

HANDOUT ON THE OLS ESTIMATOR

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1. DERIVATION OF THE OLS ESTIMATOR

- (1) Consider a linear regression model with an intercept and only one explanatory variable (for n observations):

$$Y_i = \beta_0 + \beta_1 X_i + u_i.$$

Show that the least squares estimator for the slope coefficient β_1 is given by

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^n (X_i - \bar{X})^2}$$

and the least squares estimator for the intercept is given by

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{X}$$

where $\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$ and $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$.

Solution: The least-squares estimator is the solution for

$$(\hat{\beta}_0, \hat{\beta}_1)' = \arg \min_{\beta_0, \beta_1} \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_i)^2.$$

We can find the analytical solution for this minimization problem using tools from calculus. At the critical points of a function, the first derivatives must be zero. Hence, we need to take the first (partial) derivative of the objective function with respect to β_0 and β_1 , and set them to zero. This yields two equations for two unknowns for which the solution exists.

$$\begin{aligned} \frac{\partial \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_i)^2}{\partial \beta_0} &= -2 \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_i) \stackrel{set}{=} 0 \\ \frac{\partial \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_i)^2}{\partial \beta_1} &= -2 \sum_{i=1}^n X_i (Y_i - \beta_0 - \beta_1 X_i) \stackrel{set}{=} 0 \end{aligned}$$

From the first equation, we can solve for β_0 .

$$\begin{aligned} -2 \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_i) &= 0 \Rightarrow \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_i) = 0 \\ &\Rightarrow \sum_{i=1}^n (Y_i - \beta_1 X_i) - \sum_{i=1}^n \beta_0 = 0 \\ &\Rightarrow \sum_{i=1}^n (Y_i - \beta_1 X_i) = n\beta_0 \end{aligned}$$

Solution for β_0 is

$$\hat{\beta}_0 = \frac{1}{n} \sum_{i=1}^n (Y_i - \beta_1 X_i) = \frac{1}{n} \sum_{i=1}^n Y_i - \beta_1 \frac{1}{n} \sum_{i=1}^n X_i = \bar{Y} - \beta_1 \bar{X}.$$

Substituting the solution for β_0 into the second equation yields

$$\begin{aligned} -2 \sum_{i=1}^n X_i (Y_i - [\bar{Y} - \beta_1 \bar{X}] - \beta_1 X_i) &= 0 \Rightarrow \sum_{i=1}^n X_i (Y_i - [\bar{Y} - \beta_1 \bar{X}] - \beta_1 X_i) = 0 \\ &\Rightarrow \sum_{i=1}^n X_i (Y_i - \bar{Y}) - \beta_1 \sum_{i=1}^n X_i (X_i - \bar{X}) = 0. \end{aligned}$$

Hence, solution for β_1 is

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n X_i (Y_i - \bar{Y})}{\sum_{i=1}^n X_i (X_i - \bar{X})}.$$

Let's take a closer look at the numerator and the denominator. For the numerator, we have

$$\begin{aligned} \sum_{i=1}^n X_i (Y_i - \bar{Y}) &= \sum_{i=1}^n X_i Y_i - \sum_{i=1}^n X_i \bar{Y} \\ &= \sum_{i=1}^n X_i Y_i - \bar{Y} \sum_{i=1}^n X_i - n \bar{X} \bar{Y} + n \bar{X} \bar{Y} \\ &= \sum_{i=1}^n X_i Y_i - \bar{Y} \sum_{i=1}^n X_i - \bar{X} \sum_{i=1}^n Y_i + n \bar{X} \bar{Y} \\ &= \sum_{i=1}^n X_i Y_i - \bar{Y} \sum_{i=1}^n X_i - \bar{X} \sum_{i=1}^n Y_i + \sum_{i=1}^n \bar{X} \bar{Y} \\ &= \sum_{i=1}^n (X_i Y_i - \bar{Y} X_i - \bar{X} Y_i + \bar{X} \bar{Y}) \\ &= \sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y}) \end{aligned}$$

which is a measure of sample covariance between X and Y . For the denominator, we have

$$\begin{aligned} \sum_{i=1}^n X_i (X_i - \bar{X}) &= \sum_{i=1}^n X_i^2 - \sum_{i=1}^n X_i \bar{X} \\ &= \sum_{i=1}^n X_i^2 - \sum_{i=1}^n X_i \bar{X} - n \bar{X}^2 + n \bar{X}^2 \\ &= \sum_{i=1}^n X_i^2 - \bar{X} \sum_{i=1}^n X_i - \sum_{i=1}^n \bar{X} \bar{X} + \sum_{i=1}^n \bar{X}^2 \\ &= \sum_{i=1}^n X_i^2 - \bar{X} \sum_{i=1}^n X_i - \bar{X} \sum_{i=1}^n X_i + \sum_{i=1}^n \bar{X}^2 \\ &= \sum_{i=1}^n (X_i^2 - 2\bar{X} X_i + \bar{X}^2) \\ &= \sum_{i=1}^n (X_i - \bar{X})^2. \end{aligned}$$

