

p.d.f = Probability density fⁿ

(2) p.m.f = Probability mass fⁿ

r.v = random variable

(1) Let the pdf of a r.v X be f(x)

$$f(x) = \begin{cases} x & ; 0 \leq x < 1/2 \\ c(2x-1)^2 & ; 1/2 < x \leq 1 \\ 0 & ; \text{elsewhere} \end{cases}$$

Then the value of c = _____

Solⁿ As we know that

$$\int \text{p.d.f} = 1 \quad \checkmark$$

$$\Rightarrow \int_0^{1/2} x dx + \int_{1/2}^1 c(2x-1)^2 dx = 1$$

$$\Rightarrow \left[\frac{x^2}{2} \right]_0^{1/2} + c \left[\frac{(2x-1)^3}{3 \times 2} \right]_{1/2}^1 = 1$$

$$\Rightarrow \frac{1}{8} + c \left(\frac{1}{6} - 0 \right) = 1$$

$$\Rightarrow c = \frac{24-3}{4} = \frac{21}{4}$$

$$= \frac{21}{4} = 5.25$$

(2) Let $x_1, x_2, x_3, \dots, x_n$ be a random sample from the following p.d.f for $0 < \mu < \infty$, $0 < \alpha < 1$

$$f(x; \mu, \alpha) = \begin{cases} \frac{1}{\Gamma(\alpha)} (x-\mu)^{\alpha-1} e^{-(x-\mu)} & ; x > \mu \\ 0 & ; \text{o.w} \end{cases}$$

Here α & μ are unknown parameters

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W.O.T.f statements is true

(a) Max. likelihood estimator of only μ exists.

(b) " " " " α exists.

(c) " " " of both μ & α exist.

(d) " " " of neither α & μ exist.

NB: Question based on MLE every time asked in GATE/NET.

Solⁿ

(3) Suppose X & Y are two r.v.s s.t. $ax+by$ is normal r.v. $a, b \in \mathbb{R}$. ~~Consi~~ W.O.T.f. statements - ALWAYS had TRUE. ?

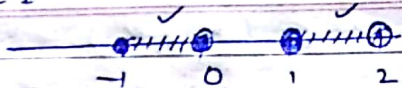
K.P: X is a std. normal r.v.

$x > \mu$ Q: The conditional distribution of $X|Y$ (X given Y) is normal.

R: The condⁿ distⁿ of $X|(X+Y)$ is normal.

X.S: $X-Y$ has mean 0.

i.e. $|[x]| = 1$



$\therefore -1 < x < 0 \cup [x] = 0 \Rightarrow -1 < x < 0$

$\therefore P[-1 < x < 0 \cap [x] = 1] = P[-1 < x < 0]$

Let $P(x \leq z) = \Phi(z)$

$$\begin{aligned} \Rightarrow P(x < 0, [x] = 1) &= P(-1 < x < 0) \\ &= P(x < 0) - P(x < -1) \\ &= \Phi(0) - \Phi(-1) \\ &= \Phi(0) - (1 - \Phi(1)) \\ &= \Phi(0) + \Phi(1) - 1 \quad \text{--- (a)} \end{aligned}$$

\therefore In std. normal distⁿ $(\sigma=1, \mu=0)$

$P(x \leq 0) = \frac{1}{2} = P(x \geq 0)$

$\Rightarrow \Phi(0) = \frac{1}{2} \Rightarrow \text{(a)} \Rightarrow \frac{1}{2} - 1 + \Phi(1)$

$= \Phi(1) - \frac{1}{2} \quad \text{--- (b)}$

$$\left\{ \because N(\sigma, \mu) = \frac{1}{\sqrt{2\pi} \cdot \sigma} e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma}\right)^2} \Rightarrow N(1, 0) = \frac{e^{-\frac{1}{2} x^2}}{\sqrt{2\pi}} \right\}$$

