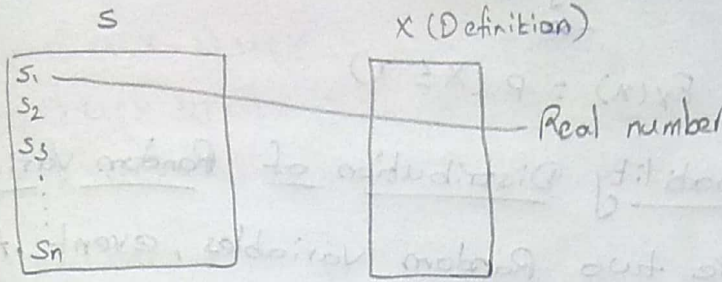
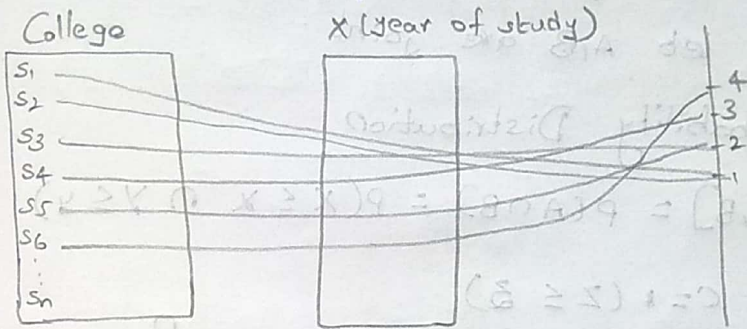


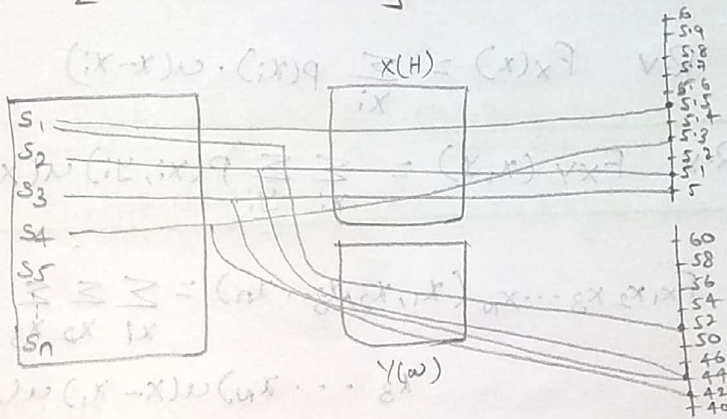
MULTIPLE RANDOM VARIABLES



Random variable \rightarrow Sample space \rightarrow Real $P(X \leq x) = F_X(x)$



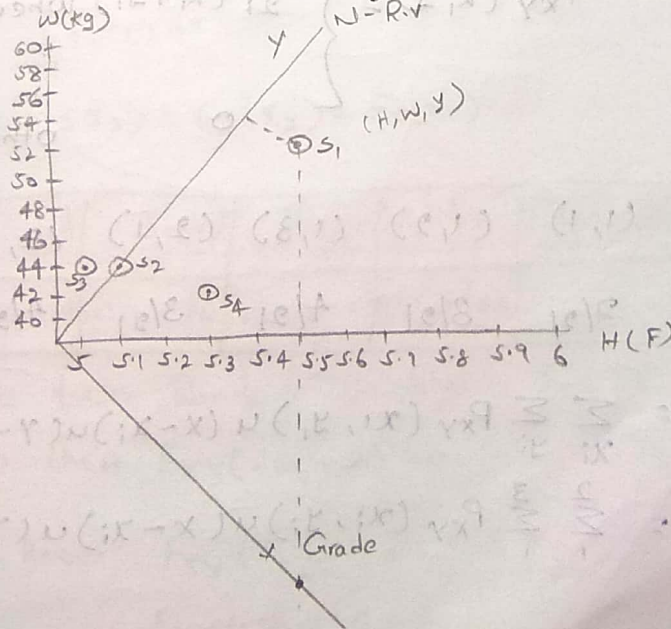
$X = \{1, 2, 3, 2, 4, \dots\}$



	s_1	s_2	s_3	s_4	s_5	s_6	s_7	...	s_n
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X(H)	5.5	5.1	5	5.3					
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Y(omega)	52	44	44	42					
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Probability Distribution of Random Variable

$$F_X(x) = \int_{-\infty}^x f_X(x) dx$$

$$F_X(x) = P(X \leq x)$$

Joint probability Distribution of Random Variable

X, Y are two Random Variables, event A is represented as $\{X \leq x\}$ and event B is represented as $\{Y \leq y\}$ let A, B are joint.

Joint probability Distribution

$$P[A, B] = P(A \cap B) = P(X \leq x \cap Y \leq y) \quad F_{XY}(x, y)$$

$$C = \{Z \leq z\}$$

$$P(A, B, C) = P(X \leq x \cap Y \leq y \cap Z \leq z)$$

Single R.V $F_X(x) = \sum_{x_i} p(x_i) \cdot u(x - x_i)$

Two R.V $F_{XY}(x, y) = \sum_{x_i} \sum_{y_i} p(x_i, y_i) u(x - x_i) u(y - y_i)$

N R.V $F_{X_1 X_2 X_3 \dots X_N}(x_1, x_2, x_3, \dots, x_N) = \sum_{x_1} \sum_{x_2} \sum_{x_3} \dots \sum_{x_N} p(x_1, x_2, x_3, \dots, x_N) u(x - x_1) u(x - x_2) \dots u(x - x_N)$

1) Find Joint probability Distribution of given probability mass function $P_{XY}(x, y) = \begin{cases} \frac{1}{21}(x+y) & \text{where } x_i = 1, 2, \\ & y_i = 1, 2, 3 \\ 0 & \text{otherwise} \end{cases}$

(x, y)	(1, 1)	(1, 2)	(1, 3)	(2, 1)	(2, 2)	(2, 3)
$P_{XY}(x, y)$	2/21	3/21	4/21	3/21	4/21	5/21

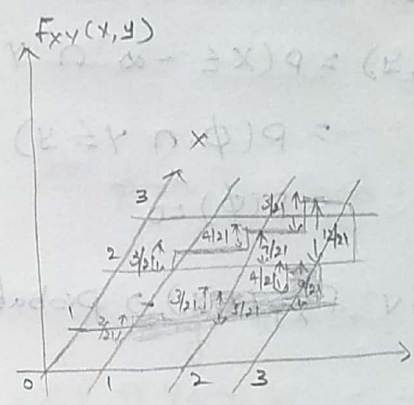
$$F_{XY}(x, y) = \sum_{x_i} \sum_{y_i} P_{XY}(x_i, y_i) u(x - x_i) u(y - y_i)$$

$$= \sum_{i=1}^2 \sum_{j=1}^3 P_{XY}(x_i, y_j) u(x - x_i) u(y - y_j)$$

$$= \sum_{i=1}^2 \left[P_{xy}(x_i, 1) u(x-x_i) u(y-1) + P_{xy}(x_i, 2) u(x-x_i) u(y-2) + P_{xy}(x_i, 3) u(x-x_i) u(y-3) \right]$$

$$= P_{xy}(1, 1) u(x-1) u(y-1) + P_{xy}(1, 2) u(x-1) u(y-2) + P_{xy}(1, 3) u(x-1) u(y-3) + P_{xy}(2, 1) u(x-2) u(y-1) + P_{xy}(2, 2) u(x-2) u(y-2) + P_{xy}(2, 3) u(x-2) u(y-3)$$

$$= \frac{2}{21} u(x-1) u(y-1) + \frac{3}{21} u(x-1) u(y-2) + \frac{4}{21} u(x-1) u(y-3) + \frac{3}{21} u(x-2) u(y-1) + \frac{4}{21} u(x-2) u(y-2) + \frac{5}{21} u(x-2) u(y-3)$$



Properties of Joint Probability Distribution :-

Probability Distribution properties of single Rv :-

- 1) $F_x(-\infty) = 0$
- 2) $F_x(\infty) = 1$
- 3) $0 \leq F_x(x) \leq 1$
- 4) $F_x(x)$ is nondecreasing.
- 5) $F_x(x)$ is non negative
- 6) $F_x(x) = \int_{-\infty}^x f_x(x) dx$
- 7) $P(x_1 < X \leq x_2) = F_x(x_2) - F_x(x_1)$

Properties of Joint Probability Distribution :-

X, Y are two Random Variables.

1) X, Y are two Random variables, $F_{xy}(x, y)$ is distribution function then $F_{xy}(-\infty, -\infty) = 0$.

Proof:- We know $F_{xy}(x, y) = P(X \leq x \cap Y \leq y)$

$F_{xy}(-\infty, -\infty) = ?$

$$\begin{aligned}
 F_{XY}(-\infty, -\infty) &= P(X \leq -\infty \cap Y \leq -\infty) \\
 &= P(\phi \cap \phi) \\
 &= P(\phi) = 0
 \end{aligned}$$

2) Let X, Y are two random variables $\rightarrow F_{XY}(x, y)$,
 $F_{XY}(-\infty, y) = 0$.

Proof:- We know

$$F_{XY}(x, y) = P(X \leq x \cap Y \leq y)$$

$$\begin{aligned}
 F_{XY}(-\infty, y) &= P(X \leq -\infty \cap Y \leq y) \\
 &= P(\phi \cap Y \leq y) \\
 &= P(\phi) = 0
 \end{aligned}$$

3) X, Y are two R.V. $F_{XY}(x, y) \rightarrow$ probability distribution
 $F_{XY}(x, -\infty) = 0$.

Proof:- We know

$$F_{XY}(x, y) = P(X \leq x \cap Y \leq y)$$

$$\begin{aligned}
 F_{XY}(x, -\infty) &= P(X \leq x \cap Y \leq -\infty) \\
 &= P(X \leq x \cap \phi) \\
 &= P(\phi) = 0.
 \end{aligned}$$

It is like
 $x \rightarrow$ nd property of single R.V

4) Let X, Y are two R.V. $F_{XY}(x, y)$ is the probability
 Distribution then $F_{XY}(\infty, \infty) = 1$

Proof:-

$$F_{XY}(x, y) = P(X \leq x \cap Y \leq y)$$

$$F_{XY}(\infty, \infty) = P(X \leq \infty \cap Y \leq \infty)$$

$$= P(S \cap S) = P(S) = 1$$

5) Let X, Y are two R.V. $F_{XY}(x, y)$ is the probability
 distribution then $F_{XY}(\infty, y) = F_Y(y)$.

This is also called as "Marginal Distribution".

Proof:- $F_{XY}(x, y) = P(X \leq x \cap Y \leq y)$

$$F_{XY}(\infty, y) = P(X \leq \infty \cap Y \leq y)$$

$$= P(S \cap Y \leq y)$$

$$= P(Y \leq y) = F_Y(y) \quad \left[\begin{array}{l} \text{Marginal distribution} \\ \text{of } Y \end{array} \right]$$

Find marginal distribution of R.V. y
 then we have to take $x = \infty, y = y$

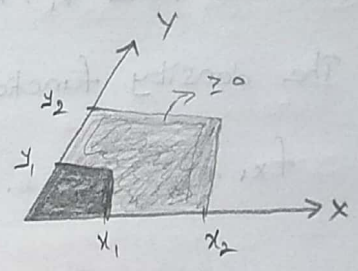
6) X, Y are two R.V., $F_{XY}(x, y)$ is the probability distribution
 $F_{XY}(x, \infty) = F_X(x)$. [Marginal distribution of x]

Proof:- $F_{XY}(x, y) = P(X \leq x \cap Y \leq y)$
 $F_{XY}(x, \infty) = P(X \leq x \cap Y \leq \infty)$
 $= P(X \leq x \cap S)$
 $= P(X \leq x) = F_X(x)$.

