

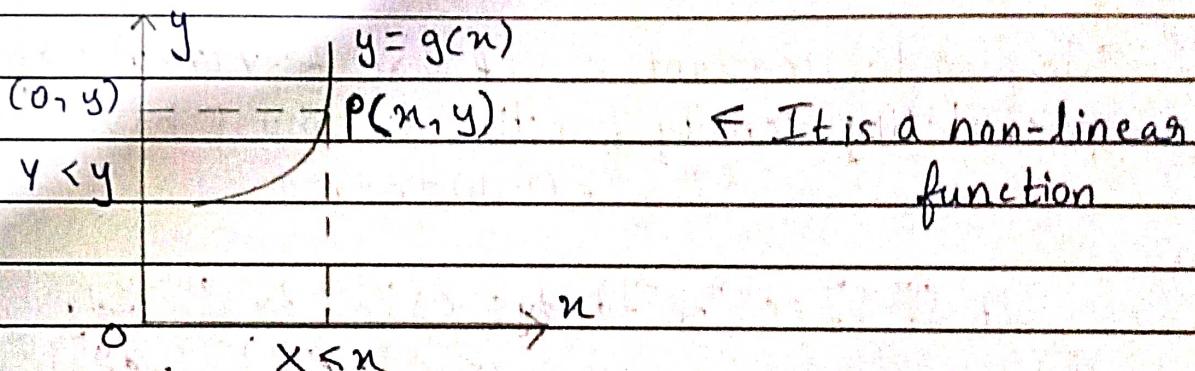
RSA Assignment-4

Q1] If X is a continuous random variable & $Y = g(X)$ is a strictly monotonic function of X then prove that

$$f_Y(y) = f_X(x) \cdot \frac{dx}{dy}$$

\rightarrow When $g(x)$ is strictly increasing function of x

Let $F_Y(y)$ be cumulative density function of Y



When x increases y also increases

Let Two points: $(x_1, y_1) < (x_2, y_2)$
if $y_2 < y_1$ & $x_2 < x_1$

$$\begin{aligned} Y < y & \quad X < x \\ P(Y < y) &= P(X < x). & \left. \begin{array}{l} y = g(x) \\ x = g^{-1}(y) \end{array} \right\} \\ F_Y(y) &= F_X(x) \\ F_Y(y) &= F_X(g^{-1}(y)) \end{aligned}$$

By differentiating it we get,

$$f_Y(y) = f_X(x) \cdot \frac{dx}{dy}$$

(Q2) The joint probability density function of two continuous random variables X & Y is given by

$$f_{XY}(x, y) = c e^{-x} \cdot e^{-y} \quad \begin{cases} 0 < x < \infty \\ 0 < y < \infty \end{cases}$$

$$= 0 \quad \text{elsewhere}$$

a) find value of normalisation constant (c).

b) $f_X(x)$, $F_Y(y)$, $f_{X|Y}(x|y)$, $f_{Y|X}(y|x)$

$E(Y|X=x)$, $E(X|Y=y)$

→ To find the constant c , so that $f_{XY}(x, y)$ represents a probability density function, we must have

$$\int_0^\infty \int_0^\infty f(x, y) dx dy = 1$$

$$\begin{aligned} \text{But } \int_0^\infty \int_0^\infty c e^{-x} \cdot e^{-y} dx dy &= c \int_0^\infty e^{-x} dx \int_0^\infty e^{-y} dy \\ &= c \left[-e^{-x} \right]_0^\infty \left[-e^{-y} \right]_0^\infty = c \end{aligned}$$

Since this is equal to 1, $c = 1$.

$$\text{(i) Now, } f_X(x) = \int_0^\infty f_{XY}(x, y) dy = \int_0^\infty e^{-x} \cdot e^{-y} dy = e^{-x} \left[-e^{-y} \right]_0^\infty \\ = e^{-x}$$

$$\text{Similarly, } f_Y(y) = e^{-y}.$$

$$\text{(ii) } F_Y(y) = \int_0^y f_Y(y) dy = \int_0^y e^{-y} dy = \left[-e^{-y} \right]_0^y = 1 - e^{-y}$$

$$\text{(iii) } f_{X|Y}(x|y) = \frac{f(x, y)}{f(y)} = \frac{e^{-x} \cdot e^{-y}}{e^{-y}} = e^{-x}$$

$$\text{(iv) } f_{Y|X}(y|x) = \frac{f(x, y)}{f(x)} = \frac{e^{-x} \cdot e^{-y}}{e^{-x}} = e^{-y}$$

$$\text{(v) } F_{X|Y}(x|y) = \int_0^x f_{X|Y}(x|y) dx = \int_0^x e^{-x} dx = \left[-e^{-x} \right]_0^x = 1 - e^{-x}$$

$$\begin{aligned}
 \text{(vi) } E(Y|X=n) &= \int_0^\infty y \cdot f_{Y|X}(y|n) dy = \int_0^\infty y \cdot e^{-y} dy \\
 &\stackrel{u=y}{=} [y(-e^{-y}) - \int -e^{-y} \cdot 1 \cdot dy]_0^\infty = [-ye^{-y} - e^{-y}]_0^\infty = 1
 \end{aligned}$$

$$\text{(vii) Similarly, } E(X|Y=y) = 1$$

Q3] The joint probability function of two dimensional random variable (x, y) is given by :

$$f_{XY}(n, y) = ce^{-3n-5y}, \quad n \geq 0, \quad y \geq 0$$

- (i) find value of c , find probability that $n < 2, y > 0$
- (ii) find marginal probability density function of n & y
- (iii) Are x & y independent
- (iv) find $E[X|Y]$ & $E[Y|X]$

