

과제 3장)

$$\begin{aligned} 3.3 \quad SST &= \sum_{i=1}^n (y_i - \bar{y})^2 = \sum_{i=1}^n y_i^2 - 2\bar{y} \sum_{i=1}^n y_i + \sum_{i=1}^n \bar{y}^2 = \sum_{i=1}^n y_i^2 - n\bar{y}^2 \\ &= y^t y - n \frac{1}{n^2} (y^t \mathbf{1}) (\mathbf{1}^t y) = y^t y - \frac{1}{n} y^t \mathbf{1} \mathbf{1}^t y \\ &= y^t (I - \frac{J}{n}) y \end{aligned}$$

$$\begin{aligned} J &= (\mathbf{1} \mathbf{1}^t) \quad T = (I - \frac{J}{n}) \quad T^2 = (I - \frac{J}{n})(I - \frac{J}{n}) = I^2 - \frac{2}{n} J + \frac{1}{n^2} J^t J \\ &= I^2 - \frac{2}{n} J + \frac{J}{n} \quad \because J^2 = nJ \\ &= I - \frac{J}{n} \quad \therefore \text{백등행렬} \end{aligned}$$

$$\therefore \text{백등행렬의 성질에 의해 } \text{rank}(T) = \text{tr}(T) = \text{tr}(I - \frac{J}{n}) = n - 1$$

$$\begin{aligned} SSE &= \sum_{i=1}^n (y_i - \hat{y}_i)^2 = (y - \hat{y})^t (y - \hat{y}) = (y - X\hat{\beta})^t (y - X\hat{\beta}) = y^t y - 2y^t X\hat{\beta} + \hat{\beta}^t X^t X \hat{\beta} \\ \therefore \hat{\beta} &= (X^t X)^{-1} X^t y \quad = y^t y - 2y^t X (X^t X)^{-1} X^t y + (X^t X)^{-1} X^t y X^t X (X^t X)^{-1} X^t y \\ &= y^t (I - X(X^t X)^{-1} X^t) y = y^t E y \end{aligned}$$

$$\begin{aligned} E &= I - X(X^t X)^{-1} X^t \quad E^2 = I^2 - 2X(X^t X)^{-1} X^t + X(X^t X)^{-1} X^t X (X^t X)^{-1} X^t \\ &= I - X(X^t X)^{-1} X^t = E \quad \therefore \text{백등행렬} \end{aligned}$$

$$\begin{aligned} \therefore \text{rank}(E) &= \text{tr}(E) = \text{tr}(I - X(X^t X)^{-1} X^t) = n - \text{tr}(X(X^t X)^{-1} X^t) \\ &= n - \text{tr}((X^t X)^{-1} X^t X) = n - \text{tr}(I_p) = n - p \end{aligned}$$

3.14 t검정)  $H_0: \beta_j = 0, \beta_j \neq 0$

$$t = \frac{\hat{\beta}_j}{S.E(\hat{\beta}_j)} = \frac{\hat{\beta}_j}{S \sqrt{C_{jj+HH}}} = \frac{\hat{\beta}_j}{\sqrt{MSE/S_{xx}}}$$

부분 F 검정)  $R(\beta_j | \beta_0, \dots, \beta_{j-1}) = SSR(\beta) - SSR(\beta_0, \dots, \beta_{j-1})$

$$\begin{aligned} &= \sum (\hat{y}_i - \bar{y})^2 - \sum_{\beta_j=0} (\hat{y}_i - \bar{y})^2 = \hat{\beta}_j^2 \sum (x_i - \bar{x})^2 - \hat{\beta}_j^2 \sum_{\beta_j=0} (x_i - \bar{x})^2 \\ &= \hat{\beta}_j^2 \sum (x_i - \bar{x})^2 = \hat{\beta}_j^2 S_{xx} \end{aligned}$$

$$\therefore F_0 = \frac{\hat{\beta}_j^2 S_{xx}}{MSE} \sim t^2$$

과제 4장.

4.4  $\text{Var}(\hat{y}_{i(\lambda)})$

$$y_i = e_i + \hat{y}_i$$

$$\hat{y}_i = w_i (e_i + \hat{y}_i) + (1-w_i) \hat{y}_{i(\lambda)}$$

$$(1-w_i) \hat{y}_i = (1-w_i) \hat{y}_{i(\lambda)} + w_i e_i$$

$$(1-w_i)(\hat{y}_i - \hat{y}_{i(\lambda)}) = w_i e_i \Rightarrow (1-w_i)(x_i'(\hat{\beta} - \hat{\beta}_{(\lambda)})) = w_i e_i$$

