

## operations on Multiple Random Variables

Function of Joint random variable:-

If  $g(x,y)$  is a function of two random variables  $x$  and  $y$  with joint density function  $f_{xy}(x,y)$  then the expected value of the function  $g(x,y)$  is given as

$$\bar{g} = E[g(x,y)]$$

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

Similarly for  $n$  random variables  $x_1, x_2, \dots, x_n$  with joint density function  $f_{x_1, x_2, \dots, x_n}(x_1, x_2, \dots, x_n)$ , the expected value of the function  $g(x_1, x_2, \dots, x_n)$  is given as

$$\bar{g} = E[g(x_1, x_2, \dots, x_n)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \dots \int_{-\infty}^{\infty} g(x_1, x_2, \dots, x_n) f_{x_1, x_2, \dots, x_n}(x_1, x_2, \dots, x_n) dx_1 dx_2 \dots dx_n$$

Joint Moments about the origin:-

The joint moments about the origin for two random variables  $x, y$  is the expected value of function  $g(x,y) = x^n y^k$  it is denoted by  $m_{nk}$ .

$$\text{In general } m_{nk} = E[x^n y^k] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^n y^k f_{xy}(x,y) dx dy$$

\* The sum  $n+k$  is called the order of the moment.

\* If  $k=0$  then  $m_{n0} = E[x^n y^0] = E[x^n]$  are the moments of  $x$ .

\* If  $n=0$  then  $m_{0k} = E[x^0 y^k] = E[y^k]$  are the moments of  $y$ .

The first order moments are

$$m_{10} = E[x'] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f_{xy}(x, y) dx dy$$

$$m_{01} = E[y'] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f_{xy}(x, y) dx dy$$

The second order moments are

$$m_{20} = E[x^2]$$

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

$$m_{11} = E[xy]$$

Correlation :-

consider two random variables  $x$  and  $y$ , the second order joint moment  $m_{11}$  is called correlation of  $x$  and  $y$ . it is denoted as

$$R_{xy} = m_{11} = E[xy] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_{xy}(x, y) dx dy$$

(continuous random variable)

For discrete random variable

$$R_{xy} = \sum_m \sum_n x_m y_n P_{xy}(x_m, y_n)$$

Properties of correlation :-

If two random variables  $x$  and  $y$  are statistically independent then  $x$  and  $y$  are said to be uncorrelated that is

$$R_{xy} = E[xy] = E[x] E[y]$$

If the random variables  $x$  and  $y$  are orthogonal then their correlation is zero i.e.  $R_{xy} = 0$

Joint central moments:-

Consider the two random variables  $x$  and  $y$  then the expected values of the function

$g(x, y) = (x - \bar{x})^n (y - \bar{y})^k$  are called Joint central moments.

In general it is denoted by  $\mu_{nk}$

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

The order of the central moment is  $n+k$ .

Note:-

1) The 0<sup>th</sup> order central moment is

$$\mu_{00} = E[1] = 1$$

2) The first order central moments are

$$\begin{aligned}\mu_{10} &= E[(x - \bar{x})^1 (y - \bar{y})^0] = E[x - \bar{x}] = E[x] - E[\bar{x}] \\ &= 0\end{aligned}$$

$$\mu_{01} = 0$$

$$\mu_{01} = E[(x - \bar{x})^0 (y - \bar{y})^1] = E[y - \bar{y}] = E[y] - E[\bar{y}] = 0$$

3) The second order central moments are

$$\mu_{20} = E[(x - \bar{x})^2] = \sigma_x^2$$

$$\mu_{02} = E[(y - \bar{y})^2] = \sigma_y^2$$

$$\mu_{11} = E[(x - \bar{x})(y - \bar{y})] = \sigma_{xy}$$

covariance:-

consider the random variables  $x$  and  $y$  the second order joint central moments  $\mu_{11}$  is called the covariance of  $x$  and  $y$ . it is expressed as  $c_{xy}$

$$\therefore c_{xy} = \mu_{11} = E[(x-\bar{x})(y-\bar{y})]$$

$$\therefore \mu_{11} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x-\bar{x})(y-\bar{y}) f_{xy}(x,y) dx dy \text{ this is}$$

for continuous random variable,

for discrete random variable

$$c_{xy} = \sum_n \sum_m (x_n - \bar{x}_n)(y_m - \bar{y}_m) P(x_n, y_m)$$

correlation coefficient:-

The normalized second order central moment is called correlation coefficient. It is denoted as  $\rho$  defined as

$$\rho = \frac{\mu_{11}}{\sqrt{\mu_{20} \mu_{02}}} = \frac{c_{xy}}{\sqrt{\sigma_x^2 \sigma_y^2}} = \frac{c_{xy}}{\sigma_x \sigma_y}$$

$$\therefore \rho = \frac{c_{xy}}{\sigma_x \sigma_y} = \frac{E[(x-\bar{x})(y-\bar{y})]}{\sigma_x \sigma_y}$$

Note:-

- 1) The range of correlation coefficient is  $-1 \leq \rho \leq 1$
- 2) If  $x$  and  $y$  are independent then  $\rho = 0$
- 3) If the correlation between  $x$  and  $y$  is perfect then  $\rho = \pm 1$
- 4) If  $x = y$  then  $\rho = 1$

Properties of covariance:-

\* If  $x$  and  $y$  are two random variables when the covariance

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

\* If two random variables  $x$  and  $y$  are independent then the covariance is zero.

$$C_{xy} = 0$$

But the converse is not true.

