

**MTH-418a: Inference-I**  
**2023-2024: II Semester**  
**Mid Semester Examination**

**Time Allowed: 120 Minutes**

**Maximum Marks: 50**

**NOTE:** (i) Start answer of every question on a new page. Moreover, attempt all the parts of a question at one place.

(ii) Answer each question legibly, clearly and concisely. Illegible answers will not be graded.

(ii) For each question, provide details of all the steps involved in arriving at the final answer(s)/conclusion(s) and box your final answer(s)/conclusion(s).

1. Identify TRUE and FALSE statements from the following ten statements. In support of your answers, provide appropriate arguments.

(i) If  $|T|$  is a sufficient statistic for  $\theta \in \Theta$ , then  $T$  is also a sufficient statistic for  $\theta \in \Theta$ .

(ii) If  $T$  is a complete statistic, then  $e^T - T - 1$  is also a complete statistic.

(iii) If  $T$  is a complete statistic and  $T^2$  is a sufficient statistic, then  $T$  is a minimal sufficient statistic.

(iv) If  $T$  is a minimal sufficient statistic, then  $T^3 - 2T^2 + 2T + 1$  is also a minimal sufficient statistic.

(v) Let  $x_1 = 1.1, x_2 = 1.5$  and  $x_3 = 0.4$  be the observed values of a random sample of size 3 from the pdf

$$f_{\theta}(x) = \frac{1}{\theta} e^{-\frac{x}{\theta}}, \quad x > 0,$$

where  $\theta \in (0, \infty) = \Theta$ . Then, the maximum likelihood estimate of  $\theta$  is 0.5.

(vi) Let  $x_1 = -1.5, x_2 = -0.2$  and  $x_3 = 0.2$  be the observed values of a random sample of size 3 from the pdf

$$f_{\theta}(x) = \frac{e^{-|x-\theta|}}{2}, \quad -\infty < x < \infty,$$

where  $\theta \in \mathbb{R} = \Theta$ . Then, the method of moment estimate of  $\theta$  is 0.2;

(vii) If  $\delta_1$  is the UMVUE of  $\psi(\theta)$ ,  $\theta \in \Theta$ , and  $\delta_2$  is an unbiased estimator of  $\psi(\theta)$ , then  $\text{Var}_\theta(\delta_1) = 2\text{Cov}_\theta(\delta_1, \delta_2)$ ,  $\forall \theta \in \Theta$ ;

(viii) Let  $X_1, X_2$  be a random sample from  $U(0, \theta)$ , where  $\theta \in (0, \infty) = \Theta$ . Let  $X_{(1)} \leq X_{(2)}$  be the corresponding order statistics. Using Basu's theorem and the distribution of order statistics,  $E_\theta\left(\frac{X_{(1)}}{X_{(2)}}\right) = 0.5$ ,  $\forall \theta > 0$ ;

(ix) A minimal sufficient statistic is always complete;

(x) If  $\delta_1$  and  $\delta_2$  are two UMVUEs of  $\psi(\theta)$ , then  $\text{Var}_\theta(\delta_1 - \delta_2) = 0$ ,  $\forall \theta \in \Theta$ , and  $P_\theta(\delta_1 = \delta_2) = 1$ ,  $\forall \theta \in \Theta$ .

1.5 × 10 = 15 Marks

2. Let  $X_1, X_2$  be a random sample from a population having the pdf

$$f_\theta(x) = \frac{1}{\pi} \cdot \frac{1}{1 + (x - \theta)^2}, \quad x \in \mathbb{R},$$

where  $\theta \in \mathbb{R} = \Theta$ . Show that  $\underline{T} = (X_{(1)}, X_{(2)})$  is a minimal sufficient statistic? Is  $\underline{T}$  a boundedly complete statistic?

6+5=11 Marks

3. Let  $X_1, X_2, X_3$  be a random sample of size 3 from the pdf

$$f_\theta(x) = \frac{2x}{\theta^2}, \quad 0 < x < \theta,$$

where  $\theta \in (0, \infty) = \Theta$ .