Since Normal distⁿ is symmetric

$\Rightarrow \Phi(x) = 1 - \Phi(-x), \Phi(1) = \text{cdf}$

$\Rightarrow P([x] \neq 1) = P[0 < x < 2]$

$\therefore [x] = 1 \Rightarrow$

$X \sim N(\sigma, \mu)$ is symmetric $\Rightarrow (-1, 0) = (0, 1)$

$$\begin{aligned} \therefore P([x] = 1) &= P(0 < x < 2) \\ &= \Phi(2) - \Phi(0) \\ &= \Phi(2) - \frac{1}{2} \quad \text{--- (c)} \end{aligned}$$

\therefore by (b) + (c)

$$P[x < 0 | [x] = 1] = \frac{\Phi(1) - \frac{1}{2}}{\Phi(2) - \frac{1}{2}}$$

(B) Let x_1, x_2, \dots, x_n be a sample from the pdf $f(x) = \begin{cases} \theta \alpha e^{-\alpha x} + (1-\theta) 2\alpha e^{-2\alpha x}, & x > 0 \\ 0 & \text{o.w.} \end{cases}$

Where $\alpha > 0, 0 \leq \theta \leq 1$ are parameters.

Consider the following testing problems —

$H_0: \theta = 1, \alpha = 1$ vs $H_1: \theta = 0, \alpha = 2$

W.O.T.f. statements is true?

- (a) Uniformly most powerful test d.o.n.e
- (b) Uniformly most powerful test is of the form $\sum_{i=1}^n x_i > c$, for some $0 < c < \infty$
- (c) Uniformly most powerful test is of the form $\sum_{i=1}^n x_i < c$, for some $0 < c < \infty$
- (d) Uniformly most powerful test is of the form $c_1 < \sum_{i=1}^n x_i < c_2$, for some $0 < c_1 < c_2 < \infty$

SolⁿHere $\theta_0 = 1, \theta_1 = 0, \alpha_0 = 1, \alpha_1 = 2$.

$$\begin{aligned} \text{Npo } f_0(x) &= \theta_0 \alpha_0 e^{-\alpha_0 x} + 2(1-\theta_0) \alpha_0 e^{-2\alpha_0 x} \\ &= 1e^{-x} + 0 \\ &= e^{-x} \end{aligned}$$

$$\begin{aligned} \text{and } f_1(x) &= \theta_1 \alpha_1 e^{-\alpha_1 x} + (1-\theta_1) 2\alpha_1 e^{-2\alpha_1 x} \\ &= 0 + 4e^{-4x} \\ &= 4e^{-4x} \end{aligned}$$

Joint pdf of x_1, \dots, x_n is $f_0(x)$
under $H_0 = f_0(x) = \prod_{i=1}^n e^{-x_i}$
 $= e^{-\sum_{i=1}^n x_i}$

$$\text{and } f_1(x) \text{ under } H_1 = f_1(x) = 4e^{-4\sum_{i=1}^n x_i}$$

and the best critical region of $(U\alpha) \cap \beta$.

test is — $\frac{f_1(x)}{f_0(x)} > k$

$$\Rightarrow \frac{4e^{-4\sum_{i=1}^n x_i}}{e^{-\sum_{i=1}^n x_i}} = 4e^{-3\sum_{i=1}^n x_i} > k$$

$$\Rightarrow e^{-3\sum_{i=1}^n x_i} > k/4$$

Now take log both side —

$$-3 \sum_{i=1}^n x_i > \log(k) - \log(4)$$

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$$\Rightarrow \sum_{i=1}^n x_i < \frac{1}{3} \log \frac{4}{k} = c \text{ (say)}$$

$$\Rightarrow \sum_{i=1}^n x_i < c$$

So, $\sum_{i=1}^n x_i < c$ is critical region
 $\Rightarrow 0 < c < \infty$

So the test ~~is~~ rejects H_0 .

Hence

Uniformly most powerful test is of the form $\sum_{i=1}^n x_i < c$ for some $0 < c < \infty$.

Proof

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- (a) Both P & Q (c) Both Q & S
 (b) Both Q & R (d) Both P & S.

Soln Hint: direct application of result.

As we know that, if X & Y are independent r.v.. The $aX + bY$ is normal distributed iff X & Y are both normal distributed.

