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### 2 Appendix

CONTENTS

## **Chapter 1**

## **Review of Advanced Calculus**

## **1.1 Differentiability**

Throughout Section 1.1, V and W be finite-dimensional vector spaces with norms  $\|\cdot\|_V$ and  $\|\cdot\|_W$  respectively. The subscripts on the norms will be dropped from the notation. Wherever  $\|\cdot\|$  appears it should be clear from the context whether  $\|\cdot\|_V$  or  $\|\cdot\|_W$  is intended.

**Definition 1.1.1.** Let  $U \subset V$  be an open set, let  $f : U \to W$  and let  $p \in U$ . We say f is *differentiable at p* if there exists a linear transformation  $T : V \to W$  such that

$$\lim_{h \to 0} \frac{\|f(p+h) - f(p) - T(h)\|_{W}}{\|h\|_{V}} = 0.$$
(1.1)

*Remark* 1.1.2. Recall that for  $n \in \mathbb{N}$  fixed, all norms on  $\mathbb{R}^n$  are equivalent. That is, if  $\|\cdot\|_1$  and  $\|\cdot\|_2$  are norms on  $\mathbb{R}^n$  there there is a constant C > 0 such that

$$\frac{1}{C} \|v\|_2 \le \|v\|_1 \le C \|v\|_2 \qquad \text{for all } v \in \mathbb{R}^n.$$

Thus, the concept of differentiability is independent of the choices of norms  $\|\cdot\|_V$  and  $\|\cdot\|_W$ . A proof of the equivalence of all norms on  $\mathbb{R}^n$  can be found in Proposition 2.0.11 of the appendix.

**Claim 1.1.3.** *With all data as in Definition 1.1.1, the linear transformation T in equation* (1.1) *is unique.* 

*Proof.* If linear transformations  $T_1$  and  $T_2$  are as in (1.1) then for all  $h \in V$ 

$$(T_2 - T_1)(h) = [f(p+h) - f(p) - T_1(h)] - [f(p+h) - f(p) - T_2(h)].$$

Therefore, for all  $0 \neq h \in V$ ,

$$\frac{f(p+h) - f(p) - T_1(h)}{\|h\|} - \frac{f(p+h) - f(p) - T_2(h)}{\|h\|} = \frac{(T_2 - T_1)(h)}{\|h\|} = (T_2 - T_1) \left(\frac{h}{\|h\|}\right),$$

where linearity was used in the final equality. Letting  $h \rightarrow 0$  shows that

$$\lim_{h \to 0} (T_2 - T_1) \left(\frac{h}{\|h\|}\right) = 0$$

Now, if  $e \in V$  is any vector of length ||e|| = 1, we may choose h = te for nonzero  $t \in \mathbb{R}$  to obtain

$$0 = \lim_{t \to 0} (T_2 - T_1) \left( \frac{te}{\|te\|} \right) = \pm (T_2 - T_1)(e).$$

Since *e* is an arbitrary unit vector and by linearity of  $T_1$  and  $T_2$  we obtain  $T_2 \equiv T_1$ .

**Definition 1.1.4.** Let V, W, U, f and p be as above. Suppose f is differentiable at p. The unique linear map  $T : V \to W$  satisfying (1.1) is called the *derivative of f at p*.

The following notations will be used for the derivative of f at p

$$(Df)_p, \quad Df|_p, \quad df|_p, \quad (df)_p.$$

**Example 1.1.5.** Let U be an open subset of V. If  $f: U \to W$  is a linear map then at each point  $p \in U$ ,  $Df|_p(v) = f(v)$  for all v (i.e if f is linear then f is its own derivative). Indeed, consider the difference quotient

$$\frac{f(p+v)-f(p)-T(v)}{\|v\|}.$$

If f is linear then this quotient may be written

$$\frac{f(v) - T(v)}{\|v\|},$$

so choose T(v) = f(v).

**Definition 1.1.6.** Let *U* be an open subset of *V*, let  $p \in U$  and let  $f : U \to W$  (with no differentiability of *f* assumed). For  $v \in V$ , the (generalized) *directional derivative of f at p in direction v* is

$$(D_p f)(v) = \frac{d}{dt} f(p+tv) \bigg|_{t=0} = \lim_{t \to 0} \frac{f(p+tv) - f(p)}{t}.$$

*Remark* 1.1.7. The limit in Definition 1.1.6 may or may not exist for a given v. Moreover, the limit may exist for some v's but not other v's.

Note that if  $(D_p f)(v)$  exists for a given v then then the map span  $v \subset V \to W$  given by  $u \mapsto (D_p f)(u)$  is homogeneous. Indeed, for any nonzero scalar  $\lambda$ ,

$$(D_p f)(\lambda v) = \lambda \lim_{t \to 0} \frac{f(p + t\lambda v) - f(p)}{\lambda t} = \lambda (D_p f)(v).$$
(1.2)

In particular, for  $v \in V$  given, by choosing  $\lambda = \frac{1}{\|v\|}$  we obtain

$$(D_p f)\left(\frac{v}{\|v\|}\right) = \frac{1}{\|v\|}(D_p f)(v).$$

From Definition 1.1.6 we also have  $(D_p f)(\lambda v) = \lambda (D_p f)(v)$  when  $\lambda = 0$ .

 $\triangle$ 

**Proposition 1.1.8.** If f is differentiable at p then all directional derivatives of f exist at p and

 $\underbrace{(D_p f)(v)}_{directional \ derivative \ derivative \ of \ f \ at \ p} = \underbrace{Df|_p(v)}_{derivative \ of \ f \ at \ p}.$ *at p in direction v* evaluated at v

*Proof.* Suppose f is differentiable at p and let  $T = Df|_p$ . Then if  $v \neq 0$ 

$$\lim_{t \to 0} \frac{f(p+tv) - f(p)}{t} = \lim_{t \to 0} \|v\| \underbrace{\frac{f(p+tv) - f(p) - T(tv)}{t \|v\|}}_{\to 0 \text{ since } f \text{ is differentiable at } p} + T(v) = T(v)$$

**Example 1.1.9.** Consider the special case that  $V = \mathbb{R}^n$  and  $W = \mathbb{R}^m$  with coordinates  ${x^i}_{i=1}^n$  and standard bases  ${e_i}_{i=1}^n$  and  ${e'_i}_{i=1}^m$ 

$$e_i = (0, \cdots, 0, 1, 0, \cdots, 0)^t, \quad f = (f_1, \cdots, f_m)^t.$$

Suppose  $f: U \subset \mathbb{R}^n \to \mathbb{R}^m$  is differentiable at  $p \in \mathbb{R}^n$ . The directional derivative of f at p in direction  $e_i$  is

$$\begin{aligned} (D_p f)(e_i) &= \lim_{t \to 0} \frac{f(p + te_i) - f(p)}{t} \\ &= \frac{\partial f}{\partial x^i}(p) \\ &= \left(\frac{\partial f^1}{\partial x^i}(p), \cdots, \frac{\partial f^m}{\partial x^i}(p)\right)^t \\ &= \sum_{j=1}^m \frac{\partial f^j}{\partial x^i}(p)e'_j. \end{aligned}$$

#### 1.2. CONTINUITY OF DERIVATIVES

For a general direction  $v = \sum_{i=1}^{n} v^{i} e_{i}$  we have

$$\begin{aligned} (D_p f)(v) &= \sum_{i=1}^n v^i (D_p f)(e_i) \\ &= \sum_{i=1}^n v^i \sum_{j=1}^m \frac{\partial f^j}{\partial x^i}(p) e'_j \\ &= \sum_{j=1}^m \left( \sum_{i=1}^n \frac{\partial f^j}{\partial x^i}(p) v^i \right) e'_j \\ &= \begin{bmatrix} \frac{\partial f^1}{\partial x^1}(p) & \frac{\partial f^1}{\partial x^2}(p) & \cdots & \frac{\partial f^1}{\partial x^n}(p) \\ \frac{\partial f^2}{\partial x^1}(p) & \frac{\partial f^2}{\partial x^2}(p) & \cdots & \frac{\partial f^m}{\partial x^n}(p) \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f^m}{\partial x^1}(p) & \frac{\partial f^m}{\partial x^2}(p) & \cdots & \frac{\partial f^m}{\partial x^n}(p) \end{bmatrix} \begin{bmatrix} v^1 \\ v^2 \\ \vdots \\ v^m \end{bmatrix}. \end{aligned}$$

Letting  $J_f(p)$  denote the  $m \times n$  matrix whose  $(ji)^{\text{th}}$  entry is  $\frac{\partial f^j}{\partial x^i}(p)$  (i.e. the matrix that appears on the right-hand side of the above string of equalities), we get

$$(D_p f)(v) = J_f(p)v.$$

This equality should be interpreted as follows:

If  $f: U \subset \mathbb{R}^n \to \mathbb{R}^m$  is differentiable at  $p \in U$  then the derivative of f at p is the linear map  $\mathbb{R}^n \to \mathbb{R}^m$  whose representation relative to the standard bases of  $\mathbb{R}^n$  and  $\mathbb{R}^m$  is given by multiplication by the Jacobian  $J_f(p)$ .