7) $0 \leq F_{XY}(x, y) \leq 1$
 Based on the 1st property and 4th property

8) $F_{XY}(x, y)$ is nondecreasing function

$F_{XY}(x_2, y_2) = P(X \leq x_2 \cap Y \leq y_2)$
 $F_{XY}(x_1, y_1) = P(X \leq x_1 \cap Y \leq y_1)$
 $P(x_1 < X \leq x_2 \cap y_1 < Y \leq y_2)$



$P(X \leq x_1 \cap Y \leq y_1) + P(x_1 < X \leq x_2 \cap y_1 < Y \leq y_2) = P(X \leq x_2 \cap Y \leq y_2)$
 $P(X \leq x_1 \cap Y \leq y_1) = P(X \leq x_2 \cap Y \leq y_2) - P(x_1 < X \leq x_2 \cap y_1 < Y \leq y_2)$
 $P(X \leq x_1 \cap Y \leq y_1) \leq P(X \leq x_2 \cap Y \leq y_2)$

9) $P(x_1 < X \leq x_2 \cap y_1 < Y \leq y_2) = F_{XY}(x_2, y_2) - F_{XY}(x_1, y_1)$

Proof:- We know,

$F_{XY}(x_2, y_2) = P(X \leq x_2 \cap Y \leq y_2)$
 $= P(X \leq x_1 \cap Y \leq y_1) + P(x_1 < X \leq x_2 \cap y_1 < Y \leq y_2)$

$F_{XY}(x_2, y_2) = F_{XY}(x_1, y_1) + P(x_1 < X \leq x_2 \cap y_1 < Y \leq y_2)$
 $P(x_1 < X \leq x_2 \cap y_1 < Y \leq y_2) = F_{XY}(x_2, y_2) - F_{XY}(x_1, y_1)$

Joint probability density function :-

density function $f_X(x) = \frac{d}{dx} F_X(x)$, $F_X(x) = \int_{-\infty}^x f_X(x) dx$

Joint density function :- Let x, y are two Random Variables

$F_{XY}(x, y)$ is the Joint Distribution function,

$f_{XY}(x, y)$ is the Joint density function.

$$f_{XY}(x, y) = \frac{\partial}{\partial x} \frac{\partial}{\partial y} F_{XY}(x, y)$$

Joint Distribution in density function :-

$$F_{XY}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{XY}(x, y) dy dx$$

Let we have $x_1, x_2, x_3, x_4, \dots, x_N$ Random Variables

The density function is represented as

$$f_{x_1, x_2, x_3, x_4, \dots, x_N}(x_1, x_2, x_3, \dots, x_N) = \frac{\partial}{\partial x_1} \frac{\partial}{\partial x_2} \frac{\partial}{\partial x_3} \dots \frac{\partial}{\partial x_N}$$

$$F_{x_1, x_2, x_3, \dots, x_N}(x_1, x_2, x_3, \dots, x_N)$$

$$F_{x_1, x_2, x_3, \dots, x_N}(x_1, x_2, x_3, \dots, x_N) = \int_{-\infty}^{x_1} \int_{-\infty}^{x_2} \dots \int_{-\infty}^{x_N} f_{x_1, x_2, x_3, \dots, x_N}$$

$$(x_1, x_2, x_3, \dots, x_N) dx_1 dx_2 dx_3 \dots dx_N$$

Properties of Joint Probability Density function :-

Let x, y are two Random Variables
and $f_{XY}(x, y)$ is the joint density function

① $f_{XY}(x, y) \geq 0$

② $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{XY}(x, y) dx dy = 1$

③ $F_{XY}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{XY}(x, y) dx dy$

④ $P(x_1 \leq X \leq x_2, y_1 \leq Y \leq y_2) = \int_{x_1}^{x_2} \int_{y_1}^{y_2} f_{XY}(x, y) dy dx$

① $f_X(x) \geq 0$

② $P(x_1 \leq X \leq x_2) = \int_{x_1}^{x_2} f_X(x) dx$

③ $F_X(x) = \int_{-\infty}^x f_X(x) dx$

④ $\int_{-\infty}^{\infty} f_X(x) dx = 1$

Marginal density function

$$F_{XY}(x, \infty) = F_X(x)$$

$$F_{XY}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{XY}(x, y) dy dx$$

$$F_X(x) = F_{XY}(x, \infty) = \int_{-\infty}^x \int_{-\infty}^{\infty} f_{XY}(x, y) dy dx$$

$$\frac{\partial F_X(x)}{\partial x} = \frac{\partial}{\partial x} F_{XY}(x, \infty) = \frac{\partial}{\partial x} \int_{-\infty}^x \int_{-\infty}^{\infty} f_{XY}(x, y) dy dx$$

$$f_X(x) = \int_{-\infty}^{\infty} f_{XY}(x, y) dy \rightarrow \text{Marginal density function of } X:$$

$$\text{Marginal density function of } Y: f_Y(y) = \int_{-\infty}^{\infty} f_{XY}(x, y) dx$$

$$F_{XY}(\infty, y) = F_Y(y)$$

$$F_{XY}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{XY}(x, y) dy dx$$

$$F_Y(y) = F_{XY}(\infty, y) = \int_{-\infty}^{\infty} \int_{-\infty}^y f_{XY}(x, y) dy dx$$

$$\frac{\partial F_Y(y)}{\partial y} = \frac{\partial}{\partial y} F_{XY}(\infty, y) = \frac{\partial}{\partial y} \int_{-\infty}^{\infty} \int_{-\infty}^y f_{XY}(x, y) dy dx$$

$$f_Y(y) = \int_{-\infty}^{\infty} f_{XY}(x, y) dx$$

Statistically Independent R.V (S.I) :-

X, Y are two R.V Joint density function $f_{XY}(x, y)$.
if ~~occure~~ the probability of one variable is not depend on another they said to be Independent R.V.

$$f_{XY}(x, y) = f_X(x) \cdot f_Y(y)$$

Conditional Joint Distribution and density function:-

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

Let X, Y are two R.V, $A = \{X \leq x\}$

$B = \{Y \leq y\}$

Conditional joint
Distribution function

$$F_{X/Y}(x/y) = \frac{P(X \leq x \cap Y \leq y)}{P(Y \leq y)} = \frac{F_{XY}(x, y)}{F_Y(y)}$$

$$F_{Y/X}(y/x) = \frac{P(X \leq x \cap Y \leq y)}{P(X \leq x)} = \frac{F_{XY}(x, y)}{F_X(x)}$$

conditional joint
Density function

$$f_{X/Y}(x/y) = \frac{f_{XY}(x, y)}{f_Y(y)}$$

$$f_{Y/X}(y/x) = \frac{f_{XY}(x, y)}{f_X(x)}$$

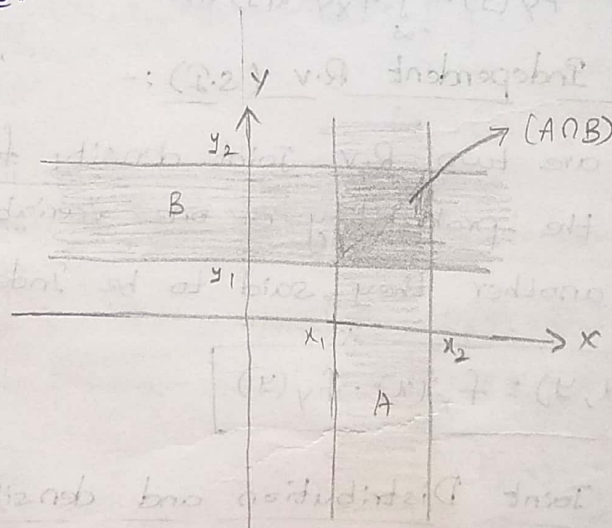
if x, y are statistically independent

$$f_{X/Y}(x/y) = \frac{f_{XY}(x, y)}{f_Y(y)} = \frac{f_X(x) \cdot f_Y(y)}{f_Y(y)} = f_X(x)$$

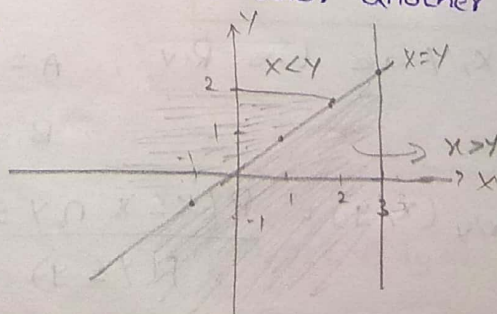
$$f_{Y/X}(y/x) = f_Y(y)$$

Sum of two Random Variables :-

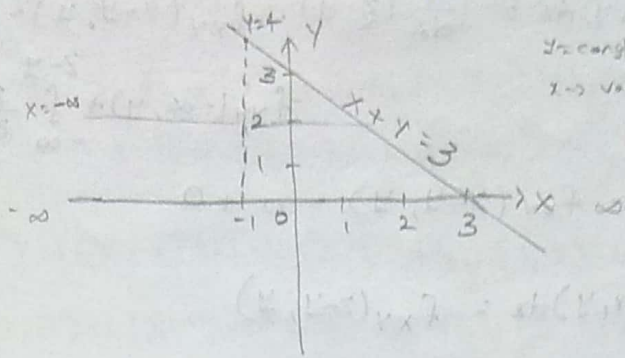
Two R.V A, B are generated by passing the sample space S through two Random variables X, Y and event A is represented as $\{x_1 \leq X \leq x_2\}$ and event B is represented as $B = \{y_1 \leq Y \leq y_2\}$. Find the Joint area on $x-y$ plane.



Let two R.V X, Y are linear one with another
map $X < Y, X > Y, X = Y$



Let X, Y are two R.V $X+Y=3$ place the representation on $x-y$ plane.



z - constant
 x - variable.

