

Statistical Methods II

Derivation of Least Squares Estimator

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We want to minimize the sum of squared errors:

$$\ell(\beta_0, \beta_1) = \sum_{i=1}^n [y_i - (\beta_0 + \beta_1 x_i)]^2,$$

in order to obtain the least squares estimators of β_0 and β_1 , denoted by $\hat{\beta}_0$ and $\hat{\beta}_1$, respectively. Let's work with $\hat{\beta}_0$, the least squares estimator for β_0 by taking the partial derivative:

$$\begin{aligned} \frac{\partial \ell}{\partial \beta_0} &= \frac{\partial \sum_{i=1}^n [y_i - (\beta_0 + \beta_1 x_i)]^2}{\partial \beta_0} \\ &= 2 \sum_{i=1}^n [y_i - (\beta_0 + \beta_1 x_i)] (-1) \\ &= 2 \sum_{i=1}^n -y_i + \sum_{i=1}^n (\beta_0 + \beta_1 x_i) \\ &= 2 \left[\sum_{i=1}^n -y_i + n\beta_0 + \beta_1 \sum_{i=1}^n x_i \right] \end{aligned}$$

To get $\hat{\beta}_0$, we need to set the above quantity to zero:

$$\begin{aligned} 2 \left[\sum_{i=1}^n -y_i + n\beta_0 + \beta_1 \sum_{i=1}^n x_i \right] &\stackrel{set}{=} 0 \\ \Rightarrow n\beta_0 &= \sum_{i=1}^n (y_i - \beta_1 x_i) \\ \Rightarrow \beta_0 &= \frac{\sum_{i=1}^n (y_i - \beta_1 x_i)}{n} \\ \Rightarrow \beta_0 &= \frac{\sum_{i=1}^n y_i - \beta_1 \sum_{i=1}^n x_i}{n} \\ \Rightarrow \hat{\beta}_0 &= \bar{y} - \beta_1 \bar{x} \end{aligned}$$

Next, let's work with $\hat{\beta}_1$:

$$\begin{aligned}
\frac{\partial L}{\partial \beta_1} &= \frac{\partial \sum_{i=1}^n [y_i - (\beta_0 + \beta_1 x_i)]^2}{\partial \beta_1} \\
&= \frac{\partial \sum_{i=1}^n [y_i - (\bar{y} - \beta_1 \bar{x} + \beta_1 x_i)]^2}{\partial \beta_1} \\
&= 2 \sum_{i=1}^n [y_i - \bar{y} - \beta_1 (x_i - \bar{x})] (-(x_i - \bar{x}))
\end{aligned}$$

Again, set this quantity to zero:

$$\begin{aligned}
2 \sum_{i=1}^n [y_i - \bar{y} - \beta_1 (x_i - \bar{x})] (-(x_i - \bar{x})) &\stackrel{set}{=} 0 \\
\beta_1 \sum_{i=1}^n (x_i - \bar{x})^2 &= \sum_{i=1}^n (y_i - \bar{y}) (x_i - \bar{x}) \\
\Rightarrow \hat{\beta}_1 &= \frac{\sum_{i=1}^n (y_i - \bar{y}) (x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2}
\end{aligned}$$