

Q1 ~~$E_{\lambda}[h(T)]$~~ $T = (X_1, X_2)$

$$E_{\lambda}[h(T)] = \int_{t \in T} h(t) \frac{e^{-\lambda} \lambda^{x_1}}{x_1!} \frac{e^{-\lambda} \lambda^{x_2}}{x_2!} dt$$

If we define $h(t) = \begin{cases} 1 & \text{for } x_1 > x_2 \\ -1 & \text{for } x_1 < x_2 \\ 0 & \text{for } x_1 = x_2 \end{cases}$

this integral $E_{\lambda}[h(T)] = \left(e^{-2\lambda} \int_{t \in T} \frac{h(t) \lambda^{x_1+x_2}}{x_1! x_2!} dt \right)$ is 0

but $h(T)$ is not equal to 0 with probability 1.

Therefore family induced by T is not complete.

$$\textcircled{2} \mu_1 = E[X] = \int_{\theta_1}^{\theta_2} x \frac{1}{\theta_2 - \theta_1} dx = \frac{\theta_2^2 - \theta_1^2}{2(\theta_2 - \theta_1)} \\ = \frac{\theta_1 + \theta_2}{2}$$

$$\mu_2 = E[X^2] = \int_{\theta_1}^{\theta_2} x^2 \times \frac{1}{(\theta_2 - \theta_1)} dx = \frac{\theta_2^3 - \theta_1^3}{3(\theta_2 - \theta_1)} \\ = \frac{\theta_1^2 + \theta_1 \theta_2 + \theta_2^2}{3}$$

By method of moments -

$$\therefore \frac{\theta_1 + \theta_2}{2} = \bar{X}$$

$$\frac{\theta_1^2 + \theta_1 \theta_2 + \theta_2^2}{3} = \frac{\sum x_i^2}{n}$$

$$\theta_1 = 2\bar{X} - \theta_2$$

$$\frac{4\bar{X}^2 + \theta_2^2 - 4\bar{X}\theta_2 + (2\bar{X} - \theta_2)^2}{3} = \frac{\sum x_i^2}{n}$$

$$3(4\bar{X}^2 + \theta_2^2 - 4\bar{X}\theta_2) = \sum x_i^2$$

$$3(\theta_2 - \bar{X})^2 = \sum x_i^2 - 4\bar{X}^2$$

$$\theta_2 = \bar{X} + \sqrt{\frac{\sum x_i^2}{3} - 3\bar{X}^2}$$

$$\theta_1 = \bar{X} - \sqrt{\frac{\sum x_i^2}{3} - 3\bar{X}^2}$$

$$(3) \quad (a) \quad f(x, \theta) = \frac{2^n}{\theta^n} x^n \exp\left[-\frac{\sum x_i^2}{\theta}\right]$$

$$\ln f(x, \theta) = n \ln 2 + n \ln(x) - n \ln(\theta) - \frac{\sum x_i^2}{\theta}$$

$$\frac{\partial \ln f(x, \theta)}{\partial \theta} = 0 \Rightarrow -\frac{n}{\theta} + \frac{\sum x_i^2}{\theta^2} = 0$$

$$\frac{n}{\theta} = \frac{\sum x_i^2}{\theta^2}$$

$$\theta = \frac{\sum x_i^2}{n}$$

$$\text{MLE for } T(\theta) = \frac{1}{\sqrt{\theta}} = \frac{1}{\sqrt{\frac{\sum x_i^2}{n}}} = \sqrt{\frac{n}{\sum x_i^2}}$$

(3) (c) ~~1x~~

$$f(x, \theta) = \frac{2}{\theta} x \exp\left(-\frac{x^2}{\theta}\right)$$

$$\ln f(x, \theta) = \ln\left(\frac{2}{\theta}\right) + \ln(x) - \frac{x^2}{\theta}$$

$$\frac{\partial}{\partial \theta} \ln f(x, \theta) = \frac{1}{(2\theta)} \left(-\frac{2}{\theta^2}\right) + \frac{x^2}{\theta^2}$$

$$= -\frac{1}{\theta} + \frac{x^2}{\theta^2}$$

$$\frac{\partial^2}{\partial \theta^2} \ln f(x, \theta) = \frac{1}{\theta^2} - \frac{2x^2}{\theta^3}$$

$$E\left[\frac{\partial^2}{\partial \theta^2} \ln f(x, \theta)\right] = \frac{1}{\theta^2} - \frac{2}{\theta^3} E[x^2]$$

$$E[x^2] = \int_0^{\infty} \frac{2}{\theta} x^2 x \exp\left(-\frac{x^2}{\theta}\right) dx$$
$$= \theta$$

$$\therefore E\left[\frac{\partial^2}{\partial \theta^2} \ln f(x, \theta)\right] = \frac{1}{\theta^2} - \frac{2}{\theta^2} = -\frac{1}{\theta^2}$$

$$I_{x_1}(\theta) = -E\left[\frac{\partial^2}{\partial \theta^2} \ln(f(x, \theta))\right] = \frac{1}{\theta^2}$$

