

UNIT 2

Part 1

UNIT-III : Operation on One Random

Syllabus :

Variable - Expectations.

1. Introduction
2. Expected Value of a Random Variable
3. function of a random variable.
4. Moments about the origin
5. Central Moments
6. Variance and Skew
7. Chebychev's Inequality
8. Characteristic function
9. Moment Generating function
10. Transformation of a Random Variable:
 - (i) Monotonic Transformations for a continuous R.V
" " "
 - (ii) Non " ,
" " "
 - (iii) Transformation of a Discrete Random Variable.

Assignment - 1, UNIT - 1

Set - 1
Set - 2

Define probability with an Axiomatic approach. (8 M)

Q2 Define and explain the following with Example

- Sample space
- Discrete Sample Space
- Continuous Sample space

(12 M)

Set - 3

Q3 Define an Event and when do we say the events are mutually exclusive. Explain with an example (8 M)

Set - 4

Show that two elements cannot be both mutually exclusive and statistically independent. What are the conditions for two ~~disjoint~~ events to be independent. (6 M)

Set - 5

Q5 Discuss Joint and conditional probability (8 M)

Set - 6

Q6 ~~When~~ are with an Example define and Explain the following.

- Equally likely Events
- Exhaustive Events
- Mutually Exclusive Events

(6 M)

Set - 7

Q7 Define probability based on set theory and fundamental axioms (8 M)

Set 4.

8. Give the classical definition of probability (4m)

Nov-06
Set-4

9. What is Bayes' theorem? Explain - (6m)

Nov-05
Set-3

10. Give the classical and axiomatic definitions of probability.

Nov-05
Set-4

11. State the ~~total~~ theorem on Total probability (4m)

INTRODUCTION:-

UNIT-III : STATISTICAL ANALYSIS

UNIT-II

In the previous chapter, we have discussed the concept of random variables and their various properties. The random variable is used as a mathematical tool for describing the characteristics of some real, physical random phenomena. In this chapter, we shall study some important statistical operations that may be performed on a random variable. Expectation, Variance, moments etc., include statistical operations. In some physical situations, the study of a average quantities (Expected value), will be useful for the study of actual distribution systems.

UNIT
ECC

MATHEMATICAL EXPECTATION := (MEAN VALUE)

The averaging process, when applied to a random variable, is called the Expectation. It is denoted by $E[X]$ and is read as Expected Value of X or Mean Value of X . or statistical average of X .

$E[X] = ?$
 Suppose X is a discrete random variable which takes on ~~the~~ ~~values~~ values in a finite set x_1, x_2, \dots, x_N , with probabilities $p(x_i) = P(X=x_i)$ for $i = 1, 2, \dots, N$, then the expectation $E[X]$ of the discrete random variable X is given by

$$E[X] = m = \sum_{i=1}^N x_i \cdot p(x_i).$$

Thus $E[X]$ is the weighted arithmetic mean of the values x_i with the weights $p(x_i)$.
 physically, the expectation $E[X]$ of a random variable X is the probability weighted average of the values of X .

If X is a continuous random variable, the concept of average can be (performed) formulated in terms of integrals as

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

provided $\int_{-\infty}^{\infty} |x| f_X(x) dx < \infty$, where $f_X(x)$ is the probability density function of the continuous random

Expected value of function of a random variable is
Mathematical expectation of some real

function "g" of the random variable X is given by

$$E[g(X)] = \sum_{i=1}^N g(x_i) \cdot p(x_i) \quad ; \quad X \text{ is discrete r.v.}$$

and

$$E[g(X)] = \int_{-\infty}^{\infty} g(x) \cdot f_x(x) dx \quad ; \quad X \text{ is continuous r.v.}$$

The expected value of random variable X of
(or mean)
often called as First moment m_1 of X .

PROPERTIES :-

1) If the probability density function $f_x(x)$ of a random variable X is symmetrical about a point " a ", i.e., $f(a-x) = f(a+x)$, then $\underline{E[X] = a}$

2) If the pdf $f_x(x)$ of a random variable X is an even function, i.e., $f(-x) = f(x)$, then

$$\underline{E[X] = 0}$$

3) The expectation of any given linear function of X , is equal to the sum of the linear functions of the expectation of X . for example

$$\underline{E[ax+b] = a E[X] + b}$$

4) The mathematical expectation of sum of random variables is equal to the sum of their individual expectations, provided all the expectations exist. for example, if x, y, z, \dots, t are r.v.s, Then

$$\underline{E[x+y+z+\dots+t] = E[X] + E[Y] + \dots + E[T]}$$

5) The mathematical expectation of the product of number of independent random variables is equal to the product of their individual expectations. for example, if x, y, z, \dots, t are n number of independent random variables, then

$$\underline{E[x \cdot y \cdot z \cdot \dots \cdot t] = E[X] \cdot E[Y] \cdot E[Z] \cdot \dots \cdot E[T]}$$

$$6) \quad |\mathbb{E}[g(x)]| \leq \mathbb{E}[|g(x)|]$$

$$7) \quad \mathbb{E}[g_1(x)] \leq \mathbb{E}[g_2(x)], \text{ if } 0 \leq g_1(x) \leq g_2(x)$$

8) The conditional expected value is defined as

$$\mathbb{E}(x | y > a) = \frac{\int_a^{\infty} x \cdot f_x(x) dx}{\int_a^{\infty} f_x(x) dx}$$

$$\mathbb{E}(x | y > a) = \frac{\int_a^{\infty} x \cdot f_x(x) dx}{\int_a^{\infty} f_y(y) dy}$$

rest of dispersion

VARIANCE $\leftarrow (\mu_2)$: second central moment

or
measures
In many physical problems, the measure of expected value $E[x]$ of random variable X , does not completely characterize the probability distribution. It may be necessary to find the spread or dispersion about the mean values. The quantity used to measure this dispersion is called the variance of the distribution.

The Variance or dispersion or spread of a random variable X is given by

$$\sigma_x^2 = E[(X - E(X))^2]$$

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

where 'm' represents the mean value of expected value of the random variable X . If X is a ~~not~~ discrete random variable, the variance is given by

$$\sigma_x^2 = \sum_{i=1}^N (x_i - m)^2 p(x_i)$$

$$\text{i.e. } \sigma_x^2 = \sum_{i=1}^N (x_i - m)^2 p(x = x_i)$$

for a continuous random variable X , the variance is written as

$$\int_{-\infty}^{\infty} (x - m)^2 f(x) dx$$

$$\sigma_x^2 = \int_{-\infty}^{\infty} (x - m)^2 f_x(x) dx$$

This expression can be further simplified as

$$\sigma_x^2 = \int_{-\infty}^{\infty} (x^2 + m^2 - 2xm) f_x(x) dx$$

$$= \int_{-\infty}^{\infty} x^2 f_x(x) dx + \int_{-\infty}^{\infty} m^2 f_x(x) dx - \int_{-\infty}^{\infty} 2xm f_x(x) dx$$

$$= E[x^2] + E[m^2] - 2E[Xm]$$

$$= E[X]^2 + m^2 - 2mE[X]$$

$$= E[X]^2 + m^2 - 2m \cdot m$$

$$= E[X]^2 + m^2 - 2m^2$$

Thus $\sigma_x^2 = E[X^2] - m^2$

$$= m_2 - m^2$$

In this expression, $E[X^2]$ is called the second moment, m_2 of the distribution.

The variable is also called as Second central moment, of the random variable. The positive square root, of the ~~negative~~ variance is called, the standard deviation of the random variable X . It is used to measure the spread of X around

§ find the Expected Value of the number on a die when thrown:

Sol: Let x be the r.v. which represents the numbers on a die when thrown. i.e. x takes on the values 1, 2, 3, 4, 5 and 6. Each with equal probability ($\frac{1}{6}$). Therefore

1	2	3	4	5	6
$p(x=i)$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$

$$\begin{aligned}
 m &= E[x] = \sum_{i=1}^6 x_i \cdot p(x_i) \\
 &= (1 \cdot \frac{1}{6}) + (2 \cdot \frac{1}{6}) + (3 \cdot \frac{1}{6}) + (4 \cdot \frac{1}{6}) + (5 \cdot \frac{1}{6}) + (6 \cdot \frac{1}{6}) \\
 &= \frac{1}{6} [1+2+3+4+5+6] = \frac{21}{6} \\
 &= \underline{\underline{3.5}}
 \end{aligned}$$

§ find the Expected Value of the discrete random variable x , whose probability distribution is given by

$x=x_i$	1	2	3	4	5
$p(x=x_i)$	0.1	0.1	0.3	0.3	0.2

$$\begin{aligned}
 \text{Sol} \quad m &= E[x] = \sum_{i=1}^5 x_i \cdot p(x_i) \\
 &= (1 \cdot 0.1) + (2 \cdot 0.1) + (3 \cdot 0.3) + (4 \cdot 0.3) \\
 &\quad + (5 \cdot 0.2) \\
 &= 0.1 + 0.2 + 0.9 + 1.2 + 1.0 \\
 &= \underline{\underline{3.4}}
 \end{aligned}$$

find the mean, of the random variable, whose probability density function is given by

$$f(x) = \frac{3}{5} \cdot 10^{-5} x (100-x), \quad 0 \leq x \leq 100$$

SOL

$$\begin{aligned} E(x) &= \int_{-\infty}^{\infty} x \cdot f_x(x) dx \\ &= \int_0^{100} x^2 \cdot \frac{3}{5} \cdot 10^{-5} (100-x) dx \\ &= \frac{3 \times 10^5}{5} \int_0^{100} (100x^2 - x^3) dx \\ &= \frac{3 \times 10^5}{5} \left[\frac{100x^3}{3} - \frac{x^4}{4} \right]_0^{100} \\ &= 50 \end{aligned}$$

The mean value = 50

find the dispersion of the discrete random variable
 X where prob. distribution is given below

x	1	2	3	4	5
$P(X=x)$	0.1	0.1	0.3	0.3	0.2

$$m = E(X) = \sum_{i=1}^n x_i \cdot p(x_i)$$

$$= 3.4$$

$$(1 \cdot 0.1) + (2 \cdot 0.1) + (3 \cdot 0.3) + (4 \cdot 0.3) + (5 \cdot 0.2)$$

$$= 3.4$$

$$\sigma^2 = \sum_{i=1}^n (x_i - m)^2 p(x_i)$$

$$= (1 - 3.4)^2 (0.1) + (2 - 3.4)^2 (0.1) +$$

$$(3 - 3.4)^2 (0.3) + (4 - 3.4)^2 (0.3) +$$

$$(5 - 3.4)^2 (0.2)$$

$$= 0.576 + 0.196 + 0.048 + 0.108 + 0.512$$

$$= 1.44$$

$$\underline{\sigma^2} = 1.44$$

f. let x be the continuous random variable with
pdf $= \frac{8}{x^3}$, $x > 2$, find $E(w)$ where $w = x/3$

$$E(w) = \int_{-\infty}^{\infty} w \cdot f_x(x) dx$$

$$= \int_2^{\infty} \frac{x}{3} \cdot \frac{8}{x^3} dx$$

$$= \frac{8}{3} \cdot \left[-\frac{1}{2x} \right]_2^{\infty}$$

$$= \frac{8}{3} \left[-0 + \frac{1}{4} \right] = \frac{2}{3}$$

$$\underline{E[w] = \frac{2}{3}}$$

$$\left(\frac{8}{x^3} \right) \rightarrow \underline{\int_2^{\infty}}$$

PROPERTIES OF VARIANCE

1. The Variance of a random variable ax is equal to a^2 times the Variance of x .

$$\begin{aligned}
 \sigma_{ax}^2 &= E[(ax - E(ax))^2] \\
 &= E[(ax - am)^2] \\
 &= E[a^2x^2 + a^2m^2 - 2a^2xm] \\
 &= a^2 E[x^2] + a^2m^2 - 2a^2m E[x] \\
 &= a^2 E[x^2] + a^2m^2 - 2a^2m^2 \\
 &= a^2 E[x^2] - a^2m^2 \\
 &= a^2 [E(x^2) - m^2] \\
 \underline{\sigma_{ax}^2 = a^2 \sigma_x^2}, \quad \text{where } \sigma_x^2 &= \frac{E(x^2) - m^2}{\underline{E(x^2) - m^2}}
 \end{aligned}$$

2. The Variance of a random variable $(x+a)$ is equal to the Variance of the random variable x itself.

$$\begin{aligned}
 \sigma_{x+a}^2 &= \sigma_x^2 \\
 \sigma_{x+a}^2 &= E\{(x+a) - E(x+a)\}^2 \\
 &= E[(x+a - m - a)^2] \\
 &= E[(x - m)^2] \\
 \underline{\sigma_{x+a}^2} &= \underline{\sigma_x^2}
 \end{aligned}$$

$$3. \quad \sigma_{x+y}^2 = \sigma_x^2 + \sigma_y^2 \pm 2 \left[E[xy] - E[x]E[y] \right]$$

The quantity $\{E[xy] - E[x]E[y]\}$ is called the "Co-Variance" of the random variables x and y .

$$\therefore \sigma_{x+y}^2 = \sigma_x^2 + \sigma_y^2 \pm 2 \underset{\text{Co-Variance}}{\overbrace{\text{cov}(x,y)}}$$

4. If the two random variables are independent, i.e. $E[xy] = E[x]E[y]$, then, the random variables x and y are uncorrelated.

Therefore,

$$\sigma_{x+y}^2 = \sigma_x^2 + \sigma_y^2$$

$$\begin{aligned} E[x+y] &= E(x) + E(y) \\ &= m_x + m_y \end{aligned}$$

Proof of 3 property is

$$\begin{aligned} \sigma_{x+y}^2 &= E[(x+y - \underbrace{E(x+y)}_{(m_x+m_y)})^2] \\ &= E\{(x+y)^2 + (m_x+m_y)^2 - 2(x+y)(m_x+m_y)\} \\ &= E\{x^2 + y^2 + 2xy + m_x^2 + m_y^2 + 2m_xm_y - \\ &\quad 2xm_x - 2ym_y - 2ym_x - 2ym_y\} \end{aligned}$$

$$\begin{aligned} &= E[x^2] + E[y^2] \pm E[2xy] + m_x^2 + m_y^2 \pm 2m_xm_y - \\ &\quad - 2m_x^2 \mp 2m_xm_y - 2m_ym_x \mp 2m_y^2 \end{aligned}$$

$$\therefore = E[x^2] - m_x^2 + E[y^2] - m_y^2 - 2m_ym_x \pm E[2xy]$$

Hence,

COVARIANCE

If x and y are two random Variables,
then the Co-variance between them is
defined as

$$\text{Cov}(x, y) = E[(x - E[x])(y - E[y])]$$

$$= E[xy - xE[y] - yE[x] + E[x]E[y]]$$

$$= E[xy] - E[x]E[y] - E[x]E[y] + \cancel{E[x]E[y]}$$

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

{

prove that $\text{Cov}[ax, by] = ab \text{Cov}(x, y)$

$$\text{Cov}[ax, by] = E\{(ax - E(ax))(by - E(by))\}$$

$$= E\{abxy - axE(by) - byE(ax) + \cancel{E(ax)E(by)}\}$$

$$= E[a\{x - E(x)\} \cdot b\{y - E(y)\}]$$

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

$$= ab \cdot \underline{\text{Cov}(x, y)}$$

Given the following Table

x	-3	-2	-1	0	1	2	3	
$p(x)$	0.05	0.1	0.3	0	0.3	0.15	0.1	

Compute

$$\textcircled{1} \quad E[x] = 0.65$$

$$\textcircled{2} \quad E[2x+3] = \frac{4.3(0.65) - 1.7}{(0.65) - 2.4} = 7.6$$

$$\textcircled{3} \quad E[x^2] = 4.55$$

$$\textcircled{4} \quad V(x) = 4.1275$$

$$\textcircled{5} \quad V(2x+3) = 16.51$$

Ans

$$\textcircled{1} \quad 0.25$$

$$\textcircled{2} \quad 3.508 - 2.5$$

$$\textcircled{3}$$

$$6$$

$$\textcircled{4}$$

$$2.95$$

$$\textcircled{5}$$

$$\textcircled{6} \quad \cancel{8.1875}$$

$$\textcircled{7}$$

$$12.75$$

$$\underline{2.88}$$

ECE-2 | 24/08/10 1 period
 G1, G2, G3, G6, G7, G8, G9, G10, G11, G12, G13, G14, A1, A2, A3, A4, A5, B1, B2, B3, B4, B5, C1, C2, C3, C4, C5, C6, C7, C8, C9, C10

qqSupply

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Obtain the mean and variance of the uniform distribution

$$f(x) = \begin{cases} \frac{1}{b-a}, & a \leq x \leq b \\ 0, & \text{otherwise} \end{cases}$$

SOL :-

$$\underline{\text{Mean}} = E[x] = \int_a^b x \cdot f_x(x) dx$$

$$= \int_a^b x \cdot \frac{1}{b-a} dx$$

$$= \frac{1}{b-a} \left[\frac{x^2}{2} \right]_a^b$$

$$= \frac{1}{b-a} \cdot \left(\frac{b^2 - a^2}{2} \right) = \frac{(b+a)(b-a)}{2(b-a)}$$

$$= \frac{(a+b)}{2}$$

$$\text{Variance } \sigma_x^2 = E[x^2] - (E[x])^2$$

$$E(x^2) = \int_a^b x^2 \cdot f_x(x) dx$$

$$= \frac{1}{b-a} \left(\frac{b^3 - a^3}{3} \right) = \frac{(b-a)(a^2 + ab + b^2)}{(b-a)(3)}$$

$$= \frac{a^2 + ab + b^2}{3}$$

$$\therefore \sigma_x^2 = E[x^2] - [E(x)]^2$$

$$= \frac{a^2 + ab + b^2}{3} - \frac{(a+b)^2}{4}$$

If x and y are two independent random variables,

such that $E(x) = d_1$, $E(y) = d_2$
 $V(x) = \sigma_1^2$, $V(y) = \sigma_2^2$,

prove that,

$$V(xy) = \sigma_1^2 \sigma_2^2 + \sigma_1^2 d_2^2 + \sigma_2^2 d_1^2.$$

Sol :-

$$Var(xy) = E(xy) - [E(x)]^2$$

$$Var(xy) = E(x^2y^2) - [E(xy)]^2$$

$$= E(x^2) \cdot E(y^2) - E(x) \cdot E(y)$$

$$= E(x^2) \cdot E(y^2) - E(x)E(y) \cdot E(y) \cdot E(y)$$

$$Var(xy) = E(x^2) \cdot E(y^2) - [E(x)]^2 [E(y)]^2$$

$$E(x^2) = Var(x) + [E(x)]^2$$

$$= \sigma_1^2 + d_1^2$$

$$E(y^2) = Var(y) + [E(y)]^2$$

$$= d_2^2 + \sigma_2^2$$

$$Var(xy) = (\sigma_1^2 + d_1^2)(\sigma_2^2 + d_2^2) - d_1^2 d_2^2$$

$$= \sigma_1^2 \sigma_2^2 + \sigma_1^2 d_2^2 + \sigma_2^2 d_1^2 - d_1^2 d_2^2$$

$$Var(xy) = \sigma_1^2 \sigma_2^2 + \sigma_1^2 d_2^2 + \sigma_2^2 d_1^2$$

MOMENTS :-

Expected value of a function $g(x)$ of a random variable x is used for calculating the moments. There are two or three types of moments, namely,

- ✓ i) Moments about the origin.
 - ✓ ii) moments about the mean, or central moments.
 - * iii) Absolute moments
- usually, the moments determined about the mean value are called central moments.

