

**MATH20802: STATISTICAL METHODS  
SECOND SEMESTER  
ANSWERS TO THE IN CLASS TEST**

**ANSWERS TO QUESTION 1**

(i) Note that

$$\begin{aligned}
 E(T(X)) &= 1 \cdot \theta^3 + 2(1-c) \cdot \theta^2(1-\theta) + 2c \cdot \theta(1-\theta) + (1-2c) \cdot \theta(1-\theta)^2 \\
 &= \theta^3 + 2(1-c) \cdot (\theta^2 - \theta^3) + 2c \cdot (\theta - \theta^2) + (1-2c) \cdot (\theta - 2\theta^2 + \theta^3) \\
 &= \theta^3 + 2(1-c) \cdot \theta^2 - 2(1-c) \cdot \theta^3 + 2c \cdot \theta - 2c \cdot \theta^2 + (1-2c) \cdot \theta - 2(1-2c) \cdot \theta^2 + (1-2c) \cdot \theta^3 \\
 &= (2c+1-2c) \cdot \theta + (2-2c-2c-2+4c) \cdot \theta^2 + (1-2+2c+1-2c) \cdot \theta^3 \\
 &= 1 \cdot \theta + 0 \cdot \theta^2 + 0 \cdot \theta^3 \\
 &= \theta
 \end{aligned}$$

Hence,  $T(X)$  is unbiased for all  $c$ . (3 marks)

(ii) Using the fact  $\sum_{i=1}^n (X_i - \bar{X})^2 \sim \sigma^2 \chi_{n-1}^2$ , we see that

$$E(S^2) - \sigma^2 = (1/n)\sigma^2 E(\chi_{n-1}^2) - \sigma^2 = -(1/n)\sigma^2$$

and

$$Var(S^2) = (1/n^2)\sigma^4 Var(\chi_{n-1}^2) = 2((n-1)/n^2)\sigma^4.$$

So,  $S^2$  is biased but is consistent. (2 marks)

(iii) We know that

$$E(\bar{X}) = (1/n)E(X_1 + X_2 + \dots + X_n) = (1/n)n\mu = \mu,$$

so

$$E(X_1 + \bar{X})/2 = (1/2)(E(X_1) + E(\bar{X})) = \mu.$$

Note that

$$Var\left(\frac{X_1 + \bar{X}}{2}\right) = \frac{1}{4}Var(X_1 + \bar{X}) \neq \frac{1}{4}[Var(X_1) + Var(\bar{X})]$$

since  $X_1$  and  $\bar{X}$  are not independent. But we can write

$$Var\left(\frac{X_1 + \bar{X}}{2}\right) = \frac{1}{4}Var(X_1 + \bar{X})$$

$$\begin{aligned}
&= \frac{1}{4} \text{Var} \left( X_1 + \frac{1}{n} \sum_{i=1}^n X_i \right) \\
&= \frac{1}{4} \text{Var} \left( X_1 + \frac{X_1}{n} + \frac{X_2}{n} + \dots + \frac{X_n}{n} \right) \\
&= \frac{1}{4} \text{Var} \left( \left(1 + \frac{1}{n}\right) X_1 + \frac{X_2}{n} + \dots + \frac{X_n}{n} \right) \\
&= \frac{1}{4} \left[ \text{Var} \left( \left(1 + \frac{1}{n}\right) X_1 \right) + \text{Var} \left( \frac{X_2}{n} + \dots + \frac{X_n}{n} \right) \right] \\
&\quad \text{since } X_1 \text{ and } X_2, \dots, X_n \text{ are independent} \\
&= \frac{1}{4} \left[ \left(1 + \frac{1}{n}\right)^2 \text{Var} (X_1) + \frac{1}{n^2} \text{Var} (X_2 + \dots + X_n) \right] \\
&= \frac{1}{4} \left[ \left(1 + \frac{1}{n}\right)^2 \text{Var} (X_1) + \frac{1}{n^2} \text{Var} \left( \sum_{i=2}^n X_i \right) \right] \\
&= \frac{1}{4} \left[ \left(1 + \frac{1}{n}\right)^2 \text{Var} (X_1) + \frac{1}{n^2} \sum_{i=2}^n \text{Var} (X_i) \right] \\
&= \frac{1}{4} \left[ \left(1 + \frac{1}{n}\right)^2 \sigma^2 + \frac{1}{n^2} \sum_{i=2}^n \sigma^2 \right] \\
&= \frac{1}{4} \left[ \left(1 + \frac{1}{n}\right)^2 \sigma^2 + \frac{1}{n^2} (n-1) \sigma^2 \right].
\end{aligned}$$

The limit of this as  $n \rightarrow \infty$  is  $\sigma^2/4$ , so the estimator is not consistent.