*** Sum of Two Random Variables

Statement:- Let X, Y are two R.V, having joint probability density function $f_{xy}(x, y)$, if X, Y are added generates R.V $Z = X+Y$, $f_z(z) = f_x(z) * f_y(z)$ [$\because X, Y$ are i.i.d]

Leibnitz's rule:- $H(x) = \int_{a(x)}^{b(x)} g(x, y) dy$

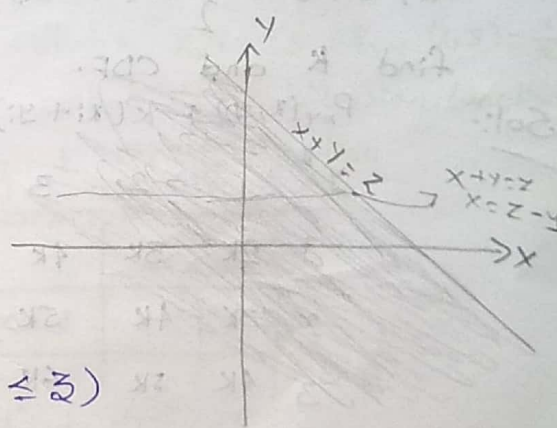
Let diff $H(x)$ w.r.t x .

$$\frac{d}{dx} H(x) = \frac{d}{dx} b(x) \cdot g(x, b(x)) - \frac{d}{dx} a(x) \cdot g(x, a(x)) + \int_{a(x)}^{b(x)} \frac{\partial}{\partial x} g(x, y) dy$$

$$X, Y \rightarrow f_{xy}(x, y)$$

$$Z = X+Y \rightarrow f_z(z) = ?$$

probability distribution function of Z



$$F_z(z) = P(Z \leq z) = P(X+Y \leq z)$$

$$F_z(z) = \int_{y=-\infty}^{\infty} \int_{x=-\infty}^{z-y} f_{xy}(x, y) dx dy$$

$$F_z(z) = \int_{-\infty}^{\infty} \left[\int_{x=-\infty}^{z-y} f_{xy}(x, y) dx \right] dy$$

Leibnitz's rule

perform diff w.r.t z to get density value $f_z(z)$

$$\frac{d}{dz} F_z(z) = \int_{y=-\infty}^{\infty} \frac{d}{dz} \left[\int_{x=-\infty}^{z-y} f_{xy}(x, y) dx \right] dy$$

$$\frac{d}{dz} \int_{x=-\infty}^{z-y} f_{xy}(x, y) dx = \frac{d}{dz} (z-y) \cdot f_{xy}(z-y, y) - \frac{d}{dz} (0) + f_{xy}(-\infty, y) + \int_{-\infty}^{z-y} \frac{\partial}{\partial x} f_{xy}(x, y) dx$$

$$= 1 \cdot f_{xy}(z-y, y) - 0 + 0$$

$$\frac{d}{dz} \int_{x=-\infty}^{z-y} f_{xy}(x, y) dx = f_{xy}(z-y, y)$$

$$f_z(z) = \int_{y=-\infty}^{\infty} f_{xy}(z-y, y) dy$$

Let x, y are s.i + $f_{xy}(x, y) = f_x(x) \cdot f_y(y)$

$$f_z(z) = \int_{-\infty}^{\infty} f_x(z-y) f_y(y) dy$$

$$f_z(z) = f_x(z) * f_y(z)$$

Problems:-

1) Joint probability mass function is given by

$$P_{xy}(x_i, y_j) = \begin{cases} k(x_i + y_j) & \text{for } x_i = 1, 2, 3, y_j = 1, 2, 3 \\ 0 & \text{otherwise} \end{cases}$$

find k and CDF.

Sol:-

$$P_{xy}(x, y) = k(x_i + y_j)$$

$x \backslash y$	1	2	3
1	2k	3k	4k
2	3k	4k	5k
3	4k	5k	6k

$$k = ? \quad \text{Total probability} = 1$$

$$2k + 3k + 4k + 3k + 4k + 5k + 4k + 5k + 6k = 1$$

$$36k = 1 \Rightarrow k = \frac{1}{36}$$

$$F_{xy}(x, y) = \sum_{x_i} \sum_{y_j} p_{xy}(x_i, y_j) u(x - x_i) u(y - y_j)$$

$$= \sum_{x_i=1}^3 \sum_{y_j=1}^3 P_{xy}(x_i, y_j) u(x - x_i) u(y - y_j)$$

$$= \sum_{x_i=1}^3 \left[P_{xy}(x_i, 1) u(x-x_i) u(y-1) \right. \\ \left. + P_{xy}(x_i, 2) u(x-x_i) u(y-2) \right. \\ \left. + P_{xy}(x_i, 3) u(x-x_i) u(y-3) \right]$$

$$= P_{xy}(1, 1) u(x-1) u(y-1) + P_{xy}(1, 2) u(x-1) u(y-2) \\ + P_{xy}(1, 3) u(x-1) u(y-3) + P_{xy}(2, 1) u(x-2) u(y-1) \\ + P_{xy}(2, 2) u(x-2) u(y-2) + P_{xy}(2, 3) u(x-2) u(y-3) \\ + P_{xy}(3, 1) u(x-3) u(y-1) + P_{xy}(3, 2) u(x-3) u(y-2) \\ + P_{xy}(3, 3) u(x-3) u(y-3)$$

$$= \frac{2}{36} u(x-1) u(y-1) + \frac{3}{36} u(x-1) u(y-2) \\ + \frac{4}{36} u(x-1) u(y-3) + \frac{3}{36} u(x-2) u(y-1) \\ + \frac{4}{36} u(x-2) u(y-2) + \frac{5}{36} u(x-2) u(y-3) \\ + \frac{4}{36} u(x-3) u(y-1) + \frac{5}{36} u(x-3) u(y-2) \\ + \frac{6}{36} u(x-3) u(y-3).$$

2) The Joint PDF of random variable X, Y is $f_{xy}(x, y) = \frac{1}{2}$
 $\forall 0 \leq x \leq 1, 0 \leq y \leq 2$ find probability distribution function
 find $F_{xy}(0.5, 1)$, find marginal density function
 $f_x(x), f_y(y)$ find X, Y are S.I. ~~not~~ ^(or) not.

Sol:- $f_{xy}(x, y) = \frac{1}{2} \quad \forall \quad 0 \leq x \leq 1, 0 \leq y \leq 2$

$$F_{xy}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{xy}(x, y) dy dx$$

$$= \int_0^x \left[\int_0^y \frac{1}{2} dy \right] dx$$

$$= \int_0^x \left[\frac{1}{2} \cdot y \right]_0^y dx$$

$$= \frac{1}{2} \int_0^x [y-0] dx = \frac{1}{2} \int_0^x y \cdot dx$$

$$= \frac{1}{2} y \int_0^x dx \Rightarrow \frac{1}{2} y [x]_0^x$$

$$= \frac{1}{2} y [x-0]$$

$$= \frac{xy}{2}$$

$$F_{xy}(x, y) = \frac{xy}{2}$$

$$(ii) F_{xy}(0.5, 1) = \int_{-\infty}^{0.5} \int_{-\infty}^1 f_{xy}(x, y) dy dx$$

$$= \int_{-\infty}^{0.5} \int_{-\infty}^1 \frac{1}{2} dy dx$$

$$= \int_0^{0.5} \int_0^1 \frac{1}{2} dy dx$$

$$= \frac{1}{2} \int_0^{0.5} dy dx$$

$$= \frac{1}{2} \int_0^{0.5} [y]_0^1 dx \Rightarrow \frac{1}{2} \int_0^{0.5} (1) dx$$

$$= \frac{1}{2} [x]_0^{0.5} \Rightarrow \frac{1}{2} (0.5) = \frac{1}{4}$$

$$F_{xy}(0.5, 1) = \frac{1}{4}$$

3) Marginal density function

$$f_x(x) = \int_{-\infty}^{\infty} f_{xy}(x, y) dy = \int_0^2 \frac{1}{2} dy = \frac{1}{2} [y]_0^2$$

$$= \frac{1}{2} [2-0] = 1$$

$$f_y(y) = \int_{-\infty}^{\infty} f_{xy}(x, y) dx = \int_0^1 \frac{1}{2} dx = \frac{1}{2} [x]_0^1$$

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

4) If x, y are two R.V statistically independent if

$$f_{xy}(x, y) = f_x(x) \cdot f_y(y)$$

$$f_{xy}(x, y) = \frac{1}{2}$$

$$f_x(x) = 1$$

$$f_y(y) = \frac{1}{2}$$

$$f_{xy}(x, y) = f_x(x) \cdot f_y(y)$$

Both x, y are s.i

3) Two R.V x, y have a Joint density function

$$f(x, y) = \frac{5}{16} x^2 y \text{ for } 0 < y < x < 2$$

① Find marginal density function of x, y

② Find x, y are s.i (or) not.

Sol:-

$$f_x(x) = \int_{-\infty}^{\infty} f_{xy}(x, y) dy = \int_0^x \frac{5}{16} x^2 y dy$$

$$= \frac{5}{16} x^2 \int_0^x y dy = \frac{5}{16} x^2 \left[\frac{y^2}{2} \right]_0^x$$

$$= \frac{5}{16} \cdot \frac{1}{2} x^2 \cdot x^2$$

$$f_x(x) = \frac{5}{32} x^4$$

$$f_y(y) = \int_{-\infty}^{\infty} f_{xy}(x, y) dx = \int_y^2 \frac{5}{16} x^2 y dx$$

$$= \frac{5}{16} y \int_y^2 x^2 dx = \frac{5}{16} y \left[\frac{x^3}{3} \right]_y^2$$

$$= \frac{5}{48} y [8 - y^3] = \frac{5}{48} y \cdot 8 - \frac{5}{48} y \cdot y^3$$

$$= \frac{5}{6} y - \frac{5}{48} y^4$$

$$f_{xy}(x, y) = \frac{5}{16} x^2 y$$

$$f_x(x) = \frac{5}{32} x^4$$

$$f_x(x) \cdot f_y(y) = \frac{5}{32} x^4 \cdot \frac{5}{48} (8y - y^4)$$

$$f_y(y) = \frac{5}{48} (8y - y^4)$$

$$\neq f_{xy}(x, y)$$

Both x, y are not statistically independent.

4) The Joint Distribution of x, y is given by

$$f_{xy}(x, y) = 4xy e^{-(x^2+y^2)} u(x) \cdot u(y) \text{ show } x, y \text{ are s.i.}$$

\downarrow \downarrow
 $x \geq 0$ $y \geq 0$

∴ Find marginal density functions

Sol:-

$$f_{xy}(x,y) = 4xy e^{-(x^2+y^2)} = u(x) \cdot u(y)$$

$$f_x(x) = \int_{-\infty}^{\infty} f_{xy}(x,y) dy = \int_0^{\infty} 4xy e^{-(x^2+y^2)} dy$$

$$= 4x e^{-x^2} \int_0^{\infty} y \cdot e^{-y^2} dy$$

$$= 4x e^{-x^2} \int_0^{\infty} \frac{1}{2} \cdot e^{-z} \cdot \frac{dz}{2y}$$

$$= 4x e^{-x^2} \int_0^{\infty} e^{-z} \cdot \frac{1}{2} \cdot dz$$

$$= 2x e^{-x^2} \left[\frac{e^{-z}}{-1} \right]_0^{\infty} = 2x e^{-x^2} \left[\frac{0-1}{-1} \right]$$

$$= 2x e^{-x^2}$$

Let $y^2 = z$

$2y dy = dz$

$dy = \frac{dz}{2y}$

$y=0 \Rightarrow z=0$

$y=\infty \Rightarrow z=\infty$

$$f_y(y) = \int_{-\infty}^{\infty} f_{xy}(x,y) dx = \int_0^{\infty} 4xy e^{-(x^2+y^2)} dx$$

$$= 4y e^{-y^2} \int_0^{\infty} x \cdot e^{-x^2} dx$$

$$= 4y e^{-y^2} \int_0^{\infty} x \cdot e^{-p} \cdot \frac{dp}{2x}$$

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

$$= 2y e^{-y^2} \left[\frac{0-1}{-1} \right]$$

$$f_y(y) = 2y e^{-y^2}$$

Let $x^2 = p$

$2x dx = dp$

$dx = \frac{dp}{2x}$

$x=0 \Rightarrow p=0$

$x=\infty \Rightarrow p=\infty$

$$f_{xy}(x,y) = 4xy e^{-(x^2+y^2)}$$

$$f_x(x) \cdot f_y(y) = 2 \cdot x \cdot e^{-x^2} \cdot 2y e^{-y^2} = 4xy e^{-x^2} \cdot e^{-y^2} = 4xy e^{-(x^2+y^2)}$$

5) Joint Density function of R.V X, Y is $f(x,y) = k e^{-(x+y)}$ in the range of $0 \leq x \leq \infty, 0 \leq y \leq \infty$ and $f(x,y) = 0$ otherwise

(a) Find value k .

