## Indian Institute of Information Technology Allahabad Probability and Statistics (PAS) C3 Review Test Tentative Marking Scheme

Program: B.Tech. 3rd Semester (IT+ECE) Duration: 02 Hours Full Marks: 46 Date: November 24, 2020 Time:: 11:00 IST - 13:00 IST

1. Let  $F(\cdot)$  be any c.d.f. and  $\lambda \in \mathbb{R}$ . Find the set A such that  $G(x) = (1+\lambda)F(x) - \lambda F^2(x)$ becomes a c.d.f. of some random variable for all  $\lambda \in A$ .

**Solution.** For all values of  $\lambda$ ,  $G(\cdot)$  is right continuous at every point,  $\lim_{x\to\infty} G(x) = 1$ , and  $\lim_{x \to -\infty} G(x) = 0.$  [1]

For G to be a c.d.f., for  $x_1 < x_2$ ,

$$
G(x_2) - G(x_1) = (F(x_2) - F(x_1))(1 + \lambda - \lambda(F(x_1) + F(x_2))) \ge 0,
$$
 [1]

which implies that

$$
1 + \lambda - \lambda(F(x_1) + F(x_2)) \ge 0, \therefore (F(x_2) - F(x_1)) \ge 0.
$$
 [1]

Case I: For  $0 \leq \lambda \leq 1$ ,  $1 + \lambda - \lambda(F(x_1) + F(x_2)) \geq 1 - \lambda > 0$ . Hence G will be a c.d.f.. Case II: For  $-1 \leq \lambda < 0$ ,  $1 + \lambda - \lambda(F(x_1) + F(x_2)) \geq 1 + \lambda \geq 0$ . Hence G will be a c.d.f..

Case III: For  $\lambda > 1$ , take an  $\epsilon > 0$  with  $\epsilon \leq \frac{\lambda - 1}{\lambda}$  $\frac{-1}{\lambda}$ . Now, we can choose  $x_1, x_2$  and a c.d.f. F (e.g. uniform) such that  $F(x_1) = 1 - \epsilon$ ,  $F(x_2) = 1$ .

This implies that  $1 + \lambda - \lambda(F(x_1) + F(x_2)) \leq 0$ . So, G is not a c.d.f..

Case IV: For  $\lambda < -1$ , take an  $\epsilon > 0$  with  $\epsilon \leq \frac{\lambda+1}{\lambda}$  $\frac{+1}{\lambda}$ . Now, we can choose  $x_1, x_2$  and a c.d.f. F (e.g. uniform) such that  $F(x_1) = 0$ ,  $F(x_2) = \epsilon$ .

This implies that  $1 + \lambda - \lambda(F(x_1) + F(x_2)) \leq 0$ . So, G is not a c.d.f..

Combining all cases, we conclude that G is a c.d.f. for all  $\lambda \in [-1, 1]$ .

2. Suppose X follows Poisson distribution with parameter  $\lambda$ . Find the point x where  $P(X = x)$  is maximum. [4]

**Solution.** 
$$
P(X = k) = \frac{e^{-\lambda} \lambda^k}{k!}
$$
 and  $P(X = k - 1) = \frac{e^{-\lambda} \lambda^{(k-1)}}{(k-1)!}$  [1]

$$
\frac{P(X=k)}{P(X=k-1)} = \frac{\lambda}{k} \tag{1}
$$

Thus,  $P(X = x)$  is increasing when  $x \leq \lambda$  and decreasing when  $x \geq \lambda$ . [1] Therefore, at  $x = |\lambda|$ ,  $P(X = x)$  is maximum. [1]

3. Let X has an exponential distribution with parameter  $\theta$ . Let  $Y = X - a$ , where  $a \ge 0$ . Find a relation between  $P(Y \le x \mid X \ge a)$  and  $P(X \le x)$  for all x. [6]

Solution.

$$
P({Y \le x} \cap {X \ge a}) = P({X - a \le x} \cap {X \ge a})
$$
  
= 
$$
P({X \le a + x} \cap {X \ge a}).
$$

If 
$$
x < 0
$$
,  $P({X \le a + x} \cap {X \ge a}) = 0$  [1]

If 
$$
x \ge 0
$$
,  $P({X \le a + x} \cap {X \ge a}) = P(a \le X \le a + x) = e^{-a\theta}(1 - e^{-\theta x}).$  [1]

 $P(X \ge a) = e^{-a\theta}$  $-a\theta$  [1]

$$
P(Y \le x | X \ge a) = 1 - e^{-\theta x} \tag{1}
$$

 $P(X \le x) = 1 - e^{-\theta x}$ , if  $x \ge 0$  and  $P(X < x) = 0$ , if  $x < 0$ . [1]

