# Rudin: Functions of Several Variables

# James Pagan

# October 2023

# Contents

| 1                              | Nor | emed Vector Spaces  | 2  |
|--------------------------------|-----|---|----|
|                                | 1.1 | Definition  | 2  |
|                                | 1.2 | Matrix Norm   | 3  |
|                                | 1.3 | Properties of Linear Maps                                 | 4  |
|                                | 1.4 | Completeness of $\mathcal{L}(\mathbb{C}^n, \mathbb{C}^m)$ | 5  |
| 2 Differentiation              |     | Gerentiation  | 7  |
|                                | 2.1 | The Derivative  | 7  |
|                                | 2.2 | Chain Rule  | 8  |
|                                | 2.3 | The Partial Derivative                                    | 9  |
|                                | 2.4 | Mixed Partial Derivatives                                 | 10 |
|                                | 2.5 | Real-Valued Functions                                     | 11 |
| 3 The Inverse Function Theorem |     | e Inverse Function Theorem                                | 12 |
|                                | 3.1 | The Contraction Principle                                 | 12 |
|                                | 3.2 | The Inverse Function Theorem                              | 13 |
|                                | 3.3 | The Implicit Function Theorem                             | 15 |

# 1 Normed Vector Spaces

### 1.1 Definition

A **normed vector space** is a complex vector space X equipped with a mapping  $\|\cdot\|: X \to \mathbb{R}$  that satisfies the following properties:

- 1. **Positivity**:  $\|\mathbf{x}\| \ge 0$ , with equality if and only if  $\mathbf{x} = \mathbf{0}$ .
- 2. Homogenity:  $\|\lambda \mathbf{x}\| = |\lambda| \|\mathbf{x}\|$  for all  $\lambda \in \mathbb{C}$ .
- 3. Triangle Inequality:  $\|\mathbf{x} + \mathbf{y}\| \le \|\mathbf{x}\| + \|\mathbf{y}\|$

A complete normed vector space is called a **Banach space**. As demonstrated in RealAnalysis/babyrudin3.tex, all the desired limit formulas hold on normed vector spaces.

**Theorem 1.** Norms are uniformly continuous mappings from X to  $\mathbb{R}$ .

*Proof.* For all  $\epsilon > 0$ , we have that

$$0 < \|\mathbf{x} - \mathbf{y}\| < \epsilon \implies \|\|\mathbf{x}\| - \|\mathbf{y}\|\| \le \|\mathbf{x} - \mathbf{y}\| < \epsilon.$$

We conclude that  $\|\cdot\|: X \to \mathbb{R}$  is uniformly continuous.

**Theorem 2.** Let X be a finite-dimensional vector space over  $\mathbb{C}$ . Then any two norms on X are equivalent.

*Proof.* Let dim X = n. We first prove the theorem for  $\mathbb{C}^n$ ; let  $\mathbf{e}_1, \dots, \mathbf{e}_n$  be the canonical basis of  $\mathbb{C}^n$ , and suppose  $\|\cdot\|_1 : \mathbb{C}^n \to [0, \infty)$  is a norm. We prove that  $\|\mathbf{z}\|_1$  is equivalent to the canonical norm  $\|\mathbf{z}\|$ .

Consider the boundary of the unit ball of the canonical norm in  $\mathbb{C}^n$ . Since  $\|\cdot\|_1$  is continuous, the Extreme Value Theorem guarantees that there exists  $\mathbf{u}, \mathbf{s} \in X$  with canonical norm 1 such that

$$\|\mathbf{u}\|' = \inf_{\|\mathbf{z}\|=1} \{\|\mathbf{z}\|'\}$$
 and  $\|\mathbf{s}\|' = \sup_{\|\mathbf{z}\|=1} \{\|\mathbf{z}\|'\}$ 

Then for all  $\mathbf{z} \in \mathbb{C}^n$ , the constants  $\|\mathbf{u}\|'$  and  $\|\mathbf{s}\|'$  allow for norm equivalence:

$$\|\mathbf{u}\|'\|\mathbf{z}\| \, \leq \, \left\|\frac{\mathbf{z}}{\|\mathbf{z}\|}\right\|'\|\mathbf{z}\| \, = \, \|\mathbf{z}\|' \, = \, \left\|\frac{\mathbf{z}}{\|\mathbf{z}\|}\right\|'\|\mathbf{z}\| \, \leq \, \|\mathbf{s}\|'\|\mathbf{z}\|.$$

We conclude that all norms on  $\mathbb{C}^n$  are equivalent to the canonical norm. Proving norm equivalence from X to  $\mathbb{C}^n$  is not challenging.

### 1.2 Matrix Norm

Let X and Y be normed vector spaces. If T is bounded, the **norm** of T is as follows:

$$\|\mathbf{T}\| = \sup\{\|\mathbf{T}\mathbf{x}\| \mid \mathbf{x} \in X, \|\mathbf{x}\| \le 1\}.$$

The **critical vector** of **T** is the vector  $\mathbf{x} \in X$  such that  $\|\mathbf{x}\| \le 1$  and  $\|\mathbf{T}\mathbf{x}\| = \|\mathbf{T}\|$ ; the critical vector always has norm 1. Naturally,  $\|\mathbf{T}\mathbf{x}\| \le \|\mathbf{T}\| \cdot \|\mathbf{x}\|$ ; since equality is attained,  $\|\mathbf{T}\mathbf{x}\| \le \lambda \mathbf{x}$  implies  $\|\mathbf{T}\| \le \lambda$ .

Theorem 3. If  $T, S \in \mathcal{B}(X, Y)$ , then  $||T + S|| \le ||T|| + ||S||$ . X = Y entails  $||TS|| \le ||T|| ||S||$ .

*Proof.* Let  $\mathbf{x}$  be the critical vector of  $\mathbf{T} + \mathbf{S}$ . Then

$$\|\mathbf{T} + \mathbf{S}\| = \|(\mathbf{T} + \mathbf{S})\mathbf{x}\| \le \|\mathbf{T}\mathbf{x}\| + \|\mathbf{S}\mathbf{x}\| \le \|\mathbf{T}\|\|\mathbf{x}\| + \|\mathbf{S}\|\|\mathbf{x}\| = \|\mathbf{T}\| + \|\mathbf{S}\|.$$

Now suppose X = Y and let w be the critical vector of **TS**. Then

$$\|TS\| = \|TSw\| \le \|T\|\|Sw\| \le \|T\|\|S\|\|w\| = \|T\|\|S\|.$$

This completes the proof.