Moments about the origin :-

$$\begin{aligned} E[(x-m)] &= E[x] \\ E[(x-m)^2] &= E[x^2] \\ E[(x-m)^3] &= E[x^3] \end{aligned}$$

↑ origin
↑ moment about mean

for each positive integer,

if m_n ($n = 0, 1, 2, \dots$), the n th moment of the continuous random variable x about the origin

is given by

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

If x is a discrete random variable, then

$$m_n = E[(x-m)^n] = \sum_{i=1}^{N'} x_i^n P(x_i)$$

\downarrow
 $x_i^n f(x_i) dx$
small

Small

UNIT 2

Part 2

Moments about the Mean & Central moments)

For each positive integer n , ($n=0, 1, 2, \dots$),
the n th central moment of the continuous random
variable X is defined by

$$\mu_n = E[(X - m)^n]$$

$$\therefore \mu_n = \int_{-\infty}^{\infty} (x - m)^n \cdot f_X(x) dx$$

If X is a discrete random variable, then

$$\mu_n = \sum_{i=1}^{N_{\text{small}}} (x_i - m)^n \cdot p(x_i)$$

Moment Generating function &

An important ^{tool} ~~device~~ that can be used to calculate the higher moments of the "moment generating function".

The moment generating function of a

random variable x , about the origin,

whose p.d.f. is $f_x(x)$ is given by

$$M_x(t) = E[e^{tx}]$$

$$= \int_{-\infty}^{\infty} e^{tx} f_x(x) dx \quad (\text{continuous r.v.})$$

for a discrete random variable

$$M_x(t) = \sum_{x=1}^{\infty} e^{tx} p(x)$$

Since $M_x(t)$ is used to generate moments, it is known as moment generating function. Now, we shall study how $M_x(t)$ is used to generate the moments.



We know that the function $e^{t\omega}$ is given by

$$e^{t\omega} = 1 + \frac{t\omega}{1!} + \frac{t^2\omega^2}{2!} + \frac{t^3\omega^3}{3!} + \dots \quad \boxed{\frac{t^n\omega^n}{n!} + \dots}$$

$$M_X(t) = E[e^{t\omega}] = E\left[1 + \frac{t\omega}{1!} + \frac{t^2\omega^2}{2!} + \dots \quad \boxed{\frac{t^n\omega^n}{n!} + \dots}\right]$$

$$= 1 + t \cdot E[\omega] + \frac{t^2}{2!} E[\omega^2] + \dots + \frac{t^n}{n!} E[\omega^n] + \dots$$

$$= 1 + tm_1 + \frac{t^2}{2!} m_2 + \dots - \frac{t^n}{n!} \cancel{m_n} + \dots \quad \rightarrow$$

where $m_r = E[\omega^r] = \int \omega^r \cdot f_X(\omega) d\omega$ for c.R.V

$$= \sum \omega^r \cdot p(\omega) \text{ for d.R.V.}$$

} and m_r is the r^{th} moment of ω about the origin, i.e. $E[\omega^r] = m_r$ is the co-efficients of $\frac{t^r}{r!}$ in the expansion of $M_X(t)$ in terms of powers of t .

In order to find m_r , we have to differentiate the moment generating function $M_X(t)$, r times with respect to "t" and substituting $t=0$

$$\text{i.e. } m_r = \left. \frac{d^r [M_X(t)]}{dt^r} \right|_{t=0}$$

Similarly, the moment generating function of X about the point $x=a$ is defined as

$$M_x(t) = E[t(X-a)]$$

Consider

$$\left. \frac{d}{dt} [m_x(t)] \right|_{t=0} = \frac{d}{dt} \left[1 + t \cdot E(x) + \frac{t^2}{2!} \cdot E(x^2) + \dots \right]_{t=0}$$

$$\left. \frac{d}{dt} [m_x(t)] \right|_{t=0} = E(x) = m_1 \text{ (first moment)}$$

Similarly $\left. \frac{d^2}{dt^2} [m_x(t)] \right|_{t=0} = E(x^2) = m_2$
(second moment)

and so on

Thus, the nth moment of r.v. can be obtained

as

$$m_n = \left. \frac{d^n}{dt^n} [m_x(t)] \right|_{t=0}$$

Properties of mgf:

1.

Show that the m.g.f. of the random variable X
having the p.d.f. (density)

$$f(x) = \frac{1}{3}, \quad -1 < x < 2 \\ = 0, \quad \text{elsewhere}$$

is given by $m_x(t) = \frac{e^{2t} - e^{-t}}{3t}, \quad t \neq 0$

$$= 1, \quad t = 0$$

SOL:

$$m(t) = \int_{-\infty}^{\infty} e^{tx} \cdot f(x) dx$$

$$= \frac{1}{3} \int_{-1}^2 e^{tx} dx$$

$$= \frac{1}{3} \left[\frac{e^{tx}}{t} \right]_{-1}^2$$

$$= \frac{1}{3} \left[\frac{2e^{2t} - e^{-t}}{t} \right] = \frac{2e^{2t} - e^{-t}}{3t}$$

$$m(t) = \frac{2e^{2t} - e^{-t}}{3t}, \quad t \neq 0$$

$$\text{when } t = 0 \quad m(t) = \frac{0}{0}$$

Applying L'Hopital's rule, $m(0) = \lim_{t \rightarrow 0} \left[\frac{2e^{2t} - e^{-t}}{3t} \right]$

Thus, $m(t) = \frac{2e^{2t} - e^{-t}}{3t}, \quad t \neq 0$

$$= \frac{2t + 1}{3} = 1$$

If a random variable X has the moment generating function $m_X(t) = \frac{2}{2-t}$, determine the variance of X .

Sol

$$m_X(t) = \frac{2}{2-t}$$

$$\frac{(x^2)}{1+xt+x^2t^2} = \frac{2}{2-t} = \left(1 - \frac{t}{2}\right)^{-1}$$

$$= 1 + \frac{t}{2} + \frac{t^2}{4} + \dots + \infty$$

$$\Rightarrow 1 + \frac{t}{1!} + \frac{t^2}{2!} + \dots$$

∴ The co-efficients of $\frac{t^n}{n!}$ in this equation

$$\therefore E(X) = Y_1$$

The co-efficients of $\frac{t^n}{n!}$ of

$$E[X^2] = Y_2$$

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

$$= Y_2 - Y_1^2 = Y_4$$

The random variable X can take the values 1 and -1 with equal probability. find the moments generating function and first 4 moments about the origin.

Sol

$$\text{m.g.f. } m_X(t) = E[e^{tX}]$$

$$= \sum_{i=-1 \text{ and } 1} e^{tx_i} \cdot p(x_i)$$

$$p(1)=\frac{1}{2}$$

$$p(-1)=\frac{1}{2}$$

$$= e^t \cdot (\gamma_2) + e^{-t} \cdot (\gamma_2)$$

$$\therefore \because m_X(t) = \frac{e^t + e^{-t}}{2}$$

$$= \gamma_2 \left(e^t + e^{-t} \right)$$

$$\frac{t^2}{2!} + \frac{t^2}{2!}$$

$$\left(\frac{t^2}{2!}\right)\gamma_2$$

$$+\frac{t^4}{2!}+1$$

$$e^t = 1 + \frac{t}{1!} + \frac{t^2}{2!} + \frac{t^3}{3!} + \frac{t^4}{4!} + \dots$$

$$e^{-t} = 1 - \frac{t}{1!} + \frac{t^2}{2!} - \frac{t^3}{3!} + \frac{t^4}{4!} - \dots$$

$$m_X(t) = E[e^{tX}] = 1 + m_1 t + m_2 \frac{t^2}{2!} + m_3 \frac{t^3}{3!} + m_4 \frac{t^4}{4!}$$

$$m_1 = 0$$

$$m_2 = 1$$

$$m_3 = 0$$

$$m_4 = 1$$

$$\frac{1}{2!} (2t^2)$$

to find the characteristic function of a random variable X defined by the density function

$$f_x(x) = \begin{cases} 0, & x < 0 \\ 1, & 0 \leq x \leq 1 \\ 0, & x > 1 \end{cases}$$

Sol:

$$\phi(t) = \int_{-\infty}^{\infty} e^{jxt} f_x(x) dx$$

$$\int_{-\infty}^{\infty} e^{jxt} f_x(x) dx \text{ or}$$

$$= \int_0^1 e^{jxt} dx$$

$$= \left[\frac{e^{jxt}}{jt} \right]_0^1 = \frac{e^{jxt}}{jt} - \frac{1}{jt}$$

$$= \frac{e^{jt} - 1}{jt}$$

\rightarrow

find the characteristic function of the random variable X with density function,

$$f(x) = \frac{1}{2}, \quad \text{for } 0 \leq x \leq 2$$

$$= 0, \quad \text{otherwise.}$$

Sol

$$\phi_X(w) = \int_{-\infty}^{\infty} e^{jw\omega} f_X(\omega) d\omega \quad (1)$$

$$= \int_0^2 \frac{1}{2} e^{jw\omega} d\omega$$

$$= \frac{1}{2} \int_0^2 \omega e^{jw\omega} d\omega$$

$$= \frac{1}{2} \int_0^2 \omega \cdot \left[\frac{d}{d\omega} \left(\frac{e^{jw\omega}}{jw} \right) \right] d\omega$$

$$\int_U V - \int_V U.$$

$$= \frac{1}{2} \left[\omega \cdot \frac{e^{jw\omega}}{jw} \Big|_0^2 - \int_0^2 \frac{jw}{jw} \cdot e^{jw\omega} d\omega \right]$$

$$= \frac{1}{jw} \left[\frac{e^{jw\omega}}{jw} \Big|_0^2 - \int_0^2 \frac{e^{jw\omega}}{jw} d\omega \right]$$

$$= \frac{1}{jw} \left[\frac{e^{jw\omega}}{jw} \Big|_0^2 - \int_0^2 \frac{e^{jw\omega}}{jw} d\omega \right]$$

$$f = \frac{1}{4} \sqrt{35}$$

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

$$f = g - h$$

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

$$S = C - g - h$$

\boxed{y} : Standard deviation of demand
 \boxed{x} : Standard deviation of supply

$$n[(x) - (x^*)] = \frac{1}{n}$$

$$\frac{\frac{1}{n} \cdot \frac{1}{n}}{(x^*)^2} = \frac{1}{n} = \frac{1}{n}$$

\boxed{y}
 $\boxed{(x^*)^2}$

the correlation coefficient of correlation between variables x and y expressed as the measure of dependence between them is given by

$$r = \frac{10 - 6}{10 - 2}$$

$$(x) - (x^*) =$$

$$(x^*) - (x) = (x) - (x^*) = \text{Cov}(x, y) \rightarrow \text{Correlation Coefficient}$$

TSP

$$r = f(x) = q \text{ and } E(y) = 10$$

$$E(x) = 2, E(y) = 3, E(z) = 10$$

correlation between two random variables x and y

→ ⑥ Correlation and Covariance find { }

$$ue^+e^- + ue^+e^- \rightarrow_{\mathcal{E}} ue^-e^+ =$$

$$ue^+e^- \rightarrow_{\mathcal{E}} ue^- + ue^+ \rightarrow_{\mathcal{E}} e^+$$

$$(ue \rightarrow e) (ue^+ + ue^- + e) \rightarrow_{\mathcal{E}} (ue \rightarrow e)$$

$(*) \exists = ue \quad \text{where}$

$$ue^+ + (v^+) \exists \cdot ue^- \rightarrow (v^+) \exists$$

$$ue^+ + (v^+) \exists \cdot ue^- \rightarrow_{\mathcal{E}} (v^+) \exists$$

$$(v^+) \exists \cdot ue^+ + (v^+) \exists \cdot ue^- \rightarrow_{\mathcal{E}} ue \neq \exists$$

$$\left[ue^+ + ue^- \rightarrow_{\mathcal{E}} ue \neq \exists \right] \exists =$$

$$\left[(ue \rightarrow e) \right] \exists =$$

Normal

and normal about the boundary of

External and internal about the inner, leftmost

Explain 3rd moment about the mean, in terms of moments about the origin of random variable X .

Sol:

$$E[(X-m)^3]$$

$$= E[X^3 - 3X^2m + 3Xm^2]$$

$$= E(X^3) - m^3 - 3m E(X^2) + 3m^2 E(X)$$

$$= E(X^3) - m^3 - 3m E(X^2) + 3m^3$$

$$= E(X^3) - 3m \cdot E(X^2) + 2m^3$$

where $m = E(X)$

$$(X-m)^3 = (X^3 - 3X^2m + 3Xm^2) (X-m)$$

$$= X^3 - X^2m + Xm^2 - m^3 - X^2m + 2Xm^2$$

$$= X^3 - m^3 - 2X^2m + 3Xm^2$$

find the coefficient of correlation between random variables X and Y from the following data.

x	1	2	3	4	5	6	7	8	9
*	0	1	2	3	4	5	6	7	8
y	9	8	10	12	11	13	14	16	15

Sol

$$\text{coefficient of correlation } \rho_{xy} = \frac{\text{cov}(x,y)}{\sigma_x \cdot \sigma_y}$$

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

$$E(x) = \frac{0+1+2+3+4+5+6+7+8+9}{9} = \frac{45}{9} = 5$$

$$E(y) = \frac{9+8+10+12+11+13+14+16+15}{9}$$

$$= 12$$

$$E(xy) = \frac{[(0 \times 9) + (1 \times 8) + (2 \times 10) + (3 \times 12) + (4 \times 11) + (5 \times 13) + (6 \times 14) + (7 \times 16) + (8 \times 15)]}{9}$$

$$= 66.3$$

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

$$E(x^2) = \frac{1+4+9+16+25+36+49+64+81}{9} \\ = 31.66$$

$$\sigma_x^2 = 31.66 - (5)^2 = 6.66$$

$$\sigma_x = 2.58$$

$$E(y^2) = \frac{81+64+100+144+121+169+196+225+256}{9} \\ = 150.66$$

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

$$= 150.66 - (12)^2 = 6.66$$

$$\sigma_y = 2.58$$

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

$$= 86.3 - (5 \times 12) = 6.3$$

$$\rho_{xy} = \frac{\text{Cov}(x,y)}{\sigma_x \cdot \sigma_y} = \frac{6.3}{(2.58)(2.58)}$$

$$= 0.946$$

Let x be the outcome from rolling of one die and y be the outcome from the rolling of a second die. Find $E(x|y)$.

Sol

Since x and y are independent

$$E\left(\frac{x}{y}\right) = E(x)$$

$$\begin{aligned}
 E(x) &= \sum_{i=1}^6 x_i p(x_i) & x & p(x) \\
 &= \frac{1+2}{6} + 2 \times \frac{1}{6} + 3 \times \frac{1}{6} + & 1 & \frac{1}{6} \\
 &\quad 4 \times \frac{1}{6} + 5 \times \frac{1}{6} + 6 \times \frac{1}{6} & 2 & \frac{1}{6} \\
 &= \frac{1}{6} (1+2+3+4+5+6) = \frac{21}{6} = 3.5 & 3 & \frac{1}{6} \\
 && 4 & \frac{1}{6} \\
 && 5 & \frac{1}{6} \\
 && 6 & \frac{1}{6}
 \end{aligned}$$

CHARACTERISTIC FUNCTION

In the previous section, we learnt that

The moment generating function $M_X(t)$ is given by

$$M_X(t) = E[e^{tX}] = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx$$

$$\text{or } M_X(t) = \sum e^{tx} \cdot p(x)$$

In some cases, the moment generating function does not exist, since the integral $\int_{-\infty}^{\infty} e^{tx} f_X(x) dx$

or $E[e^{tx} \cdot p(x)]$ does not exist for real values of t for some distributions. Under such

situations, we have to look for some other

tool to generate moments. Characteristic

function is the best alternative for moment generating function for such cases.