(i) Find the MLE of  $\theta$ ;

(ii) Find the MME of  $\theta$ ;

(iii) Using the Rao-Blackwell Theorem, find an estimator based on the complete sufficient statistic  $X_{(3)} = \max\{X_1, X_2, X_3\}$  that is better than the MME under the absolute error loss function  $L(\theta, a) = |a - \theta|$ ,  $a \in \mathbb{R} = \mathcal{A}, \theta \in \Theta$ .

4+4+4=12 Marks

4. Let  $X$  be a random variable having the pmf

$$f_\theta(x) = \begin{cases} \theta, & \text{if } x = -1 \\ (1 - \theta)^2 \theta^x, & \text{if } x = 0, 1, 2, \dots \\ 0, & \text{otherwise} \end{cases}$$

where  $\theta \in (0, 1) = \Theta$ . Show that the UMVUE of  $\psi(\theta) = \theta(1 - \theta)^2$  does not exist.

12 Marks

MTH 418: Inference I

Mid Semester Examination

Model Solutions

**Problem No. 1**

(i) **TRUE**

**0.5 MARKS**

Since the Sufficient statistic  $|T|$  is a function of  $A_{\text{statistic}} T$ ,  $T$  is a sufficient statistic. **1 MARK**

(ii) **TRUE**

**0.5 MARKS**

Any function of a complete statistic is a complete statistic. **1 MARK**

(iii) **TRUE**

**0.5 MARKS**

$T^2$  is sufficient  $\Rightarrow T$  is sufficient ( $T^2$  is a function of  $T$ )  
 $\Rightarrow T$  is complete-sufficient  
 $\Rightarrow T$  is minimal sufficient. **1 MARK**

(iv) **TRUE**

**0.5 MARKS**

Consider

$$\Psi(t+1) = t^3 - 2t^2 + 2t + 1 \quad t \in \mathbb{R}$$

$$\begin{aligned} \Psi'(t+1) &= 3t^2 - 4t + 2 \\ &= 3\left(t^2 - \frac{4t}{3} + \frac{2}{3}\right) \\ &= 3\left[\left(t - \frac{2}{3}\right)^2 + \frac{2}{9}\right] > 0, \quad \forall t \in \mathbb{R} \end{aligned}$$

$\Rightarrow \Psi(T)$  is a function of minimal sufficient statistic  
 $\Rightarrow T^3 - 2T^2 + 2T + 1$  is minimal sufficient **1 MARK**

**FALSE**

0.5 MARKS

(II) The log likelihood function is

$$l_2(\theta) = -3 \ln \theta - \frac{\sum x_i}{\theta}$$

$$\frac{\partial}{\partial \theta} l_2(\theta) = -\frac{3}{\theta} + \frac{3\bar{x}}{\theta^2} = 0 \Rightarrow \theta = \bar{x}$$

$$\left[ \frac{\partial^2}{\partial \theta^2} l_2(\theta) \right]_{\theta=\bar{x}} = \left[ \frac{3}{\theta^2} - \frac{6\bar{x}}{\theta^3} \right]_{\theta=\bar{x}} = -\frac{3}{\bar{x}^2} < 0$$

$$\Rightarrow \hat{\theta}_{MLE} = \bar{x} = 1$$

1 MARK

**FALSE**

0.5 MARKS

$$E_\theta(x_i) = \theta$$

$$\Rightarrow \hat{\theta}_{MLE} = \bar{x} = -0.5$$

1 MARK

**FALSE**

0.5 MARKS

$\delta_1$  is UMVUE and  $\delta_2$  is unbiased

$\Rightarrow \delta_1$  is UMVUE and  $\delta_1 - \delta_2 \in U$

$\Rightarrow \text{Cov}_\theta(\delta_1, \delta_1 - \delta_2) = 0$  &  $\theta \in \Theta$

