

# Introduction to Analysis II

Kon Yi

February 26, 2026

## **Abstract**

Lecture note of Introduction to Analysis II.

# Contents

<b>1 Several Variable Differential Calculus</b>	<b>2</b>
1.1 Linear Transformation . . . . .	3
1.2 Derivatives in Several Variable Calculus . . . . .	5
1.3 Partial and Directional Derivatives . . . . .	8

# Chapter 1

## Several Variable Differential Calculus

### Lecture 1

In this chapter, we want to approximate non-linear functions by linear maps. If we consider

24 Feb.

$$f : \mathbb{R}^n \rightarrow \mathbb{R}^m \quad f(\underbrace{x_1, x_2, \dots, x_n}_x) = (f_1(x), f_2(x), \dots, f_m(x)),$$

where  $f_i : \mathbb{R}^n \rightarrow \mathbb{R}$  for all  $i$ . Now given a real-valued function  $F : \mathbb{R}^n \rightarrow \mathbb{R}$  which is differentiable at a point  $x_0 \in \mathbb{R}^n$  we can approximate  $F(x)$  in the following way:

$$F(x) \approx F(x_0) + \nabla F(x_0) \cdot (x - x_0)$$

where

$$\nabla F(x_0) = \left( \frac{\partial F(x_0)}{\partial x_1}, \frac{\partial F(x_0)}{\partial x_2}, \dots, \frac{\partial F(x_0)}{\partial x_n} \right) \in \mathbb{R}^n \text{ with } x_0 = (x_1, x_2, \dots, x_n)$$

and thus

$$\begin{aligned} \nabla F(x_0) \cdot (x - x_0) &= \left\langle \frac{\partial F(x_0)}{\partial x_1}, \frac{\partial F(x_0)}{\partial x_2}, \dots, \frac{\partial F(x_0)}{\partial x_n} \right\rangle \cdot \langle x_1, x_2, \dots, x_n \rangle \\ &= \sum_{i=1}^n \frac{\partial F(x_0)}{\partial x_i} x_i. \end{aligned}$$

Hence,

$$f(x) = \begin{pmatrix} f_1(x) \\ f_2(x) \\ \vdots \\ f_n(x) \end{pmatrix} \approx \begin{pmatrix} f_1(x_0) + \nabla f_1(x)(x - x_0) \\ f_2(x_0) + \nabla f_2(x)(x - x_0) \\ \vdots \\ f_n(x_0) + \nabla f_n(x)(x - x_0) \end{pmatrix},$$

which gives

$$f(x) - f(x_0) \approx \begin{pmatrix} \nabla f_1(x)(x - x_0) \\ \nabla f_2(x)(x - x_0) \\ \vdots \\ \nabla f_n(x)(x - x_0) \end{pmatrix} = \begin{pmatrix} \nabla f_1(x) \\ \nabla f_2(x) \\ \vdots \\ \nabla f_n(x) \end{pmatrix} \cdot \underbrace{(x - x_0)}_{\text{column vector}}.$$

## 1.1 Linear Transformation

**Definition 1.1.1 (Row vectors).** Let  $n \geq 1$  be an integer. We refer to elements of  $\mathbb{R}^n$  as  $n$ -dimensional row vectors. A typical row vector is  $x = (x_1, x_2, \dots, x_n)$  which we abbreviate as  $(x_i)_{1 \leq i \leq n}$ . The components  $x_1, x_2, \dots, x_n$  are real numbers. If  $x$  and  $y$  are two row vectors in  $\mathbb{R}^n$ , we can define vector sum by

$$x + y = (x_1, x_2, \dots, x_n) + (y_1, y_2, \dots, y_n) := (x_1 + y_1, x_2 + y_2, \dots, x_n + y_n).$$

If  $c \in \mathbb{R}$  is any real number, we define scalar multiplications by

$$cx = c(x_1, x_2, \dots, x_n) = (cx_1, cx_2, \dots, cx_n).$$

### Remark 1.1.1.

- (1)  $-x := (-1) \cdot x = (-x_1, -x_2, \dots, -x_n)$ .
- (2) zero vector is denoted by 0, i.e.  $(0, 0, \dots, 0)$ .

**Lemma 1.1.1 ( $\mathbb{R}^n$  is a vector space).** Let  $x, y, z$  be vectors in  $\mathbb{R}^n$ , and let  $c, d \in \mathbb{R}$ . Then the following properties hold:

- (a)  $x + y = y + x$ .
- (b)  $(x + y) + z = x + (y + z)$ .
- (c)  $x + 0 = 0 + x = x$ .
- (d)  $x + (-x) = (-x) + x = 0$ .
- (e)  $(c \cdot d)x = c \cdot (dx)$ .
- (f)  $c(x + y) = cx + cy$ .
- (g)  $(c + d)x = cx + dx$ .
- (h)  $1x = x$ .