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**Exercise 1.1.** If *f* is differentiable at *p* then *f* is continuous at *p*.

## **1.2** Continuity of Derivatives

Let us start by saying some words about a useful norm topology on the space of linear maps between a pair of fixed vector spaces.

**Definition 1.2.1.** If *V* and *W* are finite-dimensional normed vector spaces then Hom(*V*, *W*) is the  $(\dim V)(\dim W)$ -dimensional vector space of linear maps  $V \to W$ . If  $\|\cdot\|_V$  and  $\|\cdot\|_W$  are the norms on *V* and *W* respectively, then the *operator norm* on Hom(*V*, *W*) is given by

$$||T||_{\text{op}} = \sup_{\|v\|=1} ||Tv|| = \sup_{v \neq 0} \left\| T \frac{v}{\|v\|} \right\|.$$

If *V* and *W* are finite dimensional vector spaces and  $T: V \to W$  is linear then *T* is continuous. Since  $\{v \in V : ||v|| = 1\}$  is compact in *V* (because dim $V < \infty$ ), if *T* is any linear map  $V \to W$ , the continuity of *T* ensures that  $\{Tv : ||v|| = 1\}$  is compact (hence closed) in *W*. In particular, if *T* is a linear map of finite-dimensional vector spaces then  $||T||_{op}$  is attained at some  $v \in V$  with ||v|| = 1. For  $v \neq 0$ ,

$$||Tv|| = ||v|| \left| \left| T\left(\frac{v}{||v||}\right) \right| \right| \le ||v|| ||T||.$$

If *S* and *T* are composable linear transformations then for all v,

$$||(S \circ T)(v)|| \le ||S|| ||Tv|| \le ||S|| ||T|| ||v||.$$

If  $v \neq 0$  then applying this estimate with v replaced by v/||v|| gives

$$\left\| (S \circ T) \frac{v}{\|v\|} \right\| \le \|S\| \|T\|.$$

Taking the supremum over all nonzero  $v \in V$  gives

$$||ST|| \leq ||S|| \, ||T||$$
.

The above inequality says that the operator norm is *submultiplicative*.

With a crash course in the operator-norm topology on spaces of linear transformations behind us, we can talk about continuity of the derivative of a function. Suppose  $f: U \to W$  is differentiable (at all points of U). Then f gives rise to a map  $Df: U \to$ Hom(V,W) by  $p \mapsto Df|_p$  (the derivative of f at p will also be denoted by  $D_p f$ ; see Proposition 1.1.8).

**Definition 1.2.2.** If  $f: U \to W$  is differentiable (at all points of U) we say f is *continuously differentiable* if the induced map  $U \to \text{Hom}(V, W)$  given by  $p \mapsto D_p f$  is continuous. In this case we write  $f \in C^1(U)$ .

In the special case  $V = \mathbb{R}^n$  and  $W = \mathbb{R}^m$ ,  $f \in C^1$  if and only if the map

$$p \mapsto J_f(p) = \left[\frac{\partial f^i}{\partial x^j}(p)\right]$$

is continuous. Note that the operator norm topology is the natural topology on Hom $(\mathbb{R}^n, \mathbb{R}^m)$ .

### **1.3** How to tell if f is differentiable at p

If f is differentiable at p then

- (i) The directional derivatives  $(D_p f)(v)$  exist for all directions v.
- (ii) For every v, the equality  $Df|_p(v) = (D_p f)(v)$  holds. Since  $Df|_p$  is linear  $v \mapsto (D_p f)(v)$  must also be linear.

As the next examples show, these conditions are not sufficient (of course, we have already proven the necessity of these conditions).

**Example 1.3.1** (Existence of all directional derivatives at p does not imply differentiability at p). Choose any nonlinear function that is homogeneous of degree 1. For example

$$f(x,y) = \begin{cases} \frac{x^3}{x^2 + y^2} & \text{if } (x,y) \neq (0,0) \\ 0 & \text{if } (x,y) = (0,0). \end{cases}$$

so  $f(\lambda x, \lambda y) = \lambda f(x, y)$  and

$$\left(D_{(0,0)}f\right)((a,b)^t) = \lim_{s \to 0} \frac{f(s(a,b)^t) - f((0,0)^t)}{s} = f((a,b)^t) = \frac{a^3}{a^2 + b^2}$$

Thus, for every direction  $(a,b)^t$ , the directional derivative of f at (0,0) in the direction of (a,b) exists. However, the map  $(a,b)^t \to (D_{(0,0)}f)((a,b)^t)$  is is not linear, so f is not differentiable at (0,0).

The next example shows that even if the directional derivative at p in direction v exists for all v and if the map  $v \mapsto D_p f(v)$  is linear, f need not be differentiable at p.

**Example 1.3.2.** Consider  $f : \mathbb{R}^2 \to \mathbb{R}$  given by

$$f(x,y) = \begin{cases} \frac{xy^3}{x^2 + y^4} & \text{if } (x,y) \neq (0,0) \\ 0 & \text{if } (x,y) = (0,0). \end{cases}$$

For this f we have both

 $f|_{x-\text{axis}} \equiv 0 \quad \text{and} \quad f|_{y-\text{axis}} \equiv 0,$ so  $\frac{\partial f}{\partial x}(0,0) = 0 = \frac{\partial f}{\partial y}(0,0).$  Moreover, for any  $(a,b) \neq 0,$  $\frac{f((0,0)+t(a,b)) - f(0,0)}{t} = \frac{f(ta,tb)}{t} = \frac{1}{t} \cdot \frac{t^4 a b^3}{t^2 a^2 + t^4 b^4} = \frac{tab^3}{a^2 + t^2 b^4} \to 0 \quad \text{as } t \to 0.$  Thus, all directional derivatives of f exist at (0,0) and are zero (so in particular, the map  $v \mapsto (D_{(0,0)}f)(v)$  is linear). Therefore, if f is differentiable at (0,0) the derivative of f at (0,0) must be the zero map  $\mathbb{R}^2 \to \mathbb{R}$ . On the other hand, approach (0,0) along the path  $x = y^2$  in the following quotient:

$$\lim_{(x,y)\to 0; \ x=y^2} \frac{f(x,y) - f(0,0)}{\|(x,y)\|} = \lim_{y\to 0} \frac{1}{2\sqrt{1+|y|^2}} \frac{y}{|y|}$$

This limit (and hence the derivative of f at (0,0)) does not exist.

 $\triangle$ 

Given the previous two examples, one may ask the following question: Are there any conditions on the directional derivatives of f that guarantee the existence of the derivative of f? As it turns out, the answer is "yes". The next proposition will address this.

**Proposition 1.3.3.** *If, for all*  $v \in V$  *the directional derivatives*  $(D_p f)(v)$  *exist for all*  $p \in U$  *and the map*  $p \mapsto (D_p f)(v)$  *is continuous for each fixed* v *then*  $f \in C^1(U)$ .

**Lemma 1.3.4.** Under the hypotheses of Proposition 1.3.3, the map  $v \mapsto (D_p f)(v)$  is linear for each  $p \in U$ .

*Proof of Lemma.* We have already shown that the map  $v \mapsto (D_p f)(v)$  is homogenous (see equation (1.2)), so we only need to show that  $(D_p f)(u+v) = (D_p f)(u) + (D_p f)(v)$  for all  $u, v \in V$ . The strategy is to first show that this holds for all u and v with small norm and then remove the norm-smallness requirement.