**Theorem 4.** The matrix norm is a metric of all bounded linear maps in  $\mathcal{B}(X,Y)$ .

*Proof.* Suppose  $\mathbf{T}, \mathbf{S} \in \mathcal{B}(X, Y)$  are bounded. We must perform four rather routine calculations:

1. **Positivity**: The matrix norm is nonnegative. If  $\|\mathbf{T} - \mathbf{S}\| = 0$ , then  $\|\mathbf{x}\| = 1$  implies  $(\mathbf{T} - \mathbf{S})\mathbf{x} = \mathbf{0}$ ; hence for all  $\mathbf{x} \in X$ ,

$$(\mathbf{T} - \mathbf{S})\mathbf{x} = \|\mathbf{x}\| \left( (\mathbf{T} - \mathbf{S}) \left( \frac{\mathbf{x}}{\|\mathbf{x}\|} \right) \right) = \|\mathbf{x}\|(0) = 0;$$

thus  $\mathbf{T} - \mathbf{S} = \mathbf{0}$  and  $\mathbf{T} = \mathbf{T}$ .

2. **Symmetry**: Notice that  $(\mathbf{T} - \mathbf{S})\mathbf{x} = -(\mathbf{S} - \mathbf{T})\mathbf{x}$  for all  $\mathbf{x} \in X$ . Naturally if  $\mathbf{w}$  is the critical vector of  $\mathbf{T} - \mathbf{S}$ , then  $-\mathbf{w}$  is the critical vector of  $\mathbf{S} - \mathbf{T}$ ; thus

$$\|\mathbf{T} - \mathbf{S}\| = \|\mathbf{w}\| = \|-\mathbf{w}\| = \|\mathbf{S} - \mathbf{T}\|.$$

3. Triangle Inequality: For all bounded  $\mathbf{R} \in \mathcal{L}(X,Y)$ ,

$$\|T - S\| = \|(T - R) + (R - S)\| \le \|T - R\| + \|R - S\|.$$

We conclude that the matrix norm is a metric of the bounded matricies of  $\mathcal{L}(X,Y)$ .  $\square$ It is straightforward that  $\|\lambda \mathbf{T}\| = |\lambda| \|\mathbf{T}\|$  for all  $\lambda \in \mathbb{C}$  as well.

#### 1.3 Properties of Linear Maps

**Theorem 5.** Let X be a finite-dimensional normed vector space, and let Y be a normed vector space. Then all  $\mathbf{T} \in \mathcal{L}(X,Y)$  are bounded.

*Proof.* Let dim X = n and let  $\mathbf{e}_1, \dots, \mathbf{e}_n$  be a basis of X. Then for all  $\mathbf{z} = z_1 \mathbf{e}_1 + \dots + z_n \mathbf{e}_n$ , we have

$$\|\mathbf{Tz}\| \le |z_1| \|\mathbf{Te}_1\| + \dots + |z_n| \|\mathbf{Te}_n\| \le C(|z_1| + \dots + |z_n|),$$

where  $C = \max\{\|\mathbf{T}\mathbf{e}_i\|\}$ . Realize that  $\|\mathbf{z}\|_1 = |z_1| + \cdots + |z_n|$  defines a norm on X; since all norms finite-dimensional vector spaces are equivalent, there exists another constant M such that  $|z_1| + \cdots + |z_n| = \|\mathbf{z}\|_1 \le M\|\mathbf{z}\|$ . Therefore

$$\|\mathbf{T}\mathbf{z}\| \le CM\|\mathbf{z}\|,$$

so **T** is bounded. This completes the proof.

**Theorem 6.** If  $T \in \mathcal{L}(X,Y)$  is bounded, then T is uniformly continuous.

*Proof.* Let **T** be bounded. For all  $\epsilon > 0$ , then  $0 \le \|\mathbf{x} - \mathbf{y}\| < \frac{\epsilon}{\|\mathbf{T}\|}$  implies

$$\|\mathbf{T}\mathbf{x} - \mathbf{T}\mathbf{y}\| \le \|\mathbf{T}\| \cdot \|\mathbf{x} - \mathbf{y}\| < \|\mathbf{T}\| \left(\frac{\epsilon}{\|\mathbf{T}\|}\right) = \epsilon.$$

Thus, T is uniformly continuous.

Let  $\Omega$  be the set of all bounded, invertible linear operators on X. Recall from Linear Algebra that an operator  $\mathbf{T} \in \mathcal{L}(\mathbb{C}^n)$  is invertible if and only if range  $\mathbf{T} = \mathbb{C}^n$ .

**Theorem 7.** Let X be a finite dimensional vector space. If  $\mathbf{T} \in \Omega$  and  $\mathbf{S} \in \mathcal{L}(X)$  are both bounded, then

$$\|\mathbf{T}^{-1}\| \cdot \|\mathbf{S} - \mathbf{T}\| < 1$$

implies  $\mathbf{S} \in \Omega$ .

*Proof.* Suppose  $\mathbf{S} \notin \Omega$ . Then there exists  $\mathbf{x} \in X$  of norm 1 such that  $\mathbf{S}\mathbf{x} = \mathbf{0}$ , so

$$1 = \|\mathbf{x}\|$$

$$= \|\mathbf{T}^{-1}\mathbf{T}\mathbf{x}\|$$

$$\leq \|\mathbf{T}^{-1}\| \cdot \|\mathbf{T}\mathbf{x}\|$$

$$= \|\mathbf{T}^{-1}\| \cdot \|\mathbf{S}\mathbf{x} - \mathbf{T}\mathbf{x}\|$$

$$\leq \|\mathbf{T}^{-1}\| \cdot \|\mathbf{S} - \mathbf{T}\| \cdot \|\mathbf{x}\|$$

$$= \|\mathbf{T}^{-1}\| \cdot \|\mathbf{S} - \mathbf{T}\|.$$

Taking the contrapositive yields the desired result.

**Theorem 8.** Let X be a finite-dimensional normed vector space. Then  $\Omega$  is an open subset of  $\mathcal{L}(X)$ , and the bijection  $f: \mathbf{T} \to \mathbf{T}^{-1}$  is continuous on  $\Omega$ .

