathcal{M} .



Notice in the case that $\mathcal{M} = \mathbb{R}^m$ is given Cartesian coordinate $\phi = Id$ then $x^{-1} = Id$ as well and the $t \to x^{-1}(x(p) + te_j)$ reduces to $t \to p + te_j$ which is just the *j*-th coordinate curve through *p* on

 \mathbb{R}^m . It follows that the partial derivative defined for manifolds naturally reduces to the ordinary partial derivative in the context of $\mathcal{M} = \mathbb{R}^m$ with Cartesian coordinates. The beautiful thing is that almost everything we know for ordinary partial derivatives equally well transfers to $\frac{\partial}{\partial x^j}\Big|_{p}$.

Theorem 10.2.6. Partial differentiation on manifolds

Let \mathcal{M} be a smooth *m*-dimensional manifold with coordinates x^1, x^2, \ldots, x^m near *p*. Furthermore, suppose coordinates y^1, y^2, \ldots, y^m are also defined near *p*. Suppose $f, g \in C^{\infty}(p)$ and $c \in \mathbb{R}$ then:

1. $\frac{\partial}{\partial x^{j}}\Big|_{p}\Big[f+g\Big] = \frac{\partial f}{\partial x^{j}}\Big|_{p} + \frac{\partial g}{\partial x^{j}}\Big|_{p}$ 2. $\frac{\partial}{\partial x^{j}}\Big|_{p}\Big[cf\Big] = c\frac{\partial f}{\partial x^{j}}\Big|_{p}$ 3. $\frac{\partial}{\partial x^{j}}\Big|_{p}\Big[fg\Big] = f(p)\frac{\partial g}{\partial x^{j}}\Big|_{p} + \frac{\partial f}{\partial x^{j}}\Big|_{p}g(p)$ 4. $\frac{\partial x^{i}}{\partial x^{j}}\Big|_{p} = \delta_{ij}$ 5. $\sum_{k=1}^{m} \frac{\partial x^{k}}{\partial y^{j}}\Big|_{p}\frac{\partial y^{i}}{\partial x^{k}}\Big|_{p} = \delta_{ij}$ 6. $\frac{\partial f}{\partial y^{j}}\Big|_{p} = \sum_{k=1}^{m} \frac{\partial x^{k}}{\partial y^{j}}\Big|_{p}\frac{\partial f}{\partial x^{k}}\Big|_{p}$

Proof: The proof of (1.) and (2.) follows from the calculation below:

$$\begin{aligned} \frac{\partial (f+cg)}{\partial x^{j}}(p) &= \frac{\partial}{\partial u^{j}} \left[(f+cg) \circ x^{-1} \right] \Big|_{x(p)} \\ &= \frac{\partial}{\partial u^{j}} \left[f \circ x^{-1} + cg \circ x^{-1} \right] \Big|_{x(p)} \\ &= \frac{\partial}{\partial u^{j}} \left[f \circ x^{-1} \right] \Big|_{x(p)} + c \frac{\partial}{\partial u^{j}} \left[g \circ x^{-1} \right] \Big|_{x(p)} \\ &= \frac{\partial f}{\partial x^{j}}(p) + c \frac{\partial g}{\partial x^{j}}(p) \end{aligned}$$
(10.1)

The key in this argument is that composition $(f + cg) \circ x^{-1} = f \circ x^{-1} + cg \circ x^{-1}$ along side the linearity of the partial derivative. Item (3.) follows from the identity $(fg) \circ x^{-1} = (f \circ x^{-1})(g \circ x^{-1})$ in tandem with the product rule for a partial derivative on \mathbb{R}^m . The reader may be asked to complete the argument for (3.) in the homework. Continuing to (4.) we calculate from the definition:

$$\frac{\partial x^i}{\partial x^j}\Big|_p = \frac{\partial}{\partial u^j} \left[(x^i \circ x^{-1})(u) \right] \Big|_{x(p)} = \frac{\partial u^i}{\partial u^j}\Big|_{x(p)} = \delta_{ij}.$$

where the last equality is known from multivariate calculus. In invite the reader to prove it from the definition if unaware of this fact. Before we prove (5.) it helps to have a picture and a bit

more notation in mind. Near the point p we have two coordinate charts $x: V \to U \subseteq \mathbb{R}^m$ and $y: V \to W \subseteq \mathbb{R}^m$, we take the chart domain V to be small enough so that both charts are defined. Denote Cartesian coordinates on U by u^1, u^2, \ldots, u^m and for W we likewise use Cartesian coordinates w^1, w^2, \ldots, w^m . Let us denote patches ϕ, ψ as the inverses of these charts; $\phi^{-1} = x$ and $\psi^{-1} = y$. Transition functions $\psi^{-1} \circ \phi = y \circ x^{-1}$ are mappings from $U \subseteq \mathbb{R}^m$ to $W \subseteq \mathbb{R}^m$ and we note

$$\frac{\partial}{\partial u^j} \left[(y^i \circ x^{-1})(u) \right] = \frac{\partial y^i}{\partial x^j}$$

Likewise, the inverse transition functions $\phi^{-1} \circ \psi = x \circ y^{-1}$ are mappings from $W \subseteq \mathbb{R}^m$ to $U \subseteq \mathbb{R}^m$

$$\frac{\partial}{\partial w^j} \left[(x^i \circ y^{-1})(w) \right] = \frac{\partial x^i}{\partial y^j}$$

Recall that if $F, G : \mathbb{R}^m \to \mathbb{R}^m$ and $F \circ G = Id$ then F'G' = I by the chainrule, hence $(F')^{-1} = G'$. Apply this general fact to the transition functions, we find their derivative matrices are inverses. Item (5.) follows. In matrix notation we item (5.) reads $\frac{\partial x}{\partial y} \frac{\partial y}{\partial x} = I$. Item (6.) follows from:

$$\begin{split} \frac{\partial f}{\partial y^j} \bigg|_p &= \frac{\partial}{\partial w^j} \bigg[(f \circ y^{-1})(w) \bigg] \bigg|_{y(p)} \\ &= \frac{\partial}{\partial w^j} \bigg[(f \circ x^{-1} \circ x \circ y^{-1})(w) \bigg] \bigg|_{y(p)} \\ &= \frac{\partial}{\partial w^j} \bigg[(f \circ x^{-1})(u^1(w), \dots, u^m(w)) \bigg] \bigg|_{y(p)} : \text{ where } u^k(w) = (x \circ y^{-1})^k(w) \\ &= \sum_{k=1}^m \frac{\partial (x \circ y^{-1})^k}{\partial w^j} \bigg|_{y(p)} \frac{\partial (f \circ x^{-1})}{\partial u^k} \bigg|_{(x \circ y^{-1})(y(p))} : \text{ chain rule} \\ &= \sum_{k=1}^m \frac{\partial (x^k \circ y^{-1})}{\partial w^j} \bigg|_{y(p)} \frac{\partial (f \circ x^{-1})}{\partial u^k} \bigg|_{x(p)} \\ &= \sum_{k=1}^m \frac{\partial x^k}{\partial y^j} \bigg|_p \frac{\partial f}{\partial x^k} \bigg|_p \end{split}$$

The key step was the multivariate chain rule. \Box

This theorem proves we can lift calculus on \mathbb{R}^m to \mathcal{M} in a natural manner. Moreover, we should note that items (1.), (2.) and (3.) together show $\frac{\partial}{\partial x^i}\Big|_p$ is a derivation at p. Item (6.) should remind the reader of the contravariant vector discussion. Removing the f from the equation reveals that

$$\frac{\partial}{\partial y^j}\bigg|_p = \sum_{k=1}^m \frac{\partial x^k}{\partial y^j}\bigg|_p \frac{\partial}{\partial x^k}\bigg|_p$$

A notation convenient to the current discussion is that a contravariant transformation is $(p, v_x) \rightarrow (p, v_y)$ where $v_y = Pv_x$ and $P = (y \circ x^{-1})'(x(p)) = \frac{\partial y}{\partial x}\Big|_{x(p)}$. Notice this is the inverse of what we see

in (6.). This suggests that the partial derivatives change coordinates like as a basis for the tangent space. To complete this thought we need a few well-known propositions for derivations.

Proposition 10.2.7. derivations on constant function gives zero.

If $f \in C^{\infty}(p)$ is a constant function and $X_p \in \mathcal{D}_p\mathcal{M}$ then $X_p(f) = 0$.

Proof: Suppose f(x) = c for all $x \in V$, define g(x) = 1 for all $x \in V$ and note f = fg on V. Since X_p is a derivation is satisfies the Leibniz rule hence

$$X_p(f) = X_p(fg) = f(p)X_p(g) + X(f)g(p) = cX_p(g) + X_p(f) \implies cX_p(g) = 0.$$

Moreover, by homogeneity of X_p , note $cX_p(g) = X_p(cg) = X_p(f)$. Thus, $X_p(f) = 0$. \Box

Proposition 10.2.8.

If $f, g \in C^{\infty}(p)$ and f(x) = g(x) for all $x \in V$ and $X_p \in \mathcal{D}_p\mathcal{M}$ then $X_p(f) = X_p(g)$.

Proof: Note that f(x) = g(x) implies h(x) = f(x) - g(x) = 0 for all $x \in V$. Thus, the previous proposition yields $X_p(h) = 0$. Thus, $X_p(f - g) = 0$ and by linearity $X_p(f) - X_p(g) = 0$. The proposition follows. \Box

Proposition 10.2.9.

Suppose $X_p \in \mathcal{D}_p \mathcal{M}$ and x is a chart defined near p, $X_p = \sum_{j=1}^m X_p(x^j) \frac{\partial}{\partial x^j} \Big|_p$

Proof: this is a less trivial proposition. We need a standard lemma before we begin.

Lemma 10.2.10.

Let p be a point in smooth manifold \mathcal{M} and let $f : \mathcal{M} \to \mathbb{R}$ be a smooth function. If $x: V \to U$ is a chart with $p \in V$ and x(p) = 0 then there exist smooth functions $g_j : \mathcal{M} \to \mathbb{R}$ whose values at p satisfy $g_j(p) = \frac{\partial f}{\partial x^j}(p)$. In addition, for all q near enough to p we have $f(q) = f(p) + \sum_{k=1}^m x^j(q)g_j(q)$

Proof: follows from proving a similar identity on \mathbb{R}^m then lifting to the manifold. I leave this as a nontrivial exercise for the reader. This can be found in many texts, see Burns and Gidea page 29 for one source. It should be noted that the manifold must be smooth for this construction to hold. It turns out the set of derivations on a C^k -manifold forms an infinite-dimensional vector space over \mathbb{R} , see Lawrence Conlon's *Differentiable Manifolds* page 49. ∇

Consider $f \in C^{\infty}(p)$, and use the lemma, we assume x(p) = 0 and $g_j(p) = \frac{\partial f}{\partial x^j}(p)$:

$$\begin{aligned} X_p(f) &= X_p \bigg(f(p) + \sum_{k=1}^m x^j(q) g_j(q) \bigg) \\ &= X_p(f(p)) + \sum_{k=1}^m X_p \big(x^j(q) g_j(q) \big) \\ &= \sum_{k=1}^m \bigg[X_p(x^j) g_j(q) + x^j(p) X_p(g_j(q)) \bigg] \\ &= \sum_{k=1}^m X_p(x^j) \frac{\partial f}{\partial x^j}(p). \end{aligned}$$

The calculation above holds for arbitrary $f \in C^{\infty}(p)$ hence the proposition follows. \Box

We've answered the question posed earlier in this section. It is true that every derivation of a manifold is simply a linear combination of partial derivatives. We can say more. The set of derivations at p naturally forms a vector space under the usual addition and scalar multiplication of operators: if $X_p, Y_p \in \mathcal{D}_p\mathcal{M}$ then we define $X_p + Y_p$ by $(X_p + Y_p)(f) = X_p(f) + Y_p(f)$ and cX_p by $(cX_p)(f) = cX_p(f)$ for all $f, g \in C^{\infty}(p)$ and $c \in \mathbb{R}$. It is easy to show $\mathcal{D}_p\mathcal{M}$ is a vector space under these operations. Moreover, the preceding proposition shows that $\mathcal{D}_p\mathcal{M} = span\{\frac{\partial f}{\partial x^j}|_p\}_{j=1}^m$ hence $\mathcal{D}_p\mathcal{M}$ is an m-dimensional vector space⁶.

Finally, let's examine coordinate change for derivations. Given two coordinate charts x, y at $p \in \mathcal{M}$ we have two ways to write the derivation X_p :

$$X_p = \sum_{j=1}^m X_p(x^j) \frac{\partial}{\partial x^j} \bigg|_p \quad \text{or} \quad X_p = \sum_{k=1}^m X_p(y^k) \frac{\partial}{\partial y^k} \bigg|_p$$

It is simple to connect these formulas. Whereas, for *y*-coordinates,

$$X_p(y^k) = \sum_{j=1}^m X_p(x^j) \frac{\partial y^k}{\partial x^j} \Big|_p$$
(10.2)

This is the contravariant transformation rule. In contrast, recall $\frac{\partial}{\partial y^j}\Big|_p = \sum_{k=1}^m \frac{\partial x^k}{\partial y^j}\Big|_p \frac{\partial}{\partial x^k}\Big|_p$. We should have anticipated this pattern since from the outset it is clear there is no coordinate dependence in the definition of a derivation.

Definition 10.2.11. tangent space

We denote $T_p\mathcal{M} = derT_p\mathcal{M}$.

⁶technically, we should show the coordinate derivations $\frac{\partial}{\partial x^j}\Big|_p$ are linearly independent to make this conclusion. I don't suppose we've done that directly at this juncture. You might find this as a homework

10.2.1 concerning the geometry of derivations

An obvious question we should ask:

How are derivations related to tangent vectors geometrically?

To give a proper answer, we focus our attention to \mathbb{R}^3 and I follow Barret Oneil's phenomenal text on *Elementary Differential Geometry*, second edition. Consider a function $f : \mathbb{R}^3 \to \mathbb{R}$ and calculate the directional derivative in the $v = \langle a, b, c \rangle$ -direction at the point p. We make no assumption that ||v|| = 1, this is the same directional derivative for which we discussed the relation with the Frechet derivative in an earlier chapter. If f is smooth,

$$Df(p)(v) = v \bullet (\nabla f)(p) = a\frac{\partial f}{\partial x}(p) + b\frac{\partial f}{\partial y}(p) + \frac{\partial f}{\partial z}(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial z}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial y}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y} + c\frac{\partial}{\partial y}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} + b\frac{\partial}{\partial y}\right)\Big|_{p}f(p) = \left(a\frac{\partial}{\partial x} +$$

Therefore, we find the following interpretation of the derivation $X_p = (a\partial_x + b\partial_y + c\partial_z)|_p$:

When a derivation $X_p = (a\partial_x + b\partial_y + c\partial_z)|_p$ acts on a smooth function f it describes the rate at which f changes at p in the $\langle a, b, c \rangle$ direction. In other words, a derivation at p generates directional derivatives of functions at p.

Therefore, our work over the last few pages can be interpreted as abstracting the directional derivative to manifolds. In particular, the partial derivatives with respect to manifold coordinate x^j measure the rate of change of functions along the curve on the manifold which allows x^j to vary while all the other coordinates are held fixed.

10.3 differential for manifolds, the push-forward

In this section we generalize the concept of the differential to the context of manifolds. Recall that for $F: U \subseteq \mathbb{R}^m \to V \subseteq \mathbb{R}^n$ the differential $d_pF: \mathbb{R}^m \to \mathbb{R}^n$ was a linear transformation which best approximated the change in F near p. Notice that while the domain of F could be a mere subset of \mathbb{R}^m the differential always took all of \mathbb{R}^m as its domain. This suggests we should really think of the differential as a mapping which transports tangent vectors to U to tangent vectors at V. I find the following picture helpful at times, here I picture the tangent space as if it is attached to the point p on the manifold. Keep in mind this is an abstract picture:



Often $d_p f$ is called the **push-forward** by f at p because it pushes tangent vectors in the same direction as the mapping transports points.

Definition 10.3.1. *differential for manifolds.*

Suppose \mathcal{M} and \mathcal{N} are smooth manifolds of dimension m and n respective. Furthermore, suppose $f : \mathcal{M} \to \mathcal{N}$ is a smooth mapping. We define $d_p f : T_p \mathcal{M} \to T_{f(p)} \mathcal{N}$ as follows: for each $X_p \in T_p \mathcal{M}$ and $g \in C^{\infty}(f(p))$

$$d_p f(X_p)(g) = X_p(g \circ f).$$

Notice that $g : dom(g) \subseteq \mathcal{N} \to \mathbb{R}$ and consequently $g \circ f : \mathcal{M} \to \mathcal{N} \to \mathbb{R}$ and it follows $g \circ f \in C^{\infty}(p)$ and it is natural to find $g \circ f$ in the domain of X_p . In addition, it is not hard to show $d_p f(X_p) \in \mathcal{D}_{f(p)}\mathcal{N}$. Observe:

1.
$$d_p f(X_p)(g+h) = X_p((g+h) \circ f) = X_p(g \circ f + h \circ f) = X_p(g \circ f) + X_p(h \circ f)$$

2. $d_p f(X_p)(cg) = X_p((cg) \circ f) = X_p(cg \circ f)) = cX_p(g \circ f)) = cd_p f(X_p)(g)$

The proof of the Leibniz rule is similar. In this section we generalize the concept of the differential to the context of manifolds. Recall that for $F: U \subseteq \mathbb{R}^m \to V \subseteq \mathbb{R}^n$ the differential $d_p F: \mathbb{R}^m \to \mathbb{R}^n$ was a linear transformation which best approximated the change in F near p. Notice that while the domain of F could be a mere subset of \mathbb{R}^m the differential always took all of \mathbb{R}^m as its domain. This suggests we should really think of the differential as a mapping which transports tangent vectors to U to tangent vectors at V. Therefore, $d_p f$ is called the **push-forward**.

Definition 10.3.2. differential for manifolds.

Suppose \mathcal{M} and \mathcal{N} are smooth manifolds of dimension m and n respective. Furthermore, suppose $f : \mathcal{M} \to \mathcal{N}$ is a smooth mapping. We define $d_p f : T_p \mathcal{M} \to T_{f(p)} \mathcal{N}$ as follows: for each $X_p \in T_p \mathcal{M}$ and $g \in C^{\infty}(f(p))$

$$d_p f(X_p)(g) = X_p(g \circ f).$$

Notice that $g : dom(g) \subseteq \mathcal{N} \to \mathbb{R}$ and consequently $g \circ f : \mathcal{M} \to \mathcal{N} \to \mathbb{R}$ and it follows $g \circ f \in C^{\infty}(p)$ and it is natural to find $g \circ f$ in the domain of X_p . In addition, it is not hard to show $d_p f(X_p) \in \mathcal{D}_{f(p)}\mathcal{N}$. Observe:

1.
$$d_p f(X_p)(g+h) = X_p((g+h) \circ f) = X_p(g \circ f + h \circ f) = X_p(g \circ f) + X_p(h \circ f)$$

2. $d_p f(X_p)(cg) = X_p((cg) \circ f) = X_p(cg \circ f)) = cX_p(g \circ f)) = cd_p f(X_p)(g)$

The proof of the Leibniz rule is similar.

10.3.1 intuition for the push-forward

Perhaps it will help to see how the push-forward appears in calculus III. I'll omit the pointdependence to reduce some clutter. Consider $f : \mathbb{R}^2_{r\theta} \to \mathbb{R}^2_{xy}$ defined by $f(r, \theta) = (r \cos \theta, r \sin \theta)$. Consider, for g a smooth function on \mathbb{R}^2_{xy} , using the chain-rule,

$$df\left(\frac{\partial}{\partial r}\right)(g) = \frac{\partial}{\partial r}(g \circ f) = \frac{\partial g}{\partial x}\frac{\partial(x \circ f)}{\partial r} + \frac{\partial g}{\partial y}\frac{\partial(y \circ f)}{\partial r}$$

Note $x \circ f = r \cos \theta$ and $y \circ f = r \sin \theta$. Hence:

$$df\left(\frac{\partial}{\partial r}\right)(g) = \cos\theta \frac{\partial g}{\partial x} + \sin\theta \frac{\partial g}{\partial y}$$

This holds for all g hence we derive,

$$df\left(\frac{\partial}{\partial r}\right) = \frac{x}{\sqrt{x^2 + y^2}}\frac{\partial}{\partial x} + \frac{y}{\sqrt{x^2 + y^2}}\frac{\partial}{\partial y}$$

A similar calculation shows

$$df\left(\frac{\partial}{\partial\theta}\right) = -y\frac{\partial}{\partial x} + x\frac{\partial}{\partial y}$$

We could go through the reverse calculation for f^{-1} and derive that:

$$df^{-1}\left(\frac{\partial}{\partial x}\right) = \cos\theta \frac{\partial}{\partial r} - \frac{\sin\theta}{r} \frac{\partial}{\partial \theta}$$
 and $df^{-1}\left(\frac{\partial}{\partial y}\right) = \sin\theta \frac{\partial}{\partial r} + \cos\theta \frac{\partial}{\partial \theta}$

These formulas go to show that $\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} = 0$ transforms to $\frac{\partial^2 u}{\partial r^2} + \frac{1}{r} \frac{\partial u}{\partial r} + \frac{1}{r^2} \frac{\partial^2 u}{\partial \theta^2} = 0$.

10.3.2 a pragmatic formula for the push-forward

In practice I quote the following result as the definition. However, Definition 10.3.2 is prefered by many for its coordinate independence. As we've seen in the intuition example, coordinates tend to arise in actual calculations.

Proposition 10.3.3.

If $F: M \to N$ is a differentiable mapping of manifolds and (x^i) are coordinates (i = 1, ..., m)on M and (y^j) are coordinates (j = 1, ..., n) on N which contain $p \in M$ and $F(p) \in N$ respective then:

$$(dF)_p\left(\sum_{i=1}^m X^i \frac{\partial}{\partial x^i}\Big|_p\right) = \sum_{i=1}^m \sum_{j=1}^n X^i \frac{\partial (y^j \circ F)}{\partial x^i} \frac{\partial}{\partial y^j}\Big|_{F(p)}$$

Proof: Notice the absence of the f in this formula as compared to Definition 10.3.2 $dF(X)(f) = X(f \circ F)$. To show equivalence, we can expand on our definition, we assume here that $X = \sum_{i=1}^{m} X^i \frac{\partial}{\partial x^i} \Big|_{T}$ thus:

$$X(f \circ F) = \sum_{i=1}^{m} X^{i} \frac{\partial}{\partial x^{i}} \Big|_{p} (f \circ F)$$

note f is a function on N hence the chain rule gives:

$$X(f \circ F) = \sum_{i=1}^{m} X^{i} \sum_{j=1}^{n} \frac{\partial f}{\partial y^{j}}(F(p)) \frac{\partial (y^{j} \circ F)}{\partial x^{i}}$$

But, we can write this as:

$$X(f \circ F) = \left(\left. \sum_{i=1}^{m} X^{i} \sum_{j=1}^{n} \frac{\partial(y^{j} \circ F)}{\partial x^{i}} \frac{\partial}{\partial y^{j}} \right|_{F(p)} \right) (f).$$

Therefore, as f is arbitrary, we have shown the claim of the proposition. \Box

Observe that the difference between Definition 10.3.2 and Proposition 10.3.3 is merely an application of the chain-rule.

The push-forward is more than just coordinate change. If we consider a mapping between spaces of disparate dimension then the push-forward captures something about the mapping in question and the domain and range spaces. For example, the existence of a nontrivial vector field on the whole of a manifold implies the existence of a foliation of the manifold.



If the mapping is a diffeomorphism then we expect it will carry the nontrivial vector field to the range space. However, if the mapping is not injective then there is no assurance a vector field even maps to a vector field. We could attach two vectors to a point in the range for a two-to-one map.For example, this mapping wraps around the circle and when it hits the circle the second time the vector pushed-forward does not match what was pushed forward the first time. It follows that push-forward of the vector field does not form a vector field in this case:



The pull-back (introducted in Section 10.7) is also an important tool to compare geometry of different spaces. We'll see in Section 10.10 how the pull-back even allows us to write a general formula for calculating the potential energy function of a flux-form of arbitrary degree. This captures the electric and magnetic potentials of electromagnetism and much more we have yet to discover experimentally. That said, the pull-back is formulated in terms of the push-forward we consider here thus the importance of the push-forward is hard to overstate.

Example 10.3.4. Suppose $F : \mathbb{R}^2 \to \mathbb{R}^{2 \times 2}$ is defined by

$$F(x,y) = e^{x} \begin{bmatrix} \cos y & -\sin y \\ \sin y & \cos y \end{bmatrix}$$

Let \mathbb{R}^2 have the usual (x, y)-coordinate chart and let Z^{ij} defined by

$$Z^{ij}(A) = A_{ij}$$

for $\mathbb{R}^{2\times 2}$ form the global coordinate chart for 2×2 matrices. Let us calculate the push-forward of the coordinate vector $\partial_x|_p$:

$$dF_p(\partial_x|_p) = \sum_{i,j=1}^2 \frac{\partial(Z^{ij} \circ F)}{\partial x} \frac{\partial}{\partial Z^{ij}} \Big|_{F(p)} \& dF_p(\partial_y|_p) = \sum_{i,j=1}^2 \frac{\partial(Z^{ij} \circ F)}{\partial y} \frac{\partial}{\partial Z^{ij}} \Big|_{F(p)}$$

Observe that:

$$Z^{11}(F(x,y)) = e^x \cos y = Z^{22}(F(x,y)), \qquad Z^{21}(F(x,y)) = e^x \sin y = -Z^{12}(F(x,y)).$$

From which we derive,

$$dF_p(\partial_x) = e^x \cos y(\partial_{11} + \partial_{22}) + e^x \sin y(\partial_{21} - \partial_{12})$$
$$dF_p(\partial_y) = -e^x \sin y(\partial_{11} + \partial_{22}) + e^x \cos y(\partial_{21} - \partial_{12})$$

Here ∂_x, ∂_y are at $p \in \mathbb{R}^2$ whereas ∂_{ij} is at $F(p) \in \mathbb{R}^{2 \times 2}$. However, these are constant vector fields so the point-dependence is not too interesting.

10.4 cotangent space

The tangent space to a smooth manifold \mathcal{M} is a vector space of derivations and we denote it by $T_p\mathcal{M}$. The dual space to this vector space is called the **cotangent space** and the typical elements are called **covectors**.

Definition 10.4.1. cotangent space $T_p\mathcal{M}^*$

Suppose \mathcal{M} is a smooth manifold and $T_p\mathcal{M}$ is the tangent space at $p \in \mathcal{M}$. We define, $T_p\mathcal{M}^* = \{\alpha_p : T_p\mathcal{M} \to \mathbb{R} \mid \alpha \text{ is linear}\}.$

If x is a local coordinate chart at p and $\frac{\partial}{\partial x^1}\Big|_p, \frac{\partial}{\partial x^2}\Big|_p, \dots, \frac{\partial}{\partial x^m}\Big|_p$ is a basis for $T_p\mathcal{M}$ then we denote the dual basis $d_px^1, d_px^2, \dots, d_px^m$ where $d_px^i(\partial_k|_p) = \delta_{ik}$. Moreover, if α is a covector at p then⁷:

$$\alpha = \sum_{k=1}^m \alpha_k dx^k$$

where $\alpha_k = \alpha \left(\frac{\partial}{\partial x^k} \Big|_p \right)$ and dx^k is a short-hand for $d_p x^k$. We should understand that covectors are defined at a point even if the point is not explicitly indicated in a particular context. This does lead to some ambiguity in the same way that the careless identification of the function f and it's value f(x) does throughout calculus. That said, an abbreviated notation is often important to help us see through more difficult patterns without getting distracted by the minutia of the problem.

You might worry the notation used for the differential and our current notation for the dual basis of covectors is not consistent. After all, we have two rather different meanings for $d_p x^k$ at this time:

- 1. $x^k : V \to \mathbb{R}$ is a smooth function hence $d_p x^k : T_p \mathcal{M} \to T_{x^k(p)} \mathbb{R}$ is defined as a *push-forward*, $d_p x^k(X_p)(g) = X_p(g \circ x^k)$
- 2. $d_p x^k : T_p \mathcal{M} \to \mathbb{R}$ where $d_p x^k (\partial_j |_p) = \delta_{jk}$

It is customary to identify $T_{x^k(p)}\mathbb{R}$ with \mathbb{R} hence there is no trouble. Let us examine how the dual-basis condition can be *derived* for the differential, suppose $g: \mathbb{R} \to \mathbb{R}$ hence $g \circ x^k : V \to \mathbb{R}$,

$$d_p x^k \left(\frac{\partial}{\partial x^j} \Big|_p \right) (g) = \frac{\partial}{\partial x^j} \Big|_p (g(x^k)) = \underbrace{\frac{\partial x^k}{\partial x^j} \Big|_p \frac{dg}{dt} \Big|_{x^k(p)}}_{chain \ rule} = \delta_{jk} \frac{d}{dt} \Big|_{x^k(p)} \left(\begin{array}{c} g \end{array} \right) = \delta_{jk} g$$

Where, we've made the identification $1 = \frac{d}{dt}\Big|_{x^k(p)}$ (which is the nut and bolts of $T_{x^k(p)}\mathbb{R} = \mathbb{R}$) and hence have the beautiful identity:

$$d_p x^k \left(\frac{\partial}{\partial x^j} \bigg|_p \right) = \delta_{jk}.$$

⁷we explained this for an arbitrary vector space V and its dual V^* in a previous chapter, we simply apply those results once more here in the particular context $V = T_p \mathcal{M}$

In contrast, there is no need to derive this for case (2.) since in that context this serves as the definition for the object. Personally, I find the multiple interpretations of objects in manifold theory is one of the most difficult aspects of the theory. On the other hand, the notation is really neat once you understand how subtly it assumes many theorems. You should understand the notation we enjoy at this time is the result of generations of mathematical thought. Following a similar derivation for an arbitrary vector $X_p \in T_p \mathcal{M}$ and $f : \mathcal{M} \to \mathbb{R}$ we find

$$d_p f(X_p) = X_p(f)$$

This notation is completely consistent with the *total differential* as commonly discussed in multivariate calculus. Recall that if $f : \mathbb{R}^m \to \mathbb{R}$ then we defined

$$df = \frac{\partial f}{\partial x^1} dx^1 + \frac{\partial f}{\partial x^2} dx^2 + \dots + \frac{\partial f}{\partial x^m} dx^m.$$

Notice that the *j*-th component of df is simply $\frac{\partial f}{\partial x^j}$. Notice that the identity $d_p f(X_p) = X_p(f)$ gives us the same component if we simply evaluate the covector $d_p f$ on the coordinate basis $\frac{\partial}{\partial x^j}|_p$,

$$d_p f\left(\frac{\partial}{\partial x^j}\Big|_p\right) = \frac{\partial f}{\partial x^j}\Big|_p$$

10.5 differential forms

In this section we apply the results of Chapter 9 on exterior algebra to the vector space $V = T_p M$ and its dual space $V^* = T_p M^*$. In short, this involves making the identifications:

$$e_i = \frac{\partial}{\partial x^i}\Big|_p$$
 and $e^j = d_p x^j$

however, we often omit the p-dependence of $d_p x^j$ and just write dx^j . Observe that:

$$dx^{j}(\partial_{i}|_{p}) = \partial_{i}(x^{j}) = \delta_{ij}$$

Therefore, the coordinate basis $\{\partial_1|_p, \ldots, \partial_m|_p\}$ for T_pM is indeed dual to the differentials of the coordinates $\{dx^1, \ldots, dx^m\}$ basis for the cotangent space T_pM^* .

In contrast to Chapter 9 we have a point-dependence to our basis. We establish the following terminology: for a manifold M and $p \in M$,

- (0.) $p \mapsto \mathbb{R}$ is a 0-form, or function on M
- (1.) $p \mapsto dx^j$ is a 1-form on M
- (2.) $p \mapsto dx^i \wedge dx^j$ is a 2-form on M

- (3.) $p \mapsto dx^i \wedge dx^j \wedge dx^k$ is a 3-form on M
- (4.) $p \mapsto dx^{i_1} \wedge \cdots \wedge dx^{i_k}$ is a k-form on M

Generally a k-form is formed from taking sums of the basic differential forms given above with coefficients which are smooth functions. ⁸

- (1.) a one-form $\alpha = \sum_{j=1}^{m} \alpha_j dx^j$ has smooth coefficient functions α_j .
- (2.) a two-form $\beta = \sum_{i,j=1}^{m} \beta_{ij} dx^i \wedge dx^j$ has smooth coefficient functions β_{ij} .
- (3.) a k-form $\gamma = \sum_{i_1,\ldots,i_k}^n \gamma_{i_1,\ldots,i_k} dx^{i_1} \wedge \cdots \wedge dx^{i_k}$ has smooth coefficient functions γ_{i_1,\ldots,i_k} .

The algebra of differential forms follows the same rules as the exterior algebra we previously discussed. However, instead of having scalars as numbers we now consider scalars as functions. This comment is made explicit in the theorem to follow:

Theorem 10.5.1.

If α is a *p*-form, β is a *k*-form, and γ is a *l*-form on *M* then 1. $\alpha \wedge (\beta \wedge \gamma) = (\alpha \wedge \beta) \wedge \gamma$ 2. $\alpha \wedge \beta = (-1)^{pk}(\beta \wedge \alpha)$ 3. $\alpha \wedge (a\beta + b\gamma) = a(\alpha \wedge \beta) + b(\alpha \wedge \gamma)$ $a, b \in \mathbb{R}$

Notice that in \mathbb{R}^3 the set of differential forms

$$\mathcal{B} = \{1, dx, dy, dz, dy \land dz, dz \land dx, dx \land dy, dx \land dy \land dz\}$$

is a basis of the space of differential forms in the sense that every form on \mathbb{R}^3 is a linear combination of the forms in \mathcal{B} with smooth real-valued functions on \mathbb{R}^3 as coefficients.

Example 10.5.2. Let $\alpha = f dx + g dy$ and let $\beta = 3dx + dz$ where f, g are functions. Find $\alpha \wedge \beta$, write the answer in terms of the basis defined in the Remark above,

$$\begin{aligned} \alpha \wedge \beta &= (fdx + gdy) \wedge (3dx + dz) \\ &= fdx \wedge (3dx + dz) + gdy \wedge (3dx + dz) \\ &= 3fdx \wedge dx + fdx \wedge dz + 3gdy \wedge dx + gdy \wedge dz \\ &= -gdy \wedge dz - fdz \wedge dx - 3gdx \wedge dy \end{aligned}$$
(10.3)

⁸Technically, this means the exterior algebra of differential forms is a module over the ring of smooth functions. However, the exterior algebra at a point is a vector space.

Example 10.5.3. Top form: Let $\alpha = dx \wedge dy \wedge dz$ and let β be any other form with degree p > 0. We argue that $\alpha \wedge \beta = 0$. Notice that if p > 0 then there must be at least one differential inside β so if that differential is dx^k we can rewrite $\beta = dx^k \wedge \gamma$ for some γ . Then consider,

$$\alpha \wedge \beta = dx \wedge dy \wedge dz \wedge dx^k \wedge \gamma \tag{10.4}$$

now k has to be either 1,2 or 3 therefore we will have dx^k repeated, thus the wedge product will be zero. (can you prove this?).

The proposition below and its proof are included here to remind the reader on the structure of the \otimes and \wedge products and components. One distinction, the components are functions now whereas they were scalars in the previous chapter.

Proposition 10.5.4.

If ω is a *p*-form in an *n*-dimensional space is written in the coordinate coframe dx^1, \ldots, dx^n at *p* then the components of ω are given by evaluation on the coordinate frame $\partial_1, \ldots, \partial_n$. at *p*.

Proof: Suppose ω has component functions $\omega_{i_1i_2...i_p}$ with respect to the tensor basis $dx^{i_1} \otimes \cdots \otimes dx^{i_p}$ for type (0, p) tensors.

$$\omega = \sum_{i_1 i_2 \dots i_p}^n \omega_{i_1 i_2 \dots i_p} dx^{i_1} \otimes dx^{i_2} \otimes \dots \otimes dx^{i_p}$$

the functions $\omega_{i_1i_2...i_p}$ are called the **tensor components** of ω . Consider evaluation of ω on a *p*-tuple of coordinate vector fields,

$$\omega(\partial_{j_1}, \partial_{j_2} \dots \partial_{j_p}) = \sum_{i_1, i_2, \dots, i_p=1}^n \omega_{i_1 i_2 \dots i_p} dx^{i_1} \otimes dx^{i_2} \otimes \dots \otimes dx^{i_p} (\partial_{j_1}, \partial_{j_2}, \dots, \partial_{j_p})$$
$$= \sum_{i_1, i_2, \dots, i_p=1}^n \omega_{i_1 i_2 \dots i_p} \delta_{i_1 j_1} \delta_{i_2 j_2} \dots \delta_{i_p j_p}$$
$$= \omega_{j_1 j_2 \dots j_p}$$

If ω is a *p*-form that indicated ω is a completely antisymmetric tensor and by a calculation similar to those near Equation 9.10 we can express ω by a sum over all *p*-forms (this is not a basis expansion)

$$\omega = \sum_{i_1, i_2, \dots, i_p=1}^n \frac{1}{p!} \omega_{i_1 i_2 \dots i_p} dx^{i_1} \wedge dx^{i_2} \wedge \dots \wedge dx^{i_p}.$$

But, we just found $\omega(\partial_{j_1}, \partial_{j_2} \dots \partial_{j_p}) = \omega_{i_1 i_2 \dots i_p}$ hence:

$$\omega = \sum_{i_1 i_2 \dots i_p}^n \frac{1}{p!} \omega(\partial_{i_1}, \partial_{i_2} \dots \partial_{i_p}) dx^{i_1} \wedge dx^{i_2} \wedge \dots \wedge dx^{i_p}.$$

which proves the assertion of the proposition. \Box

Note, if we work with an expansion of linearly independent p-vectors then we can write the conclusion of the proposition:

$$\omega = \sum_{i_1 < i_2 < \dots < i_p}^n \omega(\partial_{i_1}, \partial_{i_2} \dots \partial_{i_p}) dx^{i_1} \wedge dx^{i_2} \wedge \dots \wedge dx^{i_p}.$$

10.6 the exterior derivative

The operation \wedge depends only on the values of the forms point by point. We define an operator d on differential forms which depends not only on the value of the differential form at a point but on its value in an entire neighborhood of the point. Thus if β ia k-form then to define $d\beta$ at a point p we need to know not only the value of β at p but we also need to know its value at every q in a neighborhood of p.

You might note the derivative below does not directly involve the construction of differential forms from tensors. Also, the rule given below is easily taken as a starting point for formal calculations. In other words, even if you don't understand the nuts and bolts of manifold theory you can still calculate with differential forms. In the same sense that highschool students "do" calculus, you can "do" differential form calculations. I don't believe this is a futile exercise so long as you understand you have more to learn. Which is not to say we don't know some things!

Definition 10.6.1. the exterior derivative.

If β is a k-form and $x = (x^1, x^2, \dots, x^n)$ is a chart and $\beta = \sum_I \frac{1}{k!} \beta_I dx^I$ and we define a (k+1)-form $d\beta$ to be the form

$$deta = \sum_I rac{1}{k!} deta_I \wedge dx^I \; .$$

Where $d\beta_I$ is defined as it was in calculus III,

$$d\beta_I = \sum_{j=1}^n \frac{\partial \beta_I}{\partial x_j} dx^j.$$

Note that $d\beta_I$ is well-defined as

$$\beta_I=\beta_{i_1i_2\cdots i_k}$$

is just a real-valued function on dom(x). The definition in an expanded form is given by

$$d_p\beta = \frac{1}{k!} \sum_{i_1=1}^n \sum_{i_2=1}^n \cdots \sum_{i_k=1}^n (d_p\beta_{i_1i_2\cdots i_k}) \wedge d_p x^{i_1} \wedge \cdots \wedge d_p x^{i_k}$$

where

$$\beta_q = \frac{1}{k!} \sum_{i_1=1}^n \sum_{i_2=1}^n \cdots \sum_{i_k=1}^n \beta_{i_1 i_2 \cdots i_k}(q) d_q x^{i_1} \wedge \cdots \wedge d_p x^{i_k} .$$

Consequently we see that for each k the operator d maps $\wedge^k(M)$ into $\wedge^{k+1}(M)$. Also:

Theorem 10.6.2. properties of the exterior derivative.

If
$$\alpha \in \wedge^k(M)$$
, $\beta \in \wedge^l(M)$ and $a, b \in \mathbf{R}$ then
1. $d(a\alpha + b\beta) = a(d\alpha) + b(d\beta)$
2. $d(\alpha \wedge \beta) = (d\alpha \wedge \beta) + (-1)^k(\alpha \wedge d\beta)$
3. $d(d\alpha) = 0$

Remark 10.6.3.

Warning: I use Einstein's repeated index notation in the proof that follows. In fact, it's a bit worse, I use I to denote a **multi-index**. This means a repeated I indicates an implicit sum over all increasing strings of indices of a particular length. This is just a brief notation to sum over the basis of coordinate p-forms. Indeed, from this point on in the notes there is occasional use of Einstein's convention.

Proof: The proof of (1) is obvious. To prove (2), let $x = (x^1, \dots, x^n)$ be a chart on M then suppose $\alpha = \alpha_I dx^I$ and $\beta = \beta_J dx^J$

$$d(\alpha \wedge \beta) = d(\alpha_I \beta_J) \wedge dx^I \wedge dx^J = (\alpha_I d\beta_J + \beta_J d\alpha_I) \wedge dx^I \wedge dx^J = \alpha_I (d\beta_J \wedge dx^I \wedge dx^J) + \beta_J (d\alpha_I \wedge dx^I \wedge dx^J) = \alpha_I (dx^I \wedge (-1)^k (d\beta_J \wedge dx^J)) + \beta_J ((d\alpha_I \wedge dx^I) \wedge dx^J) = (\alpha \wedge (-1)^k d\beta) + \beta_J (d\alpha \wedge dx^J) = d\alpha \wedge \beta + (-1)^k (\alpha \wedge d\beta) .$$

To prove (3.) we could resort to a beautiful tensor calculation (see Equation 10.11) or:

$$d\alpha = d\alpha_I \wedge dx^I$$

hence

$$d(d\alpha) = d(d\alpha_I \wedge dx^I) = d(d\alpha_I) \wedge dx^I + \alpha_I \wedge d(dx^I).$$

Notice $d(dx^I) = d(dx^{i_1} \wedge \cdots \wedge dx^{i_k}) = d(1) \wedge dx^{i_1} \wedge \cdots \wedge dx^{i_k} = 0$. Therefore, we have reduced the problem to showing $d(d\alpha_I) = 0$ for a function α_I . I leave that problem to the reader. \Box .

10.6.1 exterior derivatives on \mathbb{R}^3

We begin by noting that vector fields may correspond either to a one-form or to a two-form. **Definition 10.6.4.** dictionary of vectors verses forms on \mathbb{R}^3 .

Let $\vec{A} = (A^1, A^2, A^3)$ denote a vector field in \mathbb{R}^3 . Define then,

$$\omega_A = \delta_{ij} A^i dx^j = A_i dx$$

which we will call the **work-form** of \vec{A} . Also define

$$\Phi_A = \frac{1}{2} \delta_{ik} A^k \epsilon_{ijk} (dx^i \wedge dx^j) = \frac{1}{2} A_i \epsilon_{ijk} (dx^i \wedge dx^j)$$

which we will call the **flux-form** of \vec{A} .

If you accept the primacy of differential forms, then you can see that vector calculus confuses two separate objects. Apparently there are two types of vector fields. In fact, if you have studied coordinate change for vector fields deeply then you will encounter the qualifiers **axial** or **polar** vector fields. Those fields which are axial correspond directly to two-forms whereas those correspondant to one-forms are called polar. Note, the magnetic field is axial whereas the electric field is polar.

Example 10.6.5. Gradient: Consider three-dimensional Euclidean space. Let $f : \mathbb{R}^3 \to \mathbb{R}$ then

$$df = \frac{\partial f}{\partial x^i} dx^i = \omega_{\nabla f}$$

which gives the one-form corresponding to ∇f .

