# MATH20410 (W25): Analysis in Rn II (accelerated)

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## 1 Single-Variable Differential Calculus

In this chapter, we consider mainly functions of the form  $f: I \to \mathbb{R}$ , where I is an interval, e.g., (a,b), [a,b], (a,b),  $(a,\infty)$ ,  $\mathbb{R}$ . This is the function we have in mind unless otherwise stated.

**Definition 1.1** (Differentiability). We say f is **differentiable at**  $x \in I$  if the limit

$$f'(x) := \lim_{t \to x} \frac{f(t) - f(x)}{t - x} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

exists. In this case, we call f'(x) the derivative of f at x. Moreover:

- We say that f is **differentiable** if f'(x) exists for each  $x \in I$ .
- We say f is **continuously differentiable**  $(f \in C^1)$  if  $f' : I \to \mathbb{R}$  is continuous.

Example 1.2.

- f(x) = |x|. Differentiable on  $\mathbb{R} \setminus \{0\}$ .
- $f(x) = \begin{cases} x \sin \frac{1}{x}, & x \neq 0 \\ 0, & x = 0 \end{cases}$ . Continuous but not differentiable at 0.
- $f(x) = \begin{cases} x^2 \sin \frac{1}{x}, & x \neq 0 \\ 0, & x = 0 \end{cases}$ . Differentiable everywhere (in particular at 0), but  $f \notin C^1$ .

**Proposition 1.3** (Rules for computing derivatives).

- (i) Linearity. (af + bg)' = af' + bg' (if f' and g' exist, such requirements are hereafter omitted).
- (ii) Product rule. (fg)' = f'g + fg'.
- (iii) Quotient rule.  $(f/g)' = (f'g fg')/g^2$ .
- (iv) Chain rule.  $(f \circ g)' = (f' \circ g) \cdot g'$ .

<sup>1</sup>Low dhigh minus high dlow. Not Haidilao...

**Proof.** We prove the quotient rule; the remaining are left as exercises. Starting from the definition

$$\left(\frac{f}{g}\right)'(x) = \lim_{t \to x} \frac{\frac{f}{g}(t) - \frac{f}{g}(x)}{t - x}$$

$$= \lim_{t \to x} \frac{\frac{f(t)}{f(t)} + \frac{f(x)}{g(t)} - \frac{f(x)}{g(t)} + \frac{f(x)}{g(x)}}{t - x}.$$

Note that

$$\frac{\frac{f(x)}{g(t)} + \frac{f(x)}{g(x)}}{t - x} = \frac{f(x)}{g(x)g(t)} \frac{g(x) - g(t)}{t - x}$$

and we have

$$\left(\frac{f}{g}\right)'(x) = \frac{f'(x)}{g(x)} - \frac{f(x)g'(x)}{g^2(x)}$$

**Theorem 1.4.** If f is differentiable at x then f is continuous at x.

**Proof.** Note that

$$\lim_{t \to x} f(t) - f(x) = \lim_{t \to x} \frac{f(t) - f(x)}{t - x} (t - x) = f'(x) \cdot 0 = 0.$$

1.1 The Mean Value Theorem

**Lemma 1.5.** Suppose  $f:[a,b] \to \mathbb{R}$  has a local maximum or minimum at  $x \in (a,b)$ . If f'(x) exists, then f'(x) = 0.

**Proof.** From the definition of the derivative, consider the limits from the left and right; one is non-positive and the other is non-negative.

**Theorem 1.6** (Rolle's Theorem). Suppose  $f : [a,b] \to \mathbb{R}$  is continuous on [a,b], differentiable on (a,b), and such that f(a) = f(b). Then there exists  $x \in (a,b)$  such that f'(x) = 0.

**Proof.** Consider the global maximum or minimum (exist since f is a continuous function defined on a compact set) and apply the previous lemma. (If both the maximum and minimum is at a or b, f is constant.)

**Theorem 1.7** (Mean Value Theorem). Let  $f : [a,b] \to \mathbb{R}$  be such that f is continuous on [a,b] and differentiable on (a,b). Then there exists  $x \in (a,b)$  such that f(b) - f(a) = f'(x)(b-a).

**Proof.** Apply Rolle's to 
$$\tilde{f} = f - [f(b) - f(a)] \cdot \frac{x-a}{b-a}$$
.

**Theorem 1.8.** Let  $f:(a,b) \to \mathbb{R}$  be differentiable.

- (a) if f' = 0, then f is constant.
- (b) if  $f' \ge 0$ , then f is increasing.
- (c) if  $f' \leq 0$ , then f is decreasing.

**Proof.** Apply the mean value theorem.

**Theorem 1.9** (The Intermediate Value Property of Derivatives). Let  $f : [a, b] \to \mathbb{R}$  be differentiable<sup>2</sup> and suppose  $f'(a) < \lambda < f'(b)$  Then there exists  $x \in (a, b)$   $f'(a) = \lambda$ .