The characteristic function of a random

variable X is defined by

$$\phi_X(w) = E\left[e^{jwX}\right], \quad j = \sqrt{-1}$$

occasionally, the letter E is used instead of " w "

$$\text{for continuous random variable, } \phi_X(w) = E(e^{jwX}) =$$

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

The equation $\phi_x(w) = \int_{-\infty}^{\infty} e^{jw\omega} f_x(\omega) d\omega$ can be
 considered as the Fourier transform of $f_x(\omega)$,
 thus the pdf can be obtained from the
 characteristic function of

$$\text{pdf } = f_x(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-jwx} \phi_x(w) dw$$

and thus can be considered as the
 FOURIER TRANSFORM of $\phi_x(w)$.
 INVERSION

②

PROPERTIES of characteristic function

1) $|\phi_x(w)| \leq 1$, i.e. the maximum magnitude of the characteristic function is Unity.

2) $\phi_x(0) = 1$ i.e. $w=0$

3) If x is symmetric function, then $\phi_x(w) = \phi_x(-w)$

4) If x and y are two independent random variables, then $\phi_{x+y}(w) = \phi_x(w) \cdot \phi_y(w)$

5) If $\phi_x(w)$ is the characteristic function of the random variable x , and if $y = ax+b$,

then $\phi_y(w) = e^{jwb} \phi_x(aw)$

where 'a' and 'b' are constants.

6) If x and y are random variables, having characteristic functions $\phi_x(w)$ and $\phi_y(w)$, then x and y are having identical distributions provided

$$\phi_x(w) = \phi_y(w)$$

$$\phi_x(-w) = \overline{\phi_x(w)}$$

7) If x is a random variable with characteristic function $\phi_x(w)$ and if the n th moment exists, it can be determined by

$$m_n = \frac{1}{n!} \left[\frac{d^n [\phi_x(w)]}{dw^n} \right]_{w=0}$$

The equation $\phi_x(w) = \int_{-\infty}^{\infty} e^{jw\omega} \cdot f_x(\omega) d\omega$ can be
 considered as the fourier transform of pdf($f_x(\omega)$),
 thus the pdf can be obtained from the
 characteristic function of

$$\text{pdf } = f_x(\omega) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-j\omega w} \cdot \phi_x(w) \cdot dw$$

and thus can be considered as the
 INVERSION FOURIER TRANSFORM of $\phi_x(w)$.

②

PROPERTIES OF characteristic function

1) $|\phi_x(w)| \leq 1$, i.e. the maximum magnitude of the characteristic function is Unity.

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6) If x and y are random variables, having characteristic functions $\phi_x(w)$ and $\phi_y(w)$, then x and y are having identical distributions provided

$$\phi_x(w) = \phi_y(w)$$

$$\phi_x(-w) = \overline{\phi_x(w)}$$

7) If x is a random variable with characteristic function $\phi_x(w)$ and if the n th moment exists, it can be determined by

$$m_n = \left[\frac{d^n [\phi_x(w)]}{dw^n} \right]_{w=0}$$

35

a) The function $\Psi(\omega) = \log_e |\phi_x(\omega)|$ called the second characteristic function,

UNIT 2

Part 3

Properties of Moment Generating function :-

1. Let x be a random variable with mgf $M_X(t)$.

Then, the mgf of $y = ax + b$ is $= e^{bt} \cdot M_X(at)$

$$\begin{aligned}
 M_y(t) &= E(e^{yt}) = E\left[e^{(ax+b)t}\right] \\
 &= E\left[e^{axt} \cdot e^{bt}\right] \\
 &= e^{bt} \cdot E\left[e^{axt}\right] \\
 &= e^{bt} \cdot E\left[e^{x(at)}\right] \\
 &= e^{bt} \cdot M_X(at)
 \end{aligned}$$

2. If $M_X(t)$ is the mgf of r.v x , then,

the mgf of $y = k \cdot x$ is $= M_X(kt)$

$$\begin{aligned}
 M_y(t) &= E\left[e^{yt}\right] \\
 &= E\left[e^{k \cdot x \cdot t}\right] \\
 &= E\left[e^{x(kt)}\right] \\
 &= M_X(kt)
 \end{aligned}$$

3. If $m_x(t)$ is the mgf of r.v. x , then,

$$\text{the mgf of } y = \frac{x+a}{b} \text{ is } = e^{\frac{at}{b}} \cdot m_x(t/b)$$

$$m_y(t) = E\left[e^{yt}\right]$$

$$= E\left[e^{t\left(\frac{y+a}{b}\right)}\right]$$

$$= E\left[e^{\frac{ty}{b}} \cdot e^{\frac{at}{b}}\right]$$

$$= e^{\frac{at}{b}} \cdot E\left[e^{ty/b}\right]$$

$$= e^{\frac{at}{b}} \cdot m_x(t/b)$$

4. If two random variables x and y having mgfs $m_x(t)$ and $m_y(t)$ such that $m_x(t) = m_y(t)$, then, x and y are said to have identical distribution i.e. identical density.

To see how to generate moments from characteristic function, consider

$$\phi_x(\omega) = E \left[e^{J\omega X} \right]$$

$$= E \left[1 + J\omega X + \frac{(J\omega X)^2}{2!} + \frac{(J\omega X)^3}{3!} + \dots \right]$$

$$= 1 + J\omega \cdot E(X) + \frac{(J\omega)^2 \cdot E(X^2)}{2!} + \frac{(J\omega)^3 \cdot E(X^3)}{3!} + \dots$$

This expansion is a polynomial in $J\omega$, where the coefficients of each term involving $J\omega$ is the moments of the random variable ie. coefficient

of $J\omega$ is the 1st moment m_1 , coefficient of $(J\omega)^2$ is the 2nd moment m_2 and so on.

Characteristic function can be used to generate moments of a random variable about origin only.

$$\text{Consider, } \left. \frac{d}{dw} [\phi_x(w)] \right|_{w=0} = \left. \frac{d}{dw} \left[1 + J\omega \cdot E(X) + \frac{(J\omega)^2 E(X^2)}{2!} + \dots \right] \right|_{w=0}$$

$$\left. \frac{d}{dw} [\phi_x(w)] \right|_{w=0} = \text{J. E}(x)$$

$$\therefore E(x) = \frac{1}{J} \cdot \left. \frac{d}{dw} [\phi_x(w)] \right|_{w=0}$$

In general, the n th moment of s.v. x
can be obtained as

$$E(x^n) = \left(\frac{1}{J} \right)^n \cdot \left. \frac{d^n}{dw^n} [\phi_x(w)] \right|_{w=0}$$

Properties of Characteristic function

$$y = ax + b$$

$$\begin{aligned}
 \Phi_y(\omega) &= E[e^{j\omega y}] \\
 &= E[e^{j\omega(ax+b)}] \\
 &= e^{j\omega b} E[e^{j\omega ax}] \\
 &= e^{j\omega b} \cdot E[e^{j\omega x}] \\
 &= e^{j\omega b} \cdot \underline{\phi_x(\omega)}
 \end{aligned}$$

②

$$\begin{aligned}
 \text{If } y &= \frac{x+a}{b}, \quad a, b \neq 0 \\
 \Phi_y(\omega) &= E[e^{j\omega \left(\frac{x+a}{b}\right)}] \\
 &= E\left[e^{\frac{j\omega x}{b}} \cdot e^{j\omega \frac{a}{b}}\right] \\
 &= e^{j\omega \frac{a}{b}} \cdot E\left[e^{j\omega \frac{x}{b}}\right] \\
 &= e^{j\omega \frac{a}{b}} \cdot \underline{\phi_x(j\omega/b)}
 \end{aligned}$$

SKEW $\hat{\mu}_3$

The 3rd central moment $E[(x-\bar{x})^3]$

If a random variable x is referred to as "skew" of its probability density function. It is a measure of asymmetry of the density function of a r.v. about its mean.

→ The Normalized third central moment

of a r.v. x , ie $\frac{E[(x-\bar{x})^3]}{\sigma_x^3}$ is referred to as "skewness" of density function or alternatively "coefficient of skewness".

$$\mu_3 / \sigma_x^3$$

∴ note: $\mu_n = 0$ for all odd values of n
 $\mu_0 = 1$

$$\mu_1 = 0$$

$$\mu_3 = 0$$

$$\mu_5 = 0$$

KURTOSIS ^{go w C Bw v} It is a measure of peakedness

of the density function. The degree of peakedness of a distribution is measured by using coefficient of kurtosis κ

and is given by

$$\frac{E[(x-\bar{x})^4]}{\sigma_x^4}, \text{ it is a dimensionless quantity.}$$

CHEBYSHEV'S INEQUALITY :-

The useful tool in some probability problems is Chebychev's Inequality.

If m is the mean and σ^2 is the variance of a r.v. X , then $|X-m|$ is measure of the amount by which value of X differs above or below from its mean.

The upper bound for the dispersion is given by "Chebychev's inequality". It is stated as

"If X is a random variable with mean m and variance σ^2 , then for any $k > 0$,

$$P\{|X-m| \geq k\} \leq \frac{\sigma^2}{k^2}$$

The alternative form of Chebychev's inequality is stated as

$$P\{|X-m| \geq k \cdot \sigma\} \leq \frac{1}{k^2}$$

i.e.

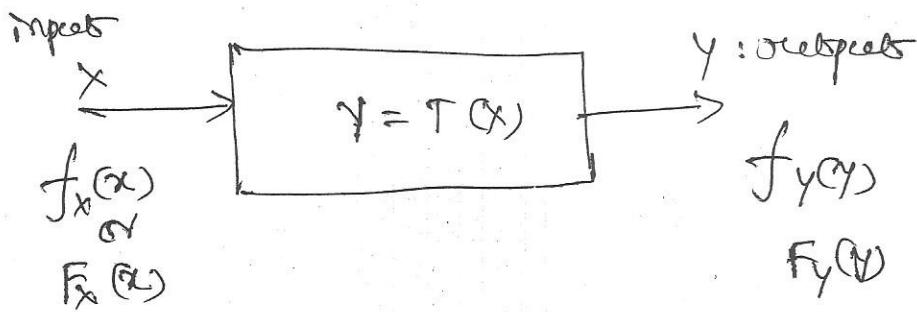
$$P\{|X-m| \leq k \cdot \sigma\} \geq 1 - \frac{1}{k^2}$$

TRANSFORMATION OF A RANDOM VARIABLE

Transform $\xrightarrow{\text{change}}$ of one random variable X into a new random variable Y by means of transformation

$$Y = T(X)$$

Typically, the density function $f_X(x)$ or distribution function $F_X(x)$ of X is known, and the problem is to determine either the density function $f_Y(y)$ or distribution function $F_Y(y)$ of Y . The problem can be viewed as "black box" with input X , output Y , and transfer characteristic $Y = T(X)$, as illustrated below.



In general X can be a discrete, continuous or mixed random variable. Intern, the transform T can be linear, non-linear, segmented, staircase --- etc.

Clearly, there are many cases to consider in a general study, depending on the form of X and T . In this section we shall consider only three cases.

- ① X and T continuous and either monotonically increasing or decreasing
- ② X and T continuous but non-monotone
- ③ X discrete and T continuous.

Note that the transformation in all three cases is assumed continuous.

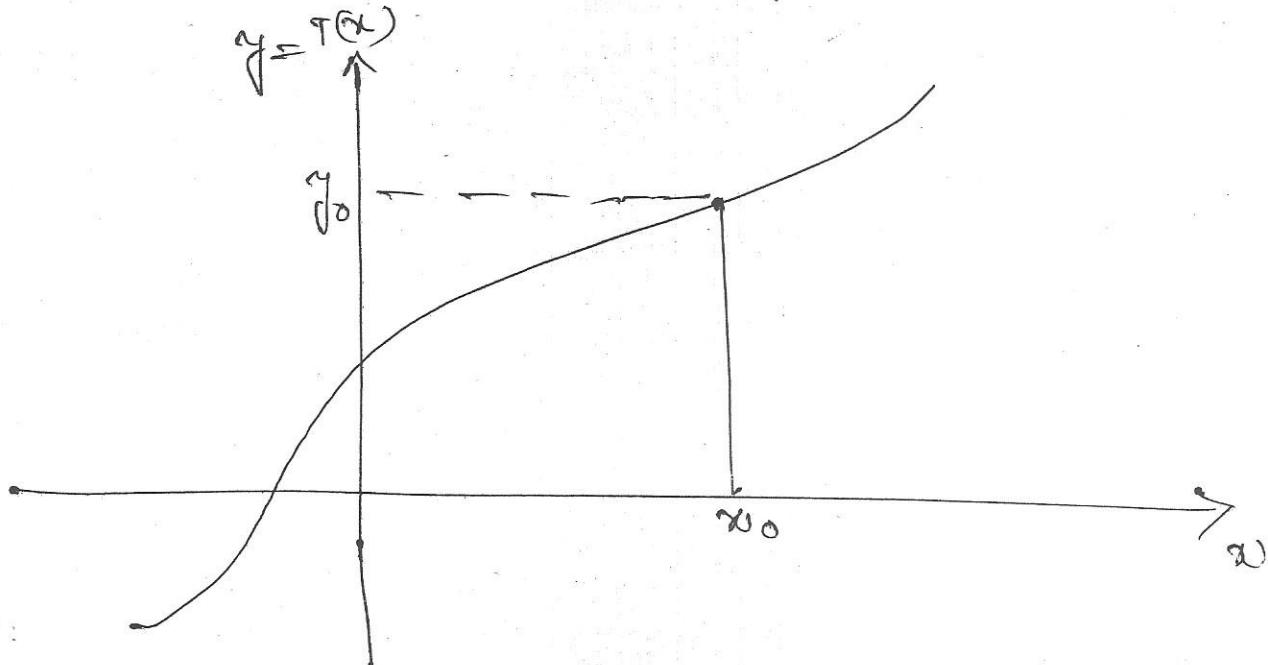
MONOTONE Transformation of a continuous random variable :-

A transformation T is called monotonically increasing if $T(x_1) < T(x_2)$, for any $x_1 < x_2$.

monotonically decreasing if $\cancel{T(x_1)} > \cancel{T(x_2)}$

$T(x_1) > T(x_2)$ for any $x_1 > x_2$

consider first the increasing transformation :



we assume that T is continuous and differentiable at all values of x for which $f(x) \neq 0$,

Let y have a particular value y_0 corresponding to the particular value x_0 of x as shown in figure. The two numbers are related by

$$y_0 = T(x_0) \quad \text{or} \quad x_0 = T^{-1}(y_0)$$

where T^{-1} represents the inverse transformation of T . Now the probability of the event $\{y \leq y_0\}$ must equal to the probability of the event $\{x \leq x_0\}$, because of the one-to-one correspondence between x and y . Thus,

$$F_y(y_0) = P\{y \leq y_0\} = P\{x \leq x_0\} \\ = F_x(x_0)$$

or

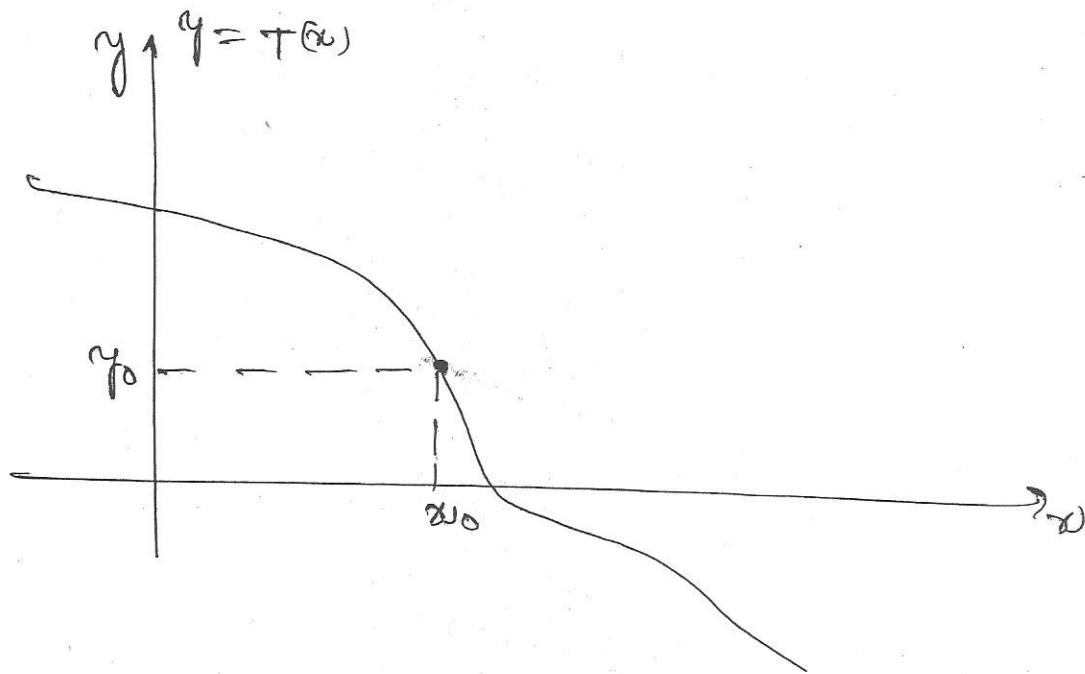
$$\int_{-\infty}^y f_y(y) dy = \int_{-\infty}^{x_0} f_x(x) dx.$$