$$* \text{Var}(x+y) = \text{Var}(x) + \text{Var}(y) + 2C_{xy}$$

$$\text{Var}(x-y) = \text{Var}(x) + \text{Var}(y) - 2C_{xy}$$

$$* |\sigma_{xy}| = \sigma_x \sigma_y$$

$$* \text{cov}(x+a, y+b) = \text{cov}(x, y) = C_{xy}$$

$$* \text{cov}(ax, by) = ab \text{cov}(x, y) = ab C_{xy}$$

i) Random variables  $x$  and  $y$  have the Joint density

$$f_{xy}(x, y) = \frac{1}{24}, \quad 0 < x < 6, \quad 0 < y < 4. \text{ what is the Expected}$$

$$\text{Value of the function } g(x, y) = (xy)^2.$$

Given-

$$f_{xy}(x, y) = \frac{1}{24}, \quad 0 < x < 6; \quad 0 < y < 4$$

$$\text{Also given } g(x, y) = (xy)^2$$

$$E[g(x, y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{xy}(x, y) dx dy$$

$$= \int_{x=0}^6 \int_{y=0}^4 (xy)^2 \frac{1}{24} dy dx$$

$$= \frac{1}{24} \int_{x=0}^6 x^2 dx \int_{y=0}^4 y^2 dy$$

$$= \frac{1}{24} \left[ \frac{x^3}{3} \right]_0^6 \left[ \frac{y^3}{3} \right]_0^4$$

$$= \frac{1}{24 \times 3 \times 3} [6^3] [4^3]$$

$$= \frac{1}{24 \times 3 \times 3} [8 \times 8 \times 8] [4 \times 4 \times 4]$$

$$= 64$$

2) show that two random variables  $x_1$  and  $x_2$  with joint probability density function

$$f_{x_1, x_2}(x_1, x_2) = \begin{cases} \frac{1}{16}, & |x_1| \leq 4, 2 < x_2 < 4 \\ 0, & \text{otherwise} \end{cases}$$

are independent random variables. Also show that they are orthogonal.

Given

$$f_{x_1, x_2}(x_1, x_2) = \begin{cases} \frac{1}{16}, & |x_1| \leq 4, 2 < x_2 < 4 \\ 0, & \text{otherwise} \end{cases}$$

i) To show that  $x_1$  and  $x_2$  are independent random variables:-

$$\text{i.e. s.t. } f_{x_1, x_2}(x_1, x_2) = f_{x_1}(x_1) f_{x_2}(x_2)$$

w.k.t

$$f_{x_1}(x_1) = \int_{-\infty}^{\infty} f_{x_1, x_2}(x_1, x_2) dx_2$$

$$x_2 = -\infty$$

$$0 = [0, \infty)$$

$$f_{x_1}(x_1) = \int_2^4 \frac{1}{16} dx_2 = \frac{1}{16} [x_2]_2^4 = \frac{2}{16} = \frac{1}{8}$$

$$f_{x_2}(x_2) = \int_{-\infty}^{\infty} f_{x_1, x_2}(x_1, x_2) dx_1 = \int_{-4}^4 \frac{1}{16} dx_1$$

$$x_1 = -\infty$$

$$-4$$

$$f_{x_2}(x_2) = \frac{1}{16} [x_1]_{-4}^4 = \frac{8}{16} = \frac{1}{2}$$

$$\therefore f_{x_1}(x_1) f_{x_2}(x_2) = \frac{1}{8} \times \frac{1}{2} = \frac{1}{16} = f_{x_1, x_2}(x_1, x_2)$$

$\therefore x_1$  and  $x_2$  are independent.

2) To show that  $x_1$  &  $x_2$  are orthogonal:

we have to show that  $E[x_1 x_2] = 0$

$$\therefore E[x_1 x_2] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1 x_2 f_{x_1, x_2}(x_1, x_2) dx_1 dx_2$$

$$= \int_{-4}^4 \int_{-2}^2 (x_1 x_2) \frac{1}{16} dx_2 dx_1$$

$$= \frac{1}{16} \left[ \int_{-4}^4 x_1 dx_1 \right] \left[ \int_{-2}^2 x_2 dx_2 \right]$$

$$= \frac{1}{16} \left[ \frac{x_1^2}{2} \right]_{-4}^4 \left[ \frac{x_2^2}{2} \right]_{-2}^2$$

$$= \frac{1}{16 \times 4} [16 - 16] [16 - 4]$$

$$E[x_1 x_2] = 0$$

$\therefore x_1$  and  $x_2$  are orthogonal.

3) A Joint density function is given by  $f_{xy}(x, y) = \begin{cases} x(y+1.5), & 0 < x < 1 \\ & 0 < y < 1 \\ 0, & \text{otherwise} \end{cases}$

Find the first order and second order moments.

Given Jpdf is

$$f_{xy}(x, y) = \begin{cases} x(y+1.5), & 0 < x < 1, 0 < y < 1 \\ 0, & \text{otherwise} \end{cases}$$

w.k.T

$$m_{nk} = E[x^n y^k] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^n y^k f_{xy}(x, y) dx dy$$

First order:-

put  $n=0$   $k=1$

$$m_{01} = E[x^0 y^1] = \int_{x=0}^1 \int_{y=0}^1 y \{x(y+1.5)\} dy dx$$

$$= \int_{x=0}^1 x dx \int_{y=0}^1 (y^2 + \frac{3}{2} y) dy$$

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

$$= \left(\frac{1}{2}\right) \left[\frac{1}{3} + \frac{3}{2} \cdot \frac{1}{2}\right]$$

$$E[y] = \frac{1}{2} \left[\frac{4+9}{12}\right] = \frac{13}{24}$$

put  $n=1$   $k=0$

$$m_{10} = E[x] = \int_{x=0}^1 \int_{y=0}^1 x \{x(y+1.5)\} dx dy$$

$$= \int_{x=0}^1 x^2 dx \int_{y=0}^1 (y + \frac{3}{2}) dy$$

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

$$= \left(\frac{1}{3}\right) \left[\frac{1}{2} + \frac{3}{2}\right]$$

$$E[x] = \frac{1}{3} [2] = \frac{2}{3}$$

Second order

put  $n=2, k=0$

$$m_{20} = E[x^2] = \int_{x=0}^1 \int_{y=0}^1 x^2 \{ x(y+1.5) \} dx dy$$

$$= \int_{x=0}^1 x^3 dx \int_{y=0}^1 (y + \frac{3}{2}) dy$$

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

put  $n=0, k=2$

$$m_{02} = E[y^2] = \int_{x=0}^1 \int_{y=0}^1 y^2 \{ x(y+1.5) \} dx dy$$

$$= \int_{x=0}^1 x dx \int_{y=0}^1 (y^3 + 1.5y^2) dy$$

$$= \left[ \frac{x^2}{2} \right]_0^1 \left[ \frac{y^4}{4} + \frac{3}{2} \left( \frac{y^3}{3} \right) \right]_0^1$$

$$E[y^2] = \frac{1}{2} \left[ \frac{1}{4} + \frac{1}{2} \right] = \frac{1}{2} \left( \frac{3}{4} \right) = \frac{3}{8}$$

put  $n=1, k=1$

$$m_{11} = E[xy] = \int_{x=0}^1 \int_{y=0}^1 xy \{ x(y+1.5) \} dx dy$$

$$= \int_{x=0}^1 x^2 dx \int_{y=0}^1 (y^2 + 1.5y) dy$$

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

$$= \frac{1}{3} \left[ \frac{1}{3} + \frac{3}{4} \right]$$

$$= \frac{1}{3} \left[ \frac{13}{12} \right] = \frac{13}{36}$$

4) A Joint density function is given as  $f_{xy}(x,y) = \begin{cases} x(y+1.5), & 0 < x < 1 \\ & 0 < y < 1 \\ 0, & \text{otherwise} \end{cases}$   
 Find all the joint moments  $m_{nk}, n, k = 0, 1, 2, \dots$