**Definition 1.1.2.** Let  $x = (x_1, x_2, \dots, x_n)$  be row vector. Its transpose is the  $n$ -dimensional column vector

$$x^T = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}.$$

**Definition 1.1.3.** The standard basis of  $\mathbb{R}^n$  consists of  $e_1, e_2, \dots, e_n$ , where  $e_j$  has 1 in the  $j$ -th position and 0 elsewhere:

$$e_j = (0, \dots, 0, \underbrace{1}_{j\text{-th}}, 0, \dots, 0).$$

Every row vector

$$x = (x_1, x_2, \dots, x_n) = \sum_{j=1}^n x_j e_j.$$

Similarly,

$$x^T = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} = \sum_{j=1}^n x_j e_j^T.$$

**Definition 1.1.4 (Linear transformation).** A linear transformation  $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$  is any function from one Euclidean space to another that satisfies the following two properties:

- (a) Additivity: For  $x, y \in \mathbb{R}^n$ ,  $T(x + y) = T(x) + T(y)$ .
- (b) Homogeneity: For  $x \in \mathbb{R}^n$  and all scalars  $c \in \mathbb{R}$ ,  $T(cx) = cT(x)$ .

**Remark 1.1.2.** This definition is equivalent to the following:

$$T(c_1v_1 + \cdots + c_kv_k) = c_1T(v_1) + \cdots + c_kT(v_k)$$

where  $v_1, \dots, v_k \in \mathbb{R}^n$  and  $c_1, c_2, \dots, c_n \in \mathbb{R}$ .

**Definition 1.1.5.** Let  $m, n \geq 1$  be integers. An  $m \times n$  ordered matrix is an ordered rectangular array of real numbers

$$A = (a_{ij})_{\substack{1 \leq i \leq m \\ 1 \leq j \leq n}} = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix}$$

consisting of  $m$  rows and  $n$  columns, where

- (a) The entry  $a_{ij}$  denote the number in the  $i$ -th row and  $j$ -th column.
- (b) We denote the set of all  $m \times n$  matrices by  $\mathbb{R}^{m \times n}$ .
- (c) In particular, a row vector is a  $1 \times n$  matrix, a column vector is a  $n \times 1$  vector.

**Definition 1.1.6 (Matrix multiplication).** Given an  $m \times n$  matrix  $A = (a_{ij})_{\substack{1 \leq i \leq m \\ 1 \leq j \leq n}}$  and an  $n \times p$  matrix  $B = (b_{jk})_{\substack{1 \leq j \leq n \\ 1 \leq k \leq p}}$ , we define  $AB$  to be the  $m \times p$  matrix  $(c_{ik})_{\substack{1 \leq i \leq m \\ 1 \leq k \leq p}}$  where

$$c_{ik} = \sum_{j=1}^n a_{ij}b_{jk}.$$

**Definition 1.1.7 (Matrix-vector multiplication).** Let  $A = (a_{ij}) \in \mathbb{R}^{m \times n}$  and  $x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} \in \mathbb{R}^n$  be a column vector. We define

$$Ax = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n \\ a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n \\ \vdots \\ a_{n1}x_1 + a_{n2}x_2 + \cdots + a_{nn}x_n \end{pmatrix}$$

**Remark 1.1.3.** In our class, we just treat  $\mathbb{R}^n, \mathbb{R}^m$  as column vector spaces, and  $L_A(x) = Ax$  is a  $m \times 1$  column vector.

**Theorem 1.1.1.** Let  $A$  be a  $m \times n$  matrix, then  $L_A(x) = Ax$  is a linear transformation from  $\mathbb{R}^n$  to  $\mathbb{R}^m$ .

**Proof.**

■

DIY

**Proposition 1.1.1.** Let  $T : \mathbb{R}^n \rightarrow \mathbb{R}^m$  be a linear transformation. For each  $j = 1, 2, \dots, n$ , let  $e_j$  denote the  $j$ -th standard basis vector in  $\mathbb{R}^n$  and write  $T(e_j) = \begin{pmatrix} a_{1j} \\ a_{2j} \\ \vdots \\ a_{mj} \end{pmatrix}$ . Define the matrix  $A = (a_{ij})$ , then  $T(x) = Ax$ .

**Proof.** Let  $x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$ . We can write  $x = \sum_{j=1}^n x_j e_j$ , then we know

$$T(x) = T\left(\sum_{j=1}^n x_j e_j\right) = \sum_{j=1}^n x_j T(e_j) = \sum_{j=1}^n x_j \begin{pmatrix} a_{1j} \\ a_{2j} \\ \vdots \\ a_{mj} \end{pmatrix} = Ax.$$

■

**Lemma 1.1.2.** Let  $A$  be a  $m \times n$  matrix and let  $B$  be a  $n \times p$  matrix. Then  $L_A \circ L_B = L_{AB}$ .