*Proof.* Let  $\mathbf{T} \in \Omega$ . Since  $\|\mathbf{T}^{-1}\|$  is nonzero, we may consider the open ball at  $\mathbf{T}$  of radius  $\frac{1}{\|\mathbf{T}^{-1}\|}$ ; more specifically, all  $\mathbf{S} \in \mathcal{L}(\mathbb{C}^n)$  such that

$$\|\mathbf{T} - \mathbf{S}\| < \frac{1}{\|\mathbf{T}^{-1}\|}.$$

Since  $\|\mathbf{T}\|$  is nonzero,  $\|\mathbf{T} - \mathbf{S}\| \cdot \|\mathbf{T}^{-1}\| < 1$ ; hence  $\mathbf{S} \in \Omega$ . The open ball is contained within  $\Omega$ , so the set  $\Omega$  is open. As per continuity, realize that

$$\lim_{S \to T^{-1}} \|\mathbf{T} - \mathbf{S}\|$$

As per continuity: **Rudin's proof is nonrigorous**, and I don't know how to rectify it. The basic idea is that

$$\|\mathbf{T}^{-1} - \mathbf{S}^{-1}\| = \|\mathbf{T}^{-1}\mathbf{S}\mathbf{S}^{-1} - \mathbf{T}^{-1}\mathbf{T}\mathbf{S}^{-1}\| \le \|\mathbf{T}^{-1}\| \cdot \|\mathbf{S} - \mathbf{T}\| \cdot \|\mathbf{S}^{-1}\|,$$

but using this to bound  $\epsilon$  depends on  $\mathbf{T}^{-1}$  and  $\mathbf{S}^{-1}$ . I will leave this unfinished until instructor clarification.

## 1.4 Completeness of $\mathcal{L}(\mathbb{C}^n, \mathbb{C}^m)$

Before we discuss the completeness of  $\mathcal{L}(\mathbb{C}^n, \mathbb{C}^m)$ , we must uncover an important inequality. Let  $\mathbf{z} = (z_1, \dots, z_n) \in \mathbb{C}^n$ ; for any  $\mathbf{T} \in \mathcal{L}(\mathbb{C}^n, \mathbb{C}^m)$ , define the components of  $\mathbf{T}$  as  $t_{ij}$  for  $i \in \{1, \dots, n\}$  and  $j \in \{1, \dots, m\}$ . Then

$$\mathbf{Tz} = \left(\sum_{j=1}^n t_{1j}z_j\right)\mathbf{e}_1 + \dots + \left(\sum_{j=1}^n t_{mj}z_j\right)\mathbf{e}_m.$$

Then via the Cauchy-Schwarz Inequality,

$$\|\mathbf{T}\mathbf{z}\|^{2} = \left(\sum_{j=1}^{n} t_{1j} z_{j}\right)^{2} + \dots + \left(\sum_{j=1}^{n} t_{mj} z_{j}\right)^{2}$$

$$\leq \left(\sum_{j=1}^{n} t_{1j}^{2}\right) \left(\sum_{j=1}^{n} z_{j}^{2}\right) + \dots + \left(\sum_{j=1}^{n} t_{mj}^{2}\right) \left(\sum_{j=1}^{n} z_{j}^{2}\right)$$

$$= \left(\sum_{j=1}^{n} z_{j}^{2}\right) \left(\sum_{i=1}^{m} \sum_{j=1}^{n} t_{ij}^{2}\right) = \|\mathbf{z}\|^{2} \left(\sum_{i=1}^{m} \sum_{j=1}^{n} t_{ij}^{2}\right).$$

Let  $\mathbf{w}$  be the critical vector of  $\mathbf{T}$ . Then

$$\|\mathbf{T}\| = \|\mathbf{T}\mathbf{w}\| \le \|\mathbf{z}\| \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} t_{ij}^2} = \sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} t_{ij}^2}.$$

While  $\mathcal{L}(\mathbb{C}^n, \mathbb{C}^m)$  and  $\mathbb{C}^{n+m}$  may be isomorphic, the relevant bijection is not an isometry.

**Theorem 9.** If Y is a Banach space, then  $\mathcal{B}(X,Y)$  is a Banach space.

*Proof.* Let  $(\mathbf{T}_n)$  be a Cauchy sequence in  $\mathcal{B}(X,Y)$ ; for all  $\epsilon > 0$ , there exists N such that

$$N \le n, m \implies \|\mathbf{T}_n - \mathbf{T}_m\| < \epsilon. \tag{1}$$

We will define the limit of  $(\mathbf{T}_n)$ . For any  $\mathbf{x} \in X$ , we have that

$$\|\mathbf{T}_n\mathbf{x} - \mathbf{T}_m\mathbf{x}\| \le \|\mathbf{T}_n - \mathbf{T}_m\|\|\mathbf{x}\| \le \epsilon \|\mathbf{x}\|.$$

By selecting  $\frac{\epsilon}{\|\mathbf{x}\|}$  in equation (1), we find that  $(\mathbf{T}_n\mathbf{x})$  is a Cauchy sequence in in Y. Thus, it converges to a unque vector in Y. Define a mapping  $\mathbf{T}: X \to Y$  as follows:

$$\mathbf{T}\mathbf{z} \stackrel{\mathrm{def}}{=} \lim_{n \to \infty} \mathbf{T}_n \mathbf{z}$$

It is relatively easy to show that **T** is linear: for all  $\mathbf{x}, \mathbf{y} \in X$  and  $\lambda \in \mathbb{C}$ , we have

$$\mathbf{T}(\mathbf{x} + \mathbf{y}) = \lim_{n \to \infty} \mathbf{T}_n(\mathbf{x} + \mathbf{y}) = \lim_{n \to \infty} \mathbf{T}_n\mathbf{x} + \lim_{n \to \infty} \mathbf{T}_n\mathbf{y} = \mathbf{T}\mathbf{x}\mathbf{T}\mathbf{y}$$
$$\mathbf{T}(\lambda\mathbf{x}) = \lim_{n \to \infty} \mathbf{T}_n(\lambda\mathbf{x}) = \lambda \lim_{n \to \infty} \mathbf{T}\mathbf{x} = \lambda\mathbf{T}_x.$$

