

Exercise 2.

Given :

$$Y_i = \beta x_i + e_i$$

$$e_i \sim N(0, \sigma^2).$$

a) show that the least squares estimate of the slope is given by.

$$\hat{\beta} = \frac{\sum x_i y_i}{\sum x_i^2}$$

Answer :

Least squares estimate

$$Q = \sum (y_i - \beta x_i)^2$$

Derivating the equation by β .

$$\frac{dQ}{d\beta} = -2 \sum x_i (y_i - \beta x_i).$$

As the errors are independent and normally distributed with constant variance.

$$-2 \sum x_i (y_i - \hat{\beta} x_i) = 0.$$

$$\sum x_i (y_i - \hat{\beta} x_i) = 0.$$

$$\sum x_i y_i - \hat{\beta} \sum x_i^2 = 0.$$

$$\sum x_i y_i = \hat{\beta} \sum x_i^2.$$

$$\hat{\beta} = \frac{\sum x_i y_i}{\sum x_i^2}$$

b). Show that $E(\hat{\beta}) = \beta$

Answer :

~~$$E(\hat{\beta} | x) = E \left\{ \frac{\sum x_i y_i}{\sum x_i^2} \mid x \right\}$$

$$= \frac{\sum x_i \beta x_i}{\sum x_i^2}$$

$$E(\hat{\beta}) = \beta$$~~

since $\sum \bar{x}(y_i - \bar{y}) = \bar{x} \sum (y_i - \bar{y}) = 0$

$$E(\hat{\beta} | x) = E \left\{ \frac{\sum x_i (y_i - \bar{y})}{\sum (x_i - \bar{x})^2} \mid x \right\}$$

$$= \frac{\sum (x_i - \bar{x}) \{ E(y_i | x) - E(\bar{y} | x) \}}{\sum (x_i - \bar{x})^2}$$

$$= \frac{\sum (x_i - \bar{x}) \{ (\beta x_i + \epsilon - \beta \bar{x}) \}}{\sum (x_i - \bar{x})^2}$$

$$= \frac{\sum (x_i - \bar{x}) \beta (x_i - \bar{x})}{\sum (x_i - \bar{x})^2}$$

$$= \beta$$

$$E(\hat{\beta}) = \beta.$$

This shows that $\hat{\beta} = b$ is unbiased for β

c). Show that $\text{Var}(\hat{\beta}) = \frac{\sigma^2}{\sum x_i^2}$.

Answer:

$$\hat{\sigma}^2 = \text{MSE} = \frac{\sum e_i^2}{n-1} = \frac{\text{SSE}}{n-1}$$

Hence, $E(\hat{\sigma}^2) = E(\text{MSE}) = \sigma^2$.

$$\begin{aligned} \hat{\sigma}^2 = S_e &= \sqrt{\frac{\sum (y_i - (\beta_0 + \beta_1 x_i))^2}{n-1}} \\ &= \sqrt{\frac{\sum e_i^2}{n-1}} \\ &= \sqrt{\frac{\text{SSE}}{n-1}} = \sqrt{\text{MSE}} \end{aligned}$$

$n-1$ is used as there is only one estimator β .