

UNIT - II

3. Operation on single random variable

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Introduction:-

The random variable was introduced in chapter-2 as a means of providing a systematic definition of events defined as a sample space specifically if formed a mathematical model for describing characteristics of some real physical world random phenomena.

Mathematical expectation:-

→ The average value of or mean value of a density function is known as mathematical expectation and it is denoted by $E(x)$ (or) m (or) μ . (or) \bar{x} .

Mathematical expectation of random variable (or) Expected value of "x" (or) Mean value of "x":-

Expected value of random variable is denoted by

$E(x)$ (or) \bar{x} (or) μ .

If "x" is a continuous random variable with density function $f_x(x)$ then the expected value of the random variable is

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

provided that the R.H.S series is absolutely convergent

$$\therefore E(x) = \left| \int_{-\infty}^{\infty} x \cdot f_x(x) dx \right| < \infty$$

If "x" is a discrete random variable with assigned values x_1, x_2, \dots, x_n having probabilities $P(x_1), P(x_2), \dots, P(x_n)$, respectively.

Then the density function is

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

The expected value of a discrete random variable is defined as

$$E(x) = \sum_{\text{all } x} x f_x(x) \quad (\text{or}) \quad = \sum_{i=1}^N x_i f_x(x_i).$$

"By using expected value of random variable "x" we will find out the centered value of density function."

Let us consider all assigned values of random variable

"x" having equal probabilities

$$\text{i.e. } P(x_1) = P(x_2) = \dots = P(x_N) = \frac{1}{N}$$

$$E(x) = x_1 P(x_1) + x_2 P(x_2) + \dots + x_N P(x_N)$$

$$= \frac{1}{N} P(x_1) + \frac{1}{N} x_2 + \dots + \frac{1}{N} x_N$$

$$E(x) = \frac{1}{N} (x_1 + x_2 + \dots + x_N)$$

Hence the probabilities of all assigned values are equal then the expected value is equal to Arithmetic mean (or) Average mean.

Expected value of a function of a random variable:-

Let us consider a random variable "x" and $g(x)$ is a function of random variable "x".

If "x" is continuous random variable then the expected value of a function of random variable is

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

If "x" is discrete random variable then the expected value of a function is defined as

$$\bar{g} = E[g(x)] = \sum_{all x} g(x) f_x(x) = \sum_{i=1}^N g(x_i) f_x(x_i)$$

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Theorems on expectation :-

Let us consider random variable "x" with density function

$f_x(x)$ is

(i) $E[\text{constant}] = \text{constant}$

$$\text{i.e. } E[k] = k.$$

Proof :- From the definition of expectation

$$E[x] = \sum_{i=1}^N x_i f_x(x_i)$$

$$E[k] = \sum_{i=1}^N k f_x(x_i) \quad \left[\because \sum_{i=1}^N f_x(x_i) = 1 \right]$$

$$= k \sum_{i=1}^N f_x(x_i)$$

$$= k (1)$$

$$\boxed{E[k] = k}$$

(ii) $E(kx) = k E(x)$

Proof :- From the definition of expectation

$$E[x] = \sum_{i=1}^N x_i f_x(x_i)$$

$$E[kx] = \sum_{i=1}^N k x_i f_x(x_i)$$

$$= k \sum_{i=1}^N x_i f_x(x_i)$$

$$= k E[x]$$

$$\boxed{\therefore E[kx] = k E[x]}$$

(iii) $E[ax+b] = a E[x] + b$

Proof :- From the definition of expectation

$$E[x] = \sum_{i=1}^N x_i f_x(x_i)$$

$$E[ax+b] = \sum_{i=1}^N (ax_i + b) f_x(x_i)$$

$$= \sum_{i=1}^N ax_i f_x(x_i) + \sum_{i=1}^N b f_x(x_i)$$

$$= a \sum_{i=1}^N x_i f_x(x_i) + b \sum_{i=1}^N f_x(x_i)$$

$$\boxed{E[ax+b] = a E[x] + b}$$

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Additional theorem on expectation :-

Let us consider two random variables "x & y" with the joint density function $f_{xy}(x,y)$ then expectation of

$$E[x+y] = E[x] + E[y]$$

Proof :- Let us consider two random variables "x and y" with joint function $f_{xy}(x,y)$

From the definition of expectation

$$E[x] = \sum_{i=1}^N x_i f_x(x_i)$$

$$E[y] = \sum_{j=1}^N y_j f_y(y_j)$$

$$E[x+y] = \sum_{i=1}^N \sum_{j=1}^N [x_i + y_j] \cdot f_{xy}(x_i, y_j)$$

$$= \sum_{i=1}^N \sum_{j=1}^N x_i f_{xy}(x_i, y_j) + \sum_{i=1}^N \sum_{j=1}^N y_j f_{xy}(x_i, y_j)$$

We know that the marginal density functions of "x & y" are

$$f_x(x_i) = \sum_{j=1}^N f_{xy}(x_i, y_j) \longrightarrow ①$$

$$f_{Yj}(y_j) = \sum_{i=1}^N f_{XY}(x_i, y_j) \rightarrow ② \quad (3.3)$$

$$\begin{aligned} E[X+Y] &= \sum_{i=1}^N x_i \cdot \sum_{j=1}^N f_{XY}(x_i, y_j) + \sum_{j=1}^N y_j \cdot \sum_{i=1}^N f_{XY}(x_i, y_j) \\ &= \sum_{i=1}^N x_i \cdot f_X(x_i) + \sum_{j=1}^N y_j \cdot f_Y(y_j) \end{aligned}$$

$$\boxed{E(X+Y) = E(X) + E(Y)}$$

(v) Multiplication theorem of expectation :-

If x & y are independent random variables then

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

Proof :- From the definition of expectation

$$E[X] = \sum_{i=1}^N x_i f_X(x_i)$$

$$E[Y] = \sum_{j=1}^N y_j f_Y(y_j)$$

$$E(XY) = \sum_{i=1}^N \sum_{j=1}^N x_i y_j \cdot f_{XY}(x_i, y_j)$$

If x & y are independent random variables then

$$f_{XY}(x_i, y_j) = f_X(x_i) f_Y(y_j)$$

$$E(XY) = \sum_{i=1}^N \sum_{j=1}^N x_i y_j \cdot f_X(x_i) f_Y(y_j)$$

$$= \sum_{i=1}^N x_i f_X(x_i) \cdot \sum_{j=1}^N y_j f_Y(y_j)$$

$$\boxed{E(XY) = E(X) \cdot E(Y)}$$

(vi) Theorem-6 :- If $x \geq 0$, then $E(x) \geq 0$.

Proof :- From the definition of expectation

$$E[x] = \sum_{i=1}^N x_i f_X(x_i)$$

Here, as per problem, $x_i \geq 0$,

From the property of $f_X(x)$,

$$f_X(x_i) \geq 0$$

$$x_i \cdot f_X(x_i) \geq 0.$$

$$\sum_{i=1}^N x_i \cdot f_X(x_i) \geq 0.$$

$$E[X] \geq 0.$$

Theorem-7 :- If $x \geq y$, then $E(x) \geq E(y)$

Proof :-

Given $x \geq y$,

$$x - y \geq y - y$$

$$x - y \geq 0.$$

Taking expectation on both sides

$$E(x - y) \geq 0$$

$$E(x) - E(y) \geq 0$$

$$E(x) \geq E(y)$$

Moments of a random variable :-

The n^{th} moments of a random variable can be divided into two types

(i) Moments about origin

(ii) Moments about mean (or) central moments :-

Moments about origin (m_n or μ'_n) :-

They are denoted by m_n or μ'_n and is defined as

$$M_n = \mu_n = E(x^n)$$

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If 'x' is a continuous random variable then

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

If 'x' is a discrete random variable then

$$M_n = \mu_n = E(x^n) = \sum_{i=1}^N x_i^n f_x(x_i)$$

Case(i): If $n=1$, then $m_1 = E(x) = \mu$

i.e. the first moment about origin is the mean value of a random variable "x".