Fix  $p \in U$  and  $\varepsilon > 0$ . Let  $\hat{u}$  and  $\hat{v}$  be unit vectors. Choose  $\delta > 0$  as in continuity of both  $p \mapsto (D_p f)(\hat{v})$  and  $p \mapsto (D_p f)(\hat{u})$ . That is if  $||q - p|| < \delta$  then both

$$\left\| (D_p f)(\hat{v}) - (D_q f)(\hat{v}) \right\| < \varepsilon \qquad \text{and} \qquad \left\| (D_p f)(\hat{u}) - (D_q f)(\hat{u}) \right\| < \varepsilon.$$

If  $u = \lambda \hat{u}$  and  $v = \alpha \hat{v}$  then by homogeneity of directional derivatives,

$$\left\| (D_p f)(v) - (D_q f)(v) \right\| < \varepsilon \|v\|$$
 and  $\left\| (D_p f)(u) - (D_q f)(u) \right\| < \varepsilon \|u\|$ .

Therefore, if  $u = \lambda \hat{u}$  and  $v = \alpha \hat{v}$  with  $||u|| < \delta/2$  and  $||v|| < \delta/2$ , then  $p + su + tv \in B_{\delta}(p)$  whenever *s* and *t* are real numbers satisfying  $|s|, |t| \le 1$ .

Now consider

$$f(p+u+v) - f(p) - (D_p f)(u) - (D_p f)(v) = [f(p+u+v) - f(p+u) - (D_p f)(v)] + [f(p+u) - f(p) - (D_p f)(u)]$$
(1.3)

and g(t) = f(p+tu) for  $0 \le t \le 1$ . We have

$$g'(t_0) = \lim_{h \to 0} \frac{f(p + t_0 u + hu) - f(p + t_0 u)}{h} = (D_{p + t_0 u} f)(u)$$

This implies

$$g'(t) = \underbrace{(D_{p+tu}f)(u)}_{\text{continuous in }t}.$$

Now,

$$f(p+u) - f(p) = g(1) - g(0) = \int_0^1 \frac{d}{dt}g(t) \, dt = \int_0^1 (D_{p+tu}f)(u) \, dt$$

so

$$f(p+u) - f(p) - (D_p f)(u) = \int_0^1 \left[ (D_{p+tu}f)(u) - \underbrace{(D_p f)(u)}_{\text{independent of } t} \right] dt$$

and

$$||f(p+u) - f(p) - (D_p f)(u)|| \le \int_0^1 ||(D_{p+tu}f)(u) - (D_p f)(u)|| dt \le \varepsilon ||u||,$$

the final estimate holding as  $p + tu \in B_{\delta}(p)$ .

Next, we handle the term  $f(p+u+v) - f(p+u) - (D_p f)(v)$  in equation (1.3). By a similar argument we have

$$\begin{aligned} \left\| f(p+u+v) - f(p+u) - (D_p f)(v) \right\| &= \left\| \int_0^1 \left[ (D_{p+u+tv} f)(v) - (D_p f)(v) \right] dt \right\| \\ &\leq \int_0^1 \left\| (D_{p+u+tv} f)(v) - (D_p f)(v) \right\| dt \\ &\leq \varepsilon \|v\|. \end{aligned}$$

Thus, in view of equation (1.3), by taking norms we have

$$\|f(p+u+v)-f(p)-(D_pf)(u)-(D_pf)(v)\| \le \varepsilon(\|u\|+\|v\|).$$

Replacing *u* by *tu* and *v* by *tv* with  $|t| \le 1$  we have

$$\frac{\left\|f(p+t(u+v)) - f(p) - t\left[(D_p f)(u) + (D_p f)(v)\right]\right\|}{|t|} \le \frac{\varepsilon |t| \left(\|u\| + \|v\|\right)}{|t|} = \varepsilon (\|u\| + \|v\|).$$

Therefore, as  $t \rightarrow 0$ , the quotient becomes arbitrarily small and we get

$$0 = \lim_{t \to 0} \frac{f(p + t(u + v)) - f(p) - t[(D_p f)(u) + (D_p f)(v)]}{t}$$
  
= 
$$\lim_{t \to 0} \underbrace{\frac{f(p + t(u + v)) - f(p)}{t}}_{\rightarrow (D_p f)(u + v) \text{ by hypothesis}} - [(D_p f)(u) + (D_p f)(v)]$$

Therefore, if *u* is a scalar multiple of  $\hat{u}$  with  $||u|| < \delta/2$  and if *v* is a scalar multiple of  $\hat{v}$  with  $||v|| < \delta/2$  then

$$(D_p f)(u+v) = (D_p f)(u) + (D_p f)(v).$$

Next we remove the restriction on the smallness conditions on ||u|| and ||v||. Given u and v (of possibly large norms) choose a scalar  $\lambda$  such that both  $||u/\lambda|| < \delta/2$  and  $||v/\lambda|| < \delta/2$ . Then

$$(D_p f)\left(\frac{u}{\lambda} + \frac{v}{\lambda}\right) = (D_p f)\left(\frac{u}{\lambda}\right) + (D_p f)\left(\frac{v}{\lambda}\right).$$

The equality  $(D_p f)(u + v) = (D_p f)(u) + (D_p f)(v)$  now follows from homogeneity of directional derivates.

*Remark* 1.3.5. Suppose instead of assuming existence and continuity of  $p \mapsto (D_p f)(v)$  for all v, we only assume for  $v \in \{e_1, \dots, e_n\}$  (a basis for V). Then

$$(D_p f)(u+v) = (D_p f)(u) + (D_p f)(v) \quad \text{for all } u \in \text{span}\{e_1\}, v \in \text{span}\{e_2\}.$$

Therefore,  $(D_p f)$  restricted to span $\{e_1, e_2\}$  is linear. Inductively, suppose  $u \in \text{span}\{e_1, e_2\}$ ,  $v \in \text{span}\{e_3\}$ . We can show that the restriction of  $(D_p f)$  to span $\{e_1, e_2, e_3\}$  is linear. Repeating this procedure a finite number of times we can obtain the linearity of  $(D_p f)$  (the "restriction" of  $(D_p f)$  to span $\{e_1, \dots, e_n\}$ ).

*Proof of Proposition 1.3.3.* Fix  $p \in U$ . We want to show there exists a linear map  $T: V \to W$  such that

$$\frac{\|f(p+v) - f(p) - T(v)\|}{\|v\|} \to 0 \qquad \text{as } \|v\| \to 0.$$

Given that  $(D_p f)(v)$  exists for all v and that the map  $v \mapsto (D_p f)(v)$  is linear, the obvious choice for T is  $T(v) = \sum_{i=1}^{n} (D_p(f)(v^i e_i))$ , where  $\{e_i\}_{i=1}^{n}$  is a basis for V relative to which  $v = \sum_{i=1}^{n} v^i e_i$ . We showed in the lemma that given  $\varepsilon > 0$  and unit vector  $\hat{u}$ , there exists  $\delta > 0$  such that

$$\left\|f(q+u) - f(q) - (D_q f)(u)\right\| \le \varepsilon \|u\|$$
(1.4)

whenever  $||u|| < \delta$  and  $u \in \text{span}\{\hat{u}\}$ . Let  $v = \sum_{i=1}^{n} v^{i} e_{i}$  satisfy  $\min(||v||_{\infty}, ||v||) < \delta$  so that  $p + v \in B_{\delta}(p)$ . For ease of notation, we set for  $j = 1, \dots, n$ ,

$$w_j = \sum_{i=1}^j v^i e_i,$$

the projection of v onto span $\{e_1, \dots, e_j\}$  and  $w_0 = 0$ . Note that for each  $j, w_j \in B_{\delta}(p)$  so we can use estimate (1.4) with q replaced by  $p + w_{j-1}$  and u replaced by  $v^j e_j$ . Accord-

ingly, we have

$$\begin{aligned} \left\| f(p+v) - f(p) - \sum_{j=1}^{n} (D_{p}f)(v^{i}e_{i}) \right\| &\leq \sum_{j=1}^{n} \left\| f(p+w_{j-1}+v^{j}e_{j}) - f(p+w_{j-1}) - (D_{p+w_{j-1}}f)(v^{j}e_{j}) \right\| \\ &+ \sum_{j=1}^{n} \left\| (D_{p+w_{j-1}}f)(v^{j}e_{j}) - (D_{p}f)(v^{j}e_{j}) \right\| \\ &\leq \sum_{j=1}^{n} \varepsilon \left\| v^{j}e_{j} \right\| + \sum_{j=1}^{n} \left| v^{j} \right| \left\| (D_{p+w_{j-1}}f)(e_{j}) - (D_{p}f)(e_{j}) \right\| \\ &\leq 2\varepsilon \|v\|_{\infty} \\ &\leq 2C\varepsilon \|v\|, \end{aligned}$$

the final estimate holding as dim $V < \infty$  (so that all norms on V are equivalent). This shows that for all nonzero  $v \in V$  with ||v|| sufficiently small,

$$\frac{\left\|f(p+v)-f(p)-\sum_{j=1}^{n}(D_{p}f)(v^{i}e_{i})\right\|}{\|v\|}<\varepsilon.$$

That is, f is differentiable at p with  $Df|_p(v) = \sum_{i=1}^n D_p f(v^i e_i)$ .