(b) Find probability density of x by considering y is independent.

(c) Find $P(0 \leq X \leq 2, 2 \leq Y \leq 3)$

1d) Prove R.V X and Y are s.i (or) not.

Sol: Given $f(x, y) = ke^{-(x+y)}$

(a)

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{xy}(x, y) dy dx = 1$$

$$\int_{0}^{\infty} \int_{0}^{\infty} k \cdot e^{-(x+y)} dy dx = 1$$

$$\int_{0}^{\infty} \int_{0}^{\infty} k \cdot e^{-x} \cdot e^{-y} dy dx = 1$$

$$k \int_{0}^{\infty} e^{-x} \left[\frac{e^{-y}}{-1} \right]_0^{\infty} dx = 1$$

$$k \int_{0}^{\infty} e^{-x} \left[\frac{0-1}{-1} \right] dx = 1$$

$$k \left[\frac{e^{-x}}{-1} \right]_0^{\infty} = 1$$

$$k \left[\frac{0-1}{-1} \right] = 1$$

$$\boxed{k=1}$$

(b) $f_x(x)$ considering y is independent.

$$f_x(x) = \int_{-\infty}^{\infty} f_{xy}(x, y) dy$$

$$= \int_{0}^{\infty} k \cdot e^{-x} \cdot e^{-y} dy$$

$$= e^{-x} \left[\frac{e^{-y}}{-1} \right]_0^{\infty} = e^{-x} \left[\frac{0-1}{-1} \right]$$

$$f_x(x) = e^{-x}$$

③ $P(0 \leq x \leq 2, 2 \leq y \leq 3)$

$$\int_{0}^2 \int_{2}^3 f_{xy}(x, y) dx dy$$

$$\int_{0}^2 \int_{2}^3 e^{-x} \cdot e^{-y} dy dx$$

$$\int_{0}^2 e^{-x} dx \int_{2}^3 e^{-y} dy$$

$$\begin{aligned}
 &= \begin{bmatrix} e^{-x} \\ -1 \\ 0 \end{bmatrix}^2 \cdot \begin{bmatrix} e^{-y} \\ -1 \\ 2 \end{bmatrix}^3 \\
 &= \frac{e^{-2} - 1}{-1} \cdot \frac{e^{-3} - e^{-2}}{-1} \\
 &= (1 - e^{-2})(e^{-2} - e^{-3})
 \end{aligned}$$

X, Y are statistically independent

Operations on Multiple R.V

Moments:-

- 1) Moment about mean
- 2) Moment about origin.

Expected value of Multiple R.V :-

$$E(x) = \int_{-\infty}^{\infty} x f_x(x) dx \rightarrow \text{single R.V}$$

Let x, y are two R.V, $E(xy) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_{xy}(x, y) dx dy$.

n^{th} moment $E[x^n] = m_n \rightarrow$ for single R.V

Multiple
 $(n+k)^{\text{th}}$ moment = $E[x^n y^k] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^n y^k f_{xy}(x, y) dx dy$.

0^{th} moment about origin of two r.v x, y

$$\begin{aligned}
 n=0 \\
 k=0 \\
 E[x^0 y^0] &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^0 y^0 f_{xy}(x, y) dx dy = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{xy}(x, y) dy dx \\
 E[1 \cdot 1] &= E[1] = 1 \\
 &= 1
 \end{aligned}$$

1^{st} moment about origin of R.V x, y

$$\begin{aligned}
 n=1 \\
 k=0
 \end{aligned}$$

$(n+k)^{\text{th}}$ moment = $(1+0)^{\text{th}}$ moment = 1^{st} moment

$$m_{10} = E[x^1 y^0] = E[x^1] = \mu_x$$

$$n=0, k=1 \quad (0+1)^{\text{th}} \text{ moment} = E[X^0 Y^1] = E[Y] = \mu_y = m_{01}$$

2nd moment about origin of m.r.v :-

$$n=2, k=0 \quad E[X^2 Y^0] = m_{20} = E[X^2] = 2^{\text{nd}} \text{ moment about origin of R.V } X.$$

$$n=0, k=2 \quad E[X^0 Y^2] = m_{02} = E[Y^2] = 2^{\text{nd}} \text{ moment about origin of R.V } Y.$$

$$n=1, k=1 \quad E[X \cdot Y] = m_{11} = E[XY] \rightarrow \text{correlation of two R.V's relation between 2 signals}$$

Relation :-

$$X = \{1, 2, 3, 4\} \quad Y \subset X$$

$$Y = \{1, 2\}$$

0th moment

$$n=k=0$$

1st moment

$$n=1, k=0 \\ n=0, k=1$$

2nd moment

$$n=2, k=0 \\ n=0, k=2 \\ n=1, k=1$$

Properties of correlation :-

$$1) X, Y \text{ are two S.I R.V's} \quad E[XY] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_{XY}(x, y) dy dx$$

If X, Y are S.I $f_{XY}(x, y) = f_X(x) \cdot f_Y(y)$.

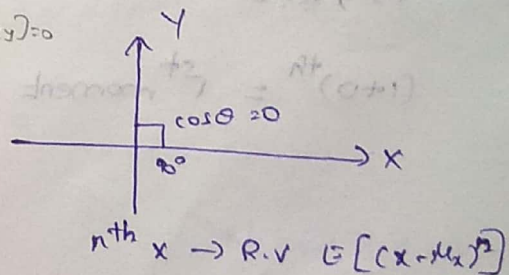
$$E[XY] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_X(x) f_Y(y) dy dx \\ = \int_{-\infty}^{\infty} x f_X(x) dx \cdot \int_{-\infty}^{\infty} y f_Y(y) dy$$

$$E[XY] = E(X) \cdot E(Y)$$

X, Y are two R.V orthogonal to each other $E[XY]=0$

2) X, Y are orthogonal

$$R_{XY} = E[XY] = 0$$



Moment about mean :-

X, Y are two R.V's

$(n+k)^{\text{th}}$ moment about mean

$$\mu_n \mu_k = E[(X - \mu_X)^n (Y - \mu_Y)^k]$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_x)^n (y - \mu_y)^k f_{xy}(x, y) dx dy$$

0th moment about mean:-

$$n=0, k=0$$

$$\mu_{0k_0} = \mu_{00} = E[(x - \mu_x)^0 (y - \mu_y)^0] = E[1 \cdot 1] = E[1] = 1.$$

Moment about mean:-

Single R.V = n^{th} moment of single RV over mean

$$E[(x - \mu_x)^n]$$

Multiple R.V:- x, y are two R.V, μ_x is the mean of x , μ_y is the mean of y

$$n, k \quad E[(x - \mu_x)^n (y - \mu_y)^k] = \mu_{nk}$$

0th moment of M.R.V about mean:-

$$n=0, k=0$$

$(n+k)^{\text{th}}$ moment = $(0+0)^{\text{th}}$ = 0th moment about mean

$$E[(x - \mu_x)^0 (y - \mu_y)^0] = E[1] = 1$$

1st moment about mean of M.R.V:-

$$n=0, k=1$$

$(n+k)^{\text{th}}$ moment = $(0+1)^{\text{th}}$ = 1st moment

$$= E[(x - \mu_x)^0 (y - \mu_y)^1] = E[y - \mu_y]$$

$$= E(y) - E(\mu_y)$$

$$= \mu_y - \mu_y = 0.$$

$$n=1, k=0$$

$(1+0)^{\text{th}}$ = 1st moment = $E[(x - \mu_x)^1 (y - \mu_y)^0]$

$$= E[(x - \mu_x)^1]$$

$$= E(x) - E(\mu_x)$$

$$= \mu_x - \mu_x = 0$$

2nd moment about mean of R.V X, Y :-

$(n+k)^{th}$ moment =

$n=2, k=0 \quad (2+0)^{th} = 2^{nd}$ moment $= E[(X-\mu_x)^2(Y-\mu_y)^0] = E[(X-\mu_x)^2]$

$= \sigma_x^2$
(Variance of X)

$n=0, k=2 \quad (0+2)^{th} = 2^{nd}$ moment $E[(X-\mu_x)^0(Y-\mu_y)^2] = E[(Y-\mu_y)^2]$

$= \sigma_y^2$
(Variance of Y)

$n=1, k=1 \quad (1+1)^{th} = 2^{nd}$ moment $E[(X-\mu_x)^1(Y-\mu_y)^1] = \text{covariance}$

Note:-

Covariance (X, Y) :- 2nd moment of R.V X, Y over their respective mean with $n=1, k=1$

$$C_{XY} = E[(X-\mu_x)(Y-\mu_y)] = \sigma_{XY}$$

Properties of co-variance :-

1) $\text{cov}(X, Y) = R_{XY} - \bar{X}\bar{Y}$

Proof:-

$$\begin{aligned} \text{cov}(X, Y) &= E[(X-\mu_x)(Y-\mu_y)] \\ &= E[XY - X\mu_y - Y\mu_x + \mu_x\mu_y] \\ &= E[XY] - E[X\mu_y] - E[Y\mu_x] + E[\mu_x\mu_y] \\ &= E[XY] - \mu_y E[X] - \mu_x E[Y] + \mu_x \cdot \mu_y \\ &= E[XY] - \mu_y \mu_x - \mu_x \mu_y + \mu_x \mu_y \\ &= E[XY] - \mu_x \mu_y \\ &= E[XY] - \bar{X}\bar{Y} \end{aligned}$$

$\text{cov}(X, Y) = R_{XY} - \bar{X}\bar{Y}$

2) X, Y are s.i R.V, $\text{cov}(X, Y) = 0$

As per

$$\text{cov}(X, Y) = R_{XY} - \bar{X}\bar{Y}$$

We know X, Y are s.i

$$\begin{aligned} R_{XY} = E[XY] &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_{XY}(x, y) dy dx \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_x(x) f_y(y) dy dx \end{aligned}$$

$$f_{XY}(x, y) = f_x(x) \cdot f_y(y)$$

$$= \int_{-\infty}^{\infty} x \cdot f_x(x) dx \int_{-\infty}^{\infty} y \cdot f_y(y) dy$$

$$= E(X) \cdot E(Y) \Rightarrow \mu_x \cdot \mu_y \Rightarrow \bar{x} \cdot \bar{y}$$

$$\text{cov}(X, Y) = E(XY) - \bar{x} \cdot \bar{y} = \bar{x} \cdot \bar{y} - \bar{x} \cdot \bar{y} = 0.$$

③ "Scalar multiplication" $\text{cov}(ax, by) = a \cdot b \cdot \text{cov}(x, y)$

