

벡터미분 / 매트릭스 미분.

① 정의 1 : 벡터로 미분.

$$\frac{\partial}{\partial \mathbf{y}} := \begin{bmatrix} \frac{\partial}{\partial y_1} \\ \vdots \\ \frac{\partial}{\partial y_n} \end{bmatrix}, \quad \mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}$$

② 정의 2 : 매트릭스로 미분.

$$\frac{\partial}{\partial \mathbf{x}} := \begin{bmatrix} \frac{\partial}{\partial x_1} & \dots & \frac{\partial}{\partial x_p} \\ \vdots & & \vdots \\ \frac{\partial}{\partial x_n} & \dots & \frac{\partial}{\partial x_p} \end{bmatrix},$$

$$\mathbf{x} = \begin{bmatrix} x_1 & \dots & x_p \\ \vdots & & \vdots \\ x_n & \dots & x_p \end{bmatrix}$$

$$\textcircled{1} \quad \frac{\partial}{\partial \mathbf{x}} (\mathbf{x}^T \mathbf{y}) = \mathbf{y}, \quad \mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}, \quad \mathbf{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix}$$

pf. $\mathbf{x}^T \mathbf{y} = [x_1 \dots x_n] \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = x_1 y_1 + x_2 y_2 + \dots + x_n y_n.$

$$\bullet \quad \frac{\partial}{\partial \mathbf{x}} = \begin{bmatrix} \frac{\partial}{\partial x_1} \\ \vdots \\ \frac{\partial}{\partial x_n} \end{bmatrix} \quad \text{오답}$$

$$\left(\frac{\partial}{\partial \mathbf{x}}\right) \mathbf{x}^T \mathbf{y} = \begin{bmatrix} \frac{\partial}{\partial x_1} \\ \vdots \\ \frac{\partial}{\partial x_n} \end{bmatrix} (x_1 y_1 + x_2 y_2 + \dots + x_n y_n)$$

$$= \begin{bmatrix} \frac{\partial}{\partial x_1} (x_1 y_1 + \dots + x_n y_n) \\ \vdots \\ \frac{\partial}{\partial x_n} (x_1 y_1 + \dots + x_n y_n) \end{bmatrix}$$

$$= \begin{bmatrix} \frac{\partial}{\partial x_1} x_1 y_1 + \frac{\partial}{\partial x_1} x_2 y_2 + \dots + \frac{\partial}{\partial x_1} x_n y_n \\ \frac{\partial}{\partial x_n} x_1 y_1 + \frac{\partial}{\partial x_n} x_2 y_2 + \dots + \frac{\partial}{\partial x_n} x_n y_n \end{bmatrix}$$

$$= \begin{bmatrix} y_1 + 0 + \dots + 0 \\ \vdots \\ 0 + 0 + \dots + y_n \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \mathbf{y}.$$

$\frac{\partial}{\partial \mathbf{x}} (\mathbf{x}^T \mathbf{y}) = \mathbf{y}$ 임을 보이는 다른 풀이

pf. $\frac{\partial}{\partial \mathbf{x}} (\mathbf{x}^T \mathbf{y}) = \left(\frac{\partial}{\partial \mathbf{x}} \mathbf{x}^T\right) \mathbf{y} = \mathbf{I} \mathbf{y} = \mathbf{y}.$

$$\frac{\partial}{\partial \mathbf{x}} \mathbf{x}^T = \begin{bmatrix} \frac{\partial}{\partial x_1} \\ \vdots \\ \frac{\partial}{\partial x_n} \end{bmatrix} [x_1 \dots x_n] = \begin{bmatrix} \frac{\partial}{\partial x_1} x_1 & \dots & \frac{\partial}{\partial x_1} x_n \\ \vdots & & \vdots \\ \frac{\partial}{\partial x_n} x_1 & \dots & \frac{\partial}{\partial x_n} x_n \end{bmatrix} = \mathbf{I}$$

$$\textcircled{2} \frac{\partial}{\partial x} (y^T x) = y.$$

$$\text{pf. } \frac{\partial}{\partial x} (y^T x) = \frac{\partial}{\partial x} (x^T y) = y.$$

$$\textcircled{3} \frac{\partial}{\partial \beta} (y^T X \beta) = X^T y. \quad \begin{array}{l} \text{즉, } \beta := p \times 1 \text{ vector} \\ X := n \times p \text{ matrix} \\ y := n \times 1 \text{ vector.} \end{array}$$