...

It remains to show  $q \mapsto Df|_q$  is continuous. We will show that  $q \mapsto Df|_q$  is continuous at fixed but arbitrary  $p \in U$ . Note that for  $q \in U$  we have  $Df|_q \in \text{Hom}(V,W)$  so we need to show that  $\left\| Df|_q - Df|_p \right\|_{\text{op}} \to 0$  as  $\|q - p\| \to 0$ . Take  $q \in B_{\delta}(p)$  and consider the difference

$$\begin{split} \left\| Df \right\|_{p}(v) - Df \right\|_{q}(v) &= \left\| \sum_{i=1}^{n} v^{i} \left[ (D_{p}f)(e_{i}) - (D_{q}f)(e_{i}) \right] \right\| \\ &\leq \sum_{i=1}^{n} |v^{i}| \left\| (D_{p}f)(e_{i}) - (D_{q}f)(e_{i}) \right\| \\ &\leq \varepsilon \sum_{i=1}^{n} |v^{i}| \\ &\leq \varepsilon C_{1} \|v\|. \end{split}$$

If  $v \neq 0$  divide through by ||v|| to get

$$\frac{\left\|Df\right|_{p}(v) - Df\Big|_{q}(v)\right\|}{\|v\|} \leq \varepsilon C_{1}$$

By homogeneity of  $\left\|\cdot\right\|$  and homogeneity of directional derivatives we get

$$\left\| \left( Df \big|_p - Df \big|_q \right) \left( \frac{v}{\|v\|} \right) \right\| \le \varepsilon C_1$$

so that

$$\left\| Df \right\|_{q} - Df \right\|_{p} = 0$$
 as  $q \to p$ .

**Definition 1.3.6.** A subset U of a vector space V is called *convex* if for all  $p, q \in U$  and all  $t \in [0,1]$ , the point  $tp + (1-t)q \in U$  (i.e. for all points p and q in U, the segment joining p and q lies entirely in U.

**Theorem 1.3.7** (Mean Value Theorem for vector-valued functions). Suppose U is an open convex subset of a vector space V and  $f \in C^1(U)$ . If there exists a constant M > 0 such that  $\left\| Df \right\|_q \leq M$  for all  $q \in U$  then

$$d(f(p), f(q)) \le Md(p,q)$$
 for all  $p, q \in U$ .

*Proof.* Fix  $f \in C^1(U)$ . For  $p, q \in U$  set v = q - p (so q = p + v) and let  $S = \{tp + (1 - t)q\}_{0 \le t \le 1}$ . Then

$$f(q) - f(p) = \int_0^1 \frac{d}{dt} f(p + tv) \, dt = \int_0^1 (D_{p+tv} f)(v) \, dt.$$

Taking norms on both sides we have

$$\begin{aligned} \|f(q) - f(p)\| &\leq \int_0^1 \left\| (D_{p+tv}f)(v) \right\| dt \\ &\leq \int_0^1 \left\| Df \right\|_{p+tv} \left\| \|v\| dt \\ &\leq \underbrace{\sup_{p' \in S} \left\| Df \right\|_{p'}}_{M} \\ &\leq M \|p-q\|. \end{aligned}$$

As the next example shows, we can not expect equality in the Mean-Value Theorem for vector-valued functions.

**Example 1.3.8.** Let  $f : \mathbb{R} \to \mathbb{R}^2$  be given by  $\theta \mapsto (\cos \theta, \sin \theta)$ . Choose p = 0 and  $q = 2\pi$ . Then

$$||f(q) - f(p)|| = ||(1,0) - (1,0)|| = 0.$$

On the other hand, for all  $p' \in \mathbb{R}$  (in particular for all p' between p = 0 and  $q = 2\pi$ ),

$$\left\| Df \right\|_{p'}(q-p) = \left\| (-\sin(p'), \cos(p')) \cdot 2\pi \right\| = 2\pi.$$

Thus, for all p' between 0 and  $2\pi$ ,

$$||f(q) - f(p)|| = 0 < 2\pi = ||Df|_{p'}(q-p)||.$$

### **1.4 Second Derivatives**

Throughout this section *V* and *W* will be finite-dimensional vector spaces. Let *U* be an open subset of *V* and suppose  $f: U \to W$  is differentiable. We get a map  $U \to \text{Hom}(V, W)$  via  $q \mapsto Df|_q$ . In view of Definition 1.1.1, this map is differentiable at  $p \in U$  if there is a linear map  $T: V \to \text{Hom}(V, W)$  such that

$$\frac{\left\|Df\right|_{p+h} - Df\Big|_p - T(h)\right\|_{\text{op}}}{\|h\|} \to 0 \qquad \text{as } h \to 0.$$

In this case, by Claim 1.1.3, the linear map  $T: V \to \text{Hom}(V, W)$  is unique and we will denote this map by  $T = D(Df)|_p = D_p(Df)$ . That is,  $D(Df)|_p \in \text{Hom}(V, \text{Hom}(V, W))$ . Evaluating this map at  $v \in V$  gives  $(D_p(Df))(v) \in \text{Hom}(V, W)$ . Evaluating the map  $(D_p(Df))(v)$  at  $u \in V$  gives  $((D_p(Df))(v))(u) \in W$ . This notion of a second derivative is complicated, so some insight on the space Hom(V, Hom(V, W)) is in order. Define  $\text{Bil}(V \times V, W)$  to be the vector space of bilinear maps  $V \times V \to W$  with norm

$$||F|| = \sup_{||u||, ||v||=1} ||F(u, v)||.$$

For our purposes an important fact is the following:

The vector spaces Hom(V, Hom(V, W)) and  $Bil(V \times V, W)$  are isometrically isomorphic.

A proof of this fact can be found in Lemma 2.0.12 of the appendix. The major consequence of this lemma is that for each  $p \in U$ , we can (naturally and linearly) identify the map  $D_p(Df) \in \text{Hom}(V, \text{Hom}(V, W))$  with a map  $D_p^2 f \in \text{Bil}(V \times V, W)$  by

$$(D_p^2 f)(u, v) = (D_p(Df)(v))(u).$$

The bilinear mapping  $D_p^2 f: V \times V \to W$  is much easier to understand than the linear, Hom(V, W)-valued mapping  $D_p(Df)$ .

**Theorem 1.4.1.** Let  $\{e_i\}$  be a basis for V. Assume  $(D_p^2 f)(e_i, e_j)$  exists for all p and all i, j and that  $p \mapsto (D_p^2 f)(e_i, e_j)$  is continuous. Then

- (a)  $(D_p^2 f)(e_i, e_j) = (D_p^2 f)(e_j, e_i)$  (equality of mixed partials)
- (b)  $(D_p^2 f)(u, v)$  exists for all  $u, v \in V$ .
- (c) Bilinearity: For each fixed  $v, u \mapsto (D_p^2 f)(u, v)$  is linear in u. For each fixed  $u, v \mapsto (D_p^2 f)(u, v)$  is linear in v.
- (d)  $D_p^2 f$  is symmetric:  $(D_p^2 f)(u, v) = (D_p^2 f)(v, u)$  for all  $u, v \in V$
- (e)  $(D_p(Df)(v))(u) = (D_p^2 f)(u, v)$ . [Note: If  $f: U \subset V \to W$ , then  $Df: U \to \text{Hom}(V, W)$ is the map  $p \mapsto D_p f$ . Thus,  $D(Df): U \to \text{Hom}(V, \text{Hom}(V, W))$  is the map  $q \mapsto D_q(Df): V \to \text{Hom}(V, W)$ . Evaluating this map at  $v \in V$  gives  $(D_q(Df))(v) \in \text{Hom}(V, W)$ . Finally, evaluating the map  $(D_q(Df))(v)$  at  $u \in V$  gives  $((D_q(Df))(v))(u) \in W$ .]

Proof. omitted.

