

326 Homework 5

$$\textcircled{1} a) \mu = \int_0^{\infty} y \cdot \frac{\partial^2}{y^3} dy = \partial \theta^2 \int_0^{\infty} \frac{1}{y^2} dy$$

$$= \partial \theta^2 \left(-\frac{1}{y} \Big|_0^{\infty} \right) = \partial \theta^2 \left(0 + \frac{1}{\epsilon} \right) = \partial \theta$$

$$\mu_1' = m_1' \Rightarrow \partial \theta = \bar{x} \Rightarrow \hat{\theta} = \frac{\bar{x}}{\partial}$$

b) Note $E[\hat{\theta}] = \frac{1}{\partial n} \sum E(x_i) = \frac{n \partial \theta}{\partial n} = \theta$.
unbiased.

For $V(\hat{\theta})$, need $E[X^2]$.

$$E[X^2] = \int_0^{\infty} y^2 \cdot \frac{\partial^2}{y^3} dy = \partial \theta^2 \int_0^{\infty} \frac{1}{y} dy$$

which diverges by the p-test.

$E[X^2]$ is infinite, hence so is $V(\hat{\theta})$,

$$2. L(x_1, x_2, \dots, x_n | \theta) = \frac{1}{\theta} e^{-x_1/\theta} \cdot \frac{1}{\theta} e^{-x_2/\theta} \cdots \frac{1}{\theta} e^{-x_n/\theta} \\ = \frac{1}{\theta^n} e^{-\sum x_i/\theta}$$

$$\text{Let } S = \sum x_i.$$

$$\text{Then } L(x_1, \dots, x_n | \theta) = g(S, \theta) \cdot h(x_1, \dots, x_n)$$

$$\text{where } g(S | \theta) = \frac{1}{\theta^n} e^{-S/\theta} \text{ and } h(\vec{x}) = 1.$$

$$\text{For MLE, } \frac{dg}{d\theta} = 0$$

$$\frac{-n}{\theta^{n+1}} e^{-S/\theta} + \frac{1}{\theta^n} e^{-S/\theta} \cdot \frac{S}{\theta^2} = 0$$

$$\frac{e^{-S/\theta}}{\theta^{n+1}} \left(-n + \frac{S}{\theta} \right) = 0$$

$$-n\theta + S = 0 \Rightarrow \theta = S/n$$

$$\hat{\theta} = \frac{S}{n} = \bar{X}.$$

Then, since $f(x) = x^2$ is H.I. fun on $[0, \infty)$,
by the invariance properties of MLE,

the MLE of θ^2 is $(\bar{X})^2$.

$$\hat{\gamma} = (\bar{X})^2 \text{ is the MLE of } \theta^2.$$

$$\begin{aligned}
 3a. L(x_1, \dots, x_n | \theta) &= \frac{1}{\theta} r x_1^{r-1} e^{-x_1^r/\theta} \cdot \frac{1}{\theta} r x_2^{r-1} e^{-x_2^r/\theta} \dots \frac{1}{\theta} r x_n^{r-1} e^{-x_n^r/\theta} \\
 &= \left(\frac{r}{\theta}\right)^n e^{-\sum x_i^r/\theta} \cdot x_1^{r-1} x_2^{r-1} \dots x_n^{r-1} \\
 &= \left(\frac{r}{\theta}\right)^n e^{-U/\theta} \cdot (x_1 \dots x_n)^{r-1} \text{ where } U = \sum_{i=1}^n x_i^r. \\
 &= g(\theta, U) \cdot h(\vec{x}) \\
 \text{where } g(\theta, U) &= \left(\frac{r}{\theta}\right)^n e^{-U/\theta}, \quad h(\vec{x}) = (x_1 \dots x_n)^{r-1}.
 \end{aligned}$$

b) By the Factorization Theorem, U is a sufficient statistic.

$$\begin{aligned}
 c) \frac{dg}{d\theta} &= n \left(\frac{r}{\theta}\right)^{n-1} \left(-\frac{r}{\theta^2}\right) e^{-U/\theta} + \left(\frac{r}{\theta}\right)^n e^{-U/\theta} \cdot \frac{U}{\theta^2} \\
 &= -n \frac{r^n}{\theta^{n+1}} e^{-U/\theta} + n \frac{r^n}{\theta^{n+1}} e^{-U/\theta} U \\
 &= \frac{n e^{-U/\theta}}{\theta^{n+1}} (-\theta + U)
 \end{aligned}$$

$$\frac{dg}{d\theta} = 0 \quad \text{when} \quad \theta = U.$$

The MLE of θ is $\hat{\theta} = U = \frac{\sum x_i^r}{n}$.

$$d) E(u) = \frac{1}{n} \sum E(x_i^r)$$

$$E(x^r) = \int_0^{\infty} x^r \cdot \frac{1}{\theta} r x^{r-1} e^{-x^r/\theta} dx$$

$$\text{Let } u = x^r$$

$$du = r x^{r-1} dx$$

$$E(x^r) = \int_0^{\infty} u \cdot \frac{1}{\theta} e^{-u/\theta} du$$

$$\text{Let } x = u$$

$$dx = du$$

$$d\beta = \frac{1}{\theta} e^{-u/\theta} du$$

$$\beta = -e^{-u/\theta}$$

$$= -u e^{-u/\theta} \Big|_0^{\infty} + \int_0^{\infty} e^{-u/\theta} du$$

$$= 0 + -\theta e^{-u/\theta} \Big|_0^{\infty}$$

$$= - - \theta$$

$$= \theta$$

e) By Rao-Blackwell Thm, since u is both unbiased and sufficient, u is the MVUE.

$$f) V(u) = \frac{1}{n^2} V(\sum x_i^{(r)}) = \frac{n V(x_i^{(r)})}{n^2} = \frac{V(x_i^{(r)})}{n}$$

$$\text{Note } V(x_i^{(r)}) = E(x_i^{(r)^2}) - \underbrace{(E(x_i^{(r)}))^2}_{= \theta^2 \text{ by (1)}}$$

$$E(x_i^{(r)}) = \int_0^\infty u \cdot \frac{1}{\theta} e^{-u/\theta} du$$

by same u-sub.

$< \infty$, finite via application of IBP twice.

Hence $V(x_i^{(r)})$ is finite.

$$g) \text{ And } \lim_{n \rightarrow \infty} V(u) = \lim_{n \rightarrow \infty} \frac{V(x_i^{(r)})}{n} = 0.$$

Thus u is a consistent estimator.

i.e. $u \rightarrow \theta$ in probability.