Given

$$\text{JPdf is } f_{xy}(x,y) = \begin{cases} x(y+1.5), & 0 < x < 1, 0 < y < 1 \\ 0, & \text{otherwise} \end{cases}$$

we know that

$$m_{nk} = E[x^n y^k] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^n y^k f_{xy}(x,y) dx dy$$

$$= \int_{x=0}^1 \int_{y=0}^1 x^n y^k x(y + \frac{3}{2}) dy dx$$

$$= \int_{x=0}^1 x^{n+1} dx \int_{y=0}^1 y^k (y + \frac{3}{2}) dy$$

$$= \int_{x=0}^1 x^{n+1} dx \int_{y=0}^1 (y^{k+1} + \frac{3}{2} y^k) dy$$

$$= \left[ \frac{x^{n+2}}{n+2} \right]_0^1 \left[ \left[ \frac{y^{k+2}}{k+2} + \frac{3}{2} \frac{y^{k+1}}{k+1} \right]_0^1 \right]$$

$$= \frac{1}{n+2} [1 - 0] \left[ \frac{1}{k+2} + \frac{3}{2(k+1)} \right]$$

$$= \frac{1}{n+2} \left[ \frac{2(k+1) + 3(k+2)}{2(k+1)(k+2)} \right]$$

$$= \frac{1}{n+2} \left[ \frac{5k+8}{2(k+1)(k+2)} \right]$$

$$m_{nk} = \frac{5k+8}{2(k+1)(k+2)(n+2)}$$

put  $n=1, k=0$

$$m_{10} = \frac{8}{4(3)} = \frac{8}{12} = \frac{2}{3}$$

put  $n=0, k=1$

$$m_{01} = \frac{13}{12(2)} = \frac{13}{24}$$

put  $n=1, k=1$

$$m_{11} = \frac{13}{12(3)} = \frac{13}{36}$$

5) The Independent random variables  $x$  and  $y$  have moments

$m_{10} = 2, m_{20} = 14, m_{02} = 12$  and  $m_{11} = -6$ . Find the moments

$\mu_{22}$ .

Given

$x$  and  $y$  are independent random variables

Also given  $m_{10} = 2, m_{02} = 12$   
 $m_{20} = 14, m_{11} = -6$

$\mu_{22}$  is a central moment, it is given by

$$\mu_{22} = E[(x-\bar{x})^2 \cdot (y-\bar{y})^2]$$

$$= \left[ E[x^2] - \{E[x]\}^2 \right] \cdot \left[ E[y^2] - \{E[y]\}^2 \right]$$

$$= [\mu_{20} - m_{10}^2] \cdot [\mu_{02} - m_{01}^2] \rightarrow \text{①}$$

Also w.k.T  $m_{11} = m_{10} \times m_{01}$

$$m_{01} = \frac{m_{11}}{m_{10}}$$

$$= \frac{-6}{2}$$

$$m_{01} = -3$$

$$\textcircled{1} \Rightarrow \mu_{22} = [14 - (2)^2] [12 - (-3)^2]$$

$$= [14 - 4] [12 - 9]$$

$$= 10 (3)$$

$$\mu_{22} = 30$$

6) Three stastically independent random variables  $x_1, x_2, x_3$

have mean values  $\bar{x}_1 = 3, \bar{x}_2 = 6$  (and  $\bar{x}_3 = -2$ ). Find

the mean values of the following functions.

a)  $g(x_1, x_2, x_3) = x_1 + 3x_2 + 4x_3$

b)  $g(x_1, x_2, x_3) = x_1 x_2 x_3$

c)  $g(x_1, x_2, x_3) = -2x_1 x_2 - 3x_1 x_3 + 4x_2 x_3$

d)  $g(x_1, x_2, x_3) = x_1 + x_2 + x_3$

Given

$x_1, x_2, x_3$  are stastically independent random variables

Also given  $\bar{x}_1 = 3 = E[x_1]$

$$\bar{x}_2 = E[x_2] = 6$$

$$\bar{x}_3 = E[x_3] = -2$$

a)  $E[g(x_1, x_2, x_3)] = E[x_1 + 3x_2 + 4x_3]$

$$= E[x_1] + 3E[x_2] + 4E[x_3]$$

$$= 3 + 3(6) + 4(-2)$$

$$= 3 + 18 - 8 = 13 \quad \text{because they are independent}$$

$$\begin{aligned}
 \text{b) } E[g(x_1, x_2, x_3)] &= E[x_1 x_2 x_3] \\
 &= E[x_1] \cdot E[x_2] \cdot E[x_3] \\
 &= (3)(6)(-2) \\
 &= -36
 \end{aligned}$$

$$\begin{aligned}
 \text{c) } E[g(x_1, x_2, x_3)] &= E[-2x_1 x_2 - 3x_1 x_3 + 4x_2 x_3] \\
 &= -2E[x_1]E[x_2] - 3E[x_1]E[x_3] + 4E[x_2]E[x_3] \\
 &= -2(3)(6) - 3(3)(-2) + 4(6)(-2) \\
 &= -36 + 18 - 48 \\
 &= -36 - 30
 \end{aligned}$$

3) three statistically independent random variables  $x_1, x_2, x_3$  have mean values 3, 6 and -2 respectively.