→ i) To find the constant c , so that $f_{XY}(n, y)$ represents a probability density function, we must have

$$\begin{aligned}
 \int_0^\infty \int_0^\infty f(n, y) dndy &= 1 \\
 \int_0^\infty \int_0^\infty ce^{-3n-5y} dndy &= 1 \\
 \Rightarrow c \int_0^\infty e^{-3n} dn \int_0^\infty e^{-5y} dy &= 1 \\
 \Rightarrow c \left[\frac{-e^{-3n}}{3} \right]_0^\infty \left[\frac{-e^{-5y}}{5} \right]_0^\infty &= 1
 \end{aligned}$$

$$\Rightarrow c \left[0 - 1 \right] \left[0 - 1 \right] = 1$$

$$\Rightarrow \frac{1}{c} = 1$$

$$\Rightarrow c = 15$$

$$\text{So, } f_{X,Y}(n,y) = 15e^{-3n-5y}, n \geq 0, y > 0$$

$$\begin{aligned} P(X < 2, Y > 0.2) &= 15 \int_0^2 e^{-3n} dn \int_2^\infty e^{-5y} dy \\ &= 15 \left[\frac{-e^{-3n}}{3} \right]_0^2 \cdot \left[\frac{-e^{-5y}}{5} \right]_0^\infty \\ &= (1 - e^{-6})(e^{-1}) \\ &= 0.367 \end{aligned}$$

$$(ii) f_X(n) = \int_0^\infty 15e^{-3n} \cdot (e^{-5y}) dy$$

$$= 15e^{-3n} \left[\frac{-e^{-5y}}{5} \right]_0^\infty = 3e^{-3n} \quad \begin{cases} n > 0 \\ 0 & \text{elsewhere} \end{cases}$$

$$f_Y(y) = \int_0^\infty 15e^{-5y} \cdot (e^{-3n}) dn$$

$$= 15e^{-5y} \left[\frac{-e^{-3n}}{3} \right]_0^\infty = 5e^{-5y} \quad \begin{cases} y > 0 \\ 0 & \text{elsewhere} \end{cases}$$

$$\begin{aligned} (iii) \text{ Now } X, Y \text{ are independent if } f_{X,Y}(n,y) &= f_X(n) \cdot f_Y(y) \\ \text{Since, } f_X(n) \cdot f_Y(y) &= (3 \cdot e^{-3n}) (5 \cdot e^{-5y}) \\ &= 15e^{-3n-5y} = f_{X,Y}(n,y) \end{aligned}$$

X & Y are independent

$$(iv) \text{ Since } (X, Y) \text{ are independent if } f_{X,Y}(n,y) = f_X(n) \cdot f_Y(y)$$

$$f_X(n) \cdot f_Y(y) = f_X(n) = 3e^{-3n}, n > 0$$

$$\therefore E[X|Y=y] = \int_0^\infty n f_{X/Y}(n/y) dn = \int_0^\infty n f_X(n) dn = \int_0^\infty n \cdot 3 \cdot e^{-3n} dn$$

$$= 3 \left[\frac{n \cdot e^{-3n}}{3} - \int e^{-3n} dn \right]_0^\infty = 3 \left[\frac{n \cdot e^{-3n}}{3} - \frac{e^{-3n}}{9} \right]_0^\infty = 3 \left[(0 - 0) - \left(0 - \frac{1}{9} \right) \right] = \frac{1}{3}$$

Similarly, we can obtain

$$E[Y|X=n] = \int_0^\infty y \cdot 5 \cdot e^{-5y} dy = \frac{1}{5}$$

Q4] A two dimensional random variable has following pdf:-

$$f_{X,Y}(x,y) = k \cdot n y e^{-(n^2+y^2)} \quad n \geq 0, y \geq 0$$

find i) value of k , ii) Marginal density of X & Y

iii) Conditional densities of X & Y iv) Are X & Y independent

→ (i) To find value of k

$$\Rightarrow \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(n,y) dn dy = 1$$

$$\Rightarrow \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} k n y e^{-(n^2+y^2)} dn dy = 1$$

$$\Rightarrow \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} k n y e^{-n^2-y^2} dn dy = 1$$

$$\Rightarrow k \int_{-\infty}^{\infty} y e^{-y^2} dy \cdot \int_{-\infty}^{\infty} n e^{-n^2} dn = 1 \text{ or } k \int_0^{\infty} y e^{-y^2} dy \cdot \int_0^{\infty} n e^{-n^2} dn = 1$$

$$\begin{aligned} \Rightarrow \int_0^{\infty} n e^{-n^2} dn &= \int_0^{\infty} \frac{\sqrt{t} e^{-t}}{2\sqrt{t}} \frac{1}{2\sqrt{t}} dt && \left. \begin{array}{l} \text{Put } n^2 = t \\ n = \sqrt{t} \\ dn = \frac{1}{2\sqrt{t}} dt \end{array} \right\} \\ &= \frac{1}{2} \int_0^{\infty} e^{-t} dt = \frac{1}{2} [-e^{-t}]_0^{\infty} \\ &= \frac{1}{2} [e^{-\infty} + e^0] = \frac{1}{2} \end{aligned}$$

