

Calculus of Several Variables

Ch.14

econMath.namun+2016f@gmail.com

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1 Definitions and Examples

Partial Derivative

Let $f : D \subset \mathbb{R}^n \rightarrow \mathbb{R}$ and \mathbf{e}_i be a vector whose i th element is 1 and others are 0.

$$\mathbf{e}_i := (\overbrace{0, 0, \dots, 0}^i, 1, 0, \dots, 0)$$

Definition 1 (Partial Derivative). Partial derivative at $\bar{\mathbf{x}}_0 \in D$ is

$$\frac{\partial f}{\partial x_i} := \lim_{h \rightarrow 0} \frac{f(\bar{\mathbf{x}}_0 + h\mathbf{e}_i) - f(\bar{\mathbf{x}}_0)}{h}$$

When $n = 1$, partial derivative is equivalent to derivative of one variable function.

Calculation Procedure

- Treat x_i as the only variable in f
- Treat x_{-i} as constant

2 Economic Interpretation

2.1 Marginal

Marginal Products

Production Function, Marginal Product of Labor [or Capital]

Let Q be the production function of a firm. If the firm's resources for production are $\mathbf{x} = (L, \mathbf{K}) = (L, K_1, K_2, \dots, K_N)$,

$$MP_L := \frac{\partial Q}{\partial L}, \quad MP_{K_i} := \frac{\partial Q}{\partial K_i}$$

Interpretation: Small change ΔK_i (*ceteris paribus*) in K_i can cause output change ΔQ around (L^*, \mathbf{K}^*)

$$\Delta Q \approx \frac{\partial Q}{\partial K_i}(L^*, \mathbf{K}^*) \Delta K_i$$

Marginal Utility

Let $U(\mathbf{x})$ be the utility function with respect to commodity bundle \mathbf{x} . Then $\frac{\partial U}{\partial x_i}$ is marginal utility of commodity i at \mathbf{x}^*

2.2 Elasticity

Elasticity

Elasticity: Multi variable version

x_i elasticity of $Q(\mathbf{x})$ around (\mathbf{x}^*, Q^*) is:

$$\epsilon_i := \frac{\frac{\partial Q}{\partial x_i}}{\frac{Q^*}{x_i^*}} = \frac{x_i^*}{Q^*} \frac{\partial Q}{\partial x_i}(\mathbf{x}^*)$$

In general, elasticity is ratio of rates of changes. When the sign of elasticity is not important, $|\epsilon|$ can be used.

3 Geometric Interpretation

Partial Derivative: Geometric Interpretation

$f : \mathbb{R}^2 \rightarrow \mathbb{R}$

- Think of $f(\mathbf{x}) = x_1^2 + x_2^2$.
- If $x_2 = \bar{x}_2$, $f(x_1, \bar{x}_2)$ is equivalent to one variable function $\tilde{f}(x_1) = x_1^2 + \bar{x}_2^2$.
- Graph of \tilde{f} is intersection of the graph of f with the slice $x_2 = \bar{x}_2$.
- $\frac{\partial f}{\partial x_1}(\bar{x}_1, \bar{x}_2) = \frac{\partial \tilde{f}}{\partial x_1}(\bar{x}_1)$ is the slope of \tilde{f} on \bar{x}_1 , slope of the tangent line to the curve \tilde{f} (on the plane $x_2 = \bar{x}_2$)