Proof:- $\text{cov}(ax, by) = E((ax - E(ax))(by - E(by)))$
 $= E((x - E(x))(y - E(y)))$

$$\text{cov}(ax, by) = E((ax - E(ax))(by - E(by)))$$

$$= E(ax \cdot by) - E(ax) \cdot E(by)$$

$$= E(abxy) - aE(x) \cdot bE(y)$$

$$= abE(xy) - abE(x)E(y)$$

$$= ab[E(xy) - E(x) \cdot E(y)]$$

$$= ab[R_{xy} - \mu_x \cdot \mu_y]$$

$$\text{cov}(ax, by) = ab \text{cov}(x, y).$$

④ $\text{cov}(x+a, y+b) = \text{cov}(x, y)$

$$\text{cov}(x+a, y+b) = E((x+a)(y+b)) - E(x+a)E(y+b)$$

$$= E[(x+a)(y+b)] - E(x+a)E(y+b)$$

$$= E[xy + xb + ay + ab] - \{[E(x) + E(a)][E(y) + E(b)]\}$$

$$= E[xy] + E[xb] + E[ay] + E[ab] - \{E(x) \cdot E(y) + E(x) \cdot E(b) + E(a) \cdot E(y) + E(a) \cdot E(b)\}$$

$$= E(xy) + bE(x) + aE(y) + ab - E(x) \cdot E(y) - bE(x) - aE(y) - E(a) \cdot E(b)$$

$$= E(xy) - E(x) \cdot E(y)$$

$$= E(xy) - \bar{x} \cdot \bar{y} = \text{cov}(x, y)$$

UNIT-3

MULTIPLE RANDOM VARIABLES

Properties of co-variance:-

$$\textcircled{5} \text{Var}(X+Y) = \text{var}(X) + \text{var}(Y) + 2C_{xy}$$

Proof:- $\text{var}(Z) = m_2 - (m_1)^2$

$$\text{var}(Z) = E(Z^2) - [E(Z)]^2$$

Let $X+Y=Z$

$$\text{var}(Z) = E(Z^2) - [E(Z)]^2$$

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

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

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

$$2E[X]E[Y] \}$$

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

$$= \text{var}(X) + \text{var}(Y) + 2[R_{xy} - \bar{X}\bar{Y}]$$

$$= \text{var}(X) + \text{var}(Y) + 2\text{cov}(XY)$$

$$\text{var}(X+Y) = \text{var}(X) + \text{var}(Y) + 2C_{xy}$$

$$\textcircled{6} \text{Var}(X-Y) = \text{var}(X) + \text{var}(Y) - 2C_{xy}$$

Proof:- $\text{var}(Z) = m_2 - (m_1)^2$

$$\text{var}(Z) = E(Z^2) - [E(Z)]^2$$

Let $X-Y=Z$

$$\text{var}(Z) = E(Z^2) - [E(Z)]^2$$

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

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

$$= E[X^2] + E[Y^2] + E[-2XY] - \{ [E(X)]^2 + [E(Y)]^2 - 2E[X]E[Y] \}$$

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

$$= \text{var}(X) + \text{var}(Y) - 2[E[XY] - E[X]E[Y]]$$

$$= \text{var}(X) + \text{var}(Y) - 2[R_{xy} - \bar{X}\bar{Y}]$$

$$= \text{var}(X) + \text{var}(Y) - 2\text{cov}(XY)$$

$$\text{var}(X-Y) = \text{var}(X) + \text{var}(Y) - 2C_{xy}$$

$$\textcircled{7} \sigma_{xy} \leq \sigma_x \cdot \sigma_y$$

$$\text{cov}(X, Y) \leq \text{s.d.}(X) \cdot \text{s.d.}(Y)$$

Proof:- Assumption:- $[(Y - \bar{y}) - k(X - \bar{x})]^2 \geq 0$

Apply Exp on both sides

$$E \{ [(Y - \bar{y}) - k(X - \bar{x})]^2 \} \geq E(0)$$

$$E [(Y - \bar{y})^2 + k^2(X - \bar{x})^2 - 2k(Y - \bar{y})(X - \bar{x})] \geq 0$$

$$E [(Y - \bar{y})^2] + E [k^2(X - \bar{x})^2] - E [2k(X - \bar{x})(Y - \bar{y})] \geq 0$$

$$\sigma_y^2 + k^2 \sigma_x^2 - 2k E [(X - \bar{x})(Y - \bar{y})] \geq 0$$

$$\sigma_y^2 + k^2 \sigma_x^2 - 2k \sigma_{xy} \geq 0$$

Divide on both sides using σ_x^2

$$\frac{\sigma_y^2 + k^2 \sigma_x^2 - 2k \sigma_{xy}}{\sigma_x^2} \geq \frac{0}{\sigma_x^2}$$

$$\frac{\sigma_y^2}{\sigma_x^2} + k^2 - 2k \frac{\sigma_{xy}}{\sigma_x^2} \geq 0$$

Add & sub with $\left(\frac{\sigma_{xy}}{\sigma_x^2}\right)^2$

$$k^2 - 2k \frac{\sigma_{xy}}{\sigma_x^2} + \frac{\sigma_y^2}{\sigma_x^2} + \left(\frac{\sigma_{xy}}{\sigma_x^2}\right)^2 - \left(\frac{\sigma_{xy}}{\sigma_x^2}\right)^2 \geq 0$$

$$k^2 - 2k \frac{\sigma_{xy}}{\sigma_x^2} + \left(\frac{\sigma_{xy}}{\sigma_x^2}\right)^2 + \frac{\sigma_y^2}{\sigma_x^2} - \left(\frac{\sigma_{xy}}{\sigma_x^2}\right)^2 \geq 0$$

$$\left(k - \frac{\sigma_{xy}}{\sigma_x^2}\right)^2 + \frac{\sigma_y^2}{\sigma_x^2} - \left(\frac{\sigma_{xy}}{\sigma_x^2}\right)^2 \geq 0$$

$$\frac{\sigma_y^2}{\sigma_x^2} \geq \left(\frac{\sigma_{xy}}{\sigma_x^2}\right)^2$$

$$\frac{\sigma_y \sigma_x^2}{\sigma_x} \geq \sigma_{xy}$$

$$\sigma_x \sigma_y \geq \sigma_{xy}$$

$$\boxed{\sigma_{xy} \leq \sigma_x \cdot \sigma_y}$$

Characteristic function of Normal density function:-

Normal density function:- $N(0, 1) = f(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$ $\forall -\infty < x < \infty$

$$\phi_X(\omega) = E[e^{j\omega x}] = \int_{-\infty}^{\infty} e^{j\omega x} \cdot f_X(x) dx.$$

$$= \int_{-\infty}^{\infty} e^{j\omega x} \cdot \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx.$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{j\omega x} \cdot e^{-x^2/2} dx.$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-x^2/2 + j\omega x} dx.$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left(\frac{x^2}{2} - j\omega x\right)} dx.$$

Add & sub $\left(\frac{j\omega}{\sqrt{2}}\right)^2$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left[\frac{x^2}{2} - x \cdot j\omega + \left(\frac{j\omega}{\sqrt{2}}\right)^2 - \left(\frac{j\omega}{\sqrt{2}}\right)^2\right]} dx.$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left[\frac{x^2}{2} - 2 \cdot \frac{x \cdot j\omega}{2} + \left(\frac{j\omega}{\sqrt{2}}\right)^2 - \left(\frac{j\omega}{\sqrt{2}}\right)^2\right]} dx.$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left[\frac{x^2}{2} - 2 \cdot \frac{x}{\sqrt{2}} \cdot \frac{j\omega}{\sqrt{2}} + \left(\frac{j\omega}{\sqrt{2}}\right)^2 - \left(\frac{j\omega}{\sqrt{2}}\right)^2\right]} dx.$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left[\left(\frac{x}{\sqrt{2}} - \frac{j\omega}{\sqrt{2}}\right)^2 + \left(\frac{j\omega}{\sqrt{2}}\right)^2\right]} dx.$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left(\frac{x}{\sqrt{2}} - \frac{j\omega}{\sqrt{2}}\right)^2} \cdot e^{\left(\frac{j\omega}{\sqrt{2}}\right)^2} dx.$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\left(\frac{x}{\sqrt{2}} - \frac{j\omega}{\sqrt{2}}\right)^2} \cdot e^{\left(\frac{j\omega}{\sqrt{2}}\right)^2} dx.$$

$$= \frac{1}{\sqrt{2\pi}} e^{\left(\frac{j\omega}{\sqrt{2}}\right)^2} \int_{-\infty}^{\infty} e^{-\frac{(x-j\omega)^2}{2}} dx$$

let $x - j\omega = t$

$dx = dt$

$$= \frac{1}{\sqrt{2\pi}} e^{-\frac{w^2}{2}} \int_{-\infty}^{\infty} e^{-\frac{t^2}{2}} dt$$

$$= e^{-\frac{w^2}{2}} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$$

$$= e^{-\frac{w^2}{2}} \int_{-\infty}^{\infty} f_T(t) dt$$

$$= e^{-\frac{w^2}{2}} \cdot 1 = e^{-\frac{w^2}{2}}$$

Center limit theorem :-

Statement:- Let N identically independent R.V as $X_1, X_2, X_3, \dots, X_N$, have mean $\bar{X}_1, \bar{X}_2, \bar{X}_3, \dots, \bar{X}_N$, variance $\sigma_{X_1}, \sigma_{X_2}, \sigma_{X_3}, \dots, \sigma_{X_N}$ by adding all the R.V we get

$$Y = X_1 + X_2 + X_3 + \dots + X_N, \quad \bar{Y} = \bar{X}_1 + \bar{X}_2 + \bar{X}_3 + \dots + \bar{X}_N$$

$\sigma_Y^2 = \sigma_{X_1}^2 + \sigma_{X_2}^2 + \sigma_{X_3}^2 + \dots + \sigma_{X_N}^2$. A normalized standard deviation represented as $W = \frac{Y - \bar{Y}}{\sigma_Y}$ its characteristic function is $e^{-\frac{w^2}{2}}$.

Proof:- $Y = X_1 + X_2 + X_3 + \dots + X_N = \sum_{n=1}^N X_n \rightarrow \textcircled{1}$

$$\bar{Y} = \bar{X}_1 + \bar{X}_2 + \bar{X}_3 + \dots + \bar{X}_N = \sum_{n=1}^N \bar{X}_n \rightarrow \textcircled{2}$$

$$\sigma_Y^2 = \sigma_{X_1}^2 + \sigma_{X_2}^2 + \sigma_{X_3}^2 + \dots + \sigma_{X_N}^2 = \sum_{n=1}^N \sigma_{X_n}^2 \rightarrow \textcircled{3}$$

$$W = \frac{Y - \bar{Y}}{\sigma_Y} \rightarrow \textcircled{4}$$

sub $\textcircled{1}, \textcircled{2}, \textcircled{3}$ in $\textcircled{4}$

$$W = \frac{\sum_{n=1}^N X_n - \sum_{n=1}^N \bar{X}_n}{\sqrt{\sum_{n=1}^N \sigma_{X_n}^2}}$$

$$= \frac{\sum_{n=1}^N X_n - \sum_{n=1}^N \bar{X}_n}{\sqrt{\sum_{n=1}^N \sigma_{X_n}^2}} \rightarrow \textcircled{5}$$

As per the statement all the R.V are i.i.d [s.i]

$$X_1 = X_2 = X_3 = \dots = X_N = X$$

$$\bar{X}_1 = \bar{X}_2 = \bar{X}_3 = \dots = \bar{X}_N = \bar{X}$$

$$\sigma_{x_1}^2 = \sigma_{x_2}^2 = \sigma_{x_3}^2 = \dots = \sigma_{x_n}^2 = \sigma_x^2$$