~~Note~~, differentiate both sides w.r.t. y_0 using Leibniz's Rule

Finally $f_y(y_0) = f_x(x_0) \cdot \frac{dx}{dy}$

for any value of y , $f_y(y) = f_x(x) \cdot \frac{dx}{dy}$

→ for the decreasing transformation:



$$f_y(y) = f_x(x) \cdot \left| \frac{dx}{dy} \right|$$

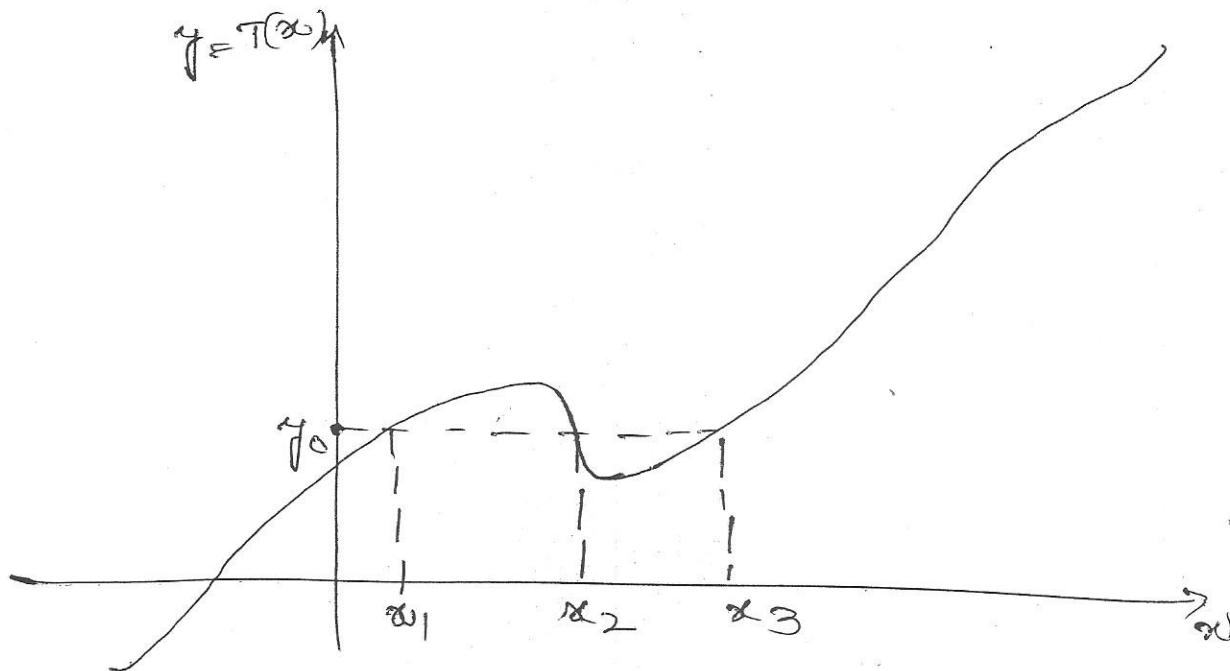
Note: A linear transformation of a gaussian random variable produces another gaussian random variable.

Nonmonotone

transformation of a continuous

Random

Variable:



Here more than one interval of x

that correspond to the event $\{Y \leq y_0\}$. for the value of y_0 shown in figure, the event

$\{Y \leq y_0\}$ corresponds to the $\{x \leq x_1 \text{ and } x_2 \leq x \leq x_3\}$

Thus the probability of the event $\{Y \leq y_0\}$, now

equal the probability of the events

$\{\omega \text{ values yielding } Y \leq y_0\}$, which we shall

write as $\{\omega | Y \leq y_0\}$. In other words

$$\begin{aligned} F_Y(y_0) &= P\{Y \leq y_0\} = P\{\omega | Y \leq y_0\} \\ &= \int f_Y(x) d\omega \end{aligned}$$

density function of Y

$$f_Y(y_0) = \frac{d}{dy_0} \left[\int_{x/y \leq y_0} f_X(x) dx \right]$$

or

$$f_Y(y_0) = \sum_n \frac{f_X(x_n)}{\left| \frac{dx}{du} \right|_{u=x_n}} \quad (\text{other form})$$

$x_n, n=1, 2, 3, \dots$

Transformations of a discrete random variable

If X is discrete, where $y = T(x)$ is a
continuous transformation, then

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$$f_x(x) = \sum_n p(x_n) \cdot \delta(x - x_n)$$
$$F_x(x) = \sum_n p(x_n) \cdot u(x - x_n)$$

where $x_n, n = 1, 2, 3, \dots$ at x .

If the transformation is monotone, there is a
one-to-one correspondence between x and y . So
that a set $\{y_n\}$ corresponds to the set $\{x_n\}$
through the equation $y_n = T(x_n)$. The
probability $p(y_n)$ equals to $p\{x_n\}$. Thus

$$f_y(y) = \sum_n p(y_n) \cdot \delta(y - y_n)$$

$$F_y(y) = \sum_n p(y_n) \cdot u(y - y_n)$$

where $y_n = T(x_n)$

$$p(y_n) = p(x_n)$$

If T is not monotone, the above procedure remains valid except there now exists the possibility that more than one value of x_n corresponds to a value of y_n . In such a case $P(y_n)$ will equal the sum of the probabilities of the various x_n for which $y_n = T(x_n)$.

→ -

① Let X and Y be independent random variables

such that $x=1$ with prob $\frac{1}{3}$

$$=0 \quad " \quad " \quad \frac{2}{3}$$

and $y=2 \quad " \quad " \quad \frac{3}{4}$

$$=-3 \quad " \quad " \quad \frac{1}{4}$$

find ① $E(3x+2y)$ ⑤ $E[2x^2+y^2]$

③ $E(XY)$ ④ $E[X^2, Y^2]$.

Sol:

① $E(3x+2y)$

Let $Z = 3x+2y$

when $x=1, y=2 \Rightarrow Z=7$

$$x=1, y=-3 \Rightarrow Z=-3$$

$$x=0, y=2 \Rightarrow Z=4$$

$$x=0, y=-3 \Rightarrow Z=-6$$

The probability distribution of Z is

Z_i

$P(Z_i)$

$$-6 \quad \underline{\hspace{2cm}} \quad P(X=0, Y=-3) = P(X=0) \cdot P(Y=-3) \\ = \frac{2}{3} \cdot \frac{1}{4} = \frac{1}{6}$$

$$-3 \quad \underline{\hspace{2cm}} \quad P(X=1) \cdot P(Y=-3) = \frac{1}{3} \cdot \frac{1}{4} = \frac{1}{12}$$

$$4 \quad \underline{\hspace{2cm}} \quad \underline{\hspace{2cm}} = \frac{1}{12}$$

$$7 \quad \underline{\hspace{2cm}} \quad \underline{\hspace{2cm}} = \frac{1}{4}$$

$$\begin{aligned}\therefore E(3x+2y) &= E(Z) = (-6 \times \frac{1}{16}) + (-3 \times \frac{1}{12}) + \\ &\quad (4 \times \frac{1}{2}) + (4 \times \frac{1}{4}) \\ &= \underline{\underline{5/2}}\end{aligned}$$

① Let $Z = 2x^2 - 4y^2$

x	y	$Z = Z_i$	$P(Z_i)$
1	2	-2	$P(x=1) \cdot P(y=-2) = \frac{1}{4}$
1	-3	-7	$\frac{1}{12}$
0	2	-4	$\frac{1}{2}$
0	-3	-9	$\frac{1}{6}$

$$\begin{aligned}E(Z) &= (-9 \times \frac{1}{16}) + (-7 \times \frac{1}{12}) + (-4 \times \frac{1}{2}) + (-2 \times \frac{1}{4}) \\ &= \underline{\underline{-55/12}}\end{aligned}$$

① Let $Z = XY$

3

$$x \quad y \quad z_i \quad P(Z=z_i)$$

$$\begin{array}{ccc} 1 & 2 & 2 \\ 1 & -3 & -3 \end{array} \quad P(X=1, Y=2) = P(X=1) \cdot P(Y=2) = 4/4$$

$$\begin{array}{ccc} 0 & 2 & 0 \\ 0 & -3 & 0 \end{array} \quad - \quad 4/2$$

$$\begin{array}{ccc} 0 & -3 & 1 \\ 0 & 0 & 1 \end{array} \quad - \quad 4/6$$

$$E(Z) = (2 \times 4/4) + (-3 \times 1/2) + (0 \times 4/2) + (0 \times 1/6)$$

$$= 2 - 1/2$$

$$= 1/4$$

② Let $Z = X^2Y$

$$x \quad y \quad z_i \quad P(Z=z_i)$$

$$\begin{array}{ccc} 1 & 2 & 2 \\ 1 & -3 & -3 \end{array} \quad 4/4$$

$$\begin{array}{ccc} 0 & 2 & 0 \\ 0 & 0 & 0 \end{array} \quad - \quad 4/12$$

$$\begin{array}{ccc} 0 & 2 & 0 \\ 0 & 0 & 0 \end{array} \quad - \quad 4/6$$

UNIT 2

Part 4
Solved problems

Example 4.1

Assume that the joint sample space has the probabilities shown in Table 4.1. Find distribution function, $F_{XY}(x, y)$ and marginal density functions.

(XY)	(0, 0)	(1, 2)	(2, 3)	(3, 2)
P(x, y)	0.2	0.3	0.4	0.1

Table 4.1: Joint probabilities $P(x, y)$

Solution

We know that

$$F_{XY}(x, y) = \sum_n^N \sum_m^M P(x, y) u(x - x_n) u(y - y_m)$$

$$\begin{aligned} F_{XY}(x, y) &= 0.2u(x)u(y) + 0.3u(x-1)u(y-2) + 0.4u(x-2)u(y-3) \\ &\quad + 0.1u(x-3)u(y-2) \end{aligned}$$

Marginal density functions are

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

$$F_x(x) = 0.2u(x) + 0.3u(x-1) + 0.4u(x-2) + 0.1u(x-3)$$

and

$$\begin{aligned} F_y(y) &= F_{xy}(\infty, y) \\ &= 0.2u(y) + 0.3u(y-2) + 0.4u(y-3) + 0.1u(y-2) \\ &= 0.2u(y) + 0.4u(y-2) + 0.4u(y-3) \end{aligned}$$

Fig. 4.1 shows the plots of marginal distributions.

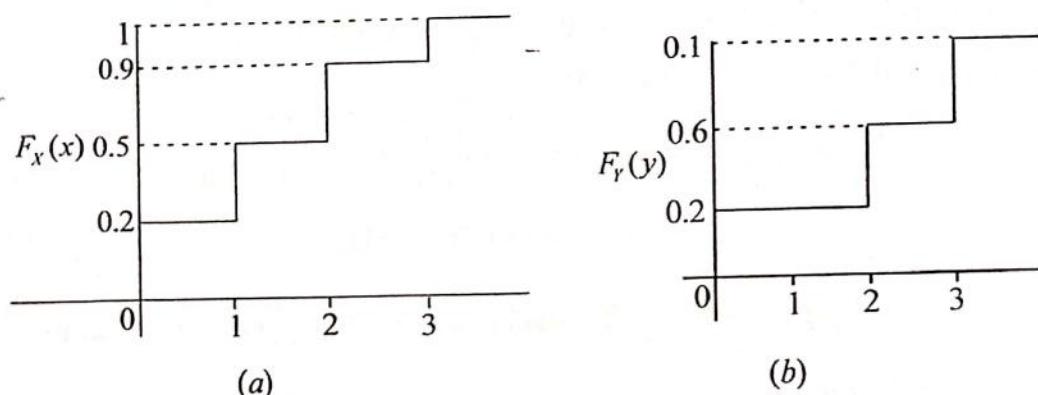


Fig.4.1: Marginal distributions of X and Y

Example 4.3

The joint pdf is given as

$$f_{XY}(x, y) = A e^{-(2x+y)} \quad \text{for } x \geq 0 \text{ and } y \geq 0$$

Find (a) the value of A and (b) the marginal density functions

Solution

(a) Given the density function is valid, if

$$\int_0^\infty \int_{-\infty}^\infty f_{XY}(x, y) dx dy = 1, \quad x \geq 0 \text{ and } y \geq 0$$

$$\int_0^\infty \int_0^\infty A \cdot e^{-(2x+y)} dx dy = 1$$

$$A \left[\int_0^\infty e^{-2x} dx \int_0^\infty e^{-y} dy \right] = 1$$

$$A \left[\left(-\frac{e^{-2x}}{2} \Big|_0^\infty \right) \left(-e^{-y} \Big|_0^\infty \right) \right] = 1$$

$$\frac{A}{2} (e^{-2x})(e^{-y}) \Big|_0^\infty = 1$$

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

$$A = 2$$

\therefore The function is

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

(b) The Marginal density functions are

$$\begin{aligned} f_X(x) &= \int_{-\infty}^{\infty} f_{X,Y}(x, y) dy \\ &= \int_0^{\infty} 2e^{-(2x+y)} dy \\ &= 2e^{-2x} \int_0^{\infty} e^{-y} dy = 2e^{-2x} (-e^{-y}) \Big|_0^{\infty} \\ &= 2e^{-2x}[1-0] = 2e^{-2x} \end{aligned}$$

$$\therefore f_X(x) = 2e^{-2x}, \quad x \geq 0$$

$$\begin{aligned} \text{and } f_Y(y) &= \int_{-\infty}^{\infty} f_{X,Y}(x, y) dx \\ &= \int_{-\infty}^{\infty} 2e^{-(2x+y)} dx \\ &= 2e^{-y} \int_0^{\infty} e^{-2x} dx = e^{-y}(1-0) = e^{-y} \end{aligned}$$

$$\therefore f_Y(y) = e^{-y}, \quad y \geq 0$$

\therefore The marginal density functions are

$$f_X(x) = 2e^{-2x}, \quad x \geq 0 \text{ and } f_Y(y) = e^{-y}, \quad y \geq 0$$

Example 4.12

Determine a constant b such that the given function is a valid joint density function.

$$f_{X,Y}(x,y) = \begin{cases} b(x^2 + 4y^2) & 0 \leq |x| < 1 \quad \text{and} \quad 0 \leq y < 2 \\ 0 & \text{elsewhere} \end{cases}$$

Solution

Given $f_{X,Y}(x,y) = \begin{cases} b(x^2 + 4y^2) & 0 \leq |x| < 1 \quad \text{and} \quad 0 \leq y < 2 \\ 0 & \text{elsewhere} \end{cases}$

Since $f_{X,Y}(x,y)$ is a valid joint density function

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

$$\int_{x=-1}^{1} \int_{y=0}^{2} b(x^2 + 4y^2) dx dy = 1$$

$$b \int_{-1}^1 \left(x^2 y + \frac{4y^3}{3} \right) \Big|_{y=0}^2 dx = 1$$

$$b \int_{-1}^1 \left(\frac{32}{3} + 2x^2 \right) dx = 1$$

$$b \left(\frac{32x}{3} + \frac{2x^3}{3} \right) \Big|_{-1}^1 = 1$$

$$2b \left[\frac{32}{3} + \frac{2}{3} \right] = 1$$

$$\frac{68b}{3} = 1 \quad \text{or} \quad b = \frac{3}{68}$$

Example 4.14

The joint density function is given by

$$f_{xy}(x, y) = \begin{cases} ax^2y & 0 < y < x < 1 \\ 0 & \text{elsewhere} \end{cases}$$

- Find 'a' so that the function is a valid density function
- Find marginal density functions.

Solution

Given $f_{xy}(x, y) = \begin{cases} ax^2y & 0 < y < x < 1 \\ 0 & \text{elsewhere} \end{cases}$

Since it is a valid density function

Then $\int_{x=0}^1 \int_{y=0}^x ax^2y dy dx = 1$

$$\begin{aligned} & \int_0^1 \left[ay \left(\frac{x^3}{3} \right) \right]_0^x dy = 1 \\ & = \int_0^1 \frac{ax^3}{3} (1 - y^3) dy = 1 \end{aligned}$$

$$\frac{a}{3} \int_0^1 (y^3 - y^6) dy = 1$$

$$\frac{a}{3} \left[\frac{y^4}{4} - \frac{y^7}{7} \right]_0^1 = 1$$

$$\frac{a}{3} \left[\frac{1}{2} - \frac{1}{7} \right] = 1$$

$$\frac{a}{3} \left[\frac{3}{10} \right] = 1$$

$$a = 10$$

The marginal density functions are

$$f_X(x) = \int_{y=x}^1 f_{xy}(x, y) dy \quad 0 < x < 1$$

$$\begin{aligned} f_X(x) &= \int_{y=x}^1 10x^2y dy = 10x^2 \left[\frac{y^2}{2} \right]_x^1 \\ &= 5x^2(1 - x^2) \end{aligned}$$

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$$\therefore f_X(x) = \begin{cases} 5x^2(1-x^2) & 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

and $f_Y(y) = \int_{x=0}^y f_{XY}(x, y) dx \quad 0 < y < 1$

$$f_Y(y) = \int_{x=0}^y 10yx^2 dx = 10y \cdot \frac{x^3}{3} \Big|_0^y \\ = 10y \cdot \frac{y^3}{3} = 3.33y^4$$

$$\therefore f_Y(y) = \begin{cases} 3.33y^4 & 0 < y < 1 \\ 0 & \text{otherwise} \end{cases}$$

Example 4.15

The joint distribution function of a bivariate random variable (X, Y) is given by

$$F_{X,Y}(x, y) = \begin{cases} 0 & x < 0, y < 0 \\ 0.2 & 0 \leq x < a, 0 \leq y < b \\ 0.4 & x \geq a, 0 \leq y < b \\ 0.8 & 0 \leq x < a, y \geq b \\ 1 & x \geq a, y \geq b \end{cases}$$

Find the marginal distributions of X and Y .