Here -
 As $X \sim N(\sigma, \mu^2)$ but NOT given $X \sim N(1, 0)$
 ~~$X \sim N(1, 0)$~~

(i) \because If $X \sim N(\sigma, \mu^2)$, $Y \sim N(\sigma, \mu^2)$ then Conditional distⁿ of $X|Y \sim N(\sigma, \mu^2)$.
 & $X|(X+Y) \sim N(\sigma, \mu^2)$.

(iv) $(X-Y) \sim N(\sigma, \mu^2)$. But mean $(X-Y)$ may or may NOT be zero (i.e. $E(X-Y) = \neq 0$)
 \Rightarrow S is NOT always true.

(4) Let X be a r.v with the following G.d.f -
 (2M)

$$F(x) = \begin{cases} 0 & x < 0 \\ x^2 & 0 \leq x < 1/2 \\ 3/4 & 1/2 \leq x < 1 \\ 1 & x \geq 1 \end{cases}$$

Then $P(1/4 < X < 1)$ is equal to -

Soln \because By C.d.f $P(a < X < b) = F(b) - F(a)$

$\therefore P(1/4 < X < 1) = F(1) - F(1/4)$

$= 3/4 - (1/4)^2 = \frac{15}{16} = \frac{15}{16}$

$= \frac{12-1}{16} = \frac{11}{16} = 0.6875$

(5) (2M) Let X_1, X_2, X_3, \dots be a seq. of i.i.d. r.v with mean 1. If N is a geo. r.v with the p.m.f $P(N=k) = \frac{1}{2^k}$, $k=1, 2, 3, \dots$ & it is independent of X_i , then -
 $E(X_1 + X_2 + \dots + X_N)$ is equal to -

Soln \because for p.m.f ∞
 $E(N) = \sum_{n=1}^{\infty} n \cdot P(N=n)$
 $= \sum_{n=1}^{\infty} n \cdot \frac{1}{2^n}$

$= 1 \cdot \frac{1}{2} + 2 \cdot \frac{1}{2^2} + 3 \cdot \frac{1}{2^3} + 4 \cdot \frac{1}{2^4} + \dots$
 $= \frac{1}{2} (1 + 2 \cdot \frac{1}{2} + 3 \cdot \frac{1}{2^2} + 4 \cdot \frac{1}{2^3} + \dots)$

$= \frac{1}{2} [(1 - \frac{1}{2})^{-2}] = \frac{1}{2} \cdot 2 = 2$

($\because (1-\theta)^{-2} = 1 + 2\theta + 3\theta^2 + 4\theta^3 + \dots$)
 Now

$\therefore E(X_1 + X_2 + \dots + X_N) = E(E(X_1 + X_2 + \dots + X_N) | N)$
 $\{ \text{As } E(X) = E(E(X|Y)) \}$
 for this E X is r.v & N is fixed
 for this E , N is r.v & X_i is fixed

(∵ X_i are i.i.d.)

$$= E(E(X_1) + E(X_2) + \dots + E(X_N) | N)$$

$$= E(N \cdot E(X_1))$$

$$= E(X_1) \cdot E(N) = E(N)$$

$$= 1 \cdot 2 = 2$$

(given $E(X_i) = 1$)

6) Let X_1 be an exp. r.v. with mean 1 & X_2 a gamma r.v. with mean 2 & variance = 2. If X_1, X_2 are indep. distributed, then $P(X_1 < X_2)$ is equal to $\frac{3}{4}$.

Solⁿ ∵ $E(X) = \text{mean} = \frac{1}{\lambda}$ for exp. r.v.

$$\Rightarrow \frac{1}{\lambda} = 1 \Rightarrow \lambda = 1 \Rightarrow f(x) = \lambda e^{-\lambda x} = e^{-x}$$

