# MAS242 해석학 II Notes

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# Chapter 1

### Differentiation

### 1.1 Higher order partial derivatives

### **Definition 1.1.1**

Given  $f: U \to \mathbb{R}$  where U is an open set in  $\mathbb{R}^m$ , define  $\partial_{ij} \triangleq \partial_i(\partial_j f)(x)$  for each  $i, j \in [m]$  to be *2nd order partial derivatives*. Any higher order partial derivatives can be defined inductively.

### **Definition 1.1.2:** $C^k$ -regularity

 $f: U \to \mathbb{R}$  is  $C^k$ -regular if all partial derivatives up to order k and they are continuous.

### Theorem 1.1.1

 $f: U(\subseteq \mathbb{R}^2) \to \mathbb{R}$  is  $C^2$  at a point  $c \in U$ , i.e.,  $\exists \delta > 0$ , f is  $C^2$  in  $B_{\delta}(c)$ . Then,  $\partial_{12} f(c) = \partial_{21} f(c)$ .

**Proof.** Let  $|h| < \delta$ . Define  $A(h) \triangleq f(c_1 + h_1, c_2 + h_2) - f(c_1 + h_1, c_2) - f(c_1, c_2 + h_2) + f(c_1, c_2)$ . Define  $u(x_1) \triangleq f(x_1, c_2 + h_2) - f(x_1, c_2)$  and  $v(x_2) \triangleq f(c_1 + h_1, x_2) - f(c_1, x_2)$ . Note that u and v are differentiable.

Then,  $A(h) = u(c_1 + h_1) - u(c_1)$  and  $A(h) = v(c_2 + h) - v(c_2)$ . By MVT,  $\exists c_1^* \in (c_1, c_1 + h_1)$  and  $c_2^* \in (c_2, c_2 + h_2)$  s.t.  $A(h) = u'(c_1^*)h_1 = h_1(\partial_1 f(c_1^*, c_2 + h) - \partial_1 f(c_1^*, c_2)) = h_1 h_2 \partial_{21} f(c_1^*, c_2^*)$  Similarly,  $\exists c_1^{**}, c_2^{**}$  such that  $A(h) = h_1 h_2 \partial_{12} f(c_1^{**}, c_2^{**})$ .  $\partial_{21} f(c_1^*, c_2^*) = \partial_{12} f(c_1^{**}, c_2^{**})$ . Hence, as  $|h| \to 0$ , due to the continuity,  $\partial_{21}(c) = \partial_{12}(c)$ .

### Corollary 1.1.1

Suppose  $f: U(\subseteq \mathbb{R}^m) \to \mathbb{R}$  is  $C^k$  at  $c \in U$ . Then  $\partial_{j_1 j_2 \cdots j_k} f(c) = \partial_{j'_1 j'_2 \cdots j'_k}$  where  $j'_1 \cdots$  are a permutation of  $j_1 \cdots$ .

### 1.2 Extreme Values of differentiable Functions

### **Definition 1.2.1: Hessian**

Let  $f: U(\subseteq \mathbb{R}^m) \to \mathbb{R}$  be  $C_2$  in U. Suppose  $p \in U$  is a critical point of f, i.e.,  $\nabla f(p) = 0$ . Define

$$\mathcal{H}f(x) \triangleq \begin{pmatrix} \partial_{11}f(x) & \partial_{21}f(x) & \cdots & \partial_{m1}f(x) \\ \partial_{12}f(x) & \partial_{22}f(x) & \cdots & \partial_{m2}f(x) \\ \vdots & \vdots & \ddots & \vdots \\ \partial_{1m}f(x) & \partial_{2m}f(x) & \cdots & \partial_{mm}f(x) \end{pmatrix}.$$

(Sometimes  $\mathcal{H}f(x) = D^2f(x)$ .)

Define  $D(x) = \det \mathcal{H}f(x)$ . (Note that  $\mathcal{H}f(x)$  is symmetric when f is  $C^2$  by the theorem above.)

### **Theorem 1.2.1** 2nd-order derivative test for two variable functions.

When m = 2 and f is  $C^2$ , a critical point p is

- a local maximum if D(p) > 0 and  $\partial_{11} f(p) > 0$  (or  $\partial_{22} f(p) > 0$ ).
- a local minimum if D(p) > 0 and  $\partial_{11} f(p) < 0$  (or  $\partial_{22} f(p) < 0$ ).
- a saddle point if D(p) < 0.

The test fails when D(p) = 0.