Solution

Given the joint distribution of X and Y is

$$F_{XY} = \begin{cases} 0 & x < 0, y < 0 \\ 0.2 & 0 \leq x < a, 0 \leq y < b \\ 0.4 & x \geq a, 0 \leq y < b \\ 0.8 & 0 \leq x < a, y \geq b \\ 1 & x \geq a, y \geq b \end{cases}$$

The marginal distribution functions are

$$F_X(x) = F_{XY}(x, \infty) = \begin{cases} 0 & x < 0 \\ 0.8 & 0 \leq x \leq a \\ 1 & x \geq a \end{cases}$$

and $F_Y(y) = F_{XY}(\infty, y) = \begin{cases} 0 & y < 0 \\ 0.4 & 0 \leq y \leq b \\ 1 & y \geq b \end{cases}$

Example 4.16

The joint pdf of a bivariate random variable (X, Y) is given by

$$f_{X,Y}(x, y) = \begin{cases} Kxy & 0 < x < y < 1 \\ 0 & \text{otherwise} \end{cases}$$

where K is a constant

- (a) Find the value of K
- (b) Are X and Y independent?

Solution

Given the joint probability density function of X and Y is

$$f_{X,Y}(x, y) = \begin{cases} Kxy & 0 < x < y < 1 \\ 0 & \text{otherwise} \end{cases}$$

- (a) Since $f_{XY}(x, y)$ is a valid density function.

we know that

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

$$K \int_{y=0}^{\infty} \int_{x=0}^y xy dx dy = 1$$

$$K \int_0^1 y dy \left. \frac{x^2}{2} \right|_0^y = 1$$

$$K \int_0^1 y \frac{y^2}{2} dy = 1$$

$$K \int_0^1 \frac{y^3}{2} dy = K \left. \frac{y^4}{8} \right|_0^1 = 1$$

$$\frac{K}{8} = 1$$

$$\therefore K = 8$$

- (b) The marginal pdfs are

$$f_X(x) = \int_{y=x}^{\infty} f_{XY}(x, y) dy \quad 0 < x < 1$$

$$f_x(x) = \int_0^x 8xy dy = 8x \cdot \frac{y^2}{2} \Big|_0^x$$

$$= 4x(1-x^2)$$

$$\therefore f_x(x) = \begin{cases} 4x(1-x^2) & 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

and $f_y(y) = \int_0^y f_{xy}(x,y) dx = \int_0^y 8xy dx$

$$= 8y \cdot \frac{x^2}{2} \Big|_0^y = 8y \cdot \frac{y^3}{2} = 4y^3 \quad 0 < y < 1$$

$$\therefore f_y(y) = \begin{cases} 4y^3 & 0 < y < 1 \\ 0 & \text{otherwise} \end{cases}$$

If X and Y are independent then

$$\begin{aligned} f_x(x)f_y(y) &= 4x(1-x^2)4y^3 \\ &= 16xy^3(1-x^2) \\ &\neq f_{xy}(x,y) \end{aligned}$$

Therefore X and Y are not independent.

Example 4.17

Consider the joint pdf of random variables, X and Y is

$$f_{xy}(x,y) = \begin{cases} \frac{1}{8}(x+y) & 0 < x < 2 \\ 0 & \text{otherwise} \end{cases}$$

Find the (a) conditional density functions and

$$(b) P((0 < Y < 1/2) / X = 1)$$

Solution

Given the joint density function,

$$f_{xy}(x,y) = \begin{cases} \frac{1}{8}(x+y), & 0 < x < 2 \\ 0 & \text{otherwise} \end{cases}$$

(a) The marginal density functions are

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$$\begin{aligned}f_X(x) &= \int_{-\infty}^{\infty} f_{XY}(x, y) dy \\&= \int_0^2 \frac{1}{8}(x+y) dy \\&= \frac{1}{8} \left[xy + \frac{y^2}{2} \right]_0^2 = \frac{1}{8}[2x+2]\end{aligned}$$

$$f_X(x) = \frac{1}{4}(x+1) \quad 0 < x < 2$$

$$\text{Similarly } f_Y(y) = \frac{1}{4}(y+1) \quad 0 < y < 2$$

The conditional density functions are

$$f_{XY}(x/y) = \frac{f_{XY}(x, y)}{f_Y(y)} = \frac{x+y}{2(y+1)}$$

$$\text{and } f_{XY}(y/x) = \frac{f_{XY}(x, y)}{f_X(x)} = \frac{x+y}{2(x+1)}$$

$$\therefore f_{X,Y}(x/y) = \begin{cases} \frac{x+y}{2(y+1)} & 0 < x < 2, \quad 0 < y < 2 \\ 0 & \text{otherwise} \end{cases}$$

$$f_{X,Y}(y/x) = \begin{cases} \frac{x+y}{2(x+1)} & 0 < x < 2, \quad 0 < y < 2 \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned}(b) \quad P((0 < Y < 1/2) / X = 1) &= \int_0^{1/2} f_{XY}(y/x = 1) dy = \int_0^{1/2} \frac{1+y}{2(1+1)} dy \\&= \frac{1}{4} \int_0^{1/2} (y+1) dy = \frac{1}{4} \left[\frac{y^2}{2} + y \right]_0^{1/2} \\&= \frac{1}{4} \left[\frac{1}{8} + \frac{1}{2} \right] = \frac{5}{32} = 0.156\end{aligned}$$

Example 4.31

Given the function

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

- (a) Find the constant b such that this is a valid joint density function.
(b) Determine the marginal density function $f_X(x)$ and $f_Y(y)$.

Solution

Given the function

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

- (a) The function is a valid density function

$$\text{Then } \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx dy = 1$$

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

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

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

$$b \int_{-2}^2 [3x^2 + 3^2 + x3^2 - (-3x^2 - 3^2 + x3^2)] dx = 1$$

$$b \int_{-2}^2 (3x^2 + 9 + 9x + 3x^2 + 9 - 9x) dx = 1$$

4 Multiple Random Variables

$$6b \int_{-2}^2 (x^2 + 3) dx = 1$$

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

$$6b \left[\frac{8}{3} + 6 - \left(\frac{-8}{3} - 6 \right) \right] = 1$$

$$12b \left[\frac{8+18}{3} \right] = 1$$

$$104b = 1$$

or $b = \frac{1}{104}$

) The marginal density functions are

$$f_x(x) = \int_{-\infty}^{\infty} b(x+y)^2 dy = \int_{-3}^3 \frac{(x+y)^2}{104} dy$$

$$= \frac{1}{104} \frac{(x+y)^3}{3} \Big|_{-3}^3 = \frac{1}{312} [(x+3)^3 - (x-3)^3]$$

$$f_x(x) = \begin{cases} \frac{1}{312} [(x+3)^3 - (x-3)^3] & -2 < x < 2 \\ 0 & \text{elsewhere} \end{cases}$$

and $f_y(y) = \int_{-2}^2 b(x+y)^2 dx = \int_{-2}^2 \frac{(x+y)^2}{104} dx$

$$= \frac{1}{312} [(y+2)^3 - (y-2)^3]$$

$$\therefore f_y(y) = \begin{cases} \frac{1}{312} [(y+2)^3 - (y-2)^3] & -3 < y < 3 \\ 0 & \text{elsewhere} \end{cases}$$

UNIT 2

Part 5

MULTIPLE RANDOM VARIABLES

- UNIT - IV

Syllabus:

1. Vector Random Variables
2. joint Distribution function
3. properties of Joint Distribution
4. marginal Distribution functions
- * 5. joint density function
6. properties of joint density function
7. marginal density function
8. conditional Distribution and density - point conditioning
9. conditional Distribution and density - Interval conditioning
10. statistical Independence
11. Sum of two random Variables
12. Sum of Several random Variables
13. central limit theorem (Proof not Expected)
14. Unequal Distribution
15. Equal Distribution.

* : Not mentioned in TNT syllabus

Introduction :-

In the previous Units, the concept of random variable was introduced and the statistics of the random variable are completed. In this Unit, all the above statistics will be extended for two random variables.

If only one characteristic of a random ~~variable~~ is considered, it leads to the concept of a single random variable. If the characteristics of the random experiment are to be considered, this leads to the principle of two random variables.

Eg: In an electrical circuit, Current only can be single random variable. Both voltage and current can be two random variables.

Vector Random Variables :-

Suppose two random variables x and y are defined on a sample space S , where specific values of x and y are denoted by α and γ , respectively. Then any ordered pair of numbers (α, γ) may be conveniently considered to be a "random point" in the xy plane.

The point may be taken as a specific value of a "vector random variable" or "random vector" (x, y) .

Def The pair (x, y) is called "bivariate" or "two dimensional

random vector.

↓ discrete

a. Bivariate, if $x \& y$ discrete

b. Bivariate, if $x \& y$ continuous.

↓ continuous

Joint Distribution function

Let $F_x(x)$ and $F_y(y)$ represent the probability distribution functions of random variables x and y respectively, i.e.

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

$$F_y(y) = P(Y \leq y)$$

The probability of the joint event ($X \leq x, Y \leq y$)

is defined as the joint probability distribution function

and is denoted by $F_{x,y}(x,y)$ and

x, y coordinates

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

$$= P(A \cap B)$$



In general, for N random variables X_1, X_2, \dots, X_N , the joint distribution function

is denoted by

$$F_{X_1, X_2, \dots, X_N}(x_1, x_2, x_3, \dots, x_N) = P[X_1 \leq x_1, X_2 \leq x_2, \dots, X_N \leq x_N]$$

$$F_X(x) = \sum_{i=1}^N P(X_i \leq x_i)$$



x and y are d. R.V

Let x have N possible values x_1, x_2, \dots, x_N and y have M

possible values y_1, y_2, \dots, y_M , then

$$F_{x,y}(x,y) = \sum_{n=1}^N \sum_{m=1}^M p(x_n, y_m) \cdot u(x-x_n) \cdot u(y-y_m)$$

Conditional Distribution and Density - Point Conditioning

we know that

$$F_x(x|B) = P\{X \leq x|B\}$$

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

$$= \frac{P\{X \leq x \cap B\}}{P(B)} \quad \textcircled{1}$$

corresponding probability density function is given by

$$f_x(x|B) = \frac{d}{dx} [F_x(x|B)] \quad \textcircled{2}$$

The distribution function of one random

variable X conditioned by second random variable
 variable y has some specific value y . This is called
 "point conditioning". Now we will define event B by

$$B = \{y - Ay < Y \leq y + Ay\} \quad \textcircled{3}$$

where Ay is a small quantity that we
 eventually let approach 0. for this event,

Eq.① can be written as

$$F_x(x | (y - Ay < Y \leq y + Ay)) = \frac{\int_{y - Ay}^x f_{x|y}(w) dw}{\int_{y - Ay}^{y + Ay} f_{x|y}(w) dw} \quad \textcircled{4}$$

Consider two cases of Eq ④

① x and y discrete R.V.s

② x and y CRV

① Both x and y are discrete random variables.

with values x_i , $i = 1, 2, 3 \dots N$ and
 y_j , $j = 1, 2, 3 \dots M$.

while the probabilities of these values are

denoted $p(x_i)$ and $p(y_j)$, respectively. The probability of joint occurrence of x_i and y_j is

$p(x_i, y_j)$. Then

$$f_y(y) = \sum_{j=1}^M p(y_j) \delta(y - y_j) \quad \text{--- ⑤}$$

$$f_{x|y}(x|y) = \sum_{i=1}^N \sum_{j=1}^M p(x_i, y_j) \delta(x - x_i) \delta(y - y_j) \quad \text{--- ⑥}$$

$$f_x(x) = \sum_{i=1}^N p(x_i) \delta(x - x_i)$$

The specific value of y of interest or y_k

With Substitution of Eqs ⑤ and ⑥ into Eq ④, and

allowing $Ay \rightarrow 0$, we obtain

coincidence at Eq ④ will be =

conditional distribution

$$F_x(x|y=y_k) = \sum_{i=1}^N \frac{P(x_i, y_k)}{P(y_k)} \cdot u(x - x_i) \quad \text{④}$$

conditional density

$$f_x(x|y=y_k) = \sum_{i=1}^N \frac{P(x_i|y_k)}{P(y_k)} \cdot \delta(x - x_i) \quad \text{⑤}$$

② If x and y are continuous random variables
and $\Delta y \rightarrow 0$

$$F_x(x|y) = \frac{\int_x^\infty f_{x,y}(x,y) dx}{f_y(y)}$$

and

$$f_x(x|y) = \frac{f_{x,y}(x,y)}{f_y(y)}$$

and also

$$f_y(y|x) = \frac{f_{x,y}(x,y)}{f_x(x)}$$

* Conditional Distribution and Density - Interval Conditioning

It is sometimes convenient to define

event B in eq ① and ② in terms of random

variable y by

$$B = \{ y_a < y \leq y_b \}$$

where y_a and y_b are real numbers and we

assume $P(B) = P\{y_a < y \leq y_b\} \neq 0$, with the
definition, it is readily shown that eq ① and ② become

$$F_x \{x | y_a < y \leq y_b\} = \frac{F_{x,y}(x, y_b) - F_{x,y}(x, y_a)}{F_y(y_b) - F_y(y_a)}$$

$$\stackrel{\textcircled{1} \rightarrow q}{=} \frac{\int_{y_a}^{y_b} \int_{-\infty}^{\infty} f_{x,y}(x, y) dy dx}{\int_{y_a}^{y_b} \int_{-\infty}^{\infty} f_{x,y}(x, y) dy dx} \stackrel{\textcircled{2} \rightarrow q}{=}$$

$$\text{and } f_x(x | y_a < y \leq y_b) = \frac{\int_{y_a}^{y_b} f_{x,y}(x, y) dy}{\int_{y_a}^{y_b} \int_{-\infty}^{\infty} f_{x,y}(x, y) dy dx}$$

Multiple Choice Questions - UNK - 1

① The joint probability matrix of two r.v.s X and Y

is given by

$$P(X, Y) = \begin{matrix} & \begin{matrix} X=1 \\ X=0 \\ X=2 \end{matrix} \\ \begin{matrix} Y=0 \\ Y=1 \\ Y=2 \end{matrix} & \begin{bmatrix} 4/18 & 4/9 & 4/6 \\ 4/9 & 4/18 & 4/9 \\ 4/6 & 4/9 & 4/18 \end{bmatrix} \end{matrix} [a]$$

Then $P\left(\frac{Y=2}{X=2}\right)$

- Ⓐ $Y \neq$
- Ⓑ $Y \leq$
- Ⓒ $Y \geq$
- Ⓓ $Y \geq 2$

$$P\left(\frac{Y=2}{X=2}\right) = \frac{P(Y=2, X=2)}{P(X=2)}$$

$$= \frac{4/18}{4/6 + 4/9 + 4/18} = \frac{4/18}{11/18} = \underline{\underline{4/18}}$$

- ② If $f(x) = k/x^2$, $x=1, 2, \dots$ of the probability
formation of RV X , then k is equal to [d]
 ④ 4 ⑥ 2 ⑦ 1 ⑧ 3

- ③ X and Y are independent random variables, with
the following respective distributions

x_i	1	2	3
$P(X_i)$	0.7	0.15	0.15

y_j	2	3	4
$P(Y_j)$	0.8	0.1	0.1

Then $P(X=2, Y=2)$ is [b]

- ④ 0.15 ⑥ 0.12 ⑦ 0.06 ⑧ 0.56

- ④ If the joint probability distribution of X and Y is

$$f(x,y) = \frac{x+y}{30} \text{ for } x=0,1,2,3; y=0,1,2 \text{ then}$$

[b]

- $P(X > Y)$ [b]
 ④ 0.5 ⑥ 0.6 ⑦ 0.3 ⑧ 0.4

- ⑤ Let X be the outcome from rolling one die and Y be
the outcome from rolling a second die. Then [a]
 [a]

- $P(X \leq 3, Y \geq 3)$ [b]
 ④ 0.25 ⑥ 0.5 ⑦ 0.75 ⑧ 0.85

⑥ The joint probability matrix of x and y is

$$P(x,y) = \begin{matrix} & \begin{matrix} y/x & 0 & 1 & 2 \end{matrix} \\ \begin{matrix} 0 \\ 1 \\ 2 \end{matrix} & \begin{bmatrix} 4/18 & 4/9 & 4/6 \\ 4/9 & 4/18 & 4/9 \\ 4/6 & 4/6 & 4/18 \end{bmatrix} \end{matrix} \quad [a]$$