**Proof.** It suffices to show that  $(L_A \circ L_B)(x) = L_{AB}(x)$  for  $x \in \mathbb{R}^p$ , and the rest is easy. ■

As previously seen.  $f : E \rightarrow \mathbb{R}$  where  $E$  is a subset of  $\mathbb{R}$ , then

$$f'(x_0) = \lim_{\substack{x \rightarrow x_0 \\ x \in E \setminus \{x_0\}}} \frac{f(x) - f(x_0)}{x - x_0}.$$

Suppose now  $f : E \subseteq \mathbb{R}^n \rightarrow \mathbb{R}^m$ , we can't define

$$f'(x) = \lim_{\substack{x \rightarrow x_0 \\ x \in E \setminus \{x_0\}}} \frac{f(x) - f(x_0)}{x - x_0}$$

since the denominator and the numerator are vectors in  $\mathbb{R}^n$  and  $\mathbb{R}^m$ .

## 1.2 Derivatives in Several Variable Calculus

**Lemma 1.2.1.** Let  $E \subseteq \mathbb{R}$ , let  $f : E \rightarrow \mathbb{R}$  be a function and let  $L \in \mathbb{R}$  and  $x_0$  be a limit point of  $E$ . Then the following two statements are equivalent:

- (a)  $f$  is differentiable at  $x_0$  and  $f'(x_0) = L$ .
- (b)  $\lim_{\substack{x \rightarrow x_0 \\ x \in E \setminus \{x_0\}}} \frac{|f(x) - f(x_0) - L(x - x_0)|}{|x - x_0|} = 0$ .

**Proof.** Note that

$$\frac{f(x) - f(x_0)}{x - x_0} = L + \frac{f(x) - f(x_0) - L(x - x_0)}{x - x_0} \text{ if } x \neq x_0,$$

so we have

$$\frac{f(x) - f(x_0)}{x - x_0} - L = \frac{f(x) - f(x_0) - L(x - x_0)}{x - x_0} \text{ if } x \neq x_0,$$

and thus

$$0 = \lim_{\substack{x \rightarrow x_0 \\ x \in E \setminus \{x_0\}}} \left| \frac{f(x) - f(x_0)}{x - x_0} - L \right| = \lim_{\substack{x \rightarrow x_0 \\ x \in E \setminus \{x_0\}}} \left| \frac{f(x) - f(x_0) - L(x - x_0)}{x - x_0} \right|.$$

## Lecture 2

**Definition 1.2.1 (Differentiability).** Let  $E$  be a subset of  $\mathbb{R}^n$ , let  $f : E \rightarrow \mathbb{R}^m$  be a function, and let  $x_0$  be a limit point of  $E$ . Let  $L : \mathbb{R}^n \rightarrow \mathbb{R}^m$  be a linear transformation. We say  $f$  is differentiable at  $x_0$  with derivative  $L$  if

$$\lim_{\substack{x \rightarrow x_0 \\ x \in E \setminus \{x_0\}}} \frac{\|f(x) - f(x_0) - L(x - x_0)\|}{\|x - x_0\|} = 0,$$

or equivalently, given  $\varepsilon > 0$ ,  $\exists \delta > 0$  s.t. for all  $x \in E$  satisfying  $0 < \|x - x_0\| < \delta$ , we have

$$\frac{\|f(x) - f(x_0) - L(x - x_0)\|}{\|x - x_0\|} < \varepsilon.$$

**Remark 1.2.1.**  $\|f(x) - f(x_0) - L(x - x_0)\|$  is the length of a vector in  $\mathbb{R}^m$  and  $\|x - x_0\|$  is the length of a vector in  $\mathbb{R}^n$ .

**Remark 1.2.2.**  $x_0$  is a limit point of  $E \subseteq \mathbb{R}^n$  if for any  $r > 0$ ,  $B(x_0, r) \cap (E \setminus \{x_0\}) \neq \emptyset$ . That is, for every  $r > 0$ ,  $\exists x \in E$  s.t.  $0 < \|x - x_0\| < r$ .

**Example 1.2.1.** Suppose  $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$  has

$$f(x) = \begin{cases} 0, & \text{if } x \in E = \{(x_1, x_2, \dots, x_n) \mid x_n \geq 0\}; \\ x, & \text{if } x \in \mathbb{R}^n \setminus E \end{cases}$$

then  $f$  is differentiable on  $E$  and  $f'(x) = 0$  and  $f$  is not differentiable on  $\mathbb{R}^n$  at 0.