**Proof** (à la Pugh). Slide a small secant of length so small that the slope around a and b is separated also by  $\lambda$ . By continuity of the slope, there exists a secant between a and b with slope  $\lambda$ . Apply the mean value theorem to this slope.  $\Box$  **Proof** (à la Joe/Rudin). We start with  $\lambda = 0$ . Then f'(a),  $f'(b) \neq 0$  and the global

min/max of f cannot be at the endpoints. At the global extrema we have the desired result. When  $\lambda \neq 0$ , consider  $\tilde{f} := f - \lambda x$ .

Example 1.10. Consider

$$f(x) = \begin{cases} x^2 \sin(1/x), & x \neq 0 \\ 0, & x = 0 \end{cases}.$$

We have

$$f(x) = \begin{cases} 2x \sin(1/x) = \cos(1/x), & x \neq 0 \\ 0, & x = 0 \end{cases}$$

which has the intermediate value property.

**Theorem 1.11** (Generalized Mean Value Theorem). Let  $f, g : [a, b] \to \mathbb{R}$  be continuous on [a, b] and differentiable on (a, b). Then there exists  $x \in (a, b)$  such that

$$(f(a) - f(b))g'(x) = (g(a) - g(b))f'(x).$$

*Remark* 1.12. When the above is not zero,

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

**Proof.** Define

$$h(t) \coloneqq \big(f(b) - f(a)\big)g(t) - \big(g(b) - g(a)\big)f(t).$$

Note that

$$h(a) = f(b)g(a) - f(a)g(b) = h(b)$$

and apply Rolle's.

## 1.2 L'Hôpital's Rule

**Theorem 1.13** (L'Hôpital's Rule, a particular case). Let  $f, g : [a, b] \to \mathbb{R}$  be continuous on [a, b] and differentiable on (a, b). If  $g(x) \neq 0$  in a neighborhood of a and f(x) = g(x) = 0, then

$$\lim_{x \to a} \frac{f(x)}{g(x)} = \lim_{x \to a} \frac{f'(x)}{g'(x)},$$

if the last limit exists.

**Proof.** Consider some small  $\delta > 0$ . The generalized MVT gives some  $x \in (a, a+\delta)$  such that

$$\frac{f(a+\delta)}{g(a+\delta)} = \frac{f'(x)}{g'(x)} \approx \lim_{t \to a} \frac{f'(t)}{g'(t)},$$

where the last approximation follows from the existence of the limit. Note that as  $\delta \to 0$ ,  $x \to a$ , and the approximation error shrinks to 0.

Refer to Rudin or something for the general case.

## 1.3 Higher Derivatives

If  $f: I \to \mathbb{R}$  is differentiable, then we can define the second derivative f'' := (f')' if f' is differentiable. Higher derivatives can be defined similarly. We usually write  $f^{(n)}$  for the n-th derivative of f.

Example 1.14.  $L(x) = f(x_0) + f'(x_0)(x - x_0)$  is a (first order) linear approximation of f at  $x_0$ . How good is this approximation? A first answer is

$$f(x) = L(x) + o(|x - x_0|),$$

since we have as  $x \to x_0$  that

$$\frac{f(x) - L(x)}{x - x_0} = \frac{f(x) - f(x_0)}{x - x_0} - f'(x_0) \longrightarrow 0.$$

But can we say even more about the quality of the approximation? – Yes, if f is twice differentiable.

**Proposition 1.15** (First-order Taylor's Theorem). *Suppose* f' *exists and is continuous on* [a,b] *and* f'' *exists on* (a,b). *Let*  $x_0, x \in [a,b]$  *with*  $x_0 \neq x$ . *Then* 

$$f(x) = f(x_0) + f'(x_0)(x - x_0) + \frac{1}{2}f''(y)(x - x_0)^2,$$

where y is between  $x_0$  and x. In particular, we have

$$|f(x) - f(x_0) - f'(x_0)(x - x_0)| \le \frac{1}{2} \sup_{y \in (a,b)} |f''(y)| \cdot |x - x_0|^2.$$

**Proof.** Find M such that we have

$$f(x) = f(x_0) + f'(x_0)(x - x_0) + \frac{M}{2}(x - x_0)^2.$$

We need only find y such that M = f''(y). Define

$$g(t) := f(t) - f(x_0) - f'(x_0)(t - x_0) - \frac{M}{2}(t - x_0)^2.$$

Note that g''(t) = f''(t) - M, so we need only find a point at which g'' vanishes. Since  $g(x_0) = g(x) = 0$ , by the MVT there exists y' between  $x_0$  and x such that g(y') = 0. Observe that  $g'(x_0) = 0$ , and so by the MVT again, there exists y between  $x_0$  and y' (and by extension between  $x_0$  and x) such that g''(y) = 0.

The more general story: given  $f : [a, b] \to \mathbb{R}$  and  $x_0 \in [a, b]$ , we may define

$$P_{0}(x) \coloneqq f(x_{0}),$$

$$P_{1}(x) \coloneqq f(x_{0}) + f'(x_{0})(x - x_{0}),$$

$$P_{2}(x) \coloneqq f(x_{0}) + f'(x_{0})(x - x_{0}) + \frac{1}{2}f''(x_{0})(x - x_{0})^{2},$$

$$\vdots$$

$$P_{n}(x) \coloneqq \sum_{k=0}^{n} \frac{f^{(k)}(x_{0})}{k!} (x - x_{0})^{k},$$

when the corresponding derivatives exist. Note that  $P_n(x)$  is the unique degree n polynomial such that  $P_n^{(k)}(x_0) = f^{(k)}(x_0)$  for k = 1, ..., n.