⇒ Similarly,

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

$$\Rightarrow \text{So, } k \cdot \frac{1}{2} \cdot \frac{1}{2} = \frac{k}{4}$$

$$\Rightarrow \frac{k}{4} = 1$$

$$\Rightarrow k = 4$$

(iii) To find marginal density functions:-

$$\begin{aligned} f_X(n) &= \int_0^\infty f_{X,Y}(n,y) dy \\ &= \int_0^\infty 4nye^{-(n^2+y^2)} dy \\ &= 4ne^{-n^2} \int_0^\infty e^{-y^2} \cdot y dy \end{aligned}$$

$$\text{Put } y^2 = t$$

$$y = \sqrt{t}$$

$$dy = \frac{1}{2\sqrt{t}} dt$$

$$\begin{aligned} &= 4ne^{-n^2} \int_0^\infty e^{-t} \left(\frac{dt}{2\sqrt{t}} \right) = \frac{4ne^{-n^2}}{2} \left[\frac{e^{-t}}{-1} \right]_0^\infty \\ &= 2ne^{-n^2}; n \geq 0 \end{aligned}$$

$$\text{Similarly, } f_Y(y) = 2ye^{-y^2}; y \geq 0$$

(iii) The conditional density of Y is

$$\begin{aligned} f_{Y|X}(y|x) &= \frac{f_{X,Y}(n,y)}{f_X(n)} = \frac{4nye^{-(n^2+y^2)}}{2ne^{-n^2}} \\ &= 2ye^{-y^2}; y \geq 0 \end{aligned}$$

The conditional density of X is

$$\begin{aligned} f_{X|Y}(n|y) &= \frac{f_{X,Y}(n,y)}{f_Y(y)} = \frac{4nye^{-(n^2+y^2)}}{2ye^{-y^2}} \\ &= 2ne^{-n^2}; n \geq 0 \end{aligned}$$

(iv) $f_X(n) = 2ne^{-n^2}$ & $f_Y(y) = 2ye^{-y^2}$ for $n \geq 0$ & $y \geq 0$

$$\begin{aligned} f_X(n) \cdot f_Y(y) &= 2ne^{-n^2} \cdot 2ye^{-y^2} \\ &= 4nye^{-(n^2+y^2)}; n \geq 0, y \geq 0 \\ &= f_{X,Y}(n,y) \end{aligned}$$

Hence, X & Y are independent random variables.

Q5] If joint pdf of (X, Y) is given as $f_{X,Y}(n, y) = e^{-(n+y)}$; $n \geq 0$, $y \geq 0$. find probability density function of (U, V) . Where $U = X$ & $V = X + Y$. Are U & V independent?

\rightarrow Since $u = n$ & $v = n+y$, we get $u = \frac{n}{v}$

$$\therefore n = uv \text{ & } y = v - x; \therefore y = v - uv = v(1-u)$$

$$\therefore J = \begin{vmatrix} \frac{\partial n}{\partial u} & \frac{\partial n}{\partial v} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial v} \end{vmatrix} = \begin{vmatrix} v & u \\ -v & 1-u \end{vmatrix} = v - uv + uv = v$$

The joint probability density function of (U, V) is

$$f_{UV}(u, v) = f_{X,Y}(n, y) |J| = e^{-(n+y)} \cdot v = e^{-v} \cdot v$$

Since $n \geq 0$, $y \geq 0$, $uv \geq 0$, $v > 0$ & $v(1-u) \geq 0 \Rightarrow v \geq 0$ & $1-u \geq 0$
 $\therefore 1 \geq u \therefore v \geq 0$ & $0 \leq u \leq 1$.

$$\therefore f_{UV}(u, v) = e^{-v} \cdot v, \quad v \geq 0, \quad 0 \leq u \leq 1$$

Now, the pdf of U is given by

$$\begin{aligned} f_U(u) &= \int_0^\infty e^{-v} v dv = [ve^{-v} - \int -e^{-v} \cdot 1 \cdot dv]_0^\infty \\ &= [ve^{-v} - e^{-v}]_0^\infty = 1, \quad 0 \leq u \leq 1 \end{aligned}$$

The pdf of V is given by

$$f_V(v) = \int_0^1 e^{-v} v du = e^{-v} v \int_0^1 du = e^{-v} \cdot v, \quad v \geq 0$$

Since, $f_{UV}(u, v) = f_U(u) \cdot f_V(v)$, the random variables U & V are independent.

Q.6] State central limit theorem & give its significance.

→ We discuss central limit theorem in two forms i.e-

1. Central Limit Theorem (Liapounoff form)

→ If X_1, X_2, \dots, X_n be a sequence of independent random variables with $E(X_i) = \mu_i$ & $\text{Var}(X_i) = \sigma_i^2$; $i=1, 2, \dots, n$
then under certain general condition, $S_n = X_1 + X_2 + \dots + X_n$
is a normal variate with mean $\mu = \sum_{i=1}^n \mu_i$ & variance
 $\sigma^2 = \sum_{i=1}^n \sigma_i^2$ as n tends to infinity.

• A particular form of the above central limit theorem known as Lindeberg - Levy's theorem is as follows:-

2. Central Limit Theorem (Lindeberg-Levy's form)

→ If X_1, X_2, \dots, X_n be a sequence of independent identically distributed random variables with $E(X_i) = \mu_i$ & $V(X_i) = \sigma_i^2$, $i=1, 2, \dots, n$ & if $S_n = X_1 + X_2 + \dots + X_n$
then under certain general conditions S_n follows a normal distribution with mean $n\mu$ & variance $n\sigma^2$ as n tends to infinity.

Significance of Central Limit Theorem :-

- 1) The central limit theorem is regarded by some statistician as the most important theorem in probability theory from both theoretical & practical point of view.
- 2) The central limit theorem is applicable for any distribution of X_i 's.
- 3) The central limit theorem deals with convergence in distribution, which works better near the centre. So, it is called the central limit theorem.

Q7] The joint probability density function of (X, Y) is
 $f_{X,Y}(x,y) = 24ny \quad n > 0, y > 0, x+y \leq 1$

$$= 0 \quad \text{elsewhere}$$

- find conditional mean & variance of Y given X .