Case(ii): If $n=0$, then $M_0 = E(x^0) = E(1) = 1$

i.e. the zeroth moment about origin is the area under the PDF

Case(iii): If $n=2$, then $M_2 = E(x^2)$

The second moment about origin is the mean square value of a random variable "x" and this is also equal to the "total average power".

Moments about mean or central moments:-

The n^{th} moment about mean (or) n^{th} central moment is denoted by H_n and is defined as $H_n = E[(x-\bar{x})^n]$

$$\mu_n = E[(x-\bar{x})^n] \text{ or } H_n = E[(x-\mu)^n].$$

Here \bar{x}, μ are mean of random variable "x". If x is

$$H_n = E(x-\bar{x})^n = \int_{-\infty}^{\infty} (x-\bar{x})^n f_x(x) dx.$$

If 'x' is discrete random variable then

$$H_n = E(x-\bar{x})^n = \sum_{i=1}^N (x_i - \bar{x})^n f_x(x_i)$$

Case(i): If $n=0$, then

$$H_0 = E[(x-\bar{x})^0] = E(1) = 1.$$

i.e. the zeroth centered moment about mean is the area under the PDF.

Case(ii): If $n=1$, then

$$H_1 = E(x-\bar{x})^1 = E(x) - \bar{x} = \bar{x} - \bar{x} = 0$$

i.e. the first centered moment about mean is equal to the zero.

Case(iii): If $n=2$, then

$$H_2 = E[(x-\bar{x})^2] = \sigma_x^2$$

i.e. the second moment about mean is the variance of random variable "x".

Variance of Random Variable "x":-

The variance of random variable "x" is denoted by $\text{Var}(x)$ or σ_x^2 . and is defined as second central moment

$$\text{ie., } \text{Var}(x) = \sigma_x^2 = E[(x-\bar{x})^2]$$

If "x" is continuous random variable then the variance of "x" is

$$\text{Var}(x) = \sigma_x^2 = E[(x-\bar{x})^2] = \int_{-\infty}^{\infty} (x-\bar{x})^2 f_x(x) dx.$$

If 'x' is discrete random variable then

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

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The variance of x is to measure the dispersion (variance) about its mean value.

If the assigned values are nearer to the mean value then the "variance is small".

If the assigned values are away to the mean value then the "variance is large".

It is dimensionless (no units) quantity because of the reason for measuring the deviation we will define the "standard deviation".

The standard deviation is denoted by " σ_x " and is defined as square root of variance

$$\text{ie. } \sigma_x = \sqrt{\text{Var}(x)}$$

It is having the units same that as random variable units

Theorems on Variance :-

$$(i) \quad \text{Theorem-1: } \text{Var}(x) = E[x^2] - [E(x)]^2 \quad (\text{or}) \quad \text{Var}(x) = E[x^2] - \bar{x}^2$$

Proof:- From the definition of the variance.

$$\begin{aligned} \text{Var}(x) &= E[(x-\bar{x})^2] \\ &= E[x^2 + (\bar{x})^2 - 2x\bar{x}] \\ &= E[x^2] + E[\bar{x}^2] - 2\bar{x}\bar{x} \\ &= E[x^2] + E[\bar{x}^2] - 2[E(x)]^2 \end{aligned}$$

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

(ii) Theorem-2: $\text{Var}(cx) = c^2 \text{Var}(x)$

Proof:- From the definition of variance

$$\text{Var}(x) = E[(x-\bar{x})^2] \rightarrow ①$$

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

$$= E[c^2(x-\bar{x})^2]$$

$$= c^2 E[(x-\bar{x})^2]$$

$$= c^2 \cdot \text{Var}(x)$$

$$\therefore \boxed{\text{Var}(cx) = c^2 \text{Var}(x)}$$

(iii)

Theorem-3: If "x & y" are independent random variable

then $\text{Var}(x+y) = \text{Var}(x) + \text{Var}(y)$. and

$$\text{Var}(x-y) = \text{Var}(x) - \text{Var}(y).$$

Proof:- From the definition of variance.

$$\begin{aligned} \text{Var}(x) &= E[(x-\bar{x})^2] \\ \text{Var}(y) &= E[(y-\bar{y})^2] \end{aligned} \quad \left. \right\} \dots \dots \quad ①$$

Here $\bar{x} = E(x)$ and $\bar{y} = E(y)$.

$$\begin{aligned} \text{Var}(x+y) &= E[(x+y) - E(x+y)]^2 \\ &= E[(x+y) - (E(x) + E(y))]^2 \\ &= E(x+y - \bar{x} - \bar{y})^2 \\ &= E((x-\bar{x}) + (y-\bar{y}))^2 \\ &= E((x-\bar{x})^2 + (y-\bar{y})^2 + 2(x-\bar{x})(y-\bar{y})) \\ &= E(x-\bar{x})^2 + E(y-\bar{y})^2 + 2 E(x-\bar{x}) E(y-\bar{y}) \end{aligned}$$

$$\begin{aligned}
 &= \text{Var}(x) + \text{Var}(y) + 2E(x-\bar{x}) \cdot E(y-\bar{y}) \\
 &= \text{Var}(x) + \text{Var}(y) + 2[E(x) - E(\bar{x})] [E(y) - E(\bar{y})] \\
 &= \text{Var}(x) + \text{Var}(y) + 2(x-\bar{x})(\bar{y}-\bar{y}) \\
 &= \text{Var}(x) + \text{Var}(y) + 2 \cdot 0 \\
 \therefore \boxed{\text{Var}(x+y) = \text{Var}(x) + \text{Var}(y)} \quad (6)
 \end{aligned}$$

$$\begin{aligned}
 \text{Var}(x-y) &= \text{Var}(x+(-y)) \\
 &= \text{Var}(x) + \text{Var}(-y) \\
 &= \text{Var}(x) + (-1)^2 \text{Var}(y) \\
 &= \text{Var}(x) + \text{Var}(y) \\
 \therefore \boxed{\text{Var}(x-y) = \text{Var}(x) + \text{Var}(y)}
 \end{aligned}$$

(iv) Theorem-4:- $\text{Var}(ax+b) = a^2 \text{Var}(x)$

Proof:- From the definition of variance

$$\begin{aligned}
 \text{Var}(x) &= E[(x-\bar{x})^2] \\
 &= E[(ax+b) - E(ax+b)]^2 \\
 &= E[(ax+b) - (aE(x)+b)]^2 \\
 &= E[ax+b-aE(x)-b]^2 \\
 &= E[ax-aE(x)]^2 \\
 &= a^2 [E(x^2) - E(E(x))^2 - 2E(x)E(x)] \\
 &= a^2 [E(x^2) + (E(x))^2 - 2(E(x))^2] \\
 &= a^2 [E(x^2) - (E(x))^2] \\
 \boxed{\text{Var}(ax+b) = a^2 \text{Var}(x)}
 \end{aligned}$$

(3.6)

(v) Theorem-5:- $\text{Var}(\text{constant}) = 0$ (or) $\text{Var}(k) = 0$

Proof:- we know that $\text{Var}(ax+b) = a^2 \text{Var}(x)$

let $a=0$

$$\text{Var}(ax+b) = 0^2 \text{Var}(x)$$

$$\text{Var}(b) = 0$$

$$\boxed{\text{Var}(k)=0}$$

Skew and coefficient of skewness :-

Skew is describing the asymmetry of the density function.

The skew is defined as the third central moment about the

mean i.e. $\boxed{M_3 = E[(x-\bar{x})^3]}$

The measure of asymmetry is known as coefficient of the skewness or skewness.

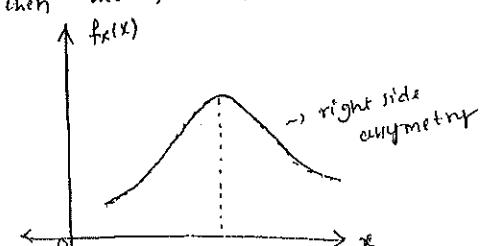
$$\alpha_3 = \frac{M_3}{\sigma^3} = \frac{E(x-\bar{x})^3}{\sigma^3}$$

(\because Here σ = standard deviation)

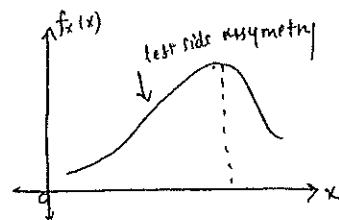
The skewness is dimensionless quantity.