Next Mean for Gamma distⁿ $G(n, \lambda)$

$$E(X) = \frac{n}{\lambda} = 2 \quad \& \quad \frac{n}{\lambda^2} = 2$$

$$\Rightarrow n = 2\lambda \quad \& \quad n = 2\lambda^2$$

$$\Rightarrow 2\lambda - 2\lambda^2 = 0 \Rightarrow \lambda = 0, 1$$

$\lambda = 0 \leftarrow$ NOT possible

$$\Rightarrow \lambda = 1$$

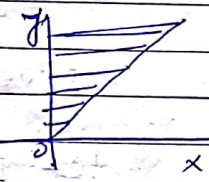
$$\Rightarrow n = 2$$

$$\therefore G(1, 2) = \frac{\lambda^n e^{-\lambda x} x^{n-1}}{\Gamma(n)} = \frac{e^{-2x} x^{2-1}}{\Gamma(2)} = 2e^{-2x}$$

Let $X_2 = Y$
 $2 \cdot \gamma e^{-\gamma}$ for r.v. Y .

∵ $P(X_1 < X_2)$

$$= P(X < Y) = \int \int (e^{-x}) (\gamma e^{-\gamma y}) dx dy$$

$$= \int_0^{\infty} \int_0^y e^{-x} \gamma e^{-\gamma y} dx dy$$


$$= \int_0^{\infty} \gamma e^{-\gamma y} [e^{-x}]_0^y dy$$

$$= \int_0^{\infty} \gamma e^{-\gamma y} [e^{-y} - 1] dy$$

$$= \int_0^{\infty} [\gamma e^{-\gamma y} - \gamma e^{-2\gamma y}] dy$$

$$= \left[-e^{-\gamma y} + e^{-2\gamma y} \right]_0^{\infty} = 1 - \frac{1}{2} = \frac{1}{2}$$

7) Let X be a std. normal random variable. Then, $P(X < 0 | |X| = 1)$ is equal to $\frac{\phi(1) - 1/2}{\Phi(1) + 1/2}$.

(a) $\frac{\phi(1) - 1/2}{\Phi(1) + 1/2}$ (b) $\frac{\phi(1) + 1/2}{\Phi(1) + 1/2}$

(c) $\frac{\phi(1) - 1/2}{\Phi(1) + 1/2}$ (d) $\frac{\phi(1) + 1}{\Phi(1) + 1}$

Solⁿ ∵ Condⁿ probability is —

$$P(X < 0 | |X| = 1) = \frac{P(X < 0, |X| = 1)}{P(|X| = 1)}$$

∵ $|X| = 1$ only if $X \in \{1, -1\}$ or $X \in \{-1, 0\}$

\therefore p.d.f for Poisson distⁿ is—

$$f(x) = \begin{cases} e^{-\theta} \theta^x & ; x=1, 2, \dots \\ 0 & ; 0, \omega \end{cases}$$

$$f(x, \theta) = \prod_{i=1}^n \frac{e^{-\theta} \theta^{x_i}}{x_i!}, \quad x=1, 2, \dots$$

$$f(x, \theta) = \frac{(e^{-\theta})^n \theta^{\sum_{i=1}^n x_i}}{\prod_{i=1}^n x_i!}, \quad x=1, 2, \dots$$

Now take log both sides—

As logⁿ fⁿ is also gives the max. likelihood—

(As, \therefore logⁿ is st cts, strictly \uparrow fⁿ over the range of the likelihood, the value which max. the likelihood will also max. its log).

$$\Rightarrow \log f(x, \theta) = \log \left[e^{-n\theta} \cdot \theta^{\sum_{i=1}^n x_i} \right] + \log \left(\frac{1}{\prod_{i=1}^n x_i!} \right)$$

$$= -n\theta + \sum_{i=1}^n x_i \log \theta + \log \frac{1}{\prod_{i=1}^n x_i!}$$

Now diff w.r.t θ for max.—

$$\frac{\partial (\log f(x, \theta))}{\partial \theta} = -n + \sum_{i=1}^n x_i = 0 \quad (\text{put } = 0)$$