We must show that **T** is bounded and is the limit of  $(\mathbf{T}_n)$ . Observe that

$$\|\mathbf{T}\mathbf{z}\| \leq \|\mathbf{T}\mathbf{z} - \mathbf{T}_n\mathbf{z}\| + \|\mathbf{T}_n\mathbf{z}\|.$$

Observe that the transformation  $\phi : \mathbf{y} \to ||\mathbf{T}_n \mathbf{x} - \mathbf{y}||$  is continuous, since it is a composition of continuous functions. Hence

$$\|\mathbf{T}_n\mathbf{z}\mathbf{x} - \mathbf{T}_m\mathbf{z}\| \le \epsilon \|\mathbf{z}\| \implies \|\mathbf{T}_n - \mathbf{T}\mathbf{z}\| = \lim_{m \to \infty} \|\mathbf{T}_n\mathbf{z} - \mathbf{T}_m\mathbf{z}\| \le \epsilon \|\mathbf{x}\|.$$

Then pick  $\epsilon = 1$  and n = N. We find that

$$\|\mathbf{T}\mathbf{x}\| \le \|(\mathbf{T} - \mathbf{T}_n)\mathbf{x}\| + \|\mathbf{T}_n\mathbf{x}\|$$

$$\le \|\mathbf{x}\| + \|\mathbf{T}_N\|\|\mathbf{x}\|$$

$$\le (1 + \|\mathbf{T}_N\|)\mathbf{x}.$$

Letting  $c = 1 + ||\mathbf{T}_N||$  yields that **T** is bounded. As per the limit condition, we have that

$$\|\mathbf{T}_n - \mathbf{T}\| = \sup_{\mathbf{x} \neq \mathbf{0}} \frac{\|(\mathbf{T}_n - \mathbf{T})\mathbf{x}\|}{\|\mathbf{x}\|} \le \epsilon,$$

which completes the proof.

**Corollary 1.** If the components of  $\mathbf{T} \in \mathcal{L}(\mathbb{C}^n, \mathbb{C}^m)$  are continuous functions from a metric space X to  $\mathbb{R}$ , then the mapping  $X \to \mathbf{T}$  is continuous.

*Proof.* Let the continuous components be  $f_{ij}$ . For all  $\epsilon > 0$ , there are  $N_{ij}$  such that

$$0 < d(x, y) < \delta_{ij} \implies |f_{ij}(x) - f_{ij}(y)| < \frac{\epsilon}{\sqrt{mn}}.$$

Then identical means as Theorem 6 demonstrate that the mapping  $X \to \mathbf{T}$  is continuous.

## 2 Differentiation

#### 2.1 The Derivative

Let  $f: E \to \mathbb{R}^m$  for an open set  $E \subset \mathbb{R}^n$ . Then f is **differentiable** at  $\mathbf{x} \in E$  if there exists a linear map  $\mathbf{J} \in \mathcal{L}(\mathbb{R}^n, \mathbb{R}^m)$  such that

$$\lim_{\mathbf{h}\to\mathbf{0}}\frac{\|f(\mathbf{x}+\mathbf{h})-f(\mathbf{x})-\mathbf{J}\mathbf{h}\|}{\|\mathbf{h}\|}=0,$$

we say that f is **differentiable** at  $\mathbf{x}$  and write  $f'(\mathbf{x}) = \mathbf{J}$ , where J is the **total derivative** of f at  $\mathbf{x}$ — also called the matrix of partial derivatives, the differential, or the total derivative. If f is differentiable at  $all \ \mathbf{x} \in U$ , we say that f itself is differentiable over U.

#### **Lemma 1.** The total derivative is unique.

*Proof.* Define f like above. Suppose that for contradiction that there exist two matricies  $\mathbf{J} \neq K$  such that

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

See that  $\mathbf{J} - K \neq 0$ , so ||J - K|| > 0. Then there exist  $d_1$  and  $d_2$  such that

$$0 < \|\mathbf{h}\| < \delta_1 \implies \frac{\|-f(\mathbf{x} + \mathbf{h}) + f(\mathbf{x}) + \mathbf{J}\mathbf{h}\|}{\|\mathbf{h}\|} < \frac{\|J - K\|}{2}$$
$$0 < \|\mathbf{h}\| < \delta_2 \implies \frac{\|f(\mathbf{x} + \mathbf{h}) - f(\mathbf{x}) - K\mathbf{h}\|}{\|\mathbf{h}\|} < \frac{\|\mathbf{J} - K\|}{2}$$

For  $0 < \|\mathbf{h}\| < \min\{\delta_1, \delta_2\}$ , we have that

$$\begin{aligned} \|\mathbf{J} - K\| &= \frac{\|J - K\|}{2} + \frac{\|J - K\|}{2} \\ &> \frac{\|-f(\mathbf{x} + \mathbf{h}) + f(\mathbf{x}) + \mathbf{J}\mathbf{h}\|}{\|\mathbf{h}\|} + \frac{\|f(\mathbf{x} + \mathbf{h}) - f(\mathbf{x}) - K\mathbf{h}\|}{\|\mathbf{h}\|} \\ &\geq \frac{\|(-f(\mathbf{x} + \mathbf{h}) + f(\mathbf{x}) + \mathbf{J}\mathbf{h}) + (f(\mathbf{x} + \mathbf{h}) - f(\mathbf{x}) - K\mathbf{h})\|}{\mathbf{h}} \\ &= \frac{\|(\mathbf{J} - K)\mathbf{h}\|}{\mathbf{h}}, \end{aligned}$$

so  $\|\mathbf{J} - K\| \|\mathbf{h}\| > \|(J - K)\mathbf{h}\|$ , which is our desired contradiction.