**Remark 1.2.3.** Recall that  $x_0$  is said to be an interior point of  $E \subseteq \mathbb{R}^n$  if there exists  $r > 0$  s.t.

$$B(x_0, r) = \{x \in \mathbb{R}^n : \|x - x_0\| < r\} \subseteq E.$$

If  $x_0$  is an interior point of  $E$ , then  $f$  is differentiable at  $x_0$  is equivalent to

$$\lim_{h \rightarrow 0} \frac{\|f(x_0 + h) - f(x_0) - L(h)\|}{\|h\|} = 0$$

since if  $\|h\| < r$ , then  $x_0 + h \in B(x_0, r)$ , which gives  $x_0 + h \in E$ , and thus  $f(x_0 + h)$  is well-defined.

**Remark 1.2.4.** Here  $\|\cdot\|$  denoted the standard Euclidean norm on  $\mathbb{R}^n$  (and on  $\mathbb{R}^m$ ):

$$\|(x_1, x_2, \dots, x_n)\| = (x_1^2 + x_2^2 + \dots + x_n^2)^{\frac{1}{2}}.$$

**Example 1.2.2.** Let  $f : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  be given by

$$f(x, y) = (x^2, y^2),$$

let  $x_0 = (1, 2)$ , and let  $L : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  be the linear map

$$L(x, y) = (2x, 4y).$$

We claim that  $f$  is differentiable at  $x_0$  with derivative  $L$ .

**Proof.** By definition,  $f$  is differentiable at  $x_0$  with derivative  $L$  if and only if

$$\lim_{h \rightarrow 0} \frac{\|f(x_0 + h) - f(x_0) - L(h)\|}{\|h\|} = 0,$$

where  $h = (a, b)$ . Thus, we know the above equation becomes

$$\frac{\|f(1+a, 2+b) - f(1, 2) - L(a, b)\|}{\|(a, b)\|} = \frac{\sqrt{a^4 + b^4}}{\sqrt{a^2 + b^2}},$$

and since

$$0 \leq \frac{\sqrt{a^4 + b^4}}{\sqrt{a^2 + b^2}} \leq \sqrt{a^2 + b^2},$$

so by the Squeeze Theorem, we have

$$\lim_{(a, b) \rightarrow (0, 0)} \frac{\sqrt{a^4 + b^4}}{\sqrt{a^2 + b^2}} = 0,$$

and we're done. (\*)

**Lemma 1.2.2 (Uniqueness of derivative).** Let  $E$  be a subset of  $\mathbb{R}^n$ , and let  $f : E \rightarrow \mathbb{R}^n$  be a function, and let  $x_0 \in E$  be an interior point of  $E$ . Suppose  $L_1, L_2 : \mathbb{R}^n \rightarrow \mathbb{R}^m$  are linear transformations s.t.  $f$  is differentiable at  $x_0$  with derivative  $L_1$  and also differentiable at  $x_0$  with derivative  $L_2$ . Then  $L_1 = L_2$ .

**Proof.** Since  $x_0$  is an interior point. By Remark 1.2.3, we have

$$\lim_{h \rightarrow 0} \frac{\|f(x_0 + h) - f(x_0) - L_1(h)\|}{\|h\|} = 0 \text{ and } \lim_{h \rightarrow 0} \frac{\|f(x_0 + h) - f(x_0) - L_2(h)\|}{\|h\|} = 0.$$

Thus,

$$\begin{aligned} 0 &\leq \frac{\|L_1(h) - L_2(h)\|}{\|h\|} = \frac{\|L_1(h) - f(x_0 + h) + f(x_0) + f(x_0 + h) - f(x_0) - L_2(h)\|}{\|h\|} \\ &\leq \frac{\|L_1(h) - f(x_0 + h) + f(x_0)\|}{\|h\|} + \frac{\|f(x_0 + h) + f(x_0) - L_2(h)\|}{\|h\|}. \end{aligned}$$

Thus, by squeeze theorem, we know

$$\lim_{h \rightarrow 0} \frac{\|L_1(h) - L_2(h)\|}{\|h\|} = 0.$$

Now take  $v \in \mathbb{R}^n \setminus \{0\}$ , and let  $h = tv$ , so

$$\lim_{t \rightarrow 0} \frac{\|L_1(tv) - L_2(tv)\|}{\|tv\|} = 0.$$

That is,

$$\lim_{t \rightarrow 0} \frac{|t| \|L_1(v) - L_2(v)\|}{|t| \|v\|} = 0.$$

Hence, we have

$$\lim_{t \rightarrow 0} \frac{\|L_1(v) - L_2(v)\|}{\|v\|} = 0,$$

and since  $v \neq 0$ , so we know  $L_1(v) = L_2(v)$ , and since  $v$  can be arbitrary non-zero vector in  $\mathbb{R}^n \setminus \{0\}$ , so  $L_1 = L_2$ . ( $L_1(0) = L_2(0) = 0$ ) ■