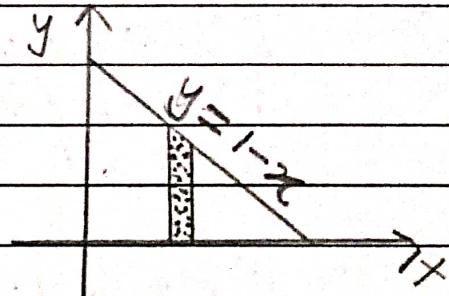
$$\rightarrow \text{By definition } E(Y|X=n) = \int_0^{1-n} y \cdot f_{Y|X}(y|n) dy$$

$$\text{Now, } f_{Y|X}(y|n) = \frac{f_{X,Y}(n,y)}{f_X(n)}$$

• The marginal probability density function of X i.e. $f_X(n)$ is given by

$$f_X(n) = \int_0^{1-n} f_{X,Y}(n,y) dy$$

$$= \int_0^{1-n} 24ny dy = 24n \left[\frac{y^2}{2} \right]_0^{1-n} = 12n(1-n)^2, \quad 0 < n < 1$$



∴ Conditional probability density function of Y for given X ,
 $f_{Y|X}(y|n)$ is given by

$$\therefore f_{Y|X}(y|n) = \frac{f_{X,Y}(n,y)}{f_X(n)} = \frac{24ny}{12n(1-n)^2} = \frac{2y}{(1-n)^2},$$

$$0 < y < 1-n$$

Conditional mean,

$$E(Y|X=n) = \int_0^{1-n} y \cdot f_{Y|X}(y|n) dy = \int_0^{1-n} \frac{2y^2}{(1-n)^2} dy$$

$$= \frac{2}{(1-n)^2} \left[\frac{y^3}{3} \right]_0^{1-n} = \frac{2}{3} (1-n)$$

$$E(Y^2|X=n) = \int_0^{1-n} y^2 \cdot f_{Y|X}(y|n) dy = \int_0^{1-n} \frac{2y^3}{(1-n)^2} dy$$

$$= \frac{2}{(1-n)^2} \left[\frac{y^4}{4} \right]_0^{1-n} = \frac{1}{2} (1-n)^2$$

\therefore Conditional variance,

$$\begin{aligned}\therefore V(Y|X=n) &= E[Y^2|X=n] - [E(Y|X=n)]^2 \\ &= \frac{1}{2}(1-n)^2 - \frac{4}{9}(1-n)^2 = \frac{1}{18}(1-n)^2\end{aligned}$$

Q8] Random variables X & Y have joint pdf

$$f_{XY}(n, y) = \begin{cases} (n-y)^2 & -1 < n < 1 \\ 40 & -3 < y < 3 \\ 0 & \text{elsewhere} \end{cases}$$

find i) $f_X(n)$ $f_Y(y)$ ii) Mean & Variance of X & Y
 iii) Second order moment of X & Y . iv) Correlation coefficient of X & Y .

\rightarrow (i) Marginal probability density functions are obtained as follows:-

$$\begin{aligned}f_X(n) &= \int_{-3}^3 f_{X,Y}(n, y) dy = \int_{-3}^3 n^2 - 2ny + y^2 dy \\ &= \frac{1}{40} \left[n^2y - ny^2 + \frac{y^3}{3} \right]_{-3}^3 = \frac{1}{40} \left[\left(3n^2 - 9n + 27 \right) - \left(-3n^2 - 9n - 27 \right) \right] \\ &= \frac{1}{40} (6n^2 + 18) = \frac{3n^2 + 9}{20}\end{aligned}$$

$$f_Y(y) = \int_{-1}^1 f_{X,Y}(n, y) dn = \int_{-1}^1 \left[\frac{n^2 - 2ny + y^2}{40} \right] dn$$

$$\begin{aligned}f_Y(y) &= \frac{1}{40} \left[\frac{n^3}{3} - n^2y + ny^2 \right]_{-1}^1 = \frac{1}{40} \left[\left[\frac{1}{3}y + y^2 \right] - \left[-\frac{1}{3}y - y^2 \right] \right] \\ &= \frac{1}{40} \left[\frac{2}{3} + 2y^2 \right] = \frac{1+3y^2}{60}\end{aligned}$$

(ii) Mean & variances are obtained as follows:-

$$\begin{aligned}m_X &= \int_{-1}^1 n \cdot f_X(n) dn = \int_{-1}^1 \left[\frac{3n^2 + 9n}{20} \right] dn \\ &= \frac{1}{20} \left[\frac{3n^4}{4} + \frac{9n^2}{2} \right]_{-1}^1 = \frac{1}{20} \left[\left(\frac{3}{4} + \frac{9}{2} \right) - \left(\frac{3}{4} + \frac{9}{2} \right) \right] = 0\end{aligned}$$

$$\begin{aligned} M_Y &= \int_{-3}^3 y \cdot f_Y(y) dy = \int_{-3}^3 \left[y + \frac{3y^3}{60} \right] dy \\ &= \frac{1}{60} \left[\frac{y^2}{2} + \frac{3y^4}{4} \right]_{-3}^3 = \frac{1}{60} \left[\left(\frac{9}{2} + \frac{243}{4} \right) - \left(\frac{9}{2} + \frac{243}{4} \right) \right] = 0 \end{aligned}$$

$$\begin{aligned} E[X^2] &= \int_{-1}^1 n^2 \cdot f_X(n) dn = \int_{-1}^1 \left[\frac{3n^4 + 9n^2}{20} \right] dn = \frac{1}{20} \left[\frac{3n^5 + 3n^3}{5} \right]_{-1}^1 \\ &= \frac{1}{20} \left[\left(\frac{3}{5} + 3 \right) - \left(-\frac{3}{5} - 3 \right) \right] = \frac{1}{20} \left[\frac{6+6}{5} \right] \\ &= \frac{36}{100} = 0.36 \end{aligned}$$

$$\therefore \sigma_X^2 = E[X^2] - [E(X)]^2 = 0.36 \text{ g}$$

$$\begin{aligned} E[Y^2] &= \int_{-3}^3 y^2 \cdot f_Y(y) dy = \int_{-3}^3 \left[\frac{y^2 + 3y^4}{60} \right] dy \\ &= \frac{1}{60} \left[\frac{y^3}{3} + \frac{3y^5}{5} \right]_{-3}^3 = \frac{1}{60} \left[\left(\frac{9+729}{5} \right) - \left(-\frac{9-729}{5} \right) \right] \\ &= \frac{1}{30} \left[\frac{9+729}{5} \right] = \frac{258}{50} = \frac{129}{25} \\ \therefore \sigma_Y^2 &= E[Y^2] - [E(Y)]^2 = \frac{129}{25} \end{aligned}$$