$$Q \quad T(\theta) = \frac{1}{\sqrt{\theta}}$$

$$T'(\theta) = \frac{-1}{2\theta\sqrt{\theta}}$$

$$\text{Cramer Rao lower bound} = \frac{(T'(\theta))^2}{n I_{\theta}}$$

$$= \frac{\frac{1}{4\theta^3}}{n \frac{1}{\theta^2}} = \frac{1}{4n\theta}$$

4. Likelihood function for Bernoulli RV is

$$L = \prod_{i=1}^n f(x_i, p) = p^{\sum x_i} (1-p)^{n - \sum x_i}$$

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

$$\frac{\partial}{\partial p} \log L = 0 \Rightarrow \frac{\sum x_i}{p} + \frac{(n - \sum x_i)(-1)}{(1-p)} = 0$$

$$\Rightarrow p = \frac{\sum x_i}{n}$$

$$p = \frac{1}{1+e^\theta}$$

$$1+e^\theta = \frac{1}{p}$$

$$e^\theta = \frac{1}{p} - 1$$

$$\theta = \ln\left(\frac{1}{p} - 1\right)$$

$$\therefore \text{MLE for } \theta = \ln\left(\frac{n}{\sum x_i} - 1\right)$$

by invariance property of MLE

$$\text{MLE exist if } \frac{n}{\sum x_i} - 1 > 0$$

$$\frac{1}{\bar{x}} > 1$$

$$\underline{\underline{\bar{x} < 1}}$$

(5) Likelihood function

$$L(\theta, n) = \frac{1}{\theta^n} e^{-\frac{\sum x_i}{\theta}} \quad \text{for } \min_i x_i > 0$$

$$\theta_0 = \{\theta_0\}$$

$$\theta_0 \cup \theta_1 = \mathbb{R}^+$$

$$\sup_{\theta \in \theta_0} L(\theta) = L(\theta_0) = \frac{1}{\theta_0^n} e^{-\frac{\sum x_i}{\theta_0}}$$

$$\begin{aligned} \sup_{\theta \in \theta_0 \cup \theta_1} L(\theta) &= L(\bar{x}) = \frac{1}{(\bar{x})^n} e^{-\left(\frac{\sum x_i}{\bar{x}}\right)} \\ &= \frac{e^{-n}}{(\bar{x})^n} \end{aligned}$$

$$\log(L(\theta)) = -n \ln \theta - \frac{\sum x_i}{\theta}$$

for MLE -

$$\frac{\partial \log(L(\theta))}{\partial \theta} = 0 = -\frac{n}{\theta} + \frac{\sum x_i}{\theta^2} = 0$$

$$\theta = \frac{\sum x_i}{n} = \bar{x}$$

$$\frac{\partial^2 \log(L(\theta))}{\partial \theta^2} = \frac{n}{\theta^2} - \frac{2 \sum x_i}{\theta^3} = \frac{1}{\theta^2} \left(n - \frac{2 \sum x_i}{\theta} \right)$$

$$\frac{\partial^2 \log(L(\theta))}{\partial \theta^2} \text{ at } \theta = \bar{x} = \frac{1}{\bar{x}^2} (n - 2n) = -\frac{n}{\bar{x}^2} < 0$$

\therefore MLE for $\theta = \hat{\theta} = \bar{x}$

$$\lambda(x) = \frac{\sup_{\theta \in \theta_0} L(\theta)}{\sup_{\theta \in \theta_0 \cup \theta_1} L(\theta)} = \frac{\frac{1}{\theta_0^n} e^{-\frac{\sum x_i}{\theta_0}}}{\frac{e^{-n}}{(\bar{x})^n}}$$

$$\lambda = \left(\frac{\bar{x}}{\theta_0}\right)^n e^{n - \frac{\sum x_i}{\theta_0}} = \left(\frac{\bar{x}}{\theta_0}\right)^n e^{n - \frac{n\bar{x}}{\theta_0}}$$

We would reject the null hypothesis if

$$\lambda(x) < K \Leftrightarrow \left(\frac{\bar{x}}{\theta_0}\right)^n e^{n - \frac{n\bar{x}}{\theta_0}} < K$$

Taking log both
side as
it as an
ineq. f^n

$$\Leftrightarrow n \ln\left(\frac{\bar{x}}{\theta_0}\right) + n\left(1 - \frac{\bar{x}}{\theta_0}\right) < \ln K$$

$$\Leftrightarrow \ln\left(\frac{\bar{x}}{\theta_0}\right) - \frac{\bar{x}}{\theta_0} < \frac{\ln K}{n} - 1$$

$$\text{let } \frac{\ln K}{n} - 1 = k_1$$

$$\text{and } \hat{x} = \frac{\bar{x}}{\theta_0}$$

\therefore ~~the~~ likelihood ratio level α test is -

$$\psi(x) = \begin{cases} 1 & \text{if } \ln \hat{x} - \hat{x} < k_1 \\ 0 & \text{o.w.} \end{cases}$$

~~For~~ For K_1 —

$$E_{\theta_0}(\psi(x)) = \alpha \Leftrightarrow P_{\theta_0}(\ln \hat{x} - \hat{x} < K_1) = \alpha$$