**Theorem 1.16** (Taylor's Theorem). *Let*  $f : [a, b] \to \mathbb{R}$  *be such that* 

- $f^{(k)}$  exists on [a,b] for  $k=1,\ldots,n$ ; and
- $f^{(n+1)}$  exists on (a,b).

Then, for any  $x_0, x \in [a, b]$  with  $x_0 \neq x$ , there exists y between  $x_0$  and x such that

$$f(x) = P_n(x) + \frac{f^{(n+1)}(y)}{(n+1)!} (x - x_0)^{n+1}.$$

for some y between  $x_0$  and x.

We proof the case n = 2, the same idea can be used to prove the general case.

### Proof. Define

$$g(t) = f(t) - P_2(t) - \frac{M}{6}(t - x_0)^3.$$

Since g''' = f''' - M, we need only find y such that g'''(y) = 0. Note that  $g(x_0) = g(x) = 0$ , and so by the MVT there exists y' between  $x_0$  and x such that g'(y') = 0. Next, note that  $g'(x_0) = 0$ , and so by the MVT there exists y'' between  $x_0$  and y' such that g''(y'') = 0. Finally, note that  $g''(x_0) = 0$ , and so by the MVT there exists y between  $x_0$  and y'' such that g'''(y) = 0.

## 2 Multivariable Differential Calculus

Some remainders about  $\mathbb{R}^n$ :

- $\mathbb{R}^n = \{x = (x_1, \dots, x_n) : x_i \in \mathbb{R}\}.$
- $\mathbb{R}^n$  is a vector space, with canonical basis  $\{e_i, \dots, e_n\}$ .
- $\mathbb{R}^n$  comes with an inner product  $\langle x, y \rangle = x \cdot y = \sum x_i y_i$ , a norm  $|x| = \sqrt{x \cdot x} = (\sum x_i y_i)^{1/2}$ , and a metric d(x, y) = |x y|.

## 2.1 Higher Dimensional Codomains

Consider a function  $f : \mathbb{R} \supset I \to \mathbb{R}^n$ .

**Definition 2.1.** f is differentiable at x if the limit

$$f'(x) := \lim_{t \to x} \frac{f(t) - f(x)}{t - x}$$

exists.

Remark 2.2. We may write  $f(t) = (f_1(t), \dots, f_n(t))$ , and  $f'(x) = (f'_1(x), \dots, f'_n(x))$ , since a sequence  $x \in \mathbb{R}^n$  converges if and only if each of its components converges.

**Theorem 2.3.** We have the following analog of the MVT:

$$|f(b) - f(a)| \le |f'(t)| \cdot |b - a|.$$

for some t between a and b.

**Proof.** Assume a < b. Define

$$h(t) := \langle f(b) - f(a), f(t) \rangle$$
.

The MVT gives

$$h(b) - h(a) = h'(t)(b - a) = \langle f(b) - f(a), f'(t) \rangle (b - a)$$
  
 
$$\leq (b - a)|f(b) - f(a)||f'(t)|,$$

where the last inequality follows from the Cauchy-Schwarz inequality. Noting that

$$h(b) - h(a) = |f(b) - f(a)|^2$$
,

we have the desired result.

## 2.2 Higher Dimensional Domain

We next consider functions  $f: U \to \mathbb{R}$ , where  $U \subset \mathbb{R}^n$  is open.

**Definition 2.4** (Partial Derivatives).

$$\frac{\partial f}{\partial x_i}(x) = D_i f(x) := \lim_{h \to 0} \frac{f(x + he_i) - f(x)}{h}.$$

**Definition 2.5** (Directional Derivatives). Fix  $u \in \mathbb{R}^n$ .

$$= D_i u f(x) := \lim_{h \to 0} \frac{f(x + hu) - f(x)}{h}.$$

#### 2.2.1 The Derivative

Intuition: A function is differentiable if a first-order Taylor expansion holds. That is, if f is "well-approximated" by a linear function.

**Definition 2.6.** We denote the set of all linear maps from  $\mathbb{R}^n$  to  $\mathbb{R}$  as  $L(\mathbb{R}^n, \mathbb{R})$ .

**Definition 2.7** (The Derivative). A function f is differentiable at x if there exists a linear map  $T \in L(\mathbb{R}^n, \mathbb{R})$  such that

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

In this case we write Df(x) = T. In other words, f(x + h) = f(x) + Df(x)(h) + o(|h|).

Remark 2.8.

• If f is differentiable, then

$$Df: U \longrightarrow L(\mathbb{R}^n, \mathbb{R}).$$

• If is easy to check that Df is well defined, that is, there is at most one T such that the limit holds.