Therefore, 
$$
P(Y \le x \mid X \ge a) = P(X \le x)
$$
. [1]

4. Let Z be the standard normal random variable. Show that

$$
P(|Z| \ge t) \le \sqrt{\frac{2}{\pi}} \frac{e^{-t^2/2}}{t}, \ \forall \ t > 0.
$$
 [6]

Solution. Given that Z is a standard normal random variable, therefore

$$
P(Z \ge t) = \frac{1}{\sqrt{2\pi}} \int_{t}^{\infty} e^{\frac{-x^2}{2}} dx.
$$
 [1]

Since  $x/t > 1$  for  $x > t$ , we have [1]

$$
P(Z \ge t) \le \int_{t}^{\infty} \frac{x}{t} e^{\frac{-x^2}{2}} dx.
$$
 [1]

This gives

$$
P(Z \ge t) \le \frac{1}{\sqrt{2\pi}} \frac{e^{\frac{-t^2}{2}}}{t}.\tag{1}
$$

Since Z is a symmetric random variable, we have  $P(|Z| \ge t) = 2P(Z \ge t)$ . [1] Hence,

$$
P(|Z| \ge t) \le \sqrt{\frac{2}{\pi}} \frac{e^{-t^2/2}}{t}.
$$
 [1]

5. Let  $X$  and  $Y$  have the joint probability density function

$$
f_{X,Y}(x,y) = \begin{cases} 24xy, & x > 0, y > 0, x+y \le 1\\ 0, & \text{otherwise.} \end{cases}
$$

Find  $Var[X|Y = y]$ . [5]

**Solution:** The marginal p.d.f. of  $Y$  is

$$
f_Y(y) = \int_{-\infty}^{\infty} f(x, y) dx = \int_0^{1-y} 24xy dx = \begin{cases} 12y(1-y)^2, & 0 < y < 1\\ 0, & \text{otherwise.} \end{cases}
$$
 [1]

The conditional p.d.f. of X, given  $Y = y$  is

$$
f_{X|Y}(x|y) = \frac{f(x,y)}{f_Y(y)} = \begin{cases} \frac{2x}{(1-y)^2}, & 0 < x < 1-y\\ 0, & \text{otherwise.} \end{cases}
$$
 [1]

$$
E[X|Y=y] = \int_{-\infty}^{\infty} x f_{X|Y}(x|y) dx = \int_{0}^{1-y} \frac{2x^2}{(1-y)^2} = \frac{2(1-y)}{3}.
$$
 [1]

$$
E[X^2|Y=y] = \int_{-\infty}^{\infty} x^2 f_{X|Y}(x|y) dx = \int_0^{1-y} \frac{2x^3}{(1-y)^2} = \frac{(1-y)^2}{2}.
$$
 [1]

$$
Var[X|Y=y] = E[X^2|Y=y] - (E[X|Y=y])^2 = \frac{(1-y)^2}{2} - \frac{4(1-y)^2}{9} = \frac{(1-y)^2}{18}.
$$
 [1]

6. Using Central Limit Theorem, find

$$
\lim_{n \to \infty} e^{-nt} \sum_{k=1}^{n-1} \frac{(nt)^k}{k!}, \ \forall \ t > 0.
$$
 [11]

**Solution.** Consider a sequence of *i.i.d* random variables  $\{X_n\}$  such that  $X_n \sim$  $Poisson(t)$  for all n. [1]

Then, 
$$
E(X_n) = Var(X_n) = t
$$
 and  $\sum_{i=1}^{n} X_i \sim Poisson(nt)$  for all *n*.  $\left[\frac{1}{2} + \frac{1}{2} + 1\right]$ 

Now,

$$
\lim_{n \to \infty} e^{-nt} \sum_{k=1}^{n-1} \frac{(nt)^k}{k!} = \lim_{n \to \infty} P\left(1 \le \sum_{i=1}^n X_i \le (n-1)\right)
$$
 [1]

$$
= \lim_{n \to \infty} P\left(\frac{1 - nt}{\sqrt{nt}} \le \frac{\sum_{i=1}^{n} X_i - nt}{\sqrt{nt}} \le \frac{(n-1) - nt}{\sqrt{nt}}\right) \qquad [1]
$$
  

$$
\left(P(-\infty < Z < \infty), \text{ if } 0 < t < 1\right)
$$

$$
= \begin{cases} P(-\infty \le Z \le \infty), \text{ if } 0 < t < 1 \\ P(-\infty \le Z \le 0), \text{ if } t = 1 \\ P(-\infty \le Z \le -\infty), \text{ if } t > 1 \end{cases} [1+1+1]
$$

$$
= \begin{cases} 1, \text{ if } 0 < t < 1 \\ \frac{1}{2}, \text{ if } t = 1 \end{cases} [1+1+1]
$$

