

Model: $Y = \beta_0 + \beta_1 X + \epsilon_i$ $\epsilon_i \sim N(0, \sigma^2)$

$$E(Y) = E[\beta_0 + \beta_1 X_i + \epsilon_i]$$

$$= E[\beta_0 + \beta_1 X_i]$$

$$E(Y|X) = \beta_0 + \beta_1 X$$

$$\text{var}(Y) = \text{var}(\beta_0 + \beta_1 X + \epsilon_i)$$

$$= \text{var}(\beta_0 + \beta_1 X) + \text{var}[\epsilon_i] \quad \leftarrow \text{from independence.}$$

$$\text{var}(Y|X) = \text{var}[\epsilon_i] = \sigma^2$$

Sample of $\{(x_1, y_1) \dots (x_n, y_n)\}$

Want to find best parameter to fit data?
 \rightarrow Least Squares or MLE

Model: $y_i = \beta_0 + \beta_1 x_i + \epsilon_i$

What is β_0, β_1 ?

$$\hat{\beta} = \arg \min_{\beta_0, \beta_1} \sum_{i=1}^n (y_i - (\beta_0 + \beta_1 x_i))^2$$

If we have that $\beta_0 = 0$

$$\hat{\beta} = \arg \min_{\beta_0, \beta_1} \sum_{i=1}^n (y_i - \beta x_i)^2$$

\rightarrow Take derivative

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

$$\rightarrow \sum_{i=1}^n -2x_i (y_i - \beta x_i) = 0$$

$$\rightarrow \sum 2\beta x_i^2 = 2 \sum x_i y_i$$

$$\hat{\beta} = \frac{\sum x_i y_i}{\sum x_i^2}$$

\rightarrow LS SOLⁿ

$\hat{\beta}$ is the slope estimate & a R.V

$$\hat{\beta} = \frac{\sum x_i y_i}{\sum x_i^2}, \quad \hat{\beta} \sim N(\beta_{\text{true}}, ?)$$

if $\hat{\beta}$ unbiased $E(\hat{\beta}) = \beta_{\text{true}}$

$$E(\hat{\beta}) = \frac{1}{n} \sum_{i=1}^n \hat{\beta}_i$$

$$(?)^{1/2} = \left(\frac{1}{n-1} \sum_{i=1}^n (\hat{\beta}_i - E(\hat{\beta}))^2 \right)^{1/2}$$

→ Estimate of the
std error of $\hat{\beta}$

↓
Std deviation