Example 10.6.6. Curl: Consider three-dimensional Euclidean space. Let \vec{F} be a vector field and let $\omega_F = F_i dx^i$ be the corresponding one-form then

$$\begin{split} d\omega_F &= dF_i \wedge dx^i \\ &= \partial_j F_i dx^j \wedge dx^i \\ &= \partial_x F_y dx \wedge dy + \partial_y F_x dy \wedge dx + \partial_z F_x dz \wedge dx + \partial_x F_z dx \wedge dz + \partial_y F_z dy \wedge dz + \partial_z F_y dz \wedge dy \\ &= (\partial_x F_y - \partial_y F_x) dx \wedge dy + (\partial_z F_x - \partial_x F_z) dz \wedge dx + (\partial_y F_z - \partial_z F_y) dy \wedge dz \\ &= \Phi_{\nabla \times \vec{F}}. \end{split}$$

Thus we recover the curl.

Example 10.6.7. Divergence: Consider three-dimensional Euclidean space. Let \vec{G} be a vector field and let $\Phi_G = \frac{1}{2} \epsilon_{ijk} G_i dx^j \wedge dx^k$ be the corresponding two-form then

$$d\Phi_G = d(\frac{1}{2}\epsilon_{ijk}G_i) \wedge dx^j \wedge dx^k$$

$$= \frac{1}{2}\epsilon_{ijk}(\partial_m G_i)dx^m \wedge dx^j \wedge dx^k$$

$$= \frac{1}{2}\epsilon_{ijk}(\partial_m G_i)\epsilon_{mjk}dx \wedge dy \wedge dz$$

$$= \frac{1}{2}2\delta_{im}(\partial_m G_i)dx \wedge dy \wedge dz$$

$$= \partial_i G_i dx \wedge dy \wedge dz$$

$$= (\nabla \cdot \vec{G})dx \wedge dy \wedge dz$$

and in this way we recover the divergence.

10.6.2 coordinate independence of exterior derivative

The Einstein summation convention is used in this section and throughout the remainder of this chapter, please feel free to email me if it confuses you somewhere. When an index is repeated in a single summand it is implicitly assumed there is a sum over all values of that index

It must be shown that this definition is independent of the chart used to define $d\beta$. Suppose for example, that

$$\beta_q = \overline{\beta}_J(q)(d_q \overline{x}^{j_1} \wedge \dots \wedge d_q \overline{x}^{j_k})$$

for all q in the domain of a chart $(\overline{x}^1, \overline{x}^2, \cdots, \overline{x}^n)$ where

$$dom(x) \cap dom(\overline{x}), \neq \emptyset$$

We assume, of course that the coefficients $\{\overline{\beta}_J(q)\}\$ are skew-symmetric in J for all q. We will have defined $d\beta$ in this chart by

$$d\beta = d\overline{\beta}_J \wedge d\overline{x}^J$$

We need to show that $d_p\overline{\beta}_J \wedge d_p\overline{x}^J = d_p\beta_I \wedge d_px^I$ for all $p \in dom(x) \cap dom(\overline{x})$ if this definition is to be meaningful. Since β is given to be a well-defined form we know

$$\beta_I(p)d_p x^I = \beta_p = \overline{\beta}_J(p)d_p \overline{x}^J \,.$$

Using the identities

$$d\overline{x}^j = \frac{\partial \overline{x}^j}{\partial x^i} dx^i$$

we have

$$\beta_I dx^I = \overline{\beta}_J \frac{\partial \overline{x}^{j_1}}{\partial x^{i_1}} \frac{\partial \overline{x}^{j_k}}{\partial x^{i_k}} \cdots \frac{\partial \overline{x}^{j_k}}{\partial x^{i_k}} dx^I$$

so that

$$\beta_I = \overline{\beta}_J \left(\frac{\partial \overline{x}^{j_1}}{\partial x^{i_1}} \ \frac{\partial \overline{x}^{j_2}}{\partial x^{i_2}} \cdots \frac{\partial \overline{x}^{j_k}}{\partial x^{i_k}} \right) \ .$$

Consequently,

$$\begin{aligned} d\beta_J \wedge dx^J &= \frac{\partial \beta_J}{\partial x^{\lambda}} (dx^{\lambda} \wedge dx^J) &= \frac{\partial}{\partial x^{\lambda}} [\overline{\beta}_I \left(\frac{\partial \overline{x}^{i_1}}{\partial x^{j_1}} \cdots \frac{\partial \overline{x}^{i_k}}{\partial x^{j_k}} \right)] (dx^{\lambda} \wedge dx^J) \\ &\stackrel{*}{=} \frac{\partial \overline{\beta}_I}{\partial x^{\lambda}} \left(\frac{\partial \overline{x}^{i_1}}{\partial x^{j_1}} \cdots \frac{\partial \overline{x}^{i_k}}{\partial x^{j_k}} \right) (dx^{\lambda} \wedge dx^J) \\ &\quad + \overline{\beta}_I \sum_r \left(\frac{\partial \overline{x}^{i_1}}{\partial x^{j_1}} \cdots \frac{\partial^2 \overline{x}^{i_r}}{\partial x^{\lambda} \partial x^{j_r}} \cdots \frac{\partial \overline{x}^{i_k}}{\partial x^{j_k}} \right) (dx^{\lambda} \wedge dx^J) \\ &= \frac{\partial \overline{\beta}_I}{\partial x^{\lambda}} dx^{\lambda} \wedge \left(\frac{\partial \overline{x}^{i_1}}{\partial x^{j_1}} dx^{j_1} \right) \wedge \cdots \wedge \left(\frac{\partial \overline{x}^{i_k}}{\partial x^{j_k}} dx^{j_k} \right) \\ &= \frac{\partial \overline{\beta}_I}{\partial \overline{x}^P} \left[\left(\frac{\partial \overline{x}^P}{\partial x^{\lambda}} dx^{\lambda} \right) \wedge d\overline{x}^{i_1} \wedge \cdots \wedge d\overline{x}^{i_k} \right] \\ &= d\overline{\beta}_I \wedge d\overline{x}^I \end{aligned}$$

where in (*) the sum \sum_{r} is zero since:

$$\frac{\partial^2 \overline{x}^{i_r}}{\partial x^{\lambda} \partial x^{j_r}} (dx^{\lambda} \wedge dx^J) = \pm \frac{\partial^2 \overline{x}^{i_r}}{\partial x^{\lambda} \partial x^{j_r}} [(dx^{\lambda} \wedge dx^{j_r}) \wedge dx^{j_1} \wedge \dots \wedge \widehat{dx^{j_r}} \wedge \dots dx^{j_k}] = 0.$$

It follows that $d\beta$ is independent of the coordinates used to define it.

10.7 the pull-back

Another important operation one can perform on differential forms is the "pull-back" of a form under a map⁹. The definition is constructed in large part by a sneaky application of the pushforward (aka differential) discussed in the preceding chapter. If you are impatient for intuition, skip ahead to the end of this section and later return to the careful calculations at the outset.

Definition 10.7.1. pull-back of a differential form.

If
$$f : \mathcal{M} \to \mathcal{N}$$
 is a smooth map and $\omega \in \wedge^k(N)$ then $f^*\omega$ is the form on \mathcal{M} defined by
 $(f^*\omega)_p(X_1, \cdots, X_k) = \omega_{f(p)}(d_p f(X_1), d_p f(X_2), \cdots, d_p f(X_k))$.
for each $p \in \mathcal{M}$ and $X_1, X_2, \ldots, X_k \in T_p \mathcal{M}$. Moreover, in the case $k = 0$ we have a smooth
function $\omega : \mathcal{N} \to \mathbb{R}$ and the pull-back is accomplished by composition $(f^*\omega)(p) = (\omega \circ f)(p)$
for all $p \in \mathcal{M}$.

This operation is linear on forms and commutes with the wedge product and exterior derivative:

Theorem 10.7.2. properties of the pull-back.

If
$$f: M \to N$$
 is a C^1 -map and $\omega \in \wedge^k(N), \tau \in \wedge^l(N)$ then
1. $f^*(a\omega + b\tau) = a(f^*\omega) + b(f^*\tau)$ $a, b \in \mathbb{R}$
2. $f^*(\omega \wedge \tau) = f^*\omega \wedge (f^*\tau)$
3. $f^*(d\omega) = d(f^*\omega)$

Proof: The proof of (1) is clear. We now prove (2).

$$\begin{aligned} f^*(\omega \wedge \tau)]_p(X_1, \cdots, X_{k+l}) &= (\omega \wedge \tau)_{f(p)} (d_p f(X_1), \cdots, d_p f(X_{k+l})) \\ &= \sum_{\sigma} (\operatorname{sgn} \sigma) (\omega \otimes \tau)_{f(p)} (d_p f(X_{\sigma_1}), \cdots, d_p f(X_{\sigma(k+l)})) \\ &= \sum_{\sigma} \operatorname{sgn} (\sigma) \omega (d_p f(X_{\sigma(1)}), \cdots d_p f(X_{\sigma(k)})) \tau (df(X_{\sigma(k+1)} \cdots df X_{\sigma(k+l)})) \\ &= \sum_{\sigma} \operatorname{sgn} (\sigma) (f^* \omega)_p (X_{\sigma(1)}, \cdots, X_{\sigma(k)}) (f^* \tau_p) (X_{\sigma(k+1)}, \cdots, X_{\sigma(k+l)}) \\ &= [(f^* \omega) \wedge (f^* \tau)]_p (X_1, X_2, \cdots, X_{(k+l)}) \end{aligned}$$

⁹thanks to my advisor R.O. Fulp for the arguments that follow

Finally we prove (3).

$$\begin{aligned} f^*(d\omega)]_p(X_1, X_2 \cdots, X_{k+1}) &= (d\omega)_{f(p)} (df(X_1), \cdots df(X_{k+1})) \\ &= (d\omega_I \wedge dx^I)_{f(p)} (df(X_1), \cdots, df(X_{k+1})) \\ &= \left(\frac{\partial \omega_I}{\partial x^\lambda} \Big|_{f(p)}\right) (dx^\lambda \wedge dx^I)_{f(p)} (df(X_1), \cdots, df(X_{k+1})) \\ &= \left(\frac{\partial \omega_I}{\partial x^\lambda} \Big|_{f(p)}\right) [d_p(x^\lambda \circ f) \wedge d_p(x^I \circ f)](X_1, \cdots, X_{k+1}) \\ &= [d(\omega_I \circ f) \wedge d(x^I \circ f)](X_1, \cdots, X_{k+1}) \\ &= d[(\omega_I \circ f)_p d_p(x^I \circ f)](X_1, \cdots, X_{k+1}) \\ &= d(f^*\omega)_p(X_1, \cdots, X_{k+1}) .\end{aligned}$$

The theorem follows. \Box .

We saw that one important application of the push-forward was to change coordinates for a given vector. Similar comments apply here. If we wish to change coordinates on a given differential form then we can use the pull-back. However, given the direction of the operation we need to use the inverse coordinate transformation to pull forms forward. Let me mirror the example from the last chapter for forms on \mathbb{R}^2 . We wish to convert from r, θ to x, y notation.

Example 10.7.3. Suppose $F : \mathbb{R}^2_{r,\theta} \to \mathbb{R}^2_{x,y}$ is the polar coordinate transformation. In particular,

$$F(r, \theta) = (r \cos \theta, r \sin \theta)$$

The inverse transformation, at least for appropriate angles, is given by

$$F^{-1}(x,y) = \left(\sqrt{x^2 + y^2}, \ \tan^{-1}(y/x)\right).$$

Let calculate the pull-back of dr under F^{-1} : let $p = F^{-1}(q)$

$$F^{-1*}(dr)_q = d_p r(\partial_x | p) d_p x + d_p r(\partial_y | p) d_p y$$

Again, drop the annoying point-dependence to see this clearly:

$$F^{-1*}(dr) = dr(\partial_x)dx + dr(\partial_y)dy = \frac{\partial r}{\partial x}dx + \frac{\partial r}{\partial y}dy$$

Likewise,

$$F^{-1*}(d\theta) = d\theta(\partial_x)dx + d\theta(\partial_y)dy = \frac{\partial\theta}{\partial x}dx + \frac{\partial\theta}{\partial y}dy$$

Note that $r = \sqrt{x^2 + y^2}$ and $\theta = \tan^{-1}(y/x)$ have the following partial derivatives:

$$\frac{\partial r}{\partial x} = \frac{x}{\sqrt{x^2 + y^2}} = \frac{x}{r}$$
 and $\frac{\partial r}{\partial y} = \frac{y}{\sqrt{x^2 + y^2}} = \frac{y}{r}$

$$\frac{\partial \theta}{\partial x} = \frac{-y}{x^2 + y^2} = \frac{-y}{r^2}$$
 and $\frac{\partial \theta}{\partial y} = \frac{x}{x^2 + y^2} = \frac{x}{r^2}$

Of course the expressions using r are pretty, but to make the point, we have changed into x, ynotation via the pull-back of the inverse transformation as advertised. We find:

$$dr = \frac{xdx + ydy}{\sqrt{x^2 + y^2}}$$
 and $d\theta = \frac{-ydx + xdy}{x^2 + y^2}$.

Once again we have found results with the pull-back that we might previously have chalked up to substitution in multivariate calculus. That's often the idea behind an application of the pull-back. It's just a formal langauge to be precise about a substitution. It takes us past simple symbol pushing and gives us a rigorous notation for substitutions. It's a bit more than that though, the *substitution* we discuss here takes us from one space to another in general.

10.7.1 intuitive computation of pull-backs

Consider the definition below: how can we understand this computationally?

$$(f^*\omega)_p(X_1,\cdots,X_k) = \omega_{f(p)}(d_p f(X_1), d_p f(X_2), \cdots, d_p f(X_k))$$

In particular, let us consider f(u, v) = (x, y, z). Furthermore, let us consider a one-form to begin $\omega = adx + bdy + cdz$ the pull-back will be formed by a suitable linear combination of du and dv. We calculate,

$$df(\partial_u) = \frac{\partial x}{\partial u}\frac{\partial}{\partial x} + \frac{\partial y}{\partial u}\frac{\partial}{\partial y} + \frac{\partial z}{\partial u}\frac{\partial}{\partial z} \qquad \& \qquad df(\partial_v) = \frac{\partial x}{\partial v}\frac{\partial}{\partial x} + \frac{\partial y}{\partial v}\frac{\partial}{\partial y} + \frac{\partial z}{\partial v}\frac{\partial}{\partial z}$$

Therefore, as $\omega = adx + bdy + cdz$,

$$\omega(df(\partial_u)) = a\frac{\partial x}{\partial u} + b\frac{\partial y}{\partial u} + c\frac{\partial z}{\partial u} \qquad \& \qquad \omega(df(\partial_v)) = a\frac{\partial x}{\partial v} + b\frac{\partial y}{\partial v} + c\frac{\partial z}{\partial v}$$

From which we deduce: by Proposition 10.5.4,

$$f^*\omega = \left[a\frac{\partial x}{\partial u} + b\frac{\partial y}{\partial u} + c\frac{\partial z}{\partial u}\right] du + \left[a\frac{\partial x}{\partial v} + b\frac{\partial y}{\partial v} + c\frac{\partial z}{\partial v}\right] dv$$
$$= a\underbrace{\left[\frac{\partial x}{\partial u}du + \frac{\partial x}{\partial v}dv\right]}_{dx \text{ for } x=x(u,v)} + b\underbrace{\left[\frac{\partial y}{\partial u}du + \frac{\partial y}{\partial v}dv\right]}_{dy \text{ for } y=y(u,v)} + c\underbrace{\left[\frac{\partial z}{\partial u}du + \frac{\partial z}{\partial v}dv\right]}_{dz \text{ for } z=z(u,v)}.$$
(10.5)

This shows the pull-back of ω is accomplished by taking $\omega = adx + bdy + cdz$ and substituting the total differentials of x = x(u, v), y = y(u, v) and z = z(u, v) into dx, dy and dz respectively.
Continuing in our somewhat special context, consider $\Omega = ady \wedge dz + bdz \wedge dx + cdx \wedge dy$ and use Theorem 10.7.2 to simplify our life. We already worked out the formula for the one-form case so we can use it to find the intuitive formula for the two-form:

$$\begin{aligned} f^*\Omega &= f^* \left[ady \wedge dz + bdz \wedge dx + cdx \wedge dy \right] \\ &= f^* (ady) \wedge f^* dz + f^* (bdz) \wedge f^* dx + f^* (cdx) \wedge f^* dy \quad \text{(by Theorem 10.7.2)} \\ &= a \left[\frac{\partial y}{\partial u} du + \frac{\partial y}{\partial v} dv \right] \wedge \left[\frac{\partial z}{\partial u} du + \frac{\partial z}{\partial v} dv \right] + b \left[\frac{\partial z}{\partial u} du + \frac{\partial z}{\partial v} dv \right] \wedge \left[\frac{\partial x}{\partial u} du + \frac{\partial x}{\partial v} dv \right] \\ &+ c \left[\frac{\partial x}{\partial u} du + \frac{\partial x}{\partial v} dv \right] \wedge \left[\frac{\partial y}{\partial u} du + \frac{\partial y}{\partial v} dv \right] \quad \text{(by Equation 10.5)} \end{aligned}$$

The formula above simplifies considerable as certain terms vanish due to $du \wedge du = 0$ and $dv \wedge dv = 0$ and $dv \wedge du = -du \wedge dv$. Furthermore, the following standard notation¹⁰

$$\frac{\partial(y,z)}{\partial(u,v)} = \frac{\partial y}{\partial u}\frac{\partial z}{\partial v} - \frac{\partial y}{\partial v}\frac{\partial z}{\partial u} \quad \& \quad \frac{\partial(x,y)}{\partial(u,v)} = \frac{\partial x}{\partial u}\frac{\partial y}{\partial v} - \frac{\partial x}{\partial v}\frac{\partial y}{\partial u}, \quad \& \quad \frac{\partial(z,x)}{\partial(u,v)} = \frac{\partial z}{\partial u}\frac{\partial x}{\partial v} - \frac{\partial z}{\partial v}\frac{\partial x}{\partial u}.$$

Generally, $\frac{\partial(x_i, x_j)}{\partial(u, v)} = \det \begin{bmatrix} \partial_u x_i & \partial_v x_i \\ \partial_u x_j & \partial_v x_j \end{bmatrix}$. Ugly equations aside, this allows us to express the pull-back of the two-form in a way which is easy to remember and is readily generalized.

$$f^*\Omega = \left[a\frac{\partial(y,z)}{\partial(u,v)} + b\frac{\partial(z,x)}{\partial(u,v)} + c\frac{\partial(x,y)}{\partial(u,v)}\right]du \wedge dv$$

I should mention, throughout this calculation I have suppressed the point-dependence. Technically, a, b, c in the expression above should be understood as $a \circ f, b \circ f, c \circ f$ which are functions of u, v. The pull-back once complete trades a form in the range coordinates (x, y, z) for a new form in the domain coordinates (u, v).

The discussion thus far is somewhat limiting since the domain only supports a nontrivial two-form. To continue, let's consider pull-backs for the mapping $G : \mathbb{R}^3_{uvw} \to \mathbb{R}^4_{txyz}$. In this case, we can consider the pull-back of

$$\gamma = adt \wedge dx \wedge dz + bdx \wedge dy \wedge dz + cdy \wedge dz \wedge dt + mdz \wedge dt \wedge dy$$

and we will obtain:

$$G^*\gamma = \left[a\frac{\partial(t,x,y)}{\partial(u,v,w)} + b\frac{\partial(x,y,z)}{\partial(u,v,w)} + c\frac{\partial(y,z,t)}{\partial(u,v,w)} + m\frac{\partial(z,t,x)}{\partial(u,v,w)}\right]du \wedge dv \wedge dw$$

Where we define the coefficients by the natural generalization of the second-order case. Multiplying out the wedge product of the pull-back of the three one-forms will produce the signs of the following determinants

$$\frac{\partial(x_i, x_j, x_k)}{\partial(u, v, w)} = \det \begin{bmatrix} \partial_u x_i & \partial_v x_i & \partial_w x_i \\ \partial_u x_j & \partial_v x_j & \partial_w x_j \\ \partial_u x_k & \partial_v x_k & \partial_w x_k \end{bmatrix}$$

¹⁰H.M. Edwards Advanced Calculus a Differential Forms approach spends dozens of pages explaining this through intuitive geometric arguments which we do not pursue here for brevity

In words, the pull-back is formed with coefficients taken from determinants of submatrices of the Jacobian matrix of G. That probably doesn't help you much. Perhaps the following two-form pull-back with respect to G will inspire: an arbitrary two-form on \mathbb{R}^4_{txyz} has the form:

$$\Xi = A_{01}dt \wedge dx + A_{02}dt \wedge dy + A_{03}dt \wedge dz + A_{23}dy \wedge dz + A_{31}dz \wedge dx + A_{12}dx \wedge dy$$

when we pull this back under G to u, v, w-space we will get a form in $dv \wedge dw, dw \wedge du$ and $du \wedge dv$. The coefficients are again obtained by appropriate determinants of submatrices of the Jacobian: in particular: $G^* \Xi =$

$$\begin{split} & \left[A_{01}\frac{\partial(t,x)}{\partial(v,w)} + A_{02}\frac{\partial(t,y)}{\partial(v,w)} + A_{03}\frac{\partial(t,z)}{\partial(v,w)} + A_{23}\frac{\partial(y,z)}{\partial(v,w)} + A_{31}\frac{\partial(z,x)}{\partial(v,w)} + A_{12}\frac{\partial(x,y)}{\partial(v,w)}\right]dv \wedge dw \\ & + \left[A_{01}\frac{\partial(t,x)}{\partial(w,u)} + A_{02}\frac{\partial(t,y)}{\partial(w,u)} + A_{03}\frac{\partial(t,z)}{\partial(w,u)} + A_{23}\frac{\partial(y,z)}{\partial(w,u)} + A_{31}\frac{\partial(z,x)}{\partial(w,u)} + A_{12}\frac{\partial(x,y)}{\partial(w,u)}\right]dw \wedge du \\ & + \left[A_{01}\frac{\partial(t,x)}{\partial(u,v)} + A_{02}\frac{\partial(t,y)}{\partial(u,v)} + A_{03}\frac{\partial(t,z)}{\partial(u,v)} + A_{23}\frac{\partial(y,z)}{\partial(u,v)} + A_{31}\frac{\partial(z,x)}{\partial(u,v)} + A_{12}\frac{\partial(x,y)}{\partial(w,u)}\right]dw \wedge dv. \end{split}$$

The arbitrary case is perhaps a bit tiresome. Let's consider a particular example

$$\Gamma = (t^2 + x^2)dy \wedge dz$$

and the mapping $G(u, v, w) = (u - 1, v^2 + 1, w^3, uvw) = (t, x, y, z)$. Observe:

 $dt=du, \ dx=2vdv, \ dy=3w^2dw, \ dz=vwdu+uwdv+uvdw$

the pull-back of Γ under G is thus:

$$G^{*}\Gamma = ((u-1)^{2} + (v^{2}+1)^{2}) 3w^{2} dw \wedge [vwdu + uwdv + uvdw]$$

= $((u-1)^{2} + (v^{2}+1)^{2}) 3w^{2} [vw dw \wedge du + uw dw \wedge dv]$
= $A_{23}(u,v) \underbrace{(-3w^{2}uw)}_{\frac{\partial(y,z)}{\partial(v,w)}} dv \wedge dw + A_{23}(u,v) \underbrace{(3w^{2}vw)}_{\frac{\partial(y,z)}{\partial(w,u)}} dw \wedge du$ (10.6)

In the above I let $A_{23}(u, v) = (u - 1)^2 + (v^2 + 1)^2$. Let's check the coefficients of Equation 10.6 in view of the general claim of $G^*\Xi$. Are the coefficients in fact the Jacobians indicated? We calculate:

$$\frac{\partial(y,z)}{\partial(v,w)} = \det \begin{bmatrix} y_v & y_w \\ z_v & z_w \end{bmatrix} = \det \begin{bmatrix} 0 & 3w^2 \\ uw & uv \end{bmatrix} = -3w^2uw$$

and

$$\frac{\partial(y,z)}{\partial(w,u)} = \det \left[\begin{array}{cc} y_w & y_u \\ z_w & z_u \end{array} \right] = \det \left[\begin{array}{cc} 3w^2 & 0 \\ uv & vw \end{array} \right] = 3w^2 vw.$$

Well, that's a relief. We can either approach the calculation of a pull-back in terms of Jacobian coefficients or we can just plug in the pull-backs of each coordinate function and multiply it out. I suppose both techinques have their place. Moreover, when faced with many abstract questions I much prefer Definition 10.7.1. The thought of sorting through the proof of Theorem 10.7.2 in Jacobian notation seems hopeless.

10.7.2 implicit function theorem in view of forms

warning: I am not certain my interpretation of the theorem that follows is sound at this time, however, I may leave this here as a reminder for me to think more on this family of conceptual problems

Previously we saw this theorem without the benefit of the calculus of differential forms, I hope this brings new light to the topic. This is the implicit function theorem as presented in H.M. Edwards' Advanced Calculus: a Differential Forms Approach.

Proposition 10.7.4.

Let us consider for $i = 1, \ldots m$,

 $y_i = f_i(x_1, \dots, x_n)$

where f_i are continuously differentiable near a point $(\bar{x}_1, \ldots, \bar{x}_n)$. Furthermore, denote $\bar{y}_i = f_i(\bar{x}_1, \ldots, \bar{x}_n)$ for $i = 1, \ldots, m$. Suppose the following conditions are satisfied:

- 1. $\frac{\partial(y_1,\ldots,y_r)}{\partial(x_1,\ldots,x_r)} \neq 0$ at $(\bar{x}_1,\ldots,\bar{x}_n)$
- 2. the pull-back of every k-form for k > r is identically zero near $(\bar{x}_1, \ldots, \bar{x}_n)$

Then near $(\bar{x}_1, \ldots, \bar{x}_n, \bar{y}_1, \ldots, \bar{y}_m) \in \mathbb{R}^{n+m}$ there exist differentiable functions g_i, h_i which solve $y_i = f_i(x_1, \ldots, x_n)$ provided we suppose:

$$x_i = g_i(y_1, \dots, y_r, x_{r+1}, \dots, x_n)$$
 (for $i = 1, \dots, r$)
 $y_i = h_i(y_1, \dots, y_r)$ (for $i = r+1, \dots, m$).

Condition (1.) implies the rank is at least r then condition (2.) assures us the rank is at most r hence the rank is r. If the graph y = f(x) is viewed as G(x, y) = y - f(x) then it is seen as a mapping from $\mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}^m$. We saw before that if $G(\bar{x}, \bar{y}) = 0$ and $rank(G'(\bar{x}, \bar{y})) = m$ then the solution set of G(x, y) = 0 near (\bar{x}, \bar{y}) forms an (n)-dimensional manifold. This generalizes that in a sense because it allows for redundant conditions as indicated by r < m. On the other hand, this is less general than the previous implicit function theorem as it assumes a linear-dependence on the m-variables y_1, \ldots, y_m for the m equations defining the level set in $\mathbb{R}^m \times \mathbb{R}^n$. The formulation of this Theorem in Edward's text falls inline with the general pattern of that text to emphasize equations over mappings. It is both the strength and weakness of the text in my opinion. The next two examples attempt to work within the confines of the notation put forth in the theorem above, then we transition to examples where we informally apply the theorem.

Example 10.7.5. Just to remind us of the counting: if $y_1 = f(x_1, x_2) = x_1 + x_2 - 1$ then

$$G(x_1, x_2, y_1) = y_1 - (x_1 + x_2 - 1) = -x_1 - x_2 + y_1 + 1 = 0$$

is a plane in (x_1, x_2, y_1) -space. Consider, $(\bar{x}_1, \bar{x}_2) = (2, 3)$ then $\bar{y}_1 = 2 + 3 - 1 = 4$. A point on this plane is (2, 3, 4) we can use (x_1, x_2) as coordinates hence I expect r = 1. Observe, as $G : \mathbb{R}^3 \to \mathbb{R}$

we consider pull-back of the one-form dt in the range,

$$G^*dt = -dx_1 - dx_2 + dy_1$$

apparently, in our context here:

$$\frac{\partial(y_1,\ldots,y_r)}{\partial(x_1,\ldots,x_r)} = \frac{\partial t}{\partial x_1} = -1 \neq 0$$

and clearly there is no 2-form which pulls back under G since the only two-form in t-space is trivial. We can explicitly write $x_1 = g_1(y_1, x_2) = -x_2 + y_1 + 1$ and there is no h_i since r + 1 = 2 > m.

Example 10.7.6. Let us attempt another example to unravel the meaning of the Implicit Function Theorem. Suppose $y_1 = x_1^2 - x_2^2$ and $y_2 = x_1^2 - x_2^2$ clearly these are redundant. The theorem should deal with this. Let $G(x_1, x_2, y_2, y_2) = (x_1^2 - x_2^2, x_1^2 - x_2^2)$ so we might hope the solution set is 4-2 = 2dimensional however, the rank of G' is usually 1 so the solution set is likely 3-dimensional. No need for guessing, let's work it out.

$$dy_1 = 2x_1 dx_1 - 2x_2 dx_2 = dy_2$$

Hence, if we attempt r = 2 then consider:

$$\frac{\partial(y_1, y_2)}{\partial(x_1, x_2)} = det \left[\begin{array}{cc} 2x_1 & -2x_2\\ 2x_1 & -2x_2 \end{array} \right] = 0.$$

So, we are forced to look at r = 1 for which $\frac{\partial y_1}{\partial x_1} = 2x_1 \neq 0$ for $x_1 \neq 0$. Consider then a point such that $x_1 \neq 0$ and see if we can derive the functions such that $x_1 = g_1(y_1, x_2)$ and $y_2 = h_2(y_1)$. Assume $x_1, x_2 > 0$ for convenience (we could replicate this calculation in other quadrants with appropriate signs adjoined),

$$x_1 = \sqrt{y_1 + x_2^2} = g_1(y_1, x_2),$$
 & $y_2 = y_1 = h_1(y_1).$

I'm mostly interested in this theorem to gain more geometric insight as to what the pull-back means. So, a better way to look at the last example is just to emphasize

$$dy_1 = 2x_1 dx_1 - 2x_2 dx_2 = dy_2$$

shows the pull-back of the basic one-forms can only give a one-form and where the coefficients are zero we cannot force the corresponding coordinate to be dependent. For example, $2x_1dx_1$ is trivial when $x_1 = 0$ hence x_1 cannot be solved for as a function of the remaining variables. This is the computational essence of the theorem. Ideally, I want to get us to the point of calculating without reliance on the Jacobians. Towards that end, let's consider an example for which m = r hence the h function is not needed and we can focus on the pull-back geometry. **Example 10.7.7.** For which variables can we solve the following system (possibly subject some condition). Let F(x, y, z) = (s, t) defined as follows:

$$s = x + z - 1 \tag{10.7}$$

$$t = y + z - 2$$

then clearly $F^*ds = dx + dz$ and $F^*dt = dy + dz$.

$$F^*(ds \wedge dt) = (dx + dz) \wedge (dy + dz) = \underbrace{dx \wedge dy}_{(1.)} + \underbrace{dx \wedge dz}_{(2.)} + \underbrace{dz \wedge dy}_{(3.)}$$

Therefore, by (1.), we can solve for x, y as functions of s, t, z. Or, by (2.), we could solve for x, z as functions of s, t, y. Or, by (3.), we could solve for z, y as functions of s, t, x. The fact that the rank is maximal is implicit within the fact that $ds \wedge dt$ is the top-form in the range. In contrast,

$$F^*ds = dx + dz$$

does not mean that I can solve Equation 10.7 by solving for x as a function of s, t, y, z. Of course, x = s - z + 1 solves the first equation, but the second equation is not contrained by the solution for x what so over. Conversely, we can solve for z = t - y + 2 but we cannot also solve for z = s - x + 1. The coefficients of 1 in $F^*ds = dx + dz$ are not applicable to the Implicit Function Theorem because this form is not the highest degree which pulls-back nontrivially. That role falls to $ds \wedge dt$ here.

Example 10.7.8. For which variables can we solve the following system (possibly subject some condition). Let F(u, v) = (x, y, z) defined as follows:

$$x = u^{2} + v^{2}$$

$$y = u^{2} - v^{2}$$

$$z = uv$$

$$(10.8)$$

then

$$dx = 2udu + 2vdv$$
$$dy = 2udu - 2vdv$$
$$dz = vdu + udv$$

We can calculate,

$$dy \wedge dz = (2udu - 2vdv) \wedge (vdu + udv) = 2(u^2 + v^2)du \wedge dv$$
$$dz \wedge dx = (vdu + udv) \wedge (2udu + 2vdv) = 2(v^2 - u^2)du \wedge dv$$
$$dx \wedge dy = (2udu + 2vdv) \wedge (2udu - 2vdv) = -8uv \, du \wedge dv$$

What does this tell us geometrically? Well, notice that the top-form $dx \wedge dy \wedge dz$ pulls-back to zero since the two-form $du \wedge dv$ is the top-form in the domain. Therefore, r = 2, that is F has rank 2.

Honestly, at this point I doubt about 1/3 of my conclusions in this section. I'm pretty sure I'm missing something big here. I may leave this in the 2013 notes for the amusement of the reader, but beware my doubt for this last subsection. I'm much more certain the push-forward calculations are fine.

10.8 integration of forms

The general strategy is generally as follows:

- (i) there is a natural way to calculate the integral of a k-form on a subset of \mathbb{R}^k
- (ii) given a k-form on a manifold we can locally pull it back to a subset of \mathbb{R}^k provided the manifold is an oriented¹¹ k-dimensional and thus by the previous idea we have an integral.
- (iii) globally we should expect that we can add the results from various local charts and arrive at a total value for the manifold, assuming of course the integral in each chart is finite.

We will only investigate items (i.) and (ii.) in these notes. There are many other excellent texts which take great effort to carefully expand on point (iii.) and I do not wish to replicate that effort here. You can read Edwards and see about *pavings*, or read Munkres' where he has at least 100 pages devoted to the careful study of multivariate integration. I do not get into those topics in my notes because we simply do not have sufficient analytical power to do them justice. I would encourage the student interested in deeper ideas of integration to find time to talk to Dr. Skoumbourdis, he has thought a long time about these matters and he really understands integration in a way we dare not cover in the calculus sequence. You really should have that conversation after you've taken real analysis and have gained a better sense of what analysis' purpose is in mathematics. That said, what we do cover in this section and the next is fascinating whether or not we understand all the analytical underpinnings of the subject!

10.8.1 integration of k-form on \mathbb{R}^k

Note that on $U \subseteq \mathbb{R}^k$ a k-form α is the top form thus there exists some smooth function f on U such that $\alpha_x = f(x)dx^1 \wedge dx^2 \wedge \cdots \wedge dx^k$ for all $x \in U$. If D is a subset of U then we define the integral of α over D via the corresponding integral of k-variables in \mathbb{R}^k . In particular,

$$\int_D \alpha = \int_D f(x) d^k x$$

where on the r.h.s. the symbol $d^k x$ is meant to denote the usual integral of k-variables on \mathbb{R}^k . It is sometimes convenient to write such an integral as:

$$\int_D f(x)d^k x = \int_D f(x)dx^1dx^2\cdots dx^k$$

but, to be more careful, the integration of f over D is a quantity which is independent of the particular order in which the variables on \mathbb{R}^k are assigned. On the other hand, the order of the variables in the formula for α certainly can introduce signs. Note

$$\alpha_x = -f(x)dx^2 \wedge dx^1 \wedge \dots \wedge dx^k.$$

¹¹we will discuss this as the section progresses

How can we reasonably maintain the integral proposed above? Well, the answer is to make a convention that we write the form to match the standard orientation of \mathbb{R}^k . The standard **orientation** of \mathbb{R}^k is given by $Vol_k = dx^1 \wedge dx^2 \wedge \cdots \wedge dx^k$. If the given form is written $\alpha_x = f(x)Vol_k$ then we define $\int_D \alpha = \int_D f(x)d^kx$. Since it is always possible to write a k-form as a function multiplying Vol_k on \mathbb{R}^k this definition suffices to cover all possible k-forms. For example, if $\alpha_x = f(x)dx$ on some subset D = [a, b] of \mathbb{R} ,

$$\int_D \alpha = \int_D f(x)dx = \int_a^b f(x)dx.$$

Or, if $\alpha_{(x,y)} = f(x,y)dx \wedge dy$ then for D a aubset of \mathbb{R}^2 ,

$$\int_D \alpha = \int_D f(x, y) dx dy = \int_D f dA.$$

If $\alpha_{(x,y,z)} = f(x,y,z)dx \wedge dy \wedge dz$ then for D a aubset of \mathbb{R}^3 ,

$$\int_{D} \alpha = \int_{D} f(x, y, z) dx dy dz = \int_{D} f dV.$$

In practice we tend to break the integrals above down into an interated integral thanks to Fubini's theorems. The integrals $\int_D f dA$ and $\int_D f dV$ are not in and of themselves dependent on orientation. However the set D may be oriented the value of those integrals are the same for a fixed function f. The orientation dependence of the form integral is completely wrapped up in our rule that the form must be written as a multiple of the volume form on the given space.

10.8.2 orientations and submanifolds

Given a k-manifold \mathcal{M} we say it is an **oriented** manifold iff all coordinates on \mathcal{M} are **consistently oriented**. If we make a choice and say $\phi_0 : U_0 \to V_0$ is **right-handed** then any overlapping patch $\phi_1 : U_1 \to V_1$ is said to be **right-handed** iff $det(d\theta_{01}) > 0$. Otherwise, if $det(d\theta_{01}) < 0$ then the patch $\phi_1 : U_1 \to V_1$ is said to be **left-handed**. If the manifold is **orientable** then as we continue to travel across the manifold we can choose coordinates such that on each overlap the transition functions satisfy $det(d\theta_{ij}) > 0$. In this way we find an atlas for an orientable \mathcal{M} which is **right-handed**.

We can also say \mathcal{M} is oriented is there exists a nonzero volume-form on \mathcal{M} . If \mathcal{M} is k-dimensional then a volume form Vol is simply a nonzero k-form. At each point $p \in \mathcal{M}$ we can judge if a given coordinate system is left or right handed. We have to make a convention to be precise and I do so at this point. We assume Vol is positive and we say a coordinate system with chart (x^1, x^2, \ldots, x^k) is **positively oriented** iff $Vol(\partial_1|_p, \partial_2|_p, \ldots, \partial_k|_p) > 0$. If a coordinate system is not positively oriented then it is said to be negatively oriented and we will find $Vol(\partial_1|_p, \partial_2|_p, \ldots, \partial_k|_p) < 0$ in that case. It is important that we suppose $Vol_p \neq 0$ at each $p \in \mathcal{M}$ since that is what allows us to demarcate coordinate systems as positive or negatively oriented.

Naturally, you are probably wondering: is a positively oriented coordinate system is the same idea as a right-handed coordinate system as defined above? To answer that we should analyze how the Vol changes coordinates on an overlap. Suppose we are given a positive volume form Vol and a point $p \in \mathcal{M}$ where two coordinate systems x and y are both defined. There must exist some function f such that

$$Vol_x = f(x)dx^1 \wedge dx^2 \wedge \dots \wedge dx^k$$

To change coordinates recall $dx^j = \sum_{j=1}^k \frac{\partial x^j}{\partial y^j} dy^j$ and subsitute,

$$Vol = \sum_{j_1,\dots,j_k=1}^k (f \circ x \circ y^{-1})(y) \frac{\partial x^1}{\partial y^{j_1}} \frac{\partial x^2}{\partial y^{j_2}} \cdots \frac{\partial x^k}{\partial y^{j_k}} dy^{j_1} \wedge dy^{j_2} \wedge \dots \wedge dy^{j_k}$$
$$= (f \circ x \circ y^{-1})(y)det \left[\frac{\partial x}{\partial y}\right] dy^1 \wedge dy^2 \wedge \dots \wedge dy^k$$
(10.9)

If you calculate the value of Vol on $\partial_{x^{I}}|_{p} = \partial_{x_{1}}|_{p}, \partial_{x_{2}}|_{p}, \ldots, \partial_{x_{k}}|_{p}$ you'll find $Vol(\partial_{x^{I}}|_{p}) = f(x(p))$. Whereas, if you evaluate Vol on $\partial_{y^{I}}|_{p} = \partial_{y_{1}}|_{p}, \partial_{y_{2}}|_{p}, \ldots, \partial_{y_{k}}|_{p}$ then the value is $Vol(\partial_{y^{I}}|_{p}) = f(x(p))det[\frac{\partial x}{\partial y}(p)]$. But, we should recognize that $det[\frac{\partial x}{\partial y}] = det(d\theta_{ij})$ hence two coordinate systems which are positively oriented must also be consistently oriented. Why? Assume $Vol(\partial_{x^{I}}|_{p}) = f(x(p)) > 0$ then $Vol(\partial_{y^{I}}|_{p}) = f(x(p))det[\frac{\partial x}{\partial y}(p)] > 0$ iff $det[\frac{\partial x}{\partial y}(p)] > 0$ hence y is positively oriented if we are given that x is positively oriented **and** $det[\frac{\partial x}{\partial y}] > 0$.

Let \mathcal{M} be an oriented k-manifold with orientation given by the volume form Vol and an associated atlas of positively oriented charts. Furthermore, let α be a p-form defined on $V \subseteq \mathcal{M}$. Suppose there exists a local parametrization $\phi : U \subseteq \mathbb{R}^k \to V \subseteq \mathcal{M}$ and $D \subset V$ then there is a smooth function h such that $\alpha_q = h(q)dx^1 \wedge dx^2 \wedge \cdots \wedge dx^k$ for each $q \in V$. We define the integral of α over D as follows:

$$\int_D \alpha = \int_{\phi^{-1}(D)} h(\phi(x)) d^k x \qquad \leftarrow [\star_x]$$

Is this definition dependent on the coordinate system $\phi: U \subseteq \mathbb{R}^k \to V \subseteq \mathcal{M}$? If we instead used coordinate system $\psi: \overline{U} \subseteq \mathbb{R}^k \to \overline{V} \subseteq \mathcal{M}$ where coordinates y^1, y^2, \ldots, y^k on \overline{V} then the given form α has a different coefficient of $dy^1 \wedge dy^2 \wedge \cdots \wedge dy^k$

$$\alpha = h(x)dx^1 \wedge dx^2 \wedge \dots \wedge dx^k = (h \circ x \circ y^{-1})(y)det\left[\frac{\partial x}{\partial y}\right]dy^1 \wedge dy^2 \wedge \dots \wedge dy^k$$

Thus, as we change over to y coordinates the function picks up a factor which is precisely the determinant of the derivative of the transition functions.

$$\int_{D} \alpha = \int_{D} (h \circ x \circ y^{-1})(y) det \left[\frac{\partial x}{\partial y}\right] dy^{1} \wedge dy^{2} \wedge \dots \wedge dy^{k}$$
$$= \int_{\psi^{-1}(D)} (h \circ x \circ y^{-1})(y) det \left[\frac{\partial x}{\partial y}\right] d^{k}y \quad \leftarrow [\star_{y}]$$

We need $\star_x = \star_y$ in order for the integral $\int_D \alpha$ to be well-defined. Fortunately, the needed equality is *almost* provided by the change of variables theorem for multivariate integrals on \mathbb{R}^k . Recall,

$$\int_{R} f(x) d^{k}x = \int_{\bar{R}} \tilde{f}(y) \left| det \frac{\partial x}{\partial y} \right| d^{k}y$$

where \tilde{f} is more pedantically written as $\tilde{f} = f \circ y^{-1}$, notation aside its just the function f written in terms of the new *y*-coordinates. Likewise, \bar{R} limits *y*-coordinates so that the corresponding *x*-coordinates are found in R. Applying this theorem to our pull-back expression,

$$\int_{\phi^{-1}(D)} h(\phi(x)) d^k x = \int_{\psi^{-1}(D)} (h \circ x \circ y^{-1})(y) \left| det \left[\frac{\partial x}{\partial y} \right] \right| d^k y.$$

Equality of \star_x and \star_y follows from the fact that \mathcal{M} is oriented and has transition functions¹² θ_{ij} which satisfy $det(d\theta_{ij}) > 0$. We see that this integral to be well-defined only for oriented manifolds. To integrate over manifolds without an orientation additional ideas are needed, but it is possible.