$$\text{pf. } y^T X \beta \text{ 는 스칼라이므로.}$$

$$y^T X \beta = (y^T X \beta)^T = \beta^T X^T y.$$

$$\frac{\partial}{\partial \beta} (y^T X \beta) = \frac{\partial}{\partial \beta} (\beta^T X^T y) = \left(\frac{\partial}{\partial \beta} \beta^T \right) X^T y = X^T y.$$

$$(\text{다르게 풀이}) \quad \frac{\partial}{\partial \beta} (y^T X \beta) = X^T y. \quad \text{앞을 보이는 다른 풀이.}$$

$$\cdot X \beta = \begin{bmatrix} x_{11} & \dots & x_{1p} \\ \vdots & & \vdots \\ x_{n1} & \dots & x_{np} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_p \end{bmatrix} = \begin{bmatrix} x_{11}\beta_1 + \dots + x_{1p}\beta_p \\ x_{21}\beta_1 + \dots + x_{2p}\beta_p \\ \vdots \\ x_{n1}\beta_1 + \dots + x_{np}\beta_p \end{bmatrix}$$

$$\cdot y^T X \beta = [y_1 \dots y_n] \begin{bmatrix} x_{11}\beta_1 + \dots + x_{1p}\beta_p \\ x_{21}\beta_1 + \dots + x_{2p}\beta_p \\ \vdots \\ x_{n1}\beta_1 + \dots + x_{np}\beta_p \end{bmatrix}$$

$$= y_1(x_{11}\beta_1 + \dots + x_{p1}\beta_p) + y_2(x_{21}\beta_1 + \dots + x_{2p}\beta_p) + \dots$$

$$+ y_n(x_{n1}\beta_1 + \dots + x_{np}\beta_p) = A_1 + A_2 + \dots + A_n.$$

* note: A_1, A_2, \dots, A_n are scalars.

$$\left(\frac{\partial}{\partial \beta}\right)(y^T X \beta) = \begin{bmatrix} \frac{\partial}{\partial \beta_1} \\ \vdots \\ \frac{\partial}{\partial \beta_p} \end{bmatrix} (A_1 + A_2 + \dots + A_n)$$

$$= \begin{bmatrix} \frac{\partial}{\partial \beta_1} A_1 \\ \vdots \\ \frac{\partial}{\partial \beta_p} A_1 \end{bmatrix} + \begin{bmatrix} \frac{\partial}{\partial \beta_1} A_2 \\ \vdots \\ \frac{\partial}{\partial \beta_p} A_2 \end{bmatrix} + \dots + \begin{bmatrix} \frac{\partial}{\partial \beta_1} A_n \\ \vdots \\ \frac{\partial}{\partial \beta_p} A_n \end{bmatrix}$$

$$\cdot \frac{\partial}{\partial \beta_1} A_1 = \frac{\partial}{\partial \beta_1} y_1(x_{11}\beta_1 + \dots + x_{p1}\beta_p) = y_1 x_{11} + 0 + \dots + 0.$$

$$\cdot \frac{\partial}{\partial \beta_2} A_1 = \frac{\partial}{\partial \beta_2} y_1(x_{11}\beta_1 + \dots + x_{p1}\beta_p) = 0 + y_1 x_{12} + 0 + \dots + 0$$

$$= \begin{bmatrix} y_1 x_{11} \\ y_1 x_{12} \\ \vdots \\ y_1 x_{1p} \end{bmatrix} + \begin{bmatrix} y_2 x_{21} \\ y_2 x_{22} \\ \vdots \\ y_2 x_{2p} \end{bmatrix} + \dots + \begin{bmatrix} y_n x_{n1} \\ y_n x_{n2} \\ \vdots \\ y_n x_{np} \end{bmatrix}$$

$$= \begin{bmatrix} y_1 x_{11} + y_2 x_{21} + \dots + y_n x_{n1} \\ y_1 x_{12} + y_2 x_{22} + \dots + y_n x_{n2} \\ \vdots \\ y_1 x_{1p} + y_2 x_{2p} + \dots + y_n x_{np} \end{bmatrix} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1p} \\ x_{21} & x_{22} & \dots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{np} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}$$

$$= X^T y.$$

$$\textcircled{4} \quad \frac{\partial}{\partial y} y^T y = 2y.$$

$$\text{pf. } y^T y = [y_1 \dots y_n] \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = y_1^2 + \dots + y_n^2.$$