$$\begin{aligned}
 \text{d) } E[g(x_1, x_2, x_3)] &= E[x_1 + x_2 + x_3] \\
 &= E[x_1] + E[x_2] + E[x_3] \\
 &= 3 + 6 - 2 \\
 &= 7
 \end{aligned}$$

7) If  $x$  and  $y$  are two independent random variables such that  $E[x] = \lambda_1$ , variance of  $x = \sigma_1^2$

$E[y] = \lambda_2$ , variance of  $y = \sigma_2^2$

Prove that  $V[xy] = \sigma_1^2 \sigma_2^2 + \lambda_1^2 \sigma_2^2 + \lambda_2^2 \sigma_1^2$

Given

$x$  and  $y$  are independent random variables

Also given  $E[x] = \lambda_1$ ,  $E[y] = \lambda_2$

Variance of  $x = \sigma_1^2$ , variance of  $y = \sigma_2^2$

$$\therefore V[xy] = E[(xy)^2] - \{E[xy]\}^2$$

$$= E[x^2 y^2] - E[xy] E[xy]$$

$$= E[x^2] E[y^2] - E[x] E[y] E[x] E[y]$$

$$V[xy] = E[x^2] E[y^2] - \{E[x]\}^2 \{E[y]\}^2 \rightarrow \textcircled{1}$$

$$V(x) = \sigma_1^2 = E[x^2] - \{E[x]\}^2$$

$$\sigma_1^2 = E[x^2] - \lambda_1^2$$

$$\sigma_1^2 + \lambda_1^2 = E[x^2]$$

$$V[y] = \sigma_2^2 = E[y^2] - \{E[y]\}^2$$

$$\sigma_2^2 = E[y^2] - \lambda_2^2$$

$$\sigma_2^2 + \lambda_2^2 = E[y^2]$$

$$\textcircled{1} \Rightarrow V[xy] = [\sigma_1^2 + \lambda_1^2] [\sigma_2^2 + \lambda_2^2] - \lambda_1^2 \lambda_2^2$$

$$= \sigma_1^2 \sigma_2^2 + \sigma_1^2 \lambda_2^2 + \sigma_2^2 \lambda_1^2 + \lambda_1^2 \lambda_2^2 - \lambda_1^2 \lambda_2^2$$

$$\therefore V[xy] = \sigma_1^2 \sigma_2^2 + \lambda_1^2 \sigma_2^2 + \lambda_2^2 \sigma_1^2$$

Hence proved

8) The Joint density function of two random variables  $x$  and  $y$

is

$$f_{xy}(x,y) = \begin{cases} \frac{(x+y)^2}{40}, & -1 < x < 1 \text{ and } -3 < y < 3 \\ 0, & \text{otherwise} \end{cases}$$

Find a) the variance of  $x$  and  $y$ . ( $\sigma_x^2, \sigma_y^2$ )

b) The correlation coefficient. ( $\rho_{xy}$ )

Given

Jpdf is

$$f_{xy}(x,y) = \begin{cases} \frac{(x+y)^2}{40}, & -1 < x < 1 \text{ and } -3 < y < 3 \\ 0, & \text{otherwise} \end{cases}$$

a) To find  $\sigma_x^2$  and  $\sigma_y^2$  :-

we know that  $\sigma_x^2 = E[x^2] - \{E[x]\}^2 \rightarrow \textcircled{1}$

$$\sigma_y^2 = E[y^2] - \{E[y]\}^2 \rightarrow \textcircled{2}$$

$$m_{10} = E[x] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f_{xy}(x, y) dx dy$$

$$= \int_{x=-1}^1 \int_{y=-3}^3 x \frac{(x+y)^2}{40} dy dx$$

$$= \frac{1}{40} \int_{x=-1}^1 x \left[ x^2 y + \frac{y^3}{3} + 2x \frac{y^2}{2} \right]_{y=-3}^3 dx$$

$$= \frac{1}{40} \int_{x=-1}^1 x \left[ \{3x^2 + 9 + 9x\} - \{-3x^2 - 9 + 9x\} \right] dx$$

$$= \frac{1}{40} \int_{x=-1}^1 x [6x^2 + 18] dx$$

$$= \frac{1}{40} \left[ \frac{3}{8} \frac{x^4}{2} + \frac{9}{8} \frac{x^2}{2} \right]_{x=-1}^1$$

$$= \frac{1}{40} \left[ \left( \frac{3}{2} + 9 \right) - \left( \frac{3}{2} + 9 \right) \right]$$

$E[x] = 0$  (The joint density function of two variables is symmetric about the vertical line  $x=0$ )

$$E[x^2] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x^2 f_{xy}(x, y) dx dy$$

$$= \int_{x=-1}^1 \int_{y=-3}^3 x^2 \frac{(x+y)^2}{40} dy dx$$

$$= \frac{1}{40} \int_{x=-1}^1 x^2 [6x^2 + 18] dx$$

$$= \frac{1}{40} \left[ \frac{6}{5} \frac{x^5}{5} + \frac{6}{8} \frac{x^3}{3} \right]_{x=-1}^1 = \frac{1}{40} \left[ \left( \frac{6}{5} + 6 \right) - \left( -\frac{6}{5} - 6 \right) \right]$$

$$= \frac{1}{40} \left[ \frac{12}{5} + 12 \right] = \frac{12^3}{40} \left[ \frac{6}{5} \right] = \frac{9}{25}$$

$$E[x^2] = \frac{9}{25}$$

$$\textcircled{1} \rightarrow \sigma_{x^2} = \frac{9}{25} - 0 = 0.36$$

$$\therefore m_{01} = E[Y] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f_{xy}(x,y) dx dy$$

$$= \int_{x=-1}^1 \int_{y=-3}^3 y \frac{(x+y)^2}{40} dy dx$$

$$= \frac{1}{40} \int_{y=-3}^3 y \left[ \frac{x^3}{3} + y^2 x + 2y \frac{x^2}{2} \right]_{x=-1}^1 dy$$

$$= \frac{1}{40} \int_{y=-3}^3 y \left[ \left\{ \frac{1}{3} + y^2 + y \right\} - \left\{ -\frac{1}{3} - y^2 + y \right\} \right] dy$$

$$= \frac{1}{40} \int_{y=-3}^3 y \left[ \frac{2}{3} + 2y^2 \right] dy$$

$$= \frac{1}{40} \left[ \frac{2}{3} \frac{y^2}{2} + 2 \frac{y^3}{3} \right]_{y=-3}^3$$