**Remark 1.2.5.** Because of Lemma 1.2.2, the derivative of  $f$  at interior points  $x_0$  is unique, and

thus we may safely write it as  $f'(x_0)$  or  $Df(x_0)$ . Thus  $f'(x_0)$  is the unique linear transformation  $f' : \mathbb{R}^n \rightarrow \mathbb{R}^m$  such that

$$\lim_{x \rightarrow x_0, x \neq x_0} \frac{\|f(x) - (f(x_0) + f'(x_0)(x - x_0))\|}{\|x - x_0\|} = 0.$$

Informally, this condition means that near  $x_0$ , the function  $f$  can be approximated by its linearization:

$$f(x) \approx f(x_0) + f'(x_0)(x - x_0).$$

This approximation is sometimes referred to as Newton's approximation in higher dimension.

**Remark 1.2.6.** A useful consequence of Lemma 1.2.2 is the following: If two functions  $f$  and  $g$  satisfy  $f(x) = g(x)$  for all  $x \in E$ , and both are differentiable at an interior point  $x_0$ , then their derivatives coincide at  $x_0$ , i.e.  $f'(x_0) = g'(x_0)$ . This will be important in later arguments, where one extends functions to larger domains or modifies them on sets of measure zero.

**Remark 1.2.7.** As we have emphasized, Lemma 1.2.2 guarantees the uniqueness of the derivative only at interior points of the domain  $E$ . If  $x_0$  is instead a boundary point of  $E$ , the derivative may fail to be uniquely determined.

### 1.3 Partial and Directional Derivatives

We now begin to relate the concept of differentiability to the more classical notions of partial and directional derivatives. Directional derivatives describe how  $f$  changes when we move from a point  $x_0$  in a fixed direction  $v$ .

**Definition 1.3.1 (Directional derivative).** Let  $E \subseteq \mathbb{R}^n$ , let  $f : E \rightarrow \mathbb{R}^m$  be a function, let  $x_0$  be an interior point of  $E$  and let  $v \in \mathbb{R}^n$ . If the limit

$$\lim_{\substack{t \rightarrow 0, t > 0 \\ x_0 + tv \in E}} \frac{f(x_0 + tv) - f(x_0)}{t} = \lim_{\substack{t \rightarrow 0^+ \\ x_0 + tv \in E}} \frac{f(x_0 + tv) - f(x_0)}{t}$$

exists, then we say  $f$  is differentiable in the direction  $v$  at  $x_0$ . This limit is called the directional derivative of  $f$  at  $x_0$  in the direction  $v$ , and we denote it by

$$D_v f(x_0) := \lim_{t \rightarrow 0^+} \frac{f(x_0 + tv) - f(x_0)}{t} \in \mathbb{R}^m.$$

**Remark 1.3.1.** Under this definition,

$$D_{-v} f(x_0) = \lim_{t \rightarrow 0^+} \frac{f(x_0 + t(-v)) - f(x_0)}{t} = \lim_{t \rightarrow 0^+} \frac{f(x_0 - tv) - f(x_0)}{t}.$$

In usual definition, one define

$$D_v f(x_0) = \lim_{t \rightarrow 0} \frac{f(x_0 + tv) - f(x_0)}{t}.$$

This usual definition implies that

$$D_v f(x_0) = -D_{-v} f(x_0)$$

since

$$\begin{aligned} D_v f(x_0) &= \lim_{t \rightarrow 0^+} \frac{f(x_0 + tv) - f(x_0)}{t} = \lim_{t \rightarrow 0^-} \frac{f(x_0 + tv) - f(x_0)}{t} \\ &= \lim_{s \rightarrow 0^+} \frac{f(x_0 + (-s)v) - f(x_0)}{(-s)} = -\lim_{s \rightarrow 0^+} \frac{f(x_0 - sv) - f(x_0)}{s} = -(D_{-v} f(x_0)). \end{aligned}$$

**Remark 1.3.2.** This definition should be compared with the definition of differentiability. Here we divide by the scalar  $t$  rather than by a vector, so the expression always makes sense algebraically. The directional derivative  $D_v f(x_0)$  is a vector in  $\mathbb{R}^m$ .

**Remark 1.3.3.** It is sometimes possible to define directional derivatives at boundary points of  $E$ , provided that the vector  $v$  points inward toward the domain. However, we shall restrict attention to interior points in what follows.

