

— Linear least squares

$$E(a, b) \text{ error} = \sum_{i=1}^n (\underbrace{f(x_i)} - y_i)^2$$

$$= \sum_{i=1}^n (ax_i + b - y_i)^2$$

$$\frac{\partial E(a, b)}{\partial a} = 0, \quad \frac{\partial E(a, b)}{\partial b} = 0 \quad \text{optimal point.}$$

$$\sum_{i=1}^n 2(ax_i + b - y_i) x_i = 0 \quad \sum_{i=1}^n 2(ax_i + b - y_i) = 0$$

$$2 \begin{pmatrix} a+b-1 \\ + \\ 2a+b-1 \\ + \\ 3a+b-2 \\ + \\ 4a+b-2 \\ + \\ 5a+b-4 \end{pmatrix} \cdot \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{matrix} = 0$$

$$2 \left(\overset{56}{(1+4+9+16+25)} a + \overset{15}{(1+2+3+4+5)} b - \overset{39}{(1+2+6+8+10)} \right) = 0$$

↓
일반화

$$p = \sum_{i=0}^n x_i \quad q = \sum_{i=0}^n y_i \quad r = \sum_{i=0}^n x_i y_i \quad s = \sum_{i=0}^n x_i^2$$

$$\begin{pmatrix} s & p \\ p & n+1 \end{pmatrix} \begin{pmatrix} a \\ b \end{pmatrix} = \begin{pmatrix} r \\ q \end{pmatrix}$$

n+1 : 정제

Cramer's rule $n+1$ rows.

$$D = \det \begin{pmatrix} s & p \\ p & n+1 \end{pmatrix} = (n+1)s - p^2$$

$$a = \frac{1}{D} \det \begin{pmatrix} r & p \\ q & n+1 \end{pmatrix} = \frac{(n+1)r - pq}{D}$$

$$b = \frac{1}{D} \det \begin{pmatrix} s & r \\ p & q \end{pmatrix} = \frac{qs - rp}{D}$$

— Non linear

Exponential

$$f(x) = a e^{bx} \rightarrow \underbrace{\ln f(x)}_{F(x)} = \underbrace{\ln a}_{\alpha} + \underbrace{bx}_{\beta}$$

\downarrow
 $\mathcal{H}_D(x_i, y_i)$ where $(x_i, \ln y_i)$ are

hyperbolic

$$f(x) = a + \frac{b}{x} \quad x \geq \frac{1}{x} \text{ min}$$

$$F(x) = bx + a \quad \mathcal{H}_D(x_i, y_i) \text{ where } (\frac{1}{x_i}, y_i) \text{ are}$$

— Multivariable least squares

$$\text{optimal } x^* = \min \|b - Ax\|_2^2 = \sqrt{I(b - Ax)^2}^2$$

$$\text{let } r = b - Ax$$

$$r=0 \rightarrow 0 = A^T r = A^T (b - Ax^*) = A^T b - A^T A x^*$$

$$\therefore \underbrace{A^T A x^*}_{\nearrow} = A^T b$$

$$x^* = \underbrace{(A^T A)^{-1} A^T}_{A^+ \text{ (pseudoinverse)}} b$$

$$\text{cond}(A) = \|A\| \cdot \|A^{-1}\| = \|A\| \cdot \|A^+\|$$

$$x^* = A^+ \cdot b$$

예

$$A^T A x^* = A^T b \quad \text{이유}$$

↑

정리