(iii) Second order moment of X & Y is given by

$$\begin{aligned} E(XY) &= \int_{-1}^1 \int_{-3}^3 ny \cdot (x^2 - 2ny + y^2) dy dx \\ &= \frac{1}{40} \int_{-1}^1 \int_{-3}^3 (n^3 y - 2n^2 y^2 + ny^3) dy dx \\ &= \frac{1}{40} \int_{-1}^1 \left[\frac{n^3 y^2}{2} - 2n^2 \cdot \frac{y^3}{3} + ny^4 \right]_{-3}^3 dx \\ &= \frac{1}{40} \int_{-1}^1 \left[\frac{n^3 \cdot 9}{2} - 2n^2 \cdot 9 + n \cdot 81 \right] - \left[\frac{n^3 \cdot 9}{2} + 2n^2 \cdot 9 + n \cdot 81 \right] dx \end{aligned}$$

$$\therefore E[XY] = \int_{-1}^1 -36n^2 dn = -\frac{36}{40} \left[\frac{n^3}{3} \right]_{-1}^1$$

$$= -\frac{12}{40} [1 - (-1)] = -\frac{12}{20} = -\frac{3}{5}$$

(iv) The correlation coefficient is given by

$$\rho_{X,Y} = \frac{E(XY) - E(X) \cdot E(Y)}{\sqrt{E(X^2)} \cdot \sqrt{E(Y^2)}} = -\frac{(3/5) - 0 \cdot 0}{\sqrt{36/100} \sqrt{129/25}} \\ = -\frac{3}{5} \cdot \frac{10}{\sqrt{129}} = -\frac{5}{\sqrt{129}}$$

Q9] If $X = \cos \theta$, $Y = \sin \theta$ where θ is uniformly distributed over $(0, 2\pi)$ prove that (i) X & Y are uncorrelated
(ii) X & Y are not independent.

$$\rightarrow \text{(i) We have } f_\theta(\theta) = \begin{cases} \frac{1}{2\pi}, & 0 < \theta < 2\pi \\ 0, & \text{elsewhere} \end{cases}$$

$$\therefore E(X) = \int_{-\infty}^{\infty} n \cdot f_X(n) dn = \int_0^{2\pi} \cos \theta \cdot \frac{1}{2\pi} d\theta = \frac{1}{2\pi} [\sin \theta]_0^{2\pi} = 0$$

$$\text{Similarly } \therefore E(Y) = 0$$

$$\text{Also } E(XY) = \int_0^{2\pi} \cos \theta \sin \theta \cdot \frac{1}{2\pi} d\theta = \frac{1}{2\pi} \int_0^{2\pi} \sin 2\theta d\theta \\ = \frac{1}{4\pi} \left[-\frac{\cos 2\theta}{2} \right]_0^{2\pi} = 0$$

$$\therefore \text{cov}(X, Y) = E(XY) - E(X) \cdot E(Y) = 0$$

$$\text{But } \rho = \frac{\text{cov}(X, Y)}{\sqrt{E(X^2)} \cdot \sqrt{E(Y^2)}} \therefore \rho = 0$$

$\therefore X$ & Y are uncorrelated

$$\text{(ii) Now, } E[X^2] = \int_0^{2\pi} \cos^2 \theta d\theta = \frac{1}{4\pi} \int_0^{2\pi} (1 + \cos 2\theta) d\theta$$

$$= \frac{1}{4\pi} \int_0^{2\pi} \left[\theta - \sin 2\theta \right] d\theta = \frac{1}{4\pi} \cdot 2\pi = \frac{1}{2}$$

Similarly, $E[Y^2] = \frac{1}{2}$

$$\begin{aligned} E[X^2 Y^2] &= \frac{1}{2\pi} \int_0^{2\pi} (\sin \theta \cos \theta)^2 d\theta = \frac{1}{8\pi} \int_0^{2\pi} \sin^2 \theta d\theta \\ &= \frac{1}{8\pi} \int_0^{2\pi} \left[\frac{1 - \cos 4\theta}{2} \right] d\theta = \frac{1}{16\pi} \int_0^{2\pi} \left[\theta - \frac{\sin 4\theta}{4} \right] d\theta \\ &= \frac{1}{16\pi} [2\pi] = 8 \end{aligned}$$

$$\therefore E[X^2] \cdot E[Y^2] \neq E[X^2 Y^2]$$

Hence X, Y are not independent

Q10] A two dimensional random variable (X, Y) has following distribution

$$f_{X,Y}(x,y) = \begin{cases} 2e^{-(x+y)} & 0 < y < x < \infty \\ 0 & \text{elsewhere} \end{cases}$$