⑤ ⇒

$$W = \frac{\sum x - \sum \bar{x}}{\sqrt{\sum \sigma_x^2}} \Rightarrow \frac{\sum (x - \bar{x})}{\sqrt{\sum \sigma_x^2}}$$

$$= \frac{\sum (x - \bar{x})}{\sqrt{N \sigma_x^2}} \Rightarrow \frac{\sum (x - \bar{x})}{\sqrt{N} \sigma_x}$$

$$W = \frac{\sum (x - \bar{x})}{\sqrt{N} \sigma_x} \quad \text{⑥}$$

General C.F

7285937979

$$\phi_x(\omega) = E[e^{j\omega x}]$$

$$\text{C.F of } W \quad \phi_W(\omega) = E[e^{j\omega W}] \quad \text{--- ⑦}$$

Sub ⑥ in ⑦

$$\phi_W(\omega) = E\left[e^{j\omega \left[\frac{\sum (x - \bar{x})}{\sqrt{N} \sigma_x} \right]} \right] = E\left[e^{j\omega \left[\frac{\sum (x - \bar{x})}{\sqrt{N} \sigma_x} \right]} \right]$$

$$= E\left[e^{\frac{\sum j\omega (x - \bar{x})}{\sqrt{N} \sigma_x}} \right]$$

$$= E\left[e^{\frac{j\omega (x - \bar{x})}{\sqrt{N} \sigma_x}} \right]^N$$

$$= E\left\{ \left[e^{\frac{j\omega (x - \bar{x})}{\sqrt{N} \sigma_x}} \right]^N \right\}$$

all the r.v are iid

$$\phi_W(\omega) = \left\{ E\left[e^{\frac{j\omega (x - \bar{x})}{\sqrt{N} \sigma_x}} \right] \right\}^N$$

apply Natural log on both sides on ⑦

$$\ln[\phi_W(\omega)] = \ln \left\{ E\left[e^{\frac{j\omega (x - \bar{x})}{\sqrt{N} \sigma_x}} \right] \right\}^N$$

$$\ln[\phi_W(\omega)] = N \ln \left\{ E\left[e^{\frac{j\omega (x - \bar{x})}{\sqrt{N} \sigma_x}} \right] \right\}$$

$$= N \ln \left\{ E\left[1 + \frac{j\omega (x - \bar{x})}{\sqrt{N} \sigma_x} + \frac{\left(\frac{j\omega (x - \bar{x})}{\sqrt{N} \sigma_x} \right)^2}{2!} + \frac{\left(\frac{j\omega (x - \bar{x})}{\sqrt{N} \sigma_x} \right)^3}{3!} + \dots \right] \right\}$$

x, y are s.i

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

$$E[e^{ax}]^3$$

$$= E[e^x] \cdot E[e^x] \cdot E[e^x]$$

$$\ln[a^n] = n \ln(a)$$

$$e^x = \frac{x^0}{0!} + \frac{x^1}{1!} + \frac{x^2}{2!} + \dots$$

$$= N \ln \left\{ E \left[1 + \frac{j\omega(x-\bar{x})}{\sqrt{N}\sigma_x} + \frac{1}{2!} \frac{(j\omega)^2(x-\bar{x})^2}{(\sqrt{N}\sigma_x)^2} + \frac{1}{3!} \frac{(j\omega)^3(x-\bar{x})^3}{(\sqrt{N}\sigma_x)^3} + \dots \right] \right\}$$

$$= N \ln \left[E(1) + E \left[\frac{j\omega(x-\bar{x})}{\sqrt{N}\sigma_x} \right] + E \left[\frac{1}{2!} \frac{(j\omega)^2(x-\bar{x})^2}{(\sqrt{N}\sigma_x)^2} \right] + E \left[\frac{1}{3!} \frac{(j\omega)^3(x-\bar{x})^3}{(\sqrt{N}\sigma_x)^3} \right] + \dots \right]$$

$$= N \ln \left[1 + \frac{j\omega}{\sqrt{N}\sigma_x} E(x-\bar{x}) + \frac{1}{2} \frac{(j\omega)^2}{(\sqrt{N}\sigma_x)^2} E(x-\bar{x})^2 + \frac{1}{6} \frac{(j\omega)^3}{(\sqrt{N}\sigma_x)^3} E(x-\bar{x})^3 + \dots \right]$$

$$\frac{-j\omega^3}{\sigma_x^3 \cdot \sqrt{N}} E(x-\bar{x})^3 \frac{R(N)}{N}$$

$$= \frac{(j\omega)^3}{\sqrt{N}\sigma_x^3} E(x-\bar{x})^3 + \frac{(j\omega)^4}{\sqrt{N}\sigma_x^4} E(x-\bar{x})^4 + \dots$$

$$= N \ln \left[1 + \frac{1}{2} \frac{(j\omega)^2}{(\sqrt{N}\sigma_x)^2} \cdot \sigma_x^2 + \frac{1}{N} R(N) \right]$$

$$= N \ln \left[1 - \frac{1}{2} \frac{\omega^2}{N\sigma_x^2} + \frac{R(N)}{N} \right]$$

$$= N \ln \left[1 - \frac{\omega^2}{2N} + \frac{R(N)}{N} \right]$$

$$= N \ln [1 - z] \quad \text{let } z = \frac{\omega^2}{2N} + \frac{R(N)}{N}$$

$$\ln(1-z) = - \left[z + \frac{z^2}{2!} + \frac{z^3}{3!} + \dots \right]$$

$$\textcircled{8} \Rightarrow \ln[\phi_w(\omega)] = N \ln[1-z]$$

$$= -N \left[z + \frac{z^2}{2!} + \frac{z^3}{3!} + \dots \right]$$

$$= -N \left[\frac{\omega^2}{2N} + \frac{R(N)}{N} + \frac{\left(\frac{\omega^2}{2N} + \frac{R(N)}{N} \right)^2}{2!} + \dots \right]$$

$$\frac{\left(\frac{\omega^2}{2N} + \frac{R(N)}{N} \right)^3}{3!} + \dots$$

$$\ln[\phi_N(\omega)] = -\frac{\omega^2}{2} - R(N) - \frac{N}{2} \left[\frac{\omega^2}{2N} + \frac{R(N)}{N} \right] - \frac{N}{3!} \left[\frac{\omega^2}{2N} + \frac{R(N)}{N} \right]^2 - \dots$$

$N \rightarrow \infty$ $x_1, x_2, x_3, \dots, x_N \rightarrow \infty$

let the number of R.V. are ∞

$$\lim_{N \rightarrow \infty} \ln[\phi_N(\omega)] = \lim_{N \rightarrow \infty} \left[-\frac{\omega^2}{2} - R(N) - \frac{N}{2} \left[\frac{\omega^2}{2N} + \frac{R(N)}{N} \right] - \frac{N}{3!} \left[\frac{\omega^2}{2N} + \frac{R(N)}{N} \right]^2 - \dots \right]$$

$$\ln[\phi_N(\omega)] = -\frac{\omega^2}{2}$$

$$\phi_N(\omega) \xrightarrow{N \rightarrow \infty} e^{-\omega^2/2} = \text{C.F. (Normal density function)}$$

Normalized s.d. $y = x_1 + x_2 + x_3 + \dots$
 $\sigma_y^2 = \sigma_{x_1}^2 + \sigma_{x_2}^2 + \sigma_{x_3}^2 + \dots$

N^{th} order Gaussian density function :-

x_1, x_2, \dots, x_N are N no. of R.V, they have respective mean as $\bar{x}_1, \bar{x}_2, \dots, \bar{x}_N$, covariance C_x , Gaussian

Density function is represented as

$$f_{x_1, x_2, x_3, \dots, x_N}(x_1, x_2, x_3, \dots, x_N) = \frac{1}{(2\pi)^{N/2} |C_x|^{1/2}} e^{-\frac{1}{2} (x-\bar{x})^T C_x^{-1} (x-\bar{x})}$$

$C_x \rightarrow$ covariance Matrix

$$C_x = \begin{bmatrix} C_{x_1 x_1} & C_{x_1 x_2} & C_{x_1 x_3} & \dots & C_{x_1 x_N} \\ C_{x_2 x_1} & C_{x_2 x_2} & C_{x_2 x_3} & \dots & C_{x_2 x_N} \\ C_{x_3 x_1} & C_{x_3 x_2} & C_{x_3 x_3} & \dots & C_{x_3 x_N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ C_{x_N x_1} & C_{x_N x_2} & C_{x_N x_3} & \dots & C_{x_N x_N} \end{bmatrix} (N \times N)$$

$(x-\bar{x}) \rightarrow$ column matrix

$$\begin{bmatrix} x_1 - \bar{x}_1 \\ x_2 - \bar{x}_2 \\ \vdots \\ x_N - \bar{x}_N \end{bmatrix}$$

$(x - \bar{x})^T \rightarrow$ Row matrix $[x_1 - \bar{x}_1, x_2 - \bar{x}_2, x_3 - \bar{x}_3, \dots, x_N - \bar{x}_N]$

Gaussian Density function

$$\frac{1}{\sqrt{2\pi\sigma_x^2}} e^{-\frac{(x-\bar{x})^2}{2\sigma_x^2}}$$

N^{th} order Gaussian

$$\frac{1}{[2\pi]^{N/2} [C_x]^{1/2}} e^{-\frac{(x-\bar{x})^T (x-\bar{x})}{2[C_x]}}$$

$$\frac{1}{[2\pi]^{N/2} [C_x]^{1/2}} e^{-\frac{1}{2} [C_x - \bar{x}]^T [C_x]^{-1} [C_x - \bar{x}]}$$

1st order Gaussian from n^{th} order Gaussian:-

$N=1$

$$f_{x_1, x_2, \dots, x_N} (x_1, x_2, \dots, x_N) = \frac{1}{[2\pi]^{N/2} [C_x]^{1/2}} e^{-\frac{1}{2} [C_x - \bar{x}]^T [C_x]^{-1} [C_x - \bar{x}]}$$

on sub $N=1$

$$f_{x_1}(x_1) = \frac{1}{[2\pi]^{1/2} [C_x]^{1/2}} e^{-\frac{1}{2} [C_x - \bar{x}_1]^T [C_x]^{-1} [C_x - \bar{x}_1]}$$

$C_x \rightarrow N \times N$

$$C_x = [C_{x_1, x_1}] = E[(x_1 - \bar{x}_1)(x_1 - \bar{x}_1)]$$

$$= E[(x_1 - \bar{x}_1)^2] = \sigma_{x_1}^2$$

$$\Rightarrow (x_1 - \bar{x}_1)^T [C_x]^{-1} (x_1 - \bar{x}_1) = (x_1 - \bar{x}_1)^T = (x_1 - \bar{x}_1)$$

$$(x_1 - \bar{x}_1) = (x_1 - \bar{x}_1)$$

$$\Rightarrow \frac{(x_1 - \bar{x}_1)^2}{[C_x]} = \frac{(x_1 - \bar{x}_1)^2}{\sigma_{x_1}^2}$$

$$f_{x_1}(x_1) = \frac{1}{[2\pi]^{1/2} (\sigma_{x_1})^{1/2}} e^{-\frac{(x_1 - \bar{x}_1)^2}{2\sigma_{x_1}^2}}$$

$$\Rightarrow \text{Covariance coefficient} = (P) = \frac{\sigma_{xy}}{\sigma_x \sigma_y} = \frac{C_{xy}}{\sigma_x \sigma_y}$$