We may think of the linear map  $T: \mathbb{R}^n \to \mathbb{R}$  as

$$T(u) = \langle u, v \rangle, \tag{1}$$

where  $v := (Te_1, \dots Te_n)$ .

**Definition 2.9** (The Gradient). If f is differentiable at x, we define  $\nabla f(x) = v$ , where v satisfies (1). In other words,

$$\lim_{h \to 0} \frac{f(x+h) - f(x) - \langle \nabla f(x), h \rangle}{|h|} = 0.$$

**Theorem 2.10.** If f is differentiable at x, then  $D_u f(x)$  exists for all  $u \in \mathbb{R}^n$  and  $D_u f(x) = D f(x) u = \langle \nabla f(x), u \rangle$ .

**Proof.** Note that as  $t \to 0$ , we have

$$\left| \frac{f(x+tu) - f(x)}{t} - Df(x)u \right| = \left| \frac{f(x+tu) - f(x) - Df(x)(tu)}{t} \right|$$
$$= \left| \frac{f(x+tu) - f(x) - Df(x)(tu)}{|tu|} \right| \cdot |u| \longrightarrow 0.$$

Remark 2.11. In particular we have  $D_i f(x) = D_{e_i} f(x) = D f(x) e_i = \langle \nabla f(x), e_i \rangle$ . In other words, if f is differentiable, then  $\nabla f(x) = (D_1 f, \dots, D_n f)$ .

Remark 2.12.

- Differentiability holds if and only if the gradient exists.
- Differentiability implies the existence of directional derivatives, which then implies the existence of partial derivatives. The converse implications are not true.

Example 2.13. Consider

$$f(x_1, x_2) := \begin{cases} \frac{x_1 x_2}{x_1^2 + x_2^2}, & x \neq 0 \\ 0, & x = 0 \end{cases}.$$

It is easy to see that  $D_1 f(0) = D_2 f(0) = 0$  but  $D_{(1,1)} f(0)$  does not exist. Indeed, f is not even continuous on the line t(1,1).

Example 2.14. Consider

$$f(x_1, x_2) := \begin{cases} \frac{x_1^3}{x_1^2 + x_2^2}, & x \neq 0 \\ 0, & x = 0 \end{cases}.$$

Note that

$$D_u f(0) = \lim_{t \to 0} \frac{t^3 u_1^3}{t^2 (u_1^2 + u_2^2)} \cdot \frac{1}{t} = \frac{u_1^3}{u_1^2 + u_2^2}.$$

However, Df(0) cannot exist, since the above mapping is not linear.

**Theorem 2.15.** If the partial derivatives  $D_1 f, ..., D_n f$  exist and are continuous (in a neighborhood of x), then f is differentiable at x.

**Proof.** Fix arbitrary  $x \in E$  and define  $Ah = \sum D_i f(x) h_i$ . We write  $\omega_k := \sum_{i=1}^k h_i e_i$  for k = 1, ..., n and  $\omega_0 := x$ . Note that  $\omega_n = h$ . By the MVT we can find  $\delta_k$  between 0 and  $h_k$  such that

$$f(x+h) - f(x) - Ah = \sum_{k=1}^{n} f(x+\omega_k) - f(x+\omega_{k-1}) - D_k f(x) h_k$$
$$= \sum_{k=1}^{n} h_k [D_k(x+\omega_k + \delta_i e_i) - D_k f(x)],$$

which by continuity of  $D_i$  is sublinear.

## 2.3 Extension to Functions with Higher Dimensional Codomains

Immediate.

We have

$$Df(x) \in L(\mathbb{R}^n, \mathbb{R}^m), \quad \mathbb{R}^n \ni h \longmapsto Df(x) \in L(\mathbb{R}^n, \mathbb{R}^m),$$

and

$$\mathrm{D}f:\mathcal{U}\longmapsto L(\mathbb{R}^n,\mathbb{R}^m).$$

Note that we may identify  $T \in L(\mathbb{R}^n, \mathbb{R}^m)$  with a unique matrix  $A = [Te_1, \dots, Te_n]$  such that we have Th = Ah for each h.

**Definition 2.16.** If f is differentiable at x, we can define  $[Df(x)] \in \mathbb{R}^{n \times m}$  to be the unique matrix such that

$$Df(x)h = [Df(x)]h.$$

This is called the **Jacobian matrix**, and its determinant is called the **Jacobian**. More generally, for  $T \in L(\mathbb{R}^n, \mathbb{R}^m)$ , we use [T] to denote the corresponding matrix.

