

# Problem from STAT5030

1. Consider the linear model

$$Y_{n \times 1} = X\beta + \epsilon, \quad E(\epsilon) = 0, \quad \text{Cov}(\epsilon) = \sigma^2 V$$

with  $\beta = (\beta_1, \dots, \beta_p)'$  and sample data  $(X, Y_{n \times 1})$ . Let  $V$  be a known positive definite matrix.

$$(X'V^{-1}X)^{-1}X'V^{-1}Y$$

(a) What is the Generalized Least Squares estimator of  $\beta$ ?

(b) (Prediction) Let

$$X_0 = \begin{bmatrix} X_{n+1,1} & X_{n+1,2} & \dots & X_{n+1,p} \\ X_{n+2,1} & X_{n+2,2} & \dots & X_{n+2,p} \\ \vdots & \vdots & \ddots & \vdots \\ X_{n+m,1} & X_{n+m,2} & \dots & X_{n+m,p} \end{bmatrix}$$

$$Xa = X_0 \\ \exists \hat{a} \text{ s.t. } X\hat{a} = X_0 \\ Xp = X_0$$

and  $Y_0$  be the values that we are interested to predict given  $X_0$ . The column space of  $X_0$  is a subset of the column space of  $X$ . Assume that

$$Y_0 = X_0\beta + \epsilon_0, \quad E(\epsilon_0) = 0, \quad \text{Cov}(\epsilon_0) = \sigma^2 V_0$$

$$A'VA$$

with  $V_0$  be a known positive definite matrix. In addition, assume that  $\text{Cov}(\epsilon, \epsilon_0) = 0$  and  $X_0\beta$  is estimable.

- What is the prediction of  $Y_0$  (denoted by  $\hat{Y}_0$ )?
- What is  $\text{Cov}(\hat{Y}_0 - Y_0)$ ?

(c) Let  $X_0$  be the same as given in Part (b), and the model is also the same EXCEPT that  $\text{Cov}(\epsilon, \epsilon_0) = \sigma^2 W$ .

Now, let  $Y_0^* = CY$  be a linear unbiased predictor of  $Y_0$ . Define the prediction mean squared error (PMSE) of  $Y_0^*$  as

$$E(Y_0^* - Y_0)'A(Y_0^* - Y_0)$$

where  $A$  is a positive definite matrix.

i. Prove that the PMSE of  $Y_0^*$  is

$$\beta'(CX - X_0)'A(CX - X_0)\beta + \sigma^2 \text{tr}[A(CVC' + V_0 - 2CW)]$$

ii. The best (minimum PMSE) linear unbiased estimator of  $Y_0$  is

$$Y_0^* = \hat{Y}_0 + D$$

Find  $D$ .

$$Y_0^* = X(X'V^{-1}X)^{-1}X'V^{-1}Y + D \triangleq CX + D, \quad Y_0^* - Y_0 \sim (D, \sigma^2[CVC' + V_0 - 2CW])$$

$$\text{PMSE of } Y_0^* = DAD + \sigma^2 \text{tr}[A(CVC' + V_0 - 2CW)]$$

attains minimum at  $D=0$

2. Let

$$X = \begin{bmatrix} X_1 \\ X_2 \end{bmatrix}, \quad Y = \begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix}$$

and assume that  $X$  and  $X_1$  have full column rank. Consider the linear model

$$Y = X\beta + \epsilon$$

where  $\epsilon \sim N(0, \sigma^2 I)$ . Let  $\hat{\beta}$  be the least squares estimator of  $\beta$  and  $\hat{Y} = X\hat{\beta} = (\hat{Y}_1, \hat{Y}_2)'$ . Further, for the linear model

$$Y_1 = X_1\beta^* + \epsilon^*$$

where  $\epsilon^* \sim N(0, \sigma^2 I)$ , the least squares estimator of  $\beta^*$  is  $\hat{\beta}^*$ . Let

$$\hat{Y}^* = X\hat{\beta}^* = \begin{bmatrix} \hat{Y}_1^* \\ \hat{Y}_2^* \end{bmatrix}$$

Define

$$Y - \hat{Y} = \begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} - \begin{bmatrix} \hat{Y}_1 \\ \hat{Y}_2 \end{bmatrix} = \begin{bmatrix} e_1 \\ e_2 \end{bmatrix}$$

$$Y - \hat{Y}^* = \begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} - \begin{bmatrix} \hat{Y}_1^* \\ \hat{Y}_2^* \end{bmatrix} = \begin{bmatrix} e_1^* \\ e_2^* \end{bmatrix}$$

(a) Prove that

$$\hat{\beta} - \hat{\beta}^* = M_1^{-1} X_2' e_2$$

where  $M_1 = X_1' X_1$ .

(b) Express  $e_2$  in terms of  $e_2^*$  and rewrite the expression of  $\hat{\beta} - \hat{\beta}^*$  in Part (a)

(c) The following is a data set with sample size = 7

$x$	-3	-2	-1	0	1	2	3
$y$	14	7	.	.	.	.	-2

For the above data and with a simple linear regression model, the parameter estimate  $\hat{\beta}^* = (6, -2)'$ .

Suppose an additional observation  $(x, y) = (4, 4)$  is obtained (You now have 8 pairs of  $(x, y)$  in your updated dataset), compute the new parameter estimate  $\hat{\beta}$ . (Hint: use Parts (a) and (b))

$$X_1 = X \quad Y_1 = Y$$

$$X_2 = 4 \quad Y_2 = 4$$

$$e_2^* = Y_2 - X_2 \hat{\beta}^*$$

$$= Y_2 - X_2 (X_1' X_1)^{-1} (X_1' Y_1)$$

$$\hat{\beta} = (X_1' X_1)^{-1} (X_1' Y_1)$$

$$e_2 = Y_2 - X_2 \hat{\beta}$$

$$X_2' X_2 (X_1' X_1 + X_2' X_2)^{-1} (X_1' Y_1 + X_2' Y_2)$$

$$X_1' X_1 (X_1' X_1 + X_2' X_2)^{-1} (X_1' Y_1 + X_2' Y_2)$$

$$= X_1' X_1 + X_2' X_2$$

$$\hat{\beta} = (X' X)^{-1} (X' Y)$$

$$= (X_1' X_1 + X_2' X_2)^{-1} (X_1' Y_1 + X_2' Y_2)$$

$$\hat{\beta} = \begin{pmatrix} X_1 \\ X_2 \end{pmatrix}$$

$$e_1 = Y_1 - X_1 \hat{\beta}$$

$$= \begin{pmatrix} X_1 \hat{\beta} \\ X_2 \hat{\beta} \end{pmatrix}$$

$$\hat{\beta}^* = (X_1' X_1)^{-1} (X_1' Y_1)$$

$$X_1' Y_1$$

$$\hat{\beta}^* = (X_1' X_1 + X_2' X_2)^{-1} (X_1' Y_1 + X_2' Y_2)$$

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