Then $P(Y=2/X=2)$ is

- Ⓐ 4/7 Ⓛ 1/5 Ⓜ 4/6 Ⓞ 4/18

⑦ Two discrete random variables x and y have

$$P(X=0, Y=0) = 4/9, \quad P(X=0, Y=1) = 4/9$$

$$P(X=1, Y=0) = 4/9, \quad P(X=1, Y=1) = 5/9$$

Are x and y

- Ⓐ Independent Ⓛ Not independent Ⓜ $f_{xy}(x,y) =$

⑧ The olp to a communication channel of a random variable x and the olp of another random variable y . The joint pmf of x and y is listed below.

$$P(x,y) = \begin{matrix} & \begin{matrix} y/x & -1 & 0 & 1 \end{matrix} \\ \begin{matrix} -1 \\ 0 \\ 1 \end{matrix} & \begin{bmatrix} 4/4 & 1/8 & 0 \\ 0 & 4/4 & 0 \\ 0 & 1/8 & 4/4 \end{bmatrix} \end{matrix} \quad [a]$$

Find $P(Y=1/X=1)$

- Ⓐ 1 Ⓛ 2 Ⓜ 3 Ⓞ 6

⑨ In above problem, find $P(X=1/Y=1)$

[b]

- Ⓐ 3/2 Ⓛ 2/3 Ⓜ 1 Ⓞ 4

Joint DENSITY Function

(67)

Assume that the outcome of a random experiment defined by two random variables x and y . Now, the joint p. distribution function of these random variables is given by $F_{x,y}(x,y)$. The joint probability density function $f_{x,y}(x,y)$ may be defined by the second derivative of the joint probability distribution function, i.e.

$$f_{x,y}(x,y) = \frac{\partial^2 F_{x,y}(x,y)}{\partial x \partial y}.$$

for N random variables, the joint density function can be obtained by N -fold partial derivative of the N -dimensional joint distribution function i.e.

$$f_{x_1, x_2, \dots, x_N}(x_1, x_2, \dots, x_N) = \frac{\partial^N F_{x_1, x_2, \dots, x_N}}{\partial x_1 \partial x_2 \dots \partial x_N}$$

If the joint density function is known, the joint probability distribution function can also be obtained of

$$F_{x_1, x_2, \dots, x_N}(x_1, x_2, \dots, x_N) = \int_{-\infty}^{x_1} \int_{-\infty}^{x_2} \dots \int_{-\infty}^{x_N} f_{x_1, x_2, \dots, x_N}(x_1, x_2, \dots, x_N) dx_1 dx_2 \dots dx_N$$

Properties of J. Distribution function :-

✓1) $F_{x,y}(-\infty, -\infty) = 0$, $F_{x,y}(-\infty, \gamma) = 0$ and

$$F_{x,y}(x, -\infty) = 0$$

✓2) $F_{x,y}(\infty, \infty) = 1$ cdf $f_{x,y}$
cdf $f_x(x)$

3) $0 \leq F_{x,y}(x, y) \leq 1$

4) $F_{x,y}(x, y)$ is a non-decreasing function of x and y

✓5) $F_{x,y}(x_2, y_2) + F_{x,y}(x_1, y_1) - F_{x,y}(x_1, y_2) -$

$$F_{x,y}(x_2, y_1) = p\{x_1 < x \leq x_2, y_1 < y \leq y_2\} > 0$$

6) $F_{x,y}(x, \infty) = F_x(x)$ and

$$F_{x,y}(\infty, y) = F_y(y)$$

Note 1: for a given function to be a valid distribution function of two random variables x and y , it must satisfy the properties ①, ②, ③, ④.

Note 2: In the 6th property, we see their two distributions functions of one random variable can be obtained by setting the other variable to infinity in $F_{x,y}(x, y)$. The functions $F_x(x)$ and $F_y(y)$ obtained in this way are called "Marginal distribution functions".

$$\textcircled{b} \quad \int_0^2 \int_{\frac{x}{2}}^3 k \cdot e^{-(x+y)} dx dy$$

$$\int_0^2 e^{-w} dw \int_2^3 e^{-y} dy$$

$$= [e^{-w}]_0^2 [e^{-y}]_2^3$$

$$= [-e^{-2} + 1] - e^{-3} - (-e^2)$$

$$= (1 - e^{-2}) (e^2 - e^{-3})$$

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

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

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

$$f_y(y) = \int_0^{\infty} e^{-(x+y)} dx$$

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

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

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f: The joint probability density of the random variables x and y is $f(x,y) = K e^{-(x+y)}$, in the range $0 \leq x \leq \infty$, $0 \leq y \leq \infty$ and $f(x,y) = 0$, otherwise.

(a) find the value of the constant K

(b) find the probability $P(0 < x < 2)$

(c) find marginal density of x and y $P(0 \leq x \leq 2, 2 \leq y \leq 3)$

(d) Are the random variable dependent or independent.

Sol

$$f(x,y) = \begin{cases} K e^{-(x+y)} & 0 \leq x \leq \infty \\ 0 & \text{otherwise} \end{cases}$$

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

$$\int_0^{\infty} \int_0^{\infty} K e^{-(x+y)} dx dy = 1$$

$$K \int_0^{\infty} e^{-x} dx \int_0^{\infty} e^{-y} dy = 1$$

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

$$= K [1][1] = 1$$

$$\therefore K = 1$$

Properties of Joint density function

A few of the important properties of the joint density function are

1) $f_{x,y}(x,y) \geq 0$

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

These two property are used to test whether some given function is a valid joint density function or not.

3) $F_x(x) = \int_{-\infty}^{\infty} \int_{-\infty}^x f_{x,y}(x_1, x_2) dx_1 dx_2$

and $F_y(y) = \int_{-\infty}^y \int_{-\infty}^{\infty} f_{x,y}(x_1, x_2) dx_1 dx_2$

This property is used to determine the marginal distribution function

4) $P\{x_1 < X \leq x_2, y_1 < Y \leq y_2\} = \int_{y_1}^{y_2} \int_{x_1}^{x_2} f_{x,y}(x_1, x_2) dx_1 dx_2$

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

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

The functions $f_x(x)$ and $f_y(y)$ determined by (5) are called "Marginal density"

derivatives of the marginal distribution functions.

$$f_x(x) = \frac{d}{dx} [F_x(x)]$$

$$f_y(y) = \frac{d}{dy} [F_y(y)]$$

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

~~$x \leq w$~~ = 1 ✓
 ~~$x \leq b$~~ = B X

? $F_x(x|B) = \frac{P(x \leq w \cap B)}{P(B)}$

$$F_{x,y}(x|b) = \frac{P(x \leq w) \cap (x \leq b)}{P(x \leq b)}$$

1)

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

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$$\int_{-\infty}^{\infty} F_x(x|B) dx = 1$$

A: $x \leq w$

$$F_x(w|B) = \frac{P((x \leq w) \cap B)}{P(B)}$$

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

a) if x ^{covar} B is defined in terms of x B: $x \leq b$

Then

$$F_x(w|(x \leq b)) = \frac{P((x \leq w) \cap (x \leq b))}{P(x \leq b)}$$

b) if event B is defined in terms of

other variable Y

 $y \leq y|B$

point conditioning

$$F_{x|y}(w|y) = \frac{P((x \leq w) \cap (y \leq y))}{P(y \leq y)} = P(x \leq w, y \leq y)$$

$$x \quad y \\ x \leq w \quad y \leq y$$

$$f_x(x) \quad f_y(y)$$

$$f_{x|y}(x|y)$$

$$f_{x,y}(x,y)$$

$$F_{x,y}(w,y) = \frac{f_{x,y}(w,y)}{f_y(y)}$$

~~Q.~~ $F_{x|y}(w|y) = \frac{F_{x,y}(w,y)}{f_y(y)}$

$$f_{x|y}(w|y) = \frac{f_{x,y}(w,y)}{f_y(y)}$$

 $(y \leq y \neq 0)$

$$f_{y|x}(y|x) = \frac{f_{x,y}(x,y)}{f_x(x)}$$

UNIT 2

Part 6

① A random variable X has a mean 3 and variance 2. Use Chebychev's inequality to obtain an upper bound for

$$\text{③ } P\{|X-3| > 12\} \quad \text{④ } P\{|X-3| \geq 1\}$$

Sol:

$$\text{③ } P\{|X-\mu| > K\} \leq \frac{\sigma^2}{K^2}$$

$$P\{|X-3| > 12\} \leq \frac{2}{144} = \frac{1}{72}$$

\therefore The upper bound is $\underline{\frac{1}{72}}$

$$\text{④ } P\{|X-3| \geq 1\} \leq \frac{2}{1} = 2$$

\therefore The upper bound is $\underline{\frac{2}{1}}$

① If x is the number obtained in throwing a fair die, find the probability of $|x - m| > 3$, where m is the mean of x .

Sol. The probability distribution of

x_i	1	2	3	4	5	6
$f(x_i)$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$

$$m = E(x) = 1 \times \frac{1}{6} + 2 \times \frac{1}{6} + 3 \times \frac{1}{6} + 4 \times \frac{1}{6} + 5 \times \frac{1}{6} + 6 \times \frac{1}{6}$$

$$= \frac{7}{2} = 3.5$$

$$E(x^2) = (1)^2 \times \frac{1}{6} + (2)^2 \times \frac{1}{6} + (3)^2 \times \frac{1}{6} + (4)^2 \times \frac{1}{6} + (5)^2 \times \frac{1}{6} + (6)^2 \times \frac{1}{6}$$

$$= \frac{91}{6}$$

$$\text{Var}(x) = E(x^2) - [E(x)]^2$$

$$= \frac{91}{6} - \frac{49}{4} = 2.9167$$

Chebyshov's inequality is stated as

$$P\{|X - \mu| \geq k\} \leq \frac{\sigma^2}{k^2} \quad \text{for } k > 0$$

since $k = 3$

$$P\{|X - 3.5| \geq 3\} \leq \frac{2.7107}{(3)^2} = 0.324$$

CENTRAL LIMIT THEOREM (proof not expected)

This theorem deals with the density function of a sum infinite number of random variables. It is stated as

"The density of the sum of n independent, equally distributed random variables approaches Gaussian density in the limits if n tends to infinity".

Let $x_1, x_2, x_3, \dots, x_N$ be the n number of independent, identically distributed random variables. Let S be random variable defined as

$$S = x_1 + x_2 + x_3 + \dots + x_N, \quad (\text{This})$$

$$E(S) = E(x_1) + E(x_2) + \dots + E(x_N)$$

since all x_i 's are identically distributed, all have same mean (m) and variance σ^2

$$\begin{aligned} \therefore E(S) &= m + m + \dots n \text{ times} \\ &= \underline{\underline{n \cdot m}} \end{aligned}$$

$$\begin{aligned}
 \text{Similarly, } \text{Var}(S) &= \text{Var}(X_1 + X_2 + \dots + X_N) \\
 &= \text{Var}(X_1) + \text{Var}(X_2) + \dots + \cancel{\text{Var}(X_N)} \\
 &= \sigma^2 + \sigma^2 + \dots + \sigma^2 \\
 &= n \cdot \sigma^2
 \end{aligned}$$

The standardized random variable S' , associated

with S' is defined as

$$S' = \frac{S - E(S)}{\sqrt{\text{Var}(S)}} = \frac{S - n \cdot m}{\sqrt{n \cdot \sigma^2}}$$

$$= \frac{S - n \cdot m}{\sigma \cdot \sqrt{n}}$$

Central Limit Theorem states that S' follows a Gaussian distribution

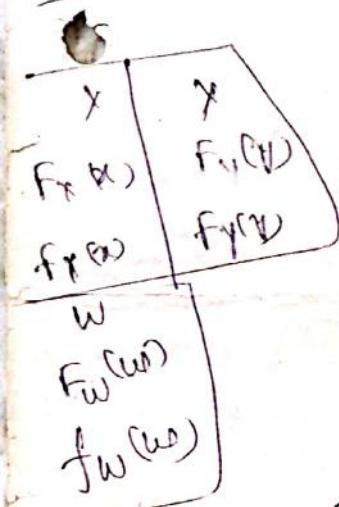
$$\rightarrow \sim N(0, 1)$$

Sum of Two Random Variables :-

Let x and y be two independent random variables and their sum be w , i.e.

$w = x + y$, Now, the probability distribution function of w is given by,

$$f_w(w) = P\{W \leq w\} = P\{x+y \leq w\}$$



$$= \int_{-\infty}^{\infty} f_y(y) \int_{x=-\infty}^{w-y} f_x(x) dx dy \quad \text{--- (1)}$$

Why $f_w(w) = \int_{-\infty}^{\infty} f_y(y) \cdot f_x(w-y) dy$

$$f_w(w) = f_x(w) * f_y(w)$$

Thus, it can be stated that the density function of the sum of two statistically independent random variables is the convolution of their individual density functions.

$$f_w(w) = f_x(w) * f_y(w)$$

This result can be extended to any number of random variables.

By differentiating eq (1), using Leibniz's rule, we get the desired density function

* Sum of Several Random Variables 5

The sum y of N independent random variables $x_1, x_2, x_3, \dots, x_N$ is to be considered.

$$\text{Let } y_1 = x_1 + x_2$$

$$f_{y_1}(y_1) = f_{x_1}(x_1) * f_{x_2}(x_2)$$

We know that x_3 will be independent of y_1

$$y_1 = x_1 + x_2, \text{ because it is independent of } x_3$$

independent of both x_1 and x_2 . They

$$y_2 = x_3 + y_1$$

$$\therefore f_{y_2}(y_2) = f_{x_3}(x_3) * f_{y_1}(y_1)$$

$$= f_{x_3}(x_3) * f_{x_2}(x_2) * f_x(x_1)$$

By continuing the process, we find the density function of $y = x_1 + x_2 + x_3 + \dots + x_N$ is the $(N-1)$ fold convolution of the N independent density functions.

$$f_y(y) = \underbrace{f_{x_N}(x_N)}_{\text{distribution}} * \underbrace{f_{x_{N-1}}(x_{N-1})}_{\text{distribution}} * \dots * f_{x_2}(x_2) * f_{x_1}(x_1)$$

$$\text{and } F_y(y) = \int f_y(y) dy$$

Joint Distribution Function

Let $F_x(x)$ and $F_y(y)$ represent the probability distribution functions of random variables X and Y respectively, i.e.

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

$$F_y(y) = P(Y \leq y)$$

The probability of the joint event ($X \leq x, Y \leq y$)

is defined as the joint probability distribution function and is denoted by $F_{x,y}(x,y)$

x, y continuous

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

(*) In general, for 'n' random variables X_1, X_2, \dots, X_n , the joint distribution function

is denoted by

$$F_{x_1, x_2, \dots, x_n}(x_1, x_2, x_3, \dots, x_n) = P[x_1 \leq x_1, x_2 \leq x_2, \\ x_3 \leq x_3, \dots, x_n \leq x_n] \\ F_x(x) = \sum_{i=1}^n P(x_i \leq x_i)$$

(**) X and Y are d. RV

Let X have N possible values and Y have M

possible values y_m, \dots, y_M

$$F_{x,y}(x,y) = \sum_{n=1}^N \sum_{m=1}^M P(x_n, y_m) \cdot u(x_n - x) \cdot u(y - y_m)$$

where $P(x_n, y_m)$ is the probability of the joint event

Properties of J. Distribution function

✓ 1) $F_{X,Y}(-\infty, -\infty) = 0$, $F_{X,Y}(-\infty, \gamma) = 0$ and
 $F_{X,Y}(\alpha, -\infty) = 0$

✓ 2) $F_{X,Y}(\infty, \alpha) = 1$ cdf $f_{X,Y}$
cdf $f_{X|Y}$

3) $0 \leq F_{X,Y}(\alpha, \gamma) \leq 1$

4) $F_{X,Y}(x, y)$ is a non-decreasing function of x and y

✓ 5) $F_{X,Y}(x_2, y_2) + F_{X,Y}(x_1, y_1) - F_{X,Y}(x_1, y_1) =$

$$F_{X,Y}(x_2, y_1) = p\{x_1 < X \leq x_2, Y_1 < Y \leq Y_2\}$$

6) $F_{X,Y}(x, \alpha) = F_X(x)$ and

$$F_{X,Y}(\alpha, y) = F_Y(y)$$

Note: for a given function to be a valid distribution function of two random variables X and Y , it must satisfy the properties (1), (2), (3).

Note: In the 6th property, we see that the distribution function of one random variable can be obtained by setting the other variable to infinity in $F_{X,Y}(x,y)$. The functions $F_X(x)$ and $F_Y(y)$ obtained in this way are called "marginal distribution functions".