Find (i) $E(XY)$ (ii) $\text{cov}(X, Y)$ (iii) $P_{X,Y}$

$$\rightarrow f_X(x) = 2 \int_0^x e^{-x} \cdot e^{-y} dy = 2e^{-x} [-e^{-y}]_0^x = -2e^{-x} [e^{-x} - 1]$$

$$= 2(e^{-x} - e^{-2x}), x > 0 \quad (\because y \text{ varies from } 0 \text{ to } x)$$

$$\& f_Y(y) = 2 \int_y^\infty e^{-n} \cdot e^{-y} dn = 2e^{-y} \int_y^\infty [-e^{-n}]_y^\infty = -2e^{-y} [-e^{-y}]_y^\infty$$

$$= 2e^{-2y}, y > 0$$

$$E(X) = \int_0^\infty n \cdot f_X(n) dn = \int_0^\infty n \cdot 2(e^{-x} - e^{-2x}) dx$$

$$= 2 \left[x \left[-e^{-x} + e^{-2x} \right] - \left[e^{-x} - \frac{e^{-2x}}{4} \right] \right]_0^\infty$$

$$= 2 \left[0 + \left[1 - \frac{1}{4} \right] \right] = 2 \cdot \frac{3}{4} = \frac{3}{2}$$

$$E[Y] = \int_0^\infty y \cdot f_Y(y) dy = \int_0^\infty y \cdot 2e^{-2y} dy$$

$$= 2 \left[y \left[-\frac{e^{-2y}}{2} \right] - 1 \cdot \left[\frac{e^{-2y}}{4} \right] \right]_0^\infty = 2 \left[0 + \frac{1}{4} \right] = \frac{1}{2}$$

$$E[X^2] = \int_0^\infty x^2 f_X(x) dx = \int_0^\infty x^2 \cdot 2(e^{-x} - e^{-2x}) dx$$

$$\begin{aligned} E[X^2] &= 2 \left[x^2 \left[-e^{-x} + \frac{e^{-2x}}{2} \right] - 2x \left[e^{-x} - \frac{e^{-2x}}{4} \right] + \right. \\ &\quad \left. 2 \left[-e^{-x} + \frac{e^{-2x}}{8} \right] \right] \\ &= 2 \left[0 - 2 \left(-1 + \frac{1}{8} \right) \right] = 2 \left[\frac{7}{4} \right] = \frac{7}{2} \end{aligned}$$

$$E[Y^2] = \int_0^\infty y^2 \cdot f_Y(y) dy = \int_0^\infty y^2 \cdot 2e^{-2y} dy$$

$$\begin{aligned} &= 2 \left[y^2 \left[-\frac{e^{-2y}}{2} \right] - (2y) \left[\frac{e^{-2y}}{4} \right] + 2 \left[-\frac{e^{-2y}}{8} \right] \right]_0^\infty \\ &= 2 \left[0 + \frac{1}{4} \right] = \frac{1}{2} \end{aligned}$$

$$E[XY] = \int_{y=0}^\infty \int_{n=y}^\infty ny f_{X,Y}(n,y) dndy = \int_{y=0}^\infty \int_{n=y}^\infty ny \cdot 2e^{-n} \cdot e^{-y} dndy$$

$$= 2 \int_{y=0}^\infty ye^{-y} \left[\int_{n=y}^\infty ne^{-n} dn \right] dy = 2 \int_{y=0}^\infty ye^{-y} \left[n \cdot \frac{e^{-n}}{-1} - \frac{e^{-n}}{+1} \right]_y^\infty dy$$

$$= 2 \int_0^\infty ye^{-y} (ye^{-y} + e^{-y}) dy = 2 \int_0^\infty (y^2 e^{-2y} + ye^{-2y}) dy$$

$$= 2 \left[\left\{ y^2 \cdot \frac{e^{-2y}}{-2} - (2y) \frac{e^{-2y}}{4} + 2 \frac{e^{-2y}}{-8} \right\} + \left\{ y \cdot \frac{e^{-2y}}{-2} - 1 \cdot \frac{e^{-2y}}{4} \right\} \right]_0^\infty$$

$$= 2 \left[0 - \left[-\frac{1}{4} - \frac{1}{4} \right] \right] = 2 \left(\frac{1}{2} \right) = 1$$

$$\therefore E(XY) = 1$$

$$\therefore \text{cov}(X, Y) = E(XY) - E(X) \cdot E(Y) = 1 - \frac{3}{2} \cdot \frac{1}{2} = 1 - \frac{3}{4} = \frac{1}{4}$$

$$\therefore \text{cov}(X, Y) = \frac{1}{4}$$

$$\text{Now, } \text{Var}(X) = E(X^2) - [E(X)]^2 = \frac{7}{2} - \left(\frac{3}{2}\right)^2 = \frac{7}{2} - \frac{9}{4} = \frac{5}{4}$$

$$\text{Var}(Y) = E(Y^2) - [E(Y)]^2 = \frac{1}{2} - \left(\frac{1}{2}\right)^2 = \frac{1}{2} - \frac{1}{4} = \frac{1}{4}$$

$$\therefore \rho = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{\frac{1}{4}}{\left(\sqrt{\frac{5}{2}}\right)\left(\frac{1}{2}\right)} = \frac{\frac{1}{4}}{\frac{1}{4} \cdot \frac{4}{\sqrt{5}}} = \frac{1}{\sqrt{5}}$$

Q11] The lifetime of a certain brand of electric bulb may be considered a random variable with mean 1200 hours & standard deviation 250 hours. Using the Central Limit theorem find the probability that the average lifetime of 60 bulbs exceeds 1250 hours

