

Properties of estimators

1. $\hat{\beta}$

For $p = 1$

By the Theorem 3.1 in page 11,

$$\begin{aligned}\hat{\beta}_0 &= \sum_{i=1}^n \left(\frac{1}{n} - \frac{(x_{i1} - \bar{x}_1)\bar{x}_1}{S_{x_1x_1}} \right) y_i \\ \hat{\beta}_1 &= \sum_{i=1}^n \left(\frac{x_{i1} - \bar{x}_1}{S_{x_1x_1}} \right) y_i\end{aligned}$$

Then

$$\begin{aligned}Var(\hat{\beta}_0) &= \left(\frac{1}{n} + \frac{\bar{x}_1^2}{S_{x_1x_1}} \right) \sigma^2 \\ &= \frac{\sigma^2 \sum_{i=1}^n x_{i1}^2}{nS_{x_1x_1}} \\ Var(\hat{\beta}_1) &= \frac{\sigma^2}{S_{x_1x_1}} \\ Cov(\hat{\beta}_0, \hat{\beta}_1) &= -\frac{\sigma^2 \sum_{i=1}^n x_{i1}}{nS_{x_1x_1}}\end{aligned}$$

$$\begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{pmatrix} \sim N \left(\begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix}, \begin{pmatrix} \sigma^2 \left(\frac{1}{n} + \frac{\bar{x}_1^2}{S_{x_1x_1}} \right) & -\frac{\bar{x}_1 \sigma^2}{S_{x_1x_1}} \\ -\frac{\bar{x}_1 \sigma^2}{S_{x_1x_1}} & \frac{\sigma^2}{S_{x_1x_1}} \end{pmatrix} \right)$$

For any p

By the Theorem 3.2 in page 14,

$$\hat{\beta} \sim N(\beta, \sigma^2(X^T X)^{-1})$$

2. \hat{e}_i

For $p = 1$

$$\hat{e}_i = \sum_{j=1}^n (\delta_{ij} - (c_j + d_j x_{i1})) y_j$$

$$\text{where } c_j = \frac{1}{n} - \frac{(x_{j1} - \bar{x}_1)\bar{x}_1}{S_{x_1x_1}}, d_j = \frac{x_{j1} - \bar{x}_1}{S_{x_1x_1}} \text{ and } \delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases}$$

For any p

$$\hat{\mathcal{E}} = (\mathcal{L} - \mathcal{H}) \mathcal{Y}$$

3. Residual Sum of Squares

For $p=1$

$$E(S_{yy}) = (n-1)\sigma^2 + \beta_1^2 Sx_1x_1 \quad \text{and}$$

$$E(\hat{\beta}_1^2) = \text{Var}(\hat{\beta}_1) + (E(\hat{\beta}_1))^2$$

$$E(RSS) = (n-2)\sigma^2$$

$$\Rightarrow \hat{\sigma}^2 = \frac{RSS}{n-2}$$

For any p

By the Theorem 3.3 in page 16,

$$E(RSS) = (n-p')\sigma^2.$$

Thus,

$$\hat{\sigma}^2 \text{ (unbiased estimator)} = \frac{RSS}{n-p'}$$