$$= \frac{1}{40} \left[ \left\{ \frac{9}{3} + \frac{81}{2} \right\} - \left\{ \frac{9}{3} + \frac{81}{2} \right\} \right]$$

$$E[Y] = 0$$

$$E[Y^2] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y^2 f_{xy}(x,y) dx dy$$

$$= \int_{x=-1}^1 \int_{y=-3}^3 y^2 \frac{(x+y)^2}{40} dx dy$$

$$= \frac{1}{40} \int_{y=-3}^3 y^2 \left[ \frac{2}{3} + 2y^2 \right] dy$$

$$= \frac{1}{40} \left[ \frac{2y^3}{3} + \frac{2y^5}{5} \right]_{y=-3}^3$$

$$= \frac{1}{40} \left[ \frac{2y^3}{9} + \frac{2y^5}{5} \right]_{y=-3}^3$$

$$= \frac{1}{40} \left[ \left\{ \frac{2(27)}{9} + \frac{2(243)}{5} \right\} - \left\{ \frac{-2(27)}{9} - \frac{2(243)}{5} \right\} \right]$$

$$= \frac{1}{40} \left[ \left\{ 6 + \frac{486}{5} \right\} - \left\{ -6 - \frac{486}{5} \right\} \right]$$

$$= \frac{1}{40} \left[ 12 + \frac{2}{5}(486) \right]$$

$$= \frac{2}{40} \left[ 6 + \frac{486}{5} \right]$$

$$= \frac{1}{20} \left[ 6 + \frac{486}{5} \right] = \frac{1}{20} \left[ \frac{30 + 486}{5} \right] = \frac{1}{20} \left[ \frac{516}{5} \right]$$

$$= \frac{516}{100}$$

$$E[Y^2] = 5.16$$

$$\sigma_y^2 = 5.16 - 0$$

$$\therefore \sigma_y^2 = 5.16$$

b) To find  $\rho_{xy}$  :-

w.k.T

$$\rho_{xy} = \frac{C_{xy}}{\sigma_x \sigma_y} \rightarrow \textcircled{3}$$

$$\text{Where } C_{xy} = R_{xy} - \bar{x}\bar{y} = E[xy] - E[x]E[y]$$

(COR)

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

$$m_{11} - m_{10} \times m_{01}$$

$$= \int_{x=-1}^1 \int_{y=-3}^3 xy \frac{(x+y)^2}{40} dx dy$$

$$= \frac{1}{40} \int_{x=-1}^1 x \left[ x^2 \frac{y^2}{2} + \frac{y^4}{4} + 2x \frac{y^3}{3} \right]_{y=-3}^3 dx$$

$$= \frac{1}{40} \int_{x=-1}^1 x \left[ \left\{ \frac{9x^2}{2} + \frac{81}{4} + 18x \right\} - \left\{ \frac{9x^2}{2} + \frac{81}{4} - 18x \right\} \right] dx$$

$$= \frac{1}{40} \int_{x=-1}^1 x [36x] dx$$

$$= \frac{1}{40} \int_{x=-1}^1 x [36x] dx = \frac{36}{40} \left[ \frac{x^3}{3} \right]_{x=-1}^1 = \frac{36}{40} [1^3 - (-1)^3]$$

$$\therefore E[xy] = \frac{3}{10} [2] = \frac{6}{10} = 0.6$$

$$\therefore \textcircled{3} \Rightarrow \rho_{xy} = \frac{0.6}{\sqrt{0.36} \sqrt{5.16}} = 0.440$$

9) For Two random variables  $x$  and  $y$  the joint density function

$$is \quad f_{xy}(x,y) = 0.15 \delta(x+1) \delta(y) + 0.1 \delta(x) \delta(y) + 0.1 \delta(x) \delta(y-2) \\ + 0.4 \delta(x-1) \delta(y+2) + 0.2 \delta(x-1) \delta(y-1) + 0.05 \delta(x-1) \delta(y-3)$$

find a) The correlation

b) The correlation coefficient of  $x$  and  $y$

c) are  $x$  and  $y$  either uncorrelated or orthogonal.

Sol: From the given data

$(x,y)$	$(-1,0)$	$(0,0)$	$(0,2)$	$(1,-2)$	$(1,1)$	$(1,3)$
$P(x,y)$	0.15	0.1	0.1	0.4	0.2	0.05

a) To find correlation:-

$$w.k.T \quad R_{xy} = E[xy] = \sum x_i y_i P(x_i, y_i)$$

$$= (-1)(0)(0.15) + 0 + 0 + (1)(-2)(0.4) + (1)(1)(0.2) + (1)(3)(0.05)$$

$$= -0.45$$

b) To find  $\rho_{xy}$  :-

$$\text{w.k.T } \rho_{xy} = \frac{C_{xy}}{\sigma_x \sigma_y} \rightarrow \textcircled{1}$$

$$C_{xy} = R_{xy} - E[x]E[y] = E[xy] - E[x]E[y]$$

$$\sigma_x^2 = E[x^2] - \{E[x]\}^2 \quad \sigma_y^2 = E[y^2] - \{E[y]\}^2$$

$$\therefore E[x] = \sum x_i p(x_i, y_i)$$

$$= (-1)(0.15) + 0 + 0 + 1(0.4) + 1(0.2) + 1(0.05)$$

$$E[x] = 0.5$$

$$E[x^2] = \sum x_i^2 p(x_i, y_i)$$

$$= (-1)^2(0.15) + 1^2(0.4) + 1^2(0.2) + 1^2(0.05)$$

$$= 0.8$$

$$\therefore E[y] = \sum y_i p(x_i, y_i)$$

$$= 0 + 0 + 2(0.1) + (-2)(0.4) + 1(0.2) + 3(0.05)$$

$$E[y] = -0.25$$

$$E[y^2] = \sum y_i^2 p(x_i, y_i)$$

$$= (2)^2(0.1) + (-2)^2(0.4) + 1^2(0.2) + 9(0.05)$$

$$E[y^2] = 2.65$$

$$\therefore C_{xy} = -0.45 - (0.5)(-0.25) = -0.325$$

$$\sigma_x^2 = 0.8 - (0.5)^2 = 0.55$$

$$\sigma_y^2 = (2.65) - (-0.25)^2 = 2.58$$

$$\text{Eq } \textcircled{1} \Rightarrow \rho_{xy} = \frac{-0.325}{\sqrt{0.55} \sqrt{2.58}} = -0.272$$

c) since  $C_{xy} \neq 0$

$\therefore x$  and  $y$  are not uncorrelated and

$$R_{xy} \neq 0$$

$\therefore x$  and  $y$  are not orthogonal

10) If the joint density function is  $f_{xy}(x,y) = \begin{cases} x+y, & 0 \leq x \leq 1, 0 \leq y \leq 1 \\ 0, & \text{otherwise} \end{cases}$

find out correlation coefficient.