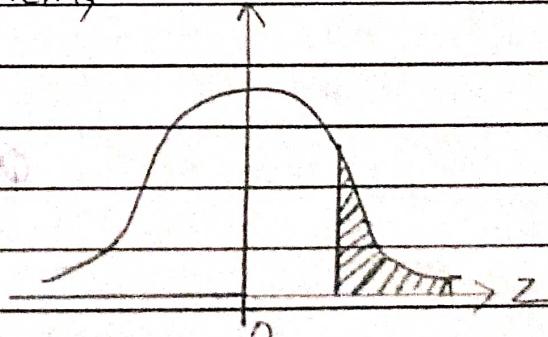
→ If \bar{X} denotes the average (mean) lifetime of 60 bulbs then by the Central Limit Theorem,

$$Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}}$$

is a SNV with $\mu = 1200$, $\sigma = 250$

$$\& n = 60$$

$$\text{if } \bar{X} = \frac{1250}{250/\sqrt{60}}, \therefore Z = \frac{1250 - 1200}{250/\sqrt{60}} = 1.55$$



$$\therefore P(Z > 1.55) = \text{area to the right of } 1.55$$

$$= 0.5 - \text{area between } z=0 \text{ & } z=1.55$$

$$= 0.5 - 0.4394 = 0.0606$$

Q.12] A distribution has unknown mean μ & variance 1.5. Using central limit theorem find the size of the sample such that the probability that difference between sample mean & the population mean will be less than 0.5 is 0.95.

→ We have $E(X_i) = \mu$ & $\text{Var}(X_i) = 1.5$

If \bar{X} is the sample mean then $Z = \frac{\bar{X} - \mu}{\sigma/\sqrt{n}}$ is a S.N.V

We have $|\bar{X} - \mu| = 0.5$,

$$\therefore |Z| = \left| \frac{\bar{X} - \mu}{\sigma/\sqrt{n}} \right| = \left| \frac{0.5}{\sqrt{1.5}/\sqrt{n}} \right| = \left| 0.4082\sqrt{n} \right|$$

We know from then table that $P(|Z|) > 0.95$

when $Z = 1.96$

$$\therefore 0.4082\sqrt{n} = 1.96$$

$$\therefore \sqrt{n} = \frac{1.96}{0.4082}$$

$$\therefore n = 23.05$$

Hence, n must be atleast 24

(Q.13] Define characteristic function of a random variable X state & prove properties of characteristic function. Find mean & variance for characteristic function

→ The characteristic function of a random variable X denoted by $\Phi_X(\omega)$ is defined by

$$\Phi_X(\omega) = E(e^{i\omega X}) \quad \text{where } \omega \text{ is an auxillary variable.}$$

$$\Phi_X(\omega) = \sum e^{i\omega x} p(x) \quad (\text{for discrete probability distribution})$$

$$\Phi_X(\omega) = \int_{-\infty}^{\infty} e^{i\omega x} f(x) dx \quad (\text{for continuous probability distribution})$$

* Properties of Characteristic function

1. $\mu_n' = \text{coeff of } i^n \omega^n \text{ in the expansion of } \phi_X(\omega)$

Proof - By definition

$$\phi_X(\omega) = E(e^{i\omega X}) = E\left[1 + i\omega X + \frac{i^2 \omega^2 X^2}{2!} + \dots + \frac{i^n \omega^n X^n}{n!} + \dots\right]$$

$$= 1 + i\omega E(X) + i^2 \omega^2 E(X^2) + \dots + \frac{i^n \omega^n E(X^n)}{n!} + \dots$$

But $\mu_n' = E(X^n)$

$\therefore \mu_n' = \text{coeff of } i^n \omega^n \text{ in the expansion of } \phi_X(\omega)$

$$2. \mu_n' = \frac{1}{i^n} \left[\frac{d^n}{d\omega^n} \phi(\omega) \right]_{\omega=0}$$

→ Proof - Differentiating both sides of (1) with respect to ω , n times & then putting $\omega=0$,

$$\left[\frac{d^n \phi_X(\omega)}{d\omega^n} \right]_{\omega=0} = i^n \cdot E(X^n) \quad \therefore \mu_n' = \frac{1}{i^n} \left[\frac{d^n \phi_X(\omega)}{d\omega^n} \right]_{\omega=0}$$

$$3. \text{ If } Y = aX + b \text{ then } \phi_Y(\omega) = e^{ib\omega} \phi_X(a\omega)$$

Proof - By definition

$$\begin{aligned} \phi_Y(\omega) &= E(e^{i\omega Y}) = E(e^{i\omega(ax+b)}) = E(e^{ia\omega} \cdot e^{ib\omega}) \\ &= e^{ib\omega} E(e^{ia\omega X}) = e^{ib\omega} \phi_X(a\omega) \end{aligned}$$

Putting $b=0$, we get if $Y=aX$ then

$$\phi_Y(\omega) = E(e^{ia\omega X}) = \phi_X(a\omega)$$

4. If X & Y are independent random variates then

$$\Phi_{X+Y}(\omega) = \Phi_X(\omega) \cdot \Phi_Y(\omega)$$

Proof - By definition $\Phi_{X+Y}(\omega) = E[e^{i\omega(X+Y)}]$

$$= E[e^{i\omega X} \cdot e^{i\omega Y}]$$

$$= E[e^{i\omega X}] \cdot E[e^{i\omega Y}]$$

[$\because X, Y$ are independent]

$$= \Phi_X(\omega) \cdot \Phi_Y(\omega)$$

5. If $\Phi(\omega)$ is the characteristic function of a continuous random variable X , whose probability density function is $f_X(x)$ then

$$f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} (\omega) e^{-ix\omega} d\omega$$

$$\text{Proof - By definition } \Phi_X(\omega) = \int_{-\infty}^{\infty} f(x) e^{i\omega x} dx$$

• But the r.h.s is the Fourier Transform of $f(x)$. Hence, $f(x)$ is the Inverse Fourier Transform of $\Phi(\omega)$

$$\text{i.e. } f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \Phi(\omega) e^{i\omega x} d\omega$$

6. If the density function of X is known then the density function of $Y = g(x)$ can be found from the characteristic function of X if $Y = g(x)$ is a one-one correspondence.

