

② Maximum likelihood Estimation Method.

Suppose That X is a r.v. with probability distribution $f(x, \theta)$ where θ is a single unknown parameter. Let x_1, x_2, \dots, x_n be the observed values in a random sample of size n , Then the likelihood function of the sample is

$$L(\theta) = f(x_1, \theta) \cdot f(x_2, \theta) \cdot \dots \cdot f(x_n, \theta) = \prod_{i=1}^n f(x_i, \theta)$$

Note That The likelihood function is now a function of θ only The unknown parameter θ .

The maximum likelihood estimator (MLE) of θ is The value of θ That maximizes The likelihood function $L(\theta)$

The method steps.

1- Find The likelihood function. $\pi(L(\theta))$

$L(\theta) = P(x_1, \theta) \cdot P(x_2, \theta) \cdot \dots \cdot P(x_n, \theta)$

2- maximize The log of The likelihood function

$\frac{\partial \ln L(\theta_1, \dots, \theta_k)}{\partial \theta_i} = 0, i=1, 2, \dots, k$, Solve k eqs

Ex1 / let $X_i, i=1, 2, \dots, n$ be r.v.s from distribution having pdf given as $f(x) = (1-\theta)^{x-1} \theta, x=1, 2, \dots, n$. Estimate θ by MLE Method.

Sol

$L(\theta) = P(x_1) \cdot P(x_2) \cdot \dots \cdot P(x_n)$
 $= (1-\theta)^{x_1-1} \theta \cdot (1-\theta)^{x_2-1} \theta \cdot \dots \cdot (1-\theta)^{x_n-1} \theta = \pi(L(\theta))$
 $= \theta^n (1-\theta)^{\sum_{i=1}^n (x_i-1)}$

$\ln L(\theta) = n \ln \theta + (\sum (x_i-1)) \ln (1-\theta)$

$= \frac{n}{\hat{\theta}} + \frac{\sum_{i=1}^n (x_i-1)}{1-\hat{\theta}} (-1) = 0$

So Then $\hat{\theta} = \frac{n}{n + \sum_{i=1}^n (x_i-1)} = \frac{n}{\sum_{i=1}^n x_i}$

$\hat{\theta} = \frac{n}{n + \sum (x_i-1)} \leftarrow S+n \div \{n = \hat{\theta} (S+n) \leftarrow \frac{n}{\hat{\theta}} = S+n\}$

EX2/ let X be normally dist. w: The mean μ and Variance σ^2 where both μ and σ^2 are unknown. The likelihood function for a random sample of size n is.

Sol/

$$L(\mu, \sigma^2) = \prod_{i=1}^n \left[\frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \frac{(x_i - \mu)^2}{\sigma^2}} \right] = \frac{1}{(2\pi\sigma^2)^{\frac{n}{2}}} e^{-\frac{1}{2\sigma^2} \sum (x_i - \mu)^2}$$

$$\ln L(\mu, \sigma^2) = \ln \left[(2\pi\sigma^2)^{-\frac{n}{2}} e^{-\frac{1}{2\sigma^2} \sum (x_i - \mu)^2} \right]$$

$$= -\frac{n}{2} \ln(2\pi\sigma^2) - \frac{1}{2\sigma^2} \sum_{i=1}^n (x_i - \mu)^2$$

$$\frac{\partial \ln(L)}{\partial \mu} = -\frac{1}{\sigma^2} \sum (x_i - \mu) \cdot (-1) = \frac{1}{\sigma^2} \sum (x_i - \mu)$$

$$= \frac{1}{\sigma^2} \sum (x_i - \hat{\mu}) = 0 \quad \text{J. } \sigma^2 \Rightarrow \sum (x_i - \hat{\mu}) = 0$$

$$= \sum x_i - \sum \hat{\mu} = 0 \Rightarrow \sum x_i = n \hat{\mu} \Rightarrow \hat{\mu} = \frac{\sum x_i}{n} = \bar{x}$$

$$\frac{\partial \ln(L)}{\partial \sigma^2} = -\frac{n}{2} (\ln(2\pi) + \ln \sigma^2) + \frac{S}{2} (\sigma^2)^{-1} \quad \text{where } S = \sum (x_i - \mu)^2$$

$$= \left[\frac{-n}{2} \cdot \frac{1}{\sigma^2} + \frac{S}{2\sigma^4} \right] \cdot \sigma^4$$

$$\frac{-n \hat{\sigma}^2}{2} + \frac{S}{2} = 0 \Rightarrow -\frac{n \hat{\sigma}^2}{2} = -\frac{S}{2} \quad \text{J. } -\frac{2}{n}$$

$$\hat{\sigma}^2 = \frac{S}{n} \Rightarrow \frac{1}{n} \sum (x_i - \hat{\mu})^2$$

$$= \frac{1}{n} \sum (x_i - \bar{x})^2$$

Ex 3/ let $P(x, \theta) = e^{-(x-\theta)}$ $0 < x < \infty$ Estimate θ by MLE method.

Sol/

$$L(\theta) = P(x_1) \cdot P(x_2) \cdots P(x_n) \\ = e^{-(x_1-\theta)} \cdot e^{-(x_2-\theta)} \cdots e^{-(x_n-\theta)} = \exp(n\theta - \sum_{i=1}^n x_i)$$

?

عند ذلك تتفق النتائج المعطاة من قبلنا n فنلاحظ
بلافاً هنا عدم إمكانية إيجاد مقدار الزمن الذي العظمى لذلك وبلافاً
أيضاً أن مجال المتغير يقدر على الحد θ ومنه فإن مقدار الحد θ يكون
من خلال الرصدات المرشحة ويكون $\hat{\theta} = \gamma = \min(x_i)$

Ex 4/ let $X_i \sim P(\theta)$ $(i=1, 2, \dots, n)$ Estimate θ by MLE Method

Sol/

$$L(\theta) = P(x_1) \cdot P(x_2) \cdots P(x_n)$$

$$\text{Since } X \sim P(\theta) \rightarrow P(x) = \frac{e^{-\theta} \cdot \theta^x}{x!}$$

$$\text{so } L(\theta) = \frac{e^{-n\theta} \cdot \theta^{\sum x_i}}{(\prod_{i=1}^n x_i)!}$$

$$\ln L(\theta) = -n\theta + \left(\sum_{i=1}^n x_i\right) \ln(\theta) - \ln\left(\prod_{i=1}^n x_i!\right)$$

$$\frac{\partial \ln L(\theta)}{\partial \theta} = -n + \frac{\sum x_i}{\hat{\theta}} \rightarrow 0$$

$$-n + \frac{\sum x_i}{\hat{\theta}} = 0 \Rightarrow n = \frac{\sum x_i}{\hat{\theta}} \Rightarrow \hat{\theta} = \frac{\sum x_i}{n} = \bar{x}$$

is The MLE estimator for θ .