

Assignment 6

Gautham Bellamkonda - CS20BTECH11017

Download all latex-tikz codes from

<https://github.com/GauthamBellamkonda/AI1103/tree/main/Assignment6>

1 PROBLEM

Let X_1, X_2, \dots, X_n be a random sample of size $n (\geq 2)$ from a distribution having the probability density function

$$f(x; \theta) = \begin{cases} \frac{1}{\theta} \exp\left(-\frac{x}{\theta}\right) & x > 0, \\ 0, & \text{otherwise,} \end{cases} \quad (1.0.1)$$

where $\theta \in (0, \infty)$. Let $X_{(1)} = \min \{X_1, X_2, \dots, X_n\}$ and $T = \sum_{i=1}^n X_i$. Then $E(X_{(1)}|T)$ equals

- (A) $\frac{T}{n^2}$
- (B) $\frac{T}{n}$
- (C) $\frac{(n+1)T}{2n}$
- (D) $\frac{(n+1)^2 T}{4n^2}$

2 PREREQUISITES

Lemma 2.1 (Sum of Gamma random variables). Suppose that $X_1, X_2, X_3, \dots, X_n$ are n gamma variables with parameters k and θ , $X_i \sim \Gamma(k, \theta)$. Then the sum $T = \sum_{i=1}^n X_i$ follows a gamma distribution with parameters nk and θ , $T \sim \Gamma(nk, \theta)$

Definition 1 (Complete Statistic). The statistic T is said to be complete for the distribution of X if, for every measurable function g , if

$$E(g(T)) = 0 \quad \forall \theta \Rightarrow \Pr(g(T) = 0) = 1 \quad (2.0.1)$$

Definition 2 (Sufficient Statistic). A statistic $t = T(X)$ is sufficient for underlying parameter θ precisely if the conditional probability distribution of the data X , given the statistic $t = T(X)$, does not depend on the parameter θ .

Theorem 2.1 (Fischer-Neymann Factorisation theorem). If the probability density function is $f_\theta(x)$, then T is sufficient for θ if and only if nonnegative functions g and h can be found such that

$$f_\theta(x) = h(x)g_\theta(T(x)) \quad (2.0.2)$$

Lemma 2.2.

$$T = \sum_{i=1}^n X_i \quad (2.0.3)$$

is a complete and sufficient statistic.

Proof. 1) (Sufficiency)

$$f_X(x_1, x_2, \dots, x_n) = f_{X_1}(x_1)f_{X_2}(x_2) \dots f_{X_n}(x_n) \quad (2.0.4)$$

$$= \frac{1}{\theta} \exp\left(-\frac{x_1}{\theta}\right) \dots \frac{1}{\theta} \exp\left(-\frac{x_n}{\theta}\right) \quad (2.0.5)$$

$$= 1 \cdot \frac{1}{\theta^n} \exp\left(-\frac{T}{\theta}\right) \quad (2.0.6)$$

$$= h(X) \cdot g(T, \theta) \quad (2.0.7)$$

with

$$g(T, \theta) = \frac{1}{\theta^n} \exp\left(-\frac{T}{\theta}\right) \quad (2.0.8)$$

$$h(X) = 1 \quad (2.0.9)$$

Therefore, T is a sufficient statistic.

2) (Completeness)

X_i follow a gamma distribution, $X_i \sim \Gamma\left(1, \frac{1}{\theta}\right)$. Hence, $T = \sum_{i=1}^n X_i$ follows a gamma distribution, $T \sim \Gamma\left(n, \frac{1}{\theta}\right)$. Therefore, the expected

value of a function g is

$$E(g(T)) = \int_0^\infty g(t) \frac{t^{n-1} e^{-\frac{t}{\theta}}}{\theta^n (n-1)!} dt \quad (2.0.10)$$

$$= \frac{1}{\theta^n (n-1)!} \int_0^\infty g(t) t^{n-1} e^{-\frac{t}{\theta}} dt \quad (2.0.11)$$

$$= \frac{1}{\theta^n (n-1)!} F\left(\frac{1}{\theta}\right) \quad (2.0.12)$$

$$= 0 \text{ for all } \theta > 0. \quad (2.0.13)$$

where,

$$f(t) = t^{n-1} g(t) \quad (2.0.14)$$

$$F\left(\frac{1}{\theta}\right) = \text{Laplace Transform of } f(t) \text{ at } \theta \quad (2.0.15)$$

Since, $E(g(T)) = 0$ for all $\theta > 0$,

$$F\left(\frac{1}{\theta}\right) = 0 \text{ for all } \theta > 0. \quad (2.0.16)$$

From the theory of Laplace transforms, it follows from (2.0.16) that

$$f(t) = 0 \text{ almost everywhere in } (0, \infty) \quad (2.0.17)$$

$$g(t) = 0 \text{ almost everywhere in } (0, \infty) \quad (2.0.18)$$

$$\Pr(g(t) = 0) = 1 \quad (2.0.19)$$

Therefore, T is a complete statistic. \square

Theorem 2.2 (Lehmann–Scheffé theorem). *If T is a complete sufficient statistic for θ and*

$$E(g(T)) = \tau(\theta) \quad (2.0.20)$$

then $g(T)$ is the uniformly minimum-variance unbiased estimator (UMVUE) of $\tau(\theta)$.