Perhaps the most interesting case to consider is that of an embedded k-manifold in \mathbb{R}^n . In this context we must deal with both the coordinates of the ambient \mathbb{R}^n and the local parametrizations of the k-manifold. In multivariate calculus we often consider vector fields which are defined on an open subset of \mathbb{R}^3 and then we calculate the flux over a surfaces or the work along a curve. What we have defined thus-far is in essence like definition how to integrate a vector field on a surface or a vector field along a curve, no mention of the vector field off the domain of integration was made. We supposed the forms were already defined on the oriented manifold, but, what if we are instead given a formula for a differential form on \mathbb{R}^n ? How can we restrict that differential form to a surface or line or more generally a parametrized k-dimensional submanifold of \mathbb{R}^n ? That is the problem we concern ourselvew with for the remainder of this section.

Let's begin with a simple object. Consider a one-form $\alpha = \sum_{i=1}^{n} \alpha_i dx^i$ where the function $p \to \alpha_i(p)$ is smooth on some subset of \mathbb{R}^n . Suppose C is a curve parametrized by $X : D \subseteq \mathbb{R} \to C \subseteq \mathbb{R}^n$ then the natural chart on C is provided by the parameter t in particular we have $T_p C = span\{\frac{\partial}{\partial t}|_{t_o}\}$ where $X(t_o) = p$ and $T_p C^* = span\{d_{t_o}t\}$ hence a vector field along C has the form $f(t)\frac{\partial}{\partial t}$ and a differential form has the form g(t)dt. How can we use the one-form α on \mathbb{R}^n to naturally obtain a one-form defined along C? I propose:

$$\alpha \big|_C(t) = \sum_{i=1}^n \alpha_i(X(t)) \frac{\partial X^i}{\partial t} dt$$

It can be shown that $\alpha|_C$ is a one-form on C. If we change coordinates on the curve by reparametrizing $t \to s$ it then the component relative to s vs. the component relative to t are related:

$$\sum_{i=1}^{n} \alpha_i(X(t(s))) \frac{\partial X^i}{ds} = \sum_{i=1}^{n} \alpha_i(X(t)) \frac{dt}{ds} \frac{\partial X^i}{\partial t} = \frac{dt}{ds} \left(\sum_{i=1}^{n} \alpha_i(X(t)) \frac{\partial X^i}{\partial t} \right)$$

This is precisely the transformation rule we want for the components of a one-form.

¹²once more recall the notation $\frac{\partial x}{\partial y}$ is just the matrix of the linear transformation $d\theta_{ij}$ and the determinant of a linear transformation is the determinant of the matrix of the transformation

Example 10.8.1. Suppose $\alpha = dx + 3x^2dy + ydz$ and C is the curve $X : \mathbb{R} \to C \subseteq \mathbb{R}^3$ defined by $X(t) = (1, t, t^2)$ we have x = 1, y = t and $z = t^2$ hence dx = 0, dy = dt and dz = 2tdt on C hence $\alpha \Big|_C = 0 + 3dt + t(2tdt) = (3 + 2t^2)dt$.

Next, consider a two-form $\beta = \sum_{i,j=1}^{n} \frac{1}{2} \beta_{ij} dx^i \wedge dx^j$. Once more we consider a parametrized submanifold of \mathbb{R}^n . In particular use the notation $X : D \subseteq \mathbb{R}^2 \to S \subseteq \mathbb{R}^n$ where u, v serve as coordinates on the surface S. We can write an arbitrary two-form on S in the form $h(u, v)du \wedge dv$ where $h : S \to \mathbb{R}$ is a smooth function on S. How should we construct h(u, v) given β ? Again, I think the following formula is quite natural, honestly, what else would you do¹³?

$$\beta\big|_{S}(u,v) = \sum_{i,j=1}^{n} \beta_{ij}(X(u,v)) \frac{\partial X^{i}}{\partial u} \frac{\partial X^{j}}{\partial v} du \wedge dv$$

The coefficient function of $du \wedge dv$ is smooth because we assume β_{ij} is smooth on \mathbb{R}^n and the local parametrization is also assumed smooth so the functions $\frac{\partial X^i}{\partial u}$ and $\frac{\partial X^i}{\partial v}$ are smooth. Moreover, the component function has the desired coordinate change property with respect to a reparametrization of S. Suppose we reparametrize by s, t, then suppressing the point-dependence of β_{ij} ,

$$\beta\big|_{S} = \sum_{i,j=1}^{n} \beta_{ij} \frac{\partial Y^{i}}{\partial s} \frac{\partial Y^{j}}{\partial t} ds \wedge dt = \frac{du}{ds} \frac{dv}{dt} \sum_{i,j=1}^{n} \beta_{ij} \frac{\partial X^{i}}{\partial u} \frac{\partial X^{j}}{\partial v} ds \wedge dt = \sum_{i,j=1}^{n} \beta_{ij} \frac{\partial X^{i}}{\partial u} \frac{\partial X^{j}}{\partial v} du \wedge dv.$$

Therefore, the restriction of β to S is coordinate independent and we have thus constructed a two-form on a surface from the two-form in the ambient space.

Example 10.8.2. Consider $\beta = y^2 dt \wedge dx + z dx \wedge dy + (x + y + z + t) dt \wedge dz$. Suppose $S \subseteq \mathbb{R}^4$ is parametrized by

$$X(u,v) = (1, u^2v^2, 3u, v)$$

In other words, we are given that

$$t = 1, \ x = u^2 v^2, \ y = 3u, \ z = v$$

Hence, dt = 0, $dx = 2uv^2 du + 2u^2 v dv$, dy = 3du and dz = dv. Computing $\beta|_S$ is just a matter of substuting in all the formulas above, fortunately dt = 0 so only the $zdx \wedge dy$ term is nontrivial:

$$\beta\big|_S = v(2uv^2du + 2u^2vdv) \wedge (3du) = 6u^2v^2dv \wedge du = -6u^2v^2du \wedge dv.$$

It is fairly clear that we can restrict any *p*-form on \mathbb{R}^n to a *p*-dimensional parametrized submanifold by the procedure we explained above for p = 1, 2. That is the underlying idea in the definitions which follow. Beyond that, once we have restricted the *p*-form β on \mathbb{R}^n to $\beta|_{\mathcal{M}}$ then we pull-back the restricted form to an open subset of \mathbb{R}^p and reduce the problem to an ordinary multivariate integral.

¹³include the $\frac{1}{2}$ you say?, we'll see why not soon enough

Remark 10.8.3. .

Just a warning, Einstein summation convention is used in what follows, by my count there are over a dozen places where we implicitly indicate a sum.

Our goal in the remainder of the section is to make contact with the¹⁴ integrals we study in calculus. Note that an embedded manifold with a single patch is almost trivially oriented since there is no overlap to consider. In particular, if $\phi : U \subseteq \mathbb{R}^k \to \mathcal{M} \subseteq \mathbb{R}^n$ is a local parametrization with $\phi^{-1} = (u^1, u^2, \dots, u^k)$ then $du^1 \wedge du^2 \wedge \dots \wedge du^k$ is a volume form for \mathcal{M} . This is the natural generalization of the normal-vector field construction for surfaces in \mathbb{R}^3 .

Definition 10.8.4. integral of one-form along oriented curve:

Let $\alpha = \alpha_i dx^i$ be a one form and let C be an oriented curve with parametrization X(t): $[a, b] \to C$ then we define the integral of the one-form α along the curve C as follows,

$$\int_{C} \alpha \equiv \int_{a}^{b} \alpha_{i}(X(t)) \frac{dX^{i}}{dt}(t) dt$$

where $X(t) = (X^1(t), X^2(t), \dots, X^n(t))$ so we mean X^i to be the i^{th} component of X(t). Moreover, the indices are understood to range over the dimension of the ambient space, if we consider forms in \mathbb{R}^2 then i = 1, 2 if in \mathbb{R}^3 then i = 1, 2, 3 if in Minkowski \mathbb{R}^4 then ishould be replaced with $\mu = 0, 1, 2, 3$ and so on.

Example 10.8.5. One form integrals vs. line integrals of vector fields: We begin with a vector field \vec{F} and construct the corresponding one-form $\omega_{\vec{F}} = F_i dx^i$. Next let C be an oriented curve with parametrization $X : [a, b] \subset \mathbb{R} \to C \subset \mathbb{R}$, observe

$$\int_{C} \omega_{\vec{F}} = \int_{a}^{b} F_{i}(X(t)) \frac{dX^{i}}{dt}(t) dt = \int_{C} \vec{F} \cdot d\vec{l}$$

You may note that the definition of a line integral of a vector field is not special to three dimensions, we can clearly construct the line integral in n-dimensions, likewise the correspondance ω can be written between one-forms and vector fields in any dimension, provided we have a metric to lower the index of the vector field components. The same cannot be said of the flux-form correspondance, it is special to three dimensions for reasons we have explored previously.

¹⁴hopefully known to you already from multivariate calculus

Definition 10.8.6. integral of two-form over an oriented surface:

Let $\beta = \frac{1}{2}\beta_{ij}dx^i \wedge dx^j$ be a two-form and let S be an oriented piecewise smooth surface with parametrization $X(u, v) : D_2 \subset \mathbb{R}^2 \to S \subset \mathbb{R}^n$ then we define the integral of the two-form β over the surface S as follows,

$$\int_{S} \beta \equiv \int_{D_2} \beta_{ij}(X(u,v)) \frac{\partial X^i}{\partial u}(u,v) \frac{\partial X^j}{\partial v}(u,v) du dv$$

where $X(u, v) = (X^1(u, v), X^2(u, v), \dots, X^n(u, v))$ so we mean X^i to be the *i*th component of X(u, v). Moreover, the indices are understood to range over the dimension of the ambient space, if we consider forms in \mathbb{R}^2 then i, j = 1, 2 if in \mathbb{R}^3 then i, j = 1, 2, 3 if in Minkowski \mathbb{R}^4 then i, j should be replaced with $\mu, \nu = 0, 1, 2, 3$ and so on.

Example 10.8.7. Two-form integrals vs. surface integrals of vector fields in \mathbb{R}^3 : We begin with a vector field \vec{F} and construct the corresponding two-form $\Phi_{\vec{F}} = \frac{1}{2} \epsilon_{ijk} F_k dx^i \wedge dx^j$ which is to say $\Phi_{\vec{F}} = F_1 dy \wedge dz + F_2 dz \wedge dx + F_3 dx \wedge dy$. Next let S be an oriented piecewise smooth surface with parametrization $X : D \subset \mathbb{R}^2 \to S \subset \mathbb{R}^3$, then

$$\int_{S} \Phi_{\vec{F}} = \int_{S} \vec{F} \cdot d\vec{A}$$

Proof: Recall that the normal to the surface S has the form,

$$N(u,v) = \frac{\partial X}{\partial u} \times \frac{\partial X}{\partial v} = \epsilon_{ijk} \frac{\partial X^i}{\partial u} \frac{\partial X^j}{\partial v} e_k$$

at the point X(u, v). This gives us a vector which points along the outward normal to the surface and it is nonvanishing throughout the whole surface by our assumption that S is oriented. Moreover the vector surface integral of \vec{F} over S was defined by the formula,

$$\int_{S} \vec{F} \cdot d\vec{A} \equiv \int \int_{D} \vec{F}(X(u,v)) \cdot \vec{N}(u,v) \, du dv.$$

now that the reader is reminded what's what, lets prove the proposition, dropping the (u,v) dependent to reduce clutter we find,

$$\begin{split} \int_{S} \vec{F} \cdot d\vec{A} &= \int \int_{D} \vec{F} \cdot \vec{N} \, du dv \\ &= \int \int_{D} F_k N_k \, du dv \\ &= \int \int_{D} F_k \epsilon_{ijk} \frac{\partial X^i}{\partial u} \frac{\partial X^j}{\partial v} \, du dv \\ &= \int \int_{D} (\Phi_{\vec{F}})_{ij} \frac{\partial X^i}{\partial u} \frac{\partial X^j}{\partial v} \, du dv \\ &= \int_{S} \Phi_{\vec{F}} \end{split}$$

notice that we have again used our convention that $(\Phi_{\vec{F}})_{ij}$ refers to the tensor components of the 2-form $\Phi_{\vec{F}}$ meaning we have $\Phi_{\vec{F}} = (\Phi_{\vec{F}})_{ij}dx^i \otimes dx^j$ whereas with the wedge product $\Phi_{\vec{F}} = \frac{1}{2}(\Phi_{\vec{F}})_{ij}dx^i \wedge dx^j$, I mention this in case you are concerned there is a half in $\Phi_{\vec{F}}$ yet we never found a half in the integral. Well, we don't expect to because we defined the integral of the form with respect to the tensor components of the form, again they don't contain the half.

Example 10.8.8. Consider the vector field $\vec{F} = (0,0,3)$ then the corresponding two-form is simply $\Phi_F = 3dx \wedge dy$. Lets calculate the surface integral and two-form integrals over the square $D = [0,1] \times [0,1]$ in the xy-plane, in this case the parameters can be taken to be x and y so X(x,y) = (x,y) and,

$$N(x,y) = \frac{\partial X}{\partial x} \times \frac{\partial X}{\partial y} = (1,0,0) \times (0,1,0) = (0,0,1)$$

which is nice. Now calculate,

$$\int_{S} \vec{F} \cdot d\vec{A} = \int_{D} \int_{D} \vec{F} \cdot \vec{N} \, dx dy$$
$$= \int_{D} \int_{D} (0, 0, 3) \cdot (0, 0, 1) \, dx dy$$
$$= \int_{0}^{1} \int_{0}^{1} 3 \, dx \, dy$$
$$= 3.$$

Consider that $\Phi_F = 3dx \wedge dy = 3dx \otimes dy - 3dy \otimes dx$ therefore we may read directly that $(\Phi_F)_{12} = -(\Phi_F)_{21} = 3$ and all other components are zero,

$$\int_{S} \Phi_{F} = \iint_{D} (\Phi_{F})_{ij} \frac{\partial X^{i}}{\partial x} \frac{\partial X^{j}}{\partial y} dxdy$$
$$= \iint_{D} \left(3 \frac{\partial X^{1}}{\partial x} \frac{\partial X^{2}}{\partial y} - 3 \frac{\partial X^{2}}{\partial x} \frac{\partial X^{1}}{\partial y} \right) dxdy$$
$$= \iint_{0}^{1} \int_{0}^{1} \left(3 \frac{\partial x}{\partial x} \frac{\partial y}{\partial y} - 3 \frac{\partial y}{\partial x} \frac{\partial x}{\partial y} \right) dxdy$$
$$= 3.$$

Definition 10.8.9. integral of a three-form over an oriented volume:

Let $\gamma = \frac{1}{6}\beta_{ijk}dx^i \wedge dx^j \wedge dx^k$ be a three-form and let V be an oriented piecewise smooth volume with parametrization $X(u, v, w) : D_3 \subset \mathbb{R}^3 \to V \subset \mathbb{R}^n$ then we define the integral of the three-form γ in the volume V as follows,

$$\int_{V} \gamma \equiv \int_{D_{3}} \gamma_{ijk}(X(u,v,w)) \frac{\partial X^{i}}{\partial u} \frac{\partial X^{j}}{\partial v} \frac{\partial X^{k}}{\partial w} \ du dv dw$$

where $X(u, v, w) = (X^1(u, v, w), X^2(u, v, w), \dots, X^n(u, v, w))$ so we mean X^i to be the i^{th} component of X(u, v, w). Moreover, the indices are understood to range over the dimension of the ambient space, if we consider forms in \mathbb{R}^3 then i, j, k = 1, 2, 3 if in Minkowski \mathbb{R}^4 then i, j, k should be replaced with $\mu, \nu, \sigma = 0, 1, 2, 3$ and so on.

Finally we define the integral of a *p*-form over an *p*-dimensional subspace of \mathbb{R} , we assume that $p \leq n$ so that it is possible to embed such a subspace in \mathbb{R} ,

Definition 10.8.10. integral of a p-form over an oriented volume:

Let $\gamma = \frac{1}{p!} \beta_{i_1 \dots i_p} dx^{i_1} \wedge \dots dx^{i_p}$ be a p-form and let S be an oriented piecewise smooth subspace with parametrization $X(u_1, \dots, u_p) : D_p \subset \mathbb{R}^p \to S \subset \mathbb{R}^n$ (for $n \geq p$) then we define the integral of the p-form γ in the subspace S as follows,

$$\int_{S} \gamma \equiv \int_{D_p} \beta_{i_1 \dots i_p} (X(u_1, \dots, u_p)) \frac{\partial X^{i_1}}{\partial u_1} \cdots \frac{\partial X^{i_p}}{\partial u_p} du_1 \cdots du_p$$

where $X(u_1, \ldots, u_p) = (X^1(u_1, \ldots, u_p), X^2(u_1, \ldots, u_p), \ldots, X^n(u_1, \ldots, u_p))$ so we mean X^i to be the *i*th component of $X(u_1, \ldots, u_p)$. Moreover, the indices are understood to range over the dimension of the ambient space.

Integrals of forms play an important role in modern physics. I hope you can begin to appreciate that forms recover all the formulas we learned in multivariate calculus and give us a way to extend calculation into higher dimensions with ease. I include a toy example at the conclusion of this chapter just to show you how electromagnetism is easily translated into higher dimensions.

10.9 Generalized Stokes Theorem

The generalized Stokes theorem contains within it most of the main theorems of integral calculus, namely the fundamental theorem of calculus, the fundamental theorem of line integrals (a.k.a the FTC in three dimensions), Greene's Theorem in the plane, Gauss' Theorem and also Stokes Theorem, not to mention a myriad of higher dimensional not so commonly named theorems. The breadth of its application is hard to overstate, yet the statement of the theorem is simple,

Theorem 10.9.1. Generalized Stokes Theorem:

Let S be an oriented, piecewise smooth (p+1)-dimensional subspace of \mathbb{R}^n where $n \ge p+1$ and let ∂S be it boundary which is consistently oriented then for a p-form α which behaves reasonably on S we have that

$$\int_{S} d\alpha = \int_{\partial S} \alpha$$

The proof of this theorem (and a more careful statement of it) can be found in a number of places, Susan Colley's Vector Calculus or Steven H. Weintraub's Differential Forms: A Complement to Vector Calculus or Spivak's Calculus on Manifolds just to name a few. I believe the argument in Edward's text is quite complete. In any event, you should already be familar with the idea from the usual Stokes Theorem where we must insist the boundary curve to the surface is related to the surface's normal field according to the right-hand-rule. Explaining how to orient the boundary $\partial \mathcal{M}$ given an oriented \mathcal{M} is the problem of generalizing the right-hand-rule to many dimensions. I leave it to your homework for the time being.

Lets work out how this theorem reproduces the main integral theorems of calculus.

Example 10.9.2. Fundamental Theorem of Calculus in \mathbb{R} : Let $f : \mathbb{R} \to \mathbb{R}$ be a zero-form then consider the interval [a, b] in \mathbb{R} . If we let S = [a, b] then $\partial S = \{a, b\}$. Further observe that df = f'(x)dx. Notice by the definition of one-form integration

$$\int_{S} df = \int_{a}^{b} f'(x) dx$$

However on the other hand we find (the integral over a zero-form is taken to be the evaluation map, perhaps we should have defined this earlier, oops., but its only going to come up here so I'm leaving it.)

$$\int_{\partial S} f = f(b) - f(a)$$

Hence in view of the definition above we find that

$$\int_{a}^{b} f'(x)dx = f(b) - f(a) \quad \Longleftrightarrow \quad \int_{S} df = \int_{\partial S} f$$

Example 10.9.3. Fundamental Theorem of Calculus in \mathbb{R}^3 : Let $f : \mathbb{R}^3 \to \mathbb{R}$ be a zeroform then consider a curve C from $p \in \mathbb{R}^3$ to $q \in \mathbb{R}^3$ parametrized by $\phi : [a, b] \to \mathbb{R}^3$. Note that $\partial C = \{\phi(a) = p, \phi(b) = q\}$. Next note that

$$df = \frac{\partial f}{\partial x^i} dx^i$$

Then consider that the exterior derivative of a function corresponds to the gradient of the function thus we are not to surprised to find that

$$\int_{C} df = \int_{a}^{b} \frac{\partial f}{\partial x^{i}} \frac{\partial x^{i}}{\partial t} dt = \int_{C} (\nabla f) \cdot d\vec{l}$$

On the other hand, we use the definition of the integral over a a two point set again to find

$$\int_{\partial C} f = f(q) - f(p)$$

Hence if the Generalized Stokes Theorem is true then so is the FTC in three dimensions,

$$\int_C (\nabla f) \cdot d\vec{l} = f(q) - f(p) \quad \Longleftrightarrow \quad \int_C df = \int_{\partial C} f(q) d\vec{l} d\vec{l} = f(q) - f(p) d\vec{l} d\vec{l} d\vec{l} = f(q) - f(p) d\vec{l} d\vec{l$$

another popular title for this theorem is the "fundamental theorem for line integrals". As a final thought here we notice that this calculation easily generalizes to 2,4,5,6,... dimensions.

Example 10.9.4. Greene's Theorem: Let us recall the statement of Greene's Theorem as I have not replicated it yet in the notes, let D be a region in the xy-plane and let ∂D be its consistently oriented boundary then if $\vec{F} = (M(x, y), N(x, y), 0)$ is well behaved on D

$$\int_{\partial D} M dx + N dy = \int \int_{D} \left(\frac{\partial N}{\partial x} - \frac{\partial M}{\partial y} \right) dx dy$$

We begin by finding the one-form corresponding to \vec{F} namely $\omega_F = Mdx + Ndy$ consider then that

$$d\omega_F = d(Mdx + Ndy) = dM \wedge dx + dN \wedge dy = \frac{\partial M}{\partial y} dy \wedge dx + \frac{\partial N}{\partial x} dx \wedge dy$$

which simplifies to,

$$d\omega_F = \left(\frac{\partial N}{\partial x} - \frac{\partial M}{\partial y}\right) dx \wedge dy = \Phi_{\left(\frac{\partial N}{\partial x} - \frac{\partial M}{\partial y}\right)\hat{k}}$$

Thus, using our discussion in the last section we recall

$$\int_{\partial D} \omega_F = \int_{\partial D} \vec{F} \cdot d\vec{l} = \int_{\partial D} M dx + N dy$$

where we have reminded the reader that the notation in the rightmost expression is just another way of denoting the line integral in question. Next observe,

$$\int_D d\omega_F = \int_D (\frac{\partial N}{\partial x} - \frac{\partial M}{\partial y})\hat{k} \cdot d\vec{A}$$

And clearly, since $d\vec{A} = \hat{k}dxdy$ we have

$$\int_{D} (\frac{\partial N}{\partial x} - \frac{\partial M}{\partial y}) \hat{k} \cdot d\vec{A} = \int_{D} (\frac{\partial N}{\partial x} - \frac{\partial M}{\partial y}) dx dy$$

Therefore,

$$\int_{\partial D} M dx + N dy = \int \int_{D} \left(\frac{\partial N}{\partial x} - \frac{\partial M}{\partial y} \right) dx dy \quad \Longleftrightarrow \quad \int_{D} d\omega_F = \int_{\partial D} \omega_F$$

Example 10.9.5. Gauss Theorem: Let us recall Gauss Theorem to begin, for suitably defined \vec{F} and V,

$$\int_{\partial V} \vec{F} \cdot d\vec{A} = \int_{V} \nabla \cdot \vec{F} \ d\tau$$

First we recall our earlier result that

$$d(\Phi_F) = (\nabla \cdot \vec{F}) dx \wedge dy \wedge dz$$

Now note that we may integrate the three form over a volume,

$$\int_{V} d(\Phi_F) = \int_{V} (\nabla \cdot \vec{F}) dx dy dz$$

whereas,

$$\int_{\partial V} \Phi_F = \int_{\partial V} \vec{F} \cdot d\vec{A}$$

so there it is,

$$\int_{V} (\nabla \cdot \vec{F}) d\tau = \int_{\partial V} \vec{F} \cdot d\vec{A} \quad \Longleftrightarrow \quad \int_{V} d(\Phi_F) = \int_{\partial V} \Phi_F$$

I have left a little detail out here, I may assign it for homework.

Example 10.9.6. Stokes Theorem: Let us recall Stokes Theorem to begin, for suitably defined \vec{F} and S,

$$\int_{S} (\nabla \times \vec{F}) \cdot d\vec{A} = \int_{\partial S} \vec{F} \cdot d\vec{l}$$

Next recall we have shown in the last chapter that,

$$d(\omega_F) = \Phi_{\nabla \times \vec{F}}$$

Hence,

$$\int_{S} d(\omega_F) = \int_{S} (\nabla \times \vec{F}) \cdot d\vec{A}$$

whereas,

$$\int_{\partial S} \omega_F = \int_{\partial S} \vec{F} \cdot d\vec{l}$$

which tells us that,

$$\int_{S} (\nabla \times \vec{F}) \cdot d\vec{A} = \int_{\partial S} \vec{F} \cdot d\vec{l} \quad \Longleftrightarrow \quad \int_{S} d(\omega_F) = \int_{\partial S} \omega_F$$

The Generalized Stokes Theorem is perhaps the most persausive argument for mathematicians to be aware of differential forms, it is clear they allow for more deep and sweeping statements of the calculus. The generality of differential forms is what drives modern physicists to work with them, string theorists for example examine higher dimensional theories so they are forced to use a language more general than that of the conventional vector calculus.

10.10 Poincare lemma

This section is in large part inspired by M. Gockeler and T. Schucker's *Differential geometry, gauge theories, and gravity* page 20-22. The converse calculation is modelled on the argument found in H. Flanders *Differential Forms with Applications to the Physical Sciences*. The original work was done around the dawn of the twentieth century and can be found in many texts besides the two I mentioned here.

10.10.1 exact forms are closed

Proposition 10.10.1.

The exterior derivative of the exterior derivative is zero. $d^2 = 0$

Proof: Let α be an arbitrary *p*-form then

$$d\alpha = \frac{1}{p!} (\partial_m \alpha_{i_1 i_2 \dots i_p}) dx^m \wedge dx^{i_1} \wedge dx^{i_2} \wedge \dots \wedge dx^{i_p}$$
(10.10)

then differentiate again,

$$d(d\alpha) = d \left[\frac{1}{p!} (\partial_m \alpha_{i_1 i_2 \dots i_p}) dx^m \wedge dx^{i_1} \wedge dx^{i_2} \wedge \dots \wedge dx^{i_p} \right]$$

= $\frac{1}{p!} (\partial_k \partial_m \alpha_{i_1 i_2 \dots i_p}) dx^k \wedge dx^m \wedge dx^{i_1} \wedge dx^{i_2} \wedge \dots \wedge dx^{i_p}$
= 0 (10.11)

since the partial derivatives commute whereas the wedge product anticommutes so we note that the pair of indices (k,m) is symmetric for the derivatives but antisymmetric for the wedge, as we know the sum of symmetric against antisymmetric vanishes (see equation ?? part *iv* if you forgot.)

Definition 10.10.2.

A differential form α is **closed** iff $d\alpha = 0$. A differential form β is **exact** iff there exists γ such that $\beta = d\gamma$.

Proposition 10.10.3.

All exact forms are closed. However, there exist closed forms which are not exact.

Proof: Exact implies closed is easy, let β be exact such that $\beta = d\gamma$ then

$$d\beta = d(d\gamma) = 0$$

using the theorem $d^2 = 0$. To prove that there exists a closed form which is not exact it suffices to give an example. A popular example (due to its physical significance to magnetic monopoles, Dirac Strings and the like..) is the following differential form in \mathbb{R}^2

$$\phi = \frac{1}{x^2 + y^2} (xdy - ydx) \tag{10.12}$$

You may verify that $d\phi = 0$ in homework. Observe that if ϕ were exact then there would exist f such that $\phi = df$ meaning that

$$rac{\partial f}{\partial x} = -rac{y}{x^2 + y^2}, \qquad rac{\partial f}{\partial y} = rac{x}{x^2 + y^2}$$

which are solved by $f = \arctan(y/x) + c$ where c is arbitrary. Observe that f is ill-defined along the y-axis x = 0 (this is the Dirac String if we put things in context), however the natural domain of ϕ is $\mathbb{R}^{n \times n} - \{(0,0)\}$. \Box

10.10.2 potentials for closed forms

Poincare' suggested the following partial converse, he said closed implies exact provided we place a topological restriction on the domain of the form. In particular, if the domain of a closed form is smoothly deformable to a point then each closed form is exact. We'll work out a proof of that result for a subset of \mathbb{R}^n . Be patient, we have to build some toys before we play.



Suppose $U \subseteq \mathbb{R}^n$ and I = [0, 1] we denote a typical point in $I \times U$ as (t, x) where $t \in I$ and $x \in \mathbb{R}^n$. Define maps,

$$J_1: U \to I \times U, \qquad J_0: U \to I \times U$$

by $J_1(x) = (1, x)$ and $J_0(x) = (0, x)$ for each $x \in U$. Flanders encourages us to view $I \times U$ as a cylinder and where the map J_1 maps U to the top and J_0 maps U to the base. We can pull-back

forms on the cylinder to the U on the top (t = 1) or to the base (t = 0). For instance, if we consider $\omega = (x + t)dx + dt$ for the case n = 1 then

$$J_0^*\omega = xdx \qquad J_1^*\omega = (x+1)dx.$$

Define a smooth mapping K of (p+1) forms on $I \times U$ to p-forms on U as follows:

(1.)
$$K(a(t,x)dx^{I}) = 0,$$
 (2.) $K(a(t,x)dt \wedge dx^{J}) = \left(\int_{0}^{1} a(t,x)dt\right)dx^{J}$

for multi-indices I of length (p + 1) and J of length p. The cases (1.) and (2.) simply divide the possible monomial¹⁵ inputs from $\Lambda^{p+1}(I \times U)$ into forms which have dt and those which don't. Then K is defined for a general (p + 1)-form on $I \times U$ by linearly extending the formulas above to multinomials of the basic monomials.

It turns out that the following identity holds for K:

Lemma 10.10.4. the K-lemma.

If
$$\omega$$
 is a differential form on $I \times U$ then

$$K(d\omega) + d(K(\omega)) = J_1^* \omega - J_0^* \omega.$$

Proof: Since the equation is given for linear operations it suffices to check the formula for monomials since we can extend the result linearly once those are affirmed. As in the definition of K there are two basic categories of forms on $I \times U$:

Case 1: If $\omega = a(t, x)dx^{I}$ then clearly $K(\omega) = 0$ hence $d(K(\omega)) = 0$. Observe,

$$d\omega = da \wedge dx^{I} = \sum_{j} \frac{\partial a}{\partial x^{j}} dx^{j} \wedge dx^{I} + \frac{\partial a}{\partial t} dt \wedge dx^{I}$$

Hence $K(d\omega)$ is calculated as follows:

$$K(d\omega) = K\left(\sum_{j} \frac{\partial a}{\partial x^{j}} dx^{j} \wedge dx^{I}\right) + K\left(\frac{\partial a}{\partial t} dt \wedge dx^{I}\right)$$
$$= \left(\int_{0}^{1} \frac{\partial a}{\partial t} dt\right) dx^{I}$$
$$= \left[a(x, 1) - a(x, 0)\right] dx^{I}$$
$$= J_{1}^{*}\omega - J_{0}^{*}\omega$$
(10.13)

where we used the FTC in the next to last step. The pull-backs in this case just amount to evaluation at t = 0 or t = 1 as there is no dt-type term to squash in ω . The identity follows.

 $^{^{15}}dx \wedge dy$ is a monomial whereas dx + dy is a binomial in this context

Case 2: Suppose $\omega = a(t, x)dt \wedge dx^J$. Calculate,

$$d\omega = \sum_{j} \frac{\partial a}{\partial x^{k}} dx^{k} \wedge dt \wedge dx^{J} + \frac{\partial a}{\partial t} \underbrace{dt \wedge dt}_{zero \ !} \wedge dx^{J}$$

Thus, using $dx^k \wedge dt = -dt \wedge dx^k$, we calculate:

$$K(d\omega) = K\left(-\sum_{k} \frac{\partial a}{\partial x^{k}} dt \wedge dx^{k} \wedge dx^{I}\right)$$
$$= -\sum_{k} \left(\int_{0}^{1} \frac{\partial a}{\partial x^{k}} dt\right) dx^{k} \wedge dx^{I}$$

at which point we cannot proceed further since a is an arbitrary function which can include a nontrivial time-dependence. We turn to the calculation of $d(K(\omega))$. Recall we defined

$$K(\omega) = \left(\int_0^1 a(t, x) dt\right) dx^J.$$

We calculate the exterior derivative of $K(\omega)$:

$$d(K(\omega)) = d\left(\int_{0}^{1} a(t, x)dt\right) \wedge dx^{J}$$

$$= \left(\frac{\partial}{\partial t} \left[\int_{0}^{1} a(\tau, x)d\tau\right] dt + \sum_{k} \frac{\partial}{\partial x^{k}} \left[\int_{0}^{1} a(t, x)dt\right] dx^{k}\right) \wedge dx^{J}$$

$$= \sum_{k} \left(\int_{0}^{1} \frac{\partial a}{\partial x^{k}} dt\right) dx^{k} \wedge dx^{J}.$$
(10.14)

Therefore, $K(d\omega) + d(K(\omega)) = 0$ and clearly $J_0^* \omega = J_1^* \omega = 0$ in this case since the pull-backs squash the dt to zero. The lemma follows. \Box .

Definition 10.10.5.

A subset $U \subseteq \mathbb{R}^n$ is deformable to a point P if there exists a smooth mapping $G : I \times U \to U$ such that G(1, x) = x and G(0, x) = P for all $x \in U$.

The map G deforms U smoothly into the point P. Recall that $J_1(x) = (1, x)$ and $J_0(x) = (0, x)$ hence the conditions on the deformation can be expressed as:

$$G(J_1(x)) = x \qquad G(J_0(x)) = P$$

Denoting Id for the identity on U and P as the constant mapping with value P on U we have

$$G \circ J_1 = Id$$
 $G \circ J_0 = P$

Therefore, if γ is a (p+1)-form on U we calculate,

$$(G \circ J_1)^* \gamma = Id^* \gamma \quad \Rightarrow \quad J_1^*[G^* \gamma] = \gamma$$

whereas,

$$(G \circ J_0)^* \gamma = P^* \gamma = 0 \quad \Rightarrow \quad J_0^* [G^* \gamma] = 0$$

Apply the K-lemma to the form $\omega = G^* \gamma$ on $I \times U$ and we find:

$$K(d(G^*\gamma)) + d(K(G^*\gamma)) = \gamma.$$

However, recall that we proved that pull-backs and exterior derivatives commute thus

$$d(G^*\gamma) = G^*(d\gamma)$$

and we find an extremely interesting identity,

$$K(G^*(d\gamma)) + d(K(G^*\gamma)) = \gamma.$$

Proposition 10.10.6.

If $U \subseteq \mathbb{R}$ is deformable to a point P then a p-form γ on U is closed iff ϕ is exact.

Proof: Suppose γ is exact then $\gamma = d\beta$ for some (p-1)-form β on U hence $d\gamma = d(d\beta) = 0$ by Proposition 10.10.1 hence γ is closed. Conversely, suppose γ is closed. Apply the boxed consequence of the K-lemma, note that $K(G^*(0)) = 0$ since we assume $d\gamma = 0$. We find,

$$d(K(G^*\gamma)) = \gamma$$

identify that $G^*\gamma$ is a *p*-form on $I \times U$ whereas $K(G^*\gamma)$ is a (p-1)-form on U by the very construction of K. It follows that γ is exact since we have shown how it is obtained as the exterior derivative of another differential form of one degree less. \Box

Where was deformability to a point P used in the proof above? The key is the existence of the mapping G. In other words, if you have a space which is not deformable to a point then no deformation map G is available and the construction via K breaks down. Basically, if the space has a hole which you get stuck on as you deform loops to a point then it is not deformable to a point. Often we call such spaces *simply connected*. Careful definition of these terms is too difficult for calculus, deformation of loops and higher dimensional objects is properly covered in algebraic topology. In any event, the connection of the deformation and exactness of closed forms allows topologists to use differential forms detect holes in spaces. In particular:

Definition 10.10.7. de Rham cohomology:

We define several real vector spaces of differential forms over some subset U of \mathbb{R} ,

 $Z^{p}(U) \equiv \{ \phi \in \Lambda^{p}U \mid \phi \text{ closed} \}$

the space of closed p-forms on U. Then,

$$B^{p}(U) \equiv \{\phi \in \Lambda^{p}U \mid \phi \text{ exact}\}$$

the space of exact p-forms where by convention $B^0(U) = \{0\}$ The de Rham cohomology groups are defined by the quotient of closed/exact,

$$H^p(U) \equiv Z^p(U)/B^p(U).$$

the $dim(H^pU) = p^{th}$ Betti number of U.

We observe that simply connected regions have all the Betti numbers zero since $Z^p(U) = B^p(U)$ implies that $H^p(U) = \{0\}$. Of course there is much more to say about de Rahm Cohomology, I just wanted to give you a taste and alert you to the fact that differential forms can be used to reveal aspects of topology. Not all algebraic topology uses differential forms though, there are several other calculational schemes based on triangulation of the space, or studying singular simplexes. One important event in 20-th century mathematics was the discovery that all these schemes described the same homology groups. The Steenrod reduced the problem to a few central axioms and it was shown that all the calculational schemes adhere to that same set of axioms.

One interesting aspect of the proof we (copied from Flanders ¹⁶) is that it is not a mere existence proof. It actually lays out how to calculate the form which provides exactness. Let's call β the potential form of γ if $\gamma = d\beta$. Notice this is totally reasonable language since in the case of classical mechanics we consider conservative forces \vec{F} which as derivable from a scalar potential V by $\vec{F} = -\nabla V$. Translated into differential forms we have $\omega_{\vec{F}} = -dV$. Let's explore how the K-mapping and proof indicate the potential of a vector field ought be calculated.

Suppose U is deformable to a point and F is a smooth conservative vector field on U. Perhaps you recall that for conservative F are irrotational hence $\nabla \times F = 0$. Recall that $d\omega_F = \Phi_{\nabla \times F} = \Phi_0 = 0$ thus the one-form corresponding to a conservative vector field is a closed form. Apply the identity: let $G: I \times U \to U \subseteq \mathbb{R}^3$ be the deformation of U to a point P,

$$d(K(G^*\omega_F)) = \omega_F$$

Hence, including the minus to make energy conservation natural,

$$V = -K(G^*\omega_F)$$

 $^{^{16}}$ I don't know the complete history of this calculation at the present. It would be nice to find it since I doubt Flanders is the originator.

For convenience, lets suppose the space considered is the unit-ball B and lets use a deformation to the origin. Explicitly, G(t,r) = tr for all $r \in \mathbb{R}^3$ such that $||r|| \leq 1$. Note that clearly G(0,r) = 0whereas G(1,r) = r and G has a nice formula so it's smooth¹⁷. We wish to calculate the pull-back of $\omega_F = Pdx + Qdy + Rdz$ under G, from the definition of pull-back we have

$$(G^*\omega_F)(X) = \omega_F(dG(X))$$

for each smooth vector field X on $I \times B$. Differential forms on $I \times B$ are written as linear combinations of dt, dx, dy, dz with smooth functions as coefficients. We can calculate the coefficients by evalutation on the corresponding vector fields $\partial_t, \partial_x, \partial_y, \partial_z$. Observe, since G(t, x, y, z) = (tx, ty, tz)we have

$$dG(\partial_t) = \frac{\partial G^1}{\partial t} \frac{\partial}{\partial x} + \frac{\partial G^2}{\partial t} \frac{\partial}{\partial y} + \frac{\partial G^3}{\partial t} \frac{\partial}{\partial z} = x \frac{\partial}{\partial x} + y \frac{\partial}{\partial y} + z \frac{\partial}{\partial z}$$

wheras,

$$dG(\partial_x) = \frac{\partial G^1}{\partial x}\frac{\partial}{\partial x} + \frac{\partial G^2}{\partial x}\frac{\partial}{\partial y} + \frac{\partial G^3}{\partial x}\frac{\partial}{\partial z} = t\frac{\partial}{\partial x}$$

and similarly,

$$dG(\partial_y) = t \frac{\partial}{\partial y} \qquad dG(\partial_x) = t \frac{\partial}{\partial z}$$

Furthermore,

$$\omega_F(dG(\partial_t)) = \omega_F(x\partial_x + y\partial_y + z\partial_z) = xP + yQ + zR$$

 $\omega_F(dG(\partial_x)) = \omega_F(t\partial_x) = tP, \qquad \omega_F(dG(\partial_y)) = \omega_F(t\partial_y) = tQ, \qquad \omega_F(dG(\partial_z)) = \omega_F(t\partial_z) = tR$ Therefore,

$$G^*\omega_F = (xP + yQ + zR)dt + tPdx + tQdy + tRdz = (xP + yQ + zR)dt + t\omega_F$$

Now we can calculate $K(G^*\omega_F)$ and hence V^{18}

$$K(G^*\omega_F)(t,x,y,z) = K\bigg(\big(xP(tx,ty,tz) + yQ(tx,ty,tz) + zR(tx,ty,tz)\big)dt\bigg)$$

Therefore,

$$V(x, y, z) = -K(G^*\omega_F) = -\int_0^1 (xP(tx, ty, tz) + yQ(tx, ty, tz) + zR(tx, ty, tz))dt$$

Notice this is precisely the line-integral of $F = \langle P, Q, R \rangle$ along the line C with direction $\langle x, y, z \rangle$ from the origin to (x, y, z). In particular, if $\vec{r}(t) = \langle tx, ty, tz \rangle$ then $\frac{d\vec{r}}{dt} = \langle x, y, z \rangle$ hence we identify

$$V(x,y,z) = -\int_0^1 \vec{F}(\vec{r}(t)) \cdot \frac{d\vec{r}}{dt} dt = -\int_C \vec{F} \cdot d\vec{r}$$

¹⁷there is of course a deeper meaning to the word, but, for brevity I gloss over this.

 $^{^{18}}$ Note that only the coefficient of dt gives a nontrivial contribution so in retrospect we did a bit more calculation than necessary. That said, I'll just keep it as a celebration of extreme youth for calculation. Also, I've been a bit careless in omiting the point up to this point, let's include the point dependence since it will be critical to properly understand the formula.

Perhaps you recall this is precisely how we calculate the potential function for a conservative vector field provided we take the origin as the zero for the potential.

Actually, this calculation is quite interesting. Suppose we used a different deformation $G: I \times U \to U$. For fixed point Q we travel to from the origin to the point by the path $t \mapsto G(t, Q)$. Of course this path need not be a line. The space considered might look like a snake where a line cannot reach from the base point P to the point Q. But, the same potential is derived. Why? Path independence of the vector field is one answer. The criteria $\nabla \times F = 0$ suffices for a simply connected region. However, we see something deeper. The criteria of a closed form paired with a simply connected (deformable) domain suffices to construct a potential for the given form. This result reproduces the familar case of conservative vector fields derived from scalar potentials and *much more*. In Flanders he calculates the potential for a closed two-form. This ought to be the mathematics underlying the construction of the so-called **vector potential** of magnetism. In junior-level electromagnetism¹⁹ the magnetic field B satisfies $\nabla \cdot B = 0$ and thus the two-form Φ_B has exterior derivative $d\Phi_B = \nabla \cdot B dx \wedge dy \wedge dz = 0$. The magnetic field corresponds to a closed form. Poincare's lemma shows that there exists a one-form ω_A such that $d\omega_A = \Phi_B$. But this means $\Phi_{\nabla \times A} = \Phi_B$ hence in the langauge of vector fields we expect the vector potential A generated the magnetic field B throught the curl $B = \nabla \times A$. Indeed, this is precisely what a typical junior level physics student learns in the magnetostatic case. Appreciate that it goes deeper still, the Poincare lemma holds for p-forms which correspond to objects which don't match up with the quaint vector fields of 19-th century physics. We can be confident to find potential for 3-form fluxes in a 10-dimensional space, or wherever our imagination takes us. I explain at the end of this chapter how to translate electromagnetics into the langauge of differential forms, it may well be that in the future we think about forms the way we currently think about vectors. This is one of the reasons I like Flanders text, he really sticks with the language of differential forms throughout. In contrast to these notes, he just does what is most interesting. I think undergraduates need to see more detail and not just the most clever calculations, but, I can hardly blame Flanders! He makes no claim to be an undergraduate work.