**Example 1.4.2.** Let  $V = \{n \times n \text{ matrices}\} = M_{n \times n}(\mathbb{R}) = W$ . So dim $(V) = n^2 = \dim(W)$ . the standard basis is  $\{e_{ij}\}$ , where  $e_{ij}$  is the matrix whose (ij)th entry is 1 and all other entries are zero. Define  $f : V \to V$  to be the squaring map

$$f(A) = A^2.$$

Let  $A, B \in M_{n \times n}(\mathbb{R})$  Then

$$(D_A f)(B) = \frac{d}{dt} (A + tB)^2 \Big|_{t=0} = \frac{d}{dt} \left( A^2 + t(AB + BA) + t^2 B^2 \right) \Big|_{t=0} = AB + BA.$$

*Remark* 1.4.3. If we fix a basis, we can get a Jacobian matrix  $n^2 \times n^2$ , however this point will not be pursued here.

For fixed *B*, the map  $A \mapsto AB + BA$  is continuous. Therefore, *f* is differentiable and  $Df|_A : M_{n \times n}(\mathbb{R}) \to M_{n \times n}(\mathbb{R})$  is given by  $Df|_A(B) = AB + BA$ . Compute $(D_A^2 f)(B,C)$ :

$$(D_A(Df))(B)(C) = (D_A^2 f)(B,C) = D_A(\underbrace{A' \mapsto (D_{A'}f)(B)}_{A'B+BA'})(C) = CB + BC.$$

Notice that this computation illustrates the fact that "the derivative of a liner map is itself" (see Example 1.1.5). So,  $(D_A^2 f)(B,C) = BC + CB$  is constant as a function of A. Conclude that  $D^3 f = 0$ .

#### 1.4. SECOND DERIVATIVES

**Example 1.4.4.** Let  $V = M_{n \times n}(\mathbb{R}) = W$  and let  $U = GL_n(\mathbb{R}) = \{A \in M_{n \times n}(\mathbb{R}) : A \text{ is invertible}\}$ . Note that *U* is an open subset of *V* as *U* is the preimage of the open set  $\mathbb{R} \setminus \{0\}$  under the continuous function det :  $M_{n \times n}(\mathbb{R}) \to \mathbb{R}$  (you can check on your own that the determinant is continuous).

In this example we will compute the first two derivatives of the inversion map i:  $GL_n(\mathbb{R}) \to GL_n(\mathbb{R})$  given by  $i(A) = A^{-1}$ . As usual, in order to guess the formula for  $Di|_A$ , we should consider  $D_A i(B)$ , the directional derivative of i at A in the direction of B. We have

$$D_A i(B) = \lim_{t \to 0} \frac{i(A+tB) - i(A)}{t},$$

whenever the limit exists. Since the numerator in this quotient is equal to

$$(A+tB)^{-1} - A^{-1} = (A(I+tA^{-1}B))^{-1} - A^{-1} = ((I+tA^{-1}B)^{-1} - I)A^{-1},$$

we see that

$$D_A i(B) = D_I i(A^{-1}B) \cdot A^{-1}.$$
(1.5)

In order to make our lives easier, let us compute  $D_I i(B)$  for  $B \in GL_n(\mathbb{R})$ . Once we have computed  $D_I i(B)$ , we can use this result with *B* replaced by  $A^{-1}B$  in equation (1.5) to recover  $D_A i(B)$ . To compute  $D_I i(B)$  we need to compute  $\frac{d}{dt}(I+tB)^{-1}|_{t=0}$ . We achieve this with a "geometric series trick".

**Claim 1.4.5.** If  $A \in M_{n \times n}(\mathbb{R})$  with ||A|| < 1 then  $S_m = \sum_{j=0}^m A^j$  converges (with respect to  $||\cdot||_{\text{op}}$ ) to  $(I-A)^{-1}$ .

*Proof of Claim.* first observe that for any integer  $j \ge 1$  and any  $x \in \mathbb{R}^n$  with ||x|| = 1,

$$||A^{j}x|| = ||AA^{j-1}x|| \le ||A|| ||A^{j-1}x||.$$

Repeating this estimate j - 1 more times gives

$$||A^{j}x|| \le ||A||^{j} ||x|| = ||A||^{j},$$

where ||x|| = 1 was used in the final equality. Taking the supremum over all ||x|| = 1 gives  $||A^j|| \le ||A||^j$ .

Next, we show that  $S_m$  converges to some (bounded) linear operator as  $m \to \infty$ . Since  $\text{Hom}(\mathbb{R}^n, \mathbb{R}^n)$  is complete, it suffices to show that  $S_m$  is a Cauchy sequence. Accordingly, let  $m, k \in \mathbb{N}$ . We have

$$\|S_{m+k} - S_k\| = \|A^{k+1} + \dots + A^{k+m}\|$$
  
 
$$\leq \|A^{k+1}\| \|S_{m-1}\|$$
  
 
$$\leq \|A\|^{k+1} \|S_{m-1}\|.$$

Now, for any  $m \in \mathbb{N}$ , by comparing to the geometric series  $\sum_{j=0}^{\infty} ||A||^j$ , we have  $||S_{m-1}|| \le (1-||A||)^{-1}$ . Therefore, letting  $k, m \to \infty$  in the above string of inequalities gives  $||S_{m+k} - S_k|| \to 0$  as  $k, m \to \infty$ .

Finally, we show that  $S_{\infty} := \sum_{j=0}^{\infty} A^j$  satisfies  $S_{\infty} = (I - A)^{-1}$ . For any  $m \in \mathbb{N}$ , we have  $(I - A)S_m = I - A^{m+1}$ , so

$$(I-A)S_{\infty} - I = -A^{m+1} - (I-A)(S_m - S_{\infty}).$$

After taking norms we get

$$||(I-A)S_{\infty}-I|| \le ||A||^{m+1} + ||I-A|| ||S_m-S_{\infty}||.$$

Letting  $m \to \infty$  in this estimate shows that  $S_{\infty}$  is a right-inverse of I - A. By a similar argument we have that  $S_{\infty}$  is a left-inverse of I - A. The claim is estiablished.

Now, using the claim, we have for |t| sufficiently small  $(|t| ||B|| < \frac{1}{2}$  is sufficient),

$$(I+tB)^{-1} = (I-(-tB))^{-1} = \sum_{k=0}^{\infty} (-1)^k t^k B^k$$

so

$$D_I i(B) = \frac{d}{dt} \left( I + tB \right)^{-1} \Big|_{t=0} = \frac{d}{dt} \sum_{k=0}^{\infty} (-1)^k t^k B^k \Big|_{t=0} = \sum_{k=1}^{\infty} (-1)^k k t^{k-1} B^k \Big|_{t=0} = -B.$$

(Note that the term-by-term differentiated series  $\sum_{k=1}^{\infty} (-1)^k k t^{k-1} B^k$  converges uniformly for |t| sufficiently small). Replacing *B* by  $A^{-1}B$  in this equality and in view of equation (1.5) we have for  $A, B \in GL_n(\mathbb{R})$ ,

$$D_A i(B) = D_I i(A^{-1}B) \cdot A^{-1} = -A^{-1}BA^{-1}.$$

Since, for fixed  $B \in GL_n(\mathbb{R})$  the map  $A \mapsto -A^{-1}BA^{-1}$  is continuous, Proposition 1.3.3 implies that *i* is differentiable and  $Di|_A : GL_n(\mathbb{R}) \to GL_n(\mathbb{R})$  is given by

$$Di|_{A}(B) = D_{A}i(B) = -A^{-1}BA^{-1}.$$

This is the matrix-version of the first-semester calculus result  $\frac{d}{dx}(x^{-1}) = -x^{-2}$  for  $x \in \mathbb{R}$ .

Now, for  $A, B, C \in GL_n(\mathbb{R})$  let us compute

$$D_A^2 i(B,C) = D_A \left( (M \mapsto Di|_M)(B) \right)(C),$$

#### 1.5. CHAIN RULE

the directional derivative of the map  $(M \mapsto Di|_M)(B) : GL_n(\mathbb{R}) \to GL_n(\mathbb{R})$  at *A* in direction *C*. We have

$$D_A \left( (M \mapsto Di \big|_M) (B) \right) (C) = \frac{d}{dt} \left( -(A + tC)^{-1} B(A + tC)^{-1} \right) \Big|_{t=0}$$
  
=  $- \left[ -A^{-1} C A^{-1} B A^{-1} - A^{-1} B A^{-1} C A^{-1} \right]$   
=  $A^{-1} C A^{-1} B A^{-1} + A^{-1} B A^{-1} C A^{-1}.$ 

This is the matrix version of the first-semester calculus result  $\frac{d^2}{dx^2}(x^{-1}) = 2x^{-3}$ .

