

**(a)**

Compute least squares estimators for  $c$  and  $d$  in

$$y_n = cx_n + d + r_n \quad (1)$$

by computing the minimum of  $J(c, d) = \sum_{n=1}^N (y_n - cx_n - d)^2$ .

**Solution:**

We differentiate  $J$  with  $c$

$$\frac{\partial J}{\partial c} = \sum_{n=1}^N 2(y_n - cx_n - d)(-x_n) = 2 \sum_{n=1}^N (-x_n y_n + cx_n^2 + dx_n) = 0$$

$$-\sum_{n=1}^N x_n y_n + c \sum_{n=1}^N x_n^2 + \sum_{n=1}^N dx_n = 0 \quad (2)$$

$$\hat{c} = \frac{\sum_{n=1}^N x_n y_n - \sum_{n=1}^N dx_n}{\sum_{n=1}^N x_n^2} \quad (3)$$

Then, we differentiate  $J$  with  $d$

$$\frac{\partial J}{\partial d} = \sum_{n=1}^N 2(y_n - cx_n - d) = 0 \quad (4)$$

$$\hat{d} = \frac{1}{N} \left( \sum_{n=1}^N y_n - \sum_{n=1}^N \hat{c} x_n \right) = \bar{y}_n - \hat{c} \bar{x}_n \quad (5)$$

Substitute  $\hat{d}$  from eq (5) into eq (3)

$$\hat{c} = \frac{\sum_{n=1}^N x_n y_n - (\bar{y}_n - \hat{c} \bar{x}_n) \sum_{n=1}^N x_n}{\sum_{n=1}^N x_n^2} \quad (6)$$

Reorganize eq (6)

$$\begin{aligned} \hat{c} \left( \sum_{n=1}^N x_n^2 \right) &= \sum_{n=1}^N x_n y_n - (\bar{y}_n - \hat{c} \bar{x}_n) \sum_{n=1}^N x_n \\ \hat{c} \left( \sum_{n=1}^N x_n^2 - \bar{x}_n \sum_{n=1}^N x_n \right) &= \sum_{n=1}^N x_n y_n - \bar{y}_n \sum_{n=1}^N x_n \end{aligned} \quad (7)$$

The estimator  $\hat{c}$  is

$$\hat{c} = \frac{\sum_{n=1}^N x_n y_n - \bar{y}_n \sum_{n=1}^N x_n}{\sum_{n=1}^N x_n^2 - \bar{x}_n \sum_{n=1}^N x_n} = \frac{\sum_{n=1}^N x_n y_n - N \bar{x}_n \bar{y}_n}{\sum_{n=1}^N x_n^2 - N \bar{x}_n^2} \quad (8)$$

The estimator  $\hat{d}$  is

$$\hat{d} = \bar{y}_n - \hat{c}\bar{x}_n \quad (9)$$

(b)

Convert the above problem into a problem of the form  $J(\mathbf{x}) = (\mathbf{y} - \mathbf{G} \mathbf{x})^T (\mathbf{y} - \mathbf{G} \mathbf{x})$ , minimize it with the given matrix expressions in the course book, and show that the result is the same as in (a). Hint: put  $x = [c, d]$ .

**Solution:**

Let  $\mathbf{x} = [c, d]^T$

$$y_n = [x_n \ 1] \begin{bmatrix} c \\ d \end{bmatrix} + r_n, \mathbf{G} = [x_n \ 1] \quad (10)$$

$$\begin{aligned} \hat{\mathbf{X}}_{LS} &= (\mathbf{G}^T \mathbf{G})^{-1} \mathbf{G}^T \mathbf{y} \\ &= \left( \begin{bmatrix} \mathbf{X}^T \\ \mathbf{1}_N \end{bmatrix} \begin{bmatrix} \mathbf{X} & \mathbf{1}_N \end{bmatrix} \right)^{-1} \begin{bmatrix} \mathbf{X} \\ \mathbf{1}_N \end{bmatrix} \mathbf{y} \\ &= \left( \begin{bmatrix} \mathbf{X}^T \mathbf{X} & \mathbf{X}^T \\ \mathbf{X} & N \end{bmatrix} \right)^{-1} \begin{bmatrix} \mathbf{X} \\ \mathbf{1}_N \end{bmatrix} \mathbf{y} \end{aligned} \quad (11)$$

Let

$$A = \begin{bmatrix} \mathbf{X}^T \mathbf{X} & \mathbf{X}^T \\ \mathbf{X} & N \end{bmatrix}$$

Then,

$$\begin{aligned} |\mathbf{A}| &= N \mathbf{X}^T \mathbf{X} + \mathbf{X}^T \mathbf{X} \\ &= N \sum_{n=1}^N x_n^2 - \left( \sum_{n=1}^N x_n \right)^2 \\ &= N \sum_{n=1}^N x_n^2 - N^2 \bar{x}^2 \end{aligned} \quad (12)$$

$$\mathbf{A}^{-1} = \frac{1}{|\mathbf{A}|} \begin{bmatrix} N & -\mathbf{X} \\ -\mathbf{X}^T & \mathbf{X}^T \mathbf{X} \end{bmatrix} \quad (13)$$

Substitute eq (13) back to (11),

$$\begin{aligned} \begin{bmatrix} \hat{c} \\ \hat{d} \end{bmatrix} &= \begin{bmatrix} \frac{1}{|\mathbf{A}|} \sum_{n=1}^N x_n y_n - \frac{1}{|\mathbf{A}|} \sum_{n=1}^N x_n \sum_{n=1}^N y_n \\ -\frac{1}{|\mathbf{A}|} \sum_{n=1}^N x_n \sum_{n=1}^N x_n y_n + \frac{1}{|\mathbf{A}|} \sum_{n=1}^N x_n^2 \sum_{n=1}^N y_n \end{bmatrix} \\ &= \begin{bmatrix} \frac{\sum_{n=1}^N x_n y_n - N \bar{x} \bar{y}}{\sum_{n=1}^N x_n^2 - N \bar{x}^2} \\ \bar{y} - \hat{c} \bar{x} \end{bmatrix} \end{aligned} \quad (14)$$