Now we can substitute $\widehat{\beta}_1$ back to $\widehat{\beta}_0$ to obtain the solution for β_0

$$\widehat{\beta}_0 = \bar{Y} - \widehat{\beta}_1 \bar{X}.$$

2. ALGEBRAIC PROPERTIES OF THE OLS ESTIMATOR

(a) The least squares residuals sum to zero: $\sum_{i=1}^n \hat{u}_i = 0$. Note that,

$$\begin{aligned}
 \sum_{i=1}^n \hat{u}_i &= \sum_{i=1}^n (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i) \\
 &= \sum_{i=1}^n (Y_i - [\bar{Y} - \hat{\beta}_1 \bar{X}] - \hat{\beta}_1 X_i) \\
 &= \sum_{i=1}^n (Y_i - \bar{Y}) - \hat{\beta}_1 \sum_{i=1}^n (X_i - \bar{X}) \\
 &= \sum_{i=1}^n (Y_i - \bar{Y}) - \left(\frac{\sum_{i=1}^n X_i (Y_i - \bar{Y})}{\sum_{i=1}^n X_i (X_i - \bar{X})} \right) \sum_{i=1}^n (X_i - \bar{X}) \\
 &= 0,
 \end{aligned}$$

because $\sum_{i=1}^n (Y_i - \bar{Y}) = \sum_{i=1}^n Y_i - \sum_{i=1}^n \bar{Y} = n\bar{Y} - n\bar{Y} = 0$ and $\sum_{i=1}^n (X_i - \bar{X}) = \sum_{i=1}^n X_i - \sum_{i=1}^n \bar{X} = n\bar{X} - n\bar{X} = 0$.

(b) The correlation between residuals and regressors is zero: $\sum_{i=1}^n X_i \hat{u}_i = 0$. Because,

$$\begin{aligned}
 \sum_{i=1}^n X_i \hat{u}_i &= \sum_{i=1}^n X_i (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i) \\
 &= \sum_{i=1}^n X_i (Y_i - [\bar{Y} - \hat{\beta}_1 \bar{X}] - \hat{\beta}_1 X_i) \\
 &= \sum_{i=1}^n X_i (Y_i - \bar{Y}) - \hat{\beta}_1 \sum_{i=1}^n X_i (X_i - \bar{X}) \\
 &= \sum_{i=1}^n X_i (Y_i - \bar{Y}) - \left(\frac{\sum_{i=1}^n X_i (Y_i - \bar{Y})}{\sum_{i=1}^n X_i (X_i - \bar{X})} \right) \sum_{i=1}^n X_i (X_i - \bar{X}) \\
 &= \sum_{i=1}^n X_i (Y_i - \bar{Y}) - \sum_{i=1}^n X_i (Y_i - \bar{Y}) = 0.
 \end{aligned}$$

(c) The regression line passes through the sample mean: $\bar{Y} = \hat{\beta}_0 + \hat{\beta}_1 \bar{X} \equiv \bar{\hat{Y}}$. Because,

$$\begin{aligned}
 \bar{Y} &= \frac{1}{n} \sum_{i=1}^n Y_i = \frac{1}{n} \sum_{i=1}^n (\hat{Y}_i + \hat{u}_i) = \frac{1}{n} \sum_{i=1}^n \hat{Y}_i + \frac{1}{n} \sum_{i=1}^n \hat{u}_i \\
 &= \frac{1}{n} \sum_{i=1}^n (\hat{\beta}_0 + \hat{\beta}_1 X_i) + \frac{1}{n} \sum_{i=1}^n \hat{u}_i = \frac{1}{n} \sum_{i=1}^n \hat{\beta}_0 + \frac{1}{n} \sum_{i=1}^n \hat{\beta}_1 X_i + \frac{1}{n} \sum_{i=1}^n \hat{u}_i \\
 &= \frac{1}{n} \sum_{i=1}^n \hat{\beta}_0 + \hat{\beta}_1 \frac{1}{n} \sum_{i=1}^n X_i + \frac{1}{n} \sum_{i=1}^n \hat{u}_i = \hat{\beta}_0 + \hat{\beta}_1 \bar{X} + 0 \\
 &= \hat{\beta}_0 + \hat{\beta}_1 \bar{X}.
 \end{aligned}$$