Similarly, one can compute for  $A, B, C, D \in GL_n(\mathbb{R})$ ,

$$D_A i(B,C,D) = \sum (\text{six terms}),$$

which is the matrix version of the first-semester calculus result  $\frac{d^3}{dx^3}(x^{-1}) = 3! x^{-4}$ .

## 1.5 Chain Rule

Throughout this section V, W and X will be finite-dimensional vector spaces and  $A \subset V$ and  $B \subset W$  will be open sets. Let  $f: V \to W$  and  $g: W \to X$  and suppose  $p \in A$  with  $f(p) \in B$ . The best statement of the chain rule is

"The derivative of a composition is the composition of the derivatives".

**Theorem 1.5.1.** With data as above, if f is differentiable at p and g is differentiable at f(p) then  $g \circ f$  is differentiable at p and

$$D(g \circ f)\big|_p = Dg\big|_{f(p)} \circ Df\big|_p.$$

*Proof.* The proof is left as an exercise. One should use the definition of the derivative.

Consider the special case where  $V = \mathbb{R}^n$ ,  $W = \mathbb{R}^m$  and  $X = \mathbb{R}^k$ . In this case, as in Example 1.1.9 we have

$$Df|_p(v) = \underbrace{J_f(p)}_{m \times n} \underbrace{v}_{\in \mathbb{R}^n} \in \mathbb{R}^m$$
 and  $Dg|_q(w) = \underbrace{J_g(q)}_{k \times m} \underbrace{w}_{\in \mathbb{R}^m} \in \mathbb{R}^k$ .

Theorem 1.5.1 implies

$$D(g \circ f)\big|_p(v) = Dg\big|_{f(p)} \left( Df\big|_p(v) \right) = \underbrace{J_g(f(p))}_{k \times m} \underbrace{J_f(p)}_{m \times n} \underbrace{v}_{\in \mathbb{R}^n} \in \mathbb{R}^k \quad \text{for all } v \in \mathbb{R}^n.$$

Therefore, (the second-best statement of the chain rule)

$$J_{g \circ f}(p) = J_g(f(p))J_f(p).$$

**Corollary 1.5.2.** In the setting of Theorem 1.5.1, if f and g are  $C^1$  then so is  $g \circ f$ .

Proof. Take a look at the the diagram in Figure 1.1. Since each of these maps is continu-

$$A \longrightarrow A \times B \longrightarrow \operatorname{Hom}(V, W) \times \operatorname{Hom}(W, X) \longrightarrow \operatorname{Hom}(V, X)$$

$$p \longmapsto (p, f(p))$$



$$(T,S) \longmapsto (S \circ T)$$

$$p \longmapsto Dg\big|_{f(p)} \circ Df\big|_p$$

Figure 1.1: Writing the map  $p \mapsto Dg|_{f(p)} \circ Df|_p$  as the composition of continuous maps ous so the map  $A \to \text{Hom}(V, X)$  given by

$$p\mapsto Dg\big|_{f(p)}\circ Df\big|_p$$

is continuous.

**Corollary 1.5.3.** Let  $1 \le k \le \infty$ . If f and g are composable  $C^k$  maps then  $g \circ f$  is also  $C^k$ .

*Proof.* Use induction and the "composition trick" from Corollary 1.5.2.

## **1.6 Inverse and Implicit Function Theorems**

Throughout this section, X and Y will denote finite-dimensional vector spaces and U will denote an open subset of X.

**Definition 1.6.1.** A map g is called a *diffeomorphism* if g is a differentiable map with differentiable inverse. If both g and  $g^{-1}$  are  $C^k$  we call g a  $C^k$ -diffeomorphism. Say g is a *local diffeomorphism at p*. if there exists a (small) neighborhood  $U \subset \text{domain}(g)$  with  $p \in U$  such that  $g|_U$  is a diffeomorphism. Say g is a *local diffeomorphism* if g is a local diffeomorphism at each  $p \in \text{domain}(g)$ .

**Theorem 1.6.2** (Inverse Function Theorem). Let X and Y be finite-dimensional vector spaces, let  $U \subset X$  be open and let  $f : U \to Y$  be a  $C^1$  map. If  $x_0 \in U$  is such that  $D_{x_0}f$  is invertible then f is a local  $C^1$ -diffeomorphism at  $x_0$ . That is, if  $D_{x_0}f$  is invertible, then there exists open neighborhoods  $U_1$  of  $x_0$  and  $V_1$  of  $f(x_0)$  such that f maps  $U_1$  to  $V_1$  bijectively and such that

$$\left(f\big|_{U_1}\right)^{-1}:V_1\to U_1$$

is  $C^1$ .

Proof. omitted.

As the next corollary shows, a simple application of the chain rule yields an expression for the derivative of  $f^{-1}$  in terms of the derivative of f.

Corollary 1.6.3 (Corollary to Inverse Function Theorem). In the setting of Theorem 1.6.2,

$$D_y f^{-1} = \left( D_{f^{-1}(y)} \right)^{-1}$$

for  $y \in V_1$ . Here,  $f^{-1}$  is the inverse of  $f|_{U_1} : U_1 \to V_1$ .

*Proof.* Let  $h = (f|_{U_1})^{-1}$ . Then  $f \circ h = id_{V_1} = id_Y|_{V_1}$ . Note that  $f \circ h$  is linear so  $f \circ h$  is "its own derivative". By the chain rule (applied to the function  $f \circ h$ ),

$$\operatorname{id}_Y = D_y(f \circ h) = D_{h(y)}f \circ D_y h$$

Therefore,  $D_y h = (D_{h(y)}f)^{-1}$ .

**Corollary 1.6.4.** In the setting of the Inverse Function Theorem, if f is  $C^k$ , where  $1 \le k \le \infty$ , then so is the locally-defined  $f^{-1} = h$ .

*Sketch of Proof.* The idea of the (beginning of the) proof is that if  $f \in C^2$  then one can to use the Inverse Function Theorem together with Corollary 1.6.3 to write  $y \mapsto D_y f^{-1}$  as a composition of  $C^1$  maps. Observe that  $Dh: V_1 \to \text{Hom}(Y, X)$  is given by

$$y \mapsto D_y h = \left(D_{f^{-1}(y)}f\right)^{-1} = (i \circ Df \circ f^{-1})(y),$$



Figure 1.2: If 
$$f \in C^k$$
, then *Dh* is a composition of  $C^{k-1}$  maps

where

$$i$$
: (open subset of Hom $(X, Y)$ )  $\rightarrow$  Hom $(Y, X)$ 

is the inversion map. Assume f is  $C^2$ . Then Df is  $C^1$ . Moreover,  $f^{-1}$  is  $C^1$  (by the Inverse Function Theorem) and i is  $C^1$  (see Example 1.4.4 for the idea behind a proof of this fact). Therefore, Dh is  $C^1$  and h is  $C^2$ . Now induct on k.

Motivation for the Implicit Function Theorem. Suppose we have a system of m scalar equations in m + n unknowns (n > 0). Write the system as follows:

$$f^{1}(x, y) = 0$$
  

$$f^{2}(x, y) = 0$$
  

$$\vdots$$
  

$$f^{m}(x, y) = 0,$$

were  $x = (x^1, \dots, x^n)$  and  $y = (y^1, \dots, y^m)$ . Want to solve for  $\{y^i\}$  in terms of  $\{x^j\}$ . Morally we should be able to use each equation to eliminate one variable iteratively: Use the first equation to write

$$y^{m}$$
 = function of  $(x, y^{1}, y^{2}, \dots, y^{m-1})$ .

Substitute this into remaining equations to get a new system of m-1 equations in m+n-1 unknowns:

$$\tilde{f}^{(2)}(x, y^1, \cdots, y^{m-1}) = 0$$
  
:  
$$\tilde{f}^{(m)}(x, y^1, \cdots, y^{m-1}) = 0.$$

Use the new first equation to solve for  $y^{m-1}$  in terms of the remaining variables to get

$$y^{m-1}$$
 = function of $(x, y^1, \cdots, y^{m-2})$ .

This expression for  $y^{m-1}$  can also be used to express  $y^m$  as a function of  $(x, y^1, \dots, y^{m-2})$ . Repeat as necessary to end up with  $y = (y^1, \dots, y^m)$  in terms of x. For notational convenience we define the vector-valued function  $F: X \times Y \to W$  by

$$F(x,y) = \begin{pmatrix} f^1(x,y) \\ \vdots \\ f^m(x,y) \end{pmatrix}$$

so that the system

$$\begin{cases} f^1(x,y) = 0\\ \vdots\\ f^m(x,y) = 0 \end{cases}$$

becomes F(x, y) = 0.