(As for critical pt. we put $f'(x) = 0$)

$$\Rightarrow n\hat{\theta} = \sum_{i=1}^n x_i \Rightarrow \hat{\theta} = \frac{\sum_{i=1}^n x_i}{n}$$

$$\Rightarrow \hat{\theta} = \bar{x}$$

\therefore Max. likelihood estimator for θ

$$= \frac{x_1 + x_2 + x_3 + x_4 + x_5 + x_6}{6}$$

$$= \frac{1+1+2+2+2}{6} = \frac{9}{6} = 1.5$$

Note: $\int_0^{\infty} [x]^n dx = \frac{\pi(n+1)}{2}$

- (9) Let X_1, X_2, X_3, \dots be a seq. of iid.
(2M) $N(\mu, 1)$ r.v.s. Then, $\lim_{n \rightarrow \infty} \frac{\sqrt{n}}{2n} \sum_{i=1}^n E(|X_i - \mu|)$
is equal to $\frac{1}{\sqrt{2}}$

Solⁿ

$$\therefore \sum_{i=1}^n E(|X_i - \mu|) = \int_{-\infty}^{\infty} |x - \mu| f(x) dx$$

(formula for $E(x) = \int x \cdot f \cdot d \cdot f dx$)

$$= \int_{-\infty}^{\infty} \frac{|x - \mu|}{\sqrt{2\pi}} e^{-\frac{(x - \mu)^2}{2}} dx$$

(By putting $\sigma = 1$ in $N(\mu, \sigma^2)$)

$$= - \int_{-\infty}^{\mu} \frac{(x - \mu)}{\sqrt{2\pi}} e^{-\frac{(x - \mu)^2}{2}} dx + \int_{\mu}^{\infty} \frac{(x - \mu)}{\sqrt{2\pi}} e^{-\frac{(x - \mu)^2}{2}} dx$$

$$= I_1 + I_2$$

I_1 let $\mu - x = y \Rightarrow -dx = dy$ in I_1
As $x \rightarrow \mu \Rightarrow y \rightarrow 0$
 $x \rightarrow -\infty \Rightarrow y \rightarrow +\infty$

I_2 let $-x + \mu = z \Rightarrow +dx = dz$ in I_2
As $x \rightarrow \mu \Rightarrow z = 0$
 $x \rightarrow \infty \Rightarrow z \rightarrow \infty$

$$\therefore I_1 + I_2 = \frac{1}{\sqrt{2\pi}} \left[\int_0^{\infty} y e^{-\frac{y^2}{2}} dy + \int_0^{\infty} z e^{-\frac{z^2}{2}} dz \right]$$

$$I_1 = \frac{1}{\sqrt{2\pi}} \left[\int_0^{\infty} y e^{-\frac{y^2}{2}} dy \right]$$

$$= \frac{1}{\sqrt{2\pi}} \int_0^{\infty} y e^{-\frac{y^2}{2}} dy$$

let $\frac{y^2}{2} = t \Rightarrow y dy = dt$

$$\therefore I_1 + I_2 = \frac{2}{\sqrt{2\pi}} \int_0^{\infty} e^{-t} dt$$

$$= \frac{2}{\sqrt{2\pi}} [1] = \sqrt{\frac{2}{\pi}}$$

which is free from x .

$$\Rightarrow E(|X_i - \mu|) = \sqrt{\frac{2}{\pi}} \quad \forall i = 1, 2, \dots, n$$

$$\therefore \sum_{i=1}^n E(|X_i - \mu|) = \sum_{i=1}^n \sqrt{\frac{2}{\pi}} = n \cdot \sqrt{\frac{2}{\pi}}$$

Hence, $\lim_{n \rightarrow \infty} \frac{\sqrt{n}}{2n} \sum_{i=1}^n E(|X_i - \mu|) = \frac{\sqrt{n}}{2n} \cdot n \cdot \sqrt{\frac{2}{\pi}}$

$$= \frac{1}{\sqrt{2}}$$

Repeated

(10)

(2M)

Let $X_1 = X_2 = X_3 = 1$, $X_4 = X_5 = X_6 = 2$ be a r. sample from a poisson r.v with mean θ , where $\theta \in \{1, 2\}$. Then, the max. likelihood estimator of θ is equal to $\frac{1}{2} = 0.5$.

Solⁿ given $X_i \sim P_i(\theta)$.