**Lemma 1.3.1.** Let  $E \subseteq \mathbb{R}^n$ , let  $f : E \rightarrow \mathbb{R}^m$ , let  $x_0 \in \text{Int}(E)$  and  $v \in \mathbb{R}^n$ . If  $f$  is differentiable at  $x_0$ , then  $f$  is differentiable in the direction  $v$  at  $x_0$ , and

$$D_v f(x_0) = f'(x_0)(v).$$

**Proof.** Since  $x_0 \in \text{Int}(E)$  and  $f$  is differentiable at  $x_0$ , so

$$\lim_{h \rightarrow 0} \frac{\|f(x_0 + h) - f(x_0) - f'(x_0)(h)\|}{\|h\|} = 0.$$

Note that for  $t \neq 0$ , we have

$$\frac{f(x_0 + tv) - f(x_0)}{t} = \frac{f(x_0 + tv) - f(x_0) - f'(x_0)(tv)}{t} + f'(x_0)(v),$$

so

$$\frac{f(x_0 + tv) - f(x_0)}{t} - f'(x_0)(v) = \frac{f(x_0 + tv) - f(x_0) - f'(x_0)(tv)}{t}.$$

Now we show that

$$\lim_{t \rightarrow 0^+} \frac{f(x_0 + tv) - f(x_0) - f'(x_0)(tv)}{t} = 0.$$

Recall that  $f$  is differentiable at  $x_0$  and  $x_0 \in \text{Int}(E)$ , so

$$\lim_{h \rightarrow 0} \frac{\|f(x_0 + h) - f(x_0) - f'(x_0)(h)\|}{\|h\|} = 0.$$

Let  $h = tv$  when  $v \neq 0$ , then

$$\lim_{t \rightarrow 0^+} \frac{\|f(x_0 + tv) - f(x_0) - f'(x_0)(tv)\|}{\|tv\|} = 0 \Rightarrow \lim_{t \rightarrow 0^+} \frac{\|f(x_0 + tv) - f(x_0) - f'(x_0)(tv)\|}{|t|} = 0,$$

which is equivalent to

$$\lim_{t \rightarrow 0^+} \frac{f(x_0 + tv) - f(x_0) - f'(x_0)(tv)}{t} = 0,$$

(since the numerator should tend to 0 so the limit will exist), so we know

$$\lim_{t \rightarrow 0^+} \frac{f(x_0 + tv) - f(x_0)}{t} - f'(x_0)(v) = 0,$$

i.e.

$$\lim_{t \rightarrow 0^+} \frac{f(x_0 + tv) - f(x_0)}{t} = f'(x_0)(v).$$

■

**Remark 1.3.4.** One consequence of this lemma is that total differentiability implies directional differentiability. However, the converse is not true: the existence of all directional derivatives does not guarantee differentiability.

**Definition 1.3.2 (Partial Derivative).** Let  $E \subseteq \mathbb{R}^n$ , let  $f : E \rightarrow \mathbb{R}^m$ , and let  $x_0 \in \text{Int}(E)$ , and let  $1 \leq j \leq n$ . The partial derivative of  $f$  with respect to the variable  $x_j$  at  $x_0$ , denoted  $\frac{\partial f}{\partial x_j}(x_0)$ , is defined by

$$\frac{\partial f}{\partial x_j}(x_0) := \lim_{t \rightarrow 0, t \neq 0} \frac{f(x_0 + te_j) - f(x_0)}{t}$$

provided the limit exists.

**Remark 1.3.5.** If  $f = \begin{pmatrix} f_1 \\ \vdots \\ f_m \end{pmatrix}$ , then differentiation is componentwise:

$$\frac{\partial f}{\partial x_j}(x_0) = \begin{pmatrix} \frac{\partial f_1}{\partial x_j}(x_0) \\ \vdots \\ \frac{\partial f_m}{\partial x_j}(x_0) \end{pmatrix}.$$

We say that  $f$  is continuously differentiable if all partial derivatives exist and are continuous.

**Remark 1.3.6.** If  $f$  is differentiable at  $x_0$ , then

$$\frac{\partial f(x_0)}{\partial x_j} = D_{e_j} f(x_0) = f'(x_0)(e_j).$$

**Remark 1.3.7.** If  $f$  is differentiable at  $x_0$ , then

$$D_v f(x_0) = f'(x_0)(v) = f'(x_0) \left( \sum_{j=1}^n v_j e_j \right) = \sum_{j=1}^n v_j f'(x_0)(e_j) = \sum_{j=1}^n v_j \frac{\partial f(x_0)}{\partial x_j}.$$

**Theorem 1.3.1.** Let  $E \subseteq \mathbb{R}^n$ , let  $f : E \rightarrow \mathbb{R}^m$ ,  $F \subseteq E$ , and let  $x_0 \in \text{Int}(F)$ . If all partial derivative  $\frac{\partial f}{\partial x_j}$  exists on  $F$  and are continuous at  $x_0$ , then  $f$  is differentiable at  $x_0$ , and

$$f'(x_0)(v) = \sum_{j=1}^n v_j \frac{\partial f}{\partial x_j}(x_0)$$

for all  $v \in \mathbb{R}^n$ .