Temporarily, for i = 1, 2, let  $D_p^{[i]} F$  for the linear map

$$\begin{cases} X \to W & \text{ if } i = 1 \\ Y \to W & \text{ if } i = 2 \end{cases}$$

obtained by differentiating with respect to the  $i^{\text{th}}$  factor of  $X \times Y$  holding variable in other factor fixed e.g.

$$(D_p^{[2]}F)(v) = (D_pF) \begin{pmatrix} 0\\ v \end{pmatrix}$$

**Theorem 1.6.5** (Implicit Function Theorem). With data as in above diagram, assume  $F : A \times B \to W$  is  $C^1$ . Let  $(x_0, y_0) \in A \times B$  and assume  $F(x_0, y_0) = 0$ . Suppose  $D_{(x_0, y_0)}^{[2]}F : Y \to W$  is invertible. Then there exists open neighborhoods  $A_1$  of  $x_0$  and  $B_1$  of  $y_0$  and a  $C^1$  function  $g : A_1 \to B_1$  such that for all  $(x, y) \in A_1 \times B_1$ , F(x, y) = 0 if and only if y = g(x). See Figure 1.3.

Under the hypotheses of the setting of the Implicit Function Theorem, the level set of F locally defines y as a  $C^1$  function of x. The next corollary shows us how to compute the derivative of this function in terms of F.

**Corollary 1.6.6** (Corollary to Implicit Function Theorem). In the setting of Theorem 1.6.5,

$$D_{x}g = -\left(D_{(x,g(x))}^{[2]}F\right)^{-1} \circ D_{(x,g(x))}^{[1]}F.$$



Figure 1.3: Figure for Implicit Function Theorem. If  $(x_0, y_0)$  is on the level-set of *F* and if  $D_{(x_0, y_0)}^{[2]}F$  is invertible then the level set of *F* locally defines *y* as a  $C^1$  function of *x*.

The proof of Corollary 1.6.6 is omitted but follows routinely from the following lemma.

**Lemma 1.6.7.** *The derivative of the map*  $h : x \mapsto F(x, g(x))$  *is given by* 

$$D_x h = D_{(x,g(x))}^{[1]} F + \left( D_{(x,g(x))}^{[2]} F \right) \circ D_x g.$$

*Proof of Lemma*. *h* is a composition as in Figure 1.4. Now you can finish the proof.

 $A_1 \longrightarrow A_1 \times B_1 \longrightarrow W$ 

 $x \longmapsto (x, g(x)) \longmapsto F(x, g(x))$ 

Figure 1.4: *h* is a composition

Note: If *x* and *y* are one-dimensional variables and F(x, y) = 0 then differentiability with respect to *x* gives

$$\frac{\partial F}{\partial x}(x,y) + \frac{\partial F}{\partial y}(x,y)\frac{dy}{dx} = 0$$

Solving for  $\frac{dy}{dx}$  yields

$$\frac{dy}{dx} = -\frac{\partial F}{\partial x} \left(\frac{\partial F}{\partial y}\right)^{-1},$$

the usual formula for "implicit differentiation" from first-semester calculus.

**Corollary 1.6.8** (Corollary to Implicit Function Theorem). *The g given by the Implicit Function Theorem is as continuously differentiable as the F*.

Proof. Do it on your own.

### **1.6.1** Equivalence of the Inverse and Implicit Function Theorems

#### This section has not been proof read

Claim 1.6.9. The Implicit Function Theorem implies the Inverse Function Theorem.

*Proof.* Assume the Implicit Function Theorem holds and assume the hypotheses of the Inverse Function Theorem. Define  $F : Y \times U \rightarrow Y$  by

$$F(y,x) = y - f(x)$$
 for  $x \in U, y \in Y$ .

It is easy to show that F is  $C^1$  since f is. Let  $y_0 = f(x_0)$  so that  $F(y_0, x_0) = 0$ .

$$D_{(x_0,y_0)}^{[2]}F = -D_{x_0}f$$

is invertible. By the Implicit Function Theorem, there exists neighborhoods  $A_1$  of  $y_0$  and  $B_1$  of  $x_0$  and a  $C^1$  map  $g: A_1 \to B_1$  such that for all  $(y, x) \in A_1 \times B_1$ , F(y, x) = 0 if and only if x = g(y) (i.e. y = f(x) if and only if x = g(y)). So

$$g = \left(f\big|_{B_1}\right)^{-1}.$$

Claim 1.6.10. The Inverse Function Theorem Implies the Implicit Function Theorem.

*Proof.* Assume the Inverse Function Theorem holds and assume the hypotheses of the Implicit Function Theorem. Have

$$F: \underbrace{A}_{\dim n} \times \underbrace{B}_{\dim m} \to \underbrace{W}_{\dim m}$$

*F* can be invertible since the dimensions of the domain of *F* and the codomain of *F* do not coincide. Define  $f : A \times B \to A \times W$  by

$$(x,y) \mapsto (x,F(x,y))$$

(so the dimension of f's domain and the dimension of f's codomain coincide). Then f is  $C^1$  and

$$(D_{(x,y)}f)\begin{pmatrix}a\\0\end{pmatrix} = \frac{d}{dt}f\begin{pmatrix}x+ta\\y\end{pmatrix}\Big|_{t=0}$$
$$= \frac{d}{dt}\begin{pmatrix}x+ta\\F(x+ta,y)\end{pmatrix}\Big|_{t=0}$$
$$= \begin{pmatrix}a\\(D_{(x,y)}^{[1]}F)(a)\end{pmatrix}.$$

Similarly,

$$(D_{(x,y)}f)\begin{pmatrix}0\\b\end{pmatrix} = \begin{pmatrix}a\\(D_{(x,y)}^{[2]}F)(b)\end{pmatrix}.$$

Take  $(x, y) = (x_0, y_0)$ . For notational convenience, define linear maps

$$S = D_{(x_0,y_0)}^{[1]}F$$
 and  $T = D_{(x_0,y_0)}^{[2]}F$ .

Then

$$\begin{pmatrix} D_{(x_0,y_0)} \end{pmatrix} \begin{pmatrix} a \\ b \end{pmatrix} = \begin{pmatrix} D_{(x_0,y_0)} \end{pmatrix} \begin{pmatrix} a \\ 0 \end{pmatrix} + \begin{pmatrix} D_{(x_0,y_0)} \end{pmatrix} \begin{pmatrix} 0 \\ b \end{pmatrix}$$

$$= \begin{pmatrix} a \\ S(a) \end{pmatrix} + \begin{pmatrix} 0 \\ T(b) \end{pmatrix}$$

$$= \begin{pmatrix} a \\ S(a) + T(b) \end{pmatrix}.$$

Therefore,  $D_{(x_0,y_0)}f$  is the map

$$\begin{pmatrix} a \\ b \end{pmatrix} \mapsto \begin{pmatrix} a \\ S(a) + T(b) \end{pmatrix}.$$

Next, we show this map is invertible. Accordingly, suppose

$$\begin{pmatrix} a \\ S(a) + T(b) \end{pmatrix} = \begin{pmatrix} c \\ d \end{pmatrix}.$$

Then a = c and  $b = T^{-1}(d - S(c))$  so the inverse exists and is given by

$$\begin{pmatrix} c \\ d \end{pmatrix} \mapsto \begin{pmatrix} a \\ T^{-1}(d - S(c)) \end{pmatrix}$$

Since  $D_{(x_0,y_0)}f$  is invertible, the Inverse Function Theorem can be applied. We obtain an open neighborhood  $U_1$  of  $(x_0,y_0) \in A_1 \times B_1 \subset X \times Y$  and an open neighborhood  $V_1$  of  $f(x_0,y_0) = (x_0,F(x_0,y_0)) = (x_0,0) \in A \times W \subset X \times W$  such that

$$f|_{U_1}: U_1 \to V_1$$

is a  $C^1$  diffeomorphism.