Finally, I should at least mention that though we can derive a potential β for a given closed form α on a simply connected domain it need not be unique. In fact, it will not be unique unless we add further criteria for the potential. This ambuity is called **gauge freedom** in physics. Mathematically it's really simple give form language. If $\alpha = d\beta$ where β is a (p-1)-form then we can take any smooth (p-2) form and calculate that

$$d(\alpha + d\lambda) = d\beta + d^2\lambda = d\beta = \alpha$$

Therefore, if β is a potential-form for α then $\beta + d\lambda$ is also a potential-form for α .

¹⁹just discussing magnetostatic case here to keep it simple

This section will likely get fixed thus shifting all page numbers past here. For this reason, I would not recommend printing past here until I finish the edit of this section and a few others in this chapter and add another 10-20 pages to the next chapter. The chapter on electromagnetism and also the chapter on variational calculus are not likely to change much, it's just this part and the next chapter which are the new part. Also, the final chapter (which we don't cover) needs some pictures. Hopefully I wrap up these additions in the first few weeks of class, long before we get here...

10.11 introduction to geometric differential equations

Differential forms, pull-backs and submanifolds provide a language in which the general theory of partial differential equations is naturally expressed. That said, let us begin with an application to the usual differential equations course.

10.11.1 exact differential equations

Throughout what follows assume that M, N, I, F are continuously differentiable functions of x, y, perhaps just defined for some open subset of \mathbb{R}^2 . Recall (or learn) that a differential equation Mdx + Ndy = 0 is said to be **exact** iff there is a function F such that dF = Mdx + Ndy. This is a very nice kind of differential equation since the solution is simply F(x, y) = c. A convenient test for exactness was provided from the fact that partial derivatives commute. This exchange of partial derivatives implies that $\partial_y M = \partial_x N$. Observe, we can recover this condition via exterior differentiation:

Proposition 10.11.1.

If a differential equation Mdx + Ndy = 0 is exact then d(Mdx + Ndy) = 0 (this zero is derived from M, N alone, independent of the given differential equation).

Proof: if Mdx + Ndy = 0 is exact then by definition dF = Mdx + Ndy hence d(Mdx + Ndy) = d(dF) = 0. \Box

Pfaff did pioneering work in the theory of differential forms. One Theorem due to Pfaff states that any first order differential equation can be made exact by the method of integrating factors. In particular, if Mdx + Ndy = 0 is not exact then there exists I such that IMdx + INdy = 0 is an exact differential equation. The catch, it is as hard or harder to find I as it is to solve the given differential equation. That said, the integrating factor method is an example of this method. Although, we don't usually think of linear ordinary differential equations as an exact equation, it can be viewed as such²⁰.

A differential equation in x_1, x_2, \ldots, x_n of the form:

 $M_1dx_1 + M_2dx_2 + \dots + M_ndx_n = 0$

²⁰see my differential equations notes, it's in there

can be written as dF = 0 locally iff

$$d(M_1 dx_1 + M_2 dx_2 + \dots + M_n dx_n) = 0.$$

The fact that exact implies closed is just $d^2 = 0$. The converse direction, assuming closed near a point, only gives the existence of a potential form F close to the point. Globally, there could be a topological obstruction as we saw in the Poincare Lemma section.

Example 10.11.2. Problem: Suppose xdy + ydx - xdz = 0. Is there a point(s) in \mathbb{R}^3 near which there exists F such that dF = xdy + ydx - xdz?

Solution: If there was the the differential form of the DEqn would vanish identically. However:

 $d(xdy + ydx - xdz) = dx \wedge dy + dy \wedge dx - dx \wedge dz = dz \wedge dx.$ Therefore, no.

We can try to find an integrating factor. Let's give it a shot, this problem is simple enough it may be possible to work it out. We want I such that I(xdy + ydx - xdz) is a closed one-form. Use the Leibniz rule and our previous calculation:

$$\begin{aligned} d[I(xdy + ydx - xdz)] &= dI \wedge (xdy + ydx - xdz) + Idz \wedge dx \\ &= (I_x dx + I_y dy + I_z dz) \wedge (xdy + ydx - xdz) + Idz \wedge dx \\ &= (xI_x - yI_y)dx \wedge dy + (xI_x + yI_z + I)dz \wedge dx + (-xI_y - xI_z)dy \wedge dz \end{aligned}$$

Therefore, our integrating factor must satisfy the following partial differential equations,

(I.)
$$xI_x - yI_y = 0$$
, (II.) $xI_x + yI_z + I = 0$, (III.) $-xI_y - xI_z = 0$

I'll leave this to the reader. I'm not sure if it has a solution. It seems possible that the differential consquences of this system are nonsensical. I just wanted to show how differential forms allow us to extend to higher dimensional problems. Notice, we could just as well have not solved a problem with 4 or 5 variables.

10.11.2 differential equations via forms

I follow Example 1.2.3. of *Cartan for Beginners: Differential Geometry via Moving Frames and Exterior Differential Systems* by Thomas A. Ivey and J.M Landsberg. I suspect understanding this text makes you quite a bit more than a *beginner*. Consider,

$$u_x = A(x, y, u)$$
 (10.15)

$$u_y = B(x, y, u)$$
 (10.16)

Chapter 11

Geometry by frames and forms

In this chapter we restrain ourselves to study three dimensional space and surfaces embedded within that context. That said, once this chapter is mastered the next natural step to consider is the study of geometric surfaces in which the ambient space is not used to frame the geometry of the surface.

The idea of this chapter is to take a guided tour through the second edition of Barret Oneil's *Elementary Differential Geometry*. Obviously we do not cover the entire text. Instead, I have carefully chosen a thread which allows us to see the central argument of the text for embedded surfaces in three dimensional space.

To begin we review once more the concept of a vector field and we adopt the notation used by Oneil¹. Frames in \mathbb{R}^3 are studied and the cartesian frame U_1, U_2, U_3 is employed to define the covariant derivative. This will be almost familar to anyone who has studied vector calculus in non-cartesian coordinates. Next we develop the connection formulas for \mathbb{R}^3 which are based on matrices of differential forms. Once the structure equations are settled we turn to the theory of surfaces. We quickly introduce the shape operator as it is derived from the normal vector field of a regular surface. Gauss and mean curvatures are defined. Principle curvature and umbilic points are described. Isometry of surfaces is introduced and we see how isometric surfaces can be surprisingly different. Finally, we turn to the problem of formulating the theory of surfaces in terms of the connection form formalism of Cartan. After some fairly simple calculation we arrive at the result that the shape operator and much of the ambient theory can be replaced with a few simple formulas. From that point the proof of Gauss' celebrated theorem on intrinsic curvature is simple.

It is certainly the case that some of the definitions in this chapter have been previously given in greater generality. However, I intend this chapter to be self-contained as much as is possible. Furthermore, whenever a definition seems unjust, you can read more background in Oneil when time permits.

¹in this way I hope reading his text is a natural extension of this study for those interested

11.1 basic terminology and vector fields

We begin by describing the directional deirvative in \mathbb{R}^3 as a derivation: if v is a vector at p then

$$v_p[f] = \lim_{h \to 0} \left[\frac{f(p+tv) - f(p)}{h} \right]$$
 (11.1)

and for functions f smooth near p we have

$$v_p[f] = \sum_{i=1}^{3} v_i \frac{\partial f}{\partial x_i}(p) = \left[v_1 \frac{\partial}{\partial x} + v_2 \frac{\partial}{\partial y} + v_3 \frac{\partial}{\partial z} \right] \Big|_p[f]$$

Clearly v_p acts on a function to reveal the rate of change of f at p as we allow p to move in the $\langle v_1, v_2, v_3 \rangle$ -direction. A vector field on \mathbb{R}^3 is rule which attaches a vector to each point in \mathbb{R}^3 . For example, $p \mapsto \frac{\partial}{\partial x}|_p$, $p \mapsto \frac{\partial}{\partial y}|_p$ and $p \mapsto \frac{\partial}{\partial z}|_p$. Each of these define a global vector field on \mathbb{R}^3 and together the triple of vector fields is known as the **cartesian frame**. A frame is set of three vector fields which provides an **orthonormal basis**² for $T_p \mathbb{R}^3$ at each $p \in \mathbb{R}^3$. Given the importance of the cartesian frame, we introduce a simple notation for future use:

Definition 11.1.1. notation for the cartesian frame

$$\mathbf{U_1} = \frac{\partial}{\partial x}, \qquad \mathbf{U_2} = \frac{\partial}{\partial y}, \qquad \mathbf{U_3} = \frac{\partial}{\partial z}.$$

The cartesian frame provides a convenient background for what follows.

Example 11.1.2. Let $v = \langle a, b, c \rangle$ then $V = a\mathbf{U_1} + b\mathbf{U_2} + c\mathbf{U_3}$ is a constant vector field on \mathbb{R}^3 where V(p) = v for all $p \in \mathbb{R}^3$.

Example 11.1.3. If $f(x, y, z) = \sqrt{x^2 + y^2 + z^2}$ then $\nabla f = \langle x/f, y/f, z/f \rangle$ hence $||(\nabla f)(p)|| = 1$ for all $p \in \mathbb{R}^3$. We can write this global gradient field as $\nabla f = \frac{1}{\sqrt{x^2 + y^2 + z^2}} [x\mathbf{U_1} + y\mathbf{U_2} + z\mathbf{U_3}]$. This vector field is part of the spherical frame field which we discuss in Example 11.1.10.

Vectors as derivations measure rates of change of functions as we move a point. The next logical study is that of vector fields. How can we capture the change of a vector field W at a point p as we move in the *v*-direction? This cannot be a number since a vector field has three components this will again be a vector³

Definition 11.1.4. covariant differentiation of vector field

Let W be a vector field and v_p a vector at p then the **covariant derivative of** W in the **direction of** v at p is defined as follows: $(\nabla_v W)(p) = W'(p + tv)(0)$.

 $^{^{2}}$ there is a generalization of this to arbitrary frames in the study of the frame-bundle, we leave that for another course, all our frames are nice and orthonormal.

³ just like the change in a path in \mathbb{R}^3 is described by a velocity vector not just a single slope

Let the derivative in the definition above be understood as differentiation of each component. You could see it as the directional derivative of each component in the v-direction. If $W = w_1 \mathbf{U_1} + w_2 \mathbf{U_2} + w_3 \mathbf{U_3}$ then (by definition)

$$W'(p+tv)(0) = w'_1(p+tv)(0)\mathbf{U}_1 + w'_2(p+tv)(0)\mathbf{U}_2 + w'_3(p+tv)(0)\mathbf{U}_3$$

however, as we discussed in Equation 11.1 these directional derivatives are best understood in terms of derivations. We tend to use the following as a method to calculate covariant derivatives:

Proposition 11.1.5.

If W is a vector field defined near p and $W = \sum_{i=1}^{3} w_i \mathbf{U}_i$ the the covariant derivative of W in the direction of v at p is given by: $(\nabla_v W)(p) = \sum_{i=1}^{3} v[w_i] \mathbf{U}_i$.

Given two vector fields W, V we can study the change in W as it moves in the direction of V at each point. In particular, at $p \in \mathbb{R}^3$ study how the vector field W evolves in the V(p) direction at p. This construction suggests the covariant derivative converts a pair of vector fields into an new vector field defined by the following:

$$(\nabla_V W)(p) = (\nabla_{V(p)} W)(p)$$

Let us pause to describe some useful properties of the covariant derivative. The proofs of these follow from properties of partial differentiation and Proposition 11.1.5

Proposition 11.1.6. Properties of the covariant derivative

Suppose V, W, Y and Z are vector fields on \mathbb{R}^3 , f, g are functions and $a, b \in \mathbb{R}$,

(a.)
$$\nabla_{fV+qW}Y = f\nabla_V Y + g\nabla_W Y$$

(b.)
$$\nabla_V(aY+bZ) = a\nabla_V Y + b\nabla_V Z$$

(c.)
$$\nabla_V(fY) = V[f]Y + f\nabla_V Y$$

(d.) $V[Y \bullet Z] = (\nabla_V Y) \bullet Z + Y \bullet (\nabla_V Z).$

Proof: We examine part (d.). Let Y, Z be vector fields with component functions Y_i, Z_i . We have $Y = \sum_{i=1}^{3} Y_i \mathbf{U_i}$ and $Z = \sum_{i=1}^{3} Z_i \mathbf{U_i}$. We calculate

$$Y \bullet Z = \left(\sum_{i=1}^{3} Y_i \mathbf{U}_i\right) \bullet \left(\sum_{j=1}^{3} Z_j \mathbf{U}_j\right) = \sum_{i=1}^{3} \sum_{j=1}^{3} Y_i Z_j \underbrace{\mathbf{U}_i \bullet \mathbf{U}_j}_{\delta_{ij}} = \sum_{i=1}^{3} Y_i Z_i$$

Suppose V be a vector field. By Proposition 11.1.5 we calculate:

$$V[Y \bullet Z] = V\left[\sum_{i=1}^{3} Y_i Z_i\right] = \sum_{i=1}^{3} V[Y_i Z_i] = \sum_{i=1}^{3} \left(V[Y_i] Z_i + Y_i V[Z_i]\right).$$

Then, note $(\nabla_V Y)_i = V[Y_i]$ and $(\nabla_V Z)_i = V[Z_i]$ hence

$$V[Y \bullet Z] = \sum_{i=1}^{3} (\nabla_V Y)_i Z_i + \sum_{i=1}^{3} Y_i (\nabla_V Z)_i = (\nabla_V Y) \bullet Z + Y \bullet (\nabla_V Z).$$

If you understand this then you can write proofs for the other parts without much trouble \Box .

Definition 11.1.7.

If a triple of vector fields $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ on \mathbb{R}^3 satisfy $\mathbf{E_i} \cdot \mathbf{E_j} = \delta_{ij}$ for all i, j then they define a **frame field** on \mathbb{R}^3 .

If $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ is a frame field on \mathbb{R}^3 then at each point $p \in \mathbb{R}^3$ they provide an orthonormal basis $\{\mathbf{E_1}(p), \mathbf{E_2}(p), \mathbf{E_3}(p)\}$ for $T_p \mathbb{R}^3$. Therefore, a given frame field allows us to have cartesian-like coordinates based at each point in \mathbb{R}^3 . In particular, we can calculate dot-products and vector lengths with respect to frame field coordinates just as we do with cartesian coordinates. Moreover, we can select frame field coordinate functions for vector fields via dot-products just as we could select cartesian coordinates of vectors by dot-products. The choice to work with orthonormal frames pays off big here. We'll use this proposition multiple times in our future work.

Proposition 11.1.8.

Suppose $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ is a frame. If V is a vector field on \mathbb{R}^3 then the component functions of V w.r.t. the $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ frame are given by $V \cdot \mathbf{E_j}$ for $1 \le j \le 3$; that is $V = \sum_{j=1}^3 (V \cdot \mathbf{E_j}) E_j$.

Proof: left to the reader. Or, see my linear algebra notes \Box .

The method I used to find these frames was to calculate the coordinates derivatives by the push-forward formulas⁴ we discussed in Subsection 10.3.1.

Example 11.1.9. For cylindrical coordinates $x = r \cos \theta$, $x = r \sin \theta$ and z = z. The cylindrical frame field is defined as follows:

$$E_1 = \cos \theta U_1 + \sin \theta U_2$$
$$E_2 = -\sin \theta U_1 + \cos \theta U_2$$
$$E_3 = U_3$$

Example 11.1.10. If spherical coordinates ρ , ϕ , θ are given by $x = \rho \cos \theta \sin \phi$, $y = \rho \sin \theta \sin \phi$ and $z = \rho \cos \phi$ then the spherical frame field is given by:

$$\mathbf{F_1} = \sin\phi(\cos\theta\mathbf{U_1} + \cos\theta\mathbf{U_2}) + \cos\phi\mathbf{U_3}$$
$$\mathbf{F_2} = -\sin\theta\mathbf{U_1} + \cos\theta\mathbf{U_2}$$
$$\mathbf{F_3} = \cos\phi(\cos\theta\mathbf{U_1} + \cos\theta\mathbf{U_2}) - \sin\phi\mathbf{U_3}$$

⁴although, to be honest, I used a better method to calculate the needed partial derivatives. The best way is to compute the total differentials of each coordinate function and read off the derivatives there. Again, probably a homework problem

Observe that $\mathbf{E_1}$ and $\mathbf{E_2}$ of Example 11.1.9 appear here and $\mathbf{F_2} = \mathbf{E_2}$ as can be expected since geometrically they play identical roles.

11.2 connection forms on \mathbb{R}^3

Let $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ be a frame field and consider a point $p \in \mathbb{R}^3$ and a vector v at p. Let us calculate the covariant derivatives of the frame field at p in the v-direction. Furthermore, we shall express the covariant derivatives in terms of the **E**-frame in view of the technique of Proposition 11.1.8

$$\nabla_{v} \mathbf{E}_{1} = [(\nabla_{v} \mathbf{E}_{1}) \cdot \mathbf{E}_{1}] \mathbf{E}_{1} + [(\nabla_{v} \mathbf{E}_{1}) \cdot \mathbf{E}_{2}] \mathbf{E}_{2} + [(\nabla_{v} \mathbf{E}_{1}) \cdot \mathbf{E}_{3}] \mathbf{E}_{3}$$

$$\nabla_{v} \mathbf{E}_{2} = [(\nabla_{v} \mathbf{E}_{2}) \cdot \mathbf{E}_{1}] \mathbf{E}_{1} + [(\nabla_{v} \mathbf{E}_{2}) \cdot \mathbf{E}_{2}] \mathbf{E}_{2} + [(\nabla_{v} \mathbf{E}_{2}) \cdot \mathbf{E}_{3}] \mathbf{E}_{3}$$

$$\nabla_{v} \mathbf{E}_{3} = [(\nabla_{v} \mathbf{E}_{3}) \cdot \mathbf{E}_{1}] \mathbf{E}_{1} + [(\nabla_{v} \mathbf{E}_{3}) \cdot \mathbf{E}_{2}] \mathbf{E}_{2} + [(\nabla_{v} \mathbf{E}_{3}) \cdot \mathbf{E}_{3}] \mathbf{E}_{3}$$

(11.2)

Think about this: for each i, j the coefficient $(\nabla_v \mathbf{E_i}) \cdot \mathbf{E_j}$ represents a linear function in $v \in T_p \mathbb{R}^3$ which assigns a particular real number. In other words, $v \mapsto (\nabla_v \mathbf{E_i}) \cdot \mathbf{E_j}$ is a one-form at p. If we allow p to vary then we obtain a one form on \mathbb{R}^3 for each i, j.

Definition 11.2.1. matrix of connection forms of \mathbb{R}^3

Let $1 \leq i, j \leq 3$ and define a one-form ω_{ij} by $(\omega_{ij}(p))(v) = [(\nabla_v \mathbf{E}_i) \cdot \mathbf{E}_j](p)$ for each vector v at $p \in \mathbb{R}^3$. Furthermore, the matrix of one-forms ω_{ij} will be denoted by ω .

This matrix of one-forms will be at the center stage of our thinking for most of the remainder of this chapter. Perhaps the most important property is given next:

Proposition 11.2.2.

Let ω_{ij} be the connection forms w.r.t. frame $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ then $\omega_{ij} = -\omega_{ji}$ for all i, j.

Proof: follows from orthonormality of the frame paired with properties of covariant differentiation. In particular, fix i, j and let $v \in T_p \mathbb{R}^3$. Calculate

$$v[\mathbf{E}_{\mathbf{i}} \bullet \mathbf{E}_{\mathbf{j}}] = [\nabla_{v} \mathbf{E}_{\mathbf{i}}] \bullet \mathbf{E}_{\mathbf{j}} + \mathbf{E}_{\mathbf{i}} \bullet [\nabla_{v} \mathbf{E}_{\mathbf{j}}]$$

However, observe that $\mathbf{E}_{\mathbf{i}} \cdot \mathbf{E}_{\mathbf{j}} = \delta_{ij}$ is a constant function thus $v[\delta_{ij}] = 0$. Hence $[\nabla_v \mathbf{E}_{\mathbf{i}}] \cdot \mathbf{E}_{\mathbf{j}} = -\mathbf{E}_{\mathbf{i}} \cdot [\nabla_v \mathbf{E}_{\mathbf{j}}]$. Therefore, $\omega_{ij}(v) = -\omega_{ji}(v)$ for arbitrary v and p. The proposition follows. \Box .

The proposition above can be formulated⁵ as $\omega^T = -\omega$. In other words, the connection matrix is **antisymmetric**. This immediately implies that $\omega_{11} = \omega_{22} = \omega_{33} = 0$ for any connection form ω .

The frame $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ is related to the cartesian frame $\mathbf{U_1}, \mathbf{U_2}, \mathbf{U_3}$ by the **attitude matrix**. It turns out this matrix provides a convenient computational tool in what follows.

Definition 11.2.3. attitude matrix of E-frame

⁵here Oneil uses the notation ${}^t\omega$ for ω^T

Let $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ be a frame field and let a_{ij} be the functions for which

$$\mathbf{E}_{\mathbf{i}} = \sum_{j=1}^{3} a_{ij} \mathbf{U}_{\mathbf{j}}.$$

We say $A = (a_{ij})$ is called the **attitude matrix** of the E_1, E_2, E_3 frame.

The definition above makes the *i*-th row of the attitude matrix the components of \mathbf{E}_{i} .

Example 11.2.4. (continuing Ex. 11.1.9) We may calculate the attitude matrix for the cylindrical frame field by inspection: (zeros and one added for clarity of A-construction)

$$\mathbf{E_1} = \cos\theta \mathbf{U_1} + \sin\theta \mathbf{U_2} + 0\mathbf{U_3} \\ \mathbf{E_2} = -\sin\theta \mathbf{U_1} + \cos\theta \mathbf{U_2} + 0\mathbf{U_3} \qquad \Rightarrow \qquad A = \begin{bmatrix} \cos\theta & \sin\theta & 0 \\ -\sin\theta & \cos\theta & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

I invite the reader to verify $AA^T = I$.

Example 11.2.5. (continuing Ex. 11.1.10) The spherical frame $\mathbf{F_1}, \mathbf{F_2}, \mathbf{F_3}$ has attitude matrix:

$$\begin{aligned} \mathbf{F_1} &= \sin\phi \left(\cos\theta \mathbf{U_1} + \sin\theta \mathbf{U_2}\right) + \cos\phi \mathbf{U_3} \\ \mathbf{F_2} &= -\sin\theta \mathbf{U_1} + \cos\theta \mathbf{U_2} \\ \mathbf{F_3} &= \cos\phi \left(\cos\theta \mathbf{U_1} + \sin\theta \mathbf{U_2}\right) - \sin\phi \mathbf{U_3} \end{aligned} \qquad \Rightarrow \quad A = \begin{bmatrix} \sin\phi\cos\theta & \sin\phi\sin\theta & \cos\phi \\ -\sin\theta & \cos\theta & 0 \\ \cos\phi\cos\theta & \cos\phi\sin\theta & -\sin\phi \end{bmatrix}$$

Once more, I invite the reader to verify that $AA^T = I$.

The attitude matrix is a matrix of functions. Notice we can construct a matrix of forms from A by taking the differential of each component. The matrix dA is then a matrix of one-forms, much like the connection matrix ω . That said, we should pause to define the operations we need to connect dA and ω explicitly.

When working with a matrix of one-forms the common notation in such a context is that matrix multiplication proceeds normally except that the component-wise multiplication is understood to be wedge products. We also calculate exterior derivatives of matrix-valued forms. The rule is simply to calculate the exterior derivative of each entry. In summary, if A is an $l \times m$ matrix of *p*-forms and B is an $m \times n$ matrix of *q*-forms then AB is defined to be a $l \times n$ matrix of (p+q)-forms:

$$(AB)_{ij} = \sum_{k=1}^{m} A_{ik} \wedge B_{kj}$$

moreover, dA is a $l \times m$ matrix of *p*-forms where we define $(dA)_{ij} = dA_{ij}$. Now we have all the terminology needed to explicitly connect the exterior derivative of the attitude matrix and the connection form:

Proposition 11.2.6.

Let $A = (a_{ij})$ be the attitude matrix for the frame field $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ then the connection matrix ω is given by: $\omega = dAA^T$.

Proof: observe $\omega = dAA^T$ indicates that $\omega(V) = dA(V)A^T$ for all vector fields V. In particular, for each i, j we should show $\omega_{ij}(V) = (dA(V)A^T)_{ij}$. Let us begin:

$$\begin{split} \omega_{ij}(V) &= (\nabla_{V} \mathbf{E}_{\mathbf{i}}) \cdot \mathbf{E}_{\mathbf{j}} \\ &= \nabla_{V} \left(\sum_{k=1}^{3} a_{ik} \mathbf{U}_{\mathbf{k}} \right) \cdot \mathbf{E}_{\mathbf{j}} \\ &= \left[\sum_{k=1}^{3} V[a_{ik}] \mathbf{U}_{\mathbf{k}} \right] \cdot \left[\sum_{l=1}^{3} a_{jl} \mathbf{U}_{l} \right] \\ &= \sum_{k=1}^{3} \sum_{l=1}^{3} V[a_{ik}] a_{jl} \mathbf{U}_{\mathbf{k}} \cdot \mathbf{U}_{l} \\ &= \sum_{k=1}^{3} da_{ik} [V] a_{jk} \\ &= \sum_{k=1}^{3} (dA[V])_{ik} (A^{T})_{kj} \\ &= (dA[V]A^{T})_{ij} \,. \end{split}$$

Therefore, as V and i, j were arbitrary the proposition follows \Box .

Example 11.2.7. (continuing Ex. 11.2.4 and Ex. 11.1.9) we calculate the connection form for the cylindrical frame via Proposition 11.2.6.

$$\omega = dAA^T = \begin{bmatrix} -\sin\theta d\theta & \cos\theta d\theta & 0\\ -\cos\theta d\theta & -\sin\theta d\theta & 0\\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \cos\theta & -\sin\theta & 0\\ \sin\theta & \cos\theta & 0\\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & d\theta & 0\\ -d\theta & 0 & 0\\ 0 & 0 & 0 \end{bmatrix}$$

Example 11.2.8. (continuing Ex. 11.2.5 and Ex. 11.1.10) we calculate the connection form for the spherical frame via Proposition 11.2.6. To begin, recall $A = \begin{bmatrix} \sin \phi \cos \theta & \sin \phi \sin \theta & \cos \phi \\ -\sin \theta & \cos \theta & 0 \\ \cos \phi \cos \theta & \cos \phi \sin \theta & -\sin \phi \end{bmatrix}$

and take the exterior derivative: (the lines are just for convenience)

$$dA = \begin{bmatrix} \cos\phi\cos\theta d\phi - \sin\phi\sin\theta d\theta & \cos\phi\sin\theta d\phi + \sin\phi\cos\theta d\theta & -\sin\phi d\phi \\ \hline -\cos\theta d\theta & & -\sin\theta d\theta & 0 \\ \hline -\sin\phi\cos\theta d\phi - \cos\phi\sin\theta d\theta & -\sin\phi\sin\theta d\phi + \cos\phi\cos\theta d\theta & -\cos\phi d\phi \end{bmatrix}$$

The transpose is simply $A^T = \begin{bmatrix} \sin\phi\cos\theta & -\sin\theta & \cos\phi\cos\theta \\ \sin\phi\sin\theta & \cos\theta & \cos\phi\sin\theta \\ \cos\phi & 0 & -\sin\phi \end{bmatrix}$. Now, multiply. I'll just consider

the interesting terms $\omega_{12}, \omega_{13}, \omega_{23}$ from $\omega = dAA^T$. I leave the details to the reader⁶

$$\omega = \begin{bmatrix} 0 & \cos \phi d\theta & d\phi \\ -\cos \phi d\theta & 0 & \sin \phi d\phi \\ -d\phi & -\sin \phi d\phi & 0 \end{bmatrix}.$$

We now return to the task of covariant differentiation. This result is important because it relates the change in the frame field $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ in terms of the frame field $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$. In some sense, this is like the Frenet Serret equations from calculus III.

Proposition 11.2.9. Connection equations of frame field $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ on \mathbb{R}^3

Let ω_{ij} be the connection forms with respect to the frame field $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ on \mathbb{R}^3 for any vector field V,

$$\nabla_V \mathbf{E_i} = \sum_{j=1}^{3} \omega_{ij}(V) \mathbf{E_j}$$

Proof: Suppose $\mathbf{E}_{\mathbf{i}} = \sum_{j=1}^{3} a_{ij} \mathbf{U}_{\mathbf{j}}$ where a_{ij} is the attitude matrix of an orthonormal frame $\mathbf{E}_{\mathbf{1}}, \mathbf{E}_{\mathbf{2}}, \mathbf{E}_{\mathbf{3}}$. Note this implies $A = (a_{ij})$ is orthonormal $(A^T A = I)$ and so the inverse relation is given by the transpose and we may express: $\mathbf{U}_{\mathbf{i}} = \sum_{j=1}^{3} a_{jj} \mathbf{E}_{\mathbf{j}}$.

$$\nabla_{V} \mathbf{E}_{\mathbf{i}} = \nabla_{V} \left[\sum_{j=1}^{3} a_{ij} \mathbf{U}_{\mathbf{j}} \right]$$

$$= \sum_{j=1}^{3} \nabla_{V} \left[a_{ij} \mathbf{U}_{\mathbf{j}} \right]$$

$$= \sum_{j=1}^{3} \left[V[a_{ij}] \mathbf{U}_{\mathbf{j}} + a_{ij} \nabla_{V} \mathbf{U}_{\mathbf{j}} \right]$$

$$= \sum_{j=1}^{3} V[a_{ij}] \sum_{k=1}^{3} a_{kj} \mathbf{E}_{\mathbf{k}}$$

$$= \sum_{k=1}^{3} \sum_{j=1}^{3} da_{ij} [V] a_{kj} \mathbf{E}_{\mathbf{k}} = \sum_{k=1}^{3} (dA[V]A^{T})_{ik} \mathbf{E}_{\mathbf{k}} = \sum_{k=1}^{3} \omega_{ik} [V] \mathbf{E}_{\mathbf{k}} \quad \Box.$$

It is worth expanding these for future reference:

$$\nabla_{V} \mathbf{E_{1}} = \omega_{12}[V] \mathbf{E_{2}} + \omega_{13}[V] \mathbf{E_{3}}$$
$$\nabla_{V} \mathbf{E_{2}} = -\omega_{12}[V] \mathbf{E_{1}} + \omega_{23}[V] \mathbf{E_{3}}$$
$$\nabla_{V} \mathbf{E_{3}} = -\omega_{13}[V] \mathbf{E_{1}} - \omega_{23}[V] \mathbf{E_{2}}$$

⁶do not attempt this unless you plan to work carefully, it's not hard, but it does require attention to detail
Compare these against the Frenet Serret Equations: (assume curve is arclength parametrized)

$$\frac{dT}{dt} = \kappa N$$
$$\frac{dN}{dt} = -\kappa T + \tau B$$
$$\frac{dB}{dt} = -\tau N.$$

11.2.1 Frenet Serret equations

Let's pause to see how the Frenet Serret equations are derived from the connection equations for a frame field. Note that the Frenet Frame on a curve can be extended beyond the curve relative to some open tubular neighborhood for a regular curve. This is geometrically evident, but I'd rather not prove it for our purposes here. The derivative with respect to arclength is naturally identified with ∇_T . Let the frame adapted to the curve be given by the Frenet frame in the usual order: $\mathbf{E_1} = T$, $\mathbf{E_2} = N$ and $\mathbf{E_3} = B$ In particular, again using t for arclength, let $V = \sum_{i=1}^{3} v_i \mathbf{U_i}$ be a vector field along the curve,

$$\nabla_T V = T(v_1)\mathbf{U_1} + T(v_2)\mathbf{U_2} + T(v_3)\mathbf{U_3} = \frac{dV}{dt}$$

Here we understand, on the curve, the $\frac{d}{dt} = \frac{dx}{dt}\frac{\partial}{\partial x} + \frac{dy}{dt}\frac{\partial}{\partial y} + \frac{dz}{dt}\frac{\partial}{\partial z}$ and $\mathbf{U_1}, \mathbf{U_2}, \mathbf{U_3}$ we recall $\frac{\partial}{\partial x} = \mathbf{U_1}$, $\frac{\partial}{\partial y} = \mathbf{U_2}$ and $\frac{\partial}{\partial z} = \mathbf{U_3}$. Also, observe: $\nabla_T \mathbf{E_i} = \sum_{j=1}^3 \omega_{ij}[T]\mathbf{E_j}$ hence $\omega_{ij}[T] = \frac{d\mathbf{E_i}}{dt} \cdot \mathbf{E_j}$. But, the definition of curvature κ and can be formulated as $T' = \kappa N$ hence $\frac{dT}{dt} \cdot N = \kappa$ and $\frac{dT}{dt} \cdot B = 0$. Moreover, torsion τ is defined by $\frac{dB}{dt} \cdot N = -\tau$. Therefore, $\omega_{12}[T] = \kappa, \omega_{13}[T] = 0$ and $\omega_{23}[T] = \tau$ and we see how the connection equations imply the Frenet Serret equations along a curve.

$$\nabla_{T} \mathbf{E}_{1} = \omega_{12}[T] \mathbf{E}_{2} + \omega_{13}[T] \mathbf{E}_{3} \quad \Rightarrow \quad \frac{dT}{dt} = \kappa N$$
$$\nabla_{T} \mathbf{E}_{2} = -\omega_{12}[T] \mathbf{E}_{1} + \omega_{23}[T] \mathbf{E}_{3} \quad \Rightarrow \quad \frac{dN}{dt} = -\kappa T + \tau B$$
$$\nabla_{T} \mathbf{E}_{3} = -\omega_{13}[T] \mathbf{E}_{1} - \omega_{23}[T] \mathbf{E}_{2} \quad \Rightarrow \quad \frac{dB}{dt} = -\tau N.$$

11.3 structure equations for frame field on \mathbb{R}^3

The cartesian frame $\mathbf{U_1}, \mathbf{U_2}, \mathbf{U_3}$ was defined by $\frac{\partial}{\partial x} = \mathbf{U_1}, \frac{\partial}{\partial y} = \mathbf{U_2}$ and $\frac{\partial}{\partial z} = \mathbf{U_3}$ hence the natural dual to the cartesian frame is dx, dy, dz. Remember we proved $dx_i(\partial_j) = \delta_{ij}$ in much greater generality in a previous chapter.

Definition 11.3.1. coframe dual to a given frame

Let $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ be a frame field then coframe field dual to $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ is $\theta_1, \theta_2, \theta_3$ which is a triple of one-forms such that $\theta_i(V) = V \cdot \mathbf{E_i}$ for all vector fields V. Naturally, $\theta_i(\mathbf{E_j}) = \delta_{ij}$.

The term *one-form* in in some sense unfortunate since what might be a better term is *one-form* field. In particular, notice the coframe $\theta_1, \theta_2, \theta_3$ provides a basis $\{\theta_1(p), \theta_2(p), \theta_3(p)\}$ for $(T_p \mathbb{R}^3)^*$ at each $p \in \mathbb{R}^3$. We often suppress the point dependence in what follows.

Suppose γ is a one-form on \mathbb{R}^3 then $\gamma = \sum_{j=1}^3 \gamma_j \theta_j$ for some functions γ_j . Furthermore,

$$\gamma(\mathbf{E}_{\mathbf{i}}) = \sum_{j=1}^{3} \gamma_j \theta_{\mathbf{j}}(\mathbf{E}_{\mathbf{i}}) = \sum_{j=1}^{3} \gamma_j \delta_{ij} = \gamma_i.$$

This discussion proves the following analog to Proposition 11.1.8.

Proposition 11.3.2.

Suppose $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ is a frame with coframe $\theta_1, \theta_2, \theta_3$ on \mathbb{R}^3 . If γ is a one-form on \mathbb{R}^3 then

$$\gamma = \sum_{i=1}^{5} \gamma(\mathbf{E}_i) \theta_i.$$

Naturally we are curious how an arbitrary coframe relates to the cartesian coframe dx, dy, dz. It turns out that the frame and coframe share the same attitude.

Proposition 11.3.3.

Suppose $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ is a frame with coframe $\theta_1, \theta_2, \theta_3$ on \mathbb{R}^3 . If A is the attitude matrix, meaning $\mathbf{E_i} = \sum_{j=1}^3 a_{ij} \mathbf{U_j}$, then $\theta_i = \sum_{j=1}^3 a_{ij} \mathbf{dx_j}$.

Proof: Here we use the natural convention $x_1 = x, x_2 = y, x_3 = z$ in the proposition above. The proof of this proposition filters through the duality condition $\theta_{\mathbf{i}}(\mathbf{E}_{\mathbf{j}}) = \delta_{ij}$ since $dx_i(\mathbf{U}_{\mathbf{j}}) = \delta_{ij}$ and δ_{ij} is common ground. In particular, by orthonormality we have inverse relations $\mathbf{U}_{\mathbf{j}} = \sum_{k=1}^{3} a_{kj} \mathbf{E}_{\mathbf{k}}$

$$\theta_{\mathbf{i}}(\mathbf{U}_{\mathbf{j}}) = \theta_{\mathbf{i}}\left(\sum_{k=1}^{3} a_{kj} \mathbf{E}_{\mathbf{k}}\right) = \sum_{k=1}^{3} a_{kj} \theta_{\mathbf{i}}\left(\mathbf{E}_{\mathbf{k}}\right) = \sum_{k=1}^{3} a_{kj} \delta_{ik} = a_{ij}.$$

Thus, by Proposition 11.3.3, $\theta_{\mathbf{i}} = \sum_{j=1}^{3} a_{ij} dx_j \square$.

A brief history: classification of curves by curvature and torsion was elegantly treated by Frenet and Serret independently around 1860. The work on frames attached to curves then prompted Darboux to try to generalize the method of frames to surfaces. Then the general method of frames was promoted and championed by E. Cartan around 1900. Research continues to this day.

Theorem 11.3.4. Cartan's Structural Equations

Suppose $\mathbf{E_1}, \mathbf{E_2}, \mathbf{E_3}$ is a frame with coframe $\theta_1, \theta_2, \theta_3$ on \mathbb{R}^3 . If ω is the connection form of the given frame then the following structure equations hold for all i, j

(1.)
$$d\theta_{\mathbf{i}} = \sum_{j=1}^{3} \omega_{ij} \wedge \theta_{\mathbf{i}}$$
 (2.) $d\omega_{ij} = \sum_{k=1}^{3} \omega_{ik} \wedge \omega_{kj}$.

Proof: It is convenient to reformulate these equations in a matrix/column notation. In particular,

$$\theta = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix} \qquad d\xi = \begin{bmatrix} dx \\ dy \\ dz \end{bmatrix}$$

The equation $\theta_i = \sum_{j=1}^3 a_{ij} dx_j$ gives $\theta = Ad\xi$. Observe that $d^2 = 0$ is true for matrices of forms since the exterior differentiation is done component-wise. Thus, $d(d\xi) = 0$. Hence,

$$d\theta = d(Ad\xi) = dA \wedge d\xi + Ad(d\xi) = dA d\xi = dAA^T Ad\xi$$

where we use $A^T A = I$ for the last step. Next, apply Proposition 11.2.6 and $\theta = Ad\xi$ to see:

$$d\theta = dAA^T A d\xi = \omega \theta.$$

The equation above is just (1.) in matrix notation. Next consider the exterior derivative of⁷ $\omega = dAA^{T}$, again use $d^{2} = 0$ and the Leibniz rule,

$$d\omega = d(dAA^T) = d^2(A)A^T - dAd(A^T) = -\underbrace{dAA^T}_{\omega}\underbrace{AdA^T}_{-\omega}$$

To see why $AdA^T = -\omega$, use the socks-shoes property of the matrix transpose to see that $AdA^T = (dAA^T)^T = \omega^T$. But, by antisymmetry of the connection form says $\omega^T = -\omega$. We've shown

$$d\omega = -\omega(-\omega) = \omega\omega$$

this is precisely the second struture equation written in matrix notation \Box .

This is one of my top ten favorite favorite theorems. However, to appreciate why I would enjoy such a strange set of formulas we probably need to spend an hour or two discussing the structure of a regular surface and a bit on diffeomorphisms. Once those issues are addressed we'll return and develop an intrinsic calculus via these equations.

⁷ note that $d(A^T) = (dA)^T$ hence dA^T is non an ambiguous notation.

11.4 surfaces in \mathbb{R}^3

A surface M in \mathbb{R}^3 is a subset which locally looks like the plane. Moreover, we suppose the surface is **oriented**. The orientation is given by a unit-normal vector field which is defined to point in the upward direction. Let us review a few technical details to make this paragraph a bit more precise.

A surface $M \subset \mathbb{R}^3$ is called regular if it can be covered by compatible regular patches. A patch $X: D \subseteq \mathbb{R}^2 \to M$ is regular iff $\partial_u X \times \partial_v X \neq 0$ for all $(u, v) \in D$. If the vector field $\partial_u X \times \partial_v X \neq 0$ then we may normalize it to form a unit-normal field $U = \frac{1}{||\partial_u X \times \partial_v X||} \partial_u X \times \partial_v X$. Furthermore, if the surface is oriented then the normal vector field on each patch may be smoothly joined to adjacent patches as to construct a global unit normal field. Throughout this section we use the notation that U is the unit-normal to the surface considered. It is geometrically clear that U(p) is orthogonal to the tangent space at $p \in M$. It is analytically clear since

$$T_p M = span\{\partial_u|_p, \partial_v|_p\}$$

and U(p) is formed from the cross product of these tangent vectors. Of course, we can expand the vectors in the ambient frame U_1, U_2, U_3 if necessary,

$$\frac{\partial}{\partial u} = \frac{\partial x}{\partial u} \mathbf{U_1} + \frac{\partial y}{\partial u} \mathbf{U_2} + \frac{\partial z}{\partial u} \mathbf{U_3}, \qquad \frac{\partial}{\partial v} = \frac{\partial x}{\partial v} \mathbf{U_1} + \frac{\partial y}{\partial v} \mathbf{U_2} + \frac{\partial z}{\partial v} \mathbf{U_3}$$

The shape of the surface is revealed from the covariant derivatives of the normal vector field. It can be shown that if v is tangent to M then $\nabla_v U$ is also tangent to M. It follows the definition below is reasonable:

Definition 11.4.1. shape operator

Let U be the unit-normal vector field to a sufface $M \subset \mathbb{R}^3$. We define a mapping $S_p : T_p M \to T_p M$ by $S_p(v) = -\nabla_v U$ for all $v \in T_p M$. This is the **shape operator at** p.

Naturally, the mapping $p \mapsto S_p$ is also called the **shape operator**. Geometrically, the value of the shape operator reflects how the normal vector field changes as p moves in the direction of v near p.

Example 11.4.2. Plane: The shape operator on a plane is zero since U is constant.

Example 11.4.3. Sphere: of radius R centered at the origin has $U = \frac{1}{R}(x\mathbf{U_1} + y\mathbf{U_2} + z\mathbf{U_3})$ therefore $\nabla_v U = \frac{1}{R}(v[x]\mathbf{U_1} + v[y]\mathbf{U_2} + v[z]\mathbf{U_3}) = v/R$. This equation expresses the geometrically obvious fact that the normal vector field on a sphere bends in the direction of v as we move from pin the v-direction. Thus $S_p(v) = -v/R$.

The sphere example is sufficiently simple in cartesian coordinates that we did not need to do much calculation. I didn't even provide a patch for the sphere, we reasoned geometrically. To understand what follows, please review the cylindrical and spherical frames. We introduced them in Examples 11.1.9 and 11.1.10.