Given

$$\text{Jpdf is } f_{xy}(x,y) = \begin{cases} x+y, & 0 \leq x \leq 1, 0 \leq y \leq 1 \\ 0, & \text{otherwise} \end{cases}$$

To find  $\rho_{xy}$  :-

$$\text{w.k.T } \rho_{xy} = \frac{C_{xy}}{\sigma_x \sigma_y} \rightarrow \textcircled{1}$$

$$C_{xy} = R_{xy} - E[x]E[y] = E[xy] - E[x]E[y]$$

$$\sigma_x^2 = E[x^2] - (E[x])^2 \quad \sigma_y^2 = E[y^2] - (E[y])^2$$

$$E[x] = \int_{-\infty}^{\infty} x f_x(x) dx$$

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

$$\therefore f_x(x) = \int_{-\infty}^{\infty} f_{xy}(x,y) dy = \int_{y=0}^1 (x+y) dy = \left[ xy + \frac{y^2}{2} \right]_0^1 = x + \frac{1}{2}$$

$$f_y(y) = \int_{-\infty}^{\infty} f_{xy}(x,y) dx = \int_{x=0}^1 (x+y) dx = \left[ \frac{x^2}{2} + yx \right]_{x=0}^1 = \frac{1}{2} + y$$

$$f_x(x) = \begin{cases} x + \frac{1}{2}, & 0 \leq x \leq 1 \\ 0, & \text{otherwise} \end{cases}$$

$$f_y(y) = \begin{cases} \frac{1}{2} + y, & 0 \leq y \leq 1 \\ 0, & \text{otherwise} \end{cases}$$

$$\therefore E[x] = \int_0^1 x(x + \frac{1}{2}) dx = \left[ \frac{x^3}{3} + \frac{1}{2} \left( \frac{x^2}{2} \right) \right]_{x=0}^1 = \frac{1}{3} + \frac{1}{4} = \frac{7}{12}$$

$$E[Y] = \int_{y=0}^1 y \left(\frac{1}{2} + y\right) dy = \left[ \frac{1}{2} \left(\frac{y^2}{2}\right) + \frac{y^3}{3} \right]_{y=0}^1 = \frac{1}{4} + \frac{1}{3} = \frac{7}{12}$$

$$\therefore E[XY] = \int_{x=0}^1 \int_{y=0}^1 xy(x+y) dy dx$$

$$= \int_{x=0}^1 x \left[ x \frac{y^2}{2} + \frac{y^3}{3} \right]_{y=0}^1 dx$$

$$= \int_{x=0}^1 x \left[ \frac{x}{2} + \frac{1}{3} \right] dx$$

$$= \left[ \frac{1}{2} \frac{x^3}{3} + \frac{1}{3} \frac{x^2}{2} \right]_{x=0}^1 = \left[ \frac{1}{6} + \frac{1}{6} \right] = \frac{1}{3}$$

$$E[X^2] = \int_{x=0}^1 x^2 \left(x + \frac{1}{2}\right) dx = \left[ \frac{x^4}{4} + \frac{1}{2} \left(\frac{x^3}{3}\right) \right]_{x=0}^1 = \frac{1}{4} + \frac{1}{6} = \frac{10}{24}$$

$$E[Y^2] = \int_{y=0}^1 y^2 \left(\frac{1}{2} + y\right) dy = \left[ \frac{1}{2} \frac{y^3}{3} + \frac{y^4}{4} \right]_{y=0}^1 = \frac{1}{6} + \frac{1}{4} = \frac{10}{24}$$

$$C_{XY} = \frac{1}{3} - \left(\frac{7}{12}\right)\left(\frac{7}{12}\right) = \frac{1}{3} - \frac{49}{144} = -0.006$$

$$\sigma_X^2 = \frac{10}{24} - \left(\frac{7}{12}\right)^2 = 0.076$$

$$\sigma_Y^2 = \frac{10}{24} - \left(\frac{7}{12}\right)^2 = 0.076$$

$$\rho_{XY} \Rightarrow \rho_{XY} = \frac{-0.006}{\sqrt{0.076} \sqrt{0.076}} = -0.078$$

- ii) For two random variables  $x$  and  $y$   $f_{XY}(x,y) = 0.5 \delta(x+1) \delta(y) + 0.1 \delta(x) \delta(y) + 0.1 \delta(x) \delta(y-2) + 0.4 \delta(x-1) \delta(y+2) + 0.2 \delta(x-1) \delta(y-1) + 0.5 \delta(x-1) \delta(y-3)$

Find a) The correlation

b) covariance

c) The correlation coefficient of  $x$  and  $y$

d) Are  $x$  and  $y$  either uncorrelated or orthogonal?