§ JOINT DENSITY Function

Assume that the outcome of a random experiment defined by two random variables X and Y now, the joint p. distribution function of these random variables is given by $F_{X,Y}(x,y)$. The joint probability density function $f_{X,Y}(x,y)$ may be defined by the second derivative of the joint probability distribution function, i.e.

$$f_{X,Y}(x,y) = \frac{\partial^2 F_{X,Y}(x,y)}{\partial x \partial y}.$$

* for N random variables, the joint density function can be obtained by N -fold partial derivative of the N -dimensional joint distribution function i.e.

$$f_{X_1, X_2, \dots, X_N}(x_1, x_2, \dots, x_N) = \frac{\partial^N F_{X_1, X_2, \dots, X_N}(x_1, x_2, \dots, x_N)}{\partial x_1 \partial x_2 \dots \partial x_N}.$$

If the joint density function is known, the joint probability distribution function can also be obtained as

$$F_{X_1, X_2, \dots, X_N}(x_1, x_2, \dots, x_N) = \int_{-\infty}^{x_1} \int_{-\infty}^{x_2} \dots \int_{-\infty}^{x_N} f_{X_1, X_2, \dots, X_N}(x_1, x_2, \dots, x_N) dx_1 dx_2 \dots dx_N$$

Properties of Joint density function

A few of the important properties of the joint density function are

$$1) f_{X,Y}(x,y) \geq 0$$

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

These two properties are used to test whether some given function is a valid joint density function or not.

$$3) F_X(x) = \int_{-\infty}^x \int_{-\infty}^{\infty} f_{X,Y}(x_1, x_2) dx_1 dx_2$$

$$\text{and } F_Y(y) = \int_{-\infty}^y \int_{-\infty}^{\infty} f_{X,Y}(x_1, x_2) dx_1 dx_2$$

This property is used to determine the marginal distribution function

$$4) P\{x_1 < X \leq x_2, y_1 < Y \leq y_2\} = \int_{y_1}^{y_2} \int_{x_1}^{x_2} f_{X,Y}(x_1, x_2) dx_1 dx_2$$

$$5) f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x, y) dy$$

$$\text{and } f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x, y) dx$$

The functions $f_X(x)$ and $f_Y(y)$ determined as in the fifth property are called "marginal density functions" and they can be defined as the

UNIT 2

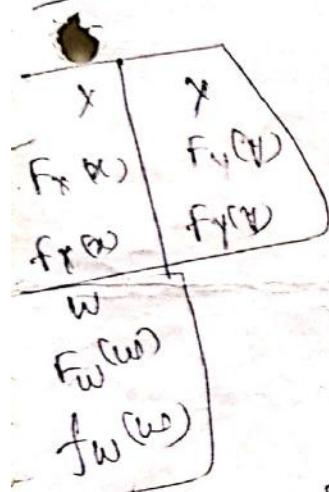
Part 7

Sum of Two Random Variables :-

Let x and y be two independent random variables and their sum be w , i.e.

$w = x+y$, Now, the probability distribution function of w is given by,

$$f_w(w) = P\{w \leq w\} = P\{x+y \leq w\}$$



$$= \int_{-\infty}^{\infty} f_y(y) \int_{x=-\infty}^{w-y} f_x(x) dx dy \quad \text{--- (1)}$$

$$\text{Hence } f_w(w) = \int_{-\infty}^{\infty} f_y(y) \cdot f_x(w-y) dy$$

$$f_w(w) = f_x(w) * f_y(w)$$

Thus, it can be stated that the density function of the sum of two statistically independent random variables is the convolution of their individual density functions.

$$f_w(w) = f_x(w) * f_y(w)$$

This result can be extended to any number of random variables.

By differentiating eq (1), using Leibniz's rule, we get the desired density function

* Sum of Several Random Variables or

The sum y of N independent random variables $x_1, x_2, x_3, \dots, x_N$ is to be considered.

$$\text{Let } y_1 = x_1 + x_2$$

$$f_{y_1}(y_1) = f_{x_1}(x_1) * f_{x_2}(x_2)$$

We know that x_3 will be independent of y_1

$y_1 = x_1 + x_2$, because it is independent of both x_1 and x_2 . They

$$y_2 = x_3 + y_1$$

$$\therefore f_{y_2}(y_2) = f_{x_3}(x_3) * f_{y_1}(y_1)$$

$$= f_{x_3}(x_3) * f_{x_2}(x_2) * f_{x_1}(x_1)$$

By continuing the process, we find the density function of $y = x_1 + x_2 + x_3 + \dots + x_N$ is the $(N-1)$ fold convolution of the N independent density functions.

$$f_y(y) = f_{x_N}(x_N) * f_{x_{N-1}}(x_{N-1}) * \dots * f_{x_2}(x_2) * f_{x_1}(x_1)$$

and $\underline{F_y(y)} = \int f_y(y)$

STATISTICAL INDEPENDENCE

The two events A and B are statistically independent if (and only if)

$$P(A \cap B) = P(A) \cdot P(B) \quad - \textcircled{1}$$

This condition can be used to apply to the random variables x and y by defining the events

$A = \{x \leq x\}$ and $B = \{y \leq y\}$ for the real numbers x and y . Then, x and y are said to be statistically independent random variables if (and only if)

$$P\{x \leq x, y \leq y\} = P(x \leq x) \cdot P(y \leq y) \quad - \textcircled{2}$$

From this expression and the definition of distribution function, it follows that

$$F_{x,y}(x,y) = F_x(x) \cdot F_y(y) \quad - \textcircled{3}$$

From the definitions of density functions

$$f_{x,y}(x,y) = f_x(x) \cdot f_y(y) \quad - \textcircled{4}$$

The form of conditional distribution function
for independent events is formed by, replacing
B by $\{y \leq y\}$ in the following

$$F_x(x/B) = P\{x \leq x \wedge B\} = \frac{P\{x \leq x \wedge B\}}{P(B)}$$

$$F_x\{x | y \leq y\} = P(x \leq x \wedge y \leq y)$$

$$= \frac{P(x \leq x)}{P(y \leq y)} \quad \frac{P(x \leq x, y \leq y)}{P(y \leq y)}$$

$$= \frac{F_{x,y}(x,y)}{F_y(y)} = \frac{F_x(x) \cdot F_y(y)}{f_y(y)} \quad (5)$$

$$\therefore F_x(x | y \leq y) = F_y(y) \quad (6)$$

$$\text{and also } F_y(y | x \leq x) = F_y(y) \quad (7)$$

Why, the conditional density function form,

$$f_x(x | y \leq y) = f_x(x) \quad (8)$$

$$\text{and } f_y(y | x \leq x) = f_y(y) \quad (9)$$

The joint probability density of the random

variables x and y is $f(x,y) = K e^{-(x+y)}$, in the range $0 \leq x \leq \infty$, $0 \leq y \leq \infty$ and $f(x,y) = 0$, otherwise.

(a) find the value of the constant K

(b) find the probability $P(x < y)$

(c) find marginal density $p(0 \leq x \leq 2, 2 \leq y \leq 3)$

(d) Are the random variables dependent or independent.

Sol

$$f(x,y) = \begin{cases} e^{-(x+y)} & , 0 \leq x \leq \infty \\ 0 & , 0 \leq y \leq \infty \\ \text{otherwise} & \end{cases}$$

(a)

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

$$\int_0^{\infty} \int_0^{\infty} K e^{-(x+y)} dx dy = 1$$

$$K \cdot \int_0^{\infty} e^{-x} dx \int_0^{\infty} e^{-y} dy = 1$$

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

$$= K [1][1] = 1$$

$$\Rightarrow K = 1$$

(b)

$$\int_0^2 \int_0^3 e^{-(x+y)} dx dy$$

$$\int_0^2 e^{-x} dx \int_0^3 e^{-y} dy$$

$$= [-e^{-x}]_0^2 [-e^{-y}]_0^3$$

$$= [-e^{-2} + 1] - e^{-3} - (-e^2)$$

$$= (1 - e^{-2}) (e^{-2} - e^{-3})$$

(c)

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

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

$$= -e^{-x} \cdot [-e^{-y}]_0^{\infty} = \frac{-x}{e}$$

$$f_y(y) = \int_0^{\infty} e^{-(x+y)} dx$$

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

$$\therefore f_{x|y}(x|y) = f_x(x) * f_y(y)$$

Two r.v. are independent

Q If x is a random variable, then, show that

$$\text{Ans} \quad \text{Var}(ax+b) = a^2 \cdot \text{Var}(x)$$

SOL

$$\text{Let } Y = ax+b$$

$$E[Y] = E[ax+b]$$

$$E[Y] = a \cdot E[X] + b$$

$$-E[Y] = -a E[X] - b$$

$$Y - E[Y] = ax+b - a E[X] - b \\ = a[x - E[X]]$$

Squaring and taking expectation on both sides

$$E\{(Y - E[Y])^2\} = a^2 E\{(x - E[X])^2\}$$

$$\text{Var}(Y) = a^2 \text{Var}(X)$$

$$\boxed{\text{Var}(ax+b) = a^2 \text{Var}(X)}$$

Hence proved.

Two random variables x and y have the following probability density functions

$$f(x,y) = \begin{cases} 2-x-y & 0 \leq x \leq 1, 0 \leq y \leq 1, \\ 0 & \text{otherwise} \end{cases}$$

- find
- marginal density functions of x and y
 - $\text{Var}(x)$ and $\text{Var}(y)$
 - co-variance between x and y

Sol

(i)

$$\begin{aligned} f_{x_1}(x) &= \int_{-\infty}^{\infty} f(x,y) dy \\ &= \int_0^1 (2-x-y) dy \\ &= \left[2y - xy - \frac{y^2}{2} \right]_0^1 \end{aligned}$$

$$= \frac{3}{2} - x$$

$$\therefore f_{y_1}(y) = \frac{3}{2} - y, \quad 0 \leq y \leq 1, \\ = 0, \quad \text{elsewhere}$$

$$\begin{aligned} f_{y_1}(y) &= \int_{-\infty}^{\infty} f(x,y) dx \\ &= \int_0^1 (2-x-y) dx \\ &= \left(2x - \frac{x^2}{2} - xy \right)_0^1 \\ &= \frac{3}{2} - y, \quad 0 \leq y \leq 1, \\ &= 0, \quad \text{elsewhere} \end{aligned}$$

$$\text{⑥} \quad \text{Var}(x) = E(x^2) - [E(x)]^2$$

$$\begin{aligned} E(x^2) &= \int_{-\infty}^{\infty} x^2 \cdot f_x(x) dx \\ &= \int_0^1 x^2 (3/2 - x) dx \\ &= \left[\frac{3}{2} \cdot \frac{x^3}{3} - \frac{x^4}{4} \right]_0^1 = 5/12 \end{aligned}$$

$$\begin{aligned} E[x^2] &= \int_0^1 x^2 (3/2 - x) dx \\ &= \left[3/2 \cdot \frac{x^3}{3} - \frac{x^4}{4} \right]_0^1 = 1/4 \end{aligned}$$

$$\therefore \text{Var}(x) = E(x^2) - [E(x)]^2$$

$$= 1/4 - (5/12)^2$$

$$= 1/4 - \frac{25}{144} = \cancel{\frac{144}{144}} \frac{36-25}{144} = \underline{\underline{\frac{11}{144}}}$$

Similarly, $E[Y] = 5/12$,

$$E[Y^2] = 1/4$$

$$\therefore \text{Var}(Y) = \cancel{\frac{144}{144}} \frac{11}{144}$$

(iii)

$$\text{Cov}(xy) = E[xy] - E(x) \cdot E(y)$$

$$E[xy] = \int_0^1 \int_0^1 xy \cdot (2-xy) dx dy$$

$$= \int_0^1 \int_0^1 (2xy - x^2y - xy^2) dx dy$$

$$= \int_0^1 \left[\frac{x^2}{2} \cdot y - \frac{x^3}{3} \cdot y - \frac{x^2}{2} y^2 \right]_0^1 dy$$

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

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

$$= \left[\frac{2}{3} \cdot \frac{y^2}{2} - \frac{y^3}{6} \right]_0^1$$

$$= \left(\frac{2}{3} \cdot \frac{1}{2} - \frac{1}{6} \right) = \frac{2}{6} - \frac{1}{6} = \underline{\underline{\frac{1}{6}}}$$

$$\therefore \text{Cov}(xy) = E[xy] - E(x) \cdot E(y)$$

$$= \frac{1}{6} - \frac{5}{12} \times \frac{5}{12}$$

$$= \frac{1}{6} - \frac{25}{144} = \frac{24 - 25}{144} = -\frac{1}{144}$$

$$\therefore \text{Cov}(x,y) = \underline{\underline{-\frac{1}{144}}}$$

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A joint density function of random variables
X and Y is given by

$$f(x,y) = 4xy e^{-(x^2+y^2)}, \quad x>0, y>0$$

Show that X, Y are statistically independent
random variables.

Sol

$$f_{x,y}(x,y) = f_x(x) * f_y(y)$$

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

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

$$= 4xe^{-x^2} \int_0^{\infty} ye^{-y^2} dy$$

$$y^2 = t$$

$$2ydy = dt$$

$$= \frac{4xe^{-x^2}}{2} \int_0^{\infty} e^{-t} dt$$

$$= xe^{-x^2} \left[-e^{-t} \right]_0^{\infty} = xe^{-x^2}$$

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

$$\therefore f_{x,y}(x,y) = f_x(x) * f_y(y)$$

Hence X, Y are independent

Let x be the outcome from the rolling of the first die and y be the outcome from the rolling of the second die. What is the joint probability of the event $x \leq 3$ and $y > 3$

$$(1,4) (1,5) (1,6) (2,4) (2,5) (2,6) \\ (3,4) (3,5) (3,6)$$

$$P(x \leq 3, y > 3) = 9/36 = 1/4$$

Two random variables x and y have a joint density function

$$f(x,y) = K(x^2y + 2xy + y^2), \quad 0 \leq x \leq 1 \\ 0 \leq y \leq 1 \\ = 0 \quad \text{elsewhere}$$

Find the value of K and for which the r.v. x and y are statistically independent

Ans

$$f_{x,y}(x,y) = f_x(x) * f_y(y)$$

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

$$= \int_0^1 K (xy + 2xy + a) dy$$

$$= K \left[\frac{a \cdot y^2}{2} + 2xy + \frac{y^2}{2} + ay \right]_0^1$$

$$= K \left[\frac{x}{2} + 2ax + \frac{a}{2} + a \right]$$

$$= K \left[\frac{5x}{2} + a + \frac{a}{2} \right] \quad \rightarrow \textcircled{1}$$

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

$$= \int_0^1 K (xy + 2xy + y + a) dx$$

$$= K \left[y \frac{dx}{2} + ax + xy + ax \right]_0^1$$

$$f_{x,y}(x,y) = \textcircled{1} * \textcircled{2}$$

$$= K \left[\frac{y}{2} + 1 + y + a \right]$$

$$= K \left[\frac{3y}{2} + a + 1 \right] \quad \rightarrow \textcircled{2}$$

$$\therefore K [xy + 2xy + y + a] = K \left[\frac{5x}{2} + a + \frac{a}{2} \right] * K \left[\frac{3y}{2} + a + 1 \right]$$

$$K = \frac{xy + 2xy + y + a}{\left[\frac{5x}{2} + a + 1 \right] \left[\frac{3y}{2} + a + 1 \right]}$$

prove the following

$$\textcircled{a} \quad \text{cov}(ax, by) = ab \cdot \text{cov}(x, y)$$

$$\textcircled{b} \quad \text{var}(ax + by) = a^2 \cdot \text{var}(x) + b^2 \cdot \text{var}(y) + 2ab \cdot \text{cov}(x, y)$$

Sol:

$$\begin{aligned}\textcircled{a} \quad \text{cov}(ax, by) &= E \left[\{ax - E(ax)\} \{by - E(by)\} \right] \\ &= E \left[\{ax - a \cdot E(x)\} \{by - b \cdot E(y)\} \right] \\ &= a \cdot b \cdot E \left[\{x - E(x)\} \{y - E(y)\} \right] \\ &= ab \cdot \text{cov}(x, y)\end{aligned}$$

$$\begin{aligned}\textcircled{b} \quad \text{var}(ax + by) &= E \left[\{(ax + by) - E(ax + by)\}^2 \right] \\ &= E \left[\{ax + by - a \cdot E(x) - b \cdot E(y)\}^2 \right] \\ &= E \left[\{a(x - E(x)) + b(y - E(y))\}^2 \right] \\ &= E \left[a^2 [x - E(x)]^2 + b^2 [y - E(y)]^2 + 2ab \cdot [x - E(x)][y - E(y)] \right] \\ &= a^2 \cdot E \left[\{x - E(x)\}^2 \right] + b^2 \cdot E \left[\{y - E(y)\}^2 \right] + \\ &\quad 2ab \cdot E \left\{ [x - E(x)][y - E(y)] \right\} \\ \Rightarrow a^2 \text{var}(x) + b^2 \text{var}(y) + 2ab \cdot \text{cov}(x, y) & ; \text{ hence proved}\end{aligned}$$

① The characteristic function of a r.v. X

is given by $\phi_x(w) = \frac{1}{(1-J_2w)^{N/2}}$ ✓

find mean and second moment of X

Sol:

$$\text{Mean } E(X) = \frac{1}{J} \cdot \frac{d}{dw} \phi_x(w) \Big|_{w=0}$$

$$\frac{d}{dw} \phi_x(w) = \frac{d}{dw} \left[\frac{1}{(1-J_2w)^{N/2}} \right]$$

$$= \frac{d}{dw} \left[(1-J_2w)^{-N/2} \right]$$

$$= +\frac{N}{2} \cdot (1-J_2w)^{\frac{-N}{2}-1} \cdot (-J_2) = \cancel{\frac{N}{2}}$$

$$= \frac{J \cdot N}{(1-J_2w)^{N/2+1}}$$

$$E(X) = \frac{1}{J} \cdot \frac{d}{dw} \phi_x(w) \Big|_{w=0} = \frac{N}{J}$$

second moment

$$E(X^2) = \left(\frac{1}{J} \right)^2 \cdot \frac{d^2}{dw^2} \phi_x(w) \Big|_{w=0}$$

Complex

$$\frac{d^N}{d\omega^N} \rho_p(\omega) = \frac{d}{d\omega} \left[JN (1 - J^2 \omega)^{-\left(\frac{N}{2} + 1\right)} \right]$$

$$= +JN \cdot \left(1 + \frac{N}{2}\right) (1 - J^2 \omega)^{-\left(\frac{N}{2} + 1\right)} \cdot \left(+ \frac{2J}{\uparrow}\right)$$

 $\frac{N}{2} + 1$

$$= \frac{(J)^N \cdot 2N \cdot \left(\frac{N}{2} + 1\right)}{(1 - J^2 \omega)^{\left(\frac{N}{2} + 1\right)}}$$

$$E(Y^N) = (1/J)^N \cdot \frac{d^N}{d\omega^N} \cdot \rho_p(\omega) \Big|_{\omega=0}$$

$$= 2N \left(\frac{N}{2} + 1\right)$$

- ② a) find a constant b (in terms of a) so that
 the function $f_{xy}(x,y) = b \cdot e^{-bx+by}$ for $0 \leq x \leq a$,
 $0 \leq y \leq a$
 $= 0$ elsewhere
 is a valid joint density function.

