

# Assignment 9

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[https://github.com/adhvik24/AI1103-PROBABILITY-AND-RANDOM-VARIABLES/blob/main/Assignment\\_9/AI1103\\_Assignment9.tex](https://github.com/adhvik24/AI1103-PROBABILITY-AND-RANDOM-VARIABLES/blob/main/Assignment_9/AI1103_Assignment9.tex)

1 GATE 2020 (ST), Q.23 (STATISTICS SECTION)

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

$$f(x, \theta) = \begin{cases} e^{-(x-2\theta)}, & x > 2\theta \\ 0, & \text{otherwise} \end{cases} \quad (1.0.1)$$

where  $\theta \in (0, \infty)$ . If  $X_{(1)} = \min\{X_1, X_2, \dots, X_n\}$  then the conditional expectation

$$E\left[\frac{1}{\theta}\left(X_{(1)} - \frac{1}{n}\right) | X_1 - X_2 = 2\right] = \text{_____}$$

2 SOLUTION

## DEFINITIONS:

- 1) **Completeness:** The statistic  $T$  is said to be complete for the distribution of  $X$  if, for every measurable function  $g$  if

$$E(g(T)) = 0 \implies P(g(T) = 0) = 1 \quad \forall \theta \quad (2.0.1)$$

- 2) **Sufficiency:** Let  $f(x, \theta)$  be the joint pdf of the sample  $X$ . A statistic  $T$  is sufficient for  $\theta$  iff there are functions  $h$  (does not depend on  $\theta$ ) and  $g$  (depends on  $\theta$ ) on the range of  $T$  such that

$$f(x, \theta) = g(T(x), \theta) h(x) \quad (2.0.2)$$

- 3) **Basu's Theorem:** If  $T(X)$  is complete and sufficient, and  $S(X)$  is ancillary, then  $S(X)$  and  $T(X)$  are independent for all  $\theta$ .

$\implies$  complete sufficient statistic is independent of any ancillary statistic.

Given PDF of the distribution as,

$$f(x, \theta) = \begin{cases} e^{-(x-2\theta)}, & x > 2\theta \\ 0, & \text{otherwise} \end{cases} \quad (2.0.3)$$

Then CDF of the distribution given is,

$$F(x, \theta) = \int_{-\infty}^x f(x, \theta) dx \quad (2.0.4)$$

Using (2.0.3) in (2.0.4),

$$F(x, \theta) = \begin{cases} 0, & x < 2\theta \\ 1 - e^{-(x-2\theta)}, & x > 2\theta \end{cases} \quad (2.0.5)$$

As given  $X_{(1)} = \min\{X_1, X_2, \dots, X_n\}$ ,

Let us find CDF of  $X_{(1)}$ ,

$$\begin{aligned} F_{X_{(1)}}(x, \theta) &= \Pr(X_{(1)} \leq x) \\ &= \Pr(\text{at least one of } X_1, X_2, \dots, X_n \leq x) \\ &= 1 - \Pr(X_{(1)} > x) \\ &= 1 - \Pr(X_1 > x, X_2 > x, \dots, X_n > x) \\ &= 1 - \Pr(X_1 > x) \cdots \Pr(X_n > x) \\ &= 1 - (1 - F(x, \theta))^n \end{aligned} \quad (2.0.6)$$

Using (2.0.5) in (2.0.6),

$$F_{X_{(1)}}(x, \theta) = \begin{cases} 0, & x < 2\theta \\ 1 - e^{-n(x-2\theta)}, & x > 2\theta \end{cases} \quad (2.0.7)$$

Using CDF of  $X_{(1)}$  to find PDF of  $X_{(1)}$ ,

$$f_{X_{(1)}}(x, \theta) = \frac{d}{dx} F_{X_{(1)}}(x, \theta) \quad (2.0.8)$$

Using (2.0.7) in (2.0.8), PDF of  $X_{(1)}$  is

$$f_{X_{(1)}}(x, \theta) = \begin{cases} ne^{-n(x-2\theta)}, & x > 2\theta \\ 0, & \text{otherwise} \end{cases} \quad (2.0.9)$$

$X_{(1)}, \dots, X_{(n)}$  are ordered statistics of  $X_1, \dots, X_n$ .

Where  $X_{(k)}$  is  $k$ th order statistic of  $X_1, \dots, X_n$ .

$$\implies \sum_{i=1}^n X_i = \sum_{i=1}^n X_{(i)} \quad (2.0.10)$$

Some results that we use in future:

- 1) Ordered statistics are complete and sufficient statistic of  $X$ .

**Proof:**

Let  $E[g(X_{(1)})] = 0$ ,

$$\Rightarrow \int_{-\infty}^{\infty} g(x) f_{X_{(1)}}(x) dx = 0 \quad (2.0.11)$$

$$\int_{2\theta}^{\infty} g(x) n e^{-n(x-2\theta)} dx = 0 \quad (2.0.12)$$

$$\int_{2\theta}^{\infty} g(x) e^{-n(x-2\theta)} dx = 0 \quad (2.0.13)$$

differentiating w.r.t  $\theta$  on both sides in (2.0.13),

$$\frac{d}{dx} \int_{2\theta}^{\infty} g(x) e^{-n(x-2\theta)} dx = 0$$

$$\frac{d}{dx} \left( \int_{2\theta}^{\infty} g(x) e^{-nx} dx \right) e^{2n\theta} = 0$$

$$2ne^{2n\theta} \int_{2\theta}^{\infty} g(x) e^{-nx} dx + e^{2n\theta} (2)g(2\theta)e^{-2n\theta} = 0$$

$$2n(0) + 2g(2\theta) = 0 \Rightarrow g(2\theta) = 0$$

$\Rightarrow X_{(1)}$  is complete statistics.