$$\therefore \frac{\partial}{\partial y} (y^T y) = \frac{\partial}{\partial y} (y_1^2 + \dots + y_n^2) = \begin{bmatrix} \frac{\partial}{\partial y_1} \\ \vdots \\ \frac{\partial}{\partial y_n} \end{bmatrix} (y_1^2 + \dots + y_n^2)$$

$$= \begin{bmatrix} \frac{\partial}{\partial y_1} (y_1^2 + \dots + y_n^2) \\ \vdots \\ \frac{\partial}{\partial y_n} (y_1^2 + \dots + y_n^2) \end{bmatrix}$$

$$= \begin{bmatrix} 2y_1 + 0 + \dots + 0 \\ 0 + 2y_2 + \dots + 0 \\ \vdots \\ 0 + 0 + \dots + 2y_n \end{bmatrix} = 2 \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = 2y.$$

(틀린표이) $\frac{\partial}{\partial y} (y^T y) = \left(\frac{\partial}{\partial y} y^T \right) y$

그런데 $\left(\frac{\partial}{\partial y} y^T \right) = I$. 이므로, $\frac{\partial}{\partial y} (y^T y) = I y = y.$

(트린플이의 스칼라 버전) $\frac{d}{dy} y^2 = \left(\frac{d}{dy} y\right) \cdot y = 1 \cdot y = y.$

(올바른 풀이) : $\frac{d}{dy} y^2 = \left(\frac{d}{dy}\right) \underbrace{y}_{f(y)} \cdot \underbrace{y}_{g(y)} = \left(\frac{d}{dy} y\right) \cdot y + y \left(\frac{d}{dy} y\right)$
 $\underbrace{\left(\frac{d}{dy} y\right)}_{f'(y)} \cdot \underbrace{y}_{g(y)} + \underbrace{y}_{f(y)} \cdot \underbrace{\left(\frac{d}{dy} y\right)}_{g'(y)}$

Note: 곱의 미분 : 함수 $f(x), g(x)$ 가 x 에 대하여 미분가능하면

$$\{f(x) \cdot g(x)\}' = f(x) g'(x) + f'(x) g(x)$$

다시 벡터로 돌아오자.

(올바른 풀이) $\left(\frac{\partial}{\partial y}\right) (\underbrace{y^T}_{A} \underbrace{y}_{B}) = A + B = \mathbf{I} \underbrace{y}_{B} + \underbrace{\mathbf{I} y}_{A} = 2y.$

$A :=$ 빨간 y 만 변수로 보고 미분

$B :=$ 파란 y 만 변수로 보고 미분

$$A = \left(\frac{\partial}{\partial y} \underbrace{y^T}_{A}\right) \underbrace{y}_{B} = \mathbf{I} \underbrace{y}_{B}$$

$$B = \left(\frac{\partial}{\partial y}\right) (\underbrace{y^T}_{A} \underbrace{y}_{B}) = \left(\frac{\partial}{\partial y}\right) (\underbrace{y^T}_{A} \underbrace{y}_{B}) = \left(\frac{\partial}{\partial y} \underbrace{y^T}_{A}\right) \underbrace{y}_{B} = \mathbf{I} \underbrace{y}_{B}$$

⑤ $\frac{\partial}{\partial b} b^T x^T x b = 2x^T x b.$

pf. $\frac{\partial}{\partial b} (b^T x^T x b) = A + B = \mathbf{I} x^T x b + \mathbf{I} x^T x b = 2x^T x b.$

$$A = \left(\frac{\partial}{\partial \beta} \beta^T \right) x^T x \beta = I x^T x \beta.$$

$$B = \left(\frac{\partial}{\partial \beta} \right) \left(\beta^T x^T x \beta \right) = \left(\frac{\partial}{\partial \beta} \right) \left(\beta^T x^T x \beta \right) = I x^T x \beta.$$

$$\text{loss} = (y - x\beta)^T (y - x\beta)$$

$$= y^T y - y^T x \beta - \beta^T x^T y + \beta^T x^T x \beta.$$

$$\frac{\partial}{\partial \beta} \text{loss} = 0 - \frac{\partial}{\partial \beta} y^T x \beta - \frac{\partial}{\partial \beta} \beta^T x^T y + \frac{\partial}{\partial \beta} \beta^T x^T x \beta$$

$$= 0 - x^T y - x^T y + 2x^T x \beta$$

$$\therefore \frac{\partial}{\partial \beta} \text{loss} = 0 \quad \Leftrightarrow \quad 2x^T y = 2x^T x \beta.$$

$$\therefore \hat{\beta} = (x^T x)^{-1} x^T y.$$