**Theorem 2.17.** If Df(x) exists, so do  $D_i f_i$ , and we have

$$[Df(x)] = [D_i f_j] = [\nabla f_1(x) \dots \nabla f_m(x)]^{\mathsf{T}}.$$

It suffices to prove the following stronger proposition:

**Proposition 2.18.** The function f is differentiable at x if and only if each  $f_i$  is differentiable at x. In this case,

$$Df(x)h = (Df_1h, \dots, Df_m(x)h) = (\langle \nabla f_1(x), h \rangle, \dots, \langle \nabla f_m(x), h \rangle) = [Df(x)]h.$$

**Proof.** Suppose  $f_i$  is differentiable. Define  $T \in L(\mathbb{R}^n, \mathbb{R}^m)$  by the formula

$$Th = (Df_1h, \ldots, Df_m(x)h).$$

Note that

$$\frac{|f(x+h)-f(x)-Th|}{|h|} = \left(\sum \frac{|f_i(x+h)-f_i(x)-\mathrm{D}f_i(x)h|^2}{|h|}\right)^{1/2} \longrightarrow 0.$$

The other direction is left as an exercise.

**Corollary 2.19.** If  $D_j f_i$  all exist and are continuous in a neighborhood of x, then f is differentiable at x.

#### 2.4 The Chain Rule

Consider

$$\mathbb{R}^n \supset \mathcal{U} \xrightarrow{g} \mathbb{R}^m \xrightarrow{f} \mathbb{R}^k.$$

**Theorem 2.20** (Chain Rule). If g is differentiable at x and f is differentiable at g(x), then  $f \circ g$  is differentiable at x and

$$D(f \circ g)(x) = Df(g(x)) \circ Dg(x).$$

A formal calculation:<sup>3</sup> We have

$$f \circ g(x+h) = f \circ g(x) + \mathrm{D}f(g(x)) \big( g(x+h) - g(x) \big) + o \big( g(x+h) - g(x) \big)$$
$$= f \circ g(x) + \mathrm{D}f(g(x)) \big( \mathrm{D}g(x)h + o(|h|) \big) + o(|h|)$$
$$= f \circ g(x) + \mathrm{D}f(g(x)) \big( \mathrm{D}g(x)h \big) + o(|h|).$$

<sup>3</sup>In math, "formal calculation" often means calculation that is "systematic but without rigorous justification."

**Proof.** For small  $h \in \mathbb{R}^p$ , we write

$$g(x+h) = g(x) + Bh + R_g,$$

where B = Dg(x) and  $\lim_{h\to 0} R_g/h = 0$ . Similarly, we write

$$f\circ g(x+h)=f(g(x)+Bh+R_g)=f\circ g(x)+ABh+AR_g+R_f,$$

where  $A = \mathrm{D} f(g(x))$  and  $\lim_{h\to 0} R_f/(Bh+R_g) \to 0$ . It remains to note that the last two terms are sublinear.

## 2.5 Continuity of the Derivative

Let  $f: \mathbb{R}^n \supset \mathcal{U} \to \mathbb{R}^M$ , where  $\mathcal{U}$  is open. Recall that if f is differentiable, we have defined

- $\mathcal{U} \ni x \to \mathrm{D}f(x) \in L(\mathbb{R}^n, \mathbb{R}^m).$
- $\mathcal{U} \ni x \to [\mathrm{D}f(x)] \in \mathbb{R}^{m \times n}$ .
- $\mathcal{U} \ni x \to D_i f_i(x) \in \mathbb{R}, i = 1, \dots, m, j = 1, \dots, n.$

**Definition 2.21.** For  $T \in (\mathbb{R}^n, \mathbb{R}^m)$ , we define the operator norm

$$||T|| = \sup_{|v|=1} |Tv| = \sup_{|v| \in \mathbb{R}^n \setminus \{0\}} \frac{|Tv|}{|v|}.$$

This gives rise to the standard norm induced metric: for  $T, S \in L(\mathbb{R}^n, \mathbb{R}^m)$ , we have

$$d(T,S) = ||T - S||.$$

**Definition 2.22.** For  $A \in \mathbb{R}^{m \times n}$ , we define the operator norm  $||A||_{\text{op}} = \sup_{|v|} |Av|$ . Thus  $||T|| = ||[A]||_{\text{op}}$ .

**Definition 2.23.** For  $A \in \mathbb{R}^{m \times n}$ , we define the Frobenius norm  $||A||_F = \left(\sum_{i,j} A_{ij}^2\right)^{1/2}$ .

**Proposition 2.24.** The following statements are equivalent:

- $x \mapsto Df(x)$  is continuous (wrt d).
- $x \mapsto [Df(x)]$  is continuous (wrt  $d_{op}$ ).
- $x \mapsto [Df(x)]$  is continuous (wrt  $d_F$ ).
- Each  $x \mapsto D_j f_i(x)$  is continuous.

**Definition 2.25.** The function f is  $C^1$  if the above equivalent conditions hold.

#### 2.6 The Inverse Function Theorem

**Theorem 2.26** (The Inverse Function Theorem). Let  $f : \mathbb{R}^n \supset E \to \mathbb{R}^n$  be  $C^1$ , where E is open. Suppose  $x_0 \in E$  and  $Df(x_0)$  is invertible. Then there exists a neighborhood U of  $x_0$  such that f is a bijection from U to V := f(U), and  $f^{-1} : V \to U$  is  $C^1$  with derivative  $D(f^{-1}(y)) = [Df(f^{-1}(y))]^{-1}$ .

Remark 2.27.