The coefficient of skewness is either positive or negative.

If α_3 is positive, then the function is asymmetry to right side.



If α_3 is negative, then the function is asymmetric to left side



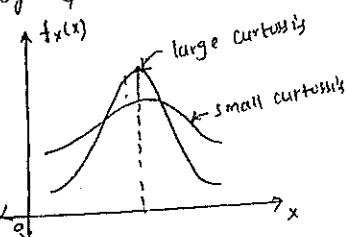
(3.7)

CURTOSIS OR KURTOSIS:-

It measures the degree of peakedness (maximum) is called coefficient of curtosis and it is denoted by α_4

$$\alpha_4 = \frac{H_4}{\sigma^4} = \frac{\mu_4}{\sigma^4}$$

$$\alpha_4 = \frac{E((x-\bar{x})^4)}{\sigma^4}$$



Here H_4 is called the 4th central moment.

σ = standard deviation

Moment generating function:-

The moment generating function of random variable "X" is denoted by $M_x(t)$ and is defined as

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

If "X" is continuous random variable, then

$$M_x(t) = E(e^{tx}) = \int_{-\infty}^{\infty} e^{tx} f_x(x) dx.$$

If "X" is discrete random variable, then

$$M_x(t) = E(e^{tx}) = \sum_{all x} e^{tx} f_x(x) = \sum_{i=1}^{\infty} e^{tx_i} f_x(x_i)$$

$$\text{① } M_x(t) = E(e^{tx}) ; M_y(t) = E(e^{ty})$$

Proof:- The moment generating function of x and y are

$$\text{generating function } M_x(t), M_y(t) \text{ then } M_{x+y}(t) = M_x(t) \cdot M_y(t)$$

③ If x and y are independent random variable with moment

$$M_y(t) = e^{\mu_y t + \frac{1}{2} \sigma_y^2 t^2}$$

$$= e^{\mu_y t + \frac{1}{2} \sigma_y^2 t^2} E(e^{tb + \frac{1}{2} \sigma_y^2 b^2})$$

$$= E(e^{ta + tb + \frac{1}{2} \sigma_y^2 b^2})$$

$$= E(e^{(a+b)t + \frac{1}{2} \sigma_y^2 b^2})$$

$$= e^{\mu_x t + \frac{1}{2} \sigma_x^2 t^2} e^{\mu_y t + \frac{1}{2} \sigma_y^2 t^2}$$

$$= e^{(\mu_x + \mu_y)t + \frac{1}{2} (\sigma_x^2 + \sigma_y^2)t^2}$$

Given the moment generating function of

then moment generating function of $y = ax + b$ is $M_y(t) = e^{bt} M_x(at)$.

② the moment generating function of random variable is $M_x(t)$

$$M_x(t) = E(e^{tx}) = E(e^{(ct)^2})$$

$$M_x(t) = E(e^{ctt})$$

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

From the definition of moment generating function

if the moment generating function of random variable is $M_x(t)$

Proof:-

If x and y are independent random variables then

$$M_{x+y}(t) = E[e^{t(x+y)}]$$

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$$M_{x+y}(t) = E(e^{tx} \cdot e^{ty})$$

N.W.T if x and y are independent random variables then

$$E(x+y) = E(x) + E(y).$$

$$M_{x+y}(t) = E(e^{tx} \cdot e^{ty})$$

$$= E(e^{tx}) \cdot E(e^{ty})$$

$$= M_x(t) \cdot M_y(t)$$

$$\therefore \boxed{M_{x+y}(t) = M_x(t) M_y(t)}$$

(4) If the moment generating function of random variable x is $M_x(t)$ then the moment generating function of random variable y , if $y = \frac{x+a}{b} e^{\frac{t}{b}x}$, then $y = \frac{x+a}{b} e^{\frac{t}{b}x} \cdot M_x(t/b)$

Proof: the moment generating function

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

$$M_y(t) = E(e^{ty})$$

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

$$= E\left(e^{\frac{tx}{b}} \cdot e^{\frac{ta}{b}}\right)$$

$$= e^{\frac{ta}{b}} E\left(e^{\frac{tx}{b}}\right)$$

$$\boxed{M_y(t) = e^{\frac{ta}{b}} M_x(t/b)}$$

Hence proved

The following steps gives the procedure for obtaining the moments about origin from moment generating function :-

Proof: we know that $M_x(t) = E(e^{tx})$.

$$M_x(t) = E\left[1 + \frac{tx}{1!} + \frac{(tx)^2}{2!} + \dots + \frac{(tx)^n}{n!} + \dots \infty\right]$$

$$= E\left[1 + \frac{tx}{1} + \frac{t^2 x^2}{2!} + \frac{t^3 x^3}{3!} + \dots + \frac{t^n x^n}{n!} + \dots \infty\right]$$

$$= 1 + E\left(\frac{tx}{1}\right) + E\left(\frac{t^2 x^2}{2!}\right) + \dots + E\left(\frac{t^n x^n}{n!}\right) + \dots \rightarrow (1)$$

Differentiate with respect to "t" on both sides

$$\frac{\partial}{\partial t} (M_x(t)) \Big|_{t=0} = 0 + E(x) + \frac{t^2 x^2}{2!} E(x^2) + \dots + \frac{t^{n-1} x^{n-1}}{n-1!} E(x^n) \rightarrow (2)$$

$$\frac{\partial}{\partial t} (M_x(t)) \Big|_{t=0} = E(x) + 0 + 0.$$

$$\therefore E(x) = \frac{\partial}{\partial t} (M_x(t)) \Big|_{t=0}$$

This is the first moment about origin

Again differentiate with respect to "t" on both sides on eq(2)

$$\frac{\partial^2}{\partial t^2} (M_x(t)) = 0 + 0 + \dots + \frac{2}{2!} E(x^2) + \frac{6t}{3!} E(x^3) + \dots$$

$$\frac{\partial^2}{\partial t^2} (M_x(t)) \Big|_{t=0} = E(x^2)$$

$$E(x^2) = \frac{\partial^2}{\partial t^2} (M_x(t)) \Big|_{t=0}$$

characteristic function :-

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The characteristic function of a random variable is denoted

by $\phi_x(\omega)$ and is defined as

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

If 'x' is continuous random variable then

$$\phi_x(\omega) = E(e^{j\omega x}) = \int_{-\infty}^{\infty} e^{j\omega x} f_x(x) dx$$

If 'x' is discrete random variable, then

$$\phi_x(\omega) = E(e^{j\omega x}) = \sum_{all x} e^{j\omega x} f_x(x) = \sum_{i=1}^n e^{j\omega x_i} f_x(x_i)$$

Properties of characteristic function :-

$$(i) |\phi_x(\omega)| < 1$$

Proof :- From the definition of characteristic function

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

$$\phi_x(\omega) = \int_{-\infty}^{\infty} e^{j\omega x} f_x(x) dx$$

$$= \left| \int_{-\infty}^{\infty} e^{j\omega x} f_x(x) dx \right|$$

$$\phi_x(\omega) < \int_{-\infty}^{\infty} |e^{j\omega x}| |f_x(x)| dx \quad [\because |ab| \leq |a||b|]$$

$$\phi_x(\omega) < \int_{-\infty}^{\infty} |f_x(x)| dx \quad [\because \int_{-\infty}^{\infty} f_x(x) dx = 1]$$

