

7. It is claimed in the text that in the case of simple linear regression of Y onto X , the R^2 statistic (3.17) is equal to the square of the correlation between X and Y (3.18). Prove that this is the case. For simplicity, you may assume that $\bar{x} = \bar{y} = 0$.

7. For a simple linear regression with $\bar{x} = \bar{y} = 0$, $\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} = 0$, $\hat{\beta}_1 = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2} = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2}$

$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{\beta}_1 x_i)^2}{\sum_{i=1}^n y_i^2}$

$\text{cov}(X, Y) = \frac{1}{n-1} \sum_{i=1}^n (x_i y_i)$

$\text{var}(X) = \frac{1}{n-1} \sum_{i=1}^n x_i^2$, $\text{var}(Y) = \frac{1}{n-1} \sum_{i=1}^n y_i^2$

$= 1 - \frac{\sum_{i=1}^n y_i^2 - 2\hat{\beta}_1 \sum_{i=1}^n x_i y_i + \hat{\beta}_1^2 \sum_{i=1}^n x_i^2}{\sum_{i=1}^n y_i^2}$

$= 1 - \frac{2\hat{\beta}_1 \sum_{i=1}^n x_i y_i - \hat{\beta}_1^2 \sum_{i=1}^n x_i^2}{\sum_{i=1}^n y_i^2}$ (substitute $\hat{\beta}_1$ into it)

$= \frac{2(\sum_{i=1}^n x_i y_i)^2 - (\sum_{i=1}^n x_i y_i)^2}{\sum_{i=1}^n x_i^2 \sum_{i=1}^n y_i^2} = \frac{\sum_{i=1}^n (x_i y_i)^2}{\sum_{i=1}^n x_i^2 \sum_{i=1}^n y_i^2}$ ①

We have $r_{xy} = \frac{\text{cov}(X, Y)}{\sqrt{\text{var}(X) \text{var}(Y)}} \Rightarrow r_{xy}^2 = \frac{[\text{cov}(X, Y)]^2}{\text{var}(X) \text{var}(Y)} = \frac{(n-1)^2 (\frac{1}{n-1})^2 [\sum_{i=1}^n x_i y_i]^2}{\frac{n-1}{n-1} \sum_{i=1}^n x_i^2 \frac{n-1}{n-1} \sum_{i=1}^n y_i^2} = \frac{\sum_{i=1}^n (x_i y_i)^2}{\sum_{i=1}^n x_i^2 \sum_{i=1}^n y_i^2}$ ②

Then, in this case, $R^2 = r_{xy}^2$ □

← Official Ans

Q7. $\text{cor}(X, Y)^2 = \frac{(\sum_{i=1}^n x_i y_i)^2}{(\sum_{i=1}^n x_i^2) \cdot (\sum_{i=1}^n y_i^2)}$

← My Sol

$R^2 = \frac{\text{SS}_{\text{reg}}}{\text{TSS}} = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^n (y_i - \bar{y})^2} = \frac{\sum_{i=1}^n \hat{y}_i^2}{\sum_{i=1}^n y_i^2}$

$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 \cdot x_i$ $\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} = 0$ $\hat{\beta}_1 = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2}$

$\therefore \hat{y}_i = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2} \cdot x_i$

$\therefore \sum_{i=1}^n \hat{y}_i^2 = \sum_{i=1}^n \left(\frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n x_i^2} \right)^2 \cdot x_i^2 = \frac{(\sum_{i=1}^n x_i y_i)^2}{(\sum_{i=1}^n x_i^2)^2} \left(\sum_{i=1}^n x_i^2 \right) = \frac{(\sum_{i=1}^n x_i y_i)^2}{\sum_{i=1}^n x_i^2}$

$\therefore R^2 = \frac{(\sum_{i=1}^n x_i y_i)^2}{\sum_{i=1}^n x_i^2} \cdot \frac{1}{\sum_{i=1}^n y_i^2} = \frac{(\sum_{i=1}^n x_i y_i)^2}{(\sum_{i=1}^n x_i^2) \cdot (\sum_{i=1}^n y_i^2)} = \text{cor}(X, Y)^2$

(a)

In the simple regression model, suppose the value of the predictor X is replaced by $Z = aX + b$, where $a \neq 0$ and b are constants. Thus, we are considering 2 simple regression models,

$$\text{I: } E(Y|X = x) = \beta_0 + \beta_1 x$$

$$\text{II: } E(Y|Z = z) = \gamma_0 + \gamma_1 z = \gamma_0 + \gamma_1(ax + b)$$

Find the relationships between β_0 and γ_0 ; between β_1 and γ_1 ; between the estimates of variance in the 2 regressions, and between the t -tests of $\beta_1 = 0$ and of $\gamma_1 = 0$.

(b) Suppose each value of the response Y is replaced by $V = dY$, for some $d \neq 0$, so we consider the two regression models

$$\text{I: } E(Y|X = x) = \beta_0 + \beta_1 x$$

$$\text{III: } E(V|X = x) = \delta_0 + \delta_1 x$$

Find the relationships between β_0 and δ_0 ; between β_1 and δ_1 ; between the estimates of variance in the 2 regressions, and between the t -tests of $\beta_1 = 0$ and of $\delta_1 = 0$.

Consider the simple linear regression.

The t -test for slope as a function of the correlation Show that the t -statistic for testing the slope $\beta_1 = 0$ can be written as a function of sample size and the sample correlation r_{xy} ,

$$t = \frac{\hat{\beta}_1}{\hat{\sigma}/\sqrt{SXX}} = \sqrt{n-2} \frac{r_{xy}}{\sqrt{1-r_{xy}^2}}$$

where $SXX = \sum_{i=1}^n (x_i - \bar{x})^2$,
(2.26)

← See the

"Q4_sol.pdf"

for sol.