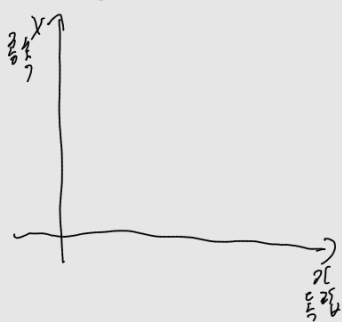


~ 다중 선형 회귀



$x \in \mathbb{R}$ (single) : 단일 선형 회귀 $\rightarrow y = wx + b$

$x \in \mathbb{R}^n$ (multiple) : 다중 선형 회귀 $\rightarrow y = w, x \dots$

$$x_i = \begin{bmatrix} x_{i1} \\ x_{i2} \\ \vdots \\ x_{im} \end{bmatrix} \rightarrow y_i = w_1 x_{i1} + w_2 x_{i2} + \dots + w_m x_{im} + b \Rightarrow x_i \in \mathbb{R}^m \quad y \in \mathbb{R}^n$$

$$\begin{pmatrix} 1 & x_1 \in \mathbb{R}^m & y_1 \\ 2 & & \\ \vdots & & \\ n & x_n \in \mathbb{R}^m & y_n \end{pmatrix}$$

< single L-R > $y = \alpha + \beta x$

i) 오차 최소화 :

$$\begin{cases} \alpha = \bar{y} - \beta \bar{x} \\ \beta = \frac{\sum x(y - \bar{y})}{\sum x(x - \bar{x})} \end{cases}$$

ii) 최적치 $\theta = \begin{bmatrix} w \\ b \end{bmatrix}$ $\hat{Y} = X\theta \simeq Y$ $\theta = (X^T X)^{-1} X^T Y$

L 오차 제곱 합 최소화

각 변수에 대해 미분하여 0이 되는 지점 찾기

Y = target = label \hat{Y} = prediction

i) $\hat{Y} = X\theta$ ii) $E = (Y - \hat{Y})^2$

~ 벡터 $A^T = A^T A$

$$\begin{aligned} (A+B)^T &= A^T + B^T \\ (AB)^T &= B^T A^T \\ (ABC)^T &= C^T B^T A^T \\ A \in \mathbb{R}^1 &\rightarrow A = A^T \end{aligned}$$

ex) $A = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}$ $L_1 = |\sum x_i| = \|X\|_1$ $L_2 = \sqrt{\sum x_i^2} = \|X\|_2$ $\|A\|_2^2 = a_1^2 + a_2^2 + a_3^2 = (a_1, a_2, a_3) \begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}$

$$\begin{aligned} E &= (Y - \hat{Y})^2 = (Y - \hat{Y})^T (Y - \hat{Y}) = (Y - X\theta)^T (Y - X\theta) \\ &= (Y^T - (X\theta)^T) (Y - X\theta) \\ &= (Y^T - \theta^T X^T) (Y - X\theta) \\ &= Y^T Y - Y^T X\theta - \theta^T X^T Y + \theta^T X^T X\theta \\ &= Y^T Y - Y^T X\theta - (Y^T X\theta)^T - \theta^T X^T X\theta \end{aligned}$$

$Y \in \mathbb{R}$
 $X \in \mathbb{R}^{3 \times 2}$ $\theta \in \mathbb{R}^2$ $\hat{Y} \in \mathbb{R}^3$

$$x = \begin{bmatrix} x_1 & 1 \\ x_2 & 1 \\ x_3 & 1 \end{bmatrix} \quad \theta = \begin{bmatrix} w \\ b \end{bmatrix} \quad \hat{Y} = \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \\ \hat{y}_3 \end{bmatrix}$$

$Y^T X \theta \rightarrow (1 \times 3) (3 \times 2) (2 \times 1) = 1 \times 2 \rightarrow 2 \times 1$

$$i) E = Y^T Y - Y^T X \theta - (Y^T X \theta)^T - \theta^T X^T X \theta = Y^T Y - 2 Y^T X \theta - \theta^T X^T X \theta$$

$$ii) \frac{dE}{d\theta} = -2 X^T Y + 2 X^T X \theta = 0 \quad \theta = (X^T X)^{-1} X^T Y \quad (\text{2x2x})$$

$$① Y = AX \Rightarrow \frac{dY}{dX} = A \quad A = R^{m \times n}$$

$$③ X^T A X$$

$$\Rightarrow \frac{d(X^T A X)}{dX} = \frac{d(X^T A X)}{dX} + \frac{d(X^T A X)}{dX}$$

$$② K = Y^T A X \Rightarrow \frac{dK}{dX} = \frac{d(Y^T A X)}{dX} = Y^T A$$

$$\frac{d(X^T A X)}{dX} = (AX)^T = X^T A^T \quad X^T A^T + X^T A = X^T (A + A^T)$$

$$iii) \frac{dE}{d\theta} = \frac{d}{d\theta} [Y^T X - 2 Y^T X \theta - \theta^T X^T X \theta]$$

$$① \frac{d}{d\theta} [Y^T X \theta] = Y^T X$$

$$② \frac{d}{d\theta} [\theta^T X^T X \theta] \rightarrow \frac{d}{d\theta} [\theta^T (X^T X) \theta] = \theta^T (X^T X + (X^T X)^T) = \theta^T (X^T X + X^T X) = 2 \theta^T X^T X$$

$$\therefore \frac{dE}{d\theta} = Y^T X - 2 \theta^T X^T X = 0$$

$$(Y^T X)^T \rightarrow X^T Y = (\theta^T X^T X)^T \rightarrow X^T X \theta \rightarrow \theta = (X^T X)^{-1} X^T Y$$

$$\hat{y} = w_1 x_{i1} + w_2 x_{i2} + \dots + w_m x_{im} + b$$

$$X_i = \begin{bmatrix} x_{i1} \\ \vdots \\ x_{im} \end{bmatrix} \in R^m \quad \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \in R^n \quad \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \in R^n \quad \theta = \begin{bmatrix} w_1 \\ \vdots \\ w_m \\ b \end{bmatrix} \in R^{m+1}$$

$$X = \begin{bmatrix} x_{11} & \dots & x_{1m} & 1 \\ \vdots & & \vdots & \vdots \\ x_{n1} & \dots & x_{nm} & 1 \end{bmatrix} \in R^{n \times (m+1)}$$

$$\hat{Y} = X \cdot \theta$$

$$\in R^{n \times 1} \quad \in R^{n \times (m+1)} \quad \in R^{(m+1) \times 1}$$

$$(n \times 1) \quad (n \times (m+1)) \quad ((m+1) \times 1)$$