Maximum Likelihood Estimation

$$\theta_{MLE} = \arg\max_{\theta \in \Theta} L(\theta)$$

the value we pick for our parameters

(out of all possible parameter values) that maximize

are the parameter values

the likelihood of the data using these parameters



 $L(y | \beta_0, \beta_1, \sigma^2) = \prod p(y_i | \beta_0, \beta_1, \sigma^2)$

likelihood function

$LL(\beta_0, \beta_1, \sigma^2) = \log L$ log-likelihood function

solved by taking partial derivatives and setting equal to 0



 ∂LL

 $\partial \mathcal{B}_0$

 ∂LL

 $\partial \beta_1$

3.4

 $\sum_{i=1}^{n} x_i y_i - n \overline{y} \overline{x} \qquad Cov(x, y)$

Var(x)

 $\sum_{i=1}^{n} x_i^2 + n\overline{x}$

[full proof: https://statproofbook.github.io/P/slr-mle]

Maximum Likelihood Estimation

$$heta_{MLE} = \mathop{\mathrm{arg\,max}}_{\theta \in \Theta} L(\theta)$$
 the likelihood of the

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likelihood function

$$L(y | \beta_0, \beta_1, \sigma^2) = \prod_{i=1}^{n} p(y_i | \beta_0, \beta_1, \sigma^2)$$

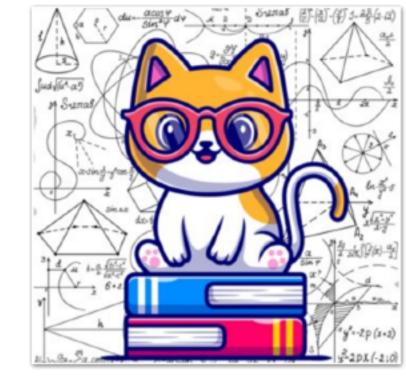
log-likelihood function

$$LL(\beta_0, \beta_1, \sigma^2) = \log L$$

solved by taking partial derivatives and setting equal to 0

$$\frac{\partial LL}{\partial \beta_0} = 0 \quad \Longrightarrow \quad \hat{\beta}_0 = \overline{y} - \hat{\beta}_1 \overline{x}$$

$$\frac{\partial LL}{\partial \beta_1} = 0 \quad \Longrightarrow \quad \hat{\beta}_1 = \frac{\sum_{i=1}^n x_i y_i - n \overline{y} \overline{x}}{\sum_{i=1}^n x_i^2 + n \overline{x}} = \frac{Cov(x, y)}{Var(x)}$$



[full proof: https://statproofbook.github.io/P/slr-mle]

Maximum Likelihood Estimation