Example 11.4.4. Cylinder: of radius R with equation $x^2 + y^2 = R^2$ has natural parametrization by θ, z for which $x = R \cos \theta$, $y = R \sin \theta$ and z = z. The cylindrical frame field then provides vector fields tangent to the cylinder. In particular,

$$\mathbf{E_2} = -\sin\theta \mathbf{U_1} + \cos\theta \mathbf{U_2}, \qquad \mathbf{E_3} = \mathbf{U_3}$$

are clearly tangent to the cylinder. On the other hand, it's geometrically clear that the normal vector field $U = \mathbf{E_1} = \cos\theta \mathbf{U_1} + \sin\theta \mathbf{U_2}$. Calculate the covariant derivatives in view of the fact that $U = \frac{1}{B}(x\mathbf{U_1} + y\mathbf{U_2})$,

$$\nabla_v U = \frac{1}{R} \left[v[x] \mathbf{U_1} + v[y] \mathbf{U_2} \right] = \frac{1}{R} \left(v_x \mathbf{U_1} + v_y \mathbf{U_2} \right)$$
(11.3)

where I denote $v = v_x \partial_x + v_y \partial_y + v_z \partial_z$.

I now work on converting the formula into the cylindrical frame. We can invert the equations for $\mathbf{E_1} = \cos\theta \mathbf{U_1} + \sin\theta \mathbf{U_2}$ and $\mathbf{E_2} = -\sin\theta \mathbf{U_1} + \cos\theta \mathbf{U_2}$ for $\mathbf{U_1}$ and $\mathbf{U_2}$. We obtain⁸:

$$\mathbf{U}_1 = \cos\theta \mathbf{E}_1 - \sin\theta \mathbf{E}_2, \qquad \mathbf{U}_2 = \sin\theta \mathbf{E}_1 + \cos\theta \mathbf{E}_2. \tag{11.4}$$

Consider $v = \mathbf{E_2} = -\sin\theta \mathbf{U_1} + \cos\theta \mathbf{U_2}$ has $v_x = -\sin\theta$ and $v_y = \cos\theta$ thus:

$$\nabla_{\mathbf{E_2}} U = \frac{1}{R} (-\sin\theta \mathbf{U_1} + \cos\theta \mathbf{U_2}) \qquad (by \ Eqn. \ 11.3)$$
$$= \frac{1}{R} [-\sin\theta(\cos\theta \mathbf{E_1} - \sin\theta \mathbf{E_2}) + \cos\theta(\sin\theta \mathbf{E_1} + \cos\theta \mathbf{E_2})] \qquad (by \ Eqn. \ 11.4)$$
$$= \frac{1}{R} \mathbf{E_1}.$$

In summary, if $v = a\mathbf{E_2} + b\mathbf{E_3}$ where $\mathbf{E_2} = \frac{1}{R}\partial_{\theta}$ and $\mathbf{E_3} = \partial_z$ then we find:

$$S_p(v) = -\nabla_v U = -\frac{a}{R} \mathbf{E_1}.$$

The matrix of this shape operator has the form: $[S_p] = \begin{bmatrix} -1/R & 0 \\ 0 & 0 \end{bmatrix}$. The shape operator reflects our intuition that the cylinder is curved in the θ -direction whereas in the z-direction it is flat.

I will use some calculus which is developed in my calculus III lecture notes in what follows. In those notes I show how $\hat{\rho}$, $\hat{\theta}$ and $\hat{\phi}$ form the spherical frame. The difference between that context and our current one is that the vector fields were viewed as passive objects. In calculus III we did not think of vector fields as derivations. That said, all the algebra/geometric formulas derived for the passive frame hold for the derivation-based frame we consider here. In particular, when I consider the cone below, it is geometrically obvious that $\hat{\phi}|_p$ is the normal vector field at each $p \neq 0$

⁸to see \mathbf{U}_1 , multiply \mathbf{E}_1 by $\cos\theta$ and \mathbf{E}_2 by $-\sin\theta$ the terms attached to \mathbf{U}_2 cancel. To see \mathbf{U}_2 , multiply \mathbf{E}_1 by $\sin\theta$ and \mathbf{E}_2 by $\cos\theta$ the terms attached to \mathbf{U}_1 cancel

for the cone M defined by $\phi = \phi_o$. Orthonormality immediately informs be that $\widehat{\phi}|_p, \widehat{\rho}|_p$ form an orthonormal basis for T_pM at each $p \neq 0$ on the cone M.

Recall for what follows that: (here \mapsto denotes the transition from calculus III notation to our current derivation-based formalism for vectors)

$$\widehat{\rho} \mapsto \mathbf{F_1} = \sin \phi (\cos \theta \mathbf{U_1} + \sin \theta \mathbf{U_2}) + \cos \phi \mathbf{U_3}$$
$$\widehat{\theta} \mapsto \mathbf{F_2} = -\sin \theta \mathbf{U_1} + \cos \theta \mathbf{U_2}$$
$$\widehat{\phi} \mapsto \mathbf{F_3} = \cos \phi (\cos \theta \mathbf{U_1} + \sin \theta \mathbf{U_2}) - \sin \phi \mathbf{U_3}$$

Example 11.4.5. Cone at angle ϕ_o . We consider points other than the origin, the cone is not smooth at that singular point. To be more accurate, the results we derive in this example apply to some open subset of the cone. In cylindrical coordinates $r = \rho \sin(\phi_o)$ thus the cartesian equation of this cone is easily derived from $r^2 = \rho^2 \sin^2(\phi_o)$ gives $x^2 + y^2 = \sin^2(\phi_o)(x^2 + y^2 + z^2)$ hence, for $\phi_o \neq \pi/2$, we find $x^2 + y^2 = \tan^2(\phi_o)z^2$. In cylindrical coordinates this cone has equation $r = \tan(\phi_o)z$. From spherical coordinates we find a natural parametrization,

$$x = \rho \cos(\theta) \sin(\phi_o), \qquad y = \rho \sin(\theta) \sin(\phi_o), \qquad z = \rho \cos(\phi_o)$$

Furthermore, this gives $U = \mathbf{F_3} = \cos\phi(\cos\theta \mathbf{U_1} + \sin\theta \mathbf{U_2}) - \sin\phi \mathbf{U_3}$. Consider that:

$$\nabla_{v} \mathbf{F}_{3} = v [\cos \phi \cos \theta] \mathbf{U}_{1} + v [\cos \phi \sin \theta] \mathbf{U}_{2} + v [\sin \phi] \mathbf{U}_{3}$$

On the cone $\phi = \phi_o$ we have $\sin \phi_o$ is constant thus the **U**₃-term vanishes. In what follows we consider tangent vectors on the cone, hence $\phi = \phi_o$ throughout. If $v = \partial_{\rho}$:

$$\nabla_{\partial_{\rho}} U = \partial_{\rho} [\cos \phi_o \cos \theta] \mathbf{U}_1 + \partial_{\rho} [\cos \phi_o \sin \theta] \mathbf{U}_2 = 0$$

Note $\mathbf{F_1} = \partial_{\rho}$ hence $\nabla_{\mathbf{F_1}} U = 0$. Continuing, let $v = \partial_{\theta}$ and consider:

$$\nabla_{\partial_{\theta}} U = \partial_{\theta} [\cos \phi_o \cos \theta] \mathbf{U}_1 + \partial_{\theta} [\cos \phi_o \sin \theta] \mathbf{U}_2 = \cos \phi_o (-\sin \theta \mathbf{U}_1 + \cos \theta \mathbf{U}_2) = \cos \phi_o \mathbf{F}_2$$

However, as $\frac{\partial}{\partial \theta} = -\rho \sin \phi \sin \theta \mathbf{U_1} + \rho \sin \phi \cos \theta \mathbf{U_2}$ we see $\mathbf{F_2} = \frac{1}{\rho \sin \phi_o} \frac{\partial}{\partial \theta}$. Thus, by part (a.) of Proposition 11.1.6,

$$\nabla_{\mathbf{F_2}} U = \frac{\cos \phi_o}{\rho \sin \phi_o} \mathbf{F_2}$$

In summary, if $v = a\mathbf{F_1} + b\mathbf{F_2}$ then

$$S_p(v) = \frac{b\cos\phi_o}{\rho\sin\phi_o}\mathbf{F_2}$$

The matrix of this shape operator has the form: $[S_p] = \begin{bmatrix} 0 & 0 \\ 0 & -\frac{\cos \phi_o}{\rho \sin \phi_o} \end{bmatrix}$. Observe that if we hold θ fixed on the cone we trace out a line as ρ varies. The line is not curved and thus the normal

is transported parallel to such lines as is reflected in the triviality of the covariant derivative in the $\mathbf{F_1}$ -direction on the cone. On the other hand, if we fix ρ and vary θ on the cone then we trace out a circle of radius $\rho \sin \phi_o$. The component of the normal which is radial to this circle is $\cos \phi_o U$. Notice how that component ($\cos \phi_o U$) of the normal bends in the direction of $\mathbf{F_2}$ at a rate proportional to the reciprocal of the radius ($\rho \sin \phi_o$) of the circle. This is the same as we saw in the example of the cylinder. In contrast to the cylinder, we have a family of surfaces to consider here, as ϕ varies we have distinct cones. Consider that as $\phi \to \pi/2$ we find $S_p = 0$. This verifies, modulo the deleted point at the origin, that the plane does have a trivial shape operator.

Definition 11.4.6.

If S is the shape operator on a regular surface M then the Gaussian curvature K and the mean curvature H are defined by $K = \det(S)$ and $H = \operatorname{trace}(S)$.

The eigenvalues of a 2×2 matrix correspond uniquely to the trace and determinant of the matrix. They also have geometric meaning here. Principle curvatures are defined in the theorem:

Theorem 11.4.7.

The shape operator is symmetric thus there exist real eigenvalues and an orthonormal eigenbasis for T_pM with respect to S at each $p \in M$. The orthonormal eigenvectors define the **principle directions** and the corresponding eigenvalues are called the **principle curvatures**. If the principle curvatures are k_1, k_2 then $K = k_1k_2$ and $H = k_1 + k_2$.

Recall, eigenvalues of a diagonal matrix are simply the diagonal entries.

Example 11.4.8. Plane: the principle curvatures are $k_1 = k_2 = 0$. It follows that the mean curvature H = 0 and the Gaussian curvature K = 0 on the entire plane.

Example 11.4.9. Sphere: the principle curvatures are $k_1 = k_2 = -1/r$. It follows that the mean curvature H = -2/r and the Gaussian curvature $K = 1/r^2$ on the entire sphere.

Example 11.4.10. Cylinder: the principle curvatures are $k_1 = -1/r$ and $k_2 = 0$. It follows that the mean curvature H = -1/r and the Gaussian curvature K = 0 on the entire clylinder.

Example 11.4.11. Cone: (without the point) the principle curvatures are $k_1 = 0$ and $k_2 = -\frac{\cos \phi_o}{\rho \sin \phi_o}$. It follows that the mean curvature $H = -\frac{\cos \phi_o}{\rho \sin \phi_o}$ and the Gaussian curvature K = 0 on the entire cone. Here we have an example of a surface which has non-constant mean curvature whilst⁹ having constant Gaussian curvature.

Surfaces with constant Gaussian curvature play special roles in many applications. All the examples above have constant gaussian curvature. As a point of language, we usually intend the unqualified term "curvature" to mean Gaussian curvature. It has a deeper meaning than the mean curvature. For example, any surface with constant Gaussian curvature K = 0 is called **flat** because it is essentially a plane from an intrinsic point of view. In contrast, the principle and mean curvatures are

⁹yes there is doubtless a better way to write this sentence

not intrinsic; the principle and mean curvatures have to do with how the surface is embedded in some ambient space. Here I've touched on an idea you may not have encountered before¹⁰. What do we mean by *intrinsic*? One of my goals in the remainder of this chapter is to unwrap that idea. We'll not do it here just yet.

Another important concept to the study of surface geometry is the **umbilic point**. A point is said to be an **umbilic point** if the principle curvatures are equal at the point in question. If every point on the surface is umbilic then the surface is called, shockingly, an **umbilic surface**. Planes and spheres are umbilic surfaces. Are there others? We'll discuss this in the final section of this chapter where I present a number of theorems without proof¹¹.

11.5 isometry

 $^{^{10}{\}rm if}$ you've seen Flatland then you may have at least a fictional concept of it $^{11}{\rm most}$ of the proofs are found in Oneil

Chapter 12

Electromagnetism in differential form

Warning: I will use Einstein's implicit summation convention throughout this section. I have made a point of abstaining from Einstein's convention in these notes up to this point. However, I just can't bear the summations in this section. They're just too ugly.

12.1 differential forms in Minkowski space

The logic here follows fairly close to the last section, however the wrinkle is that the metric here demands more attention. We must take care to raise the indices on the forms when we Hodge dual them. First we list the basis differential forms, we have to add time to the mix (again c = 1 so $x^0 = ct = t$ if you worried about it)

Name	Degree	Typical Element	"Basis" for $\Lambda^p(\mathbb{R}^4)$
function	p = 0	f	1
one-form	p = 1	$\alpha = \alpha_{\mu} dx^{\mu}$	dt, dx, dy, dz
two-form	p=2	$eta = rac{1}{2} eta_{\mu u} dx^{\mu} \wedge dx^{ u}$	$dy \wedge dz, dz \wedge dx, dx \wedge dy$
			$dt \wedge dx, \ dt \wedge dy, \ dt \wedge dz$
three-form	p = 3	$\gamma = \frac{1}{3!} \gamma_{\mu\nu\alpha} dx^{\mu} \wedge dx^{\nu} \wedge dx^{\alpha}$	$dx \wedge dy \wedge dz, dt \wedge dy \wedge dz$
			$dt \wedge dx \wedge dz, dt \wedge dx \wedge dy$
four-form	p = 4	$gdt \wedge dx \wedge dy \wedge dz$	$dt \wedge dx \wedge dy \wedge dz$

Greek indices are defined to range over 0, 1, 2, 3. Here the top form is degree four since in four dimensions we can have four differentials without a repeat. Wedge products work the same as they have before, just now we have dt to play with. Hodge duality may offer some surprises though.

Definition 12.1.1. The antisymmetric symbol in flat \mathbb{R}^4 is denoted $\epsilon_{\mu\nu\alpha\beta}$ and it is defined by the value

 $\epsilon_{0123} = 1$

plus the demand that it be completely antisymmetric.

We must not assume that this symbol is invariant under a cyclic exhange of indices. Consider,

$$\begin{aligned} \epsilon_{0123} &= -\epsilon_{1023} & \text{flipped } (01) \\ &= +\epsilon_{1203} & \text{flipped } (02) \\ &= -\epsilon_{1230} & \text{flipped } (03). \end{aligned}$$
(12.1)

Example 12.1.2. We now compute the Hodge dual of $\gamma = dx$ with respect to the Minkowski metric $\eta_{\mu\nu}$. First notice that dx has components $\gamma_{\mu} = \delta^{1}_{\mu}$ as is readily verified by the equation $dx = \delta^{1}_{\mu} dx^{\mu}$. We raise the index using η , as follows

$$\gamma^{\mu} = \eta^{\mu\nu}\gamma_{\nu} = \eta^{\mu\nu}\delta^{1}_{\nu} = \eta^{1\mu} = \delta^{1\mu}$$

Beginning with the definition of the Hodge dual we calculate

$$= (1/6)[-dt \wedge dy \wedge dz - dy \wedge dz \wedge dt - dz \wedge dt \wedge dy + dz \wedge dy \wedge dt + dy \wedge dt \wedge dz + dt \wedge dz \wedge dy]$$

$$= -dy \wedge dz \wedge dt.$$

The difference between the three and four dimensional Hodge dual arises from two sources, for one we are using the Minkowski metric so indices up or down makes a difference, and second the antisymmetric symbol has more possibilities than before because the Greek indices take four values.

Example 12.1.3. We find the Hodge dual of $\gamma = dt$ with respect to the Minkowski metric $\eta_{\mu\nu}$. Notice that dt has components $\gamma_{\mu} = \delta^{0}_{\mu}$ as is easily seen using the equation $dt = \delta^{0}_{\mu} dx^{\mu}$. Raising the index using η as usual, we have

$$\gamma^{\mu} = \eta^{\mu\nu}\gamma_{\nu} = \eta^{\mu\nu}\delta^0_{\nu} = -\eta^{0\mu} = -\delta^{0\mu}$$

where the minus sign is due to the Minkowski metric. Starting with the definition of Hodge duality we calculate

$$(dt) = -(1/6)\delta^{0\mu}\epsilon_{\mu\nu\alpha\beta}dx^{\nu} \wedge dx^{\alpha} \wedge dx^{\beta}$$

$$= -(1/6)\epsilon_{0\nu\alpha\beta}dx^{\nu} \wedge dx^{\alpha} \wedge dx^{\beta}$$

$$= -(1/6)\epsilon_{0ijk}dx^{i} \wedge dx^{j} \wedge dx^{k}$$

$$= -(1/6)\epsilon_{ijk}dx^{i} \wedge dx^{j} \wedge dx^{k}$$

$$= -dx \wedge dy \wedge dz.$$
(12.3)

for the case here we are able to use some of our old three dimensional ideas. The Hodge dual of dt cannot have a dt in it which means our answer will only have dx, dy, dz in it and that is why we were able to shortcut some of the work, (compared to the previous example).

Example 12.1.4. Finally, we find the Hodge dual of $\gamma = dt \wedge dx$ with respect to the Minkowski metric $\eta_{\mu\nu}$. Recall that $^*(dt \wedge dx) = \frac{1}{(4-2)!} \epsilon_{01\mu\nu} \gamma^{01}(dx^{\mu} \wedge dx^{\nu})$ and that $\gamma^{01} = \eta^{0\lambda} \eta^{1\rho} \gamma_{\lambda\rho} = (-1)(1)\gamma_{01} = -1$. Thus

Notice also that since $dt \wedge dx = -dx \wedge dt$ we find $*(dx \wedge dt) = dy \wedge dz$

 $= -dy \wedge dz.$

The other Hodge duals of the basic two-forms follow from similar calculations. Here is a table of all the basic Hodge dualities in Minkowski space, In the table the terms are grouped as they are to

$1 = dt \wedge dx \wedge dy \wedge dz$	$^{*}(dt \wedge dx \wedge dy \wedge dz) = -1$
$ (dx \wedge dy \wedge dz) = -dt $	$^{*}dt = -dx \wedge dy \wedge dz$
$ ^*(dt \wedge dy \wedge dz) = -dx$	$^{*}dx = -dy \wedge dz \wedge dt$
$*(dt \wedge dz \wedge dx) = -dy$	$^{*}dy = -dz \wedge dx \wedge dt$
$*(dt \wedge dx \wedge dy) = -dz$	$^{*}dz = -dx \wedge dy \wedge dt$
$ *(dz \wedge dt) = dx \wedge dy $	$^{\ast}(dx \wedge dy) = -dz \wedge dt$
$^{*}(dx \wedge dt) = dy \wedge dz$	$^{*}(dy \wedge dz) = -dx \wedge dt$
$^{*}(dy \wedge dt) = dz \wedge dx$	$^{*}(dz \wedge dx) = -dy \wedge dt$

emphasize the isomorphisms between the one-dimensional $\Lambda^0(M)$ and $\Lambda^4(M)$, the four-dimensional $\Lambda^1(M)$ and $\Lambda^3(M)$, the six-dimensional $\Lambda^2(M)$ and itself. Notice that the dimension of $\Lambda(M)$ is 16 which just happens to be 2⁴.

Now that we've established how the Hodge dual works on the differentials we can easily take the Hodge dual of arbitrary differential forms on Minkowski space. We begin with the example of the 4-current \mathcal{J}

Example 12.1.5. Four Current: often in relativistic physics we would even just call the four current simply the current, however it actually includes the charge density ρ and current density \vec{J} . Consequently, we define,

$$(\mathcal{J}^{\mu}) \equiv (\rho, \vec{J}),$$

moreover if we lower the index we obtain,

$$(\mathcal{J}_{\mu}) = (-\rho, \vec{J})$$

which are the components of the current one-form,

$$\mathcal{J} = \mathcal{J}_{\mu}dx^{\mu} = -\rho dt + J_x dx + J_y dy + J_z dz$$

This equation could be taken as the definition of the current as it is equivalent to the vector definition. Now we can rewrite the last equation using the vectors \mapsto forms mapping as,

$$\mathcal{J} = -\rho dt + \omega_{\vec{J}}.$$

Consider the Hodge dual of \mathcal{J} ,

we will find it useful to appeal to this calculation in a later section.

Example 12.1.6. Four Potential: often in relativistic physics we would call the four potential simply the potential, however it actually includes the scalar potential V and the vector potential \vec{A} (discussed at the end of chapter 3). To be precise we define,

$$(A^{\mu}) \equiv (V, \vec{A})$$

we can lower the index to obtain,

$$(A_{\mu}) = (-V, A)$$

which are the components of the current one-form,

$$A = A_{\mu}dx^{\mu} = -Vdt + A_{x}dx + A_{y}dy + A_{z}dz$$

Sometimes this equation is taken as the definition of the four potential. We can rewrite the four potential vector field using the vectors \mapsto forms mapping as,

$$A = -Vdt + \omega_{\vec{A}}.$$

The Hodge dual of A is

$$^*A = Vdx \wedge dy \wedge dz - \Phi_{\vec{A}} \wedge dt.$$
(12.6)

Several steps were omitted because they are identical to the calculation of the dual of the 4-current above.

Definition 12.1.7. Faraday tensor.

Given an electric field $\vec{E} = (E_1, E_2, E_3)$ and a magnetic field $\vec{B} = (B_1, B_2, B_3)$ we define a 2-form F by

$$F = \omega_E \wedge dt + \Phi_B.$$

This 2-form is often called the **electromagnetic field tensor or the Faraday tensor.** If we write it in tensor components as $F = \frac{1}{2}F_{\mu\nu}dx^{\mu} \wedge dx^{\nu}$ and then consider its matrix $(F_{\mu\nu})$ of components then it is easy to see that

$$(F_{\mu\nu}) = \begin{pmatrix} 0 & -E_1 & -E_2 & -E_3 \\ E_1 & 0 & B_3 & -B_2 \\ E_2 & -B_3 & 0 & B_1 \\ E_3 & B_2 & -B_1 & 0 \end{pmatrix}$$
(12.7)

Convention: Notice that when we write the matrix version of the tensor components we take the first index to be the row index and the second index to be the column index, that means $F_{01} = -E_1$ whereas $F_{10} = E_1$.

Example 12.1.8. In this example we demonstrate various conventions which show how one can transform the field tensor to other type tensors. Define a type (1,1) tensor by raising the first index by the inverse metric $\eta^{\alpha\mu}$ as follows,

$$F^{\alpha}{}_{\nu} = \eta^{\alpha\mu}F_{\mu\nu}$$

The zeroth row,

$$(F^0_{\nu}) = (\eta^{0\mu} F_{\mu\nu}) = (0, E_1, E_2, E_3)$$

Then row one is unchanged since $\eta^{1\mu} = \delta^{1\mu}$,

$$(F^{1}_{\nu}) = (\eta^{1\mu}F_{\mu\nu}) = (E_1, 0, B_3, -B_2)$$

and likewise for rows two and three. In summary the (1,1) tensor $F' = F_{\nu}^{\alpha}(\frac{\partial}{\partial x^{\alpha}} \otimes dx^{\nu})$ has the components below

$$(F^{\alpha}{}_{\nu}) = \begin{pmatrix} 0 & E_1 & E_2 & E_3 \\ E_1 & 0 & B_3 & -B_2 \\ E_2 & -B_3 & 0 & B_1 \\ E_3 & B_2 & -B_1 & 0 \end{pmatrix}.$$
 (12.8)

At this point we raise the other index to create a (2,0) tensor,

$$F^{\alpha\beta} = \eta^{\alpha\mu}\eta^{\beta\nu}F_{\mu\nu}$$
(12.9)

and we see that it takes one copy of the inverse metric to raise each index and $F^{\alpha\beta} = \eta^{\beta\nu}F^{\alpha}{}_{\nu}$ so we can pick up where we left off in the (1,1) case. We could proceed case by case like we did with the (1,1) case but it is better to use matrix multiplication. Notice that $\eta^{\beta\nu}F^{\alpha}{}_{\nu} = F^{\alpha}{}_{\nu}\eta^{\nu\beta}$ is just the (α,β) component of the following matrix product,

$$(F^{\alpha\beta}) = \begin{pmatrix} 0 & E_1 & E_2 & E_3 \\ E_1 & 0 & B_3 & -B_2 \\ E_2 & -B_3 & 0 & B_1 \\ E_3 & B_2 & -B_1 & 0 \end{pmatrix} \begin{pmatrix} -1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 0 & E_1 & E_2 & E_3 \\ -E_1 & 0 & B_3 & -B_2 \\ -E_2 & -B_3 & 0 & B_1 \\ -E_3 & B_2 & -B_1 & 0 \end{pmatrix}.$$
 (12.10)

So we find a (2,0) tensor $F'' = F^{\alpha\beta}(\frac{\partial}{\partial x^{\alpha}} \otimes \frac{\partial}{\partial x^{\beta}})$. Other books might even use the same symbol F for F' and F'', it is in fact typically clear from the context which version of F one is thinking about. Pragmatically physicists just write the components so its not even an issue for them.

Example 12.1.9. Field tensor's dual: We now calculate the Hodge dual of the field tensor,

$$\begin{aligned} {}^{*}F &= {}^{*}(\omega_{E} \wedge dt + \Phi_{B}) \\ &= E_{x}{}^{*}(dx \wedge dt) + E_{y}{}^{*}(dy \wedge dt) + E_{z}{}^{*}(dz \wedge dt) \\ &+ B_{x}{}^{*}(dy \wedge dz) + B_{y}{}^{*}(dz \wedge dx) + B_{z}{}^{*}(dx \wedge dy) \\ &= E_{x}dy \wedge dz + E_{y}dz \wedge dx + E_{z}dx \wedge dy \\ &- B_{x}dx \wedge dt - B_{y}dy \wedge dt - B_{z}dz \wedge dt \\ &= \Phi_{E} - \omega_{B} \wedge dt. \end{aligned}$$

we can also write the components of *F in matrix form:

$$({}^{*}F_{\mu\nu}) = \begin{pmatrix} 0 & B_1 & B_2 & B_3 \\ -B_1 & 0 & E_3 & -E_2 \\ -B_2 & -E_3 & 0 & E_1 \\ -B_3 & E_2 & -E_1 & 0. \end{pmatrix}$$
(12.11)

Notice that the net-effect of Hodge duality on the field tensor was to make the exchanges $\vec{E} \mapsto -\vec{B}$ and $\vec{B} \mapsto \vec{E}$.

12.2 exterior derivatives of charge forms, field tensors, and their duals

In the last chapter we found that the single operation of the exterior differentiation reproduces the gradiant, curl and divergence of vector calculus provided we make the appropriate identifications under the "work" and "flux" form mappings. We now move on to some four dimensional examples.

Example 12.2.1. Charge conservation: Consider the 4-current we introduced in example 12.1.5. Take the exterior derivative of the dual of the current to get,

$$\begin{aligned} d(*\mathcal{J}) &= d(\rho dx \wedge dy \wedge dz - \Phi_{\vec{J}} \wedge dt) \\ &= (\partial_t \rho) dt \wedge dx \wedge dy \wedge dz - d[(J_x dy \wedge dz + J_y dz \wedge dx + J_z dx \wedge dy) \wedge dt] \\ &= d\rho \wedge dx \wedge dy \wedge dz \\ &- \partial_x J_x dx \wedge dy \wedge dz \wedge dt - \partial_y J_y dy \wedge dz \wedge dx \wedge dt - \partial_z J_z dz \wedge dx \wedge dy \wedge dt \\ &= (\partial_t \rho + \nabla \cdot \vec{J}) dt \wedge dx \wedge dy \wedge dz. \end{aligned}$$

We work through the same calculation using index techniques,

$$\begin{aligned} d(*\mathcal{J}) &= d(\rho dx \wedge dy \wedge dz - \Phi_{\vec{J}} \wedge dt) \\ &= d(\rho) \wedge dx \wedge dy \wedge dz - d[\frac{1}{2}\epsilon_{ijk}J_i dx^j \wedge dx^k \wedge dt) \\ &= (\partial_t \rho) dt \wedge dx \wedge dy \wedge dz - \frac{1}{2}\epsilon_{ijk}\partial_\mu J_i dx^\mu \wedge dx^j \wedge dx^k \wedge dt \\ &= (\partial_t \rho) dt \wedge dx \wedge dy \wedge dz - \frac{1}{2}\epsilon_{ijk}\partial_m J_i dx^m \wedge dx^j \wedge dx^k \wedge dt \\ &= (\partial_t \rho) dt \wedge dx \wedge dy \wedge dz - \frac{1}{2}\epsilon_{ijk}\epsilon_{mjk}\partial_m J_i dx \wedge dy \wedge dz \wedge dt \\ &= (\partial_t \rho) dt \wedge dx \wedge dy \wedge dz - \frac{1}{2}2\delta_{im}\partial_m J_i dx \wedge dy \wedge dz \wedge dt \\ &= (\partial_t \rho + \nabla \cdot \vec{J}) dt \wedge dx \wedge dy \wedge dz. \end{aligned}$$

Observe that we can now phrase charge conservation by the following equation

 $d(^*\mathcal{J}) = 0 \qquad \Longleftrightarrow \qquad \partial_t \rho + \nabla \cdot \vec{J} = 0.$

In the classical scheme of things this was a derived consequence of the equations of electromagnetism, however it is possible to build the theory regarding this equation as fundamental. Rindler describes that formal approach in a late chapter of "Introduction to Special Relativity".

Proposition 12.2.2.

If $(A_{\mu}) = (-V, \vec{A})$ is the vector potential (which gives the magnetic field) and $A = -Vdt + \omega_{\vec{A}}$, then $dA = \omega_{\vec{E}} + \Phi_{\vec{B}} = F$ where F is the electromagnetic field tensor. Moreover, $F_{\mu\nu} = \partial_{\mu}A_{\nu} - \partial_{\nu}A_{\mu}$.

Proof: The proof uses the definitions $\vec{E} = -\nabla V - \partial_t A$ and $\vec{B} = \nabla \times \vec{A}$ and some vector identities:

$$\begin{split} dA &= d(-Vdt + \omega_{\vec{A}}) \\ &= -dV \wedge dt + d(\omega_{\vec{A}}) \\ &= -dV \wedge dt + (\partial_t A_i)dt \wedge dx^i + (\partial_j A_i)dx^j \wedge dx^i \\ &= \omega_{(-\nabla V)} \wedge dt - \omega_{\partial_t \vec{A}} \wedge dt + \Phi_{\nabla \times \vec{A}} \\ &= (\omega_{(-\nabla V)} - \omega_{\partial_t \vec{A}}) \wedge dt + \Phi_{\nabla \times \vec{A}} \\ &= \omega_{(-\nabla V - \partial_t \vec{A})} \wedge dt + \Phi_{\nabla \times \vec{A}} \\ &= \omega_{\vec{E}} \wedge dt + \Phi_{\vec{B}} \\ &= F = \frac{1}{2} F_{\mu\nu} dx^\mu \wedge dx^\nu. \end{split}$$

Moreover we also have:

$$dA = d(A_{\nu}) \wedge dx^{\nu}$$

= $\partial_{\mu}A_{\nu}dx^{\mu} \wedge dx^{\nu}$
= $\frac{1}{2}(\partial_{\mu}A_{\nu} - \partial_{\nu}A_{\mu})dx^{\mu} \wedge dx^{\nu} + \frac{1}{2}(\partial_{\mu}A_{\nu} + \partial_{\nu}A_{\mu})dx^{\mu} \wedge dx^{\nu}$
= $\frac{1}{2}(\partial_{\mu}A_{\nu} - \partial_{\nu}A_{\mu})dx^{\mu} \wedge dx^{\nu}.$

Comparing the two identities we see that $F_{\mu\nu} = \partial_{\mu}A_{\nu} - \partial_{\nu}A_{\mu}$ and the proposition follows.

Example 12.2.3. Exterior derivative of the field tensor: We have just seen that the field tensor is the exterior derivative of the potential one-form. We now compute the exterior derivative of the field tensor expecting to find Maxwell's equations since the derivative of the fields are governed by Maxwell's equations,

$$dF = d(E_i dx^i \wedge dt) + d(\Phi_{\vec{B}}) = \partial_m E_i (dx^m \wedge dx^i \wedge dt) + (\nabla \cdot \vec{B}) dx \wedge dy \wedge dz + \frac{1}{2} \epsilon_{ijk} (\partial_t B_i) (dt \wedge dx^j \wedge dx^k).$$
(12.12)

W pause here to explain our logic. In the above we dropped the $\partial_t E_i dt \wedge \cdots$ term because it was wedged with another dt in the term so it vanished. Also we broke up the exterior derivative on the flux form of \vec{B} into the space and then time derivative terms and used our work in example 10.6.7.

Continuing the calculation,

$$dF = [\partial_j E_k + \frac{1}{2} \epsilon_{ijk} (\partial_t B_i)] dx^j \wedge dx^k \wedge dt + (\nabla \cdot \vec{B}) dx \wedge dy \wedge dz$$

$$= [\partial_x E_y - \partial_y E_x + \epsilon_{i12} (\partial_t B_i)] dx \wedge dy \wedge dt$$

$$+ [\partial_z E_x - \partial_x E_z + \epsilon_{i31} (\partial_t B_i)] dz \wedge dx \wedge dt$$

$$+ [\partial_y E_z - \partial_z E_y + \epsilon_{i23} (\partial_t B_i)] dy \wedge dz \wedge dt$$

$$+ (\nabla \cdot \vec{B}) dx \wedge dy \wedge dz$$

$$= (\nabla \times \vec{E} + \partial_t \vec{B})_i \Phi_{e_i} \wedge dt + (\nabla \cdot \vec{B}) dx \wedge dy \wedge dz$$

$$= \Phi_{\nabla \times \vec{E} + \partial_t \vec{B}} \wedge dt + (\nabla \cdot \vec{B}) dx \wedge dy \wedge dz$$

(12.13)

where we used the fact that Φ is an isomorphism of vector spaces (at a point) and $\Phi_{e_1} = dy \wedge dz$, $\Phi_{e_2} = dz \wedge dx$, and $\Phi_{e_3} = dx \wedge dy$. Behold, we can state two of Maxwell's equations as

$$dF = 0 \quad \Longleftrightarrow \quad \nabla \times \vec{E} + \partial_t \vec{B} = 0, \quad \nabla \cdot \vec{B} = 0$$
(12.14)

Example 12.2.4. We now compute the exterior derivative of the dual to the field tensor:

$$d^*F = d(-B_i dx^i \wedge dt) + d(\Phi_{\vec{E}}) = \Phi_{-\nabla \times \vec{B} + \partial_t \vec{E}} \wedge dt + (\nabla \cdot \vec{E}) dx \wedge dy \wedge dz$$
(12.15)

This follows directly from the last example by replacing $\vec{E} \mapsto -\vec{B}$ and $\vec{B} \mapsto \vec{E}$. We obtain the two inhomogeneous Maxwell's equations by setting d^*F equal to the Hodge dual of the 4-current,

$$d^*F = \mu_o^* \mathcal{J} \quad \Longleftrightarrow \quad -\nabla \times \vec{B} + \partial_t \vec{E} = -\mu_o \vec{J}, \quad \nabla \cdot \vec{E} = \rho$$
(12.16)

Here we have used example 12.1.5 to find the RHS of the Maxwell equations.

We now know how to write Maxwell's equations via differential forms. The stage is set to prove that Maxwell's equations are Lorentz covariant, that is they have the same form in all inertial frames.

12.3 coderivatives and comparing to Griffith's relativitic E & M

Optional section, for those who wish to compare our tensorial E & M with that of Griffith's, you may skip ahead to the next section if not interested

I should mention that this is not the only way to phrase Maxwell's equations in terms of differential forms. If you try to see how what we have done here compares with the equations presented in Griffith's text it is not immediately obvious. He works with $F^{\mu\nu}$ and $G^{\mu\nu}$ and J^{μ} none of which are the components of differential forms. Nevertheless he recovers Maxwell's equations as $\partial_{\mu}F^{\mu\nu} = J^{\nu}$ and $\partial_{\mu}G^{\mu\nu} = 0$. If we compare the components of *F with equation 12.119 (the matrix form of $G^{\mu\nu}$) in Griffith's text,

$$(G^{\mu\nu}(c=1)) = \begin{pmatrix} 0 & B_1 & B_2 & B_3 \\ -B_1 & 0 & -E_3 & E_2 \\ -B_2 & -E_3 & 0 & -E_1 \\ -B_3 & E_2 & -E_1 & 0 \end{pmatrix} = -({}^*F^{\mu\nu}).$$
(12.17)

we find that we obtain the negative of Griffith's "dual tensor" (recall that raising the indices has the net-effect of multiplying the zeroth row and column by -1). The equation $\partial_{\mu}F^{\mu\nu} = J^{\nu}$ does not follow directly from an exterior derivative, rather it is the component form of a "coderivative". The coderivative is defined $\delta = *d^*$, it takes a *p*-form to an (n-p)-form then *d* makes it a (n-p+1)-form then finally the second Hodge dual takes it to an (n - (n - p + 1))-form. That is δ takes a *p*-form to a p - 1-form. We stated Maxwell's equations as

$$dF = 0 \qquad \qquad d^*F = {}^*\mathcal{J}$$

Now we can take the Hodge dual of the inhomogeneous equation to obtain,

$${}^{*}d^{*}F = \delta F = {}^{**}\mathcal{J} = \pm \mathcal{J}$$

where I leave the sign for you to figure out. Then the other equation

$$\partial_{\mu}G^{\mu\nu} = 0$$

can be understood as the component form of $\delta^* F = 0$ but this is really dF = 0 in disguise,

$$0 = \delta^* F = {}^*d^{**}F = \pm^*dF \iff dF = 0$$

so even though it looks like Griffith's is using the dual field tensor for the homogeneous Maxwell's equations and the field tensor for the inhomogeneous Maxwell's equations it is in fact not the case. The key point is that there are **coderivatives** implicit within Griffith's equations, so you have to read between the lines a little to see how it matched up with what we've done here. I have not entirely proved it here, to be complete we should look at the component form of $\delta F = \mathcal{J}$ and explicitly show that this gives us $\partial_{\mu} F^{\mu\nu} = J^{\nu}$, I don't think it is terribly difficult but I'll leave it to the reader.

Comparing with Griffith's is fairly straightforward because he uses the same metric as we have. Other texts use the mostly negative metric, its just a convention. If you try to compare to such a book you'll find that our equations are almost the same up to a sign. One good careful book is Reinhold A. Bertlmann's *Anomalies in Quantum Field Theory* you will find much of what we have done here done there with respect to the other metric. Another good book which shares our conventions is Sean M. Carroll's *An Introduction to General Relativity: Spacetime and Geometry*, that text has a no-nonsense introduction to tensors forms and much more over a curved space (in contrast to our approach which has been over a vector space which is flat). By now there are probably thousands of texts on tensors; these are a few we have found useful here.

12.4 Maxwell's equations are relativistically covariant

Let us begin with the definition of the field tensor once more. We define the components of the field tensor in terms of the 4-potentials as we take the view-point those are the basic objects (not the fields). If

$$F_{\mu\nu} \equiv \partial_{\mu}A_{\nu} - \partial_{\nu}A_{\mu},$$

then the field tensor $F = F_{\mu\nu} dx^{\mu} \otimes dx^{\nu}$ is a tensor, or is it ? We should check that the components transform as they ought according to the discussion in section ??. Let $\bar{x}^{\mu} = \Lambda^{\mu}_{\nu} x^{\nu}$ then we observe,

(1.)
$$\bar{A}_{\mu} = (\Lambda^{-1})^{\alpha}_{\mu} A_{\alpha}$$

(2.) $\frac{\partial}{\partial \bar{x}^{\nu}} = \frac{\partial x^{\beta}}{\partial \bar{x}^{\nu}} \frac{\partial}{\partial x^{\beta}} = (\Lambda^{-1})^{\beta}_{\nu} \frac{\partial}{\partial x^{\beta}}$
(12.18)

where (2.) is simply the chain rule of multivariate calculus and (1.) is not at all obvious. We will assume that (1.) holds, that is we assume that the 4-potential transforms in the appropriate way for a one-form. In principle one could prove that from more base assumptions. After all electromagnetism is the study of the interaction of charged objects, we should hope that the potentials are derivable from the source charge distribution. Indeed, there exist formulas to calculate the potentials for moving distributions of charge. We could take those as definitions for the potentials, then it would be possible to actually calculate if (1.) is true. We'd just change coordinates via a Lorentz transformation and verify (1.). For the sake of brevity we will just assume that (1.) holds. We should mention that alternatively one can show the electric and magnetic fields transform as to make $F_{\mu\nu}$ a tensor. Those derivations assume that charge is an invariant quantity and just apply Lorentz transformations to special physical situations to deduce the field transformation rules. See Griffith's chapter on special relativity or look in Resnick for example.

Let us find how the field tensor transforms assuming that (1.) and (2.) hold, again we consider $\bar{x}^{\mu} = \Lambda^{\mu}_{\nu} x^{\nu}$,

$$F_{\mu\nu} = \partial_{\mu}A_{\nu} - \partial_{\nu}A_{\mu}$$

= $(\Lambda^{-1})^{\alpha}_{\mu}\partial_{\alpha}((\Lambda^{-1})^{\beta}_{\nu}A_{\beta}) - (\Lambda^{-1})^{\beta}_{\nu}\partial_{\beta}((\Lambda^{-1})^{\alpha}_{\mu}A_{\alpha})$
= $(\Lambda^{-1})^{\alpha}_{\mu}(\Lambda^{-1})^{\beta}_{\nu}(\partial_{\alpha}A_{\beta} - \partial_{\beta}A_{\alpha})$
= $(\Lambda^{-1})^{\alpha}_{\mu}(\Lambda^{-1})^{\beta}_{\nu}F_{\alpha\beta}.$ (12.19)

therefore the field tensor really is a tensor over Minkowski space.

Proposition 12.4.1.

The dual to the field tensor is a tensor over Minkowski space. For a given Lorentz transformation $\bar{x}^{\mu} = \Lambda^{\mu}_{\nu} x^{\nu}$ it follows that

$${}^*\bar{F}_{\mu\nu} = (\Lambda^{-1})^{\alpha}_{\mu} (\Lambda^{-1})^{\beta}_{\nu} {}^*F_{\alpha\beta}$$

Proof: homework (just kidding in 2010), it follows quickly from the definition and the fact we already know that the field tensor is a tensor.

Proposition 12.4.2.

The four-current is a four-vector. That is under the Lorentz transformation $\bar{x}^{\mu} = \Lambda^{\mu}_{\nu} x^{\nu}$ we can show,

$$\mathcal{J}_{\mu} = (\Lambda^{-1})^{\alpha}_{\mu} \mathcal{J}_{\alpha}$$

Proof: follows from arguments involving the invariance of charge, time dilation and length contraction. See Griffith's for details, sorry we have no time.

Corollary 12.4.3.

The dual to the four current transforms as a 3-form. That is under the Lorentz transformation $\bar{x}^{\mu} = \Lambda^{\mu}_{\nu} x^{\nu}$ we can show,

$${}^{*}\bar{\mathcal{J}}_{\mu\nu\sigma} = (\Lambda^{-1})^{\alpha}_{\mu} (\Lambda^{-1})^{\beta}_{\nu} (\Lambda^{-1})^{\gamma}_{\sigma} \mathcal{J}_{\alpha\beta\gamma}$$

Up to now the content of this section is simply an admission that we have been a little careless in defining things up to this point. The main point is that if we say that something is a tensor then we need to make sure that is in fact the case. With the knowledge that our tensors are indeed tensors the proof of the covariance of Maxwell's equations is trivial.

$$dF = 0 \qquad \qquad d^*F = {}^*\mathcal{J}$$

are coordinate invariant expressions which we have already proved give Maxwell's equations in one frame of reference, thus they must give Maxwell's equations in all frames of reference. The essential point is simply that

$$F = \frac{1}{2} F_{\mu\nu} dx^{\mu} \wedge dx^{\nu} = \frac{1}{2} \bar{F}_{\mu\nu} d\bar{x}^{\mu} \wedge d\bar{x}^{\nu}$$

Again, we have no hope for the equation above to be true unless we know that $\bar{F}_{\mu\nu} = (\Lambda^{-1})^{\alpha}_{\mu} (\Lambda^{-1})^{\beta}_{\nu} F_{\alpha\beta}$. That transformation follows from the fact that the four-potential is a four-vector. It should be mentioned that others prefer to "prove" the field tensor is a tensor by studying how the electric and magnetic fields transform under a Lorentz transformation. We in contrast have derived the field transforms based ultimately on the seemingly innocuous assumption that the four-potential transforms according to $\bar{A}_{\mu} = (\Lambda^{-1})^{\alpha}_{\mu} A_{\alpha}$. OK enough about that.