$$x_i'(\hat{\beta} - \hat{\beta}_{(\lambda)}) = w_i (e_i + x_i'(\hat{\beta} - \hat{\beta}_{(\lambda)}))$$

$$w_i = \frac{x_i'(\hat{\beta} - \hat{\beta}_{(\lambda)})}{e_i + x_i'(\hat{\beta} - \hat{\beta}_{(\lambda)})} = \frac{\frac{x_i'(x'x)^{-1}x_i e_i}{1-h_{ii}}}{e_i + \frac{x_i'(x'x)^{-1}x_i e_i}{1-h_{ii}}} = \frac{\frac{h_{ii}}{1-h_{ii}} e_i}{e_i + \frac{h_{ii}}{1-h_{ii}} e_i} = \frac{\frac{h_{ii}}{1-h_{ii}}}{1 + \frac{h_{ii}}{1-h_{ii}}} = h_{ii}$$

$$\hat{y}_{i(\lambda)} = \frac{\hat{y}_i - h_{ii} y_i}{1-h_{ii}} = \frac{\hat{y}_i - h_{ii} e_i - h_{ii} \hat{y}_i}{1-h_{ii}} = \hat{y}_i - h_{ii} e_i$$

$$\text{Var}(\hat{y}_{i(\lambda)}) = \text{Var}(\hat{y}_i) = h_{ii} \sigma^2$$

$$\therefore h_{ii} \sigma^2$$

4.8  $\hat{\beta} - \hat{\beta}_{(\lambda)} = \frac{(x'x)^{-1}x_i e_i}{1-h_{ii}}$

$$\hat{\beta}_{(\lambda)} = (x_i' x_i)^{-1} x_i' y_{(\lambda)} = (x'x - x_i x_i')^{-1} (x'y - x_i y_i) \quad \because \text{using update formula}$$

$$x'x = A, \quad x_i = u, \quad x_i' = v'$$

$$\hat{\beta}_{(\lambda)} = \left( (x'x)^{-1} + \frac{(x'x)^{-1}x_i x_i' (x'x)^{-1}}{1-x_i' (x'x)^{-1} x_i} \right) (x'y - x_i y_i) = \hat{\beta} + \frac{(x'x)^{-1}x_i x_i' (x'x)^{-1}}{1-x_i' (x'x)^{-1} x_i} (x'y - x_i y_i) - (x'x)^{-1} x_i y_i$$

$$= \hat{\beta} + \frac{(x'x)^{-1}x_i x_i' \hat{\beta}}{1-h_{ii}} - \frac{(x'x)^{-1}x_i h_{ii} y_i}{1-h_{ii}} - (x'x)^{-1} x_i y_i$$

$$= \hat{\beta} + \frac{(x'x)^{-1}}{1-h_{ii}} (x_i y_i - x_i h_{ii} y_i - (1-h_{ii}) x_i y_i) = \hat{\beta} - \frac{(x'x)^{-1}}{1-h_{ii}} x_i (y_i - \hat{y}_i)$$

$$= \hat{\beta} - \frac{(x'x)^{-1}x_i e_i}{1-h_{ii}}$$

$$\therefore \hat{\beta} - \hat{\beta}_{(\lambda)} = \frac{(x'x)^{-1}x_i e_i}{1-h_{ii}}$$



5장 과제.

5.3  $n=20, X_1 \sim X_4$

$$C_p = \frac{SSE_p}{S^2} - (n-2p)$$

↓ 최대도형  $SSE_p = (n-p)S^2$

$$\therefore C_p = p$$

$$\therefore 5$$

5.4.  $n=10, S^2=3$

$$PRESS_p = \sum_{i=1}^{10} \left( \frac{e_i}{1-h_{ii}} \right)^2 = \frac{e_1^2 + \dots + e_{10}^2}{(1-h)^2} \quad \because h_{11} = \dots = h_{10,10} = h$$

$$= \frac{\sum (e_i)^2 - 0}{n(1-h)^2} = \frac{\text{var}(e_i)}{n(1-h)^2} = \frac{(1-h)S^2}{10(1-h)^2} = \frac{3}{10(1-h)}$$

$$\therefore \frac{3}{10(1-h)}$$

5.5.  $X \geq 0, \text{Var}(X) \Rightarrow \text{finite}, E(X) = \mu.$

$\phi(x) = x^2$  이라 가정하면.

$\phi$ 는 열린구간  $I$ 에서 아래로 볼록 (convex function)이고,

$P(X \in I) = 1, E(X) = \mu < \infty$  이므로,

$\phi(E(X)) = \mu^2 \leq E(X^2)$  이 항상 성립된다.  $\therefore$  Jensen 부등식.

$$\therefore \mu^2 < E(X^2).$$