**Proof.** Define a linear map  $L : \mathbb{R}^n \rightarrow \mathbb{R}^m$  by

$$L(v) := \sum_{j=1}^n v_j \frac{\partial f}{\partial x_j}(x_0).$$

We prove that  $f$  is differentiable at  $x_0$  with derivative  $L$ . It suffices to show that for any  $\varepsilon > 0$ ,  $\exists \delta > 0$  s.t.

$$\|f(x) - f(x_0) - L(x - x_0)\| < \varepsilon \|x - x_0\| \text{ whenever } x \in F \text{ and } \|x - x_0\| < \delta$$

Since  $x_0 \in \text{Int}(F)$ ,  $\exists r > 0$  s.t.  $B(x_0, r) \subseteq F$ . Because each partial derivative  $\frac{\partial f_i}{\partial x_j}$  is continuous at

$x_0$ , for every pair  $(i, j)$  there exists  $\delta_{ij} > 0$  s.t.

$$\left| \frac{\partial f_i}{\partial x_j}(x) - \frac{\partial f_i}{\partial x_j}(x_0) \right| < \frac{\varepsilon}{nm} \text{ whenever } \|x - x_0\| < \delta_{ij}.$$

Let  $\delta := \min \{r, \delta_{ij} : 1 \leq i \leq m, 1 \leq j \leq n\}$ . Now fix  $x \in F$  with  $\|x - x_0\| < \delta$  and write

$$x - x_0 = \sum_{j=1}^n v_j e_j, \text{ so } x = x_0 + \sum_{j=1}^n v_j e_j.$$

Then

$$\|x - x_0\| = \sqrt{v_1^2 + v_2^2 + \cdots + v_n^2}, \quad |v_j| \leq \|x - x_0\|,$$

Write  $f = (f_1, f_2, \dots, f_m)$ . To estimate  $f(x) - f(x_0)$ , we vary the coordinates one at a time. Consider

$$\begin{aligned} x^{(0)} &= x_0, \\ x^{(j)} &= x_0 + \sum_{k=1}^j v_k e_k \text{ for } j = 1, 2, \dots, n. \end{aligned}$$

Thus,  $x^{(n)} = x$  and

$$f(x) - f(x_0) = \sum_{j=1}^n \left( f(x^{(j)}) - f(x^{(j-1)}) \right) = \sum_{j=1}^n \sum_{i=1}^m \left( f_i(x^{(j)}) - f_i(x^{(j-1)}) \right) e_i.$$

Fix  $j$  and consider the  $j$ -th increment. For each component  $f_i$ , define

$$\varphi_i^j(t) = f_i \left( x^{(j-1)} + tv_j e_j \right), \quad 0 \leq t \leq 1.$$

Then

$$f_i(x^{(j)}) - f_i(x^{(j-1)}) = \varphi_i^j(1) - \varphi_i^j(0).$$

Since  $f_i$  has continuous partial derivatives,  $\varphi_i^j$  is differentiable. By MVT, there exists  $t_j \in (0, 1)$  s.t.

$$\varphi_i^j(1) - \varphi_i^j(0) = \varphi_i^{j\prime}(t_j).$$

By the chain rule,

$$\varphi_i^{j\prime}(t) = \nabla f_i \left( x^{(j-1)} + tv_j e_j \right) \cdot (v_j e_j) = \frac{\partial f_i}{\partial x_j} \left( x^{(j-1)} + tv_j e_j \right) v_j.$$

Hence,

$$f_i(x^{(j)}) - f_i(x^{(j-1)}) = \frac{\partial f_i}{\partial x_j}(\xi_j) v_j,$$

where

$$\xi_j = x^{(j-1)} + t_j v_j e_j.$$

Subtracting  $\frac{\partial f_i}{\partial x_j}(x_0)v_j$ , we obtain

$$\left| f_i(x^{(j)}) - f_i(x^{(j-1)}) - \frac{\partial f_i}{\partial x_j}(x_0)v_j \right| = \left| \frac{\partial f_i}{\partial x_j}(\xi_j) - \frac{\partial f_i}{\partial x_j}(x_0) \right| |v_j|.$$

Because  $\|\xi_j - x_0\| < \delta$ , continuity of partial derivatives yields,

$$\left| f_i(x^{(j)}) - f_i(x^{(j-1)}) - \frac{\partial f_i}{\partial x_j}(x_0)v_j \right| < \frac{\varepsilon}{nm} |v_j|.$$

Summing over  $i = 1, 2, \dots, m$  and using  $\|u\| \leq \sum_i |u_i|$ , we conclude

$$\begin{aligned} \left\| f(x^{(j)}) - f(x^{(j-1)}) - \frac{\partial f}{\partial x_j}(x_0)v_j \right\| &= \left\| \sum_{i=1}^m \left( f(x^{(j)}) - f(x^{(j-1)}) - \frac{\partial f}{\partial x_j}(x_0)v_j \right) e_i \right\| \\ &\leq \sum_{i=1}^m \left| f(x^{(j)}) - f(x^{(j-1)}) - \frac{\partial f}{\partial x_j}(x_0)v_j \right| \leq m \frac{\varepsilon}{nm} |v_j| = \frac{\varepsilon}{n} |v_j| \leq \frac{\varepsilon}{n} \|x - x_0\|. \end{aligned}$$

