

M339G: September 10th, 2025.

Simple Linear Regression.

The Model.

In general: $f(x) \dots f$ is the ideal fit, i.e.,

$$Y = f(x) + \varepsilon \quad \text{w/ } \varepsilon \text{ is independent of } x \text{ and } \varepsilon \sim N(0, \sigma^2) \text{ for all predictors}$$

$$\underline{f(x) = \mathbb{E}[Y \mid X=x]}$$

Solve the optimization problem

$$\mathbb{E}[(Y - g(x))^2 \mid X=x] \rightarrow \min$$

$\hat{f} \dots$ the fitted function/fit in a family of candidates g

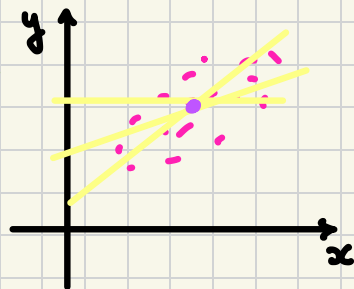
Def'n. In simple linear regression the model is

$$Y = \beta_0 + \beta_1 \cdot X + \varepsilon$$

w/ ε and X independent and $\varepsilon \sim N(0, \sigma^2)$

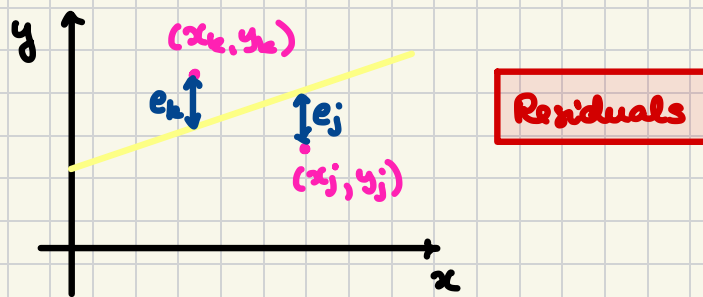
Method: Find ESTIMATORS $\hat{\beta}_0$ and $\hat{\beta}_1$ for β_0 and β_1

Set up:



data set:

$$(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$$



Every line of fit would have the form

$$\hat{y} = \hat{b}_0 + \hat{b}_1 \cdot x$$

w/ \hat{b}_0 and \hat{b}_1
"candidate"
coefficients

\Rightarrow Residuals

$$SSE = RSS = \sum_{j=1}^n (y_j - \hat{y}_j)^2 \xrightarrow{\hat{b}_0, \hat{b}_1} \min$$

$$\sum_{j=1}^n (y_j - \hat{b}_0 - \hat{b}_1 \cdot x_j)^2 \xrightarrow{\hat{b}_0, \hat{b}_1} \min$$

Additionally: For Unbiasedness: $\sum e_i = 0$ ←

Differentiate w/ respect to \hat{b}_0 and \hat{b}_1

$$\frac{\partial RSS}{\partial \hat{b}_0} = -2 \sum_{j=1}^n (y_j - \hat{b}_0 - \hat{b}_1 x_j) = 0$$

$$\begin{aligned} \left(\sum_{j=1}^n y_j = \sum_{j=1}^n (\hat{b}_0 + \hat{b}_1 x_j) \right) &= \\ &= n \hat{b}_0 + \hat{b}_1 \sum_{j=1}^n x_j \end{aligned}$$

$$\rightarrow: \bar{y} = \hat{b}_0 + \hat{b}_1 \cdot \bar{x}$$

normal equation

$$\frac{\partial RSS}{\partial \hat{b}_1} = -2 \sum_{j=1}^n ((y_j - \hat{b}_0 - \hat{b}_1 \cdot x_j) \cdot x_j)$$

= 0

$$\sum_{j=1}^n x_j y_j - \hat{b}_0 \sum_{j=1}^n x_j - \hat{b}_1 \sum_{j=1}^n x_j^2 = 0$$

$$\begin{aligned} \hat{b}_1 &= \frac{\frac{1}{n} \sum_{j=1}^n (x_j - \bar{x})(y_j - \bar{y})}{\frac{1}{n} \sum_{j=1}^n (x_j - \bar{x})^2} = \frac{n \sum_{j=1}^n x_j y_j - \sum_{j=1}^n x_j \cdot \sum_{j=1}^n y_j}{n \cdot \sum_{j=1}^n x_j^2 - (\sum_{j=1}^n x_j)^2} \\ &= \frac{\sum_{j=1}^n x_j y_j - \frac{1}{n} \sum_{j=1}^n x_j \cdot \sum_{j=1}^n y_j}{\sum_{j=1}^n x_j^2 - \frac{1}{n} (\sum_{j=1}^n x_j)^2} \end{aligned}$$

Q: $\sum_{j=1}^n e_j x_j = \cancel{X} 0$

Our estimators:

$$\hat{\beta}_1 = \frac{\text{Cov}[X, Y]}{\text{Var}[X]} = \frac{S_{xy}}{S_x^2}$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \cdot \bar{x}$$