

Question 1

[Total marks= 25]

(a)

$$\begin{aligned}
f(x|\theta) &= \frac{1}{3!\theta^4} x^3 \exp\left(-\frac{x}{\theta}\right) \\
&= \exp\left(-\frac{x}{\theta} - 4\ln(\theta) - \ln(3!) + 3\ln(x)\right) \\
&= \exp\left(-\eta x - 4\ln(\eta^{-1}) - \ln(3!) + 3\ln(x)\right) \\
&= \exp\{\eta t(x) - \psi(\eta) + g(x)\}
\end{aligned}$$

$$\text{where } \eta = \frac{1}{\theta}, t(x) = -x, \psi(\eta) = -4\ln(\eta) \text{ and } g(x) = 3\ln(x) - \ln(3!). \quad (4)$$

$$(b) \sum_{i=1}^n t(X_i) = -\sum_{i=1}^n X_i \text{ since } f(x|\theta) \text{ belongs to regular exponential family.} \quad (3)$$

$$(c) l(\theta) = -\frac{1}{\theta} \sum_{i=1}^n x_i - 4n\ln(\theta) - n\ln(3!) + 3\sum_{i=1}^n \ln(x_i) \quad (4)$$

$$(d) E[X] = -\psi'(\eta) = 4\eta^{-1} = 4\theta \text{ and } l''(\theta) = -\frac{2}{\theta^3} \sum_{i=1}^n x_i + \frac{4n}{\theta^2} \implies$$

$$I_n(\theta) = -E[l''(\theta)] = \frac{2}{\theta^3} \sum_{i=1}^n E[X_i] - \frac{4n}{\theta^2} = \frac{8n\theta}{\theta^3} - \frac{4n}{\theta^2} = \frac{4n}{\theta^2}. \quad (4)$$

(e) The MLE of θ is $\hat{\theta}$ which solves the equation

$$0 = l'(\hat{\theta}) = \frac{1}{\hat{\theta}^2} \sum_{i=1}^n x_i - \frac{4n}{\hat{\theta}}$$

The solution is $\hat{\theta} = \frac{1}{4n} \sum_{i=1}^n x_i$ which depends on the sample through complete sufficient statistic (4)

$$(f) CRLB = \frac{[\theta']^2}{I_n(\theta)} = \frac{\theta^2}{4n}. \quad (3)$$

(g) That $\hat{\theta}$ is a function of a complete sufficient statistic and $E[\hat{\theta}] = \frac{4n\theta}{4n} = \theta$ implies that $\hat{\theta}$ is a MVUE of θ . (3)

Question 2

[Total marks=25]

(a) Note

$$\begin{aligned}
f(y|\theta) &= \frac{2}{\theta} y \exp\left(-\frac{y^2}{\theta}\right) \text{ if } y > 0 \text{ and } \theta > 0 \\
&= \exp\left\{-\frac{y^2}{\theta} + \ln\left(\frac{2}{\theta}y\right)\right\} \\
&= \exp\left\{-\frac{y^2}{\theta} - \ln(\theta) + \ln(2y)\right\} \\
&= \exp\{-\eta y^2 - \ln(\eta^{-1}) + \ln(2y)\} = f(y|\eta)
\end{aligned}$$

which is in the form of the pdf in Question 1 with $t(y) = -y^2$, $\theta = 1/\eta$ and $\psi(\eta) = -\ln(\eta)$. Hence complete sufficient statistic for θ is $\sum_{i=1}^n t(Y_i) = -\sum_{i=1}^n Y_i^2$. (5)

(b) $\sum_{i=1}^n Y_i^2$ is a minimal sufficient statistic for θ because it is a complete sufficient statistic for θ . (2)

(c) From Question 1,

$$E\left[-\sum_{i=1}^n Y_i^2\right] = -nE[Y^2] = \frac{\partial -\ln \eta}{\partial \eta} = -n/\eta = -n\theta \equiv E\left[\sum_{i=1}^n Y_i^2\right] = n\theta,$$

and

$$\text{Var}\left[-\sum_{i=1}^n Y_i^2\right] = \text{Var}\left[\sum_{i=1}^n Y_i^2\right] = n\text{Var}[Y^2] = \frac{\partial^2 - \ln \eta}{\partial \eta^2} = n/\eta^2 = n\theta^2.$$

(2+2=4)

- (d) $l(\eta) = \ln L(\eta|\mathbf{y}) = -\eta \sum_{i=1}^n y_i^2 + n \ln(\eta) + \sum_{i=1}^n \ln(2y_i) \implies l'(\eta) = -\sum_{i=1}^n y_i^2 + \frac{n}{\eta} \implies$ the MLE of η is $\hat{\eta}$ which solves the equation

$$l'(\hat{\eta}) = -\sum_{i=1}^n y_i^2 + \frac{n}{\hat{\eta}} = 0.$$

The solution is $\hat{\eta} = \frac{n}{\sum_{i=1}^n y_i^2} \implies$ the MLE of θ is

$$\hat{\theta} = 1/\hat{\eta} = \frac{1}{n} \sum_{i=1}^n y_i^2$$

by the invariance property of MLEs.