As an example, if  $T \in \mathcal{L}(\mathbb{R}^n, \mathbb{R}^m)$  and  $\mathbf{x} \in \mathbb{R}^n$ , then the derivative of T at  $\mathbf{x}$  is T, as

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

It is very intuitive to think of **J** as an approximation of f at  $\mathbf{x}_0$  — namely, that there exists  $r(\mathbf{h})$  such that  $f(\mathbf{x}_0 + \mathbf{h}) - f(\mathbf{x}_0) = J\mathbf{h} - r(\mathbf{h})$  and  $\lim_{\mathbf{h}\to\mathbf{0}} \frac{r(\mathbf{h})}{\mathbf{h}} = 0$ . This strategy will be exhibited in the following proof:

#### 2.2 Chain Rule

**Theorem.** Let  $f: \mathbb{R}^n \to \mathbb{R}^m$  and  $g: \mathbb{R}^m \to \mathbb{R}^k$ . If f is differentiable at  $\mathbf{x}_0$  and g is differentiable at  $f(\mathbf{x}_0)$  — and if  $\mathbf{x}_0$  and  $f(\mathbf{x}_0)$  are contained within open sets in the domains of f and g respectively — then  $g \circ f$  is differentiable at  $\mathbf{x}_0$ , and

$$(g \circ f)' = g'(f(\mathbf{x}_0))f'(\mathbf{x}_0).$$

*Proof.* Let  $f'(\mathbf{x}_0) = \mathbf{J}$  and  $g'(f(\mathbf{x}_0)) = K$ . We have that

$$\lim_{\mathbf{h}\to\mathbf{0}} \frac{\|f(\mathbf{x}_0+\mathbf{h})-f(\mathbf{x}_0)-\mathbf{J}\mathbf{h}\|}{\|\mathbf{h}\|} = 0 = \lim_{\mathbf{h}\to\mathbf{0}} \frac{\|g(f(\mathbf{x}_0)+\mathbf{h})-g(f(\mathbf{x}_0))-K\mathbf{h}\|}{\|h\|}.$$

Define the function  $\mathbf{k} = f(\mathbf{x}_0 + \mathbf{h}) - f(\mathbf{x}_0)$ ; clearly,  $\lim_{\mathbf{h} \to \mathbf{0}} \mathbf{k} = 0$ . We have that

$$g(f(\mathbf{x}_0 + \mathbf{h})) - g(f(\mathbf{x}_0)) - (K\mathbf{J})\mathbf{h}$$

$$= g(f(\mathbf{x}_0) + \mathbf{k}) - g(f(\mathbf{x}_0)) - K(\mathbf{J}\mathbf{h} - f(\mathbf{x}_0 + \mathbf{h}) - f(\mathbf{x}_0) + \mathbf{k})$$

$$= g(f(\mathbf{x}_0) + \mathbf{k}) - g(f(\mathbf{x}_0)) - K\mathbf{k} + K(f(\mathbf{x}_0 + \mathbf{h}) - f(\mathbf{x}_0) - \mathbf{J}\mathbf{h}).$$

We now establish bounds for  $\|\mathbf{k}\|$ :

$$\|\mathbf{k}\| = \|f(\mathbf{x}_0 + \mathbf{h}) - f(\mathbf{x}_0) - \mathbf{J}\mathbf{h} + J\mathbf{h}\| \le \|\mathbf{h}\| \left( \|J\| + \frac{\|f(\mathbf{x}_0 + \mathbf{h}) - f(\mathbf{x}_0) - J\mathbf{h}\|}{\|\mathbf{h}\|} \right)$$

Then using the composition rule for limits,

$$0 \leq \lim_{\mathbf{h} \to \mathbf{0}} \frac{\|g(f(\mathbf{x}_0 - \mathbf{h})) - g(f(\mathbf{x}_0)) - (K\mathbf{J})\mathbf{h}\|}{\|\mathbf{h}\|}$$

$$\leq \lim_{\mathbf{h} \to \mathbf{0}} \frac{\|g(f(\mathbf{x}_0) + \mathbf{k}) - g(f(\mathbf{x}_0)) - K\mathbf{k}\|}{\|\mathbf{h}\|} + \lim_{\mathbf{h} \to \mathbf{0}} \frac{\|K\|\|f(\mathbf{x}_0 + \mathbf{h}) - f(\mathbf{x}_0) - \mathbf{J}\mathbf{h}\|}{\|\mathbf{h}\|}$$

$$\leq \lim_{\mathbf{h} \to \mathbf{0}} \frac{\|g(f(\mathbf{x}_0) + \mathbf{k}) - g(f(\mathbf{x}_0)) - K\mathbf{k}\|}{\|\mathbf{k}\|} \lim_{\mathbf{h} \to \mathbf{0}} \left(\|\mathbf{J}\| + \frac{\|f(\mathbf{x}_0 + \mathbf{h}) - f(\mathbf{x}_0) - J\mathbf{h}\|}{\mathbf{h}}\right)$$

$$= (0)(\|\mathbf{J}\| + 0) = 0.$$

so  $(g \circ f)'(\mathbf{x}_0) = K\mathbf{J} = g'(f(\mathbf{x}_0))f'(\mathbf{x}_0)$  as required. Yes, that last step of Rudin's is nonrigorous — define it as a piecewise expression equal to 0 whenever  $\mathbf{k} = \mathbf{0}$ , etc.

#### 2.3 The Partial Derivative

Consider  $f: U \subset \mathbb{R}^n \to \mathbb{R}^m$ , where U is an open subset of  $\mathbb{R}^n$ ; let  $\mathbf{e}_1, \dots, \mathbf{e}_n$  and  $\mathbf{e}_1, \dots, \mathbf{e}_m$  be the standard bases of  $\mathbb{R}^n$  and  $\mathbb{R}^m$ . The **components** of f are the real functions  $f_1, \dots, f_m$  defined by

$$f(\mathbf{x}) = f_1(\mathbf{x})\mathbf{e}_1 + \dots + f_m(\mathbf{x})\mathbf{e}_m,$$

or equivalently by  $f_i(\mathbf{x}) = f(\mathbf{x}) \cdot \mathbf{e}_i$  for each  $i \in \{1, ..., m\}$ . Then for  $x \in U$ ,  $i \in \{1, ..., m\}$ , and  $j \in \{1, ..., n\}$ , we define the **partial derivative** of  $f_i$  with respect to  $x_j$  as

$$\frac{\partial f_i}{\partial x_j} = \lim_{t \to 0} \frac{f_i(\mathbf{x} + t\mathbf{e}_j) - f_i(\mathbf{x})}{t}.$$

The fact this is a one-variable limit explains why the computation of partial derivatives aligns so closely with differentiation of univarite functions.