**Proof.** Given a unit vector  $\mathbf{u} = (u_1, u_2) \in \mathbb{R}^2$ ,  $D_{\mathbf{u}} f = \nabla f \cdot \mathbf{u} = u_1 \partial_1 f + u_2 \partial_2 f$ , and thus

$$D_{\mathbf{u}}^{2}f = (u_{1}\partial_{1} + u_{2}\partial_{2})(u_{1}\partial_{1}f + u_{2}\partial_{2}f) = u_{1}^{2}\partial_{11}f + u_{1}u_{2}(2\partial_{12}f) + u_{2}^{2}\partial_{22}f.$$

WLOG,  $u_1 \neq 0$ . Set  $z = u_2/u_1$ . Then,

$$D_{\mathbf{u}}^{2}f(p) = u_{1}^{2}(\partial_{11}f(p) + 2\partial_{12}f(p)z + \partial_{22}f(p)z^{2}).$$

Note that, if D(p) > 0,  $D_{\mathbf{n}}^2 f(p)$  has no real root.

- If D(p) > 0 and  $\partial_{11} f(p) < 0$ , Then,  $D^2 \mathbf{u} < 0$  for all unit vector  $\mathbf{u}$ .
- If D(p) > 0 and  $\partial_{11}f(p) > 0$ , Then,  $D^2\mathbf{u} > 0$  for all unit vector  $\mathbf{u}$ .
- If D(p) < 0, D<sub>u</sub><sup>2</sup>f(p) has different signs depending on u.
   For general m?

$$D_{\mathbf{u}}(D_{\mathbf{u}}f) = D_{\mathbf{u}} \sum_{j=1}^{m} \partial_{j} f u_{j} = \sum_{j=1}^{m} ((\nabla \partial_{j} f) \cdot \mathbf{u}) u_{j} = \sum_{j=1}^{m} \sum_{k=1}^{m} u_{k} u_{j} \partial_{kj} f.$$

Hence,

$$D_{\mathbf{u}}^{2}f(p) = \mathbf{u}^{\mathrm{T}} \cdot D^{2}f(p) \cdot \mathbf{u}$$

Since  $D^2f(p)$  is symmetric, its eigenvalues  $\lambda_1, \dots, \lambda_m$  exists and they are real numbers. Also, there exists an  $m \times m$  orthogonal matrix  $\mathcal{O}$  such that  $D^2f(p) = \mathcal{O}\Lambda(p)\mathcal{O}^T$  where  $\Lambda(p)$  is the diagonal matrix with entries are the eigenvalues.

Then, we can write  $D_{\mathbf{u}}^2 f(p) = \mathbf{u} \mathcal{O} \Lambda(p) \mathcal{O}^{\mathsf{T}} \mathbf{u}^{\mathsf{T}} = (\mathbf{u} \mathcal{O}) \Lambda(p) = (\mathbf{u} \mathcal{O})^{\mathsf{T}}$ . Since  $\mathcal{O}$  is orthogonal,  $\mathbf{u} \mathcal{O}$  is another arbitrary unit vector.

### Theorem 1.2.2 Generalized 2nd order partial derivatives test

When f is  $C^2$ , a critical point p is

• a local maximum if all eigenvalues of  $D^2 f(p)$  are negative.

- a local minimum if all eigenvalues of D<sup>2</sup>f(p) are positive.
  a saddle point if there are both negative eigenvalues and positive eigenvalues.
  The test fails when there are zero eigenvalues.

# Chapter 2

### **Inverse Function Theorem**

#### Jacobian 2.1

### Definition 2.1.1: Jacobian

Let  $f: U(\subseteq \mathbb{R}^m) \to \mathbb{R}^n$  be differentiable. The function  $J_f: U \to \mathbb{R}$  defined by

$$J_{\mathbf{f}}(\mathbf{x}) = \det \begin{bmatrix} \partial_1 f_1(\mathbf{x}) & \cdots & \partial_n f_1(\mathbf{x}) \\ \vdots & \ddots & \vdots \\ \partial_1 f_n(\mathbf{x}) & \cdots & \partial_n f_n(\mathbf{x}) \end{bmatrix}$$

is called the *Jacobian* of f at x.

#### Lemma 2.1.1

If  $f: V(\subseteq \mathbb{R}^n) - \mathbb{R}$  and  $g: U \to V$  are differentiable, then

$$J_{f \circ g}(\mathbf{x}) = J_f(\mathbf{g}(\mathbf{x})) \cdot J_{\mathbf{g}}(\mathbf{x}).$$

### Note:-

The linear mapping df(c) is invertible if and only if  $J_f(c)$  is nonzero.