7. One observation X is taken from a 
$$
N(0, \sigma^2)
$$
 population. [4]

 $\overline{\mathcal{L}}$ 

0, if  $t > 1$ 

- (a) Find an unbiased estimator of  $\sigma^2$ . **Solution.** Given that X follows  $N(0, \sigma^2)$ . This implies  $E(X) = 0$  and  $Var(x) = E(X^2) - (E(X))^2$ . Therefore,  $E(X^2) = \sigma^2$ .  $[1]$ Hence,  $X^2$  is an unbiased estimator of  $\sigma^2$ .  $\begin{bmatrix} 1 \end{bmatrix}$
- (b) Find the method of moments estimator for  $\sigma$ . **Solution.** To obtain moment estimator, we have  $E(X) = 0$ , Equating the second population moment to the second sample moment we get,  $E(X^2) = \sigma^2 = \sum_{i=1}^n X_i^2 = X^2$ .  $[1]$  $\Rightarrow \sigma^2 = X^2 \Rightarrow \hat{\sigma} = |X|.$ Hence, the moment estimator of  $\sigma$  is |X|. [1]
- 8. Let  $X_1, \ldots, X_n$  be a random sample from the probability density function

$$
f(x|\mu,\lambda) = \left(\frac{\lambda}{2\pi x^3}\right)^{1/2} \exp\left\{-\lambda(x-\mu)^2/(2\mu^2 x)\right\}, \ x > 0.
$$

Find the maximum likelihood estimator for  $\mu$  and  $\lambda$ . [7]

**Solution.** Given that  $X_1, \ldots, X_n$  is a random sample from the probability density function  $1/2$ 

$$
f(x|\mu,\lambda) = \left(\frac{\lambda}{2\pi x^3}\right)^{1/2} \exp\{-\lambda(x-\mu)^2/(2\mu^2 x)\}, \ x > 0.
$$

The likelihood function is given by

$$
L(\lambda, \mu | x) = \prod_{i=1}^{n} \left[ \left( \frac{\lambda}{2\pi x_i^3} \right)^{1/2} \exp \left\{ -\lambda (x_i - \mu)^2 / (2\mu^2 x_i) \right\} \right].
$$
 [1]

Therefore, the log likelihood function is given by

$$
\log L(\lambda, \mu | x) = l = \frac{n}{2} \log \lambda - \frac{n}{2} \log 2\pi - \frac{3}{2} \sum_{i=1}^{n} \log x_i - \frac{\lambda}{2\mu^2} \sum_{i=1}^{n} \left( \frac{(x_i - \mu)^2}{x_i} \right). \tag{1}
$$

The likelihood equation with respect to  $\mu$  is given by  $\frac{\partial l}{\partial \mu} = 0$ . This gives

$$
\frac{-\lambda}{2} \frac{\partial}{\partial \mu} \left( \frac{1}{\mu^2} \sum_{i=1}^n \left( \frac{(x_i - \mu)^2}{x_i} \right) \right) = 0.
$$
  

$$
\frac{1}{n} \sum_{i=1}^n x_i = \bar{x}.
$$
 [2]

 $\Rightarrow \hat{\mu} = \frac{1}{n}$ 

The likelihood equation with respect to  $\lambda$  is given by  $\frac{\partial l}{\partial \lambda} = 0$ . This gives

$$
\frac{n}{2\lambda} - \frac{1}{2\mu^2} \sum_{i=1}^n \left( \frac{(x_i - \mu)^2}{x_i} \right) = 0.
$$
\n
$$
\sum_{i=1}^n \left( \frac{(x_i - \mu)^2}{x_i} \right) = 0.
$$
\n
$$
(2)
$$

 $\Rightarrow \hat{\lambda} = \frac{n}{\sum_{i=1}^{n}$  $\sum_{i=1}^n \left(\frac{1}{x_i} - \frac{1}{\bar{x}}\right)$ Hence, the maximum likelihood estimator for  $\mu$  and  $\lambda$  are  $\bar{X}$  and  $\frac{n}{\sum_{i=1}^{n} (\frac{1}{X_i} - \frac{1}{X})}$  respectively. [1]

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