(3 marks)

(iv) We know that

$$E(\bar{X}) = (1/n)E(X_1 + X_2 + \dots + X_n) = (1/n)n\lambda = \lambda$$

and

$$\text{Var}(\bar{X}) = (1/n^2) \text{Var}(X_1 + X_2 + \dots + X_n) = (1/n^2) n\lambda = \lambda/n.$$

So,

$$E(\bar{X}^2) = \text{Var}(\bar{X}) + (E(\bar{X}))^2 = \lambda/n + \lambda^2.$$

Hence, the estimator is biased.

(2 marks)

## ANSWERS TO QUESTION 2

(i) Let  $X_1, X_2, \dots, X_n$  be a random sample from  $f(x) = 2\alpha^{-2}x \exp\{-x^2/\alpha^2\}$ . The log-likelihood function is

$$\log L(\alpha) = n \log 2 - 2n \log \alpha + \sum_{i=1}^n \log X_i - \alpha^{-2} \sum_{i=1}^n X_i^2.$$

The normal equation is:

$$\frac{\partial \log L(\alpha)}{\partial \alpha} = -\frac{2n}{\alpha} + \frac{2}{\alpha^3} \sum_{i=1}^n X_i^2 = 0.$$

The root of this equation,  $\sqrt{(1/n) \sum_{i=1}^n X_i^2}$ , is the mle of  $\alpha$ . (2 marks)

(ii) Let  $X_1, X_2, \dots, X_n$  be a random sample from a normal population with mean  $\theta$  and standard deviation  $\theta$ . The log-likelihood function is

$$\log L(\theta) = \frac{n}{2} \log(2\pi) - n \log \theta - \frac{1}{2\theta^2} \sum_{i=1}^n (X_i - \theta)^2.$$

The normal equation is:

$$\frac{\partial \log L(\theta)}{\partial \theta} = -\frac{n}{\theta} + \frac{1}{\theta^3} \sum_{i=1}^n X_i^2 - \frac{1}{\theta^2} \sum_{i=1}^n X_i = 0.$$

This is a quadratic equation on  $\theta$ . Its two roots are:

$$-\frac{1}{2n} \sum_{i=1}^n X_i \pm \frac{1}{2n} \sqrt{\left(\sum_{i=1}^n X_i\right)^2 + 4n \sum_{i=1}^n X_i^2}.$$

The positive sign gives the valid mle for  $\theta$ . (3 marks)

(iii) Let  $X_1, X_2, \dots, X_n$  be a random sample from  $f(x) = \lambda^{-2}x \exp\{-x/\lambda\}$ . The log-likelihood function is

$$\log L(\lambda) = -2n \log \lambda + \sum_{i=1}^n \log X_i - \lambda^{-1} \sum_{i=1}^n X_i.$$

The normal equation is:

$$\frac{\partial \log L(\lambda)}{\partial \lambda} = -\frac{2n}{\lambda} + \frac{1}{\lambda^2} \sum_{i=1}^n X_i = 0.$$

The root of this equation,  $(1/(2n)) \sum_{i=1}^n X_i$ , is the mle of  $\lambda$ . (2 marks)

(iv) Let  $X_1, X_2, X_3$  be a random sample from the discrete uniform distribution between 1 and  $N$ , inclusive. The likelihood function is

$$\begin{aligned} L(N) &= N^{-3} I \{1 \leq X_1 \leq N, 1 \leq X_2 \leq N, 1 \leq X_3 \leq N\} \\ &= N^{-3} I \{\max(X_1, X_2, X_3) \leq N, \min(X_1, X_2, X_3) \geq 1\}, \end{aligned}$$

a monotonic decreasing function of  $N$  for all  $N \geq \max(X_1, X_2, X_3)$ . So, the mle  $\hat{N} = \max(X_1, X_2, X_3)$ . (3 marks)