#### 2.2 The Inverse Function Theorem

### **Lemma 2.2.1** Contraction Mapping Principle

Let (X,d) be a complete metric space. Let  $\varphi: X \to X$ . Suppose that there exists  $M \in$ [0,1) such that  $d(\varphi(x_1),\varphi(x_2)) \leq Md(x_1,x_2)$ . (We call it a contraction mapping.) Then, there uniquely exists  $x_* \in X$  such that  $\varphi(x_*) = x_*$ .

**Proof.** Fix any  $x_0 \in X$ . Since  $\{x_j\}_{j \in \mathbb{Z}_+}$ , where  $x_j = \varphi(x_{j-1})$  for each  $j \in \mathbb{Z}_+$ , is continuous. It converges to some  $x_*$ . As  $\varphi$  is continuous, we have  $\varphi(x_*) = x_*$ . The uniqueness follows trivially.

### 🛉 Note:- 🛉

- For each  $v \in \mathbb{R}^n \setminus \{0\}$ ,  $|Av| = |v| \cdot |A\frac{v}{|v|}| \le ||A||_L \cdot |v|$ . The result is trivial when v = 0. For each  $u \in \mathbb{R}^n$  with |u| = 1,  $|ABu| \le ||A||_L ||Bu| \le ||A||_L ||B||_L$ . Hence,  $||AB||_L = ||A|| ||B||$ .
- Given invertible  $A \in L(\mathbb{R}^n.\mathbb{R}^n)$ ,  $A^{-1}: \mathbb{R}^n \to \mathbb{R}^n$  is linear. Moreover,  $||A||_L > 0$ .

### Lemma 2.2.2

Given two linear mappings  $A, B : \mathbb{R}^n \to \mathbb{R}^n$  with invertibility of A,

$$||A-B||_L ||A^{-1}||_L < 1 \implies B$$
 is invertible.

**Proof.** (Hint: show that  $B\mathbf{x} = 0$  has only the trivial solution, i.e., if  $\mathbf{x} \neq 0$ , then  $B\mathbf{x} \neq 0$ .)

### Theorem 2.2.1 Inverse Function Theorem

Let  $\mathbf{f} : E(\subseteq \mathbb{R}^n) \to \mathbb{R}^n$  be  $C^1$  in U,  $\mathbf{a} \in E$ , and  $\mathbf{b} = f(a)$ . Suppose that  $J_{\mathbf{f}}(a) \neq 0$ . Then,

$$\exists \delta \in \mathbb{R}_+, \ \mathbf{f}|_{B_{\delta}(a)} \colon B_{\delta}(a) \to \mathbf{f}(B_{\delta}(a)) \text{ is invertible.}$$

 $\exists \delta \in \mathbb{R}_+, \ \mathbf{f}\big|_{B_\delta(a)} \colon B_\delta(a) \to \mathbf{f}\big(B_\delta(a)\big) \text{ is invertible}.$  Moreover,  $\mathbf{f}\big(B_\delta(a)\big)$  is an open set, and  $\big(\mathbf{f}\big|_{B_\delta(a)}\big)^{-1}$  is  $C^1$ .

**Proof.** Let  $A \triangleq d\mathbf{f}(\mathbf{c})$ . Define  $\lambda$  by  $\lambda \triangleq \frac{1}{2\|A^{-1}\|_L} > 0$  so  $2\lambda \|A^{-1}\|_L = 1$ . Since df is continuous, there exists  $\delta \in \mathbb{R}_+$  such that  $\| d\mathbf{f}(\mathbf{x}) - d\ddot{\mathbf{f}}(\mathbf{c}) \|_L^2 < \lambda$  for each  $B_{\delta}(\mathbf{c})$ .