Example

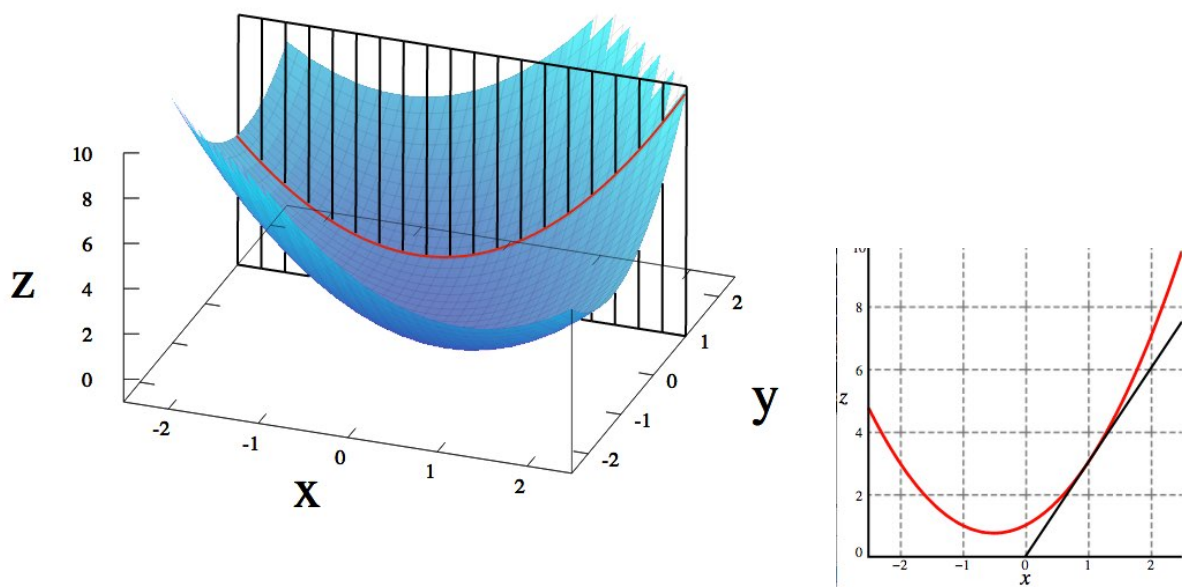


Figure 1: Graph of $z = x^2 + xy + y^2$ with intersection $y = 1$

4 The Total Derivative

Geometrical Approach

Finding Tangent Plane

Let $f : \mathbb{R}^2 \rightarrow \mathbb{R}$ is differentiable. When finding a tangent plane on (\bar{x}_1, \bar{x}_2) , we need to get at least two independent vectors: $\left(1, 0, \frac{\partial f}{\partial x_1}(\bar{x}_1, \bar{x}_2)\right)$ (slice $x_2 = 0$), and $\left(0, 1, \frac{\partial f}{\partial x_2}(\bar{x}_1, \bar{x}_2)\right)$ (slice $x_1 = 0$)

Then the tangent plane with two parameters $\Delta x_1, \Delta x_2$ is:

$$\begin{aligned} & (\bar{x}_1, \bar{x}_2, f(\bar{\mathbf{x}})) + \Delta x_1 \left(1, 0, \frac{\partial f}{\partial x_1}(\bar{x}_1, \bar{x}_2)\right) + \Delta x_2 \left(0, 1, \frac{\partial f}{\partial x_2}(\bar{x}_1, \bar{x}_2)\right) \\ &= \left(\bar{x}_1 + \Delta x_1, \bar{x}_2 + \Delta x_2, f(\bar{\mathbf{x}}) + \frac{\partial f}{\partial x_1}(\bar{x}_1, \bar{x}_2)\Delta x_1 + \frac{\partial f}{\partial x_2}(\bar{x}_1, \bar{x}_2)\Delta x_2\right) \end{aligned}$$

This interpretation can be extended to n dimension.

The Total Derivative

Changes in All Direction: $f : \mathbb{R}^n \rightarrow \mathbb{R}^1$

Let $d\mathbf{x} = (dx_1, \dots, dx_n)$ and $f : \mathbb{R}^n \rightarrow \mathbb{R}$, differentiable. Then small change of $d\mathbf{x}$ will cause small change of $df = f(\bar{\mathbf{x}} + d\bar{\mathbf{x}}) - f(\bar{\mathbf{x}}) \in \mathbb{R}$ and

$$df = f(\bar{\mathbf{x}} + d\bar{\mathbf{x}}) - f(\bar{\mathbf{x}}) = \frac{\partial f}{\partial x_1}(\bar{\mathbf{x}})dx_1 + \dots + \frac{\partial f}{\partial x_n}(\bar{\mathbf{x}})dx_n = Df_{\mathbf{x}}d\mathbf{x}$$

And $Df_{\mathbf{x}} := \left(\frac{\partial f}{\partial x_1}(\bar{\mathbf{x}}) \quad \frac{\partial f}{\partial x_2}(\bar{\mathbf{x}}) \quad \dots \quad \frac{\partial f}{\partial x_n}(\bar{\mathbf{x}})\right)$: (Jacobian) derivative of f at $\bar{\mathbf{x}}$ or The linear approximation of f at $\bar{\mathbf{x}}$, or Gradient vector ∇f

Note: In this case, $Df_{\mathbf{x}}$ is a vector or $1 \times n$ matrix.

