

Lecture 5: Maximum likelihood estimation

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Recap: maximum likelihood estimation

Definition: Let $\mathbf{Y} = (Y_1, \dots, Y_n)$ be a sample of n observations, and let $f(\mathbf{y}|\theta)$ denote the joint pdf or pmf of \mathbf{Y} , with parameter(s) θ . The *likelihood function* is

$$L(\theta|\mathbf{Y}) = f(\mathbf{Y}|\theta)$$

Definition: Let $\mathbf{Y} = (Y_1, \dots, Y_n)$ be a sample of n observations. The *maximum likelihood estimator* (MLE) is

$$\hat{\theta} = \operatorname{argmax}_{\theta} L(\theta|\mathbf{Y})$$

Example: $N(\mu, \sigma^2)$

Linear regression with normal errors

$$Y_i \sim N(\mu_i, \sigma^2)$$

$$\mu_i = \beta_0 + \beta_1 X_{i,1} + \cdots + \beta_k X_{i,k}$$

Suppose we observe independent samples $(X_1, Y_1), \dots, (X_n, Y_n)$.
Write down the likelihood function

$$L(\beta | \mathbf{X}, \mathbf{Y}) \propto \prod_{i=1}^n f(Y_i | \beta, X_i)$$

Logistic regression

$$Y_i \sim \text{Bernoulli}(p_i)$$

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 X_{i,1} + \cdots + \beta_k X_{i,k}$$

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