

Question 3. In the two-variable model

$$y_i = \beta_1 x_{1i} + \beta_2 x_{2i} + \epsilon_i, \quad i = 1, \dots, 11$$

Suppose that $x'_1 x_1 = 2, x'_2 x_2 = 2, x'_1 x_2 = 1, x'_1 y = 2, x'_2 y = 1, y' y = 7/3$ where x_1, x_2 and y are the column vectors with typical elements x_{1i}, x_{2i} and y_i respectively.

Assume $\epsilon_i \sim \text{i.i.d. } N(0, \sigma_\epsilon^2)$. Suppose you would like to make out-of-sample predictions about the left-hand-side (dependent) variable for two hypothetical observations with the following characteristics:

Obs.	x_1	x_2
12	5	-2
13	3	-7

sol)

$$x'_1 x_1 = \begin{bmatrix} x_{11} & \cdots & x_{1i} \end{bmatrix} \begin{bmatrix} x_{11} \\ \vdots \\ x_{1i} \end{bmatrix} = \sum x_{1i}^2$$

$$x'_1 y = \begin{bmatrix} x_{11} & \cdots & x_{1i} \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_i \end{bmatrix} = \sum x_{1i} y_i$$

$$y' y = \begin{bmatrix} y_1 & \cdots & y_i \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_i \end{bmatrix} = \sum y_i^2$$

$$x'_2 x_2 = \sum x_{2i}^2$$

$$x'_2 y = \sum x_{2i} y_i$$

$$x'_1 x_2 = \sum x_{1i} x_{2i}$$

Denote

$$X = \begin{bmatrix} x_{11} & x_{21} \\ \vdots & \vdots \\ x_{1i} & x_{2i} \end{bmatrix} \quad X' = \begin{bmatrix} x_{11} & \cdots & x_{1i} \\ x_{21} & \cdots & x_{2i} \end{bmatrix} \quad y = \begin{bmatrix} y_1 \\ \vdots \\ y_i \end{bmatrix}$$

Then

$$X^T X = \begin{bmatrix} x_{11} & \cdots & x_{1i} \\ x_{21} & \cdots & x_{2i} \end{bmatrix} \begin{bmatrix} x_{11} & x_{21} \\ \vdots & \vdots \\ x_{1i} & x_{2i} \end{bmatrix} = \begin{bmatrix} \sum_i x_{1i}^2 & \sum_i x_{1i} x_{2i} \\ \sum_i x_{2i} x_{1i} & \sum_i x_{2i}^2 \end{bmatrix} = \begin{bmatrix} x'_1 x_1 & x'_1 x_2 \\ x'_2 x_1 & x'_2 x_2 \end{bmatrix} = \begin{bmatrix} 2 & 1 \\ 1 & 2 \end{bmatrix}$$

$$(X^T X)^{-1} = \frac{1}{2 \cdot 2 - 1 \cdot 1} \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix}$$

$$X' y = \begin{bmatrix} x_{11} & \cdots & x_{1i} \\ x_{21} & \cdots & x_{2i} \end{bmatrix} \begin{bmatrix} y_1 \\ \vdots \\ y_i \end{bmatrix} = \begin{bmatrix} \sum_i x_{1i} y_i \\ \sum_i x_{2i} y_i \end{bmatrix} = \begin{bmatrix} x'_1 y \\ x'_2 y \end{bmatrix} = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

Using the formula

$$\begin{aligned} \hat{\beta} &= \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix} = (X' X)^{-1} X' y \\ &= \frac{1}{3} \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} 2 \\ 1 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 3 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \\ \therefore \hat{\beta}_1 &= 1, \hat{\beta}_2 = 0 \end{aligned}$$

Insert the observations in the formula

$$\hat{y}_{12} = \hat{\beta}_1 x_{1,12} + \hat{\beta}_2 x_{2,12} = 1 \cdot 5 + 0 \cdot (-2) = 5$$

$$\hat{y}_{13} = \hat{\beta}_1 x_{1,12} + \hat{\beta}_2 x_{2,12} = 1 \cdot 3 + 0 \cdot (-7) = 3$$

$$\therefore \hat{y} = x_{1i}$$

$$\begin{aligned}\hat{\sigma}^2 &= \frac{1}{n-2} \sum \hat{\epsilon}_i^2 = \frac{1}{n-2} \sum (y_i - \hat{y})^2 = \frac{1}{n-2} \sum (y_i - x_{1i})^2 \\ &= \frac{1}{n-2} \left(\sum y_i^2 - 2 \sum y_i x_{1i} + \sum x_{1i}^2 \right) = \frac{1}{11-2} \left(\frac{7}{3} - 2 \cdot 2 + 2 \right) = \frac{1}{27}\end{aligned}$$