$$\phi_x(\omega) < \int_{-\infty}^{\infty} f_x(x) dx$$

$$\boxed{\phi_x(\omega) < 1}$$

$$(2) \phi_x(0) = 1$$

Proof :- From the definition of characteristic function

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

$$= \int_{-\infty}^{\infty} e^{j\omega x} f_x(x) dx$$

$$\phi_x(0) = \int_{-\infty}^{\infty} e^0 \cdot f_x(x) dx$$

$$= \int_{-\infty}^{\infty} 1 \cdot f_x(x) dx$$

$$\boxed{\phi_x(0) = 1}$$

$$[\because \int_{-\infty}^{\infty} f_x(x) dx = 1]$$

(3) $\phi_x(\omega)$ and $\phi_x(-\omega)$ are complex conjugate functions

$$\text{i.e. } \phi_x(\omega) = \phi_x(-\omega)$$

Proof :- From the definition of characteristic function

$$\phi_x(\omega) = E(e^{j\omega x}) \rightarrow (1)$$

$$\phi_x(-\bar{\omega}) = E(e^{j\bar{\omega} x}) \rightarrow (2)$$

$$\phi_x(\bar{\omega}) = E(e^{-j\bar{\omega} x})$$

$$\text{from eq (1)} \quad \phi_x(-\bar{\omega}) = E[e^{j(-\bar{\omega})x}]$$

$$\phi_x(-\bar{\omega}) = E(e^{-j\bar{\omega} x}) \rightarrow (3)$$

From (2) and (3)

$$\phi_x(\bar{\omega}) = \phi_x(-\omega)$$

(4) $\phi_x(\omega)$ is continuous function $\forall \omega \in \mathbb{R} (-\infty < \omega < \infty)$

$$(5) \phi_{cx}(\omega) = \phi_x(\omega)$$

Proof :- From the characteristic function

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

$$\phi_{cx}(\omega) = E(e^{j\omega x_c})$$

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

$$\boxed{\phi_x(\omega) = \phi_x(\omega)}$$

$$(6) \quad \phi_{ax+b}(\omega) = e^{jb\omega} \phi_x(a\omega)$$

Proof :- From the characteristic function

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

$$\phi_{ax+b}(\omega) = E[e^{j\omega(ax+b)}]$$

$$= E[e^{j\omega ax + j\omega b}]$$

$$= E(e^{j\omega ax} e^{j\omega b})$$

$$= e^{jb\omega} E e^{j\omega(ax)}$$

$$\boxed{\phi_{ax+b}(\omega) = e^{jb\omega} \phi_x(\omega)}$$

(7) If "x" and "y" are individual random variables then the

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

Proof :- From the definition of characteristic function

$$\phi_x(\omega) = \cdot E(e^{j\omega x}) \quad \}$$

$$\phi_y(\omega) = E(e^{j\omega y}) \quad \} \rightarrow ①$$

$$\therefore \phi_{x+y}(\omega) = E[e^{j\omega(x+y)}]$$

$$= E[e^{j\omega x + j\omega y}]$$

$$= E[e^{j\omega x} \cdot e^{j\omega y}]$$

$$= E(e^{j\omega x}) \cdot E(e^{j\omega y})$$

If "x & y" are independent random variable, then

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

⑥, ⑦

$$\therefore \phi_{x+y}(\omega) = \cdot E[e^{j\omega x}] \cdot E[e^{j\omega y}]$$

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

steps for obtaining the moments from characteristic function:-

From the definition of characteristic function

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

$$\phi_x(\omega) = E \left[1 + \frac{j\omega x}{1!} + \frac{(j\omega x)^2}{2!} + \dots + \frac{(j\omega x)^n}{n!} \right]$$

$$= 1 + \frac{j\omega}{1!} E(x) + \frac{(j\omega)^2}{2!} E(x^2) + \dots + \frac{(j\omega)^n}{n!} E(x^n) \rightarrow ①$$

Differentiate eq ① wrt to "ω" on both sides, we get

$$\frac{d}{d\omega} (\phi_x(\omega)) = 0 + \frac{j}{1!} E(x) + \frac{j^2}{2!} E(x^2) + \dots + \frac{j^n n! j \omega^{n-1}}{n!} E(x^n) \rightarrow ②$$

$$\left. \frac{d}{d\omega} (\phi_x(\omega)) \right|_{\omega=0} = 0 + j E(x) + 0 + \dots$$

$$E(x) = \left. \frac{1}{j} \frac{d}{d\omega} (\phi_x(\omega)) \right|_{\omega=0}$$

This expression gives the 1st moment about the origin or a mean value of "x".

Again differentiate wrt "ω" in eq ②, we get

$$\frac{d^2}{d\omega^2} (\phi_x(\omega)) = 0 + \frac{2j^2}{2!} E(x^2) + \frac{j^3 6\omega}{3!} E(x^3) + \dots + \frac{j^n n(n-1) \omega^{n-2}}{n!} E(x^n)$$

$$\left. \frac{d^2}{d\omega^2} (\phi_x(\omega)) \right|_{\omega=0} = 0 + 0 + j^2 E(x^2) + 0 + \dots$$

$$\left. \frac{d^2}{d\omega^2} (\phi_x(\omega)) \right|_{\omega=0} = j^2 E(x^2)$$

$$\left. \frac{d^r}{dw^r} (\phi_x(w)) \right|_{w=0} = j^r E(x^r)$$

(3.11)

$$E(x^r) = \left. \frac{1}{j^r} \frac{d^r}{dw^r} (\phi_x(w)) \right|_{w=0}$$

This expression gives the 2nd moment about the origin. (or) mean squared value of "x".

Similarly, the nth moment about origin of "x" is given by

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

The steps shows the characteristic function having more advantage than moment generating function.

→ The characteristic function is absolutely convergent

$$\text{i.e. } |\phi_x(w)| \leq 1$$

→ If the characteristic function is known then the distribution function can be find by using characteristic function.

→ If characteristic function is known then we can find the density function by using characteristic function

$$\text{i.e. } \phi_x(w) = E(e^{jwx}) = \int_{-\infty}^{\infty} f_x(x) e^{jwx} dx$$

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

i.e. the characteristic function and density functions are Fourier transform pairs

$$F_x(x) \xleftarrow{FT} \phi_x(w)$$

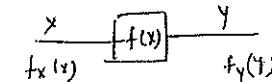
$$\phi_x(w) \xleftarrow{FT} F_x(x)$$

Transformation of random variable

Transformation means to change one random variable to new random variable (y)

$$\text{i.e. } Y = T[X].$$

The block diagram of this transformation is



[∴ only assigned values are changed but not the probabilities]

In general X is continuous, discrete, and mixed, and T is linear, non-linear, segmented staircase etc

But we will consider only following two cases :-

i) 'X' - continuous to 'T' continuous

ii) 'X' - Discrete to 'T' continuous

→ 'X' - continuous to 'T' continuous :-

This transformation can be divided into two types. They are

→ Monotonic transformation

→ Non monotonic transformation

→ Monotonic transformation :-

Monotonic transformation means one-one transformation

and is divided into two types. They are

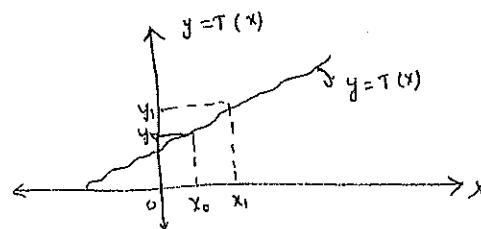
→ Monotonically increasing transformation
..... decreasing transformation

Monotonically Increasing transformation :-

(3.12)

A transformation is said to be monotonically increasing.

