

MATH 2010?

$$\vec{x} = (x_1, x_2, \dots, x_n)$$

$$f(\vec{x}) = \sum_{i=1}^n x_i.$$

$$f(\vec{x}) = x_1 + x_2 + \dots + x_n = f\left(\begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix}\right).$$

matrix calculus. (wikipedia).

n - layout notation.

d - layout notation

$$\frac{d}{d\vec{x}} f(\vec{x}) = \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{pmatrix} = \begin{pmatrix} | \\ | \\ \vdots \\ | \end{pmatrix}$$

$$f(\vec{x}) = \vec{x}^T A \vec{x}. \quad A \text{ is fixed, known.}$$

$$g(x) = ax^2 \Rightarrow g'(x) = \frac{d}{dx}(ax \cdot x) = a \cdot x + ax \cdot 1 = 2ax.$$

$$\frac{d}{d\vec{x}} f(\vec{x}) = \frac{d}{d\vec{x}} (\underbrace{\vec{x}^T}_{\textcircled{1}} \underbrace{A \vec{x}}_{\textcircled{2}}) = \vec{x}^T A^T + \vec{x}^T A = 2\vec{x}^T A.$$

$$A \text{ is symmetric. } \vec{x}^T A \vec{x} = (\vec{x}^T A \vec{x})^T = \vec{x}^T A^T \vec{x} \in \mathbb{R}. \quad a \in \mathbb{R}. \quad a^T = a.$$

$$A^* = \frac{1}{2}(A + A^T).$$

$$\rightarrow \vec{x}^T A \vec{x} = \vec{x}^T A^T \vec{x} = \vec{x}^T A^* \vec{x}. \quad \leftarrow A \text{ is symmetric.}$$

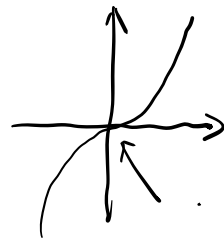
$$(\text{new } A) = \frac{1}{2}(A + A^T)$$

Second order condition.  $f(\vec{x})$ .

$$\min_x f(x).$$

$$f'(x) = 0.$$

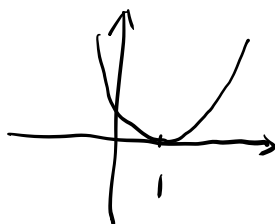
$$f(x) = x^3.$$



$$f'(x) = 3x^2 \quad f'(0) = 0.$$

$$f''(x) > 0.$$

$$f(x) = (x-1)^2.$$



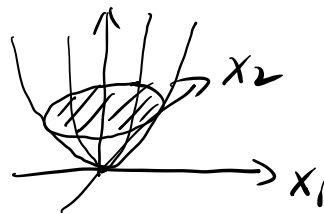
$$f'(x) = 2(x-1). \quad f'(x) = 0 \Rightarrow x = 1.$$

$$f''(x) = 2 > 0.$$

Hessian matrix.

$$f''(\vec{x}) > 0.$$

$$f(\vec{x}) = f\left(\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}\right) = x_1^2 + x_2^2.$$



$$f'(\vec{x}) = \begin{pmatrix} 2x_1 \\ 2x_2 \end{pmatrix}$$

$$= \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \end{pmatrix}$$

$$f''(\vec{x}) = \begin{pmatrix} \frac{\partial}{\partial x_1} \left( \frac{\partial f}{\partial x_1} \right) & \frac{\partial}{\partial x_2} \left( \frac{\partial f}{\partial x_1} \right) \\ \frac{\partial}{\partial x_1} \left( \frac{\partial f}{\partial x_2} \right) & \frac{\partial}{\partial x_2} \left( \frac{\partial f}{\partial x_2} \right) \end{pmatrix}$$

$$\begin{pmatrix} \frac{\partial}{\partial x_2} \left( \frac{\partial f}{\partial x_1} \right) & \frac{\partial}{\partial x_2} \left( \frac{\partial f}{\partial x_2} \right) \end{pmatrix}$$

$$= \begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix} > 0. \quad \text{positive definite.}$$

$$v \in \mathbb{R}^2, \quad v^T f''(\bar{x}) v > 0. \quad \text{for } \forall v \neq 0.$$

$$\begin{matrix} \uparrow \\ (=0) \end{matrix}$$

$$(v_1 \ v_2) \begin{pmatrix} 2 & 0 \\ 0 & 2 \end{pmatrix} \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = (2v_1, 2v_2) \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = 2(v_1^2 + v_2^2) > 0.$$

$$v = (v_1, v_2) \neq \vec{0}.$$

satisfying 2-order condition.  $\leftarrow$   $f$  differentiable.

$$\boxed{\frac{d}{d\vec{x}} f} = \vec{0}. \quad \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = 0 \Rightarrow \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}.$$

$$H = X(X^T X)^{-1} X^T.$$

$$v. \quad f(v) = Hv. \quad f(v) \text{ projects } v \text{ onto } C(X).$$

$$Y = X\beta + \epsilon. \quad \hat{\beta} = (X^T X)^{-1} X^T Y. \quad \hat{y} = X\hat{\beta} = X(X^T X)^{-1} X^T Y = \underline{HY}.$$

$$\begin{cases} \textcircled{1} \quad v \perp C(X). & Hv = 0. \\ \textcircled{2} \quad v \in C(X). & Hv = v. \end{cases}$$



$$v = v_1 + v_2.$$

$$f(C(X)) \perp C(X).$$

$$H(v) = v_1 + 0 = v_1.$$

$$\textcircled{1} \quad v \perp C(X) \quad v^T X = 0. \Rightarrow X^T v = 0.$$

$$Hv = X(X^T X)^{-1} \underbrace{X^T v}_{=0} = 0.$$

$$\textcircled{2} \quad v \in C(X) \quad v = X\vec{\lambda}. \quad X_{n \times p}. \quad \vec{\lambda}_{p \times 1}.$$

$$\Rightarrow Hv = X(X^T X)^{-1} X^T v = X \underbrace{(X^T X)^{-1} X^T X}_I \lambda.$$

$$= X\lambda$$

$$= v.$$