sol:- From the given data

$(x, y)$	$(-1, 0)$	$(0, 0)$	$(0, 2)$	$(1, -2)$	$(1, 1)$	$(1, 3)$
$P(x, y)$	0.5	0.1	0.1	0.4	0.2	0.5

a) To find correlation:

$$\text{w.k.T } R_{xy} = E[xy] = \sum x_i y_i P(x_i, y_i)$$

$$= (-1)(-2)(0.4) + (1)(1)(0.2) + (1)(3)(0.5)$$

$$= 0.9$$

c) To find  $\rho_{xy} = \frac{C_{xy}}{\sigma_x \sigma_y}$

$$\text{w.k.T } \rho_{xy} = \frac{C_{xy}}{\sigma_x \sigma_y} \rightarrow \text{①}$$

$$C_{xy} = R_{xy} - E[x]E[y] = E[xy] - E[x]E[y]$$

$$\sigma_x^2 = E[x^2] - \{E[x]\}^2 \quad \sigma_y^2 = E[y^2] - \{E[y]\}^2$$

$$\therefore E[x] = \sum x_i P(x_i, y_i)$$

$$= (-1)(0.5) + 1(0.4) + 1(0.2) + 1(0.5)$$

$$= 0.6$$

$$E[x^2] = \sum x_i^2 P(x_i, y_i)$$

$$= (-1)^2(0.5) + (0.4) + 0.2 + 0.5$$

$$= 1.6$$

$$\therefore E[y] = \sum y_i P(x_i, y_i)$$

$$= 2(0.1) + (-2)(0.4) + 1(0.2) + 3(0.5)$$

$$= 1.1$$

$$E[y^2] = \sum y_i^2 P(x_i, y_i)$$

$$= 4(0.1) + 4(0.4) + 1(0.2) + 9(0.5)$$

$$= 6.7$$

$$\therefore C_{xy} = 0.9 - (0.6)(1.1)$$

$$= 0.24$$

$$\sqrt{x^2} = 1.6 - (0.6)^2$$

$$= 1.24$$

$$\sqrt{y^2} = 6.7 - (1.1)^2$$

$$= 5.49$$

$$\text{Eq ①} \Rightarrow \rho_{xy} = \frac{0.24}{\sqrt{1.24} \sqrt{5.49}}$$

$$\therefore \rho_{xy} = 0.091$$

b) w.k.T

$$\text{cov}(x, y) = E[xy] - E[x]E[y] = C_{xy}$$

$$\text{cov}(x, y) = 0.24$$

d) since  $C_{xy} \neq 0$

$\therefore x$  and  $y$  are not uncorrelated

$$R_{xy} \neq 0$$

$\therefore x$  and  $y$  are not orthogonal

Joint characteristic function

The JCF of two random variables  $x$  and  $y$  is defined as the expected value of the joint function  $g(x, y) =$

$e^{j\omega_1 x} e^{j\omega_2 y}$  it is given as

$$\phi_{xy}(\omega_1, \omega_2) = E[e^{j\omega_1 x + j\omega_2 y}]$$

$$= E[e^{j(\omega_1 x + \omega_2 y)}]$$

where  $\omega_1$  &  $\omega_2$  are real variables

$$\phi_{xy}(\omega_1, \omega_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{j\omega_1 x + j\omega_2 y} f_{xy}(x, y) dx dy$$

Note:-

1) Above expression is known as the two dimensional Fourier transform of Joint density function.

2) The Inverse Fourier transform of the JCF gives the JDF. i.e

$$f_{xy}(x, y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \phi_{xy}(\omega_1, \omega_2) e^{-j(\omega_1 x + \omega_2 y)} d\omega_1 d\omega_2$$

3) If  $x$  and  $y$  are discrete random variable with probability mass function  $p(x, y)$

$$\phi_{xy}(\omega_1, \omega_2) = \sum_m \sum_n e^{j\omega_1 x_m + j\omega_2 y_n} p(x_m, y_n)$$

$$\text{And } p(x_m, y_n) = \sum_m \sum_n e^{-j\omega_1 x_m - j\omega_2 y_n} \phi_{xy}(\omega_1, \omega_2)$$

properties of Joint characteristic function:-

1) Marginal characteristic function are given by

$$\phi_x(\omega_1) = \phi_{xy}(\omega_1, 0)$$

$$\phi_y(\omega_2) = \phi_{xy}(0, \omega_2)$$

2) If two random variable  $x$  and  $y$  are independent then the JCF is equal to the product of the individual characteristic function.

$$\phi_{xy}(\omega_1, \omega_2) = \phi_x(\omega_1) \phi_y(\omega_2)$$

3) If  $x$  and  $y$  are independent random variables then

$$\phi_{x+y}(\omega) = \phi_x(\omega) \cdot \phi_y(\omega)$$

4) If  $x$  and  $y$  are two random variables, the joint moments can be derived from the JCF has

$$m_{nk} = (-j)^{n+k} \left. \frac{\partial^{n+k} \phi_{xy}(\omega_1, \omega_2)}{\partial \omega_1^n \partial \omega_2^k} \right|_{\omega_1 = \omega_2 = 0}$$

## Joint moment Generating function:-

The Joint moment Generating function of two random variables  $x$  and  $y$  is defined as the expected value of the Joint function,  $g(x, y) = e^{v_1 x + v_2 y}$  it is expressed as

$$M_{xy}(v_1, v_2) = E[e^{v_1 x + v_2 y}]$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{v_1 x + v_2 y} f_{xy}(x, y) dx dy$$

for discrete random variable

$$M_{xy}(v_1, v_2) = \sum_m \sum_n e^{v_1 x_m + v_2 y_n} p_{xy}(x_m, y_n)$$

properties of Joint moment Generating function:-

1) The marginal moment Generating functions are

$$M_x(v_1) = M_{xy}(v_1, 0)$$

$$M_y(v_2) = M_{xy}(0, v_2)$$

2) If two random variables  $x$  and  $y$  are independent then

$$M_{xy}(v_1, v_2) = M_x(v_1) M_y(v_2)$$

$$M_{x+y}(v) = M_x(v) M_y(v)$$

3) If  $x$  and  $y$  are two random variables then the Joint moments can be derived from the JMGF as

$$m_{nk} = \left. \frac{\partial^{n+k} M_{xy}(v_1, v_2)}{\partial v_1^n \partial v_2^k} \right|_{v_1=v_2=0}$$

1) Two Random Variables  $x$  and  $y$  have Joint characteristic function  $\phi_{xy}(\omega_1, \omega_2) = \exp(-2\omega_1^2 - 8\omega_2^2)$

i) show that  $x$  and  $y$  are zero mean random variables.

ii) Are  $x$  and  $y$  correlated?