$\Rightarrow \text{Cov}_\theta(\delta_1, \delta_2) = \text{Var}_\theta(\delta_1)$  &  $\theta \in \Theta$

1 MARK

**TRUE**

0.5 MARKS

$X_{(2)}$  is complete-sufficient and  $\frac{X_{(1)}}{X_{(2)}}$  is ancillary

$\Rightarrow X_{(2)}$  and  $\frac{X_{(1)}}{X_{(2)}}$  are independent

$\Rightarrow E_\theta(X_{(1)}) = E_\theta(X_{(2)} \frac{X_{(1)}}{X_{(2)}}) = E_\theta(X_{(2)}) E_\theta(\frac{X_{(1)}}{X_{(2)}})$

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$$\Rightarrow E_\theta \left( \frac{X_{(1)}}{X_{(2)}} \right) = \frac{E_\theta(X_{(1)})}{E_\theta(X_{(2)})}$$

$$= \frac{2 \int_0^1 x (1-x) dx}{2 \int_0^1 x^2 dx} = \frac{1}{2} = 0.5$$

1 MARK  
0.5 MARKS

(ix) FALSE

Let  $x_1, x_2$  be iid  $\sim U(0, \theta+1)$   $\forall \theta \in \mathbb{R} = \mathbb{H}$ . Then  $(x_{(1)}, x_{(2)})$  is minimal sufficient and  $x_{(2)} - x_{(1)}$  is ancillary.

$$\Rightarrow E_\theta [x_{(2)} - x_{(1)}] = \frac{2}{3} - \frac{1}{3} = \frac{1}{3} \quad \forall \theta \in \mathbb{R}$$

$$\Rightarrow E_\theta [x_{(2)} - x_{(1)} - \frac{1}{3}] = 0 \quad \forall \theta \in \mathbb{R}$$

$$\text{But } P_\theta (x_{(2)} - x_{(1)} - \frac{1}{3} = 0) = 0 \quad \forall \theta \in \mathbb{R}$$

$$\Rightarrow (x_{(1)}, x_{(2)}) \text{ is not complete.}$$

0.5 MARKS

(x) TRUE  
By (vii)

$$V_{\text{ave}}(\delta_1) = V_{\text{ave}}(\delta_2) = G_\theta(\delta_1, \delta_2) \quad \forall \theta \in \mathbb{H}$$

$$\Rightarrow E_\theta(\delta_1 - \delta_2) = 0 \quad \forall \theta \in \mathbb{H}$$

$$\text{and } V_{\text{ave}}(\delta_1 - \delta_2) = 0 \quad \forall \theta \in \mathbb{H}$$

$$\Rightarrow P_\theta (\delta_1 - \delta_2 = 0) = 1 \quad \forall \theta \in \mathbb{H}$$

1 MARK

**Problem No. 2**

For sample points  $\underline{x} = (x_1, x_2)$  and  
 $\underline{y} = (y_1, y_2)$

$$\begin{aligned}\frac{g_0(\underline{x})}{g_0(\underline{y})} &= \frac{[1 + (\theta - x_{(1)})^2] [1 + (\theta - x_{(2)})^2]}{[1 + (\theta - y_{(1)})^2] [1 + (\theta - y_{(2)})^2]} \\ &= \frac{(\theta - x_{(1)} + i) (\theta - x_{(1)} - i) (\theta - x_{(2)} + i) (\theta - x_{(2)} - i)}{(\theta - y_{(1)} + i) (\theta - y_{(1)} - i) (\theta - y_{(2)} + i) (\theta - y_{(2)} - i)}\end{aligned}$$

is independent of  $\theta \in \mathbb{R}$  iff for some  $k(\underline{x}, \underline{y})$  (independent of  $\theta$ )

$$(\theta - x_{(1)} + i) (\theta - x_{(1)} - i) (\theta - x_{(2)} + i) (\theta - x_{(2)} - i)$$

$$(\theta - y_{(1)} + i) (\theta - y_{(1)} - i) (\theta - y_{(2)} + i) (\theta - y_{(2)} - i), \forall \theta \in \mathbb{R}$$