Figure 1.5: Put the figure

Since  $U_1$  is open, choose open neighborhoods  $A_1$  of  $x_0$  and  $B_1$  of  $y_0$  such that  $A_1 \times B_1 \subset U_1$ . Since f is an open, so is  $f(A_1 \times B_1)$ . Choose open neighborhoods  $A_2$  of  $x_0$  and  $C_2$  of  $0 \in W$  such that  $A_2 \times C_2 \subset f(A_1 \times B_2)$ . Set  $\tilde{g} = \left(f\Big|_{A_1 \times B_1}\right)^{-1}$ ,  $\tilde{g}: f(A_1 \times B_1) \to A_1 \times B_1$ . Write

 $\tilde{g}(x,w) = (g_1(x,w), g_2(x,w)) \qquad \text{for } x, w \in f(A_1 \times B_1)$ 

f is a  $C^1$  diffeomorphism, so  $\tilde{g}$  is  $C^1$ . Moreover, so are the component functions  $g_1$  and  $g_2$ . We have

$$f \circ \tilde{g} = \mathrm{id}$$
 on  $A_2 \times C_2$ 

(this is true on a larger set, but we only care about  $A_2 \times C_2$ ). So, for all  $(x, w) \in A_2 \times C_2$ ,

$$\begin{aligned} (x,w) &= f(g_1(x,w),g_2(x,w)) \\ &= (g_1(x,w),F(g_1(x,w),g_2(x,w))). \end{aligned}$$

Therefore,  $x = g_1(x, w)$  and

$$w = F(g_1(x, w), g_2(x, w)) = F(x, g_2(x, w)).$$

Taking w = 0 shows that

$$F(x, g_2(x, 0)) = 0$$
 for all  $x \in A_2$ .

Define  $\hat{g}: A_2 \to B_1$  by  $\hat{g}(x) = g_2(x, 0)$ . Then  $F(x, \hat{g}(x)) = 0$  for all  $x \in A_2$ . In other words, if  $(x, y) \in A_2 \times B_1$  and  $y = \hat{g}(x)$ , then F(x, y) = 0.

Now, consider  $\tilde{g} \circ f = \text{id on } A_1 \times B_1$ . For all  $(x, y) \in A_1 \times B_1$ ,

$$\begin{aligned} &(x,y) &= \tilde{g}(f(x,y)) \\ &= \tilde{g}(x,F(x,y)) \\ &= (g_1(x,F(x,y)),g_2(x,F(x,y))) \\ &= (x,g_2(x,F(x,y))). \end{aligned}$$

Implies

$$g_2(x,F(x,y)) = y$$
 for all  $(x,y) \in A_1 \times B_1$ .

Taking (x, y) to satisfy F(x, y) = 0, we have  $g_2(x, 0) = y$ . Set  $A_3 = A_1 \cap A_2$  and define  $g(x) = \hat{g}(x)$ . Then g is  $C^1$  and for all  $x \in A_3$ ,  $y \in B_1$  we have

$$y = g(x)$$
 whenever  $F(x, y) = 0$ .

Therefore, for all  $x, y \in A_2 \times B_1$ , F(x, y) = 0 if and only if y = g(x).

## Chapter 2

# Appendix

**Proposition 2.0.11.** If V is a vector space of finite dimension n then all norms on V are equivalent.

The proof will be given for  $V = \mathbb{R}^n$ . By a standard argument, one can obtain the conclusion of the proposition for general *n*-dimensional vector spaces.

*Proof.* Let  $\{e_j\}_{j=1}^n$  be the standard basis for  $\mathbb{R}^n$ . It suffices to show that every norm on  $\mathbb{R}^n$  is equivalent to the norm  $\|\cdot\|_{\infty}$  given by  $\left\|\sum_{j=1}^n x^j e_j\right\|_{\infty} = \max_j |x^j|$ . Accordingly, let  $\|\cdot\|$  be a norm on  $\mathbb{R}^n$ . For any  $x \in \mathbb{R}^n$  using the triangle inequality and the homogeneity of  $\|\cdot\|$  we have

$$\|x\| = \left\|\sum_{j=1}^{n} x^{j} e_{j}\right\| \le \sum_{j=1}^{n} \|x^{j} e_{j}\| = \sum_{j=1}^{n} |x^{j}| \|e_{j}\| \le n \max_{j} \|e_{j}\| \|x\|_{\infty}.$$
 (2.1)

It remains to show that there is a constant  $C_1 > 0$  such that for all  $x \in \mathbb{R}^n$ , the estimate

$$C_1 \|x\|_{\infty} \le \|x\| \tag{2.2}$$

holds. Define  $f: V \to \mathbb{R}$  by f(x) = ||x||. By the triangle inequality and using equation (2.1) we have

$$|||x|| - ||y||| \le ||x - y|| \le C ||x - y||_{\infty}$$

where  $C = n \max_j ||e_j||$  as in (2.1). This estimate says that f is continuous from V with the  $||\cdot||_{\infty}$ -topology to  $\mathbb{R}$  with the usual topology. Since dim  $V = n < \infty$ , the unit sphere  $S^{n-1} = \{x \in V : ||x||_{\infty} = 1\}$  is compact. Therefore, f attains its minimum value over  $S^{n-1}$  at some point of  $S^{n-1}$ . That is, there is  $x_0 \in S^{n-1}$  such that  $||x_0|| = \min_{x \in S^{n-1}} ||x||$ . Finally, if  $x \neq 0$  we have

$$||x|| = ||x||_{\infty} \left| \left| \frac{x}{||x||_{\infty}} \right| \ge ||x_0|| \, ||x||_{\infty},$$

while the estimate  $||x|| \ge ||x_0|| ||x||_{\infty}$  holds trivially for x = 0. Thus, we have established estimate (2.2) with  $C_1 = ||x_0||$ .

**Lemma 2.0.12.** *The vector spaces* Hom(V, Hom(V, W)) *and*  $Bil(V \times V, W)$  *are isometrically isomorphic.* 

*Proof.* Define the map  $\phi$  : Hom $(V, \text{Hom}(V, W)) \rightarrow \text{Bil}(V \times V, W)$  by

$$(\phi(T))(u,v) = (T(v))(u)$$
 for  $u, v \in V$ .

First we show that Range( $\phi$ )  $\subset$  Bil( $V \times V, W$ ). Fix  $T \in$  Hom(V, Hom(V, W)). For  $a, b \in \mathbb{R}$  and  $u, v \in V$ ,

$$\phi(T)(au,bv) = (T(bv))(au)$$
  
=  $a(T(bv))(u)$   
=  $ab(T(v))(u)$   
=  $ab\phi(T)(u,v).$ 

the second equality holding as  $T(bv) \in \text{Hom}(V, W)$  and the third equality holding by the linearity of *T*. Similarly, for  $u_i, v_i \in V$  (i = 1, 2) we have

$$\begin{split} \phi(T)(u_1 + u_2, v_1 + v_2) &= (T(v_1 + v_2))(u_1 + u_2) \\ &= (T(v_1 + v_2))(u_1) + (T(v_1 + v_2))(u_2) \\ &= (T(v_1))(u_1) + (T(v_2))(u_1) + (T(v_1))(u_2) + (T(v_2))(u_2) \\ &= \phi(T)(u_1, v_1) + \phi(T)(u_1, v_2) + \phi(T)(u_2, v_1) + \phi(T)(u_2, v_2). \end{split}$$

Next we show that  $\phi$  is linear. Fix  $a \in \mathbb{R}$  and  $S, T \in \text{Hom}(V, \text{Hom}(V, W))$ . For  $u, v \in V$  we have

$$\begin{aligned} (\phi(aS+T))(u,v) &= ((aS+T)(v))(u) \\ &= (aS(v)+T(v))(u) \\ &= a(S(v))(u) + (T(v))(u) \\ &= a\phi(S)(u,v) + \phi(T)(u,v). \end{aligned}$$

Next we show that  $\phi$  is injective. Suppose  $T \in \text{Hom}(V, \text{Hom}(V, W))$  and that  $\phi(T)$  is the zero map  $V \times V \to W$ . Then for all  $u, v \in V$ ,

$$0 = \phi(T)(u, v) = (T(v))(u).$$

Thus, for all  $v \in V$ , T(v) is the zero map  $V \to W$ . We conclude that T is the zero map  $V \to \text{Hom}(V,W)$ .

Next, surjectivity of  $\phi$  follows as Hom(V, Hom(V, W)) and Bil $(V \times V, W)$  have the same dimension.

It remains to show that  $||T|| = ||\phi(T)||$  for all  $T \in \text{Hom}(V, \text{Hom}(V, W))$ . We have

$$\begin{aligned} \|\phi(T)\| &= \sup_{\|v\|, \|u\|=1} \|\phi(T)(u, v)\| \\ &= \sup_{\|v\|, \|u\|=1} \|(T(v))(u)\| \\ &= \sup_{\|v\|=1} \left( \sup_{\|u\|=1} \|(T(v))(u)\| \right) \\ &= \sup_{\|v\|=1} \|T(v)\| \\ &= \|T\|. \end{aligned}$$