3 SOLUTION

Proposition 3.1. *$E(X_{(1)}|T)$ is the uniformly minimum-variance unbiased estimator (UMVUE) of $E(X_{(1)})$*

Proof. By the law of total expectation,

$$E(E(X_{(1)}|T)) = E(X_{(1)}) \quad (3.0.1)$$

We know that $T = \sum_{i=1}^n X_i$ is a complete and sufficient statistic by 2.2. By Lehmann–Scheffé theorem, with

$$\theta = X_{(1)}, \quad (3.0.2)$$

$$\tau(x) = E(x), \quad (3.0.3)$$

$$g(T) = E(X_{(1)}|T). \quad (3.0.4)$$

it follows from (3.0.1) that $E(X_{(1)}|T)$ is the UMVUE of $E(X_{(1)})$. \square

Proposition 3.2. *$\frac{T}{n^2}$ is uniformly minimum-variance unbiased estimator (UMVUE) of $E(X_{(1)})$*

Proof. 1) Let's find the probability distribution function and the expectation value of $X_{(1)}$:

$$\Pr(X_{(1)} > x) = \Pr(X_1 > x) \dots \Pr(X_n > x) \quad (3.0.5)$$

$$= (1 - F_{X_1}(x)) \dots (1 - F_{X_n}(x)) \quad (3.0.6)$$

$$= (1 - F_{X_1}(x))^n \quad (3.0.7)$$

$$= \exp\left(-\frac{nx}{\theta}\right) \quad (3.0.8)$$

$$F_{X_{(1)}}(x) = 1 - \exp\left(-\frac{nx}{\theta}\right) \quad (3.0.9)$$

$$f_{X_{(1)}}(x) = \frac{n}{\theta} \exp\left(-\frac{nx}{\theta}\right) \quad (3.0.10)$$

Therefore, $X_{(1)}$ follows an exponential distribution with mean $\frac{\theta}{n}$.

$$E(X_{(1)}) = \frac{\theta}{n} \quad (3.0.11)$$

2) $\frac{T}{n^2}$ is uniformly minimum-variance unbiased estimator (UMVUE) of $E(X_{(1)})$, since $E\left(\frac{T}{n^2}\right) = E(X_{(1)})$:

Note that,

$$E\left(\frac{T}{n^2}\right) = E\left(\frac{\sum_{i=1}^n X_i}{n^2}\right) \quad (3.0.12)$$

$$= \frac{E(\sum_{i=1}^n X_i)}{n^2} \quad (3.0.13)$$

$$= \sum_{i=1}^n \frac{E(X_i)}{n^2} \quad (3.0.14)$$

$$= \sum_{i=1}^n \frac{\theta}{n^2} \quad (3.0.15)$$

$$= \frac{\theta}{n} \quad (3.0.16)$$

$$= E(X_{(1)}) \quad (3.0.17)$$

Therefore, by Lehmann–Scheffé theorem, with

$$\theta = X_{(1)}, \quad (3.0.18)$$

$$\tau(x) = E(x), \quad (3.0.19)$$

$$g(T) = \frac{T}{n^2}, \quad (3.0.20)$$

it follows that $\frac{T}{n^2}$ is UMVUE of $E(X_{(1)})$. \square

Since there exists a unique UMVUE for $E(X_{(1)})$, it follows from Proposition 3.1 and Proposition 3.2 that

$$E(X_{(1)}|T) = \frac{T}{n^2} \quad (3.0.21)$$

Hence, option A is correct.

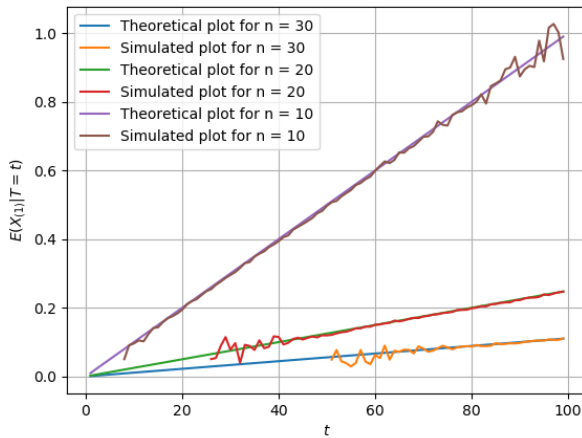


Fig. 2: Theory vs Simulated plot of $E(X_{(1)}|T)$