So the fact that Maxwell's equations have the same form in all **relativistically inertial** frames of reference simply stems from the fact that we found Maxwell's equation were given by an arbitrary frame, and the field tensor looks the same in the new barred frame so we can again go through all the same arguments with barred coordinates. Thus we find that Maxwell's equations are the same in all relativistic frames of reference, that is if they hold in one inertial frame then they will hold in any other frame which is related by a Lorentz transformation.

12.5 Electrostatics in Five dimensions

We will endeavor to determine the electric field of a point charge in 5 dimensions where we are thinking of adding an extra spatial dimension. Lets call the fourth spatial dimension the *w*-direction so that a typical point in space time will be (t, x, y, z, w). First we note that the electromagnetic field tensor can still be derived from a one-form potential,

$$A = -\rho dt + A_1 dx + A_2 dy + A_3 dz + A_4 dw$$

we will find it convenient to make our convention for this section that $\mu, \nu, \dots = 0, 1, 2, 3, 4$ whereas $m, n, \dots = 1, 2, 3, 4$ so we can rewrite the potential one-form as,

$$A = -\rho dt + A_m dx^m$$

This is derived from the vector potential $A^{\mu} = (\rho, A^m)$ under the assumption we use the natural generalization of the Minkowski metric, namely the 5 by 5 matrix,

$$(\eta_{\mu\nu}) = \begin{pmatrix} -1 & 0 & 0 & 0 & 0\\ 0 & 1 & 0 & 0 & 0\\ 0 & 0 & 1 & 0 & 0\\ 0 & 0 & 0 & 1 & 0\\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} = (\eta^{\mu\nu})$$
(12.20)

we could study the linear isometries of this metric, they would form the group O(1, 4). Now we form the field tensor by taking the exterior derivative of the one-form potential,

$$F = dA = \frac{1}{2} (\partial_{\mu} \partial_{\nu} - \partial_{\nu} \partial_{\mu}) dx^{\mu} \wedge dx^{\nu}$$

now we would like to find the electric and magnetic "fields" in 4 dimensions. Perhaps we should say 4+1 dimensions, just understand that I take there to be 4 spatial directions throughout this discussion if in doubt. Note that we are faced with a dilemma of interpretation. There are 10 independent components of a 5 by 5 antisymmetric tensor, naively we wold expect that the electric and magnetic fields each would have 4 components, but that is not possible, we'd be missing two components. The solution is this, the time components of the field tensor are understood to correspond to the electric part of the fields whereas the remaining 6 components are said to be magnetic. This aligns with what we found in 3 dimensions, its just in 3 dimensions we had the fortunate quirk that the number of linearly independent one and two forms were equal at any point. This definition means that the magnetic field will in general not be a vector field but rather a "flux" encoded by a 2-form.

$$(F_{\mu\nu}) = \begin{pmatrix} 0 & -E_x & -E_y & -E_z & -E_w \\ E_x & 0 & B_z & -B_y & H_1 \\ E_y & -B_z & 0 & B_x & H_2 \\ E_z & B_y & -B_x & 0 & H_3 \\ E_w & -H_1 & -H_2 & -H_3 & 0 \end{pmatrix}$$
(12.21)

Now we can write this compactly via the following equation,

$$F = E \wedge dt + B$$

I admit there are subtle points about how exactly we should interpret the magnetic field, however I'm going to leave that to your imagination and instead focus on the electric sector. What is the generalized Maxwell's equation that E must satisfy?

$$d^*F = \mu_o^*\mathcal{J} \implies d^*(E \wedge dt + B) = \mu_o^*\mathcal{J}$$

where $\mathcal{J} = -\rho dt + J_m dx^m$ so the 5 dimensional Hodge dual will give us a 5 - 1 = 4 form, in particular we will be interested in just the term stemming from the dual of dt,

$$^{*}(-\rho dt) = \rho dx \wedge dy \wedge dz \wedge dw$$

the corresponding term in d^*F is $d^*(E \wedge dt)$ thus, using $\mu_o = \frac{1}{\epsilon_o}$,

$$d^*(E \wedge dt) = \frac{1}{\epsilon_o} \rho dx \wedge dy \wedge dz \wedge dw$$
(12.22)

is the 4-dimensional Gauss's equation. Now consider the case we have an isolated point charge which has somehow always existed at the origin. Moreover consider a 3-sphere that surrounds the charge. We wish to determine the generalized Coulomb field due to the point charge. First we note that the solid 3-sphere is a 4-dimensional object, it the set of all $(x, y, z, w) \in \mathbb{R}^4$ such that

$$x^2 + y^2 + z^2 + w^2 \le r^2$$

We may parametrize a three-sphere of radius r via generalized spherical coordinates,

$$x = rsin(\theta)cos(\phi)sin(\psi)$$

$$y = rsin(\theta)sin(\phi)sin(\psi)$$

$$z = rcos(\theta)sin(\psi)$$

$$w = rcos(\psi)$$

(12.23)

Now it can be shown that the volume and surface area of the radius r three-sphere are as follows,

$$vol(S^3) = \frac{\pi^2}{2}r^4$$
 $area(S^3) = 2\pi^2 r^3$

We may write the charge density of a smeared out point charge q as,

$$\rho = \begin{cases} 2q/\pi^2 a^4, & 0 \le r \le a \\ 0, & r > a \end{cases}.$$
(12.24)

Notice that if we integrate ρ over any four-dimensional region which contains the solid three sphere of radius *a* will give the enclosed charge to be *q*. Then integrate over the Gaussian 3-sphere S^3 with radius *r* call it *M*,

$$\int_{M} d^{*}(E \wedge dt) = \frac{1}{\epsilon_{o}} \int_{M} \rho dx \wedge dy \wedge dz \wedge dw$$

now use the Generalized Stokes Theorem to deduce,

$$\int_{\partial M} {}^*(E \wedge dt) = \frac{q}{\epsilon_o}$$

but by the "spherical" symmetry of the problem we find that E must be independent of the direction it points, this means that it can only have a radial component. Thus we may calculate the integral with respect to generalized spherical coordinates and we will find that it is the product of $E_r \equiv E$ and the surface volume of the four dimensional solid three sphere. That is,

$$\int_{\partial M} {}^*(E \wedge dt) = 2\pi^2 r^3 E = \frac{q}{\epsilon_o}$$

Thus,

$$E = \frac{q}{2\pi^2 \epsilon_o r^3}$$

the Coulomb field is weaker if it were to propogate in 4 spatial dimensions. Qualitatively what has happened is that the have taken the same net flux and spread it out over an additional dimension, this means it thins out quicker. A very similar idea is used in some *brane world* scenarios. String theorists posit that the gravitational field spreads out in more than four dimensions while in contrast the standard model fields of electromagnetism, and the strong and weak forces are confined to a four-dimensional brane. That sort of model attempts an explaination as to why gravity is so weak in comparison to the other forces. Also it gives large scale corrections to gravity that some hope will match observations which at present don't seem to fit the standard gravitational models.

This example is but a taste of the theoretical discussion that differential forms allow. As a final comment I remind the reader that we have done things for flat space for the most part in this course, when considering a curved space there are a few extra considerations that must enter. Coordinate vector fields e_i must be thought of as derivations $\partial/\partial x^{\mu}$ for one. Also the metric is not a constant tensor like δ_{ij} or $\eta_{\mu\nu}$ rather is depends on position, this means Hodge duality aquires a coordinate dependence as well. Doubtless I have forgotten something else in this brief warning. One more advanced treatment of many of our discussions is Dr. Fulp's Fiber Bundles 2001 notes which I have posted on my webpage. He uses the other metric but it is rather elegantly argued, all his arguments are coordinate independent. He also deals with the issue of the magnetic induction and the dielectric, issues which we have entirely ignored since we always have worked in free space.

References and Acknowledgements:

I have drawn from many sources to assemble the content of the last couple chapters, the references are listed approximately in the order of their use to the course, additionally we are indebted to Dr. Fulp for his course notes from many courses (ma 430, ma 518, ma 555, ma 756, ...). Also Manuela Kulaxizi helped me towards the correct (I hope) interpretation of 5-dimensional E&M in the last example.

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12.5. ELECTROSTATICS IN FIVE DIMENSIONS

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Chapter 13

introduction to variational calculus

13.1 history

The problem of variational calculus is almost as old as modern calculus. Variational calculus seeks to answer questions such as:

Remark 13.1.1.

- 1. what is the shortest path between two points on a surface ?
- 2. what is the path of least time for a mass sliding without friction down some path between two given points ?
- 3. what is the path which minimizes the energy for some physical system ?
- 4. given two points on the x-axis and a particular area what curve has the longest perimeter and bounds that area between those points and the x-axis?

You'll notice these all involve a variable which is not a real variable or even a vector-valued-variable. Instead, the answers to the questions posed above will be **paths** or **curves** depending on how you wish to frame the problem. In variational calculus the variable is a function and we wish to find extreme values for a **functional**. In short, a functional is an abstract function of functions. A functional takes as an input a function and gives as an output a number. The space from which these functions on the **space of admissable solutions**. To read about the full generality of the problem you should look in a text such as Hans Sagan's. Our treatment is introductory in this chapter, my aim is to show you why it is plausible and then to show you how we use variational calculus.

We will see that the problem of finding an extreme value for a functional is equivalent to solving the Euler-Lagrange equations or Euler equations for the functional. Euler predates Lagrange in his discovery of the equations bearing their names. Eulers's initial attack of the problem was to chop the hypothetical solution curve up into a polygonal path. The unknowns in that approach were the coordinates of the vertices in the polygonal path. Then through some ingenious calculations he arrived at the Euler-Lagrange equations. Apparently there were logical flaws in Euler's original treatment. Lagrange later derived the same equations using the viewpoint that the variable was a function and the **variation** was one of shifting by an arbitrary function. The treatment of variational calculus in Edwards is neither Euler nor Lagrange's approach, it is a refined version which takes in the contributions of generations of mathematicians working on the subject and then merges it with careful functional analysis. I'm no expert of the full history, I just give you a rough sketch of what I've gathered from reading a few variational calculus texts.

Physics played a large role in the development of variational calculus. Lagrange was a physicist as well as a mathematician. At the present time, every physicist takes course(s) in *Lagrangian Mechanics*. Moreover, the use of variational calculus is fundamental since Hamilton's principle says that all physics can be derived from the principle of least action. In short this means that nature is lazy. The solutions realized in the physical world are those which minimize the action. The action

$$S[y] = \int L(y, y', t) \, dt$$

is constructed from the Lagrangian L = T - U where T is the kinetic energy and U is the potential energy. In the case of classical mechanics the Euler Lagrange equations are precisely Newton's equations. The Hamiltonian H = T + U is similar to the Lagrangian except that the fundamental variables are taken to be momentum and position in contrast to velocity and position in Lagrangian mechanics. Hamiltonians and Lagrangians are used to set-up new physical theories. Euler-Lagrange equations are said to give the so-called *classical limit* of modern field theories. The concept of a force is not so useful to quantum theories, instead the concept of energy plays the central role. Moreover, the problem of quantizing and then renormalizing field theory brings in very sophisiticated mathematics. In fact, the math of modern physics is not understood. In this chapter I'll just show you a few famous classical mechanics problems which are beatifully solved by Lagrange's approach. We'll also see how expressing the Lagrangian in non-Cartesian coordinates can give us an easy way to derive forces that arise from geometric contraints. Hopefully we can derive the coriolis force in this manner. I also plan to include a problem or two about Maxwell's equations from the variational viewpoint. There must be at least a dozen different ways to phrase Maxwell's equations, one reason I revisit them is to give you a concrete example as to the fact that physics has many formulations.

I am following the typical physics approach to variational calculus. Edwards' last chapter is more natural mathematically but I think the math is a bit much for your first exposure to the subject. The treatment given here is close to that of Arfken and Weber's Mathematical Physics text, however I suspect you can find these calculations in dozens of classical mechanics texts. More or less our approach is that of Lagrange.

13.2 the variational problem

Our goal in what follows here is to maximize or minimize a particular function of functions. Suppose \mathcal{F}_o is a set of functions with some particular property. For now, we may could assume that all the functions in \mathcal{F}_o have graphs that include (x_1, y_1) and (x_2, y_2) . Consider a functional $J : \mathcal{F}_o \to \mathcal{F}_o$ which is defined by an integral of some function f which we call the **Lagrangian**,

$$J[y] = \int_{x_1}^{x_2} f(y, y', x) \, dx.$$

We suppose that f is given but y is a variable. Consider that if we are given a function $y^* \in \mathcal{F}_o$ and another function η such that $\eta(x_1) = \eta(x_2) = 0$ then we can reach a whole family of functions indexed by a real variable α as follows (relabel $y^*(x)$ by y(x, 0) so it matches the rest of the family of functions):

$$y(x,\alpha) = y(x,0) + \alpha \eta(x)$$

Note that $x \mapsto y(x, \alpha)$ gives a function in \mathcal{F}_o . We define the **variation** of y to be

$$\delta y = \alpha \eta(x)$$

This means $y(x, \alpha) = y(x, 0) + \delta y$. We may write J as a function of α given the variation we just described:

$$J(\alpha) = \int_{x_1}^{x_2} f(y(x,\alpha), y(x,\alpha)', x) \, dx.$$

It is intuitively obvious that if the function $y^*(x) = y(x, 0)$ is an extremum of the functional then we ought to expect

$$\left[\frac{\partial J(\alpha)}{\partial \alpha}\right]_{\alpha=0} = 0$$

Notice that we can calculate the derivative above using multivariate calculus. Remember that $y(x, \alpha) = y(x, 0) + \alpha \eta(x)$ hence $y(x, \alpha)' = y(x, 0)' + \alpha \eta(x)'$ thus $\frac{\partial y}{\partial \alpha} = \eta$ and $\frac{\partial y'}{\partial \alpha} = \eta' = \frac{d\eta}{dx}$. Consider that:

$$\frac{\partial J(\alpha)}{\partial \alpha} = \frac{\partial}{\partial \alpha} \left[\int_{x_1}^{x_2} f(y(x,\alpha), y(x,\alpha)', x) \, dx \right] \\
= \int_{x_1}^{x_2} \left(\frac{\partial f}{\partial y} \frac{\partial y}{\partial \alpha} + \frac{\partial f}{\partial y'} \frac{\partial y'}{\partial \alpha} + \frac{\partial f}{\partial x} \frac{\partial x}{\partial \alpha} \right) dx \\
= \int_{x_1}^{x_2} \left(\frac{\partial f}{\partial y} \eta + \frac{\partial f}{\partial y'} \frac{d\eta}{dx} \right) dx$$
(13.1)

Observe that

$$\frac{d}{dx}\left[\frac{\partial f}{\partial y'}\eta\right] = \frac{d}{dx}\left[\frac{\partial f}{\partial y'}\right]\eta + \frac{\partial f}{\partial y'}\frac{d\eta}{dx}$$

Hence continuing Equation 13.1 in view of the product rule above,

$$\frac{\partial J(\alpha)}{\partial \alpha} = \int_{x_1}^{x_2} \left(\frac{\partial f}{\partial y} \eta + \frac{d}{dx} \left[\frac{\partial f}{\partial y'} \eta \right] - \frac{d}{dx} \left[\frac{\partial f}{\partial y'} \right] \eta \right) dx$$

$$= \frac{\partial f}{\partial y'} \eta \Big|_{x_1}^{x_2} + \int_{x_1}^{x_2} \left(\frac{\partial f}{\partial y} \eta - \frac{d}{dx} \left[\frac{\partial f}{\partial y'} \right] \eta \right) dx$$

$$= \int_{x_1}^{x_2} \left(\frac{\partial f}{\partial y} - \frac{d}{dx} \left[\frac{\partial f}{\partial y'} \right] \right) \eta dx$$
(13.2)

Note we used the conditions $\eta(x_1) = \eta(x_2)$ to see that $\frac{\partial f}{\partial y'}\eta\Big|_{x_1}^{x_2} = \frac{\partial f}{\partial y'}\eta(x_2) - \frac{\partial f}{\partial y'}\eta(x_1) = 0$. Our goal is to find the extreme values for the functional J. Let me take a few sentences to again restate our set-up. Generally, we take a function y then J maps to a new function J[y]. The family of functions indexed by α gives a whole ensemble of functions in \mathcal{F}_o which are near y^* according to the formula,

$$y(x,\alpha) = y^*(x) + \alpha \eta(x)$$

Let's call this set of functions W_{η} . If we took another function like η , say ζ such that $\zeta(x_1) = \zeta(x_2) = 0$ then we could look at another family of functions:

$$y(x,\alpha) = y^*(x) + \alpha\zeta(x)$$

and we could denote the set of all such functions generated from ζ to be W_{ζ} . The total variation of y based at y^* should include all possible families of functions in \mathcal{F}_o . You could think of W_{η} and W_{ζ} be two different subspaces in \mathcal{F}_o . If $\eta \neq \zeta$ then these subspaces of \mathcal{F}_o are likely disjoint except for the proposed extremal solution y^* . It is perhaps a bit unsettling to realize there are infinitely many such subspaces because there are infinitely many choices for the function η or ζ . In any event, each possible variation of y^* must satisfy the condition $\left[\frac{\partial J(\alpha)}{\partial \alpha}\right]_{\alpha=0} = 0$ since we **assume** that y^* is an extreme value of the functional J. It follows that the Equation 13.2 holds for all possible η . Therefore, we ought to expect that any extreme value of the functional $J[y] = \int_{x_1}^{x_2} f(y, y', x) dx$ must solve the **Euler Lagrange Equations:**

$$\left|\frac{\partial f}{\partial y} - \frac{d}{dx}\left[\frac{\partial f}{\partial y'}\right] = 0 \quad \text{Euler-Lagrange Equations for} \quad J[y] = \int_{x_1}^{x_2} f(y, y', x) \, dx$$

13.3 variational derivative

The role that η played in the discussion in the preceding section is somewhat similar to the role that the "h" plays in the definition $f'(a) = \lim_{h\to 0} \frac{f(a+h)-f(a)}{h}$. You might hope we could replace arguments in η with a more direct approach. Physicists have a heuristic way of making such arguments in terms of the variation δ . They would cast the arguments in the last page by just

"taking the variation of J". Let me give you their formal argument,

$$\delta J = \delta \left[\int_{x_1}^{x_2} f(y, y', x) \, dx \right]$$

$$= \left[\int_{x_1}^{x_2} \delta f(y, y', x) \, dx \right]$$

$$= \int_{x_1}^{x_2} \left(\frac{\partial f}{\partial y} \delta y + \frac{\partial f}{\partial y'} \delta \left(\frac{dy}{dx} \right) + \frac{\partial f}{\partial x} \delta x \right) \, dx$$

$$= \int_{x_1}^{x_2} \left(\frac{\partial f}{\partial y} \delta y + \frac{\partial f}{\partial y'} \frac{d}{dx} \left(\delta y \right) \right) \, dx$$
(13.3)

$$= \frac{\partial f}{\partial y'} \delta y \Big|_{x_1}^{x_2} + \int_{x_1}^{x_2} \left(\frac{\partial f}{\partial y} - \frac{d}{dx} \left[\frac{\partial f}{\partial y'} \right] \right) \delta y \, dx$$

Therefore, since $\delta y = 0$ at the endpoints of integration, the Euler-Lagrange equations follow from $\delta J = 0$. Now, if you're like me, the argument above is less than satisfying since we never actually defined what it means to "take δ " of something. Also, why could I commute the variational δ and $\frac{d}{dx}$)? That said, the formal method is not without use since it allows the focus to be on the Euler Lagrange equations rather than the technical details of the variation.

Remark 13.3.1.

The more adept reader at this point should realize the hypocrisy of me calling the above calculation formal since even my presentation here was formal. I also used an analogy, I assumed that the theory of extreme values for multivariate calculus extends to function space. But, \mathcal{F}_o is not \mathbb{R}^n , it's much bigger. Edwards builds the correct formalism for a rigourous calculation of the variational derivative. To be careful we'd need to develop the norm on function space and prove a number of results about infinite dimensional linear algebra. Take a look at the last chapter in Edwards' text if you're interested. I don't believe I'll have time to go over that material this semester.

13.4 Euler-Lagrange examples

I present a few standard examples in this section. We make use of the calculation in the last section. Also, we will use a result from your homework which states an equivalent form of the Euler-Lagrange equation is

$$\frac{\partial f}{\partial x} - \frac{d}{dx} \left[f - y' \frac{\partial f}{\partial y'} \right] = 0.$$

This form of the Euler Lagrange equation yields better differential equations for certain examples.

13.4.1 shortest distance between two points in plane

If s denotes the arclength in the xy-plane then the pythagorean theorem gives $ds^2 = dx^2 + dy^2$ infinitesimally. Thus, $ds = \sqrt{1 + \frac{dy^2}{dx}} dx$ and we may add up all the little distances ds to find the total length between two given points (x_1, y_1) and (x_2, y_2) :

$$J[y] = \int_{x_1}^{x_2} \sqrt{1 + (y')^2} \, dx$$

Identify that we have $f(y, y', x) = \sqrt{1 + (y')^2}$. Calculate then,

$$\frac{\partial f}{\partial y} = 0$$
 and $\frac{\partial f}{\partial y'} = \frac{y'}{\sqrt{1 + (y')^2}}$

Euler Lagrange equations yield,

$$\frac{d}{dx} \left[\frac{\partial f}{\partial y'} \right] = \frac{\partial f}{\partial y} \qquad \Rightarrow \qquad \frac{d}{dx} \left[\frac{y'}{\sqrt{1 + (y')^2}} \right] = 0 \qquad \Rightarrow \qquad \frac{y'}{\sqrt{1 + (y')^2}} = k$$

where $k \in \mathbb{R}$ is constant with respect to x. Moreover, square both sides to reveal

$$\frac{(y')^2}{1+(y')^2} = k^2 \qquad \Rightarrow \qquad (y')^2 = \frac{k^2}{1-k^2} \qquad \Rightarrow \qquad \frac{dy}{dx} = \pm \sqrt{\frac{k^2}{1-k^2}} = m^2$$

where I have defined m is defined in the obvious way. We find solutions y = mx + b. Finally, we can find m, b to fit the given pair of points (x_1, y_1) and (x_2, y_2) as follows:

$$y_1 = mx_1 + b$$
 and $y_2 = mx_2 + b$ \Rightarrow $y = y_1 + \frac{y_2 - y_1}{x_2 - x_1}(x - x_1)$

provided $x_1 \neq x_2$. If $x_1 \neq x_2$ and $y_1 \neq y_2$ then we could perform the same calculation as above with the roles of x and y interchanged,

$$J[x] = \int_{y_1}^{y_2} \sqrt{1 + (x')^2} \, dy$$

where x' = dx/dy and the Euler Lagrange equations would yield the solution

$$x = x_1 + \frac{x_2 - x_1}{y_2 - y_1}(y - y_1).$$

Finally, if both coordinates are equal then $(x_1, y_1) = (x_2, y_2)$ and the shortest path between these points is the trivial path, the armchair solution. Silly comments aside, we have shown that a straight line provides the curve with the shortest arclength between any two points in the plane.

13.4.2 surface of revolution with minimal area

Suppose we wish to revolve some curve which connects (x_1, y_1) and (x_2, y_2) around the x-axis. A surface constructed in this manner is called a **surface of revolution**. In calculus we learn how to calculate the surface area of such a shape. One can imagine deconstructing the surface into a sequence of ribbons. Each ribbon at position x will have a "radius" of y and a width of dx however, because the shape is tilted the area of the ribbon works out to $dA = 2\pi y ds$ where ds is the arclength.

If we choose x as the parameter this yields $dA = 2\pi y \sqrt{1 + (y')^2} dx$. To find the surface of minimal surface area we ought to consider the functional:

$$A[y] = \int_{x_1}^{x_2} 2\pi y \sqrt{1 + (y')^2} \, dx$$

Identify that $f(y, y', x) = 2\pi y \sqrt{1 + (y')^2}$ hence $f_y = 2\pi \sqrt{1 + (y')^2}$ and $f_{y'} = 2\pi y y' / \sqrt{1 + (y')^2}$. The usual Euler-Lagrange equations are not easy to solve for this problem, it's easier to work with the equations you derived in homework,

$$\frac{\partial f}{\partial x} - \frac{d}{dx} \left[f - y' \frac{\partial f}{\partial y'} \right] = 0.$$

Hence,

$$\frac{d}{dx} \left[2\pi y \sqrt{1 + (y')^2} - \frac{2\pi y (y')^2}{\sqrt{1 + (y')^2}} \right] = 0$$

Dividing by 2π and making a common denominator,

$$\frac{d}{dx} \left[\frac{y}{\sqrt{1 + (y')^2}} \right] = 0 \qquad \Rightarrow \qquad \frac{y}{\sqrt{1 + (y')^2}} = k$$

where k is a constant with respect to x. Squaring the equation above yields

$$\frac{y^2}{1 + (\frac{dy}{dx})^2} = k^2 \qquad \Rightarrow \qquad y^2 - k^2 = k^2 (\frac{dy}{dx})^2$$

Solve for dx, integrate, assuming the given points are in the first quadrant,

$$x = \int dx = \int \frac{kdy}{\sqrt{y^2 - k^2}} = k \cosh^{-1}(\frac{y}{k}) + c$$

Hence,

$$y = k \cosh\left(\frac{x-c}{k}\right)$$

generates the surface of revolution of least area between two points. These shapes are called **Catenoids** they can be observed in the formation of soap bubble between rings. There is a vast literature on this subject and there are many cases to consider, I simply exhibit a simple solution. For a given pair of points it is not immediately obvious if there exists a solution to the Euler-Lagrange equations which fits the data. (see page 622 of Arfken).

13.4.3 Braichistochrone

Suppose a particle slides freely along some curve from (x_1, y_1) to $(x_2, y_2) = (0, 0)$ under the influence of gravity where we take y to be the vertical direction. What is the curve of quickest descent? Notice that if $x_1 = 0$ then the answer is easy to see, however, if $x_1 \neq 0$ then the question is not trivial. To solve this problem we must first offer a functional which accounts for the time of descent. Note that the speed v = ds/dt so we'd clearly like to minimize $J = \int_{(0,0)}^{(x_1,y_1)} \frac{ds}{v}$. Since the object is assumed to fall freely we may assume that energy is conserved in the motion hence

$$\frac{1}{2}mv^2 = mg(y - y_1) \qquad \Rightarrow \qquad v = \sqrt{2g(y_1 - y)}$$

As we've discussed in previous examples, $ds = \sqrt{1 + (y')^2} dt$ so we find

$$J[y] = \int_0^{x_1} \underbrace{\sqrt{\frac{1 + (y')^2}{2g(y_1 - y)}}}_{f(y, y', x)} dx$$

Notice that the modified Euler-Lagrange equations $\frac{\partial f}{\partial x} - \frac{d}{dx} \left[f - y' \frac{\partial f}{\partial y'} \right] = 0$ are convenient since $f_x = 0$. We calculate that

$$\frac{\partial f}{\partial y'} = \frac{1}{2\sqrt{\frac{1+(y')^2}{2g(y_1-y)}}} \frac{2y'}{2g(y_1-y)} = \frac{y'}{\sqrt{2g(y_1-y)(1+(y')^2)}}$$

Hence there should exist some constant $1/(k\sqrt{2g})$ such that

$$\sqrt{\frac{1+(y')^2}{2g(y_1-y)} - \frac{(y')^2}{\sqrt{2g(y_1-y)(1+(y')^2)}}} = \frac{1}{k\sqrt{2g}}$$

It follows that,

$$\frac{1}{\sqrt{(y_1 - y)(1 + (y')^2)}} = \frac{1}{k} \qquad \Rightarrow \qquad \left(y_1 - y\right) \left(1 + \left(\frac{dy}{dx}\right)^2\right) = k^2$$

We need to solve for dy/dx,

$$(y_1 - y)\left(\frac{dy}{dx}\right)^2 = k^2 - y_1 + y \qquad \Rightarrow \qquad \left(\frac{dy}{dx}\right)^2 = \frac{y + k^2 - y_1}{y_1 - y}$$

Or, relabeling constants $a = y_1$ and $b = k^2 - y_1$ and we must solve

$$\frac{dy}{dx} = \pm \sqrt{\frac{b+y}{a-y}} \qquad \Rightarrow \qquad x = \pm \int \sqrt{\frac{a-y}{b+y}} \, dy$$

The integral is not trivial. It turns out that the solution is a cycloid (Arfken p. 624):

$$x = \frac{a+b}{2}\left(\theta + \sin(\theta)\right) - d \qquad y = \frac{a+b}{2}\left(1 - \cos(\theta)\right) - b$$

This is the curve that is traced out by a point on a wheel as it travels. If you take this solution and calculate $J[y_{cycloid}]$ you can show the time of descent is simply

$$T=\frac{\pi}{2}\sqrt{\frac{y_1}{2g}}$$

if the mass begins to descend from (x_2, y_2) . But, this point has no connection with (x_1, y_1) except that they both reside on the same cycloid. It follows that the period of a pendulum that follows a cycloidal path is indpendent of the starting point on the path. This is not true for a circular pendulum in general, we need the small angle approximation to derive simple harmonic motion. It turns out that it is possible to make a pendulum follow a cycloidal path if you let the string be guided by a frame which is also cycloidal. The neat thing is that even as it loses energy it still follows a cycloidal path and hence has the same period. The "Brachistochrone" problem was posed by Johann Bernoulli in 1696 and it actually predates the variational calculus of Lagrange by some 50 or so years. This problem and ones like it are what eventually prompted Lagrange and Euler to systematically develop the subject. Apparently Galileo also studied this problem however lacked the mathematics to crack it.

13.5 Euler-Lagrange equations for several dependent variables

We still consider problems with just one independent parameter underlying everything. For problems of classical mechanics this is almost always time t. In anticipation of that application we choose to use the usual physics notation in the section. We suppose that our functional depends on functions y_1, y_2, \ldots, y_n of time t along with their time derivatives $\dot{y}_1, \dot{y}_2, \ldots, \dot{y}_n$. We again suppose the functional of interest is an integral of a **Lagrangian** function f from time t_1 to time t_2 ,

$$J[(y_i)] = \int_{t_1}^{t_2} f(y_i, \dot{y}_i, t) \, dt$$

here we use (y_i) as shorthand for (y_1, y_2, \ldots, y_n) and (\dot{y}_i) as shorthand for $(\dot{y}_1, \dot{y}_2, \ldots, \dot{y}_n)$. We suppose that *n*-conditions are given for each of the endpoints in this problem; $y_i(t_1) = y_{i1}$ and $y_i(t_2) = y_{i2}$. Moreover, we define \mathcal{F}_o to be the set of paths from \mathbb{R} to \mathbb{R}^n subject to the conditions just stated. We now set out to find necessary conditions on a proposed solution to the extreme value problem for the functional J above. As before let's assume that an extremal solution $y^* \in \mathcal{F}_o$ exists. Moreover, imagine varying the solution by some variational function $\eta = (\eta_i)$ which has $\eta(t_1) = (0, 0, \ldots, 0)$ and $\eta(t_2) = (0, 0, \ldots, 0)$. Consequently the family of paths defined below are all in \mathcal{F}_o ,

$$y(t,\alpha) = y^*(t) + \alpha \eta(t)$$

Thus $y(t,0) = y^*$. In terms of component functions we have that

$$y_i(t,\alpha) = y_i^*(t) + \alpha \eta_i(t)$$

You can identify that $\delta y_i = y_i(t, \alpha) - y_i^*(t) = \alpha \eta_i(t)$. Since y^* is an extreme solution we should expect that $\left(\frac{\partial J}{\partial \alpha}\right)_{\alpha=0} = 0$. Differentiate the functional with respect to α and make use of the chain rule for f which is a function of some 2n + 1 variables,

$$\frac{\partial J(\alpha)}{\partial \alpha} = \frac{\partial}{\partial \alpha} \left[\int_{t_1}^{t_2} f(y_i(t,\alpha), \dot{y}_i(t,\alpha), t) dt \right] \\
= \int_{t_1}^{t_2} \sum_{j=1}^n \left(\frac{\partial f}{\partial y_j} \frac{\partial y_j}{\partial \alpha} + \frac{\partial f}{\partial \dot{y}_j} \frac{\partial \dot{y}_j}{\partial \alpha} \right) dt \\
= \int_{t_1}^{t_2} \sum_{j=1}^n \left(\frac{\partial f}{\partial y_j} \eta_j + \frac{\partial f}{\partial \dot{y}_j} \frac{d\eta_j}{dt} \right) dt \qquad (13.4) \\
= \sum_{j=1}^n \frac{\partial f}{\partial \dot{y}_j} \eta \Big|_{t_1}^{t_2} + \int_{t_1}^{t_2} \sum_{j=1}^n \left(\frac{\partial f}{\partial y_j} - \frac{d}{dt} \frac{\partial f}{\partial \dot{y}_j} \right) \eta_j dt$$

Since $\eta(t_1) = \eta(t_2) = 0$ the first term vanishes. Moreover, since we may repeat this calculation for all possible variations about the optimal solution y^* it follows that we obtain a set of Euler-Lagrange equations for each component function of the solution:

$$\frac{\partial f}{\partial y_j} - \frac{d}{dt} \left[\frac{\partial f}{\partial \dot{y}_j} \right] = 0 \quad j = 1, 2, \dots n \quad \text{Euler-Lagrange Eqns. for} \quad J[(y_i)] = \int_{t_1}^{t_2} f(y_i, \dot{y}_i, t) \, dt$$

Often we simply use $y_1 = x$, $y_2 = y$ and $y_3 = z$ which denote the position of particle or perhaps just the component functions of a path which gives the geodesic on some surface. In either case we should have 3 sets of Euler-Lagrange equations, one for each coordinate. We will also use non-Cartesian coordinates to describe certain Lagrangians. We develop many useful results for set-up of Lagrangians in non-Cartesian coordinates in the next section.

13.5.1 free particle Lagrangian

For a particle of mass m the kinetic energy K is given in terms of the time derivatives of the coordinate functions x, y, z as follows:

$$K = \frac{m}{2} \left(\dot{x}^2 + \dot{y}^2 + \dot{z}^2 \right)$$

Construct a functional by integrating the kinetic energy over time t,

$$S = \int_{t_1}^{t_2} \frac{m}{2} \left(\dot{x}^2 + \dot{y}^2 + \dot{z}^2 \right) dt$$

The Euler-Lagrange equations for this functional are

$$\frac{\partial K}{\partial x} = \frac{d}{dt} \left[\frac{\partial K}{\partial \dot{x}} \right] \qquad \frac{\partial K}{\partial y} = \frac{d}{dt} \left[\frac{\partial K}{\partial \dot{y}} \right] \qquad \frac{\partial K}{\partial z} = \frac{d}{dt} \left[\frac{\partial K}{\partial \dot{z}} \right]$$

Since $\frac{\partial K}{\partial \dot{x}} = m\dot{x}$, $\frac{\partial K}{\partial \dot{y}} = m\dot{y}$ and $\frac{\partial K}{\partial \dot{z}} = m\dot{z}$ it follows that

 $0 = m\ddot{x} \qquad 0 = m\ddot{y} \qquad 0 = m\ddot{z}.$

You should recognize these as Newton's equation for a particle with no force applied. The solution is $(x(t), y(t), z(t)) = (x_o + tv_x, y_o + tv_y, z_o + tv_z)$ which is uniform rectilinear motion at constant velocity (v_x, v_y, v_z) . The solution to Newton's equation minimizes the integral of the Kinetic energy. Generally the quantity S is called the **action** and Hamilton's Principle states that the laws of physics all arise from minimizing the action of the physical phenomena. We'll return to this discussion in a later section.

13.5.2 geodesics in \mathbb{R}^3

A **geodesic** is the path of minimal length between a pair of points on some manifold. Note we already proved that geodesics in the plane are just lines. In general, for \mathbb{R}^3 , the square of the infinitesimal arclength element is $ds^2 = dx^2 + dy^2 + dz^2$. The arclength integral from p = 0 to $q = (q_x, q_y, q_z)$ in \mathbb{R}^3 is most naturally given from the parametric viewpoint:

$$S = \int_0^1 \sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2} \, dt$$

We assume (x(0), y(0), z(0)) = (0, 0, 0) and (x(1), y(1), z(1)) = q and it should be clear that the integral above calculates the arclength. The Euler-Lagrange equations for x, y, z are

$$\frac{d}{dt} \left[\frac{\dot{x}}{\sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}} \right] = 0, \qquad \frac{d}{dt} \left[\frac{\dot{y}}{\sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}} \right] = 0, \qquad \frac{d}{dt} \left[\frac{\dot{z}}{\sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}} \right] = 0.$$

It follows that there exist constants, say a, b and c, such that

$$a = \frac{\dot{x}}{\sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}}, \qquad b = \frac{\dot{y}}{\sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}}, \qquad c = \frac{\dot{z}}{\sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}}.$$

These equations are said to be **coupled** since each involves derivatives of the others. We usually need a way to uncouple the equations if we are to be successful in solving the system. We can calculate, and equate each with the constant 1:

$$1 = \frac{\dot{x}}{a\sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}} = \frac{\dot{y}}{b\sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}} = \frac{\dot{z}}{c\sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}}$$

But, multiplying by the denominator reveals an interesting identity

$$\sqrt{\dot{x}^2 + \dot{y}^2 + \dot{z}^2} = \frac{\dot{x}}{a} = \frac{\dot{y}}{b} = \frac{\dot{z}}{c}$$

The solution has the form, $x(t) = tq_x$, $y(t) = tq_y$ and $z(t) = tq_z$. Therefore,

$$(x(t), y(t), z(t)) = t(q_x, q_y, q_z) = tq.$$

for $0 \le t \le 1$. These are the parametric equations for the line segment from the origin to q.

13.6 the Euclidean metric

The square root in the functional of the last subsection certainly complicated the calculation. It is intuitively clear that if we add up squared line elements ds^2 to give a minimum then that ought to correspond to the minimum for the sum of the positive square roots ds of those elements. Let's check if my conjecture works for \mathbb{R}^3 :

$$S = \int_0^1 (\underbrace{\dot{x}^2 + \dot{y}^2 + \dot{z}^2}_{f(x,y,z,\dot{x},\dot{y},\dot{z})}) dt$$

This gives us the Euler Lagrange equations below:

$$\ddot{x} = 0, \qquad \ddot{y} = 0, \qquad \ddot{z} = 0$$

The solution of these equations is clearly a line. In this formalism the equations were uncoupled from the outset.
Definition 13.6.1.

The Euclidean metric is $ds^2 = dx^2 + dy^2 + dz^2$. Generally, for orthogonal curvelinear coordinates u, v, w we calculate $ds^2 = \frac{1}{||\nabla u||^2} du^2 + \frac{1}{||\nabla v||^2} dv^2 + \frac{1}{||\nabla w||^2} dw^2$. We use this as a guide for constructing functionals which calculate arclength or speed

The beauty of the metric is that it allows us to calculate in other coordinates, consider

$$x = r\cos(\theta)$$
 $y = r\sin(\theta)$

For which we have implicit inverse coordinate transformations $r^2 = x^2 + y^2$ and $\theta = \tan^{-1}(y/x)$. From these inverse formulas we calculate:

$$\nabla r = \langle x/r, y/r \rangle$$
 $\nabla \theta = \langle -y/r^2, x/r^2 \rangle$

Thus, $||\nabla r|| = 1$ whereas $||\nabla \theta|| = 1/r$. We find that the metric in polar coordinates takes the form:

$$ds^2 = dr^2 + r^2 d\theta^2$$

Physicists and engineers tend to like to think of these as arising from calculating the length of infinitesimal displacements in the r or θ directions. Generically, for u, v, w coordinates

$$dl_u = \frac{1}{||\nabla u||} du \qquad dl_v = \frac{1}{||\nabla v||} dv \qquad dl_w = \frac{1}{||\nabla w||} du$$

and $ds^2 = dl_u^2 + dl_v^2 + dl_w^2$. So in that notation we just found $dl_r = dr$ and $dl_\theta = rd\theta$. Notice then that cylindircal coordinates have the metric,

$$ds^2 = dr^2 + r^2 d\theta^2 + dz^2.$$

For spherical coordinates $x = r \cos(\phi) \sin(\theta)$, $y = r \sin(\phi) \sin(\theta)$ and $z = r \cos(\theta)$ (here $0 \le \phi \le 2\pi$ and $0 \le \theta \le \pi$, physics notation). Calculation of the metric follows from the line elements,

$$dl_r = dr$$
 $dl_\phi = r\sin(\theta)d\phi$ $dl_\theta = rd\theta$

Thus,

$$ds^{2} = dr^{2} + r^{2}\sin^{2}(\theta)d\phi^{2} + r^{2}d\theta^{2}.$$

We now have all the tools we need for examples in spherical or cylindrical coordinates. What about other cases? In general, given some *p*-manifold in \mathbb{R}^n how does one find the metric on that manifold? If we are to follow the approach of this section we'll need to find coordinates on \mathbb{R}^n such that the manifold *S* is described by setting all but *p* of the coordinates to a constant. For example, in \mathbb{R}^4 we have generalized cylindrical coordinates (r, ϕ, z, t) defined implicitly by the equations below

$$x = r\cos(\phi),$$
 $y = r\sin(\phi),$ $z = z,$ $t = t$

On the hyper-cylinder r = R we have the metric $ds^2 = R^2 d\theta^2 + dz^2 + dw^2$. There are mathematicians/physicists whose careers are founded upon the discovery of a metric for some manifold. This is generally a difficult task.

13.7 geodesics

A geodesic is a path of smallest distance on some manifold. In general relativity, it turns out that the solutions to Eistein's field equations are geodesics in 4-dimensional curved spacetime. Particles that fall freely are following geodesics, for example projectiles or planets in the absense of other frictional/non-gravitational forces. We don't follow a geodesic in our daily life because the earth pushes back up with a normal force. Also, do be honest, the idea of length in general relativity is a bit more abstract that the geometric length studied in this section. The metric of general relativity is non-Euclidean. General relativity is based on semi-Riemannian geometry whereas this section is all Riemannian geometry. The metric in Riemannian geometry is positive definite. The metric in semi-Riemannian geometry can be written as a quadratic form with both positive and negative eigenvalues. In any event, if you want to know more I know some books you might like.

13.7.1 geodesic on cylinder

The equation of a cylinder of radius R is most easily framed in cylindrical coordinates (r, θ, z) ; the equation is merely r = R hence the metric reads

$$ds^2 = R^2 d\theta^2 + dz^2$$

Therefore, we ought to minimize the following functional in order to locate the parametric equations of a geodesic on the cylinder: note $ds^2 = \left(R^2 \frac{d\theta^2}{dt^2} + \frac{dz^2}{dt^2}\right) dt^2$ thus:

$$S = \int (R^2 \dot{\theta}^2 + \dot{z}^2) \ dt$$

Euler-Lagrange equations for the dependent variables θ and z are simply:

$$\ddot{\theta} = 0 \qquad \ddot{z} = 0.$$

We can integrate twice to find solutions

$$\theta(t) = \theta_o + At$$
 $z(t) = z_o + Bt$

Therefore, the geodesic on a cylinder is simply the line connecting two points in the plane which is curved to assemble the cylinder. Simple cases that are easy to understand:

- 1. Geodesic from $(R \cos(\theta_o), R \sin(\theta_o), z_1)$ to $(R \cos(\theta_o), R \sin(\theta_o), z_2)$ is parametrized by $\theta(t) = \theta_o$ and $z(t) = z_1 + t(z_2 z_1)$ for $0 \le t \le 1$. Technically, there is some ambiguity here since I never declared over what range the t is to range. Could pick other intervals, we could use z at the parameter is we wished then $\theta(z) = \theta_o$ and z = z for $z_1 \le z_2$
- 2. Geodesic from $(R\cos(\theta_1), R\sin(\theta_1), z_o)$ to $(R\cos(\theta_2), R\sin(\theta_2), z_o)$ is parametrized by $\theta(t) = \theta_1 + t(\theta_2 \theta_1)$ and $z(t) = z_o$ for $0 \le t \le 1$.
- 3. Geodesic from $(R\cos(\theta_1), R\sin(\theta_1), z_1)$ to $(R\cos(\theta_2), R\sin(\theta_2), z_2)$ is parametrized by

$$\theta(t) = \theta_1 + t(\theta_2 - \theta_1)$$
 $z(t) = z_1 + t(z_2 - z_1)$

You can eliminate t and find the equation $z = \frac{z_2 - z_1}{\theta_2 - \theta_1} (\theta - \theta_1)$ which again just goes to show you this is a line in the curved coordinates.

