

## Problem Set 9

You are strongly encouraged to solve the following exercises before next week's tutorial:

- Starting on page 230 (end of Chapter 13): 3, 6, 7
- Starting on page 591 (end of Chapter 14): 2, 3, 7, 11, 21.

### Additional Exercise:

In class we proved that the variance of the least squares estimator of the linear regression slope was

$$\text{Var}[\hat{\beta}_1] = \frac{\sigma^2}{\sum_j (x_j - \bar{x})^2}.$$

We also managed to express

$$\hat{\beta}_1 = \frac{\sum_i (x_i - \bar{x})y_i}{\sum_j (x_j - \bar{x})^2} \quad \text{and} \quad \hat{\beta}_0 = \sum_i \left[ \frac{1}{n} - \frac{\bar{x}(x_i - \bar{x})}{\sum_j (x_j - \bar{x})^2} \right] y_i.$$

- (a) Show that  $\hat{\beta}_0$  is an unbiased estimator of  $\beta_0$ .
- (b) Calculate the variance of  $\hat{\beta}_0$ .
- (c) Calculate  $\text{Cov}(\hat{\beta}_0, \hat{\beta}_1)$ .
- (d) Show that  $\hat{\beta}_1 = r_{xy} \frac{S_Y}{S_X}$ .

### Solution:

- (a) First note that since  $\mathbb{E}[\varepsilon_i] = 0 \ \forall i$ ,

$$\mathbb{E}[\bar{y}] = \frac{1}{n} \sum_{i=1}^n \mathbb{E}[y_i] = \frac{1}{n} \sum_{i=1}^n \mathbb{E}[\beta_0 + \beta_1 x_i + \varepsilon_i] = \beta_0 + \beta_1 \bar{x}.$$

Now,

$$\mathbb{E}[\hat{\beta}_0] = \mathbb{E}[\bar{y} - \hat{\beta}_1 \bar{x}] = \mathbb{E}[\bar{y}] - \bar{x} \mathbb{E}[\hat{\beta}_1] = \beta_0 + \beta_1 \bar{x} - \beta_1 \bar{x} = \beta_0.$$

$$\begin{aligned} \text{(b)} \quad \text{Var}[\hat{\beta}_0] &= \sum_i \left[ \frac{1}{n} - \frac{\bar{x}(x_i - \bar{x})}{\sum_j (x_j - \bar{x})^2} \right]^2 \text{Var}[y_i] = \sigma^2 \sum_i \left[ \frac{1}{n} - \frac{\bar{x}(x_i - \bar{x})}{\sum_j (x_j - \bar{x})^2} \right]^2 \\ &= \sigma^2 \sum_i \left[ \frac{1}{n^2} - \frac{2\bar{x}(x_i - \bar{x})}{n \sum_j (x_j - \bar{x})^2} + \frac{\bar{x}^2 (x_i - \bar{x})^2}{\left\{ \sum_j (x_j - \bar{x})^2 \right\}^2} \right] \\ &= \sigma^2 \left[ \frac{1}{n} - \underbrace{\frac{2\bar{x} \sum_i (x_i - \bar{x})}{n \sum_j (x_j - \bar{x})^2}}_0 + \frac{\bar{x}^2 \sum_i (x_i - \bar{x})^2}{\left\{ \sum_j (x_j - \bar{x})^2 \right\}^2} \right] = \sigma^2 \left[ \frac{1}{n} + \frac{\bar{x}^2}{\sum_j (x_j - \bar{x})^2} \right]. \end{aligned}$$

$$\begin{aligned} \text{(c)} \quad \text{Cov}(\hat{\beta}_0, \hat{\beta}_1) &= \text{Cov}(\bar{y} - \bar{x} \hat{\beta}_1, \hat{\beta}_1) = \text{Cov}(\bar{y}, \hat{\beta}_1) - \bar{x} \text{Var}[\hat{\beta}_1] \\ &= \text{Cov} \left( \frac{1}{n} \sum_k y_k, \frac{\sum_i (x_i - \bar{x})}{\sum_j (x_j - \bar{x})^2} y_i \right) - \frac{\sigma^2 \bar{x}}{\sum_j (x_j - \bar{x})^2} \\ &= \frac{1}{n \sum_j (x_j - \bar{x})^2} \sum_k \sum_i (x_i - \bar{x}) \text{Cov}(y_k, y_i) - \frac{\sigma^2 \bar{x}}{\sum_j (x_j - \bar{x})^2} \\ &= \frac{1}{n \sum_j (x_j - \bar{x})^2} \sum_i (x_i - \bar{x}) \text{Cov}(y_i, y_i) - \frac{\sigma^2 \bar{x}}{\sum_j (x_j - \bar{x})^2} \\ &= \frac{\sigma^2}{n \sum_j (x_j - \bar{x})^2} \underbrace{\sum_i (x_i - \bar{x})}_0 - \frac{\sigma^2 \bar{x}}{\sum_j (x_j - \bar{x})^2} \\ &= -\frac{\sigma^2 \bar{x}}{\sum_j (x_j - \bar{x})^2}. \end{aligned}$$

$$\text{(d)} \quad \hat{\beta}_1 = \frac{S_{xy}}{S_x^2} = \frac{S_{xy}}{S_x S_x} \cdot \frac{S_y}{S_y} = \frac{S_{xy}}{S_x S_y} \cdot \frac{S_y}{S_x} = r_{xy} \frac{S_y}{S_x}.$$