From above and part (a), $\hat{\theta}$ is a function of a complete sufficient statistic, and from part(c) $E[\hat{\theta}] = \theta$ ($\hat{\theta}$ is an unbiased estimator of θ). Therefore, $\hat{\theta}$ also the MVUE of θ . (4+3=7)

- (e) By the invariance property of MLE's, the MLE of the variance of the complete sufficient statistic found in part(a) is $n\theta^2$. (3)

- (f) From part (d), the MLE of θ is $\hat{\theta} = \frac{100}{200} = 0.5$. (1)

$$se(\hat{\theta}) = -\frac{1}{\sqrt{l''(\hat{\theta})}} = \sqrt{\frac{\hat{\theta}^2}{n}} = 0.5/\sqrt{200} = 0.035355. \quad (1+3=4)$$

Question 3

[Total marks=25]

- (a) MME : $E[X] = n\theta \implies E[X/n] = \theta \implies$ MME of θ is x/n . (3)

$$\text{MLE} : L(\theta) = \frac{n!}{(n-x)!x!} \theta^x (1-\theta)^{n-x} \text{ and}$$

$l(\theta) = \ln L(\theta) = \ln\left(\frac{n!}{(n-x)!x!}\right) + x \ln(\theta) + (n-x) \ln(1-\theta) \implies l'(\theta) = \frac{x}{\theta} - \frac{n-x}{1-\theta} \implies$ the MLE of θ is $\hat{\theta}$ which solves $\frac{x}{\hat{\theta}} - \frac{n-x}{1-\hat{\theta}} = 0 \equiv x - n\hat{\theta} = 0$ and the solution is $\hat{\theta} = x/n$ which is also the MME of θ . (6)

- (b) $l''(\theta) = -\frac{x}{\theta^2} + \frac{n-x}{(1-\theta)^2} \implies I_1(\theta) = -E[l''(\theta)] = \frac{E[X]}{\theta^2} + \frac{n-E[X]}{(1-\theta)^2} = \frac{n}{\theta} + \frac{n}{1-\theta} = \frac{n}{\theta(1-\theta)}$. (4)

- (c) $\text{Var}(\hat{\theta}) = \frac{1}{n^2} \text{Var}(X) = \frac{n\theta(1-\theta)}{n^2} = \frac{\theta(1-\theta)}{n}$. (4)

- (d) $g(\theta) = E(\hat{\theta}) = E(X/n) = \theta \implies g'(\theta) = 1 \implies \text{CRLB} = \frac{[g'(\theta)]^2}{I_1(\theta)} = \frac{\theta(1-\theta)}{n} = \text{Var}(\hat{\theta})$. (4)

- (e) Since $E(\hat{\theta}) = \theta$ and $\text{Var}(\hat{\theta}) = \text{CRLB}$, this means $\hat{\theta}$ is a MVUE of θ . (4)

Question 4

[Total marks=25]

- (a)

$$\begin{aligned} \text{MSE}(T) &= E[(T - \theta)^2] = E[(T - E[T] + E[T] - \theta)^2] \\ &= E[(T - E[T])^2 + 2(T - E[T])(E[T] - \theta) + (E[T] - \theta)^2] \\ &= E[(T - E[T])^2] + 2(E[T] - \theta)E[(T - E[T])] + E[(E[T] - \theta)^2] \\ &= \text{Var}[T] + 0 + (E[T] - \theta)^2 \end{aligned}$$

(5)

- (b) If T is any unbiased estimator of θ then $E[T] - \theta = 0 \implies \text{MSE}(T) = \text{Var}(T)$. (2)

- (c) $E[cT_1 + (1-c)T_2] = cE[T_1] + (1-c)E[T_2] = c\theta + (1-c)\theta = \theta$. (3)

(d)

$$\begin{aligned} \text{Var}[T] &= c^2 \text{Var}[T_1] + (1-c)^2 \text{Var}[T_2] = 2c^2 \text{Var}[T_2] + (1-c)^2 \text{Var}[T_2] \\ &= (3c^2 - 2c + 1) \text{Var}[T_2] \end{aligned} \tag{2}$$

$$0 = \frac{\partial \text{Var}[T]}{\partial c} = (6c - 2) \text{Var}[T_2] \implies c = \frac{2}{6} = \frac{1}{3}$$

minimizes the variance of the estimator $T = cT_1 + (1-c)T_2$ of θ . (3)

(e) $re(T_2, T_1) = 2$ and $re(T_2, T) = \frac{2}{3}$. T is the best estimator because it has the smallest variance. (1+3+2=6)

(f) $0.95 = P(0.1 \leq \frac{T}{\theta} \leq 10) = P(0.1 \leq \frac{\theta}{T} \leq 10) = P(0.1T \leq \theta \leq 10T)$ which means the 95% confidence interval for θ is $[0.1T; 10T]$. (4)

TOTAL [100]