More General Case

Changes in All Direction: $\mathbf{f} : \mathbb{R}^n \rightarrow \mathbb{R}^m$

Let $d\mathbf{x} = (dx_1, \dots, dx_n)$ and $\mathbf{f} : \mathbb{R}^n \rightarrow \mathbb{R}^m$, differentiable. Then small change of $d\mathbf{x}$ will cause small change of $d\mathbf{f} = \mathbf{f}(\bar{\mathbf{x}} + d\bar{\mathbf{x}}) - \mathbf{f}(\bar{\mathbf{x}}) \in \mathbb{R}^m$ and

$$d\mathbf{f} = \mathbf{f}(\bar{\mathbf{x}} + d\bar{\mathbf{x}}) - \mathbf{f}(\bar{\mathbf{x}}) = \frac{\partial \mathbf{f}}{\partial x_1}(\bar{\mathbf{x}})dx_1 + \dots + \frac{\partial \mathbf{f}}{\partial x_n}(\bar{\mathbf{x}})dx_n = D\mathbf{f}_{\mathbf{x}}d\mathbf{x}$$

Note: In this case, $D\mathbf{f}_{\mathbf{x}}$ is $m \times n$ matrix

5 The Chain Rule

Curve in \mathbb{R}^n

Definition 2 (curve). A curve in \mathbb{R}^n is n -tuple of continuous one variable functions

$$\mathbf{x}(t) = (x_1(t), \dots, x_n(t))$$

x_i : coordination function, t : parameter

Velocity (or Tangent) Vector

\mathbf{x}' is the velocity (tangent) vector of the curve at t

$$\mathbf{x}' := \lim_{h_j \rightarrow 0} \frac{\mathbf{x}(t + h_j) - \mathbf{x}(t)}{h_j} = (x'_1(t), \dots, x'_n(t))$$

Geometrically, The velocity (tangent) vector is a limit of secant vector

Regular, cusp

Definition 3 (regular). A curve $\mathbf{x}(t)$ is regular iff $x'_i(t)$ is continuous and $\mathbf{x}'(t) \neq \mathbf{0} \quad \forall t$
When $\mathbf{x}'(\bar{t}) = \mathbf{0}$, this curve has cusp at $\mathbf{x}(\bar{t})$

Geometrically, regular curve means smooth curve

Definition 4 (continuously differentiable). $f : \mathbb{R}^n \rightarrow \mathbb{R}$ is continuously differentiable (or C^1) on an open set $D \subset \mathbb{R}^n$ iff

$$\forall \mathbf{x} \in D, \forall i, \quad \exists \frac{\partial f}{\partial x_i}(\mathbf{x}) \quad \wedge \quad \text{continuous}$$

Chain Rule I

Chain Rule I

Let $g(t) = f(\mathbf{x}(t))$, $g : \mathbb{R} \rightarrow \mathbb{R}$, $f : \mathbb{R}^n \rightarrow \mathbb{R}$, $\mathbf{x} : \mathbb{R} \rightarrow \mathbb{R}^n$. Then,

$$\frac{dg}{dt} = Df_{\mathbf{x}}(\mathbf{x}) \frac{d\mathbf{x}(t)}{dt} = \frac{\partial f}{\partial x_1} \frac{dx_1}{dt} + \dots + \frac{\partial f}{\partial x_n} \frac{dx_n}{dt}$$