Given

JCF is  $\phi_{xy}(\omega_1, \omega_2) = \exp(-2\omega_1^2 - 8\omega_2^2)$

$$\phi_{xy}(\omega_1, \omega_2) = e^{(-2\omega_1^2 - 8\omega_2^2)}$$

w.k.t

The Joint moment of order  $n+k$  or  $m+k$

$$m_{nk} = (-j)^{n+k} \left. \frac{\partial^{n+k} \phi_{xy}(\omega_1, \omega_2)}{\partial \omega_1^n \partial \omega_2^k} \right|_{\omega_1=\omega_2=0} \rightarrow \textcircled{1}$$

1) To show that  $x$  and  $y$  are zero mean r.v.:-

$$m_{10} = E[x] = 0$$

$$m_{01} = E[y] = 0$$

Put  $n=1, k=0$  in eq ①

$$\begin{aligned} m_{10} &= (-j)^1 \left. \frac{\partial [e^{(-2\omega_1^2 - 8\omega_2^2)}]}{\partial \omega_1} \right|_{\omega_1=\omega_2=0} \\ &= (-j) \left[ e^{-2\omega_1^2 - 8\omega_2^2} (-4\omega_1 + 0) \right] \Big|_{\omega_1=0} \end{aligned}$$

$$m_{10} = 0$$

Put  $n=0, k=1$  in eq ①

$$\begin{aligned} m_{01} &= (-j)^1 \left. \frac{\partial [e^{(-2\omega_1^2 - 8\omega_2^2)}]}{\partial \omega_2} \right|_{\omega_2=\omega_1=0} \\ &= (-j) \left[ e^{-2\omega_1^2 - 8\omega_2^2} (-16\omega_2 + 0) \right] \Big|_{\omega_2=0} \end{aligned}$$

Two random variables \$x\$ and \$y\$ are said to be jointly Gaussian if their joint characteristic function is given by

$$m_{01} = 0$$

ii) To find correlation:

w.k.T  $C_{xy} = R_{xy} - E[x]E[y]$

$$C_{xy} = R_{xy} - 0$$

$$C_{xy} = E[xy]$$

Put \$n=1, k=1\$ in eq (1)

$$m_{11} = (-j)^2 \frac{\partial^2 [e^{(-2\omega_1^2 - 8\omega_2^2)}]}{\partial \omega_1 \partial \omega_2} \Big|_{\omega_1 = \omega_2 = 0}$$

$$= \frac{\partial}{\partial \omega_1} (e^{-2\omega_1^2}) \frac{\partial}{\partial \omega_2} (e^{-8\omega_2^2}) \Big|_{\omega_1 = \omega_2 = 0}$$

$$= \left[ e^{-2\omega_1^2} (-4\omega_1) \quad e^{-8\omega_2^2} (-16\omega_2) \right] \Big|_{\omega_1 = \omega_2 = 0}$$

$$= 0$$

$$\therefore E_{xy} = 0$$

\$x\$ and \$y\$ are uncorrelated.

### Gaussian Random Variables:

i) Two Random variables:

If two random variables \$x\$ and \$y\$ are said to be jointly Gaussian then Joint density function is given as

$$f_{xy}(x, y) = \frac{1}{2\pi \sigma_x \sigma_y \sqrt{1-\rho^2}} \exp \left\{ -\frac{1}{2(1-\rho^2)} \left[ \frac{(x-\bar{x})^2}{\sigma_x^2} - \frac{2\rho(x-\bar{x})(y-\bar{y})}{\sigma_x \sigma_y} + \frac{(y-\bar{y})^2}{\sigma_y^2} \right] \right\}$$

This is called bivariate Gaussian density function

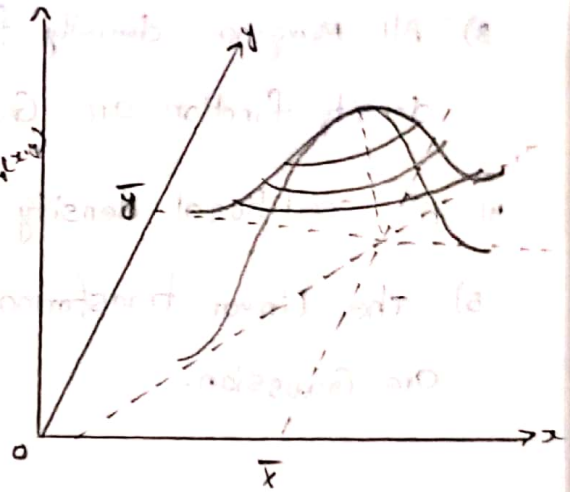
where  $\bar{x} = E[x]$

$$\bar{y} = E[y]$$

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

$$\sigma_y^2 = E[y^2] - (E[y])^2$$

$$\rho = \frac{C_{xy}}{\sigma_x \sigma_y}$$



$$\text{Maximum of } f_{xy}(x,y) = \frac{1}{2\pi \sigma_x \sigma_y \sqrt{1-\rho^2}}$$

ii) N Random Variables:-

Consider 'N' Random Variables  $x_n, n=1,2,3,\dots,N$  are said to be jointly Gaussian, if their joint density function is given by

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

$$\text{where } [C_x] = \begin{bmatrix} c_{11} & c_{12} & \dots & c_{1N} \\ c_{21} & c_{22} & \dots & c_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ c_{N1} & c_{N2} & \dots & c_{NN} \end{bmatrix}$$

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

Properties of Gaussian random variables:-

- 1) Gaussian random variables are completely defined by their means, variance, & covariances.
- 2) If the Gaussian random variables are uncorrelated then they are statistically independent.

3) All marginal density functions derived from N-Gaussian density function are Gaussian.

4) All conditional density functions are also Gaussian.

5) The linear transformation of Gaussian random variables are Gaussian.

$$f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{x-\mu}{\sigma}^2} \rightarrow \text{Maximum of the curve}$$

Linear transformation of random variables

Let \$X\$ and \$Y\$ be random variables with joint density function \$f(x,y)\$ and marginal density functions \$f\_X(x)\$ and \$f\_Y(y)\$ respectively. Then the linear transformation of \$X\$ and \$Y\$ is also Gaussian.

$$\begin{cases} [x \ y]^T [a \ b]^T [x \ y] \\ \dots \end{cases} \rightarrow \text{Linear transformation}$$

$$\begin{bmatrix} \mu_1 & \sigma_{11} & \sigma_{12} \\ \mu_2 & \sigma_{21} & \sigma_{22} \end{bmatrix} \rightarrow \text{Covariance matrix}$$

$$\begin{bmatrix} \mu_1 & \sigma_{11} \\ \mu_2 & \sigma_{22} \end{bmatrix} \rightarrow \text{Mean and variance}$$