13.7.2 geodesic on sphere

The equation of a sphere of radius R is most easily framed in spherical coordinates (r, ϕ, θ) ; the equation is merely r = R hence the metric reads

$$ds^2 = R^2 \sin^2(\theta) d\phi^2 + R^2 d\theta^2.$$

Therefore, we ought to minimize the following functional in order to locate the parametric equations of a geodesic on the sphere: note $ds^2 = \left(R^2 \sin^2(\theta) \frac{d\phi^2}{dt^2} + R^2 \frac{d\theta^2}{dt^2}\right) dt^2$ thus:

$$S = \int (\underbrace{R^2 \sin^2(\theta) \dot{\phi}^2 + R^2 \dot{\theta}^2}_{f(\theta, \phi, \dot{\theta}, \dot{\phi})}) dt$$

Euler-Lagrange equations for the dependent variables ϕ and θ are simply: $f_{\theta} = \frac{d}{dt}(f_{\dot{\theta}})$ and $f_{\phi} = \frac{d}{dt}(f_{\dot{\phi}})$ which yield:

$$2R^2\sin(\theta)\cos(\theta)\dot{\phi}^2 = \frac{d}{dt}(2R^2\dot{\theta}) \qquad 0 = \frac{d}{dt}\left(2R^2\sin^2(\theta)\dot{\phi}\right).$$

We find a **constant of motion** $L = 2R^2 \sin^2(\theta) \dot{\phi}$ inserting this in the equation for the azmuthial angle θ yields:

$$2R^2\sin(\theta)\cos(\theta)\dot{\phi}^2 = \frac{d}{dt}(2R^2\dot{\theta}) \qquad 0 = \frac{d}{dt}\left(2R^2\sin^2(\theta)\dot{\phi}\right)$$

If you can solve these and demonstrate through some reasonable argument that the solutions are great circles then I will give you points. I have some solutions but nothing looks too pretty.

13.8 Lagrangian mechanics

13.8.1 basic equations of classical mechanics summarized

Classical mechanics is the study of massive particles at relatively low velocities. Let me refresh your memory about the basics equations of Newtonian mechanics. Our goal in this section will be to rephrase Newtonian mechanics in the variational langauge and then to solve problems with the Euler-Lagrange equations. Newton's equations tell us how a particle of mass m evolves through time according to the net-force impressed on m. In particular,

$$m\frac{d^2\vec{r}}{dt^2} = \vec{F}$$

If m is not constant then you may recall that it is better to use momentum $\vec{P} = m\vec{v} = m\frac{d\vec{r}}{dt}$ to set-up Newton's 2nd Law:

$$\frac{d\vec{P}}{dt} = \vec{F}$$

In terms of components we have a system of differential equations with indpendent variable time t. If we use position as the dependent variable then Newton's 2nd Law gives three second order ODEs,

$$m\ddot{x} = F_x$$
 $m\ddot{y} = F_y$ $m\ddot{z} = F_z$

where $\vec{r} = (x, y, z)$ and the dots denote time-derivatives. Moreover, $\vec{F} = \langle F_x, F_y, F_z \rangle$ is the sum of the forces that act on m. In contrast, if you work with momentum then you would want to solve six first order ODEs,

$$\dot{P}_x = F_x$$
 $\dot{P}_y = F_y$ $\dot{P}_z = F_z$

and $P_x = m\dot{x}$, $P_y = m\dot{y}$ and $P_z = m\dot{z}$. These equations are easiest to solve when the force is not a function of velocity or time. In particular, if the force \vec{F} is conservative then there exists a potential energy function $U : \mathbb{R}^3 \to \mathbb{R}$ such that $\vec{F} = -\nabla U$. We can prove that in the case the force is conservative the total energy is conserved.

13.8.2 kinetic and potential energy, formulating the Lagrangian

Recall the kinetic energy is $T = \frac{1}{2}m||\vec{v}||^2$, in Cartesian coordinates this gives us the formula:

$$T = \frac{1}{2}m(\dot{x}^2 + \dot{y}^2 + \dot{z}^2).$$

If \vec{F} is a conservative force then it is independent of path so we may construct the potential energy function as follows:

$$U(\vec{r}) = -\int_{\mathcal{O}}^{\vec{r}} \vec{F} \cdot d\vec{r}$$

Here \mathcal{O} is the origin for the potential and we can prove that the potential energy constructed in this manner has $\vec{F} = -\nabla U$. We can prove that the total (mechanical) energy E = T + U for a conservative system is a constant; dE/dt = 0. Hopefully these comments are at least vaguely familiar from some physics course in your distant memory. If not relax, calculationally this chapter is self-contained, read onward.

We already calculated that if we use T as the Lagrangian then the Euler-Lagrange equations produce Newton's equations in the case that the force is zero (see 13.5.1). Suppose that we define the Lagrangian to be L = T - U for a system governed by a conservative force with potential energy function U. We seek to prove the Euler-Lagrange equations are precisely Newton's equations for this conservative system¹ Generically we have a Lagrangian of the form

$$L(x, y, z, \dot{x}, \dot{y}, \dot{z}) = \frac{1}{2}m(\dot{x}^2 + \dot{y}^2 + \dot{z}^2) - U(x, y, z).$$

¹don't mistake this example as an admission that Lagrangian mechanics is limited to conservative systems. Quite the contrary, Lagrangian mechanics is actually more general than the orginal framework of Newton!

We wish to find extrema for the functional $S = \int L(t) dt$. This yields three sets of Euler-Lagrange equations, one for each dependent variable x, y or z

$$\frac{d}{dt} \begin{bmatrix} \frac{\partial L}{\partial \dot{x}} \end{bmatrix} = \frac{\partial L}{\partial x} \qquad \frac{d}{dt} \begin{bmatrix} \frac{\partial L}{\partial \dot{y}} \end{bmatrix} = \frac{\partial L}{\partial y} \qquad \frac{d}{dt} \begin{bmatrix} \frac{\partial L}{\partial \dot{z}} \end{bmatrix} = \frac{\partial L}{\partial z}.$$

Note that $\frac{\partial L}{\partial \dot{x}} = m\dot{x}$, $\frac{\partial L}{\partial \dot{y}} = m\dot{y}$ and $\frac{\partial L}{\partial \dot{z}} = m\dot{z}$. Also note that $\frac{\partial L}{\partial x} = -\frac{\partial U}{\partial x} = F_x$, $\frac{\partial L}{\partial y} = -\frac{\partial U}{\partial y} = F_y$ and $\frac{\partial L}{\partial z} = -\frac{\partial U}{\partial z} = F_z$. It follows that

$$m\ddot{x} = F_x \qquad m\ddot{y} = F_y \qquad m\ddot{z} = F_z.$$

Of course this is precisely $m\vec{a} = \vec{F}$ for a net-force $\vec{F} = \langle F_x, F_y, F_z \rangle$. We have shown that **Hamilton's principle** reproduces Newton's Second Law for conservative forces. Let me take a moment to state it.

Definition 13.8.1. Hamilton's Principle:

If a physical system has generalized coordinates q_j with velocities \dot{q}_j and Lagrangian L = T - U then the solutions of physics will minimize the action S defined below:

$$S = \int_{t_1}^{t_2} L(q_j, \dot{q_j}, t) \, dt$$

Mathematically, this means the variation $\delta S = 0$ for physical trajectories.

This is a necessary condition for solutions of the equations of physics. Sufficient conditions are known, you can look in any good variational calculus text. You'll find analogues to the second derivative test for variational differentiation. As far as I can tell physicists don't care about this logical gap, probably because the solutions to the Euler-Lagrange equations are the ones for which they are looking.

13.8.3 easy physics examples

Now, you might just see this whole exercise as some needless multiplication of notation and formalism. After all, I just told you we just get Newton's equations back from the Euler-Lagrange equations. To my taste the impressive thing about Lagrangian mechanics is that you get to start the problem with energy. Moreover, the Lagrangian formalism handles non-Cartesian coordinates with ease. If you search your memory from classical mechanics you'll notice that you either do constant acceleration, circular motion or motion along a line. What if you had a particle constrained to move in some frictionless ellipsoidal bowl. Or what if you had a pendulum hanging off another pendulum? How would you even write Newtons' equations for such systems? In contrast, the problem is at least easy to set-up in the Lagrangian approach. Of course, solutions may be less easy to obtain.

Example 13.8.2. Projectile motion: take z as the vertical direction and suppose a bullet is fired with initial velocity $v_o = \langle v_{ox}, v_{oy}, v_{oz} \rangle$. The potential energy due to gravity is simply U = mgz and kinetic energy is given by $T = \frac{1}{2}m(\dot{x}^2 + \dot{y}^2 + \dot{z}^2)$. Thus,

$$L = \frac{1}{2}m(\dot{x}^2 + \dot{y}^2 + \dot{z}^2) - mgz$$

Euler-Lagrange equations are simply:

$$\frac{d}{dt}\left[m\dot{x}\right] = 0 \qquad \frac{d}{dt}\left[m\dot{y}\right] = 0 \qquad \frac{d}{dt}\left[m\dot{z}\right] = \frac{\partial}{\partial z}(-mgz) = -mg$$

Integrating twice and applying initial conditions gives us the (possibly familiar) equations

$$x(t) = x_o + v_{ox}t,$$
 $y(t) = y_o + v_{oy}t,$ $z(t) = z_o + v_{oz}t - \frac{1}{2}gt^2.$

Example 13.8.3. Simple Pendulum: let θ denote angle measured off the vertical for a simple pendulum of mass m and length l. Trigonmetry tells us that

$$x = l\sin(\theta)$$
 $y = l\cos(\theta)$ \Rightarrow $\dot{x} = l\cos(\theta)\dot{\theta}$ $y = -l\sin(\theta)\dot{\theta}$

Thus $T = \frac{1}{2}m(\dot{x}^2 + \dot{y}^2) = \frac{1}{2}ml^2\dot{\theta}^2$. Also, the potential energy due to gravity is $U = -mgl\cos(\theta)$ which gives us

$$L = \frac{1}{2}ml^2\dot{\theta}^2 + mgl\cos(\theta)$$

Then, the Euler-Lagrange equation in θ is simply:

$$\frac{d}{dt} \left[\frac{\partial L}{\partial \dot{\theta}} \right] = \frac{\partial L}{\partial \theta} \qquad \Rightarrow \qquad \frac{d}{dt} (ml^2 \dot{\theta}) = -mgl\sin(\theta) \qquad \Rightarrow \qquad \ddot{\theta} + \frac{g}{l}\sin(\theta) = 0.$$

In the small angle approximation, $\sin(\theta) = \theta$ then we have the solution $\theta(t) = \theta_o \cos(\omega t + \phi_o)$ for angular frequency $\omega = \sqrt{g/l}$

Chapter 14

leftover manifold theory

In this short chapter I collect a few discussions which extend constructions which we have only considered for low-dimensional cases. In addition, I include a few other calculations which I saw fit to omit from the 2013 notes as they did not fit the narrative this semester. I leave them here for the interested reader, you don't need to print these for the 2013 offering of Advanced Calculus.

I intend to give you a fairly accurate account of the modern definition of a manifold¹. In a nutshell, a manifold is simply a set which allows for calculus locally. Alternatively, many people say that a manifold is simply a set which is locally "flat", or it locally "looks like \mathbb{R}^{n} ". This covers most of the objects you've seen in calculus III. However, the technical details most closely resemble the parametric view-point.

¹the definitions we follow are primarily taken from Burns and Gidea's *Differential Geometry and Topology With a View to Dynamical Systems*, I like their notation, but you should understand this definition is known to many authors

14.1 manifold defined

The definition I offer here is given in terms of patches, you can also state it in terms of charts. We primarily used charts earlier in these notes.

Definition 14.1.1.

We define a **smooth manifold of dimension** m as follows: suppose we are given a set M, a collection of open subsets U_i of \mathbb{R}^m , and a collection of mappings $\phi_i : U_i \subseteq \mathbb{R}^m \to V_i \subseteq M$ which satisfies the following three criteria:

1. each map $\phi_i : U_i \to V_i$ is injective

2. if $V_i \cap V_j \neq \emptyset$ then there exists a smooth mapping

$$\theta_{ij}: \phi_i^{-1}(V_i \cap V_j) \to \phi_i^{-1}(V_i \cap V_j)$$

such that $\phi_j = \phi_i \circ \theta_{ij}$

3.
$$M = \bigcup_i \phi_i(U_i)$$

Moreover, we call the mappings ϕ_i the **local parametrizations** or **patches** of M and the space U_i is called the **parameter space**. The range V_i together with the inverse ϕ_i^{-1} is called a **coordinate chart** on M. The component functions of a chart (V, ϕ^{-1}) are usually denoted $\phi_i^{-1} = (x^1, x^2, \ldots, x^m)$ where $x^j : V \to \mathbb{R}$ for each $j = 1, 2, \ldots, m$.

We could add to this definition that i is taken from an *index set* \mathcal{I} (which could be an infinite set). The union given in criteria (3.) is called a **covering of** M. Most often, we deal with finitely covered manifolds. You may recall that there are infinitely many ways to parametrize the lines or surfaces we dealt with in calculus III. The story here is no different. It follows that when we consider classification of manifolds the definition we just offered is a bit lacking. We would also like to lump in all other possible compatible parametrizations. In short, the definition we gave says a manifold is a set together with an **atlas of compatible charts**. If we take that atlas and adjoin to it all possible compatible charts then we obtain the so-called **maximal atlas** which defines a **differentiable structure** on the set M. Many other authors define a manifold as a set together with a differentiable structure. That said, our less ambtious definition will do.

We should also note that $\theta_{ij} = \phi_i^{-1} \circ \phi_j$ hence $\theta_{ij}^{-1} = (\phi_i^{-1} \circ \phi_j)^{-1} = \phi_j^{-1} \circ \phi_i = \theta_{ji}$. The functions θ_{ij} are called the **transition functions** of \mathcal{M} . These explain how we change coordinates locally.

I now offer a few examples so you can appreciate how general this definition is, in contrast to the level-set definition we explored previously. We will recover those as examples of this more general definition later in this chapter.

Example 14.1.2. Let $M = \mathbb{R}^m$ and suppose $\phi : \mathbb{R}^m \to \mathbb{R}^m$ is the identity mapping ($\phi(u) = u$ for all $u \in \mathbb{R}^m$) defines the collection of paramterizations on M. In this case the collection is just one

mapping and $U = V = \mathbb{R}^m$, clearly ϕ is injective and V covers \mathbb{R}^m . The remaining overlap criteria is trivially satisfied since there is only one patch to consider.

Example 14.1.3. Let $U = \mathbb{R}^m$ and suppose $p_o \in \mathbb{R}^p$ then $\phi : U \to \mathbb{R}^p \times \mathbb{R}^m$ defined by $\phi(u) = p_o \times u$ makes $\phi(U) = M$ an m-dimensional manifold. Again we have no overlap and the covering criteria is clearly satisfied so that leaves injectivity of ϕ . Note $\phi(u) = \phi(u')$ implies $p_o \times u = p_o \times u'$ hence u = u'.

Example 14.1.4. Suppose V is an m-dimensional vector space over \mathbb{R} with basis $\beta = \{e_i\}_{i=1}^n$. Define $\phi : \mathbb{R}^m \to V$ as follows, for each $u = (u^1, u^2, \dots, u^m) \in \mathbb{R}^m$

$$\phi(u) = u^1 e_1 + u^2 e_2 + \dots + u^m e_m.$$

Injectivity of the map follows from the linear independence of β . The overlap criteria is trivially satisfied. Moreover, $\operatorname{span}(\beta) = V$ thus we know that $\phi(\mathbb{R}^m) = V$ which means the vector space is covered. All together we find V is an m-dimensional manifold. Notice that the inverse of ϕ of the coordinate mapping Φ_{β} from out earlier work and so we find the coordinate chart is a coordinate mapping in the context of a vector space. Of course, this is a very special case since most manifolds are not spanned by a basis.

You might notice that there seems to be little contact with criteria two in the examples above. These are rather special cases in truth. When we deal with curved manifolds we cannot avoid it any longer. I should mention we can (and often do) consider other coordinate systems on \mathbb{R}^m . Moreover, in the context of a vector space we also have infinitely many coordinate systems to use. We will have to analyze compatibility of those new coordinates as we adjoin them. For the vector space it's simple to see the transition maps are smooth since they'll just be invertible linear mappings. On the other hand, it is more work to show new curvelinear coordinates on \mathbb{R}^m are compatible with Cartesian coordinates. The inverse function theorem would likely be needed.

Example 14.1.5. Let $M = \{(\cos(\theta), \sin(\theta)) \mid \theta \in [0, 2\pi)\}$. Define $\phi_1(u) = (\cos(u)\sin(u))$ for all $u \in (0, 3\pi/2) = U_1$. Also, define $\phi_2(v) = (\cos(v)\sin(v))$ for all $v \in (\pi, 2\pi) = U_2$. Injectivity follows from the basic properties of sine and cosine and covering follows from the obvious geometry of these mappings. However, overlap we should check. Let $V_1 = \phi_1(U_1)$ and $V_2 = \phi_2(U_2)$. Note $V_1 \cap V_2 = \{(\cos(\theta), \sin(\theta)) \mid \pi < \theta < 3\pi/2\}$. We need to find the formula for

$$\theta_{12}: \phi_2^{-1}(V_1 \cap V_2) \to \phi_1^{-1}(V_1 \cap V_2)$$

In this example, this means

$$\theta_{12}: (\pi, 3\pi/2) \to (\pi, 3\pi/2)$$

Example 14.1.6. Let's return to the vector space example. This time we want to allow for all possible coordinate systems. Once more suppose V is an m-dimensional vector space over \mathbb{R} . Note that for each basis $\beta = \{e_i\}_{i=1}^n$. Define $\phi_\beta : \mathbb{R}^m \to V$ as follows, for each $u = (u^1, u^2, \ldots, u^m) \in \mathbb{R}^m$

$$\phi_{\beta}(u) = u^1 e_1 + u^2 e_2 + \dots + u^m e_m$$

Suppose β, β' are bases for V which define local parametrizations $\phi_{\beta}, \phi_{\beta'}$ respective. The transition functions $\theta : \mathbb{R}^m \to \mathbb{R}^m$ are given by

$$\theta = \phi_{\beta}^{-1} \circ \phi_{\beta'}$$

Note θ is the composition of linear mappings and is therefore a linear mapping on \mathbb{R}^m . It follows that $\theta(x) = Px$ for some $M \in GL(m) = \{X \in \mathbb{R}^{m \times m} \mid det(X) \neq 0\}$. It follows that θ is a smooth mapping since each component function of θ is simply a linear combination of the variables in \mathbb{R}^m . Let's take a moment to connect with linear algebra notation. If $\theta = \phi_{\beta}^{-1} \circ \phi_{\beta'}$ then $\theta \circ \phi_{\beta'}^{-1} = \phi_{\beta}^{-1}$ hence $\theta \circ \Phi_{\beta'} = \Phi_{\beta}$ as we used $\Phi_{\beta} : V \to \mathbb{R}^m$ as the coordinate chart in linear algebra and $\phi_{\beta}^{-1} = \Phi_{\beta}$. Thus, $\theta \circ \Phi_{\beta'}(v) = \Phi_{\beta}(v)$ implies $P[v]_{\beta'} = [v]_{\beta}$. This matrix P is the coordinate change matrix from linear algebra.

The contrast of Examples 14.1.3 and 14.1.6 stems in the allowed coordinate systems. In Example 14.1.3 we had just one coordinate system whereas in Example 14.1.6 we allowed inifinitely many. We could construct other manifolds over the set V. We could take all coordinate systems that are of a particular type. If $V = \mathbb{R}^m$ then it is often interesting to consider only those coordinate systems for which the Pythagorean theorem holds true, such coordinates have transition functions in the group of orthogonal transformations. Or, if $V = \mathbb{R}^4$ then we might want to consider only inertially related coordinates. Inertially related coordinates on \mathbb{R}^4 preserve the *interval* defined by the Minkowski product and the transition functions form a group of Lorentz transformations. In my opinion this is one nice feature of saving the maximal atlas concept for the differentiable structure. Manifolds as we have defined them give us a natural mathematical context to restrict the choice of coordinates. From the viewpoint of physics, the maximal atlas contains many coordinate systems which are unnatural for physics. Of course, it is possible to take a given theory of physics and translate physically natural equations into less natural equations in non-standard coordinates. For example, look up how Newton's simple equation $\vec{F} = m\vec{a}$ is translated into rotating coordinate systems.

14.1.1 embedded manifolds

The manifolds in Examples 14.1.2, 14.1.3 and 14.1.5 were all defined as subsets of euclidean space. Generally, if a manifold is a subset of Euclidean space \mathbb{R}^n then we say the manifold is **embedded** in \mathbb{R}^n . In contrast, Examples 14.1.4 and 14.1.6 are called **abstract manifolds** since the points in the manifold were not found in Euclidean space². If you are only interested in embedded manifolds³ then the definition is less abstract:

Definition 14.1.7. embedded manifold.

We say \mathcal{M} is a **smooth embedded manifold of dimension** m iff we are given a set $\mathcal{M} \subseteq \mathbb{R}^n$ such that at each $p \in \mathcal{M}$ there is a set an open subsets U_i of \mathbb{R}^m and open subsets V_i of \mathcal{M} containing p such that the mapping $\phi_i : U_i \subseteq \mathbb{R}^m \to V_i \subseteq \mathcal{M}$ satisfies the following criteria:

- 1. each map $\phi_i: U_i \to V_i$ is injective
- 2. each map $\phi_i: U_i \to V_i$ is smooth
- 3. each map $\phi_i^{-1}: V_i \to U_i$ is continuous
- 4. the differential $d\phi_x$ has rank m for each $x \in U_i$.

You may identify that this definition more closely resembles the parametrized objects from your multivariate calculus course. There are two key differences with this definition:

- 1. the set V_i is assumed to be "open in \mathcal{M} " where $\mathcal{M} \subseteq \mathbb{R}^n$. This means that for each point $p \in V_i$ there exists and open *n*-ball $B \subset \mathbb{R}^n$ such that $B \cap \mathcal{M}$ contains *p*. This is called the **subspace topology** for \mathcal{M} induced from the euclidean topology of \mathbb{R}^n . No topological assumptions were given for V_i in the abstract definition. In practice, for the abstract case, we use the charts to lift open sets to \mathcal{M} , we need not assume any topology on \mathcal{M} since the machinery of the manifold allows us to build our own. However, this can lead to some pathological cases so those cases are usually ruled out by stating that our manifold is *Hausdorff* and the covering has a countable basis of open sets⁴. I will leave it at that since this is not a topology course.
- 2. the condition that the inverse of the local parametrization be continuous and ϕ_i be smooth were not present in the abstract definition. Instead, we assumed smoothness of the transition functions.

One can prove that the embedded manifold of Definition 14.1.7 is simply a subcase of the abstract manifold given by Definition 14.1.1. See Munkres Theorem 24.1 where he shows the transition

 $^{^{2}}$ a vector space could be euclidean space, but it could also be a set of polynomials, operators or a lot of other rather abstract objects.

 $^{^{3}}$ The defition I gave for embedded manifold here is mostly borrowed from Munkres' excellent text *Analysis on Manifolds* where he primarily analyzes embedded manifolds

⁴see Burns and Gidea page 11 in Differential Geometry and Topology With a View to Dynamical Systems

functions of an embedded manifold are smooth. In fact, his theorem is given for the case of a manifold with boundary which adds a few complications to the discussion. We'll discuss manifolds with boundary at the conclusion of this chapter.

Example 14.1.8. A line is a one dimensional manifold with a global coordinate patch:

$$\phi(t) = \vec{r}_o + t\vec{v}$$

for all $t \in \mathbb{R}$. We can think of this as the mapping which takes the real line and glues it in \mathbb{R}^n along some line which points in the direction \vec{v} and the new origin is at \vec{r}_o . In this case $\phi : \mathbb{R} \to \mathbb{R}^n$ and $d\phi_t$ has matrix \vec{v} which has rank one iff $\vec{v} \neq 0$.

Example 14.1.9. A plane is a two dimensional manifold with a global coordinate patch: suppose \vec{A}, \vec{B} are any two linearly independent vectors in the plane, and \vec{r}_o is a particular point in the plane,

$$\phi(u,v) = \vec{r}_o + u\vec{A} + v\vec{B}$$

for all $(u, v) \in \mathbb{R}^2$. This amounts to pasting a copy of the xy-plane in \mathbb{R}^n where we moved the origin to \vec{r}_o . If we just wanted a little paralellogram then we could restrict $(u, v) \in [0, 1] \times [0, 1]$, then we would envision that the unit-square has been pasted on to a paralellogram. Lengths and angles need not be maintained in this process of gluing. Note that the rank two condition for $d\phi$ says the derivative $\phi'(u, v) = \left[\frac{\partial \phi}{\partial u} \middle| \frac{\partial \phi}{\partial v}\right] = [\vec{A} \middle| \vec{B} \bigr|$ must have rank two. But, this amounts to insisting the vectors \vec{A}, \vec{B} are linearly independent. In the case of \mathbb{R}^3 this is conveniently tested by computation of $\vec{A} \times \vec{B}$ which happens to be the normal to the plane.

Example 14.1.10. A cone is almost a manifold, define

$$\phi(t, z) = (z\cos(t), z\sin(t), z)$$

for $t \in [0, 2\pi]$ and $z \ge 0$. What two problems does this potential coordinate patch $\phi : U \subseteq \mathbb{R}^2 \to \mathbb{R}^3$ suffer from? Can you find a modification of U which makes $\phi(U)$ a manifold (it could be a subset of what we call a cone)

The cone is not a manifold because of its point. Generally a space which is mostly like a manifold except at a finite, or discrete, number of *singular* points is called an **orbifold**. Recently, in the past decade or two, the orbifold has been used in string theory. The singularities can be used to fit various *charge* to fields through a mathematical process called the *blow-up*.

Example 14.1.11. Let $\phi(\theta, \gamma) = (\cos(\theta) \cosh(\gamma), \sin(\theta) \cosh(\gamma), \sinh(\gamma))$ for $\theta \in (0, 2\pi)$ and $\gamma \in \mathbb{R}$. This gives us a patch on the hyperboloid $x^2 + y^2 - z^2 = 1$

Example 14.1.12. Let $\phi(x, y, z, t) = (x, y, z, R\cos(t), R\sin(t))$ for $t \in (0, 2\pi)$ and $(x, y, z) \in \mathbb{R}^3$. This gives a copy of \mathbb{R}^3 inside \mathbb{R}^5 where a circle has been attached at each point of space in the two transverse directions of \mathbb{R}^5 . You could imagine that R is nearly zero so we cannot traverse these extra dimensions.

14.1. MANIFOLD DEFINED

Example 14.1.13. The following patch describes the **Mobius band** which is obtained by gluing a line segment to each point along a circle. However, these segments twist as you go around the circle and the structure of this manifold is less trivial than those we have thus far considered. The mobius band is an example of a manifold which is not oriented. This means that there is not a well-defined normal vectorfield over the surface. The patch is:

$$\phi(t,\lambda) = \left(\left[1 + \frac{1}{2}\lambda\cos(\frac{t}{2})\right]\cos(t), \ \left[1 + \frac{1}{2}\lambda\sin(\frac{t}{2})\right]\sin(t), \ \frac{1}{2}\lambda\sin(\frac{t}{2}) \right) \right)$$

for $0 \le t \le 2\pi$ and $-1 \le \lambda \le 1$. To understand this mapping better try studying the map evaluated at various values of t;

$$\phi(0,\lambda) = (1 + \lambda/2, 0, 0), \quad \phi(\pi,\lambda) = (-1, 0, \lambda/2), \quad \phi(2\pi,\lambda) = (1 - \lambda/2, 0, 0)$$

Notice the line segment parametrized by $\phi(0, \lambda)$ and $\phi(2\pi, \lambda)$ is the same set of points, however the orientation is reversed.

Example 14.1.14. A regular surface is a two-dimensional manifold embedded in \mathbb{R}^3 . We need $\phi_i : U_i \subseteq \mathbb{R}^2 \to S \subset \mathbb{R}^3$ such that, for each i, $d\phi_{i_{u,v}}$ has rank two for all $(u,v) \in U_i$. Moreover, in this case we can define a normal vector field $N(u,v) = \partial_u \phi \times \partial_v \phi$ and if we visualize these vectors as attached to the surface they will point in or out of the surface and provide the normal to the tangent plane at the point considered. The surface S is called **orientable** iff the normal vector field is non-vanishing on S.

14.1.2 diffeomorphism

At the outset of this study I emphasized that the purpose of a manifold was to give a natural languague for calculus on curved spaces. This definition begins to expose how this is accomplished.

Definition 14.1.15. smoothness on manifolds.

Suppose \mathcal{M} and \mathcal{N} are smooth manifolds and $f : \mathcal{M} \to \mathcal{N}$ is a function then we say f is **smooth** iff for each $p \in \mathcal{M}$ there exists local parametrizations $\phi_M : U_M \subseteq \mathbb{R}^m \to V_M \subseteq \mathcal{M}$ and $\phi_N : U_N \subseteq \mathbb{R}^n \to V_N \subseteq \mathcal{N}$ such that $p \in U_M$ and $\phi_N^{-1} \circ f \circ \phi_M$ is a smooth mapping from \mathbb{R}^m to \mathbb{R}^n . If $f : \mathcal{M} \to \mathcal{N}$ is a smooth bijection then we say f is a **diffeomorphism**. Moreover, if f is a diffeomorphism then we say \mathcal{M} and \mathcal{N} are **diffeomorphic**.

In other words, f is smooth iff its local coordinate representative is smooth. It suffices to check one representative since any other will be related by transition functions which are smooth: suppose we have patches $\bar{\phi}_M : \bar{U}_M \subseteq \mathbb{R}^m \to \bar{V}_M \subseteq \mathcal{M}$ and $\bar{\phi}_N : \bar{U}_N \subseteq \mathbb{R}^n \to \bar{V}_N \subseteq \mathcal{N}$ such that $p \in \bar{U}_M$,

$$\underbrace{\phi_N^{-1} \circ f \circ \phi_M}_{local \ rep. \ of \ f} = \underbrace{\phi_N^{-1} \circ \bar{\phi}_N}_{trans. \ fnct.} \circ \underbrace{\bar{\phi}_N^{-1} \circ f \circ \bar{\phi}_M}_{local \ rep. \ of \ f} \circ \underbrace{\bar{\phi}_M^{-1} \circ \phi_M}_{trans. \ fnct.}$$

follows from the chain rule for mappings. This formula shows that if f is smooth with respect to a particular pair of coordinates then its representative will likewise be smooth for any other pair of compatible patches.

Example 14.1.16. Recall in Example 14.1.3 we studied $\mathcal{M} = \{p_o\} \times \mathbb{R}^m$. Recall we have one parametrization $\phi : \mathbb{R}^m \to \mathcal{M}$ which is defined by $\phi(u) = p_o \times u$. Clearly $\phi^{-1}(p_o, u) = u$ for all $(p_o, u) \in \mathcal{M}$. Let \mathbb{R}^m have Cartesian coordinates so the identity map is the patch for \mathbb{R}^m . Consider the function $f = \phi : \mathbb{R}^m \to \mathcal{M}$, we have only the local coordinate representative $\phi^{-1} \circ f \circ Id$ to consider. Let $x \in \mathbb{R}^m$,

$$\phi^{-1} \circ f \circ Id = \phi^{-1} \circ \phi \circ Id = Id.$$

Hence, ϕ is a smooth bijection from \mathbb{R}^m to \mathcal{M} and we find \mathcal{M} is diffeomorphic to \mathbb{R}^m

The preceding example naturally generalizes to an arbitrary coordinate chart. Suppose \mathcal{M} is a manifold and $\phi^{-1}: V \to \mathbb{R}^m$ is a coordinate chart around the point $p \in \mathcal{M}$. We argue that ϕ^{-1} is a diffeomorphism. Once more take the Cartesian coordinate system for \mathbb{R}^m and suppose $\bar{\phi}: \bar{U} \to \bar{V}$ is a local parametrization with $p \in \bar{V}$. The local coordinate representative of ϕ^{-1} is simply the transition function since:

$$\bar{\phi} \circ \phi^{-1} \circ Id = \bar{\phi} \circ \phi^{-1}.$$

We find ϕ^{-1} is smooth on $V \cap \overline{V}$. It follows that ϕ^{-1} is a diffeomorphism since we know transition functions are smooth on a manifold. We arrive at the following characterization of a manifold: *a manifold is a space which is locally diffeomorphic to* \mathbb{R}^m .

However, just because a manifold is locally diffeomorphic to \mathbb{R}^m that does not mean it is actually diffeomorphic to \mathbb{R}^n . For example, it is a well-known fact that there does not exist a smooth bijection between the 2-sphere and \mathbb{R}^2 . The curvature of a manifold gives an obstruction to making such a mapping.

14.2 tangent space

Since a manifold is generally an abstract object we would like to give a definition for the tangent space which is not directly based on the traditional geometric meaning. On the other hand, we should expect that the definition which is given in the abstract reduces to the usual geometric meaning for the context of an embedded manifold. It turns out there are three common viewpoints.

- 1. a tangent vector is an *equivalence class* of curves.
- 2. a tangent vector is a *contravariant vector*.
- 3. a tangent vector is a *derivation*.

I will explain each case (except derivations, those are discussed earlier in Section 10.2) and we will find explicit isomorphisms between each language. We assume that \mathcal{M} is an *m*-dimensional smooth manifold throughout this section.

14.2.1 equivalence classes of curves

I essentially used case (1.) as the definition for the tangent space of a level-set. Suppose $\gamma : I \subseteq \mathbb{R} \to \mathcal{M}$ is a smooth curve with $\gamma(0) = p$. In this context, this means that all the local coordinate representatives of γ are smooth curves on \mathbb{R}^m ; that is, for every parametrization $\phi : U \subseteq \mathbb{R}^m \to V \subseteq \mathcal{M}$ containing $p \in V$ the mapping⁵ $\phi^{-1} \circ \gamma$ is a smooth mapping from \mathbb{R} to \mathbb{R}^m . Given the coordinate system defined by ϕ^{-1} , we define two smooth curves γ_1, γ_2 on \mathcal{M} with $\gamma_1(0) = \gamma_2(0) = p \in \mathcal{M}$ to be similar at p iff $(\phi^{-1} \circ \gamma_1)'(0) = (\phi^{-1} \circ \gamma_2)'(0)$. If smooth curves γ_1, γ_2 are similar at $p \in \mathcal{M}$ then we denote this by writing $\gamma_1 \sim_p \gamma_2$. We insist the curves be parametrized such that they reach the point of interest at the parameter t = 0, this is not a severe restriction since we can always reparametrize a given curve which reaches p at $t = t_o$ by replacing the parameter with $t - t_o$. Observe that \sim_p defines an equivalence relation on the set of smooth curves through p which reach p at t = 0 in their domain.

- (i) reflexive: $\gamma \sim_p \gamma$ iff $\gamma(0) = p$ and $(\phi^{-1} \circ \gamma)'(0) = (\phi^{-1} \circ \gamma)'(0)$. If γ is a smooth curve on \mathcal{M} with $\gamma(0) = p$ then clearly the reflexive property holds true.
- (ii) symmetric: Suppose $\gamma_1 \sim_p \gamma_2$ then $(\phi^{-1} \circ \gamma_1)'(0) = (\phi^{-1} \circ \gamma_2)'(0)$ hence $(\phi^{-1} \circ \gamma_2)'(0) = (\phi^{-1} \circ \gamma_1)'(0)$ and we find $\gamma_2 \sim_p \gamma_1$ thus \sim_p is a symmetric relation.
- (iii) transitive: if $\gamma_1 \sim_p \gamma_2$ and $\gamma_2 \sim_p \gamma_3$ then $(\phi^{-1} \circ \gamma_1)'(0) = (\phi^{-1} \circ \gamma_2)'(0)$ and $(\phi^{-1} \circ \gamma_2)'(0) = (\phi^{-1} \circ \gamma_3)'(0)$ thus $(\phi^{-1} \circ \gamma_1)'(0) = (\phi^{-1} \circ \gamma_3)'(0)$ which shows $\gamma_1 \sim_p \gamma_3$.

The equivalence classes of \sim_p partition the set of smooth curves with $\gamma(0) = p$. Each equivalence class $\tilde{\gamma} = \{\beta : I \subseteq \mathbb{R} \to \mathcal{M} \mid \beta \sim_p \gamma\}$ corresponds uniquely to a particular vector $(\phi^{-1} \circ \gamma)'(0)$ in \mathbb{R}^m . Conversely, given $v = (v^1, v^2, \ldots, v^m) \in \mathbb{R}^m$ we can write the equation for a line in \mathbb{R}^m with direction v and base-point $\phi^{-1}(p)$:

$$\vec{r}(t) = \phi^{-1}(p) + tv.$$

We compose \vec{r} with ϕ to obtain a smooth curve through $p \in \mathcal{M}$ which corresponds to the vector v. In invite the reader to verify that $\gamma = \phi \circ \vec{r}$ has

(1.)
$$\gamma(0) = p$$
 (2.) $(\phi^{-1} \circ \gamma)'(0) = v$.

Notice that the correspondence is made between a vector in \mathbb{R}^m and a whole family of curves. There are naturally many curves that share the same tangent vector to a given point.

Moreover, we show these equivalence classes are not coordinate dependent. Suppose $\gamma \sim_p \beta$ relative to the chart $\phi^{-1} : V \to U$, with $p \in V$. In particular, we suppose $\gamma(0) = \beta(0) = p$ and $(\phi^{-1} \circ \gamma)'(0) = (\phi^{-1} \circ \beta)'(0)$. Let $\bar{\phi}^{-1} : \bar{V} \to \bar{U}$, with $p \in \bar{V}$, we seek to show $\gamma \sim_p \beta$ relative to the chart $\bar{\phi}^{-1}$. Note that $\bar{\phi}^{-1} \circ \gamma = \bar{\phi}^{-1} \circ \phi \circ \phi^{-1} \circ \gamma$ hence, by the chain rule,

$$(\bar{\phi}^{-1} \circ \gamma)'(0) = (\bar{\phi}^{-1} \circ \phi)'(\phi^{-1}(p))(\phi^{-1} \circ \gamma)'(0)$$

⁵Note, we may have to restrict the domain of $\phi^{-1} \circ \gamma$ such that the image of γ falls inside V, keep in mind this poses no threat to the construction since we only consider the derivative of the curve at zero in the final construction. That said, keep in mind as we construct composites in this section we always suppose the domain of a curve includes some nbhd. of zero. We need this assumption in order that the derivative at zero exist.

Likewise, $(\bar{\phi}^{-1} \circ \beta)'(0) = (\bar{\phi}^{-1} \circ \phi)'(\phi^{-1}(p))(\phi^{-1} \circ \beta)'(0)$. Recognize that $(\bar{\phi}^{-1} \circ \phi)'(\phi^{-1}(p))$ is an invertible matrix since it is the derivative of the invertible transition functions, label $(\bar{\phi}^{-1} \circ \phi)'(\phi^{-1}(p)) = P$ to obtain:

$$(\bar{\phi}^{-1} \circ \gamma)'(0) = P(\phi^{-1} \circ \gamma)'(0)$$
 and $(\bar{\phi}^{-1} \circ \beta)'(0) = P(\phi^{-1} \circ \beta)'(0)$

the equality $(\bar{\phi}^{-1} \circ \gamma)'(0) = (\bar{\phi}^{-1} \circ \beta)'(0)$ follows and this shows that $\gamma \sim_p \beta$ relative to the $\bar{\phi}$ coordinate chart. We find that the equivalence classes of curves are independent of the coordinate system.

With the analysis above in mind we define addition and scalar multiplication of equivalence classes of curves as follows: given a coordinate chart $\phi^{-1}: V \to U$ with $p \in V$, equivalence classes $\tilde{\gamma}_1, \tilde{\gamma}_2$ at p and $c \in \mathbb{R}^m$, if $\tilde{\gamma}_1$ has $(\phi^{-1} \circ \gamma_1)'(0) = v_1$ in \mathbb{R}^m and $\tilde{\gamma}_2$ has $(\phi^{-1} \circ \gamma_2)'(0) = v_2$ in \mathbb{R}^m then we define

(i)
$$\tilde{\gamma}_1 + \tilde{\gamma}_2 = \tilde{\alpha}$$
 where $(\phi^{-1} \circ \alpha)'(0) = v_1 + v_2$

(ii)
$$c\tilde{\gamma_1} = \tilde{\beta}$$
 where $(\phi^{-1} \circ \beta)'(0) = cv_1$.

We know α and β exist because we can simply push the lines in \mathbb{R}^m based at $\phi^{-1}(p)$ with directions $v_1 + v_2$ and cv_1 up to \mathcal{M} to obtain the desired curve and hence the required equivalence class. Moreover, we know this construction is coordinate independent since the equivalence classes are indpendent of coordinates.

Definition 14.2.1.

Suppose \mathcal{M} is an *m*-dimensional smooth manifold. We define the **tangent space at** $p \in \mathcal{M}$ to be the set of \sim_p -equivalence classes of curves. In particular, denote:

$$curveT_p\mathcal{M} = \{\tilde{\gamma} \mid \gamma \text{ smooth and } \gamma(0) = p\}$$

Keep in mind this is just one of three equivalent definitions which are commonly implemented.

14.2.2 contravariant vectors

If $(\bar{\phi}^{-1} \circ \gamma)'(0) = \bar{v}$ and $(\phi^{-1} \circ \gamma)'(0) = v$ then $\bar{v} = Pv$ where $P = (\bar{\phi}^{-1} \circ \phi)'(\phi^{-1}(p))$. With this in mind we could use the pair (p, v) or (p, \bar{v}) to describe a tangent vector at p. The cost of using (p, v) is it brings in questions of coordinate dependence.

The equivalence class viewpoint is at times quite useful, but the definition of vector offered here is a bit easier in certain respects. In particular, relative to a particular coordinate chart $\phi^{-1}: V \to U$, with $p \in V$, we define (temporary notation)

$$vectT_p\mathcal{M} = \{(p,v) \mid v \in \mathbb{R}^m\}$$

Vectors are added and scalar multiplied in the obvious way:

$$(p, v_1) + (p, v_2) = (p, v_1 + v_2)$$
 and $c(p, v_1) = (p, cv_1)$

for all $(p, v_1, (p, v_2) \in vectT_p\mathcal{M}$ and $c \in \mathbb{R}$. Moreover, if we change from the ϕ^{-1} chart to the $\overline{\phi}^{-1}$ coordinate chart then the vector changes form as indicated in the previous subsection; $(p, v) \to (p, \overline{v})$ where $\overline{v} = Pv$ and $P = (\overline{\phi}^{-1} \circ \phi)'(\phi^{-1}(p))$. The components of (p, v) are said to transform **contravariantly**.

Technically, this is also an equivalence class construction. A more honest notation would be to replace (p, v) with (p, ϕ, v) and then we could state that $(p, \phi, v) \sim (p, \bar{\phi}, \bar{v})$ iff $\bar{v} = Pv$ and $P = (\bar{\phi}^{-1} \circ \phi)'(\phi^{-1}(p))$. However, this notation is tiresome so we do not pursue it further. I prefer the notation of the next viewpoint.

14.2.3 dictionary between formalisms

We have three competing views of how to characterize a tangent vector.