If $T(x_1) < T(x_2)$ for all $x_1 < x_2$ and is shown in figure



$$\text{From figure } y_0 = T(x_0)$$

$$y_1 = T(x_1)$$

From the definition of transformation, $P(y=y_0) = P(x=x_0)$

$$\Rightarrow P(y \leq y_0) = P(x \leq x_0)$$

$$\Rightarrow \int_{-\infty}^{y_0} f_y(y) dy = \int_{-\infty}^{x_0} f_x(x) dx$$

taking differentiation on both sides by using Leibniz rule

$$f_y(y_0) = f_x(x_0) \cdot \left. \frac{\partial x_0}{\partial y_0} \right|_{x_0=T^{-1}(y_0)}$$

For all values of 'x'

$$f_y(y) = f_x(x) \left. \frac{\partial x}{\partial y} \right|_{x=T^{-1}(y)}$$

Monotonically decreasing transformation :-

A transformation is said to be monotonically decreasing

If $T(x_1) > T(x_2)$ for all $x_1 < x_2$ and shown in figure

From Figure :- $y_0 = T(x_0)$

$$y_1 = T(x_1)$$

$$P(y \leq y_0) = P(x \geq x_0)$$

$$P(y \leq y_0) = P(x \geq x_0) = 1 - P(x < x_0)$$

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

Differentiate by using Leibniz theorem.

$$f_y(y_0) = \left. -f_x(x_0) \frac{\partial x_0}{\partial y_0} \right|_{x_0=T^{-1}(y_0)}$$

$$\boxed{f_y(y) = \left. -f_x(x) \frac{\partial x}{\partial y} \right|_{x=T^{-1}(y)}}$$

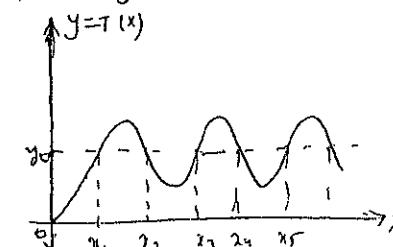
Finally for monotonic transformation

$$f_y(y) = \left. f_x(x) \frac{\partial x}{\partial y} \right|_{x=T^{-1}(y)}$$

→ NON-MONOTONIC TRANSFORMATION :-

A transformation is said to be not monotonic when it is known as "non-monotonic transformation".

Non-monotonic transformation is many-one-transformation and is shown in figure



From figure -

$$P(Y=y_0) = P(X=x_1) + P(X=x_2) + P(X=x_3) + \dots + P(X=x_N) \quad (3.13)$$

$$P(Y \leq y_0) = P(X \leq x_N)$$

$$\int_{-\infty}^{y_0} f_Y(y) dy = \int_{\{x/x \leq x_N\}} f_X(x) dx$$

taking transformation on both sides by using Trentbitz's theorem.

$$f_Y(y) = \sum_{n=1}^N f_X(x_n) \cdot \left| \frac{dx_n}{dy} \right| \Big|_{x_n = T^{-1}(y_n)}$$

(ii) 'X' discrete and 'T' continuous :-

The density and distribution functions of 'Y' is

$$f_X(x) = \sum_{n=1}^N P(X=x_n) \delta(x-x_n)$$

$$F_X(x) = \sum_{n=1}^N P(X=x_n) u(x-x_n)$$

Let us consider the transformation

$$Y = T(X)$$

$$X = T^{-1}(Y)$$

The density and distribution functions of 'Y' is

$$f_Y(y) = \sum_{n=1}^N P(Y=y_n) \delta(y-y_n)$$

$$F_Y(y) = \sum_{n=1}^N P(Y=y_n) u(y-y_n)$$

here x_n is $T^{-1}(y_n)$

For monotonic transformation $P(Y=y_n) = P(X=x_n)$

For non monotonic transformation $P(Y=y_n) = P(X=x_1) + P(X=x_2) + \dots + P(X=x_N)$

3(14)

in the following way.

(i) 1st moment about origin :-

$$\mu_1 = \frac{1}{j} \frac{d}{dw} (\phi_x(w)) \Big|_{w=0}$$

$$E[e^{jwX}] = 1 + j\omega r + \frac{(j\omega)^2}{2!} + \dots$$

$$\begin{aligned} \frac{d}{dw} E(e^{jwX}) \Big|_{w=0} &= 0 + j E(X) + 2 \frac{d^2 w}{2!} E(X^2) + \dots \\ &= j E(X). \end{aligned}$$

$$E(X) = \frac{1}{j} \frac{d}{dw} [E(e^{jwX})] \Big|_{w=0}$$

(ii) 2nd moment about origin :-

$$\mu_2 = \left(\frac{1}{j}\right)^2 \frac{d^2}{dw^2} (\phi_x(w)) \Big|_{w=0}$$

nth moment about origin :-

$$\mu_n = \left(\frac{1}{j}\right)^n \frac{d^n}{dw^n} (\phi_x(w)) \Big|_{w=0}$$

* Chebychev's inequality :-

→ A powerful inequality that is used to determine an upper boundary of the distribution is "Chebychev's inequality".

If "x" is a random variable with mean "m" & variance σ_x^2 . Then for any positive value of "k". The Chebychev's Inequality is given by probability of

$$\boxed{\begin{aligned} P(|x-m| > k\sigma_x) &\leq \frac{1}{k^2} \\ P(|x-m| < k\sigma_x) &\geq 1 - \frac{1}{k^2} \end{aligned}}$$

Proof: If the mean of a random variable "x" is "m" and variance σ_x^2 . with density function $f_x(x)$. Then from the definition of variance.

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

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

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

$$= \int_{m-K\sigma_x}^{m+K\sigma_x} (x-m)^2 f_x(x) dx + \int_{m+K\sigma_x}^{m+K\sigma_x} (x-m)^2 f_x(x) dx + \int_{m-K\sigma_x}^{m-K\sigma_x} (x-m)^2 f_x(x) dx \rightarrow ①$$

From eq(1). right side of eq(1). the upper limit of "x" is

$m+K\sigma_x$ for part (1)

$$x \leq m+K\sigma_x$$

$$x-m \leq K\sigma_x$$

$$(x-m) \geq -K\sigma_x$$

$$(m-x) \geq K\sigma_x \rightarrow ②$$

3(5)

→ from the second part of eq(1) . the lower limit of \underline{x} is

$$M - K\sigma_x$$

$$x \leq M - K\sigma_x$$

$$x - M \leq -K\sigma_x$$

$$\boxed{M - x \geq K\sigma_x}$$

→ from the second part of the eq(1) . the upper limit of \underline{x} is

$$x \geq M + K\sigma_x$$

$$x - M \geq K\sigma_x \rightarrow (3)$$

$$(2) \Rightarrow (M-x)^{\vee} \geq (K\sigma_x)^{\vee}$$

$$(x-M)^{\vee} \geq (K\sigma_x)^{\vee}$$

$$(3) \Rightarrow (x-M)^{\vee} \geq (K\sigma_x)^{\vee}$$

$$\sigma_x^{\vee} \geq \int_{-\infty}^{M-K\sigma_x} (x-M)^{\vee} f_x(x) dx + \int_{M+K\sigma_x}^{\infty} (x-M)^{\vee} f_x(x) dx.$$

$$\sigma_x^{\vee} \geq \int_{-\infty}^{M-K\sigma_x} K^{\vee} \sigma_x^{\vee} f_x(x) dx + \int_{M+K\sigma_x}^{\infty} K^{\vee} \sigma_x^{\vee} f_x(x) dx$$

$$\sigma_x^{\vee} \geq K^{\vee} \sigma_x^{\vee} \left[\int_{-\infty}^{M-K\sigma_x} f_x(x) dx + \int_{M+K\sigma_x}^{\infty} f_x(x) dx \right]$$

$$\frac{1}{K^{\vee}} \geq p(-\infty \leq x \leq M - K\sigma_x) + p(M + K\sigma_x \leq x \leq \infty)$$

$$\therefore p(-\infty \leq x \leq M - K\sigma_x) = p(x < M - K\sigma_x).$$

$$\frac{1}{K^{\vee}} \geq p(x \leq M - K\sigma_x) + p(M + K\sigma_x \leq x)$$

$$= \frac{1}{K^{\vee}} \geq p(|x-M| \geq K\sigma_x)$$

$$\therefore p(|x-M| \geq K\sigma_x) \leq \frac{1}{K^{\vee}}$$

$$\text{N.K.T } p((x-M) \geq K\sigma_x) + p((x-M) \leq -K\sigma_x) = 1$$

$$\therefore p((x-M) \leq K\sigma_x) = 1 - p(|x-M| \geq K\sigma_x)$$

$$= 1 - y_{K^{\vee}}$$

$$\boxed{p((x-M) \leq K\sigma_x) = 1 - y_{K^{\vee}}}$$

* Markov's inequality :-

→ this inequality gives the relation between probability of an event $x > a$ and expected value of x i.e. for non-negative values of random variable x ($x > 0$). The markov's inequality is given by $p(x > a) \geq \frac{E(x)}{a}$.

proof Let us consider x is not negative i.e. $(x \geq 0)$.

and continuous function $f_x(x)$.