- Thus if the first order Taylor expansion is invertible, then f is invertible locally.
- Consider the identities

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

Differentiating

$$I = Df^{-1}(f(x)) \circ Df(x), \quad I = Df(f^{-1}(y)) \circ Df^{-1}(y).$$

This shows that  $D(f^{-1}(y))$  and  $Df(f^{-1}(x))$  are inverses of each other, provided that the functions are differentiable.

• Remember the one-dimensional case! We have that  $(f^{-1})' = 1/f'$ :

**Proof** (Inverse Function Theorem, n = 1). Let  $Df(x_0) \in L(\mathbb{R}, \mathbb{R})$  be invertible. Then  $f'(x_0) \neq 0$ , say  $f'(x_0) > 0$  without loss of generality. By continuity of f', there exists an open interval U containing  $x_0$  such that f' > 0 on U. Thus f is strictly increasing and thus one-to-one on U. It is easy to verify that V := f(U) = (f(a), f(b)), so V is open.

Next, we show that  $f^{-1}$  is continuous. For that, consider sequence  $y_k \to y$ . We seek to show that  $f^{-1}(y_k) \to f^{-1}(y)$ . Equivalently, given  $f(x_k) \to f(x)$ , we show  $x_k \to x$ . To that end, suppose not. Then, without loss of generality, there exists infinitely many  $x_k$  such that  $x_k > x + \epsilon$  for some  $\epsilon$ . Thus  $f(x_k) > f(x + \epsilon) > f(x)$ , a contradiction.

Finally, we show that  $f^{-1}$  is differentiable. Write  $x := f^{-1}(y)$  and  $f^{-1}(y+h) = x+k$ , that is, define  $k := f^{-1}(y+h) - f^{-1}(y)$ . We have then that h = f(x+k) - f(x). Then as  $h \to 0$ , we have  $\lim_{h\to 0} k = 0$ , by the continuity of  $f^{-1}$ , and so

$$\frac{f^{-1}(y+h)-f^{-1}(y)}{h}=\frac{k}{f(x+h)-f(x)}\longrightarrow \frac{1}{f'(x)}.$$

Before the general proof, we need the following result:

**Theorem 2.28** (Contraction Mapping). Let (X, d) be a complete metric space. Let  $\phi: X \to X$  be a **contraction**, that is, there exists c < 1 such that

$$d(\phi(x), \phi(y)) \le cd(x, y).$$

*Then, there is a unique fixed point of*  $\phi$ *.* 

**Proof.** Pick any  $x_0 \in X$ . Define  $x_n := \phi(x_{n-1})$  for  $n \ge 1$ . Note that

$$\phi(x_n, x_{n-1}) \le c^n \phi(x_1, x_0).$$

Thus, for n > m, we have

$$d(x_n, x_m) \le \sum_{k=m+1}^n d(x_k, x_{k-1}) \le d(x_1, x_0) \sum_{k=m+1}^n c^{k-1}.$$

Since  $\sum c^j$  is a converging series, the last term tends to 0 and so  $(x_n)$  is Cauchy. Then, setting  $x = \lim x_n$ , we have

$$\phi(x) = \lim \phi(x_n) = \lim x_{n+1} = x.$$

Uniqueness follows from the contraction property.

We may now proceed with the general proof of the Inverse Function Theorem. We recall first the result:

**Theorem 2.29** (The Inverse Function Theorem). Let  $f : \mathbb{R}^n \supset E \to \mathbb{R}^n$  be  $C^1$ , where E is open. Suppose  $x_0 \in E$  and  $Df(x_0)$  is invertible. Then there exists a neighborhood U of  $x_0$  such that f is a bijection from U to V := f(U), and  $f^{-1} : V \to U$  is  $C^1$  with derivative  $D(f^{-1}(y)) = [Df(f^{-1}(y))]^{-1}$ .

**Proof** (Inverse Function Theorem, the General Case).

**Step 1:** Local Invertibility. Choose  $\delta$  small enough that

- $\|\mathbf{D}f(x)^{-1}\|$  is bounded in  $B_{\delta}(x_0)$ .
- $\|Df(x) Df(x')\|$  is "really small" if  $x, x' \in B_{\delta}(x_0)$ .

<sup>4</sup>Here, we used the fact that inversion is a continuous operation.

We check that f is injective on  $U := B_{\delta}(x)$ . Note that f(x) = y if and only if  $Df(x_0)^{-1}(y - f(x)) = 0$ , which is equivalent to x being a fixed point of the function

$$\phi_{y}(x) := x + Df(x_0)^{-1} (y - f(x)).$$

Thus, to prove injectivity, we need only show that  $\phi_v$  is a contraction. Observe that

$$D\phi_y(x) = I - Df(x_0)^{-1}Df(x) = Df(x_0)^{-1}[Df(x_0) - Df(x)].$$

Then,

$$\|D\phi_y(x)\| \le \|Df(x_0)^{-1}\| \|Df(x_0) - Df(x)\|$$

can be made arbitrarily small, and in particular smaller than 1/2, by choosing  $\delta$  small enough. The function  $\phi_y$  is then a contraction. While the image of  $\phi_y$  may not be a subset of its domain U (and so Banach contraction does not apply), the same argument in the proof of the Banach contraction theorem shows that  $\phi_y$  has at most one fixed point, if any, in U. Injectivity of f in U thus follows.

