

Q. Let X_1, X_2, \dots, X_n be a n.s from $U(\theta_1, \theta_2)$. Find the MLE of θ_1, θ_2 .

$$X \sim U(\theta_1, \theta_2) \quad \text{p.d.f} \quad f(x) = \frac{1}{(\theta_2 - \theta_1)}, \quad \theta_1 \leq x \leq \theta_2.$$

$$(i) L(\theta_1, \theta_2) = \prod_{i=1}^n f_{\theta_1, \theta_2}(x_i) = \prod_{i=1}^n \frac{1}{(\theta_2 - \theta_1)} = \frac{1}{(\theta_2 - \theta_1)^n}$$

Obj: Max $L(\theta_1, \theta_2)$. $L(\theta_1, \theta_2)$ will be maximized if θ_2 is as small as possible and θ_1 is as large as possible.

$$\text{H.s: } \theta_1 \leq X_1, X_2, \dots, X_n \leq \theta_2$$

Construct the ordered sample: $\theta_1 \leq x_{(1)} \leq x_{(2)} \leq \dots \leq x_{(n)} \leq \theta_2$

$$\hat{\theta}_{1, \text{MLE}} = x_{(n)} \quad \hat{\theta}_{2, \text{MLE}} = x_{(1)}$$

Q. Suppose X_1, X_2, \dots, X_n be a n.s from $U(-\theta, \theta)$. Find MLE of θ .

Method of Moments

Let X_1, X_2, \dots, X_n be a n.s from $f_{\theta}(x)$, $\theta = \text{unknown}$ population parameter.

<u>Population</u>	<u>Sample</u>
(i) μ^{th} order moment about $x=a$: $= E(X-a)^{\mu}, \mu=0,1,2,\dots$	(i) μ^{th} order moment about $x=a$: $= \frac{1}{n} \sum_{i=1}^n (x_i - a)^{\mu}, \mu=0,1,\dots$
(ii) If $a=0$, we call it μ^{th} order raw moment: $\mu'_\mu = E(X^\mu)$	(ii) If $a=0$, μ^{th} order raw moment: $m'_\mu = \frac{1}{n} \sum_{i=1}^n x_i^\mu$
(iii) If $a=\mu$, we call it μ^{th} order central moment: $\mu_\mu = E(X-\mu)^\mu$	(iii) If $a=\bar{x}$, μ^{th} order central moment: $m_\mu = \frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^\mu$

\therefore As per method of moments: $\mu'_\mu = m'_\mu \Rightarrow$ using these eqns, find estimates of unknown population parameters.

Q. Let X_1, X_2, \dots, X_n be a n.s from $\text{Exp}(\theta)$. Find MOM estimate for θ .

$$X_1, X_2, \dots, X_n, \quad f(x) = \theta e^{-\theta x}, \quad x \geq 0.$$

\therefore Consider first order raw moments for sample & popln.

$$m'_1 = \frac{1}{n} \sum_{i=1}^n x_i = \bar{x}$$

$$\mu'_1 = E(X) = \int_0^{\infty} x f(x) dx = \int_0^{\infty} x \theta e^{-\theta x} dx \quad \checkmark$$

$$= \int_0^{\infty} (t) \cdot \theta \cdot e^{-t} dt$$

$$\mu'_1 = E(X) = \int_0^{\infty} x f(x) dx = \int_0^{\infty} x \theta e^{-\theta x} dx \quad \checkmark$$

$$\text{Let } \theta x = t \Rightarrow x = \left(\frac{t}{\theta}\right)$$

$$\theta dx = dt \Rightarrow dx = \frac{dt}{\theta}$$

$$x=0, t=0$$

$$x \rightarrow \infty, t \rightarrow \infty$$

$$= \int_0^{\infty} \left(\frac{t}{\theta}\right) \cdot \theta \cdot e^{-t} \left(\frac{dt}{\theta}\right)$$

$$= \frac{1}{\theta} \int_0^{\infty} t e^{-t} dt \quad \left[\begin{array}{l} \text{Gamma} \\ \text{Function} \end{array} \right]$$

$$= \frac{1}{\theta} \int_0^{\infty} t^{2-1} e^{-t} dt = \frac{\Gamma 2}{\theta}$$

$$= \frac{1}{\theta}$$

Gamma Integral:

$$\Gamma p = \int_0^{\infty} e^{-x} x^{p-1} dx$$

If p is an integer: $\Gamma p = (p-1)!$

If p is not an integer: $\Gamma p = (p-1) \Gamma(p-1)$

$$\Gamma \frac{1}{2} = \sqrt{\pi}$$

Using MoM:

$$\mu'_1 = m'_1$$

$$\frac{1}{\theta} = \bar{x}$$

$$\hat{\theta}_{\text{MoM}} = \frac{1}{\bar{x}}$$

Q. Let X_1, X_2, \dots, X_n be a r.v.s from $N(\mu, \sigma^2)$. Find the MoM estimate for μ, σ .

$$\mu'_1 = \mu_1' \quad \text{and} \quad \mu'_2 = \mu_2'$$

$$\text{For sample: } m'_1 = \frac{1}{n} \sum_{i=1}^n x_i = \bar{x}$$

$$m'_2 = \frac{1}{n} \sum_{i=1}^n x_i^2$$

$$E(X) = \mu$$

$$\text{Var}(X) = \sigma^2$$

$$E(X^2) - [E(X)]^2 = \sigma^2$$

$$E(X^2) - \mu^2 = \sigma^2$$

$$E(X^2) = \sigma^2 + \mu^2$$

For pop'n: $\mu_1' = E(X) = \mu$

$$\mu_2' = E(X^2) = \sigma^2 + \mu^2$$

From MoM estimation:

$$\mu_1' = m_1'$$

$$\hat{\mu}_{\text{MoM}} = \bar{x}$$

$$\mu_2' = m_2'$$

$$\sigma^2 + \mu^2 = \frac{1}{n} \sum_{i=1}^n x_i^2$$

$$\hat{\sigma}_{\text{MoM}}^2 = \frac{1}{n} \sum x_i^2 - \hat{\mu}_{\text{MoM}}^2$$

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

$$\therefore \hat{\sigma}_{\text{MoM}} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i - \bar{x})^2}$$

Note: If we have a pop'n with k unknown parameters

$(\theta_1, \theta_2, \dots, \theta_k)$. The MoM estimation will

$$\left. \begin{array}{l} \mu_1' = m_1' \\ \mu_2' = m_2' \\ \dots \\ \mu_k' = m_k' \end{array} \right\} \text{ usings } 'k' \text{ equations, solve for } \theta_1, \theta_2, \dots, \theta_k.$$

i.e. solving these give us: $\hat{\theta}_{1, \text{MoM}}, \hat{\theta}_{2, \text{MoM}}, \dots, \hat{\theta}_{k, \text{MoM}}$