1. Construct 80% prediction interval for the dependent variable y_{12} and y_{13} .

Let X^* be a row vector containing the values of the future observation.

$$y_f = X\hat{\beta} + \hat{\epsilon} \quad , \quad \hat{\beta} = (X'X)^{-1} X'y$$

If, $\text{Var}(\hat{\epsilon}) = \hat{\sigma}_\epsilon^2 I$, X is Full rank

$$\begin{aligned}\text{Var}(y_f) &= \text{Var}(X^* \hat{\beta} + \hat{\epsilon}) \\ &= \text{Var}(X^* (X'X)^{-1} X'y) + \text{Var}(\hat{\epsilon}) \\ &= X^* (X'X)^{-1} X' \text{Var}(y) [X^* (X'X)^{-1} X']' + \hat{\sigma}^2 \\ &= \hat{\sigma}^2 X^* (X'X)^{-1} X' X (X'X)^{-1} X^{*'} + \hat{\sigma}^2 \\ &= \hat{\sigma}^2 (X^* (X'X)^{-1} X^{*'} + 1)\end{aligned}$$

Denote

$$X_{12} = \begin{bmatrix} 5 & -2 \end{bmatrix}$$

$$X'_{12} = \begin{bmatrix} 5 \\ -2 \end{bmatrix}$$

$$(X'X)^{-1} = \frac{1}{3} \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix}$$

$$\hat{\sigma}^2 = \frac{1}{27}$$

$$\text{Var}(y_{12}) = \frac{1}{27} \left(\begin{bmatrix} 5 & -2 \end{bmatrix} \frac{1}{3} \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} 5 \\ -2 \end{bmatrix} + 1 \right) = 1$$

$$\text{Var}(y_{13}) = \frac{1}{27} \left(\begin{bmatrix} 3 & -7 \end{bmatrix} \frac{1}{3} \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} 3 \\ -7 \end{bmatrix} + 1 \right) = \frac{1}{27} \left(\frac{158}{3} + 1 \right)$$

Thus

$$80\% \text{ PI for } y_{12} = \left[\hat{y}_{12} \pm t_{(0.1,9)} \sqrt{\text{Var}(y_{12})} \right] = 5 \pm 1.383 = [3.617, 6.383]$$

$$80\% \text{ PI for } y_{13} = \left[\hat{y}_{13} \pm t_{(0.1,9)} \sqrt{\text{Var}(y_{13})} \right] = 3 \pm 1.383 \times 1.41 = [1.050, 4.949]$$

2. Construct 80% prediction interval for the expected value of y_{12} and y_{13} .

$$\begin{aligned}
 \text{Var}(y_f | x) &= \text{Var}(X^* \hat{\beta}) \\
 &= \text{Var}(X^* (X'X)^{-1} X'y) \\
 &= X^* (X'X)^{-1} X' \text{Var}(y) [X^* (X'X)^{-1} X']' \\
 &= \hat{\sigma}^2 X^* (X'X)^{-1} X' X (X'X)^{-1} X^{*'} \\
 &= \hat{\sigma}^2 X^* (X'X)^{-1} X^{*'}
 \end{aligned}$$

$$\begin{aligned}
 \text{Var}(y_{12} | x_{12}) &= \frac{1}{27} \left(\begin{bmatrix} 5 & -2 \end{bmatrix} \frac{1}{3} \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} 5 \\ -2 \end{bmatrix} \right) = \frac{26}{27} \\
 \text{Var}(y_{13} | x_{13}) &= \frac{1}{27} \left(\begin{bmatrix} 3 & -7 \end{bmatrix} \frac{1}{3} \begin{bmatrix} 2 & -1 \\ -1 & 2 \end{bmatrix} \begin{bmatrix} 3 \\ -7 \end{bmatrix} \right) = \frac{1}{27} \cdot \frac{158}{3} = 1.951
 \end{aligned}$$

$$80\% \text{ PI for } E(y_{12} | x_{12}) = \left[\hat{y}_{12} \pm t_{(0.1,9)} \cdot \sqrt{\text{Var}(y_{12} | x_{12})} \right] = 5 \pm 1.383 \cdot \frac{26}{27} = [3.642, 6.357]$$

$$80\% \text{ PI for } E(y_{13} | x_{13}) = \left[\hat{y}_{13} \pm t_{(0.1,9)} \cdot \sqrt{\text{Var}(y_{13} | x_{13})} \right] = 3 \pm 1.383 \cdot 1.397 = [1.068, 4.932]$$

3. Do the answers above differ? Why?

Prediction intervals for y_{12} and y_{13} are wider than PI for $E[y_{12} | x_{12}]$ and $E[y_{13} | x_{13}]$.
Because PI for y_{12} and y_{13} including the uncertainty (the error term ε).