Using (2.0.10) in (2.0.16)

$$f_X(x, \theta) = f(x_1, \theta) f(x_2, \theta) \cdots f(x_n, \theta) \quad (2.0.14)$$

$$= e^{-(x_1-2\theta)} e^{-(x_2-2\theta)} \cdots e^{-(x_n-2\theta)} \quad (2.0.15)$$

$$= e^{-\left(\sum_{i=1}^n x_i - 2n\theta\right)} = e^{-\left(\sum_{i=1}^n x_{(i)} - 2n\theta\right)} \quad (2.0.16)$$

$$= \underbrace{\prod_{j=1}^n e^{-(x_{(j)}-2\theta)}}_g \times \underbrace{(1)}_h \quad (2.0.17)$$

$\therefore$  Ordered statistics of  $X$  are sufficient statistics for  $\theta$ .

$\therefore X_{(1)}$  is complete and sufficient statistics of  $\theta$ .

2)  $X_1 - X_2$  is ancillary of  $\theta$ .

**Proof:** Let  $U = X_1 - X_2$  then,

$$\begin{aligned} F_U(x) &= \Pr(X_1 - X_2 < x) \\ &= \int_{-\infty}^{\infty} \Pr(X_1 < x + k) \Pr(X_2 > k) dk \\ &= \int_{2\theta}^{\infty} (1 - e^{-(x+k-2\theta)}) (e^{-(k-2\theta)}) dk \\ &= \int_{2\theta}^{\infty} e^{-(k-2\theta)} - e^{-(2k+x-2\theta)} dk \\ &= \left[ \frac{e^{-(k-2\theta)}}{-1} - \frac{e^{-(2k+x-2\theta)}}{-2} \right]_{2\theta}^{\infty} \\ &= (0 - 0) - \left( -1 + \frac{e^{-x}}{2} \right) \end{aligned}$$

$$F_U(x) = 1 - \frac{e^{-x}}{2} \quad (2.0.18)$$

$$\Rightarrow f_U(x) = \frac{d}{dx} F_U(x) \quad (2.0.19)$$

$$= \frac{e^{-x}}{2} \quad (2.0.20)$$

$\therefore U = X_1 - X_2$  is an ancillary statistic of  $\theta$ .

Let  $U$  be a random variable such that  $U = X_1 - X_2$ .

$$\begin{aligned} E \left[ \frac{1}{\theta} \left( X_{(1)} - \frac{1}{n} \right) | X_1 - X_2 = 2 \right] \\ = E \left[ \frac{1}{\theta} \left( X_{(1)} - \frac{1}{n} \right) | U = 2 \right] \end{aligned} \quad (2.0.21)$$

As  $X_1, X_2, \dots, X_n$  are independent and from Basu's theorem  $X_{(1)}$  and  $U$  are also independent.

As we know that if  $X$  and  $Y$  are independent then  $E[X|Y] = E[X]$ . Using this in (2.0.21)

$$\begin{aligned} E \left[ \frac{1}{\theta} \left( X_{(1)} - \frac{1}{n} \right) | U = 2 \right] &= E \left[ \frac{1}{\theta} \left( X_{(1)} - \frac{1}{n} \right) \right] \\ &= \frac{1}{\theta} \left( E[X_{(1)}] - \frac{1}{n} \right) \end{aligned} \quad (2.0.22)$$

We have to find expectation of  $X_{(1)}$ ,

$$E[X_{(1)}] = \int_{-\infty}^{\infty} x f_{X_{(1)}}(x, \theta) dx \quad (2.0.23)$$

Using (2.0.9) in (2.0.23).

$$\begin{aligned} E[X_{(1)}] &= \int_{2\theta}^{\infty} nx e^{-(x-2\theta)n} dx \\ &= e^{2n\theta} \int_{2\theta}^{\infty} nx e^{-nx} dx \end{aligned} \quad (2.0.24)$$

Using integration by parts in (2.0.24),

$$\begin{aligned} E[X_{(1)}] &= e^{2n\theta} \int_{2\theta}^{\infty} nx e^{-nx} dx \\ &= e^{2n\theta} \left( \left[ nx \frac{e^{-nx}}{-n} \right]_{2\theta}^{\infty} - \int_{2\theta}^{\infty} n \frac{e^{-nx}}{-n} dx \right) \\ &= e^{2n\theta} \left( \left[ nx \frac{e^{-nx}}{-n} \right]_{2\theta}^{\infty} + \left[ \frac{e^{-nx}}{-n} \right]_{2\theta}^{\infty} \right) \\ &= e^{2n\theta} \left( 2\theta e^{-2n\theta} + \frac{e^{-2n\theta}}{n} \right) \\ E[X_{(1)}] &= 2\theta + \frac{1}{n} \end{aligned} \quad (2.0.25)$$

Use (2.0.25) in (2.0.22),

$$\begin{aligned} E \left[ \frac{1}{\theta} \left( X_{(1)} - \frac{1}{n} \right) | U = 2 \right] &= \frac{1}{\theta} \left( E[X_{(1)}] - \frac{1}{n} \right) \\ &= \frac{1}{\theta} \left( 2\theta + \frac{1}{n} - \frac{1}{n} \right) \\ E \left[ \frac{1}{\theta} \left( X_{(1)} - \frac{1}{n} \right) | U = 2 \right] &= 2 \end{aligned} \quad (2.0.26)$$

Using (2.0.26) in (2.0.21),

$$\therefore E \left[ \frac{1}{\theta} \left( X_{(1)} - \frac{1}{n} \right) | X_1 - X_2 = 2 \right] = 2$$