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

$$= \int_0^{\infty} x \cdot f_x(x) dx$$

$$= \int_0^a x \cdot f_x(x) dx + \int_a^{\infty} x \cdot f_x(x) dx$$

3.(4)

$$E(x) \geq \int_a^{\infty} x \cdot f_x(x) dx$$

$$E(x) \geq \int_a^{\infty} a \cdot f_x(x) dx \quad \left(\because \text{For inequality we will sub. the lower limit value in } x \text{ place} \right)$$

$$\frac{E(x)}{a} \geq \int_a^{\infty} f_x(x) dx$$

$$\frac{E(x)}{a} \geq p(x \geq a)$$

$$p(x \geq a) \leq \frac{E(x)}{a}$$

$$\boxed{p(x \geq a) \leq \frac{E(x)}{a}}$$

* Find out mean, variance, moment generating function,

characteristic function for binomial distribution :-

(2.17)

Note :- $(p+q)^n = n_{c_0} \cdot p^0 q^n + n_{c_1} \cdot p^1 q^{n-1} + \dots + n_{c_n} p^n q^0$

$$\sum_{x=0}^n (n_{c_x}) p^x q^{n-x} = 1$$

$$n_{c_x} = \frac{n}{x} \cdot \binom{n-1}{x-1} = \left(\frac{n}{x}\right) \binom{n-1}{x-1} \binom{n-2}{x-2} \dots$$

Prob :- The binomial density function is

$$f_X(x) = n_{c_x} \cdot p^x q^{n-x}$$

mean of binomial distribution :-

$$\text{mean } (m_1) = \bar{x} = E(X)$$

$$\begin{aligned} &= \sum_{\text{all } x} x \cdot f_X(x) \\ &= \sum_{x=0}^n x \cdot (n_{c_x}) p^x q^{n-x} \\ &= \sum_{x=1}^n x \cdot \frac{n}{x} \cdot \binom{n-1}{x-1} p^x q^{n-x} \\ &= \sum_{x=1}^n n \cdot \binom{n-1}{x-1} p^x p^1 \bar{p}^{n-x} q^1 \bar{q}^1 \\ &= n \sum_{x=1}^n \binom{n-1}{x-1} p^{x-1} \cdot p \cdot \bar{p}^{n-x-1+1} \end{aligned}$$

$$= np \cdot \sum_{x=1}^n \binom{n-1}{x-1} \cdot p^{x-1} q^{(n+1)-(x-1)}$$

$$= np(1)$$

mean = $m_1 = \bar{x} = np$

mean square value of binomial distribution :-

$$\begin{aligned} m_2 &= E(X^2) \\ &= \sum x^2 (n_{c_x}) p^x q^{n-x} \end{aligned}$$

$$\begin{aligned} &= \sum_{x=0}^n x^2 \cdot (n_{c_x}) \cdot p^x q^{n-x} \\ &= \sum_{x=0}^n (x(x-1)+x) \cdot (n_{c_x}) p^x q^{n-x} \\ &= \sum_{x=0}^n x(x-1) \cdot (n_{c_x}) p^x q^{n-x} + \sum_{x=0}^n x(n_{c_x}) p^x q^{n-x} \\ &= \sum_{x=2}^n x(x-1) \cdot \frac{n}{x} \cdot \frac{(n-1)}{(x-1)} \binom{n-2}{x-2} p^{x-2} p^x q^{(n+2)-(x-2)} + np \\ &= n(n-1) p^2 + np \end{aligned}$$

$E(X^2) = n(n-1) p^2 + np$

Variance of binomial distribution :-

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

$$= E(X^2) - (E(X))^2$$

$$= n(n-1) p^2 + np - n^2 p^2$$

$$= n^2 p^2 - np^2 + np - n^2 p^2$$

$$= np - np^2$$

$$= np(1-p)$$

$\text{Var}(X) = npq$

Moment generating function of binomial distribution :-

$$M_X(t) = E(e^{tx})$$

$$= \sum_{\text{all } x} e^{tx} f_X(x)$$

$$= \sum_{\text{all } x} e^{tx} (n_{c_x}) p^x q^{n-x}$$

$$= \sum_{\text{all } x} (n_{c_x}) (e^t)^x p^x q^{n-x}$$

$$= \sum_{n=0}^{\infty} (n c_x) (p e^t)^x q^{n-x}.$$

$$\boxed{M_X(t) = (q + e^t p)^n}$$

Characteristic function of binomial distribution :-

$$\phi_x(w) = E(e^{jwX})$$

$$= \sum_{all x} e^{jwX} \cdot f_X(x)$$

$$= \sum_{all x} e^{jwX} (n c_x) p^x q^{n-x}$$

$$= \sum_{x=0}^n (n c_x) (e^{jw})^x p^x q^{n-x}$$

$$= \sum_{x=0}^n (n c_x) (p \cdot e^{jw})^x q^{n-x}$$

$$\boxed{\phi_x(w) = (q + e^{jw} p)^n}$$

* Find out mean, variance, moment generating function,

Characteristic function of poisson distribution :-

Note! $e^x = 1 + \frac{x}{1!} + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots \infty$

$$e^b = 1 + \frac{b}{1!} + \frac{b^2}{2!} + \dots \infty$$

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

Proof :- Mean or First moment about origin of a poisson distribution :-

The density function of poisson distribution is

$$f_X(x) = \frac{e^{-b} b^x}{x!}$$

$$\text{mean} = m_1 = \bar{x} = E[X]$$

$$= \sum x \cdot f_X(x)$$

(1)

$$= \sum_{x=0}^{\infty} x \cdot \frac{e^{-b} b^x}{x!}$$

$$= e^{-b} \sum_{x=0}^{\infty} x \cdot \frac{b^x}{x!}$$

$$= e^{-b} \sum_{x=1}^{\infty} x \cdot \frac{b^{x-1} \cdot b}{x(x-1)!}$$

$$= e^{-b} b \cdot e^b$$

$$\boxed{m_1 = \bar{x} = E(X) = b}$$

Mean square value or second moment about origin of poisons distribution :-

$$m_2 = E[X^2]$$

$$= \sum_{all x} x^2 \cdot f_X(x)$$

$$= \sum_{all x} x^2 \cdot \frac{e^{-b} b^x}{x!}$$

$$= \sum_{all x} [x(x-1)+x] \cdot \frac{e^{-b} b^x}{x!}$$

$$= \sum_{all x} x(x-1) \cdot \frac{e^{-b} b^x}{x!} + \sum_{all x} x \cdot \frac{e^{-b} b^x}{x!}$$

$$= e^{-b} b^2 \cdot \sum_{x=2}^{\infty} \frac{b^{x-2}}{(x-2)!} + b$$

$$= e^{-b} b^2 e^b + b$$

$$= b + b^2$$

$$\boxed{E(X^2) = b(b+1)}$$

Variance of poisons distribution :-

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

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

$$= b^x + b - b^x$$

$$= b$$

$$\boxed{f(x) = b}$$

Moment generating function of Poisson distribution:-

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

$$= \sum_{all\ x} e^{tx} \cdot f_x(x)$$

$$= \sum_{x=0}^{\infty} e^{tx} \frac{e^{-b} b^x}{x!}$$

$$= e^{-b} \sum_{x=0}^{\infty} \frac{(b \cdot e^t)^x}{x!}$$

$$= e^{-b} \left[1 + \frac{b e^t}{1!} + \frac{b^2 e^{2t}}{2!} + \dots + \infty \right]$$

$$= e^{-b} e^{bt}$$

$$= e^{-b} e^{tb}$$

$$\boxed{M_x(t) = e^{(t-1)b}}$$

Characteristic function of Poisson distribution:-

$$\phi_x(w) = E[e^{jw x}]$$

$$= \sum_{all\ x} e^{jw x} f_x(x)$$

$$= \sum_{x=0}^{\infty} e^{jw x} \frac{e^{-b} b^x}{x!}$$

$$= \sum_{x=0}^{\infty} \frac{(e^{jw b})^x \cdot e^{-b}}{x!}$$

$$= e^{-b} \sum_{x=0}^{\infty} \frac{(e^{jw b})^x}{x!}$$

$$= e^{-b} \left[1 + \frac{e^{jw b}}{1!} + \frac{(e^{jw b})^2}{2!} + \dots \right]$$

(19)

$$= \bar{e}^b \cdot e^{jwb}$$

$$= e^{(jw-1)b}$$

$$\boxed{\phi_x(w) = e^{(jw-1)b}}$$

* Find out mean, variances, moment generating function, and characteristic function of uniform distribution function of interval \underline{a} to \underline{b} .