2nd order Gaussian from n^{th} order Gaussian:-

$N=2$

$$f_{x_1, x_2}(x_1, x_2) = \frac{1}{[2\pi]^{2/2} [C_x]^{1/2}} e^{-\frac{1}{2} [C_x - \bar{x}]^T [C_x]^{-1} [C_x - \bar{x}]}$$

$$\text{Covariance matrix } [C_X]_{2 \times 2} = \begin{bmatrix} C_{X_1 X_1} & C_{X_1 X_2} \\ C_{X_2 X_1} & C_{X_2 X_2} \end{bmatrix}$$

$$C_{X_1 X_1} = E[(X_1 - \bar{X}_1)^2] = \sigma_{X_1}^2$$

$$C_{X_1 X_2} = E[(X_1 - \bar{X}_1)(X_2 - \bar{X}_2)] = C_{X_2 X_1} = \sigma_{X_1 X_2}$$

$$C_{X_2 X_1} = E[(X_2 - \bar{X}_2)(X_1 - \bar{X}_1)] = C_{X_1 X_2} = \sigma_{X_2 X_1}$$

$$C_{X_2 X_2} = E[(X_2 - \bar{X}_2)^2] = \sigma_{X_2}^2$$

$$[C_X] = \begin{bmatrix} \sigma_{X_1}^2 & \sigma_{X_1 X_2} \\ \sigma_{X_2 X_1} & \sigma_{X_2}^2 \end{bmatrix}$$

$$[C_X]^{-1} = \frac{1}{|C_X|} \begin{bmatrix} \sigma_{X_2}^2 & -\sigma_{X_1 X_2} \\ -\sigma_{X_2 X_1} & \sigma_{X_1}^2 \end{bmatrix}$$

$$= \frac{1}{\sigma_{X_1}^2 \sigma_{X_2}^2 - \sigma_{X_1 X_2} \sigma_{X_2 X_1}} \begin{bmatrix} \sigma_{X_2}^2 & -\sigma_{X_1 X_2} \\ -\sigma_{X_2 X_1} & \sigma_{X_1}^2 \end{bmatrix}$$

$$= \frac{1}{\sigma_{X_1}^2 \cdot \sigma_{X_2}^2 \left[1 - \frac{\sigma_{X_1 X_2} \sigma_{X_2 X_1}}{\sigma_{X_1}^2 \sigma_{X_2}^2}\right]} \begin{bmatrix} \sigma_{X_2}^2 & -\sigma_{X_1 X_2} \\ -\sigma_{X_2 X_1} & \sigma_{X_1}^2 \end{bmatrix}$$

$$P = \frac{\sigma_{XY}}{\sigma_X \cdot \sigma_Y} = \frac{1}{\sigma_{X_1}^2 \sigma_{X_2}^2 (1 - P^2)} \begin{bmatrix} \sigma_{X_2}^2 & -\sigma_{X_1 X_2} \\ -\sigma_{X_2 X_1} & \sigma_{X_1}^2 \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1}{\sigma_{X_1}^2 (1 - P^2)} & \frac{-\sigma_{X_1 X_2}}{\sigma_{X_1}^2 \sigma_{X_2}^2 (1 - P^2)} \\ \frac{-\sigma_{X_2 X_1}}{\sigma_{X_1}^2 \sigma_{X_2}^2 (1 - P^2)} & \frac{1}{\sigma_{X_2}^2 (1 - P^2)} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1}{\sigma_{X_1}^2 (1 - P^2)} & \frac{-P}{\sigma_{X_1} \sigma_{X_2} (1 - P^2)} \\ \frac{-P}{\sigma_{X_1} \sigma_{X_2} (1 - P^2)} & \frac{1}{\sigma_{X_2}^2 (1 - P^2)} \end{bmatrix}$$

$$\begin{bmatrix} x_1(x) & y_1(x) \\ x_2(x) & y_2(x) \end{bmatrix} = \frac{1}{|x|} \begin{bmatrix} x_1^0 \\ x_2^0 \end{bmatrix} x_1(x) x_2(x)$$

$$x_1^0 = \begin{bmatrix} e^x (x - 1) \\ e^x \end{bmatrix} \quad x_2^0 = \begin{bmatrix} e^x (x - 1) \\ e^x \end{bmatrix}$$

$$x_1(x) = x_1(x) = \begin{bmatrix} (e^x - 1) (x - 1) \\ e^x \end{bmatrix} \quad x_2(x) = x_2(x) = \begin{bmatrix} (e^x - 1) (x - 1) \\ e^x \end{bmatrix}$$

$$x_1(x) = x_1(x) = \begin{bmatrix} (e^x - 1) (x - 1) \\ e^x \end{bmatrix} \quad x_2(x) = x_2(x) = \begin{bmatrix} (e^x - 1) (x - 1) \\ e^x \end{bmatrix}$$

$$x_1^0 = \begin{bmatrix} e^x (x - 1) \\ e^x \end{bmatrix} \quad x_2^0 = \begin{bmatrix} e^x (x - 1) \\ e^x \end{bmatrix}$$

$$\begin{bmatrix} x_1^0 & x_2^0 \\ x_1^0 & x_2^0 \end{bmatrix} = \begin{bmatrix} x_1^0 \\ x_2^0 \end{bmatrix}$$

$$\begin{bmatrix} x_1^0 & x_2^0 \\ x_1^0 & x_2^0 \end{bmatrix} \frac{1}{|x|} = \begin{bmatrix} x_1^0 \\ x_2^0 \end{bmatrix}$$

$$\begin{bmatrix} x_1^0 & x_2^0 \\ x_1^0 & x_2^0 \end{bmatrix} \frac{1}{|x|} = \begin{bmatrix} x_1^0 \\ x_2^0 \end{bmatrix}$$

$$\begin{bmatrix} x_1^0 & x_2^0 \\ x_1^0 & x_2^0 \end{bmatrix} \frac{1}{|x|} = \begin{bmatrix} x_1^0 \\ x_2^0 \end{bmatrix}$$

$$\begin{bmatrix} x_1^0 & x_2^0 \\ x_1^0 & x_2^0 \end{bmatrix} \frac{1}{|x|} = \frac{x_1^0}{x_2^0} = 9$$

$$\begin{bmatrix} \frac{x_1^0}{(e^x - 1) e^x} & \frac{1}{(e^x - 1) e^x} \\ \frac{1}{(e^x - 1) e^x} & \frac{1}{(e^x - 1) e^x} \end{bmatrix} =$$

$$\begin{bmatrix} 9 & 1 \\ \frac{1}{(e^x - 1) e^x} & \frac{1}{(e^x - 1) e^x} \end{bmatrix} =$$

Problems

1) Gaussian R.V has first and 2nd order moment $m_{10} = -1.1$,
 $m_{20} = -1.16$, $m_{01} = 1.5$, $m_{02} = 2.89$, $R_{xy} = -1.72$.

Find C_{xy} and $\rho = \frac{\sigma_{xy}}{\sigma_x \cdot \sigma_y}$.

Sol:-

$C_{xy} = ?$

$\rho =$ covariance coefficient

Given data:-

$$m_{10} = E[x^1 y^0] = E[x] = \mu_x = \bar{x} = -1.1$$

$$m_{20} = E[x^2 y^0] = E[x^2] = -1.16$$

$$m_{01} = E[x^0 y^1] = E[y] = \mu_y = \bar{y} = 1.5$$

$$m_{02} = E[x^0 y^2] = E[y^2] = 2.89$$

$$C_{xy} = E[(x - \bar{x})(y - \bar{y})] = E[xy] - \bar{x}\bar{y}$$

$$= R_{xy} - \bar{x}\bar{y}$$

$$= -1.72 - (-1.1 \times 1.5)$$

$$= -1.72 + 1.65$$

$$= -0.07$$

$$\rho = \frac{\sigma_{xy}}{\sigma_x \cdot \sigma_y}$$

$$\sigma_x = \sqrt{\sigma_x^2} = \sqrt{E[x^2] - \{E[x]\}^2} = \sqrt{E[x^2] - [\bar{x}]^2}$$

$$= \sqrt{-1.16 - (-1.1)^2} = \sqrt{-1.16 - 1.21}$$

$$= \sqrt{-2.37}$$

$$\sigma_y = \sqrt{\sigma_y^2} = \sqrt{E[y^2] - [E[y]]^2} = \sqrt{2.89 - (1.5)^2}$$

$$= \sqrt{2.89 - 2.25} = \sqrt{0.64}$$

$$\rho = \frac{\sigma_{xy}}{\sigma_x \cdot \sigma_y}$$

$$= \frac{-0.07}{\sqrt{-2.37} \cdot \sqrt{0.64}}$$

$$= \frac{-0.07}{\sqrt{-2.37} \cdot \sqrt{0.64}}$$

2.) Prove $\text{var}(X+Y) = \text{var}(X) + \text{var}(Y)$ if X, Y are s.i.

Sol:- Proof:-

Let $X+Y = a$

$$\begin{aligned} \text{var}(a) &= E(a^2) - [E(a)]^2 \\ &= E[(X+Y)^2] - \{E[(X+Y)]\}^2 \\ &= E[X^2 + Y^2 + 2XY] - [E(X) + E(Y)]^2 \\ &= E[X^2] + E[Y^2] + 2E[XY] - \{[E(X)]^2 + [E(Y)]^2 + 2E(X) \cdot E(Y)\} \\ &= E(X^2) + E(Y^2) + 2E(XY) - [E(X)]^2 - [E(Y)]^2 - 2E(X) \cdot E(Y) \\ &= \underbrace{E(X^2) - [E(X)]^2}_{\text{var}(X)} + \underbrace{E(Y^2) - [E(Y)]^2}_{\text{var}(Y)} + 2E(XY) - 2E(X) \cdot E(Y) \\ &= \text{var}(X) + \text{var}(Y) + 2E(XY) - 2E(X) \cdot E(Y). \end{aligned}$$

If X, Y are s.i then $E[XY] = E(X) \cdot E(Y)$.

$$\begin{aligned} &= \text{var}(X) + \text{var}(Y) + 2E(X) \cdot E(Y) - 2E(X) \cdot E(Y) \\ &= \text{var}(X) + \text{var}(Y). \end{aligned}$$

3.) Let X, Y be R.V having Joint density function

$f_{XY}(X, Y) = X+Y$ for all $0 \leq X \leq 1, 0 \leq Y \leq 1$. Find $\text{var}(X)$, $\text{var}(Y)$, σ_{XY} , ρ .