Chain Rule II

Let $g(\mathbf{t}) = f(\mathbf{x}(\mathbf{t}))$, $g : \mathbb{R}^s \rightarrow \mathbb{R}$, $f : \mathbb{R}^n \rightarrow \mathbb{R}$, $\mathbf{x} : \mathbb{R}^s \rightarrow \mathbb{R}^n$. Then,

$$Dg_{\mathbf{t}} = Df_{\mathbf{x}}(\mathbf{x}) D\mathbf{x}_{\mathbf{t}}(\mathbf{t})$$

$$\frac{\partial g}{\partial t_i} = \left(\frac{\partial f}{\partial x_1} \quad \dots \quad \frac{\partial f}{\partial x_n} \right) \begin{pmatrix} \frac{\partial x_1}{\partial t_i} \\ \vdots \\ \frac{\partial x_n}{\partial t_i} \end{pmatrix}$$

6 Directional Derivatives and Gradients

Directional Derivatives and Gradients

Directional Derivative

Let $\mathbf{x} = \bar{\mathbf{x}} + t\bar{\mathbf{v}}$: line passing $\bar{\mathbf{x}}$ with direction $\bar{\mathbf{v}}$ and $g(t) = f(\bar{\mathbf{x}} + t\bar{\mathbf{v}})$. From chain rule I,

$$\left. \frac{dg}{dt} \right|_{t=0} = \left. \frac{df}{dt} \right|_{t=0} = Df_{\mathbf{x}}(\bar{\mathbf{x}}) \cdot \frac{d\mathbf{x}}{dt} = Df_{\mathbf{x}}(\bar{\mathbf{x}}) \cdot \bar{\mathbf{v}}$$

This is the derivative of f at $\bar{\mathbf{x}}$ in the direction $\bar{\mathbf{v}}$, and other notations are $\frac{\partial f}{\partial \bar{\mathbf{v}}}(\bar{\mathbf{x}})$ and $D_{\bar{\mathbf{v}}}f(\bar{\mathbf{x}})$

Theorem 1 (14.2). At any point $\mathbf{x} \in D$ and $\nabla f \neq 0$, $\nabla f(\mathbf{x})$ points at x into the direction in which f increases most rapidly

This theorem will be used for finding normal vector of tangent hyperplane to level set.

7 Explicit Functions from \mathbb{R}^n to \mathbb{R}^m

Chain Rule III

Chain Rule III

Let $\mathbf{f}(\mathbf{x}) : \mathbb{R}^n \rightarrow \mathbb{R}^m$, $\mathbf{a}(t) : \mathbb{R} \rightarrow \mathbb{R}^n$, and $\mathbf{g}(t) = \mathbf{f} \circ \mathbf{a}(t)$. Then,

$$\frac{dg}{dt} = Df_{\mathbf{a}}(\mathbf{a}(t)) \cdot \mathbf{a}'(t)$$

Chain Rule IV

Let $\mathbf{f}(\mathbf{x}) : \mathbb{R}^n \rightarrow \mathbb{R}^m$, $\mathbf{a}(\mathbf{t}) : \mathbb{R}^s \rightarrow \mathbb{R}^n$, and $\mathbf{g}(\mathbf{t}) = \mathbf{f} \circ \mathbf{a}(\mathbf{t})$. Then,

$$D\mathbf{g}_{\mathbf{t}} = Df_{\mathbf{a}}(\mathbf{a}(\mathbf{t})) \cdot D\mathbf{a}_{\mathbf{t}}$$

8 Higher-order Derivatives

Hessian

Definition 5. *Hessian matrix*

$$D^2 f_{\mathbf{x}} = D(Df)_{\mathbf{x}} := \begin{pmatrix} \frac{\partial^2 f}{\partial x_1 \partial x_1} & \frac{\partial^2 f}{\partial x_2 \partial x_1} & \cdots & \frac{\partial^2 f}{\partial x_n \partial x_1} \\ \frac{\partial^2 f}{\partial x_1 \partial x_2} & \frac{\partial^2 f}{\partial x_2 \partial x_2} & \cdots & \frac{\partial^2 f}{\partial x_n \partial x_2} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial x_1 \partial x_n} & \frac{\partial^2 f}{\partial x_2 \partial x_n} & \cdots & \frac{\partial^2 f}{\partial x_n \partial x_n} \end{pmatrix}$$

Theorem 2 (14.5:Young's theorem).

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\partial^2 f}{\partial x_j \partial x_i} \quad \forall i, j$$

This means hessian is symmetric.