Proof:- The uniform density of a random variable x in interval (a, b) is $f_x(x) = \frac{1}{b-a}$; $a \leq x \leq b$

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

(i) Mean or first moment about origin:-

$$\text{Mean} = \bar{x} = m_1 = E[x]$$

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

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

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

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

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

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

(ii) Mean square value (or) second moment about origin:-

$$m_2 = E(x^2)$$

$$= \sum_{all\ x} x^2 \cdot f_x(x)$$

$$\begin{aligned}
 &= \int_{-\infty}^{\infty} x^2 f_X(x) dx \\
 &= \int_a^b x^2 \left(\frac{1}{b-a}\right) dx \\
 &= \frac{1}{b-a} \left(\frac{x^3}{3}\right)_a^b \\
 &= \frac{(b^3 - a^3)}{3(b-a)} \\
 &= \frac{b^2 + ab + a^2}{3}
 \end{aligned}$$

$$E[X^2] = \frac{a^2 + ab + b^2}{3}$$

Variance of uniform distribution :-

$$\begin{aligned}
 \text{Var}(x) &= E((x-\bar{x})^2) \\
 &= E(x^2) - (E(x))^2 \\
 &= \frac{b^2 + ab + a^2}{3} - \left(\frac{b+a}{2}\right)^2 \\
 &= \frac{b^2 + ab + a^2}{3} - \left(\frac{a^2 + b^2 + 2ab}{4}\right) \\
 &= \frac{4b^2 + 4ab + 4a^2 - 3b^2 - 3a^2 - 6ab}{12} \\
 &= \frac{b^2 - 2ab + a^2}{12} \\
 &\approx \frac{(b-a)^2}{12}
 \end{aligned}$$

$$\boxed{\text{Var}(x) = \frac{(b-a)^2}{12}}$$

Moment generation function of uniform distribution :-

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

(S.20)

$$\begin{aligned}
 &= \frac{1}{b-a} \int_a^b e^{tx} dx \\
 &= \frac{1}{b-a} \left(\frac{e^{tx}}{t}\right)_a^b \\
 &= \frac{1}{b-a} \left(\frac{e^{tb}}{t} - \frac{e^{ta}}{t}\right)
 \end{aligned}$$

$$\boxed{M_X(t) = \left[\frac{e^{tb} - e^{ta}}{bt - at} \right]}$$

Characteristic function of uniform distribution :-

$$\begin{aligned}
 \phi_X(\omega) &= E[e^{j\omega x}] \\
 &= \int_{-\infty}^{\infty} e^{j\omega x} f_X(x) dx \\
 &= \int_a^b e^{j\omega x} \frac{1}{b-a} dx \\
 &= \frac{1}{b-a} \left(\frac{e^{j\omega x}}{j\omega}\right)_a^b \\
 &= \frac{1}{b-a} \left(\frac{e^{j\omega b} - e^{j\omega a}}{j\omega}\right)
 \end{aligned}$$

$$\boxed{\phi_X(\omega) = \left[\frac{e^{j\omega b} - e^{j\omega a}}{j\omega(b-a)} \right]}$$

* show that the characteristic function $\phi_X(\omega)$ satisfies the
 $| \phi_X(\omega) | \leq |\phi_X(0)| = 1$

Proof:- Let us consider the density function of a r.v "x" is

$f_X(x)$. from the definition

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

$$\phi_X(\omega) := \int_{-\infty}^{\infty} e^{j\omega x} f_X(x) dx$$

(3.2)

$$|\phi_X(\omega)| = \left| \int_{-\infty}^{\infty} e^{j\omega x} f_X(x) dx \right|$$

$$|\phi_X(\omega)| \leq \int_{-\infty}^{\infty} |e^{j\omega x}| |f_X(x)| dx$$

$$\leq \int_{-\infty}^{\infty} 1 \cdot |f_X(x)| dx,$$

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

$$\boxed{|\phi_X(\omega)| \leq 1} \rightarrow \textcircled{1}$$

$$\phi_X(\omega) = E[e^{j\omega X}]$$

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

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

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

$$\boxed{\phi_X(0) = 1} \rightarrow \textcircled{2}$$

From \textcircled{1} and \textcircled{2}

$$\boxed{|\phi_X(\omega)| \leq |\phi_X(0)| = 1}$$

* * * Find mean, variance, skewness, or coefficient of skewness, moment generating function and characteristic function of the exponential distribution.

\textcircled{1} prove: The exponential distribution function of random

variable "x" is given by $f_X(x) = \frac{1}{b} e^{-(x-a)/b}, x \geq a$

(i) mean of the first moment about origin

mean = $\bar{x} = E[X]$

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

$$= \int_a^{\infty} x \cdot \frac{1}{b} e^{-(x-a)/b} dx$$

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

$$= \frac{1}{b} e^{a/b} \left[-e^{-x/b} \left(\frac{x}{b} - \frac{1}{(-b)^2} \right) \right]_a^{\infty}$$

$$= \frac{1}{b} e^{a/b} \left[0 + 0 - e^{-a/b} \cdot \frac{a}{-b} - \frac{1}{(-b)^2} \right]$$

$$= \frac{1}{b} e^{a/b} \cdot (0 - e^{-a/b} (-ab - b^2))$$

$$= \frac{1}{b} e^{a/b} e^{-a/b} (-ab - b^2)$$

$$= -1/b (-ab - b^2)$$

$$\boxed{E(X) = a + b}$$

(ii) Mean square value or second moment about origin

$$\bar{x}^2 = E(X^2)$$

$$= \int_{-\infty}^{\infty} x^2 \cdot f_X(x) dx$$

$$= \int_a^{\infty} x^2 \cdot \frac{1}{b} e^{-(x-a)/b} dx$$

$$= \frac{1}{b} e^{a/b} \int_a^{\infty} x^2 e^{-x/b} dx$$

$$= \frac{1}{b} e^{a/b} \left[-e^{-x/b} \left(\frac{x^2}{b} - \frac{2x}{(-b)^2} + \frac{2}{(-b)^3} \right) \right]_a^{\infty}$$

$$= \frac{1}{b} e^{a/b} \left[0 - \bar{e}^{-a/b} \left[\frac{a^2}{-V_b} - \frac{2a}{-V_b} + \frac{2}{-V_b^3} \right] \right]$$