Proof - Let the probability density function of X be $f_X(x)$

$$\text{Then } \Phi_{g(x)}(\omega) = \int_{-\infty}^{\infty} e^{ig(x)\omega} \cdot f_X(x) dx$$

Putting $g(x) = y$ & $g(x) = y$, suppose $f_X(x) dx$ changes to say $h(y) dy$

$$\therefore \Phi_Y(\omega) = \int_{-\infty}^{\infty} e^{iy\omega} h(y) dy$$

$\therefore h(y)$ is the probability density function of y .

7. Uniqueness Theorem :- Characteristic function uniquely determines the distribution i.e. if two probability density functions $f_1(x)$ & $f_2(x)$ have the characteristic functions $\Phi_1(t)$ & $\Phi_2(t)$ they are identical if $\Phi_1(t) = \Phi_2(t)$ & conversely.

Proof - (i) Let $f_1(x) = f_2(x)$

$$\text{Now } \Phi_1(\omega) = \int_{-\infty}^{\infty} e^{i\omega x} f_1(x) dx \text{ &}$$

$$\Phi_2(\omega) = \int_{-\infty}^{\infty} e^{i\omega x} f_2(x) dx$$

Since $f_1(x) = f_2(x)$; $\Phi_1(\omega) = \Phi_2(\omega)$.

* (Characteristic Function of standard distribution

• Binomial distribution

$$\rightarrow \text{Mean} = \mu' = np$$

$$\begin{aligned} \text{Variance} = \mu'_2 - \mu'^2 &= n^2 p^2 - np^2 + np - n^2 p^2 \\ &= np(1-p) = npq \end{aligned}$$

• Poisson distribution

$$\rightarrow \text{Mean} = \mu' = m$$

$$\text{Variance} = \mu'_2 - \mu'^2 = m$$

• Geometric distribution

$$\rightarrow \text{Mean} = \mu' = q/p$$

$$\text{Variance} = \mu'_2 - \mu'^2 = q/p^2 + q^2/p^2 - q^2/p^2 = q/p^2$$

• Standard Normal distribution

$$\rightarrow \text{Mean} = b+a/2$$

$$\text{Variance} = (b-a)^2/12$$

• Exponential distribution

$$\rightarrow \text{Mean} = 1/m = \mu'$$

$$\text{Variance} = \mu'_2 - \mu'^2 = 2/m^2 - 1/m^2 = 1/m^2$$

Q14] Define correlation, covariance, correlation coefficient. When are X, Y uncorrelated? When are they orthogonal?
 prove that $C_{XY}(x,y) = R_{XY}(x,y) - E(X) \cdot E(Y)$
 prove that $|C_{XY}| \leq \sigma_X \sigma_Y$. Reduce that $-1 \leq p \leq 1$

- Correlation - If $\text{Var}(X) > 0$ & $\text{Var}(Y) > 0$ then the correlation of X & Y is defined by
- $$p(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}}$$
- Covariance - If X & Y are two random variables then the covariance between them denoted by $\text{Cov}(X, Y)$ or C_{XY} & is defined by

$$C_{XY} = E[(X - E[X])(Y - E[Y])]$$

On expanding the r.h.s we get

$$C_{XY} = E[XY] - E[X] \cdot E[Y]$$

- Correlation coefficient - If X & Y are two random variables then the correlation coefficient between them is denoted by $r_{X,Y}$ or $p_{X,Y}$ & is defined by

$$p_{X,Y} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

Where σ_X & σ_Y are the standard deviation of X & Y .

* If $E[XY] = E[X] \cdot E[Y]$ then the variables are uncorrelated.

• If $E[XY] = 0$ the variables are orthogonal.

a) • $C_{XY} = E[(X - E[X])(Y - E[Y])]$

On expanding the L.H.S

$$C_{XY} = E[XY - XE[Y] - YE[X] + E[X] \cdot E[Y]]$$

$$= E[XY] - E[X] \cdot E[Y] - E[Y] \cdot E[X] + E[X] \cdot E[Y]$$

$$C_{XY} = E[XY] - E[X] \cdot E[Y]$$

$$C_{XY}(x, y) = R_{XY}(x, y) - E[X] \cdot E[Y]$$

$$\therefore R_{XY}(x, y) = E[XY]$$

$$\therefore C_{XY} = C_{XY}(x, y) = \text{Cov}(X, Y)$$

b) • $|C_{XY}| < \sigma_X \cdot \sigma_Y$

→ Let a be any real number & consider

$$E[(a(X - E[X]) + (Y - E[Y]))^2]$$

On expansion,

$$E[(a(X - E[X]) + (Y - E[Y]))^2]$$

$$= E[a^2(X - E[X])^2 + (Y - E[Y])^2 + 2a(X - E[X]) \\ [Y - E[Y])]$$

$$= E[a^2(X - E[X])^2 + E(Y - E[Y])^2] + E[2a(X - E[X]) \\ [Y - E[Y])]$$

$$= a^2 E[(X - E[X])^2] + E[(Y - E[Y])^2] + 2a E[(X - E[X])(Y - E[Y])]$$

$$= a^2 \sigma_X^2 + \sigma_Y^2 + 2a C_{XY}$$

$$= a^2 \sigma_X^2 + 2a C_{XY} + \sigma_Y^2$$

Since the LHS is positive, the RHS must also be positive. Hence, its discriminant must be negative

$$\Delta = \sqrt{4C_{XY}^2 - 4\sigma_X^2\sigma_Y^2} \leq 0$$

$$C_{XY}^2 \leq \sigma_X^2 \sigma_Y^2$$

$$|C_{XY}| \leq \sigma_X \sigma_Y$$

Since $\rho = \frac{C_{XY}}{\sigma_X \sigma_Y}$ & $|C_{XY}| \leq \sigma_X \sigma_Y$

$$|\rho| \leq 1$$

i.e. $-1 \leq \rho \leq 1$