Given a point  $\mathbf{y} \in \mathbb{R}^n$ , we define  $\varphi(\cdot; \mathbf{y})$  by

$$\varphi(\cdot; \mathbf{y}) : B_{\delta}(\mathbf{c}) \longrightarrow \mathbb{R}^{n}$$
$$\mathbf{x} \longmapsto \varphi(\mathbf{x}; \mathbf{y}) = \mathbf{x} + A^{-1}(\mathbf{y} - \mathbf{f}(\mathbf{x}))$$

Note that  $\mathbf{x}$  is a fixed point of  $\varphi(\cdot; \mathbf{y})$  if and only if  $A^{-1}(\mathbf{y} - \mathbf{f}(\mathbf{x})) = 0$ , i.e.,  $\mathbf{y} = \mathbf{f}(\mathbf{x})$ . Note also that  $\varphi$  is differentiable and  $d\varphi(\mathbf{x}; \mathbf{y}) = \mathrm{Id} - A^{-1} d\mathbf{f}(\mathbf{x}) = A^{-1} (A - d\mathbf{f}(\mathbf{x}))$  for each  $x \in B_{\delta}(\mathbf{c})$ . Let  $U \triangleq B_{\delta}(\mathbf{c})$  and  $V \triangleq \mathbf{f}(U)$ .

Hence, for all  $x \in U$ ,

$$\| d\varphi(\mathbf{x}; \mathbf{y}) \|_{L} = \| A^{-1} (A - d\mathbf{f}(\mathbf{x})) \|_{L} \le \| A^{-1} \|_{L} \cdot \| A - d\mathbf{f}(\mathbf{x}) \|_{L} < 1/(2\lambda) \cdot \lambda = 1/2.$$

Now, fix any  $\mathbf{y} \in V$ . Fix  $\mathbf{x}_1, \mathbf{x}_2 \in U$ . Define  $\Psi \colon [0,1] \to \mathbb{R}$  by  $t \mapsto \varphi(t\mathbf{x}_1 + (1-t)\mathbf{x}_2; \mathbf{y})$ .  $\Psi(0) = \varphi(\mathbf{x}_2; \mathbf{y})$  and  $\Psi(1) = \varphi(\mathbf{x}_1; \mathbf{y})$ . Note that  $\Psi$  is differentiable on (0, 1). By MVT, there exists  $t_* \in (0,1)$  such that  $\Psi(1) - \Psi(0) = \Psi'(t_*)$ . The chain rule gives

$$\Psi'(t_*) = d\varphi(t_* \mathbf{x}_1 + (1 - t_*) \mathbf{x}_2)(\mathbf{x}_1 - \mathbf{x}_2).$$

Hence,

$$|\varphi(\mathbf{x}_1) - \varphi(\mathbf{x}_2)| = |\operatorname{d}\varphi(t_*\mathbf{x}_1 + (1 - t_*)\mathbf{x}_2)| \cdot |(\mathbf{x}_1 - \mathbf{x}_2)| \le |\mathbf{x}_1 - \mathbf{x}_2|/2.$$

We want to show that f is locally invertible. It suffices to show that it is injective. Hence,  $\varphi$  has at most one fixed point, i.e., there exists at most one x such that y = f(x); thus f is injective on U.

Let  $\mathbf{x}_0 \in U$  and  $\mathbf{y}_0 = \mathbf{f}(\mathbf{x}_0)$ . Fix any  $r \in \mathbb{R}_+$  such that  $\overline{B_r(\mathbf{x}_0)} \subseteq U$ . Let  $B = B_r(\mathbf{x}_0)$ . Take any  $y \in B_{\lambda r}(y_0)$ . Then,

$$|\varphi(\mathbf{x}_0; \mathbf{y}) - \mathbf{x}_0| = |A^{-1}(\mathbf{y} - \mathbf{y}_0)| < ||A^{-1}||_L \lambda r = \frac{r}{2}.$$

Moreover, for any  $x \in \overline{B}$ ,

$$|\varphi(\mathbf{x};\mathbf{y}) - \mathbf{x}_0| \le |\varphi(\mathbf{x};\mathbf{y}) - \varphi(\mathbf{x}_0;\mathbf{y})| + |\varphi(\mathbf{x}_0) - \mathbf{x}_0| \le \frac{1}{2}|\mathbf{x} - \mathbf{x}_0| + \frac{r}{2} < r.$$

This directly implies that  $\varphi(\overline{B}) \subseteq B \subseteq \overline{B}$ . Hence,  $\varphi$  is a contraction mapping on a complete metric space B. By Lemma 2.2.1, there exists a fixed point  $x \in B$ , which satisfies y = f(x). Thus,  $\mathbf{y} \in f(\overline{B}) \subseteq f(U) = V$ . Hence,  $B_{\lambda r}(\mathbf{y}_0) \subseteq V$ , V is open.

Now, let  $g: V \to U$  be the local inverse of f. Take any  $y \in V$  and  $y + k \in V$ . There are unique  $x \in U$  and  $x + h \in U$  such that y = f(x) and y + k = f(x + h).