Set V := f(U). Note that  $f^{-1}$  is well defined on V.

**Step 2:** *V* is open. Fix  $f(x_0) \in V$ . Pick r > 0 such that  $B_r(x_0) \subset U$ . Note that

$$|x - x_0| \le ||Df(x_0)^{-1}|||f(x) - f(x_0)|.$$

Thus for y = f(x) within  $r/2 \|Df(x_0)^{-1}\|$  of  $f(x_0)$ , we have  $x \in U$  and so  $y \in V$ .

**Step 3:**  $f^{-1}$  **is continuous** (**Lipschitz**). Recall that  $\phi_y(x)$  is a contraction in x with Lipschitz constant 1/2, and note that it is also Lipschitz in y, with Lipschitz constant say C. From

$$x - x' = \phi_y(x) - \phi_{y'}(x') = \phi_y(x) - \phi_y(x') + \phi_y(x') - \phi_{y'}(x')$$

we thus know

$$|x - x'| \le \frac{1}{2}|x - x'| + C|y - y'|.$$

Then,

$$\left|f^{-1}(y) - f^{-1}(y')\right| = |x - x'| \le 2C|y - y'|$$

and  $f^{-1}$  is Lipschitz.

**Step 4: The formula for**  $Df^{-1}$ . Write y = f(x). Set  $h = f^{-1}(y+k) - f^{-1}(y)$ . Note that  $f^{-1}(y+k) = x + h$  and so k = f(x+h) - f(x). We have then that

$$\begin{split} & \frac{\left| f^{-1}(y+k) - f^{-1}(y) - \mathrm{D}f(x)^{-1}k \right|}{|k|} \\ & = \frac{\left| h - \mathrm{D}f(x)^{-1} \left( f(x+h) - f(x) \right) \right|}{|f(x+h) - f(x)|} \\ & \leq \frac{\left\| \mathrm{D}f(x)^{-1} \right\| \left\| \mathrm{D}f(x)h - f(x+h) + f(x) \right\|}{|h|} \cdot \frac{|h|}{|f(x+h) - f(x)|}. \end{split}$$

Note that the first term tends to 0 and the second is bounded. We have established then that that  $Df^{-1}(y) = Df(x)^{-1}$  is continuous. It remains to note that as a composition of continuous functions,  $Df^{-1}$  is continuous.

## 2.7 The Implicit Function Theorem

Example 2.30. Consider function f and the equation f(x, y) = 0. What does it mean to "solve for x"? We seek a function g such that f(g(y), y) = 0.

We will deal with the more general case of  $f: \mathbb{R}^{n+m} \supset E \to \mathbb{R}^n$ . If f is differentiable at (x, y), then  $\mathrm{D} f(x, y) \in L(\mathbb{R}^{n+m}, \mathbb{R}^n)$ . For  $(h, k) \in \mathbb{R}^{n+m}$ , then  $\mathrm{D} f(x, y)(h, k) \in \mathbb{R}^n$ . Write  $\mathrm{D}_x f(x, y)h = \mathrm{D} f(x, y)(h, 0)$  and  $\mathrm{D}_y f(x, y)k = \mathrm{D} f(x, y)(0, k)$ . Note that  $\mathrm{D}_x f \in (\mathbb{R}^n, \mathbb{R}^n)$  and  $\mathrm{D}_y f \in (\mathbb{R}^m, \mathbb{R}^m)$ .

**Theorem 2.31** (Implicit Function Theorem). Let  $f: \mathbb{R}^{n+m} \supset E \to \mathbb{R}^n$ . Suppose f is  $C^1$  in a neighborhood of some point  $(x_0, y_0)$  such that  $f(x_0, y_0) = 0$ . If  $D_x f(x_0, y_0)$  is invertible, then there exists a neighborhood U of  $x_0$  and a neighborhood V of  $y_0$  such that for each  $y \in V$ , there exist a unique x such that f(x, y) = 0. Moreover, the function g such that f(g(y), y) = 0 is  $C^1$ , with  $Dg(y) = -D_x f(g(x), y)^{-1}D_y f(g(y), y)$ .

Remark 2.32.

- Consider the linear map  $f(x, y) = A_x x + A_y y$ . The condition f(x, y) = 0 is equivalent to  $A_x x = -A_y y$ . If  $A_x$  is invertible, then we have  $g(y) = -A_x^{-1}A_y y$ .
- If h(y) := f(g(y), y) = 0, then  $Dh(y) = D_x f(g(y), y) Dg(y) + D_y f(g(y), y) = 0$ , giving  $Dg = -(D_x f)^{-1} D_y f$ .

• Remember the case of n = 1: when the partial derivative in the direction of x is nonzero, we can solve for x locally.

