

MAS242 해석학 II

Notes

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September 19, 2023

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Chapter 1

Differentiation

1.1 Higher order partial derivatives

Definition 1.1.1

Given $f : U \rightarrow \mathbb{R}$ 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

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

Theorem 1.1.1

$f : U(\subseteq \mathbb{R}^2) \rightarrow \mathbb{R}$ 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 $|h| \rightarrow 0$, due to the continuity, $\partial_{21}(c) = \partial_{12}(c)$. \square

Corollary 1.1.1

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

1.2 Extreme Values of differentiable Functions

Definition 1.2.1: Hessian

Let $f : U(\subseteq \mathbb{R}^m) \rightarrow \mathbb{R}$ 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 $\mathbf{u} = (u_1, u_2) \in \mathbb{R}^2$, $D_{\mathbf{u}}f = \nabla f \cdot \mathbf{u} = u_1\partial_1f + u_2\partial_2f$, and thus

$$D_{\mathbf{u}}^2f = (u_1\partial_1 + u_2\partial_2)(u_1\partial_1f + u_2\partial_2f) = u_1^2\partial_{11}f + u_1u_2(2\partial_{12}f) + u_2^2\partial_{22}f.$$

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

$$D_{\mathbf{u}}^2f(p) = u_1^2(\partial_{11}f(p) + 2\partial_{12}f(p)z + \partial_{22}f(p)z^2).$$

Note that, if $D(p) > 0$, $D_{\mathbf{u}}^2f(p)$ 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 $D(p) < 0$, $D_{\mathbf{u}}^2f(p)$ has different signs depending on \mathbf{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,

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

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

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 $D^2f(p)$ are negative.

- a local minimum if all eigenvalues of $D^2f(p)$ 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

2.1 Jacobian

Definition 2.1.1: Jacobian

Let $\mathbf{f}: U(\subseteq \mathbb{R}^m) \rightarrow \mathbb{R}^n$ be differentiable. The function $J_{\mathbf{f}}: U \rightarrow \mathbb{R}$ 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 \mathbf{f} at \mathbf{x} .

Lemma 2.1.1

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

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

Note:-

The linear mapping $df(c)$ is invertible if and only if $J_{\mathbf{f}}(c)$ is nonzero.

2.2 The Inverse Function Theorem

Lemma 2.2.1 Contraction Mapping Principle

Let (X, d) be a complete metric space. Let $\varphi: X \rightarrow X$. Suppose that there exists $M \in [0, 1)$ such that $d(\varphi(x_1), \varphi(x_2)) \leq M d(x_1, x_2)$. (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 φ is continuous, we have $\varphi(x_*) = x_*$. The uniqueness follows trivially. \square

Note:-

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

Lemma 2.2.2

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

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

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

Theorem 2.2.1 Inverse Function Theorem

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

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

Moreover, $\mathbf{f}(B_\delta(\mathbf{a}))$ is an open set, and $(\mathbf{f}|_{B_\delta(\mathbf{a})})^{-1}$ is C^1 .

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

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

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

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 φ is differentiable and $d\varphi(\mathbf{x}; \mathbf{y}) = \text{Id} - A^{-1}d\mathbf{f}(\mathbf{x}) = A^{-1}(A - d\mathbf{f}(\mathbf{x}))$ for each $\mathbf{x} \in B_\delta(\mathbf{c})$.

Hence, for all $\mathbf{x} \in B_\delta(\mathbf{c})$,

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

Now, fix any $\mathbf{y} \in \mathbb{R}^n$. Fix $\mathbf{x}_1, \mathbf{x}_2 \in B_\delta(\mathbf{c})$. Define $\Psi: [0, 1] \rightarrow \mathbb{R}^n$ 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 Ψ 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,

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

\square

End.