- 1. $curveT_p\mathcal{M} = \{\tilde{\gamma} \mid \gamma \text{ smooth and } \gamma(0) = p\}$
- 2. $vectT_p\mathcal{M} = \{(p,v) \mid v \in \mathbb{R}^m\}$
- 3. $derT_p\mathcal{M} = \mathcal{D}_p\mathcal{M}$

Perhaps it is not terribly obvious how to get a derivation from an equivalence class of curves. Suppose $\tilde{\gamma}$ is a tangent vector to \mathcal{M} at p and let $f, g \in C^{\infty}(p)$. Define an operator V_p associated to $\tilde{\gamma}$ via $V_p(f) = (f \circ \gamma)'(0)$. Consider, $(f + cg) \circ \gamma)(t) = (f + cg)(\gamma(t)) = f(\gamma(t)) + cg(\gamma(t))$ differentiate at set t = 0 to verify that $V_p(f + cg)(p) = (f + cg) \circ \gamma)'(0) = V_p(f)(p) + cV_p(g)$. Furthermore, observe that $((fg) \circ \gamma)(t) = f(\gamma(t))g(\gamma(t))$ therefore by the product rule from calculus I,

$$((fg) \circ \gamma)'(t) = (f \circ \gamma)'(t)g(\gamma(t)) + f(\gamma(t))(g \circ \gamma)'(t)$$

hence, noting $\gamma(0) = p$ we verify the Leibniz rule for V_p ,

$$V_p(fg) = ((fg) \circ \gamma)'(0) = (f \circ \gamma)'(0)g(p) + f(p)(g \circ \gamma)'(0) = V_p(f)g(p) + f(p)V_p(g)$$

In view of these calculations we find that $\Xi : curveT_p\mathcal{M} \to derT_p\mathcal{M}$ defined by $\Xi(\tilde{\gamma}) = V_p$ is well-defined. Moreover, we can show Ξ is an isomorphism. To be clear, we define:

$$\Xi(\tilde{\gamma})(f) = V_p(f) = (f \circ \gamma)'(0).$$

I'll begin with injectivity. Suppose $\Xi(\tilde{\gamma}) = \Xi(\tilde{\beta})$ then for all $f \in C^{\infty}(p)$ we have $\Xi(\tilde{\gamma})(f) = \Xi(\tilde{\beta})(f)$ hence $(f \circ \gamma)'(0) = (f \circ \beta)'(0)$ for all smooth functions f at p. Take $f = x : V \to U$ and it follows that $\gamma \sim_p \beta$ hence $\tilde{\gamma} = \tilde{\beta}$ and we have shown Ξ is injective. Linearity of Ξ must be judged on the basis of our definition for the addition of equivalence classes of curves. I leave linearity and surjectivity to the reader. Once those are established it follows that Ξ is an isomorphism and $curveT_p\mathcal{M} \approx derT_p\mathcal{M}.$

The isomorphism between $vectT_p\mathcal{M}$ and $derT_{\mathcal{M}}$ was nearly given in the previous subsection. Essentially we can just paste the components from $vectT_p\mathcal{M}$ onto the partial derivative basis for derivations. Define $\Upsilon : vectT_p\mathcal{M} \to derT_p\mathcal{M}$ for each $(p, v_x) \in vectT_p\mathcal{M}$, relative to coordinates x at $p \in \mathcal{M}$,

$$\Upsilon\left(p,\sum_{k=1}^{m}v_{x}^{k}e_{k}\right)=\sum_{k=1}^{m}v_{x}^{k}\frac{\partial}{\partial x^{k}}\Big|_{p}$$

Note that if we used a different chart y then $(p, v_x) \to (p, v_y)$ and consequently

$$\Upsilon\left(p,\sum_{k=1}^{m}v_{y}^{k}e_{k}\right)=\sum_{k=1}^{m}v_{y}^{k}\frac{\partial}{\partial y^{k}}\Big|_{p}=\sum_{k=1}^{m}v^{k}\frac{\partial}{\partial x^{k}}\Big|_{p}.$$

Thus Υ is single-valued on each equivalence class of vectors. Furthermore, the inverse mapping is simple to write: for a chart x at p,

$$\Upsilon^{-1}(X_p) = (p, \sum_{k=1}^m X_p(x^k)e_k)$$

and the value of the mapping above is related contravariantly if we were to use a different chart y

$$\Upsilon^{-1}(X_p) = (p, \sum_{k=1}^m X_p(y^k)e_k).$$

See Equation 10.2 and the surrounding discussion if you forgot. It is not hard to verify that Υ is bijective and linear thus Υ is an isomorphism. We have shown $vectT_p\mathcal{M} \approx derT_p\mathcal{M}$. Let us summarize:

$$vectT_p\mathcal{M} \approx derT_p\mathcal{M} \approx curveT_p\mathcal{M}$$

It is my custom to assume $T_p\mathcal{M} = derT_p\mathcal{M}$ for most applications. This was the definition we adopted earlier in these notes.

14.3 Gauss map to a sphere

Suppose $S \subset \mathbb{R}^3$ is an embedded two-dimensional manifold. In particular suppose S is a **regular** surface which means that for each parametrization $\phi : U \to V$ the normal vector field $N(u, v) = (\phi_u \times \phi_v)(u, v)$ is a smooth non-vanishing vector field on S. Recall that the unit-sphere $S_2 = \{x \in \mathbb{R}^3 \mid ||x|| = 1\}$ is also manifold, perhaps you showed this in a homework. In any event, the mapping $U: S \to S_2$ defined by

$$G(u,v) = \frac{\phi_u \times \phi_v}{||\phi_u \times \phi_v||}$$

provides a smooth mapping from the surface to the unit sphere. The change in G measures how the normal deflects as we move about the surface S. One natural scalar we can use to quantify that curving of the normal is called the **Gaussian curvature** which is defined by K = det(dG). Likewise, we define H = trace(dG) which is the **mean curvature** of S. If k_1, k_2 are the eigenvalues the operator d_pG then it is a well-known result of linear algebra that $det(d_pG) = k_1k_2$ and $trace(d_pG) = k_1 + k_2$. The eigenvalues are called the **principal curvatures**. Moreover, it can be shown that the matrix of d_pG is symmetric and a theorem of linear algebra says that the eigenvalues are real and we can select an orthogonal basis of eigenvectors for T_pS .

Example 14.3.1. Consider the plane S with base point r_o and containing the vectors \vec{A}, \vec{B} , write

$$\phi(u,v) = r_o + u\vec{A} + v\vec{B}$$

to place coordinates u, v on the plane S. Calculate the Gauss map,

$$G(u,v) = \frac{\phi_u \times \phi_v}{||\phi_u \times \phi_v||} = \frac{\vec{A} \times \vec{B}}{||\vec{A} \times \vec{B}||}$$

This is constant on S hence $d_pG = 0$ for each $p \in S$. The curvatures (mean, Gaussian and principles) are all zero for this case. Makes sense, a plane isn't curved!

Let me outline how to calculate the curvature directly when G is not trivial. Calculate,

$$d_p G\left(\frac{\partial}{\partial x^k}\right)(y^j) = \frac{\partial}{\partial x^k} \left(y^j \circ G\right) = \frac{\partial(y^j \circ G)}{\partial x^k}$$

Thus, using the discussion of the preceding section,

$$d_p G\left(\frac{\partial}{\partial x^k}\right) = \sum_{j=1}^2 \frac{\partial (y^j \circ G)}{\partial x^k} \frac{\partial}{\partial y^j}$$

Therefore, the matrix of $d_p G$ is the 2×2 matrix $\left[\frac{\partial (y^j \circ G)}{\partial x^k}\right]$ with respect to the choice of coordinates x^1, x^2 on S and y^1, y^2 on the sphere.

Example 14.3.2. Suppose $\phi(u, v) = (u, v, \sqrt{R^2 - u^2 - v^2})$ parameterizes part of a sphere S_R of radius R > 0. You can calculate the Gauss map and the result should be geometrically obvious:

$$G(u,v) = \frac{1}{R} (u, v, \sqrt{R^2 - u^2 - v^2})$$

Then the u and v components of G(u, v) are simply u/R and v/R respective. Calculate,

$$[d_p G] = \begin{bmatrix} \frac{\partial}{\partial u} \begin{bmatrix} u \\ R \end{bmatrix} & \frac{\partial}{\partial v} \begin{bmatrix} u \\ R \end{bmatrix} \\ \frac{\partial}{\partial u} \begin{bmatrix} v \\ R \end{bmatrix} & \frac{\partial}{\partial v} \begin{bmatrix} v \\ R \end{bmatrix} = \begin{bmatrix} \frac{1}{R} & 0 \\ 0 & \frac{1}{R} \end{bmatrix}$$

Thus the Gaussian curvature of the sphere $K = 1/R^2$. The principle curvatures are $k_1 = k_2 = 1/R$ and the mean curvature is simply H = 2/R. Notice that as $R \to \infty$ we find agreement with the curvature of a plane. **Example 14.3.3.** Suppose S is a cylinder which is parametrized by $\phi(u, v) = (R \cos u, R \sin u, v)$. The Gauss map yields $G(u, v) = (\cos u, \sin u, 0)$. I leave the explicit details to the reader, but it can be shown that $k_1 = 1/R$, $k_2 = 0$ and hence K = 0 whereas H = 1/R.

The differential is actually easier to frame in the equivalence class curve formulation of $T_p\mathcal{M}$. In particular, suppose $\tilde{\gamma} = [\gamma]$ as a more convenient notation for what follows. In addition, suppose $F : \mathcal{M} \to \mathcal{N}$ is a smooth function and $[\gamma] \in curveT_p\mathcal{M}$ then we define $d_pF : curveT_p\mathcal{M} \to curveT_{F(p)}\mathcal{N}$ as follows:

$$d_p F([\gamma]) = [F \circ \gamma]$$

There is a chain-rule for differentials. It's the natural rule you'd expect. If $F : \mathcal{M} \to \mathcal{N}$ and $G : \mathcal{N} \to \mathcal{P}$ then, denoting q = F(p),

$$d_p(G \circ F) = d_q G \circ d_p F.$$

The proof is simple in the curve notation:

$$(d_q G \circ d_p F)([\gamma]) = d_q G(d_p F([\gamma])) = d_q G([F \circ \gamma]) = [G \circ (F \circ \gamma)] = d_p (G \circ F)[\gamma].$$

You can see why the curve formulation of tangent vectors is useful. It does simply certain questions. That said, we will insist $T_p \mathcal{M} = \mathcal{D}_p \mathcal{M}$ in sequel.

14.4 tensors at a point

Given a smooth *m*-dimensional manifold \mathcal{M} and a point $p \in \mathcal{M}$ we have a tangent space $T_p\mathcal{M}$ and a cotangent space $T_p\mathcal{M}^*$. The set of tensors at $p \in \mathcal{M}$ is simply the set of all multilinear mappings on the tangent and cotangent space at p. We again define the set of all type (r, s) tensors to be $T_s^r\mathcal{M}_p$ meaning $L \in T_s^r\mathcal{M}_p$ iff L is a multilinear mapping of the form

$$L: \underbrace{T_p\mathcal{M} \times \cdots \times T_p\mathcal{M}}_{r \ copies} \times \underbrace{T_p\mathcal{M}^* \times \cdots \times T_p\mathcal{M}^*}_{s \ copies} \to \mathbb{R}.$$

Relative to a particular coordinate chart x at p we can build a basis for $T_s^r \mathcal{M}_p$ via the tensor product. In particular, for each $L \in T_s^r \mathcal{M}_p$ there exist constants $L_{i_1 i_2 \dots i_r}^{j_1 j_2 \dots j_s}$ such that

$$L_p = \sum_{i_1,\dots,i_r,j_1,\dots,j_s=1}^m (L^{j_1j_2\dots j_s}_{i_1i_2\dots i_r})(p)d_p x^{i_1} \otimes \dots \otimes d_p x^{i_r} \otimes \frac{\partial}{\partial x^{j_1}}\Big|_p \otimes \dots \otimes \frac{\partial}{\partial x^{j_s}}\Big|_p.$$

The components can be calculated by contraction with the appropriate vectors and covectors:

$$(L_{i_1i_2\dots i_r}^{j_1j_2\dots j_s})(p) = L\left(\frac{\partial}{\partial x^{i_1}}\bigg|_p, \dots, \frac{\partial}{\partial x^{i_r}}\bigg|_p, d_p x^{j_1}, \dots, d_p x^{j_s}\right).$$

We can summarize the equations above with multi-index notation:

$$d_p x^I = d_p x^{i_1} \otimes d_p x^{i_2 \otimes \cdots \otimes d_p x^{i_r}}$$
 and $\frac{\partial}{\partial x^J}\Big|_p = \frac{\partial}{\partial x^{j_1}}\Big|_p \otimes \cdots \otimes \frac{\partial}{\partial x^{j_s}}\Big|_p$

Consequently, $\left| L_p = \sum_{I,J} L_I^J(p) d_p x^I \otimes \frac{\partial}{\partial x^J} \right|_p$. We may also construct wedge products and build the

exterior algebra as we did for an arbitrary vector space. Given a metric $g_p \in T_2^0 \mathcal{M}_p$ we can calculate hodge duals in $\Lambda \mathcal{M}_p$. All these constructions are possible at each point in a smooth manifold⁶.

14.5smoothness of differential forms

In this section we apply the results of the previous section on exterior algebra to the vector space $V = T_p M$. Recall that $\{\frac{\partial}{\partial x^i}|_p\}$ is a basis of $T_p M$ and thus the basis $\{e_i\}$ of V utilized throughout the previous section on exterior algebra will be taken to be

$$e_i = \frac{\partial}{\partial x^i}|_p, \quad 1 \le i \le n$$

in this section. Also recall that the set of covectors $\{dx^i\}$ is a basis of T_p^*M which is dual to $\{\frac{\partial}{\partial x^i}|_p\}$ and consequently the $\{e^j\}$ in the previous section is taken to be

$$e^{j} = dx^{j} , \quad 1 \le j \le n$$

in the present context. With these choices the machinery of the previous section takes over and one obtains a vector space $\wedge^k(T_pM)$ for each $1 \leq k$ and for arbitrary $p \in M$. We write $\wedge^k TM$ for the set of ordered pairs (p, α) where $p \in M$ and $\alpha \in \wedge^k(T_pM)$ and we refer to $\wedge^k(TM)$ as the k-th exterior power of the tangent bundle TM. There is a projection $\pi : \wedge^k(TM) \to M$ defined by $\pi(p,\alpha) = p$ for $(p,\alpha) \in \wedge^k(TM)$. One refers to $(\wedge^k TM,\pi)$ as a vector bundle for reasons we do not pursue at this point. To say that $\hat{\alpha}$ is a section of this vector bundle means that $\hat{\alpha}: M \to \wedge^k(TM)$ is a (smooth) function such that $\hat{\alpha}(p) \in \wedge^k(T_nM)$ for all $p \in M$. Such functions are also called differential forms, or in this case, k-forms.

Definition 14.5.1. vector field on open subset of \mathbb{R}^n .

To say that X is a vector field on an open subset U of M means that

$$X = X^{1} \frac{\partial}{\partial x^{1}} + X^{2} \frac{\partial}{\partial x^{2}} + \cdots + X^{n} \frac{\partial}{\partial x^{n}}$$

where X^1, X^2, \dots, X^n are smooth functions from U into **R**.

 $^{^{6}}$ I assume \mathcal{M} is Hausdorff and has a countable basis, see Burn's and Gidea Theorem 3.2.5 on page 116.

Note that in this context we implicitly require that differential forms be smooth. To explain this we write out the requirements more fully below.

If β is a function with domain M such that for each $p \in M$, $\beta(p) \in \wedge^k(T_pM)$ then β is called a <u>differential k-form</u> on M if for all local vector fields X_1, X_2, \dots, X_k defined on an arbitrary open subset U of M it follows that the map defined by

$$p \to \beta_p(X_1(p), X_2(p), \cdots, X_k(p))$$

is smooth on U. For example if (x^1, x^2, \dots, x^n) is a chart then its domain $V \subset M$ is open in M and the map

$$p \to d_p x^i$$

is a differential 1-form on U. Similarly the map

$$p \to d_p x^i \wedge d_p x^j$$

is a differential 2-form on U. Generally if β is a 1-form and (x^1, x^2, \dots, x^n) is a chart then there are functions (b_i) defined on the domain of x such that

$$\beta(q) = \sum_{\mu} b_i(q) d_q x^i$$

for all q in the domain of x.

Similarly if γ is a 2-form on M and $x = (x^1, x^2, \dots, x^n)$ is any chart on M then there are smooth functions c_{ij} on dom(x) such that

$$\gamma_p = \frac{1}{2} \sum_{i,j=1}^n c_{ij}(p) (d_p x^i \wedge d_p x^j)$$

and such that $c_{ij}(p) = -c_{ji}(p)$ for all $p \in dom(x)$. Generally if α is a k-form and x is a chart then on dom(x)

$$\alpha_p = \sum \frac{1}{k!} a_{i_1 i_2 \cdots i_k}(p) (d_p x^{i_1} \wedge \cdots \wedge d_p x^{i_k})$$

where the $\{a_{i_1i_2\cdots i_k}\}$ are smooth real-valued functions on U = dom(x) and $\alpha_{i_{\sigma_1}i_{\sigma_2}\cdots i_{\sigma_k}} = sgn(\sigma)a_{i_1i_2\cdots i_k}$, for every permutation σ . (this is just a fancy way of saying if you switch any pair of indices it generates a minus sign).

14.6 tensor fields

Since the tangent and cotangent space are defined at each point in a smooth manifold we can construct the tangent bundle and cotangent bundle by simply taking the union of all the tangent or cotangent spaces:

Definition 14.6.1. tangent and cotangent bundles.

Suppose \mathcal{M} is a smooth manifold the we define the **tangent bundle** $T\mathcal{M}$ and the **cotangent bundle** $T\mathcal{M}^*$ as follows:

$$T\mathcal{M} = \bigcup_{p \in \mathcal{M}} T_p \mathcal{M}$$
 and $T\mathcal{M}^* = \bigcup_{p \in \mathcal{M}} T_p \mathcal{M}^*$.

The cannonical projections $\pi, \tilde{\pi}$ tell us where a particular vector or covector are found on the manifold:

$$\pi(X_p) = p \text{ and } \tilde{\pi}(\alpha_p) = p$$

I usually picture this construction as follows:

XXX- add projection pictures

Notice the fibers of π and $\tilde{\pi}$ are $\pi^{-1}(p) = T_p \mathcal{M}$ and $\tilde{\pi}^{-1}(p) = T_p \mathcal{M}^*$. Generally a fiber bundle (E, \mathcal{M}, π) consists of a base manifold \mathcal{M} , a bundle space E and a projection

 $\pi : E \to \mathcal{M}$. A local section of E is a mapping $s : V \subseteq \mathcal{M} \to E$ such that $\pi \circ s$ is injective. In other words, the image of a section hits each fiber over its domain just once. A section selects a particular element of each fiber. Here's an abstract picture of section, I sometimes think of the section as its image although technically the section is actually a mapping:

XXX- add section picture-

Given the language above we find a natural language to define vector and covector-fields on a manifold. However, for reasons that become clear later, we call a covector-field a *differential one-form*.

Definition 14.6.2. tensor fields.

Let $V \subseteq \mathcal{M}$, we define:

- 1. X is a vector field on V iff X is a section of $T\mathcal{M}$ on V
- 2. α is a differential one-form on V iff α is a section of $T\mathcal{M}^*$ on V.
- 3. L is a type (r, s) tensor-field on V iff L is a section of $T_s^r \mathcal{M}$ on V.

We consider only **smooth sections** and it turns out this is equivalent⁷ to the demand that the component functions of the fields above are smooth on V.

⁷all the bundles above are themselves manifolds, for example $T\mathcal{M}$ is a 2*m*-dimensional manifold, and as such the term smooth has already been defined. I do not intend to delve into that aspect of the theory here. See any text on manifold theory for details.

14.7 metric tensor

I'll begin by discussing briefly the informal concept of a metric. The calculations given in the first part of this section show you how to think for nice examples that are embedded in \mathbb{R}^m . In such cases the metric can be deduced by setting appropriate terms for the metric on \mathbb{R}^m to zero. The metric is then used to set-up arclength integrals over a curved space, see my Chapter on Varitional Calculus from the previous notes if you want examples.

In the second part of this chapter I give the careful definition which applies to an arbitrary manifold. I include this whole section mostly for informational purposes. Our main thrust in this course is with the calculus of differential forms and the metric is actually, ignoring the task of hodge duals, not on the center stage. That said, any student of differential geometry will be interested in the metric. The problem of paralell transport⁸, and the definition and calculation of geodesics⁹ are fascinating problems beyond this course.

14.7.1 classical metric notation in \mathbb{R}^m

Definition 14.7.1.

The Euclidean metric is $ds^2 = dx^2 + dy^2 + dz^2$. Generally, for orthogonal curvelinear coordinates u, v, w we calculate $ds^2 = \frac{1}{||\nabla u||^2} du^2 + \frac{1}{||\nabla v||^2} dv^2 + \frac{1}{||\nabla w||^2} dw^2$.

The beauty of the metric is that it allows us to calculate in other coordinates, consider

$$x = r\cos(\theta)$$
 $y = r\sin(\theta)$

For which we have implicit inverse coordinate transformations $r^2 = x^2 + y^2$ and $\theta = \tan^{-1}(y/x)$. From these inverse formulas we calculate:

$$abla r = \langle x/r, y/r \rangle$$
 $\nabla \theta = \langle -y/r^2, x/r^2 \rangle$

Thus, $||\nabla r|| = 1$ whereas $||\nabla \theta|| = 1/r$. We find that the metric in polar coordinates takes the form:

$$ds^2 = dr^2 + r^2 d\theta^2$$

Physicists and engineers tend to like to think of these as arising from calculating the length of infinitesimal displacements in the r or θ directions. Generically, for u, v, w coordinates

$$dl_u = \frac{1}{||\nabla u||} du \qquad dl_v = \frac{1}{||\nabla v||} dv \qquad dl_w = \frac{1}{||\nabla w||} dw$$

and $ds^2 = dl_u^2 + dl_v^2 + dl_w^2$. So in that notation we just found $dl_r = dr$ and $dl_\theta = rd\theta$. Notice then that cylindircal coordinates have the metric,

$$ds^2 = dr^2 + r^2 d\theta^2 + dz^2.$$

⁸how to move vectors around in a curved manifold

⁹curve of shortest distance on a curved space, basically they are the lines on a manifold

For spherical coordinates $x = r \cos(\phi) \sin(\theta)$, $y = r \sin(\phi) \sin(\theta)$ and $z = r \cos(\theta)$ (here $0 \le \phi \le 2\pi$ and $0 \le \theta \le \pi$, physics notation). Calculation of the metric follows from the line elements,

$$dl_r = dr$$
 $dl_\phi = r\sin(\theta)d\phi$ $dl_\theta = rd\theta$

Thus,

$$ds^{2} = dr^{2} + r^{2}\sin^{2}(\theta)d\phi^{2} + r^{2}d\theta^{2}.$$

We now have all the tools we need for examples in spherical or cylindrical coordinates. What about other cases? In general, given some *p*-manifold embedded in \mathbb{R}^n how does one find the metric on that manifold? If we are to follow the approach of this section we'll need to find coordinates on \mathbb{R}^n such that the manifold *S* is described by setting all but *p* of the coordinates to a constant. For example, in \mathbb{R}^4 we have generalized cylindircal coordinates (r, ϕ, z, t) defined implicitly by the equations below

$$x = r\cos(\phi), \qquad y = r\sin(\phi), \qquad z = z, \qquad t = z$$

On the hyper-cylinder r = R we have the metric $ds^2 = R^2 d\theta^2 + dz^2 + dw^2$. There are mathematicians/physicists whose careers are founded upon the discovery of a metric for some manifold. This is generally a difficult task.

14.7.2 metric tensor on a smooth manifold

A metric on a smooth manifold \mathcal{M} is a type (2,0) tensor field on \mathcal{M} which is at each point p a metric on $T_p\mathcal{M}$. In particular, g is a metric iff g makes the assignment $p \to g_p$ for each $p \in \mathcal{M}$ where the mapping $g_p : T_p\mathcal{M} \times T_p\mathcal{M} \to \mathbb{R}$ is a metric. Recall the means g_p is a symmetric, nondegenerate bilinear form on $T_p\mathcal{M}$. Relative to a particular coordinate system x at p we write

$$g = \sum_{i,j} g_{ij} dx^i \otimes dx^j$$

In this context $g_{ij}: V \to \mathbb{R}$ are assumed to be smooth functions, the values may vary from point to point in V. Furthermore, we know that $g_{ij} = g_{ji}$ for all $i, j \in \mathbb{N}_m$ and the matrix $[g_{ij}]$ is invertible by the nondegneracy of g. Recall we use the notation g^{ij} for components of the inverse matrix, in particular we suppose that $\sum_{k=1}^{m} g_{ik}g^{kj} = \delta_{ij}$.

Recall that according to Sylvester's theorem we can choose coordinates at some point p which will diagonalize the metric and leave $diag(g_{ij}) = \{-1, -1, \ldots, -1, 1, 1, \ldots, 1\}$. In other words, we can orthogonalize the coordinate basis at a paricular point p. The interesting feature of a curved manifold \mathcal{M} is that as we travel away from the point where we straightened the coordinates it is generally the case the components of the metric will not stay diagonal and constant over the whole coordinate chart. If it is possible to choose coordinates centered on V such that the coordinates are constantly orthogonal with respect the metric over V then the manifold \mathcal{M} is said to be **flat** on V. Examples of flat manifolds include \mathbb{R}^m , cylinders and even cones without their point. A manifold is said to be curved if it is not flat. The definition I gave just now is not probably one you'll find in a mathematics text¹⁰. Instead, the curvature of a manifold is quantified through various tensors which are derived from the metric and its derivatives. In particular, the Ricci and Riemann tensors are used to carefully characterize the geometry of a manifold. It is very tempting to say more about the general theory of curvature, but I will resist. If you would like to do further study I can recommend a few books. We will consider some geometry of embedded two-dimensional manifolds in \mathbb{R}^3 . That particular case was studied in the 19-th century by Gauss and others and some of the notation below goes back to that time.

Example 14.7.2. Consider a regular surface S which has a global parametrization $\phi : U \subseteq \mathbb{R}^2 \to S \subseteq \mathbb{R}^3$. In the usual notation in \mathbb{R}^3 ,

$$\phi(u, v) = (x(u, v), y(u, v), z(u, v))$$

Consider a curve $\gamma : [0,1] \to S$ we can calculate the arclength of γ via the usal calculation in \mathbb{R}^3 . The magnitude of velocity $\gamma'(t)$ is $||\gamma'(t)||$ and naturally this gives us $\frac{ds}{dt}$ hence $ds = ||\gamma'(t)||dt$ and the following integral calculates the length of γ ,

$$s_{\gamma} = \int_0^1 ||\gamma'(t)|| dt$$

Since $\gamma[0,1] \subset S$ it follows there must exist some two-dimesional curve $t \to (u(t), v(t))$ for which $\gamma(t) = \phi(u(t), v(t))$. Observe by the chain rule that

$$\gamma'(t) = \left(\frac{\partial x}{\partial u}\frac{du}{dt} + \frac{\partial x}{\partial v}\frac{dv}{dt}, \ \frac{\partial y}{\partial u}\frac{du}{dt} + \frac{\partial y}{\partial v}\frac{dv}{dt}, \ \frac{\partial z}{\partial u}\frac{du}{dt} + \frac{\partial z}{\partial v}\frac{dv}{dt}\right)$$

We can calculate the square of the speed in view of the formula above, let $\frac{du}{dt} = \dot{u}$ and $\frac{dv}{dt} = \dot{v}$,

$$||\gamma'(t)||^{2} = \left(\begin{array}{c} x_{u}^{2}\dot{u}^{2} + 2x_{u}x_{v}\dot{u}\dot{v} + x_{v}^{2}\dot{v}^{2}, \\ y_{u}^{2}\dot{u}^{2} + 2y_{u}y_{v}\dot{u}\dot{v} + y_{v}^{2}\dot{v}^{2}, \\ z_{u}^{2}\dot{u}^{2} + 2z_{u}z_{v}\dot{u}\dot{v} + z_{v}^{2}\dot{v}^{2} \end{array} \right)$$
(14.1)

Collecting together terms which share either \dot{u}^2 , $\dot{u}\dot{v}$ or \dot{v}^2 and noting that $x_u^2 + y_u^2 + z_u^2 = \phi_u \cdot \phi_u$, $x_u x_v + y_u y_v + z_u z_v = \phi_u \cdot \phi_v$ and $x_v^2 + y_v^2 + z_v^2 = \phi_v \cdot \phi_v$ we obtain:

$$||\gamma'(t)||^2 = \phi_u \cdot \phi_u \dot{u}^2 + \phi_u \cdot \phi_v \dot{u}\dot{v} + \phi_v \cdot \phi_v \dot{v}^2$$

Or, in the notation of Gauss, $\phi_u \cdot \phi_u = E$, $\phi_u \cdot \phi_v = F$ and $\phi_v \cdot \phi_v = G$ hence the arclength on S is given by

$$s_{\gamma} = \int_0^1 \sqrt{E\dot{u}^2 + 2F\dot{u}\dot{v} + G\dot{v}^2} \, dt$$

¹⁰this was the definitin given in a general relativity course I took with the physicisist Martin Rocek of SUNY Stony Brook. He then introduced non-coordinate form-fields which kept the metric constant. I may find a way to show you some of those calculations at the end of this course.

We discover that on S there is a metric induced from the ambient euclidean metric. In the current coordinates, using $(u, v) = \phi^{-1}$,

$$g = Edu \otimes du + 2Fdu \otimes dv + Gdv \otimes dv$$

hence the length of a tangent vector is defined via $||X|| = \sqrt{g(X,X)}$, we calcate the length of a curve by integrating its speed along its extent and the speed is simply the magnitude of the tangent vector at each point. The new thing here is that we judge the magnitude on the basis of a metric which is intrinsic to the surface.

If arclength on S is given by Gauss' E, F, G then what about surface area?. We know the magnitude of the cross product of the tangent vectors ϕ_u , ϕ_v on S will give us the area of a tiny paralellogram corresponding to a change du in u and dv in v. Thus:

$$dA = \sqrt{||\phi_u \times \phi_v||^2} \, dudv$$

However, Lagrange's identity says $||\phi_u \times \phi_v||^2 = ||\phi_u||^2 ||\phi_v||^2 - \phi_u \cdot \phi_v$ hence $dA = \sqrt{EF - G^2} du dv$ and we can calculate surface area (if this integral exists!) via

$$Area(S) = \int_{U} \sqrt{EG - F^2} du \, dv.$$

I make use of the standard notation for double integrals from multivariate calculus and the integration is to be taken over the domain of the parametrization of S.

Many additional formulas are known for E, F, G and there are entire texts devoted to exploring the geometric intracies of surfaces in \mathbb{R}^3 . For example, John Oprea's Differential Geometry and its Applications. Theorem 4.1 of that text is the celebrated Theorem Egregium of Gauss which states the curvature of a surface depends only on the metric of the surface as given by E, F, G. In particular,

$$K = \frac{-1}{2\sqrt{EG}} \left(\frac{\partial}{\partial v} \left(\frac{E_v}{\sqrt{EG}} \right) + \frac{\partial}{\partial u} \left(\frac{G_u}{\sqrt{EG}} \right) \right).$$

Where curvature at p is defined by $K(p) = det(S_p)$ and S_p is the shape operator is defined by the covariant derivative $S_p(v) = -\nabla_v U = -(v(U_1), v(U_2), v(U_3))$ and U is simply the normal vector field to S defined by $U(u, v) = \phi_u \times \phi_v$ in our current notation.

It turns out there is an easier way to calculate curvature via wedge products. I will hopefully show how that is done in the next chapter. However, I do not attempt to motivate why the curvature is called curvature. You really should read something like Oprea if you want those thoughts.

Example 14.7.3. Let $\mathcal{M} = \mathbb{R}^4$ and choose an atlas of charts which are all intertially related to the standard Cartesian coordinates on \mathbb{R}^4 . In other words, we allow coordinates \bar{x} which can be obtained from a Lorentz transformation; $\bar{x} = \Lambda x$ and $\Lambda \in \mathbb{R}^{4 \times 4}$ such that $\Lambda^T \eta \Lambda = \eta$. Define $g = \sum_{\mu,\nu=0}^{3} \eta_{\mu\nu} dx^{\mu} \otimes dx^{\nu}$ for the standard Cartesian coordinates on \mathbb{R}^4 . We can show that the metric is invariant as we change coordinates, if you calculate the components of g in some other

coordinate system then you will once more obtain $\eta_{\mu\nu}$ as the components. This means that if we can write the equation for the interval between events in one coordinate system then that interval equation must also hold true in any other inertial coordinate system. In particle physics this is a very useful observation because it means if we want to analyze an relativistic interaction then we can study the problem in the frame of reference which makes the problem simplest to understand.

In physics a coordinate system if also called a "frame of reference", technically there is something missing from our construction of \mathcal{M} from a relativity perspective. As a mathematical model of spacetime \mathbb{R}^4 is not quite right. Why? Because Einstein's first axiom or postulate of special relativity is that there is no "preferred frame of reference". With \mathbb{R}^4 there certainly is a preferred frame, it's impicit within the very definition of the set \mathbb{R}^4 , we get Cartesian coordinates for free. To eliminate this convenient set of, according to Einstein, unphysical coordinates you have to consider an affine space which is diffeomorphic to \mathbb{R}^4 . If you take modern geometry you'll learn all about affine space. I will not pursue it further here, and as a bad habit I tend to say \mathcal{M} paired with η is "minkowski space". Technically this is not quite right for the reasons I just explained.

14.8 on boundaries and submanifolds

A manifold with boundary¹¹ is basically just a manifold which has an edge which is also a manifold. The boundary of a disk is a circle. In fact, in general, a closed ball in (n+1)-dimensional euclidean space has a boundary which is the S_n sphere.

The boundary of quadrants I and II of the xy-plane is the x-axis. Or, to generalize this example, we define the upper-half of \mathbb{R}^n as follows:

$$\mathbb{H}^{n} = \{ (x^{1}, x^{2}, \dots, x^{n-1}, x^{n}) \in \mathbb{R}^{n} \mid x^{n} \ge 0 \}.$$

The boundary of \mathbb{H}^n is the $x^1 x^2 \cdots x^{n-1}$ -hyperplane which is the solution set of $x^n = 0$ in \mathbb{R}^n ; we can denote the boundary by $\partial \mathbb{H}^n$ hence, $\partial \mathbb{H}^n = \mathbb{R}^{n-1} \times \{0\}$. Furthermore, we define

$$\mathbb{H}_{+}^{n} = \{ (x^{1}, x^{2}, \dots, x^{n-1}, x^{n}) \in \mathbb{R}^{n} \mid x^{n} > 0 \}.$$

It follows that $\mathbb{H}^n = \mathbb{H}^n_+ \cup \mathbb{R}^{n-1} \times \{0\}$. Note that a subset U of \mathbb{H}^n is said to be **open in** \mathbb{H}^n iff there exists some open set $U' \subseteq \mathbb{R}^n$ such that $U' \cap \mathbb{H}^n = U$. For example, if we consider \mathbb{R}^3 then the open sets in the *xy*-plane are formed from intesecting open sets in \mathbb{R}^3 with the plane; an open ball intersects to give an open disk on the plane. Or for \mathbb{R}^2 an open disks intersected with the *x*-axis give open intervals.

Definition 14.8.1.

 $^{^{11}}$ I am glossing over some analytical details here concerning extensions and continuity, smoothness etc... see section 24 of Munkres a bit more detail in the embedded case.

We say \mathcal{M} is a **smooth** *m*-dimensional manifold with boundary iff there exists a family $\{U_i\}$ of open subsets of \mathbb{R}^m or \mathbb{H}^m and local parameterizations $\phi_i : U_i \to V_i \subseteq \mathcal{M}$ such that the following criteria hold:

- 1. each map $\phi_i: U_i \to V_i$ is injective
- 2. if $V_i \cap V_i \neq \emptyset$ then there exists a smooth mapping

$$\theta_{ij}: \phi_i^{-1}(V_i \cap V_j) \to \phi_i^{-1}(V_i \cap V_j)$$

such that $\phi_j = \phi_i \circ \theta_{ij}$

3. $M = \bigcup_i \phi_i(U_i)$

We again refer to the inverse of a local paramterization as a **coordinate chart** and often use the notation $\phi^{-1}(p) = (x^1(p), x^2(p), \dots, x^m(p))$. If there exists U open in \mathbb{R}^m such that $\phi: U \to V$ is a local parametrization with $p \in V$ then p is an **interior point**. Any point $p \in \mathcal{M}$ which is not an interior point is a boundary point. The set of all boundary points is called **boundary** of \mathcal{M} is denoted $\partial \mathcal{M}$.

A more pragmatic characterization¹² of a boundary point is that $p \in \partial \mathcal{M}$ iff there exists a chart at p such that $x^m(p) = 0$. A manifold without boundary is simply a manifold in our definition since the definitions match precisely if there are no half-space-type charts. In the case that $\partial \mathcal{M}$ is nonempty we can show that it forms a manifold without boundary. Moreover, the atlas for $\partial \mathcal{M}$ is naturally induced from that of \mathcal{M} by restriction.

Proposition 14.8.2.

Suppose \mathcal{M} is a smooth *m*-dimensional manifold with boundary $\partial \mathcal{M} \neq \emptyset$ then $\partial \mathcal{M}$ is a smooth manifold of dimension m-1. In other words, $\partial \mathcal{M}$ is an m-1 dimensional manifold with boundary and $\partial(\partial \mathcal{M}) = \emptyset$.

Proof: Let $p \in \partial \mathcal{M}$ and suppose $\phi : U \subseteq \mathbb{H}^m \to V \subseteq \mathcal{M}$ is a local parametrization containing $p \in V$. It follows $\phi^{-1} = (x^1, x^2, \dots, x^{m-1}, x^m) : V \to U$ is a chart at p with $x^m(p) = 0$. Define the **restriction** of ϕ^{-1} to $x^m = 0$ by $\psi : U' \to V \cap (\partial \mathcal{M})$ by $\psi(u) = \phi(u, 0)$ where $U' = \{(u^1, \dots, u^{m-1}) \in \mathbb{R}^{m-1} \mid (u^1, \dots, u^{m-1}, u^m) \in U\}$. It follows that $\psi^{-1} : V \cap (\partial \mathcal{M}) \to U' \subseteq \mathbb{R}^{m-1}$ is just the first m - 1 coordinates of the chart ϕ^{-1} which is to say $\psi^{-1} = (x^1, x^2, \dots, x^{m-1})$. We construct charts in this fashion at each point in $\partial \mathcal{M}$. Note that U' is open in \mathbb{R}^{m-1} hence the manifold $\partial \mathcal{M}$ only has interior points. There is no parametrization in $\partial \mathcal{M}$ which takes a boundary-type subset half-plane as its domain. It follows that $\partial(\partial \mathcal{M}) = \emptyset$. I leave compatibility and smoothness of the restricted charts on $\partial \mathcal{M}$ to the reader. \Box

Given the terminology in this section we should note that there are shapes of interest which simply do no fit our terminology. For example, a rectangle $R = [a, b] \times [c, d]$ is not a manifold with bound-

 $^{^{12}}$ I leave it to the reader to show this follows from the words in green.

ary since if it were we would have a boundary with sharp edges (which is not a smooth manifold!).

I have not included a full discussion of **submanifolds** in these notes. However, I would like to give you some brief comments concerning how they arise from particular functions. In short, a submanifold is a subset of a manifold which also a manifold in a natural manner. Burns and Gidea define for a smooth mapping f from a manifold \mathcal{M} to another manifold \mathcal{N} that

- a $p \in \mathcal{M}$ is a **critical point** of f if $d_p f : T_p \mathcal{M} \to T_{f(p)} \mathcal{N}$ is not surjective. Moreover, the image f(p) is called the critical value of f.
- b $p \in \mathcal{M}$ is a **regular point** of f if p is not critical. Moreover, $q \in \mathcal{N}$ is called a **regular value** of f iff $f^{-1}\{q\}$ contains no critical points.

It turns out that:

Theorem 14.8.3.

If $f : \mathcal{M} \to \mathcal{N}$ is a smooth function on smooth manifolds \mathcal{M} , \mathcal{N} of dimensions m, n respective and $q \in \mathcal{N}$ is a regular value of f with nonempty fiber $f^{-1}\{q\}$ then the fiber $f^{-1}\{q\}$ is a submanifold of \mathcal{M} of dimension (m-n).

Proof: see page 46 of Burns and Gidea. \Box .

The idea of this theorem is a variant of the implicit function theorem. Recall if we are given $G: \mathbb{R}^k \times \mathbb{R}^n \to \mathbb{R}^n$ then the local solution y = h(x) of G(x, y) = k exists provided $\frac{\partial G}{\partial y}$ is invertible. But, this local solution suitably restricted is injective and hence the mapping $\phi(x) = (x, h(x))$ is a local parametrization of a manifold in $\mathbb{R}^k \times \mathbb{R}^n$. In fact, the graph y = h(x) gives k-dimensional submanifold of the manifold $\mathbb{R}^k \times \mathbb{R}^n$. (think of $\mathcal{M} = \mathbb{R}^k \times \mathbb{R}^n$ hence m = k + n and m - n = k so we find agreement with the theorem above at least in the concrete case of level-sets)

Example 14.8.4. Consider $f : \mathbb{R}^2 \to \mathbb{R}$ defined by $f(x, y) = x^2 + y^2$. Calculate df = 2xdx + 2ydywe find that the only critical value of f is (0,0) since otherwise either x or y is nonzero and as a consequence df is surjective. It follows that $f^{-1}\{\mathbb{R}^2\}$ is a submanifold of \mathbb{R}^2 for any $\mathbb{R} > 0$. I think you've seen these submanifolds before. What are they?

Example 14.8.5. Consider $f : \mathbb{R}^3 \to \mathbb{R}$ defined by $f(x, y, z) = z^2 - x^2 - y^2$ calculate that df = -2xdx - 2ydy + 2zdz. Note (0, 0, 0) is a critical value of f. Furthermore, note $f^{-1}\{0\}$ is the cone $z^2 = x^2 + y^2$ which is not a submanifold of \mathbb{R}^3 . It turns out that in general just about anything can arise as the inverse image of a critical value. It could happen that the inverse image is a submanifold, it's just not a given.

Theorem 14.8.6.

If \mathcal{M} be a smooth manifold without boundary and $f : \mathcal{M} \to \mathbb{R}$ is a smooth function with a regular value $a \in \mathbb{R}$ then $f^{-1}(-\infty, a]$ is a smooth manifold with boundar $f^{-1}\{a\}$.

Proof: see page 50 of Burns and Gidea. \Box .

Example 14.8.7. Suppose $f : \mathbb{R}^m \to \mathbb{R}$ is defined by $f(x) = ||x||^2$ then x = 0 is the only critical value of f and we find $f^{-1}(-\infty, R^2]$ is a submanifold with boundary $f^{-1}\{r^2\}$. Note that $f^{-1}(-\infty, 0) = \emptyset$ in this case. However, perhaps you also see $B^m = f^{-1}[0, R^2]$ is the closed m-ball and $\partial B^m = S_{m-1}(R)$ is the (m-1)-sphere of radius R.

Theorem 14.8.8.

Let \mathcal{M} be a smooth manifold with boundary ∂M and \mathcal{N} a smooth manifold without boundary. If $f: \mathcal{M} \to \mathcal{N}$ and $f|_{\partial \mathcal{M}}: \partial \mathcal{M} \to \mathcal{N}$ have regular value $q \in \mathcal{N}$ then $f^{-1}\{q\}$ is a smooth (m-n)-dimensional manifold with boundary $f^{-1}\{q\} \cap \partial \mathcal{M}$.

Proof: see page 50 of Burns and Gidea. \Box .

This theorem would seem to give us a generalization of the implicit function theorem for some closed sets. Interesting. Finally, I should mention that it is customary to also allow use the set $\mathbb{L}^1 = \{x \in \mathbb{R} \mid x \leq 0\}$ as the domain of a parametrization in the case of one-dimensional manifolds.