Finally, summing over  $j = 1, 2, \dots, n$  and applying the triangle inequality,

$$\begin{aligned} \left\| f(x) - f(x_0) - \sum_{j=1}^n \frac{\partial f}{\partial x_j}(x_0)v_j \right\| &= \left\| \sum_{j=1}^n \left( f(x^{(j)}) - f(x^{(j-1)}) - \frac{\partial f}{\partial x_j}(x_0)v_j \right) \right\| \\ &\leq \sum_{j=1}^n \left\| \left( f(x^{(j)}) - f(x^{(j-1)}) - \frac{\partial f}{\partial x_j}(x_0)v_j \right) \right\| \leq \sum_{j=1}^n \frac{\varepsilon}{n} \|x - x_0\| = \varepsilon \|x - x_0\|. \end{aligned}$$

Since  $L(x - x_0) = \sum_{j=1}^n v_j \frac{\partial f}{\partial x_j}(x_0)$ , so we have

$$\|f(x) - f(x_0) - L(x - x_0)\| \leq \varepsilon \|x - x_0\|,$$

and we're done. ■

**Remark 1.3.8.** From [Theorem 1.3.1](#) and [Lemma 1.3.1](#) we conclude the following important fact:

If the partial derivatives of a function  $f : E \rightarrow \mathbb{R}^m$  exist and are continuous on a set  $F \subseteq E$ , then at every interior point  $x_0$  of  $F$  all directional derivatives exist, and they are given by

$$D_{(v_1, v_2, \dots, v_n)} f(x_0) = \sum_{j=1}^n v_j \frac{\partial f}{\partial x_j}(x_0).$$

- The scalar-valued case. If  $f : E \rightarrow \mathbb{R}$  is real-valued, we define the gradient of  $f$  at  $x_0$  to be the row vector

$$\nabla f(x_0) := \left( \frac{\partial f}{\partial x_1}(x_0), \dots, \frac{\partial f}{\partial x_n}(x_0) \right).$$

Whenever  $x_0$  lies in the interior of a region where the partial derivatives exist and are continuous, the directional derivative takes the familiar form

$$D_v f(x_0) = v \cdot \nabla f(x_0).$$

- The vector-valued case. Now let  $f : E \rightarrow \mathbb{R}^m$  be vector-valued, say

$$f = \begin{pmatrix} f_1 \\ \vdots \\ f_m \end{pmatrix}.$$

If  $x_0$  lies in the interior of a region where all partial derivatives exist and are continuous, then

$$f'(x_0)(v_1, v_2, \dots, v_n) = \sum_{j=1}^n v_j \frac{\partial f}{\partial x_j}(x_0).$$

Writing this componentwise,

$$f'(x_0)(v_1, \dots, v_n) = \sum_{j=1}^n v_j \begin{pmatrix} \frac{\partial f_1}{\partial x_j}(x_0) \\ \vdots \\ \frac{\partial f_m}{\partial x_j}(x_0) \end{pmatrix} = \begin{pmatrix} \sum_{j=1}^n v_j \frac{\partial f_1}{\partial x_j}(x_0) \\ \vdots \\ \sum_{j=1}^n v_j \frac{\partial f_m}{\partial x_j}(x_0) \end{pmatrix} = \begin{pmatrix} \nabla f_1(x_0) \cdot v \\ \vdots \\ \nabla f_m(x_0) \cdot v \end{pmatrix} = \begin{pmatrix} \nabla f_1(x_0) \\ \vdots \\ \nabla f_m(x_0) \end{pmatrix} v$$

- The derivative matrix (Jacobian matrix). We therefore define the derivative matrix (or Jacobian matrix) of  $f$  at  $x_0$  by

$$Df(x_0) := \left( \frac{\partial f_i}{\partial x_j}(x_0) \right)_{\substack{1 \leq i \leq m \\ 1 \leq j \leq n}}.$$

Explicitly,

$$Df(x_0) = \begin{pmatrix} \frac{\partial f_1}{\partial x_1}(x_0) & \cdots & \frac{\partial f_1}{\partial x_n}(x_0) \\ \vdots & \ddots & \vdots \\ \frac{\partial f_m}{\partial x_1}(x_0) & \cdots & \frac{\partial f_m}{\partial x_n}(x_0) \end{pmatrix}.$$

With this notation, the derivative acts by matrix multiplication:

$$D_v f(x_0) = f'(x_0)v = Df(x_0)v.$$

# Appendix