On the LHS and RHS we have two polynomials that match on whole  $\mathbb{R}$  and thus

$$\Rightarrow k(\underline{x}, \underline{y}) = 1$$

$$\text{and } (\theta - x_{(1)} + i) (\theta - x_{(1)} - i) (\theta - x_{(2)} + i) (\theta - x_{(2)} - i) = 0$$

$$(\theta - y_{(1)} + i) (\theta - y_{(1)} - i) (\theta - y_{(2)} + i) (\theta - y_{(2)} - i) = 0$$

3 MARKS

with have the same roots

$$\Rightarrow \{x_{(1)} - i, x_{(1)} + i, x_{(2)} - i, x_{(2)} + i\} = \{y_{(1)} - i, y_{(1)} + i, y_{(2)} - i, y_{(2)} + i\}$$

$$\Rightarrow \{x_{(1)}, x_{(2)}\} = \{y_{(1)}, y_{(2)}\}$$

$$\Rightarrow (x_{(1)}, x_{(2)}) = (y_{(1)}, y_{(2)})$$

$$\Rightarrow T = (x_{(1)}, x_{(2)}) \text{ is minimal sufficient}$$

3 MARKS

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Note that  $x_{(2)} - x_{(1)}$  is ancillary. Consider Then  
 $P_\theta(x_{(2)} - x_{(1)} \leq 1) = c$  ( $c$  does not depend on  $\theta$ ).

Consider

$$\Psi(x_{(1)}, x_{(2)}) = \begin{cases} +c, & \text{if } x_{(2)} - x_{(1)} \leq c \\ -c & \text{if } x_{(2)} - x_{(1)} > c \end{cases}$$

The  $\Psi$  is a bounded function

$$E_\theta(\Psi(x_{(1)}, x_{(2)})) = (1-c)c - c(1-c) = 0, \quad \forall \theta \in \Theta$$

but

$$P_\theta(\Psi(x_{(1)}, x_{(2)}) = 0) \geq 0, \quad \forall \theta \in \Theta$$

$\Rightarrow I = (x_{(1)}, x_{(2)})$  is not bounded) complete.

4 MARKS

### Problem 10.3

(i) The likelihood function

$$L_2(\theta) = \frac{\theta^3}{\theta^6} \prod_{i=1}^3 x_i, \quad \theta \geq 2x_3,$$

is maximized at  $\theta = 2x_3$

$$\text{Thus } \hat{\theta}_{MLE} = x_{(3)}$$

4 MARKS

$$(ii) E_\theta(x_1) = \frac{2}{3}\theta$$

$$\Rightarrow \frac{2}{3}\hat{\theta}_{MLE} = \bar{x}$$

$$\Rightarrow \hat{\theta}_{MLE} = \frac{3}{2}\bar{x}$$

4 MARKS

(iii) The dominating estimator is

$$\hat{\theta}^* = E_{\theta} \left[ \frac{3}{2} \bar{X} \mid X_{(3)} \right]$$

$$= \frac{3}{2} \sum_{i=1}^3 E_{\theta} [X_i \mid X_{(3)}]$$

$$= \frac{3}{2} E_{\theta} [X_1 \mid X_{(3)}] = \frac{3}{2} E_{\theta} \left[ \frac{X_1}{X_{(3)}} X_{(3)} \mid X_{(3)} \right] = \frac{3}{2} E_{\theta} \left[ \frac{X_1}{X_{(3)}} \mid X_{(3)} \right] X_{(3)}$$

$X_{(3)}$  is complete sufficient and  $\frac{X_1}{X_{(3)}}$  are independent  
 $\Rightarrow X_{(3)}$  and  $\frac{X_1}{X_{(3)}}$  are independent