**Lemma.** The entries of the total derivative are the partial derivatives: namely, if  $f: U \subset \mathbb{R}^n \to \mathbb{R}^m$  (where U is open) and f is differentiable at  $x_0$ , then the partial derivatives exist and

$$f'(\mathbf{x}_0)\mathbf{e}_j = \sum_{i=1}^m \left(\frac{\partial f_i}{\partial x_j}\right)(\mathbf{x})\mathbf{e}_i$$

*Proof.* Let j be any integer in the set  $\{1,\ldots,n\}$ . Since f is differentiable at  $\mathbf{x}$ ,

$$\lim_{t \to 0} \frac{f(\mathbf{x}_0 + t\mathbf{e}_j) - f(\mathbf{x}_0)}{t} - f'(\mathbf{x})\mathbf{e}_j = \lim_{t \to 0} \frac{\|f(\mathbf{x}_0 + t\mathbf{e}_j) - f(\mathbf{x}_0) - f'(\mathbf{x}_0)(t\mathbf{e}_j)\|}{\|t\mathbf{e}_j\|} = 0.$$

Therefore,

$$f'(\mathbf{x})\mathbf{e}_{j} = \lim_{t \to 0} \frac{f(\mathbf{x}_{0} + t\mathbf{e}_{j}) - f(\mathbf{x}_{0})}{t}$$

$$= \lim_{t \to 0} \frac{\sum_{i=1}^{m} (f_{1}(\mathbf{x}_{0} + t\mathbf{e}_{j})\mathbf{e}_{i}) - \sum_{i=1}^{m} (f_{i}(\mathbf{x}_{0})\mathbf{e}_{i})}{t}$$

$$= \sum_{i=1}^{m} \left(\lim_{t \to 0} \frac{f(\mathbf{x}_{0} + t\mathbf{e}_{j}) - f(\mathbf{x}_{0})}{t}\mathbf{e}_{i}\right)$$

$$= \sum_{i=1}^{m} \left(\frac{\partial f_{i}}{\partial x_{j}}\right) (\mathbf{x}_{0})\mathbf{e}_{i},$$

as desired.

We denote  $D_{21}$  as the double partial derivative of f with respect to the first, then the second, variable.

#### 2.4 Mixed Partial Derivatives

**Lemma.** Suppose f is defined in an open set  $U \subset R^2$  and  $D_1$  and  $D_{21}$  exist at every point of U. Let  $Q \subset U$  be a closed rectangle with sides parallel to the coordinate exes with opposite verticies (a,b) and (a+h,b+k) for  $h,k \neq 0$ , and define

$$\triangle(f,Q) = f(a+h,b-k) - f(a+h,b) - f(a,b+k) + f(a,b).$$

Then there is a point (x, y) in the interior of Q such that

$$\triangle(f,Q) = hk(D_{21}f)(x,y).$$

*Proof.* Define u(t) = f(t, b+k) - f(t, b). Then by the Mean Value Theorem, there exists a x between a and a + h and y between b and b + K such that

$$\triangle(f,Q) = u(a+h) - u(a)$$
=  $hu'(x)$   
=  $h(D_1 f(x, b+k) - D_1 f(x, b))$   
=  $hkD_{21} f(x, y)$ .

**Theorem 10.** Suppose f is defined in an open set  $U \in \mathbb{R}^2$ , that  $D_1$  and  $D_2$  exist at all points of U, and that  $D_{21}$  is continuous at some point  $(a,b) \in U$ . Then  $D_{12}$  exists at (a,b), and

$$D_{12}f(a,b) = D_{21}f(a,b).$$

Proof.

#### 2.5 Real-Valued Functions

Let  $f: \mathbb{R}^n \to \mathbb{R}$  be a differentiable real-valued function. Then f' is a 1-by-n matrix:

$$f' = \begin{bmatrix} \frac{\partial f}{\partial x_1} & \cdots & \frac{\partial f}{\partial x^n} \end{bmatrix}.$$

The transpose of this matrix is called the **gradient** of f;

$$\nabla f = f'^{\top} = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{bmatrix} = \frac{\partial f}{\partial x_1} \mathbf{e}_1 + \dots + \frac{\partial f}{\partial x_n} \mathbf{e}_n,$$

where  $\mathbf{e}_1, \dots, \mathbf{e}_n$  is the standard basis of  $\mathbb{R}^n$ . Observe that  $f'\mathbf{v} = \nabla f \cdot \mathbf{v}$  for all  $\mathbf{v} \in \mathbb{R}^n$  — so the gradient and the derivative of a real-valued function are dual concepts. We can define the derivative of f as a vector  $\nabla f$  such that

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

The directional derivative of f at  $\mathbf{x}$  along a unit vector  $\mathbf{v}$  is defined as

$$\nabla_{\mathbf{v}} f = \lim_{t \to 0} \frac{f(\mathbf{x} + t\mathbf{v}) - f(\mathbf{x})}{t}$$

Observe that  $\nabla_{\mathbf{e}_i} f = \frac{\partial f}{\partial x_i} = \nabla f \cdot \mathbf{e}_i$  for all  $i \in \{1, \dots, n\}$ . This might lead us to conclude the following lemma:

**Lemma.** If  $f : \mathbb{R}^n \to \mathbb{R}$  is differentiable at  $\mathbf{x}_0$ , then  $\nabla_{\mathbf{v}} f = \mathbf{v} \cdot (\nabla f)$  for all unit vectors  $\mathbf{v}$ .

*Proof.* Observe that  $f'\mathbf{v} = \nabla f \cdot \mathbf{v}$ , so we may express the definition of the total derivative in terms of the gradient of f, and that  $||t\mathbf{v}|| = |t|$ :

$$\begin{split} \nabla_{\mathbf{v}} f &= \lim_{t \to 0} \frac{f(\mathbf{x} + t\mathbf{v}) - f(\mathbf{x})}{t} \\ &= \lim_{t \to 0} \frac{f(\mathbf{x} + t\mathbf{v}) - f(\mathbf{x}) - \nabla f \cdot (t\mathbf{v})}{t} + \lim_{t \to 0} \frac{\nabla f \cdot (t\mathbf{v})}{t} \\ &= 0 + \lim_{t \to 0} \nabla f \cdot \mathbf{v} \\ &= \nabla f \cdot \mathbf{v}, \end{split}$$

as required.

**Lemma.** If  $f : \mathbb{R}^n \to \mathbb{R}$  is differentiable at  $\mathbf{x}_0$ , then the maximum of  $\nabla_{\mathbf{v}} f(\mathbf{x}_0)$  across all unit vectors  $\mathbf{v}$  occurs when  $\mathbf{v}$  points in the direction of  $\nabla f(\mathbf{x}_0)$ .

