

Maximum Likelihood Estimate for θ (MLE)

Let $X_1, X_2, X_3, \dots, X_n$ be a random sample from random variable X and let $x_1, x_2, x_3, \dots, x_n$ be sample values. We define likelihood function L as following function

$$L(X_1, X_2, X_3, \dots, X_n; \theta) = f(x_1, \theta) f(x_2, \theta) \dots f(x_n, \theta).$$

MLE of θ say $\hat{\theta}$ based on random sample $X_1, X_2, X_3, \dots, X_n$ is that value of θ that maximizes $L(X_1, X_2, X_3, \dots, X_n; \theta)$.

Example 1. Let $X_1, X_2, X_3, \dots, X_n$ denote a random sample of size n from a distribution having

$$\text{pdf } f(x, \theta) = \begin{cases} \theta^x (1 - \theta^{1-x}), & 0 \leq \theta \leq 1 \\ 0, & \text{elsewhere} \end{cases}. \quad \text{Find a MLE for } \theta.$$

$$\text{Solution: } L(X_1, X_2, X_3, \dots, X_n; \theta) = f(x_1, \theta) f(x_2, \theta) \dots f(x_n, \theta)$$

$$= \theta^{x_1} (1 - \theta^{1-x_1}) \cdot \theta^{x_2} (1 - \theta^{1-x_2}) \dots \theta^{x_n} (1 - \theta^{1-x_n}),$$

$$= \theta^{\sum_{i=1}^n x_i} (1 - \theta)^{n - \sum_{i=1}^n x_i}$$

Taking logarithm on both sides, and then partially differentiating with respect to θ ,

$$\frac{\partial(\log L)}{\partial \theta} = \sum_{i=1}^n x_i \cdot \frac{1}{\theta} + \left(n - \sum_{i=1}^n x_i \right) \left(\frac{-1}{1 - \theta} \right)$$

$$\text{For maximum, } \frac{\partial(\log L)}{\partial \theta} = 0.$$

On simplifying, MLE of θ , $\hat{\theta} = \bar{X}$.

Example 2. Let $X_1, X_2, X_3, \dots, X_n$ denote a random sample of size n from a distribution having

$$\text{pdf } f(x, \theta) = \begin{cases} \frac{\theta^x e^{-\theta}}{x!}, & 0 \leq \theta \leq 1 \\ 0, & \text{elsewhere} \end{cases}. \quad \text{Find MLE for } \theta.$$

$$\text{Solution. } L(X_1, X_2, X_3, \dots, X_n; \theta) = f(x_1, \theta) f(x_2, \theta) \dots f(x_n, \theta)$$

$$= \frac{\theta^{x_1} e^{-\theta}}{x_1!} \cdot \frac{\theta^{x_2} e^{-\theta}}{x_2!} \dots \frac{\theta^{x_n} e^{-\theta}}{x_n!}$$

$$= \frac{\theta^{\sum_{i=1}^n x_i} n e^{-\theta}}{\prod_{i=1}^n x_i!}.$$

Taking log and then putting $\frac{\partial(\log L)}{\partial \theta} = 0$, we get $\hat{\theta} = \bar{X}$.

Example 3. Find MLE for normal distribution $N(\theta_1, \theta_2)$ where $-\infty < \theta_1 < \infty$, $0 < \theta_2 < \infty$.

Solution:

$$\text{Pdf: } f(x, \theta_1, \theta_2) = \frac{1}{\sqrt{2\pi\theta_2}} e^{-\frac{(x-\theta_1)^2}{2\theta_2^2}}$$

$$\begin{aligned} L(X_1, X_2, X_3, \dots, X_n; \theta_1, \theta_2) &= f(x_1, \theta_1, \theta_2) f(x_2, \theta_1, \theta_2) \dots f(x_n, \theta_1, \theta_2) \\ &= \frac{1}{\sqrt{2\pi\theta_2}} e^{-\frac{(x_1-\theta_1)^2}{2\theta_2^2}} \cdot \frac{1}{\sqrt{2\pi\theta_2}} e^{-\frac{(x_2-\theta_1)^2}{2\theta_2^2}} \dots \frac{1}{\sqrt{2\pi\theta_2}} e^{-\frac{(x_n-\theta_1)^2}{2\theta_2^2}} \end{aligned}$$

Taking logarithm on both sides and then differentiating partially with respect to θ_1 ,

$$\frac{\partial}{\partial \theta_1} (\log L) = \frac{1}{2\theta_2} \left[2 \sum_{i=1}^n (x_i - \theta_1) \right]$$

For maximum, $\frac{\partial}{\partial \theta_1} (\log L) = 0$. Simplifying, $\hat{\theta}_1 = \bar{X}$.

Differentiating partially with respect to θ_2 ,

$$\frac{\partial}{\partial \theta_2} (\log L) = -\frac{n}{2\theta_2} + \frac{1}{2\theta_2^2} \left[\sum_{i=1}^n (x_i - \theta_1)^2 \right]$$

For maximum, $\frac{\partial}{\partial \theta_2} (\log L) = 0$, we get

$$\theta_2 = \frac{\sum_{i=1}^n (x_i - \bar{X})^2}{n} = s^2.$$