$\Rightarrow$

$$\Rightarrow \hat{\theta}^* = \frac{3}{2} E_{\theta} \left( \frac{X_1}{X_{(3)}} \right) X_{(3)}$$

2 MARKS

Again using Barn's Theorem we get

$$E_{\theta} (X_1) = E_{\theta} \left( \frac{X_1}{X_{(3)}} X_{(3)} \right) = E_{\theta} \left( \frac{X_1}{X_{(3)}} \right) E_{\theta} (X_{(3)})$$

$$\Rightarrow E_{\theta} \left( \frac{X_1}{X_{(3)}} \right) = \frac{E_{\theta}(X_1)}{E_{\theta}(X_{(3)})} = \frac{2/3}{3 \int_0^1 x^4 x^{2/3} dx}$$

$$= \frac{7}{9}$$

$$\hat{\theta}^* = \frac{3}{2} \times \frac{7}{9} X_{(3)} = \frac{7}{6} X_{(3)} \quad \dots \quad \boxed{2 MARKS}$$

Problem 10.4

An unbiased estimator of  $\psi(\theta) = (1-\theta)\theta^{1/2}$

$$\delta_0(x) = \begin{cases} 1, & \text{if } x=1 \\ 0, & \text{otherwise} \end{cases}$$

At  $\theta=\theta_0$ , the LNUUE of  $\psi(\theta)$  is

$$S_{\psi}(x) = \delta_0(x) - \psi(x)$$

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where  $U^* \in U$  is known that

$$E_{\theta_0}[(\delta_0(x) - U^*(x))^2] = \inf_{U \in U} E_{\theta_0}[(\delta_0(x) - U(x))^2] \quad \boxed{3 \text{ MARKS}}$$

We have

$$U \in U \Leftrightarrow E_{\theta_0}[U(x)] = 0 \quad \forall \theta \in (0, 1)$$

$$\Leftrightarrow U(-1)\theta + \sum_{k=0}^{\infty} U(k)(1-\theta)^2 \theta^k = 0 \quad \forall \theta \in (0, 1)$$

$$\Leftrightarrow U(-1)\theta(1-\theta)^{-2} + \sum_{k=0}^{\infty} U(k)\theta^k = 0 \quad \forall \theta \in (0, 1)$$

$$\Leftrightarrow U(-1)\theta(1+2\theta+3\theta^2+\dots) + \sum_{k=0}^{\infty} U(k)\theta^k = 0 \quad \forall \theta \in (0, 1)$$

$$\Leftrightarrow U(0) = 0, \quad U(-1) + U(1) = 0, \quad \forall U(-1) + U(k) = 0, \quad k=2, \dots$$

$$\Leftrightarrow U(x) = ax \quad \text{for some } a \in \mathbb{R} \quad \boxed{5 \text{ MARKS}}$$

unique

The LMMUE of  $\psi(\theta)$  is

$$\delta_U(x) = \delta_0(x) - \hat{a}x,$$

where  $\hat{a} = \hat{a}^{(\theta_0)}$  minimizes

$$E_{\theta_0}[(\delta_0(x) - ax)^2] = a^2 \theta_0 + (1-a)^2 \theta_0 (1-\theta_0)^2 + a^2 \sum_{k=2}^{\infty} k^2 (1-\theta_0)^2 \theta_0^k$$

We have

$$\begin{aligned} a^{(\theta_0)} &= \frac{\theta_0(1-\theta_0)}{\theta_0 + \theta_0(1-\theta_0)^2 + \sum_{k=2}^{\infty} k^2 (1-\theta_0)^2 \theta_0^k} \\ &= \frac{\theta_0(1-\theta_0)}{1 - P_{\theta_0}(x=0)} = \frac{\theta_0(1-\theta_0)}{1 - (1-\theta_0)^2} \\ &\rightarrow \text{depends on } \theta_0 \end{aligned}$$

4 MARKS

Thus the MMUE of  $\psi(\theta)$  does not exist.