*Proof.* If **v** is a unit vector, then the Cauchy-Schwarz Inequality guarantees that

$$\nabla_{\mathbf{v}} f(\mathbf{x}_0) = \mathbf{v} \cdot \nabla f(\mathbf{x}_0) \le \|\mathbf{v}\| \|\nabla f(\mathbf{x}_0)\| = \|\nabla f(\mathbf{x}_0)\| = \left(\frac{\nabla f(\mathbf{x}_0)}{\|\mathbf{x}_0\|}\right) \cdot \nabla f(\mathbf{x}_0)$$

so the maximum of  $\nabla_{\mathbf{v}} f(\mathbf{x}_0)$  occurs when  $\mathbf{v}$  is the normalization of the gradient vector and points in the direction of  $\nabla f(\mathbf{x}_0)$ .

More generally, we have that if  $\theta$  is the angle between the unit vector  $\mathbf{v}$  and  $\nabla f$ , then

$$\nabla_{\mathbf{v}} f = \mathbf{v} \cdot \nabla f = \|\mathbf{v}\| \|\nabla f\| \cos(\theta) = \|\nabla f\| \cos(\theta).$$

The directional derivative oscilates like a sine wave as  $\mathbf{v}$  walks around the unit hypersphere.

# 3 The Inverse Function Theorem

## 3.1 The Contraction Principle

Let X be a metric space with metric d. If  $\varphi: X \to X$  and there exists a real c < 1 such that

$$d(\varphi(x), \varphi(y)) \le c \cdot d(x, y)$$

for all  $x, y \in X$ , then  $\varphi$  is a **contraction** of X into X.

**Theorem.** If X is a complete metric space and if  $\varphi$  is a contraction of X into X, then there exists a unique element  $x \in X$  such that  $\varphi(x) = x$ 

*Proof.* Let c be a constant such that  $d(\varphi(x), \varphi(y)) \leq c \cdot d(x, y)$  for all  $x, y \in X$ , and select from X some element  $x_0$ . We define the sequence  $x_0, x_1, \ldots$  recursively by setting

$$x_{n+1} = \varphi(x_n)$$

for all  $n \in \mathbb{Z}_{\geq 0}$ . We have via induction that

$$d(x_{n+1}, x_n) = d(\varphi(x_n), \varphi(x_{n-1})) = c \cdot d(x_n, x_{n-1}) = \dots = c^n \cdot d(x_1, x_0).$$

We seek to invoke the completeness of X. Observe that for all N < n < m,

$$d(x_m, x_n) \le d(x_{n+1}, x_n) + d(x_{n+2}, x_{n+1}) + \dots + d(x_m, x_{m-1})$$

$$\le (c^n + c^{n+1} + \dots + c^{m-1})d(x_1, x_0)$$

$$= c^n (1 + \dots + c^{m-n-1})d(x_1, x_0)$$

$$= \left(\frac{c^m - c^n}{c - 1}\right) d(x_1, x_0)$$

As the right-hand side of this equation gets arbitrarily small (select  $N = \log_c(\epsilon)$  and let magic happen), we find that  $x_0, x_1, \ldots$  is a Cauchy sequence. By completeness, it converges to some  $x \in X$ . Therefore,

$$x = \lim_{n \to \infty} x_n = \lim_{n \to \infty} \varphi(x_n) = \varphi(f).$$

To prove that f is unique, note that if  $\varphi(x) = x$  and  $\varphi(y) = y$  for  $x, y \in X$ , then

$$d(x,y) = d(\varphi(x), \varphi(y)) \le c \cdot d(x,y).$$

As c < 1, we must have that d(x, y) = 0, so x = y.

#### 3.2 The Inverse Function Theorem

**Theorem.** Suppose that C is a  $C^1$  mapping of an open set  $E \subset \mathbb{R}^n$  to  $\mathbb{R}^n$ , that the matrix  $f'(\mathbf{a})$  is invertible for  $\mathbf{a} \in E$ , and define  $\mathbf{b} = f(\mathbf{a})$  — then there exist open sets  $U, V \in \mathbb{R}^n$  such that  $\mathbf{a} \in U$ ,  $\mathbf{b} \in V$ , and f is a bijective mapping from U to V — and the inverse  $g: V \to U$  of f defined by  $g(f(\mathbf{x})) = \mathbf{x}$  for all  $\mathbf{x} \in U$  is  $C^1$ .

*Proof.* Let  $f'(\mathbf{a}) = \mathbf{J}$ , and let  $\lambda = \frac{1}{2\|J^{-1}\|}$ , and let U be the open ball defined by all vectors  $\mathbf{x}$  such that

$$||f'(\mathbf{x}) - \mathbf{J}|| < \lambda.$$

Further define V = f(U) (or more formally,  $\mathbf{y} \in \mathbb{R}^m \mid \exists \mathbf{x} \in U, \mathbf{x} = \mathbf{y}$ ). We must prove that f is invertible, that V is open, and that g is  $C^1$ .

Invertability of f: We now associate to each  $y \in \mathbb{R}^n$  a function  $\varphi_y$  defined by

$$\varphi_{\mathbf{y}}(\mathbf{x}) = \mathbf{x} + \mathbf{J}^{-1}(\mathbf{y} - f(\mathbf{x})).$$

Clearly,  $f(\mathbf{x}) = \mathbf{y}$  if and only if  $\varphi_{\mathbf{y}}(\mathbf{x}) = \mathbf{x}$ . Since  $\varphi'_{\mathbf{y}}(\mathbf{x}) = I - \mathbf{J}^{-1}f'(\mathbf{x}) = J^{-1}(J - f'(\mathbf{x}))$  for all  $\mathbf{x}$ ), we find that

$$\|\varphi'_{\mathbf{y}}(\mathbf{x})\| = \|\mathbf{J}^{-1}(J - f'(\mathbf{x}))\| \le \|J^{-1}\|\|J - f'(\mathbf{x})\| < \|J^{-1}\|\lambda = \frac{1}{2}.$$

We use an above theorem to conclude that for all  $x_1, x_2 \in U$ ,

$$\|\varphi_{\mathbf{y}}(\mathbf{x}_1) - \varphi_{\mathbf{y}}(\mathbf{x}_2)\| < \frac{1}{2} \|\mathbf{x}_1 - \mathbf{x}_2\|.$$

We conclude that the Contraction Principle guarantees that  $\varphi_{\mathbf{y}}(\mathbf{x}) = \mathbf{x}$  has exactly one solution — so  $f(\mathbf{x}) = \mathbf{y}$  has exactly one solution. We conclude that f is bijective (and thus invertible) over U.