Sol:- $f_{XY}(X, Y) = X+Y \quad \forall \quad \begin{matrix} 0 \leq X \leq 1 \\ 0 \leq Y \leq 1 \end{matrix}$

$$\text{var}(X) = E(X - \mu_X)^2 = E[X^2] - [E(X)]^2$$

$$E(X) = \int_{-\infty}^{\infty} x \cdot f_X(x) dx$$

$f_X(x)$ from $f_{XY}(X, Y)$ using Marginal density function

$$\begin{aligned} f_X(x) &= \int_{-\infty}^{\infty} f_{XY}(X, Y) dy = \int_0^1 (x+y) dy = \int_0^1 x dy + \int_0^1 y dy \\ &= x[y]_0^1 + \left[\frac{y^2}{2}\right]_0^1 \Rightarrow x[1] + \frac{1}{2} \end{aligned}$$

$$= x + \frac{1}{2} \quad \forall \quad 0 \leq x \leq 1.$$

$$\begin{aligned} E[X] &= \int_{-\infty}^{\infty} x \cdot f_X(x) dx = \int_0^1 x \cdot (x + \frac{1}{2}) dx = \int_0^1 x^2 dx + \int_0^1 \frac{x}{2} dx \\ &= \left[\frac{x^3}{3}\right]_0^1 + \frac{1}{2} \left[\frac{x^2}{2}\right]_0^1 \Rightarrow \frac{1}{3} + \frac{1}{4} = \frac{7}{12} \end{aligned}$$

$$E[x^2] = \int_0^1 x^2(x + \frac{1}{2}) dx = \int_0^1 x^3 dx + \int_0^1 \frac{x^2}{2} dx$$

$$= \left[\frac{x^4}{4} \right]_0^1 + \frac{1}{2} \left[\frac{x^3}{3} \right]_0^1 = \frac{1}{4} + \frac{1}{6} = \frac{10}{24} = \frac{5}{12}$$

$$\text{var}(x) = E(x^2) - [E(x)]^2 = \frac{5}{12} - \left(\frac{7}{12}\right)^2 = \frac{5}{12} - \frac{49}{144} = \frac{11}{144}$$

$$\text{var}(y) = E(y - \mu_y)^2 = E(y^2) - [E(y)]^2$$

$$E(y) = \int_{-\infty}^{\infty} y \cdot f_y(y) dy$$

$f_y(y)$ from $f_{xy}(x, y)$ using marginal density function.

$$f_y(y) = \int_{-\infty}^{\infty} f_{xy}(x, y) dx = \int_0^1 (x+y) dx = \int_0^1 x dx + \int_0^1 y dx$$

$$= \left[\frac{x^2}{2} \right]_0^1 + y[x]_0^1 = \frac{1}{2} + y \quad \forall 0 \leq y \leq 1$$

$$E(y) = \int_{-\infty}^{\infty} y \cdot f_y(y) dy = \int_0^1 y \left(\frac{1}{2} + y \right) dy$$

$$= \int_0^1 \frac{y}{2} dy + \int_0^1 y^2 dy = \left[\frac{y^2}{4} \right]_0^1 + \left[\frac{y^3}{3} \right]_0^1$$

$$= \frac{1}{4} + \frac{1}{3} = \frac{7}{12}$$

$$E(y^2) = \int_0^1 y^2 \left(\frac{1}{2} + y \right) dy = \int_0^1 \frac{y^2}{2} dy + \int_0^1 y^3 dy$$

$$= \left[\frac{y^3}{6} \right]_0^1 + \left[\frac{y^4}{4} \right]_0^1 = \frac{1}{6} + \frac{1}{4} = \frac{10}{24} = \frac{5}{12}$$

$$\text{var}(y) = E(y^2) - [E(y)]^2 = \frac{5}{12} - \frac{49}{144} = \frac{11}{144}$$

$$\sigma_{xy} = E[xy] - \bar{x} \cdot \bar{y}$$

$$E[xy] = \int_0^1 \int_0^1 xy \cdot f_{xy}(x, y) dy dx$$

$$= \int_0^1 \int_0^1 xy(x+y) dy dx = \int_0^1 \left[x^2 \frac{y^2}{2} + x \frac{y^3}{3} \right]_0^1 dx$$

$$= \int_0^1 \left[x^2 \frac{1}{2} + x \frac{1}{3} \right] dx$$

$$= \int_0^1 \left(\frac{x^2}{2} + \frac{x}{3} \right) dx = \left[\frac{x^3}{6} + \frac{x^2}{6} \right]_0^1 \Rightarrow \frac{1}{6} + \frac{1}{6} = \frac{2}{6}$$

$$= \frac{1}{3}$$

$$\sigma_{xy} = E[XY] - \bar{X} \cdot \bar{Y} = \frac{1}{3} - \frac{7}{12} \cdot \frac{7}{12} = \frac{1}{3} - \frac{49}{144} = \frac{-1}{144}$$

$$\rho = \frac{\sigma_{xy}}{\sigma_x \cdot \sigma_y} = \frac{-\frac{1}{144}}{\sqrt{\frac{11}{144}} \cdot \sqrt{\frac{11}{144}}} = \frac{-\frac{1}{144}}{\frac{11}{144}} = -\frac{1}{11}$$

$$= \frac{-\frac{1}{144}}{\frac{11}{144}} = -\frac{1}{11}$$

4) Two random variables X and Y have the joint density

$$f_{xy}(x,y) = \begin{cases} \frac{xy}{9} & 0 < x < 2, 0 < y < 3 \\ 0 & \text{otherwise} \end{cases}$$

show that X and Y

are uncorrelated and also statistically independent.

Sol: $f_{xy}(x,y) = f_x(x) \cdot f_y(y) \rightarrow X, Y$ are s.i.

"Marginal density"

$$f_x(x) = \int_{-\infty}^{\infty} f_{xy}(x,y) dy = \int_0^3 \frac{xy}{9} dy = \frac{x}{9} \left[\frac{y^2}{2} \right]_0^3 = \frac{x}{9} \left[\frac{9}{2} \right] = \frac{x}{2}$$

$$f_y(y) = \int_{-\infty}^{\infty} f_{xy}(x,y) dx = \int_0^2 \frac{xy}{9} dx = \frac{y}{9} \left[\frac{x^2}{2} \right]_0^2 = \frac{y}{9} \left[\frac{4}{2} \right]$$

$$f_y(y) = \frac{2y}{9}$$

$$f_x(x) \cdot f_y(y) = \frac{x}{2} \cdot \frac{2y}{9} = \frac{xy}{9} = f_{xy}(x,y) \rightarrow X, Y \text{ are s.i.}$$

5) Find the marginal densities of the joint density.

$$f_{xy}(x,y) = \begin{cases} b(x+y)^2 & -2 < x < 2 \text{ and } -3 < y < 3 \\ 0 & \text{elsewhere.} \end{cases}$$

$$\begin{aligned} \text{Sol: } f_x(x) &= \int_{-\infty}^{\infty} f_{xy}(x,y) dy = \int_{-3}^3 b(x+y)^2 dy = b \left[\int_{-3}^3 (x^2 + y^2 + 2xy) dy \right] \\ &= b \left[\int_{-3}^3 x^2 dy + \int_{-3}^3 y^2 dy + \int_{-3}^3 2xy dy \right] \\ &= b \left[x^2 \left[y \right]_{-3}^3 + \left[\frac{y^3}{3} \right]_{-3}^3 + 2x \left[\frac{y^2}{2} \right]_{-3}^3 \right] \\ &= b \left[x^2(6) + \frac{1}{3}(27+27) + x[9-9] \right] \\ &= b(6x^2 + 18) \end{aligned}$$

$$\begin{aligned} f_y(y) &= \int_{-\infty}^{\infty} f_{xy}(x,y) dx = \int_{-2}^2 b(x^2 + y^2 + 2xy) dx \\ &= b \left[\frac{x^3}{3} \right]_{-2}^2 + y^2 \left[x \right]_{-2}^2 + 2y \left[\frac{x^2}{2} \right]_{-2}^2 \\ &= b \left[\frac{1}{3}(8+8) + y^2[4] \right] \end{aligned}$$

$$f_y(y) = b \left(\frac{16}{3} + 4y^2 \right)$$

$$f_x(x) \cdot f_y(y) = b(6x^2 + 18) \cdot b \left(\frac{16}{3} + 4y^2 \right)$$

$\begin{matrix} x^2 \cdot y^2 \\ \uparrow \\ (x+y)^2 \end{matrix}$

x, y are not s.i

6) For two random variables X and Y

$$\begin{aligned} f_{xy}(x,y) &= 0.15 \delta(x+1) \delta(y) + 0.1 \delta(x) \delta(y) + 0.18 \delta(x) \delta(y-2) \\ &+ 0.4 \delta(x-1) \delta(y+2) + 0.2 \delta(x-1) \delta(y-1) + \\ &0.5 \delta(x-1) \delta(y-3) \end{aligned}$$

Find the correlation coefficient of x and y .

$$\text{Sol: } R_{xy} = \sum_x \sum_y x \cdot y \cdot P_{xy}(x,y)$$

$y \backslash x$	-1	0	1
0	0.15	0.1	
1			0.2
2		0.1	
3			0.5
-2			0.4

$$\begin{aligned} &\therefore \delta(x+1) \\ &x+1=0 \\ &x=-1 \end{aligned}$$

$$R_{xy} = \sum_{x=-1}^1 \sum_{y=-2}^3 x \cdot y \cdot P_{xy}(x,y)$$

$$\begin{aligned} &\sum_{x=-1}^1 \left[x(-2) \cdot P_{xy}(x,-2) + x(-1) P_{xy}(x,-1) + x(0) \cdot P_{xy}(x,0) \right. \\ &\quad \left. + x(1) \cdot P_{xy}(x,1) + x(2) \cdot P_{xy}(x,2) + x(3) \cdot P_{xy}(x,3) \right] \\ &= (-1)(-2) P_{xy}(-1,-2) + 0(-2) P_{xy}(0,-2) + (1)(-2) P_{xy}(1,-2) \\ &\quad + (-1)(0) P_{xy}(-1,0) + 0(0) \cdot P_{xy}(0,0) + (1)(0) \cdot P_{xy}(1,0) \end{aligned}$$

$$\begin{aligned}
& + (-1)(1) \cdot P_{xy}(-1, 1) + (0)(1) P_{xy}(0, 1) + (1)(1) P_{xy}(1, 1) + \\
& (-1)(2) \cdot P_{xy}(-1, 2) + (0)(2) P_{xy}(0, 2) + (1)(2) P_{xy}(1, 2) + \\
& (-1)(3) P_{xy}(-1, 3) + (0)(3) P_{xy}(0, 3) + (1)(3) P_{xy}(1, 3) \\
& = 2 P_{xy}(-1, -2) - 2 P_{xy}(1, -2) - 1 P_{xy}(-1, 1) + P_{xy}(1, 1) - 2 P_{xy}(-1, 2) \\
& + 2 P_{xy}(1, 2) - 3 P_{xy}(-1, 3) + 3 P_{xy}(1, 3) \\
& = 2(0) - 2(0.4) - 1(0) + 0.2 - 2(0) + 2(0) - 3(0) + 3(0.3) \\
& = -0.8 + 0.2 + 1.5 \\
& = 0.9
\end{aligned}$$

$$\int_{-\infty}^{\infty} x^2 (kx + k^2 x^2) dx = \int_{-\infty}^{\infty} (kx^3 + k^2 x^4) dx = (k/4)x^4 + (k^2/5)x^5$$

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

$$\int_{-\infty}^{\infty} \left[\frac{1}{2} \right] dx + \int_{-\infty}^{\infty} [2+2] \frac{1}{2} dx =$$

$$\int_{-\infty}^{\infty} \left[\frac{e^{-x}}{3} + \frac{dx}{3} \right] dx = (k/3)x^3$$

$$\int_{-\infty}^{\infty} (e^{-x} + 2) dx \cdot \int_{-\infty}^{\infty} (2x + 2) dx = (k/3)x^3 \cdot (k/3)x^3$$

For two random variables X and Y, find the correlation coefficient of X and Y.

$$\begin{aligned}
& (0.12)(2)(1.0) + (0.18)(x)(2)(1.0) + (0.1)(2)(1-x)(2)(1.0) + \\
& (0.1)(2)(1-x)(2)(1.0) + (0.18)(1-x)(2)(1.0) + (0.12)(1-x)(2)(1.0)
\end{aligned}$$

Find the correlation coefficient of X and Y.