- b) find an expression for the joint distribution function

Sol:-

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

$$= \int_0^a \int_0^a b \cdot e^{-bx+by} dx dy = 1$$

$$= b \cdot \int_0^a e^{-bx} \left[-e^{by} \right]_0^a dx = 1$$

$$= b \cdot \int_0^a e^{-bx} dx = 1$$

$$= b \left[-e^{-bx} \right]_0^a = 1$$

$$= b (1 - e^{-a}) = 1$$

$$\Rightarrow b = \frac{1}{1 - e^{-a}}$$

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

$$= \int_0^{\infty} \int_0^y \frac{1}{1-e^a} \cdot e^{-w} \cdot e^{-y} dw dy$$

$$= \frac{1}{1-e^a} \int_0^{\infty} e^{-w} (-e^{-y})_0^y dw$$

$$= \frac{1-e^{-y}}{1-e^a} \int_0^{\infty} e^{-w} dw$$

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

$$= \frac{(1-e^{-y})(1-e^{-\infty})}{(1-e^a)}$$

$$\therefore F_{X,Y}(x,y) = 0 \quad \text{for } w < 0, y < 0$$

$$= \frac{(1-e^{-w})(1-e^{-y})}{(1-e^a)} \quad \text{for } 0 < w < a, 0 < y < a$$

$$= 1, \quad w > a$$

Ex-15-1

If the function $f(x,y) = b e^{-2x} \cdot \cos(y/h)$ for
 $0 \leq x \leq 1,$
 $0 \leq y \leq \pi$

$= 0,$ elsewhere

where 'b' is a positive constant, is valid joint
 probability density function, find 'b'. ✓

Sol:

$$= b \int_0^1 \int_0^\pi b e^{-2x} \cos(y/h) dy dx = 1$$

$$= b \int_0^1 e^{-2x} \left[\int_0^\pi \cos(y/h) dy \right] dx = 1$$

$$= b \int_0^1 e^{-2x} \left[\frac{h}{2} \sin(y/h) \right]_0^\pi dx = 1$$

$$= b \int_0^1 e^{-2x} dx = 1$$

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

$$= b (1 - e^{-2}) = 1$$

$$\Rightarrow b = \frac{1}{(1 - e^{-2})}$$

$\rightarrow \leftarrow$

① The density function

$$f_{xy}(x,y) = \frac{1}{9}, \quad 0 \leq x \leq 2, 0 \leq y \leq 3 \\ = 0, \quad \text{elsewhere}$$

② Show that x, y are st. independent

③ " , y, y are uncorrelated

S8

$$f_x(x) = \int_{y=0}^3 f(x,y) dy$$

$$= \frac{x}{9} \int_0^3 y dy = \frac{x}{9} \cdot \left[\frac{y^2}{2} \right]_0^3$$

$$= x/2$$

$$\therefore f_x(x) = x/2 \quad \text{for } 0 \leq x \leq 2 \\ = 0 \quad \text{elsewhere}$$

$$f_y(y) = \frac{1}{9} \int_{x=0}^2 x dx = \frac{1}{9} \cdot \left[\frac{x^2}{2} \right]_0^2 \\ = 2/9$$

$$f_y(y) = \frac{2y}{9}, \quad \text{for } 0 \leq y \leq 3 \\ = 0, \quad \text{elsewhere}$$

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

∴ independent

⑥ x, y are uncorrelated, if $\rho_{xy} = 0$

$$\rho_{xy} = \frac{\text{cov}(x, y)}{\sigma_x \cdot \sigma_y}$$

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

Since x, y are independent

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

$$\Rightarrow \text{cov}(x, y) = 0$$

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

x, y are uncorrelated

✓

①.

Two r.v.s x and y are related by the expression $y = ax + b$, where a and b are any real numbers.

② Show that their covariance $C_{xy} = a \cdot \sigma_y^2$

③ Show that their correlation coefficient is

$\rho = 1$, if $a > 0$ for any b
 $= -1$ if $a < 0$ for any b

Sol

$$\begin{aligned} \text{cov}(xy) &= E(xy) - E(x) \cdot E(y) \\ &= E[x(ax+b)] - E(x) \cdot E(ax+b) \\ &= E[ax^2 + bx] - E(x)[a \cdot E(x) + b] \\ &= a \cdot E(x^2) + b \cdot E(x) - a \cdot [E(x)]^2 + b \cdot E(x) \\ &= a [E(x^2) - \{E(x)\}^2] \\ &= a \cdot \text{var}(x) \end{aligned}$$

$$\therefore a \cdot \sigma_y^2$$

$$\text{④ } \rho_{xy} = \frac{\text{cov}(xy)}{\sigma_x \cdot \sigma_y}$$

$$\sigma_y^2 = \text{var}(y) = \text{var}(ax+b) = a^2 \cdot \text{var}(x)$$

$$\sigma_y = a \cdot \sqrt{\text{var}(x)}$$

$$\rho_{xy} = \frac{a \cdot \text{var}(x)}{\sqrt{\text{var}(x) \cdot a \cdot \sqrt{\text{var}(x)}} \cdot a}$$

$$\therefore \rho_{xy} = 1$$

if $a < 0$, $\text{cov}(x, y) = -a \cdot \text{var}^2 = -a \cdot \text{var}(x)$

$$\therefore \rho_{xy} = \frac{-a \cdot \text{var}(x)}{\sqrt{\text{var}(x)} \cdot a \cdot \sqrt{\text{var}(x)}}$$
$$= -1$$

$\therefore \rho = 1$ if $a > 0$ for any b
 $\rho = -1$ if $a < 0$ for any b

b

EXTRA PROBLEMS — U-4

① Let $f(x,y) = xy$ for $0 \leq x \leq 1, 0 \leq y \leq 1$
 $= 0$, otherwise

- find the conditional density of ① x given y
- ② y given x

Sol: ① $f(x|y) = \frac{f(x,y)}{f(y)}$

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

$$\therefore f(x|y) = \frac{xy}{y+y^2} \quad \text{for } 0 \leq x \leq 1, 0 \leq y \leq 1 \\ = 0 \quad \text{for other } x, 0 \leq y \leq 1$$

② $f(y|x) = \frac{f(x,y)}{f(x)}$

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

$$\therefore f(y|x) = \frac{xy}{x + \frac{1}{2}} \quad \text{for } 0 \leq x \leq 1, 0 \leq y \leq 1 \\ = 0, \quad 0 \leq x \leq 1, \text{ other } y$$

⑧ Given the function $f_{x,y}(x,y) = b(x+y)^2$ for
 $-2 < x < 2$,
 $-3 < y < 3$.
 $= 0$, elsewhere

- ① find the constant 'b' such that this is a valid joint density function

- ② Determine the marginal density functions $f_x(x)$ & $f_y(y)$

Sol:

$$\textcircled{1} \quad \int_{-2}^2 \int_{-3}^3 b(x+y)^2 dx dy = 1 \quad \begin{matrix} \text{small} \\ \text{small} \end{matrix}$$

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

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

$$\Leftrightarrow b \int_{-2}^2 (6x^2 + 18) dx = 1$$

$$\Leftrightarrow b \left[\frac{6x^3}{3} + 18x \right]_{-2}^2 = 1$$

$$b = \underline{\underline{1/104}}$$

⑥

$$f_x(x) = \int_{-3}^3 f_{xy}(xy) dy$$

y > 0 only

$$= \frac{1}{104} \left[xy + \frac{y^3}{3} + x y^2 \right]_{-3}^3$$

$$= \frac{1}{104} (8x^2 + 18) \quad \text{for } -2 < x < 2$$

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

$$f_y(y) = \int_{-2}^2 f_{xy}(xy) dx$$

$$= \frac{1}{104} \int_{-2}^2 (x+ey^2)^2 dx$$

$$= \frac{1}{104} \int_{-2}^2 (x^2 + 4y^2 + 2xy) dx$$

$$= \frac{1}{104} \left[\frac{x^3}{3} + 4y^2x + 2xy^2 \right]_{-2}^2$$

$$= \frac{1}{104} [4y^2 + 16/3]$$

$$\therefore f_y(y) = \frac{1}{104} [4y^2 + 16/3] \quad \text{for } -3 < y < 3$$

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

①

Two discrete random variables x and y have

$$P(x=0, y=0) = 2/9, \quad P(x=0, y=1) = 4/9$$

$$P(x=1, y=0) = 4/9, \quad P(x=1, y=1) = 5/9$$

Are x and y independent?

Sol:

for independence

$x \setminus y$

$$P(x=x_i, y=y_j) = P(x=x_i) \cdot P(y=y_j)$$

0 1

$$P(x,y) = \begin{matrix} & 0 \\ 0 & \begin{bmatrix} 2/9 & 4/9 \\ 4/9 & 5/9 \end{bmatrix} \end{matrix}$$

$$P(x=0, y=0) = 2/9$$

$$P(x=0) = 2/9 + 4/9 = 6/9$$

$$P(y=0) = 2/9 + 4/9 = 6/9$$

$$\therefore P(x=0, y=0) \neq P(x=0) \cdot P(y=0)$$

Hence, x and y are not independent.

(1998-Supply)

① The joint pdf of the random variables

$$x \text{ and } y \text{ is } f_{x,y}(x,y) = \frac{1}{4} \cdot e^{-|x| - |y|} \text{ for } -\infty < x < \infty, -\infty < y < \infty$$

② Are x and y statistically independent?

③ Find $E(P(X \leq 1, Y \leq 0))$

Sol: ② x and y are statistically independent, if

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

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

$$= \int_{-\infty}^{\infty} \frac{1}{4} \cdot e^{-|x| - |y|} dy$$

$$= \frac{1}{4} \cdot e^{-|x|} \cdot \int_{-\infty}^{\infty} e^{-|y|} dy$$

$$= \frac{1}{4} \cdot e^{-|x|} \cdot \left[\int_{-\infty}^0 e^y dy + \int_0^{\infty} e^{-y} dy \right]$$

$$= \frac{1}{4} \cdot e^{-|x|} [1+1] = \frac{e^{-|x|}}{2} \text{ for } -\infty < x < \infty$$

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

$$= \frac{1}{4} \cdot e^{-|y|} \cdot \int_{-\infty}^{\infty} \frac{-|x|}{e^{-|x|}} dx$$

$$= \frac{1}{4} \cdot e^{-|y|} \cdot \left[\int_{-\infty}^0 e^x dx + \int_0^{\infty} e^{-x} dx \right]$$

$$= \frac{1}{4} \cdot e^{-|y|} [1+1]$$

$$= \frac{e^{-|y|}}{2} \text{ for } -\infty < y < \infty$$

$$\therefore f_x(x) \cdot f_y(y) = \frac{1}{4} \cdot e^{-|x| - |y|}$$

$$= f_{x,y}(x,y)$$

Hence, x and y are independent

$$\textcircled{b} \quad P(x \leq 1, y \leq 0) = \int_{-\infty}^1 \int_{-\infty}^0 f(x,y) dy dx$$

$$= \int_{-\infty}^1 \int_{-\infty}^0 \frac{1}{4} e^{-|x| - |y|} dx \cdot dy$$

$$= \frac{1}{4} \int_{-\infty}^1 e^{-|x|} \left[\int_{-\infty}^0 e^{-|y|} dy \right] dx$$

$$= \frac{1}{4} \int_{-\infty}^1 e^{-|x|} \left[\int_{-\infty}^0 e^{-y} dy \right] dx$$

$$= \frac{1}{4} \cdot \int_{-\infty}^1 e^{-|x|} dx$$

$$= \frac{1}{4} \left[\int_{-\infty}^0 e^x dx + \int_0^1 e^{-x} dx \right]$$

$$= \frac{1}{4} \left[1 + [-e^{-x}]_0^1 \right]$$

$$= \frac{1}{4} \cdot [2 - e^1]$$

— 4 —

Let x and y be independent and random variables ①
 identically distributed
 UNIT-5

Each having density function

$$f_x(x) = \begin{cases} 2e^{-2x}, & x > 0 \\ 0, & \text{elsewhere} \end{cases}$$

Find ① $E(x+y)$ ② $E(x^2+y^2)$ ③ $E(xy)$

Sol

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

\therefore Since it is given that x and y are
 identically distributed independent r.v.'s

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

$$\textcircled{1} \quad \therefore E(x+y) = \int_0^{\infty} \int_0^{\infty} (x+y) \cdot 2e^{-2x} \cdot 2e^{-2y} dx dy$$

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

$$\textcircled{2} \quad E(x^2+y^2) = \int_0^{\infty} \int_0^{\infty} (x^2+y^2) \cdot 2e^{-2x} \cdot 2e^{-2y} dx dy$$

$$\textcircled{3} \quad E(xy) = \int_0^{\infty} \int_0^{\infty} xy \cdot 2e^{-2x} \cdot 2e^{-2y} dx dy$$

$$= Y_4$$

① The joint space for two random variables x and y and corresponding probabilities are shown in table

xy	(1,1)	(2,2)	(3,3)	(4,4)
P	0.12	0.3	0.35	0.15

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→ KM

① find $F_{X,Y}(x,y)$

$$= P\{x=1, y=1\} + P\{x=2, y=2\} + \dots$$

$$= 0.12 + 0.3 + 0.35 + 0.15 = 1$$

② $P\{x \leq 2, y \leq 2\} = P(x=1, y=1) + P(x=2, y=2)$
 $= 0.12 + 0.3 = 0.5$

③ $P\{1 < x \leq 3, y \geq 3\}$
 $x=2, 3 \quad y=3, 4$

$$= P(x=2, y=3) + P(x=2, y=4) + P(x=3, y=3) + P(x=3, y=4)$$

$$= 0 + 0 + 0.35 + 0 = 0.35$$

Let x and y be two random variables, each taking three values -1, 0 and 1 and having the joint probability distribution shown

$x \backslash y$	-1	0	1	Total
-1	0	0.2	0	0.2
0	0.1	0.2	0.1	0.4
1	0.1	0.2	0.1	0.4
Total	0.2	0.6	0.2	1.0

find (i) $E[x]$ and $E[y]$

(ii) prove that x and y are uncorrelated random variables

(iii) find $V[x]$ and $V[y]$

Sol: (i) $E[x] = \sum_{i=-1}^1 x_i p(x_i)$

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

$$= -0.2 + 0 + 0.4 = \underline{0.2}$$

$$E[y] = \sum_{j=-1}^1 y_j p(y_j)$$

$$= (-1)(0.2) + (0)(0.6) + (1)(0.2)$$

$$= -0.2 + 0 + 0.2 = \underline{0}$$

Q. If x and y are uncorrelated, $E[xy] = E[x] \cdot E[y]$.

\therefore Their covariance is zero.

$$E[xy] = \sum_{i,j=1}^1 x_i y_j P(x_i, y_j)$$

$$\begin{aligned} &= (-1)(-1) \cdot 0 + (0)(-1) \cdot 0 \cdot 1 + (1)(-1) \cdot 0 \cdot 1 + \\ &\quad (-1) \cdot 0 \cdot 0 \cdot 2 + (0) \cdot 0 \cdot 0 \cdot 2 + (1) \cdot 0 \cdot 0 \cdot 2 + \\ &\quad (1)(1) \cdot 0 + (0)(1) \cdot 0 \cdot 1 + (1)(1) \cdot 0 \cdot 1 \end{aligned}$$

$$= -0.1 + 0.1 = 0$$

$$E(x) \times E(y) = 0.2 \times 0 = 0$$

$E[xy] = E[x] \cdot E[y]$, the random variables

x and y are uncorrelated.

$$V(x) = E[x^2] - [E(x)]^2$$

$$E(x^2) = \sum_{i=1}^1 x^2 P(x_i)$$

$$= (-1)^2 \cdot 0.3 + (0)^2 \cdot 0.4 + (1)^2 \cdot 0.4$$

$$= 0.1 + 0.2 + 0.4 = 0.6$$

$$V(x) = 0.6 - (0.2)^2 = 0.56$$

$$\begin{aligned} E(y^2) &= \\ &= (-1)^2 \cdot 0.2 + (0)^2 \cdot 0.1 + (1)^2 \cdot 0.1 \\ &= 0.1 + 0.1 = 0.2 \end{aligned}$$

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

$$= 0.2 - (0.2)^2 = 0.4$$

UNIT 2

Part 8

UNIT 2

Part 9

UNIT 2

Part 10