**Openness of** V: For all  $\mathbf{y}_0 \in V$ , select  $\mathbf{x}_0$  such that  $f(\mathbf{x}_0) = \mathbf{y}_0$ , and let r be the radius of an open ball  $B_{\mathbf{x}_0}$  centered at  $\mathbf{x}_0$  contained within U. We claim that if  $\|\mathbf{y} - \mathbf{y}_0\| < \lambda r$ , then  $\mathbf{y} \in V$ .

We must construct  $\mathbf{x} \in U$  such that  $f(\mathbf{x}) = \mathbf{y}$ , which we do by proving that  $\varphi_{\mathbf{y}}$  is a contraction of  $B_{\mathbf{x}_0}$  into U. If  $\|\mathbf{y} - \mathbf{y}_0\| < \lambda r$ , observe that

$$\|\varphi_{\mathbf{y}}(\mathbf{x}_0) - \mathbf{x}_0\| = \|\mathbf{J}^{-1}(\mathbf{y} - \mathbf{y}_0)\| < \|J^{-1}\|\lambda r < \frac{r}{2}.$$

Then if  $\mathbf{x} \in B$ ,  $\|\mathbf{x} - \mathbf{x}_0\| < r$ , so

$$\|\varphi_{\mathbf{y}}(\mathbf{x}) - \mathbf{x}_0\| \le \|\varphi_{\mathbf{y}}(\mathbf{x}) - \varphi_{\mathbf{y}}(\mathbf{x}_0)\| + \|\varphi_{\mathbf{y}}(\mathbf{x}_0) - \mathbf{x}_0\| < \frac{1}{2}\|\mathbf{x} - \mathbf{x}_0\| + \frac{r}{2} \le r,$$

so  $\varphi_{\mathbf{y}}(\mathbf{x}) \in B_{\mathbf{x}_0}$ . We conclude that  $\varphi_{\mathbf{y}}$  is a contraction of the complete metric space  $B_{\mathbf{x}_0}$  into itself, so it must have some fixed point  $\mathbf{x} \in B_{\mathbf{x}_0}$  such that  $\varphi_{\mathbf{y}}(\mathbf{x}) = \mathbf{x}$ . Then  $f(\mathbf{x}) = \mathbf{y}$ , so  $\mathbf{y} \in f(B_{\mathbf{x}_0}) \subset f(U) = V$ . Thus V is an open set.

Smoothness of Inverse: For all  $\mathbf{y} \in V$  and  $\mathbf{y} + \mathbf{k} \in V$ , there exists  $\mathbf{x}$  and  $\mathbf{x} + \mathbf{h} \in U$  such that  $\mathbf{y} = f(\mathbf{x})$  and  $\mathbf{y} + \mathbf{k} = f(\mathbf{x} + \mathbf{h})$ . Then

$$\begin{aligned} \left\| \mathbf{h} - \mathbf{J}^{-1} \mathbf{k} \right\| &= \left\| \mathbf{h} + J^{-1} (f(\mathbf{x} + \mathbf{h}) - f(\mathbf{x})) \right\| \\ &= \left\| \varphi_{\mathbf{y}} (\mathbf{x} + \mathbf{h}) - \varphi_{\mathbf{y}} (\mathbf{x}) \right\| \\ &\leq \frac{1}{2} \|\mathbf{x} + \mathbf{h} - \mathbf{x} \| \\ &= \frac{1}{2} \|\mathbf{h} \|. \end{aligned}$$

Then  $\|\mathbf{J}^{-1}\mathbf{k}\| \geq \frac{1}{2}\|\mathbf{h}\|$ , so  $\mathbf{h} \leq 2\|J^{-1}\|\mathbf{k} = \frac{1}{\lambda}\mathbf{k}$ . We begin to now investigate the derivative: see that as

$$||f'(\mathbf{a}) - \mathbf{J}|| ||J^{-1}|| < \lambda ||J^{-1}|| = \frac{1}{2} < 1$$

 $f'(\mathbf{a})$  is invertible. Since

$$g(\mathbf{y} + \mathbf{k}) - g(\mathbf{y}) - f'(\mathbf{x})^{-1}\mathbf{k} = \mathbf{h} - f'(\mathbf{x})\mathbf{k} = -f'(\mathbf{x})^{-1}(f(\mathbf{x} + \mathbf{h}) - f(\mathbf{x}) - f'(\mathbf{x})\mathbf{h}),$$

we have that

$$\frac{\left\|g(\mathbf{y}+\mathbf{k})-g(\mathbf{y})-f'(\mathbf{x})^{-1}\mathbf{k}\right\|}{\|\mathbf{k}\|} \leq \frac{\left\|f'(\mathbf{x})^{-1}\right\|}{\lambda} \frac{\left\|f(\mathbf{x}+\mathbf{h})-f(\mathbf{x})-f'(\mathbf{x})\mathbf{h}\right\|}{\mathbf{h}}.$$

As  $\mathbf{k} \to \mathbf{0}$ , we have that  $\mathbf{h} \to \mathbf{0}$  (this is nonrigorous; we'd need to define a piecewise function in the instance that  $\mathbf{k} = 0$ ). Then as the right-hand side of this inequality tends to 0, the left-hand side does by the Squeeze Theorem. Thus,

$$g'(\mathbf{y}) = f'(\mathbf{x})^{-1} = f(g(\mathbf{y}))^{-1}$$

Finally, note that as g is a continuous mapping of V onto U, that f' is a continuous mapping of U into  $\Omega$ , then  $(f')^{-1}$  is a continuous mapping of U into  $\Omega$ , so  $g'(\mathbf{y})$  is a continuous mapping of V into  $\Omega$ . This completes the proof of the most complex (and beautiful) theorem I've ever studied.

If we lessen the restriction that f need be  $C^1$ , the only part of the Inverse Function Theorem that fails is that g is  $C^1$ ; if f is merely differentiable, we may derive that g is differentiable too.

### 3.3 The Implicit Function Theorem