**Proof.** Define  $F: E \to \mathbb{R}^{n+m}$  by F(x, y) = (f(x, y), y). The Jacobian matrix of F at  $(x_0, y_0)$  is

$$[DF(x_0, y_0)] = \begin{bmatrix} D_x f(x_0, y_0) & D_y f(x_0, y_0) \\ 0 & I \end{bmatrix}.$$

It turns out that

$$\det DF(x_0, y_0) = \det D_x f(x_0, y_0) \det I - \det 0 \det D_y f(x_0, y_0) = \det D_x f(x_0, y_0) \neq 0.$$

By the Inverse Function Theorem, then, F is invertible in a neighborhood of  $(x_0, y_0)$ . By the construction of F, there then exists G such that  $(G(x, y), y) = F^{-1}(x, y)$ . Define then g(y) := G(0, y). We have

$$f(g(y), y) = f(G(0, y), y) = f(F^{-1}(0, y)) = 0.$$

Remark 2.33 (Using the Implicit Function Theorem). Consider the function  $f: \mathbb{R}^{n+m} \to \mathbb{R}^n$  with f(a,b) = 0. Suppose we want to solve the equation f(x,y) = 0 for x in terms of y. This may be thought of as solving a system of n equations in n unknowns. We seek to find  $g: V \to \mathbb{R}^n$  such that f(g(y), y) = 0.

By the Implicit Function Theorem, such g exists if  $D_x f(a, b)$  is invertible (and  $f \in C^1$ ). Intuition: if the Jacobian of f is invertible, then we change the output of f to set f = 0 no matter how g is changed.

Example 2.34. Consider  $f: \mathbb{R}^{2+3} \to \mathbb{R}^2$  with

$$f_1 := 2e^{x_1} + x_2y_1 - 4y_2 + 3$$
,  $f_2 = x_2\cos(x_1) - 6x_1 + 2y_1 - y_3$ .

Set a = (0, 1) and b = (3, 2, 7). Note that we have f(a, b) = 0. We have

$$D_x f(x, y) = \begin{bmatrix} 2x^{x_1} & y_1 \\ -x_2 \sin(x_1) & \cos(x_1) \end{bmatrix}.$$

At (a,b),

$$\det D_x f(a, b) = \det \begin{bmatrix} 2 & 3 \\ -6 & 1 \end{bmatrix} = 20 \neq 0.$$

Then

$$Dg(b) = -\left[D_x f(a, b)\right]^{-1} \left[D_y f(x, b)\right] = \begin{bmatrix} 1/4 & 1/5 & -3/20 \\ -1/2 & 6/5 & 1/10 \end{bmatrix},$$

using which we can compute the first order approximation of g.

## 2.8 Higher Partial Derivatives

Let  $f: \mathbb{R}^n \to \mathbb{R}$ . Note that  $D_i f: \mathbb{R}^n \to \mathbb{R}$ .

**Definition 2.35.** Suppose  $D_i f$  exists. Define  $D_{ji} f(x) = D_j [D_i f](x)$  if the latter exists.

**Definition 2.36.** The function f is  $C^2$  if all  $D_{ii}f$  exist and are continuous.

**Theorem 2.37** (Clairaut's Theorem). If f is  $C^2$ , then  $D_{ii}f = D_{ij}f$ .

**Proof** (n = 2). By the MVT, we have

$$D_{12}f(x,y) = \lim_{h \to 0} \frac{D_2(x+h,y) - D_2(x,y)}{h}$$

$$= \lim_{h \to 0} \lim_{k \to 0} \frac{f(x+h,y+k) - f(x+h,y) - f(x,y+k) + f(x,y)}{hk}$$

$$= \lim_{h \to 0} \lim_{k \to 0} D_{21}f(t,s),$$

where t is between x and x + h and s is between y and y + k.

## 2.9 Higher Derivatives: An Informal Discussion

Recall that

$$f(x+h) = f(x) + Df(x)h + o(h).$$

The "total" second order derivative of  $f: \mathbb{R}^n \to \mathbb{R}$  should thus satisfy

$$f(x+h) = f(x) + \mathrm{D} f(x) h + \frac{1}{2} \mathrm{D}^2 f(x) (h,h) + o(h^2).$$

Consider then  $\gamma(t) = x + tv$  and  $f \circ \gamma$ . We have

$$(f \circ \gamma)''(0) = \lim_{t \to 0} \frac{\mathrm{d}}{\mathrm{d}t} \left[ \sum_{i \to 0} \mathrm{D}_i f(x + tv) v_i \right]$$
  
= 
$$\lim_{t \to 0} \sum_{i \to 0} \left\langle \nabla \mathrm{D}_i f(x + tv) v_i, v \right\rangle$$
  
= 
$$\lim_{t \to 0} \sum_{i,j} \mathrm{D}_{ij} f(x) v_i v_j = v^{\mathsf{T}} \mathrm{D}^2 f(x) v,$$

where  $D^2 f(x)$  is the Hessian. That is,

$$D^{2}f: \mathbb{R}^{n} \times \mathbb{R}^{n} \longrightarrow \mathbb{R}$$
$$(h, k) \longmapsto h^{\mathsf{T}} \operatorname{Hess}(f)(x)k.$$