

# Introduction to Analysis II

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## **Abstract**

Lecture note of Introduction to Analysis II.

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# Chapter 1

## Several Variable Differential Calculus

### Lecture 1

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

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

where  $f_i : \mathbb{R}^n \rightarrow \mathbb{R}$  for all  $i$ . Now given a real-valued function  $F : \mathbb{R}^n \rightarrow \mathbb{R}$ . We know that near 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,

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

which gives

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

## 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

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

**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.** ■

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**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

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

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**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  $\mathbb{R}^m$ .

**Lemma 1.1.3.** 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

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

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# Appendix