(3.22)

$$= \frac{1}{b} e^{a/b} \bar{e}^{-a/b} \cdot (-a^2 b - 2ab^2 - 2b^3)$$

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

$$\boxed{\bar{x}^3 = a^3 + 2ab^2 + 2b^3}$$

(iii) Third moment about origin:-

$$\bar{x}^3 = E(x^3)$$

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

$$= \int_a^{\infty} x^3 \frac{1}{b} \cdot \bar{e}^{-(x-a)/b} dx$$

$$= e^{a/b} \frac{1}{b} \int_a^{\infty} x^3 \bar{e}^{-x/b} dx$$

$$= \frac{e^{a/b}}{b} \left[\bar{e}^{-x/b} \left(\frac{x^3}{-V_b} - \frac{3x^2}{(-V_b)^2} + \frac{6x}{(-V_b)^3} + \frac{6}{(-V_b)^4} \right) \right]_a^{\infty}$$

$$= \frac{-e^{a/b}}{b} \left[-\bar{e}^{-a/b} - a^3 b - a^2 b^2 - 6ab^3 - 6b^4 \right]$$

$$\boxed{\bar{x}^3 = a^3 + 3a^2b + 6ab^2 + 6b^3}$$

(iv) Variance :-

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

$$= a^2 + 2ab + 2b^2 - (a+b)^2$$

$$= b^2$$

$$\boxed{\text{Var}(x) = b^2}$$

(v) Skewness (or) coefficient of skewness:-
 $n = H_3 /$

$$= E \left[\frac{(x - \bar{x})^3}{\sigma^3} \right]$$

$$= E \left(x^3 - 3x^2 \bar{x} + 3x \bar{x}^2 - \bar{x}^3 \right)$$

$$= E(x^3) - 3E(x^2) \bar{x} + 3E(x) \cdot \bar{x}^2 - E(\bar{x}^3)$$

$$= a^3 + 3a^2b + 6ab^2 + 6b^3 - (3a^2 - 6ab - 6b^2) * a + 2(a^3 + b^3 + 3ab^2 + 3b^3) \approx$$

$$= -a^3 + 3a^2b + 6ab^2 + 6b^3 - 3a^3 - 3ab^2 - 3a^2b + 12ab^2 + 6b^3 + 3a^3 + 3ab^2 + b^3$$

$$6a^2b + 6ab^2 + 9ab^2 + 3b^3 - a^3 + 3a^2b + 3ab^2 + b^3$$

$$= 2b^3$$

$$\sigma = \sqrt{\text{Var}(x)}$$

$$\sigma = \sqrt{b^2}$$

$$\sigma = b$$

$$\sigma^3 = b^3$$

$$\therefore \text{coefficient of skewness } d_3 = \frac{H_3}{\sigma^3} = \frac{2b^3}{b^3} = 2$$

(vi) Moment generating function :-

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

$$= \int_{-\infty}^{\infty} e^{tx} \frac{1}{b} \bar{e}^{-(x-a)/b} dx$$

$$= \int_a^{\infty} e^{tx} \frac{1}{b} \bar{e}^{-x/b} \cdot e^{a/b} dx$$

$$= \frac{e^{a/b}}{b} \int_a^{\infty} \bar{e}^{(t-a)/b} \cdot dx$$

$$= \frac{e^{a/b}}{b} \int_a^{\infty} \bar{e}^{-(V_b-t)x} dx$$

$$= y_b e^{at/b} \cdot \left[\frac{e^{-x/(y_b-t)}}{- (y_b-t)} \right]_a^\infty$$

(3-23)

$$= \frac{1}{b} e^{at/b} \left[\infty + \frac{e^{-a(y_b-t)}}{y_b-t} \right].$$

$$= y_b \cdot \frac{e^{at}}{(y_b-t)}$$

$$M_x(t) = e^{at} \frac{y_b}{(y_b-t)}$$

(iii) Characteristic function :-

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

$$= \int_{-\infty}^{\infty} e^{j\omega x} \frac{1}{b} e^{-(x-a)/b} dx$$

$$= \frac{1}{b} e^{a/b} \int_a^{\infty} e^{j\omega x} (y_b - j\omega) dx$$

$$= y_b \cdot e^{a/b} \cdot \left[\frac{e^{j\omega x} (y_b - j\omega)}{-(y_b - j\omega)} \right]_a^\infty$$

$$= y_b e^{a/b} \left[\infty + \frac{e^{j\omega (y_b - j\omega)}}{(y_b - j\omega)} \right]$$

$$\phi_x(\omega) = e^{j\omega a} \cdot \frac{y_b}{1/j - j\omega}$$

Plot :- The gaussian density function of a random variable X is

$$\text{i.e. } f_x(x) = \frac{1}{\sqrt{2\pi\sigma_x^2}} \cdot e^{-(x-\mu)^2/2\sigma_x^2}, -\infty < x < \infty$$

Here $\mu_x = \text{mean}$, $\sigma_x = \text{R.V. } X$

$\sigma_x^2 = \text{variance of R.V. } X$

(i) Mean of gaussian random variable "X" :-

$$\text{Mean of } X = \bar{x} = E[x] = \int_{-\infty}^{\infty} x \cdot f_x(x) dx$$

$$= \int_{-\infty}^{\infty} x \cdot \frac{1}{\sqrt{2\pi\sigma_x^2}} e^{-(x-\mu)^2/2\sigma_x^2} dx$$

$$\text{Let } \frac{x-\mu}{\sigma_x} = z \quad \Rightarrow \quad x = z\sigma_x + \mu$$

$$dx = \sigma_x dz$$

$$E(x) = \int_{-\infty}^{\infty} (z\sigma_x + \mu) \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz$$

$$= \int_{-\infty}^{\infty} (z\sigma_x + \mu) \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz$$

$$= \int_{-\infty}^{\infty} z\sigma_x \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz + \int_{-\infty}^{\infty} \mu \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz \rightarrow \textcircled{1}$$

(A)

(B)

$$\textcircled{1} \quad \int_{-\infty}^{\infty} z\sigma_x \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz =$$

$$= \frac{\sigma_x}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z (-e^{-z^2/2}) dz$$

$$= \frac{\sigma_x}{\sqrt{2\pi}} \left(-e^{-z^2/2} \right) = 0$$

** Find mean variance, moment generating function and characteristic function of gaussian density function

$$\text{NOTE:- (i) } \frac{1}{\sqrt{2\pi\sigma_x^2}} \int_{-\infty}^{\infty} e^{-(x-\mu)^2/2\sigma_x^2} dx = 1$$

$$(ii) \int_{-\infty}^{\infty} \sigma_x^2 e^{-x^2/2} dx = 1$$

$$\textcircled{B} \quad \frac{ax}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-2\gamma_2} dz$$

$$= ax \text{ (1)}$$

$$= ax$$

Sub \textcircled{A} by \textcircled{B} in \textcircled{1}

$$E(x) = 0 + ax$$

$$\boxed{E(x) = ax}$$

\textcircled{11) Mean square value of random variable 'x' :-

$$\begin{aligned} \bar{x}^2 &= E(x^2) = \int_{-\infty}^{\infty} x^2 f_x(x) dx \\ &= \int_{-\infty}^{\infty} x^2 \frac{1}{\sqrt{2\pi}\sigma_x} e^{-\frac{(x-a_x)^2}{2\sigma_x^2}} dx \end{aligned}$$

$$\text{Let } \frac{x-a_x}{\sigma_x} = z \Rightarrow x = \sigma_x z + a_x \\ dx = \sigma_x dz$$

$$\begin{aligned} E(x^2) &= \int_{-\infty}^{\infty} (\sigma_x z + a_x)^2 \frac{1}{\sqrt{2\pi}\sigma_x} e^{-2\gamma_2} \sigma_x dz \\ &= \int_{-\infty}^{\infty} (\sigma_x^2 z^2 + a_x^2 + 2\sigma_x z a_x) \frac{1}{\sqrt{2\pi}\sigma_x} e^{-2\gamma_2} \sigma_x dz \\ &= \frac{1}{\sqrt{2\pi}} \left[\underbrace{\int_{-\infty}^{\infty} \sigma_x^2 z^2 e^{-2\gamma_2} dz}_{\textcircled{A}} + \underbrace{\int_{-\infty}^{\infty} a_x^2 e^{-2\gamma_2} dz}_{\textcircled{B}} + \underbrace{\int_{-\infty}^{\infty} 2\sigma_x z a_x e^{-2\gamma_2} dz}_{\textcircled{C}} \right] \end{aligned}$$

$$\textcircled{A} \Rightarrow \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \sigma_x^2 z^2 e^{-2\gamma_2} dz$$

$$= \frac{\sigma_x^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z^2 (z e^{-2\gamma_2}) dz$$

\textcircled{3.24)

$$= \frac{\sigma_x^2}{\sqrt{2\pi}} \left[2(-e^{-2\gamma_2}) \Big|_{-\infty}^{\infty} - \int_{-\infty}^{\infty} (-e^{-2\gamma_2}) dz \right]$$

$$= \frac{\sigma_x^2}{\sqrt{2\pi}} \cdot \int_{-\infty}^{\infty} e^{-2\gamma_2} dz$$

$$\textcircled{4} = \sigma_x^2$$

$$\textcircled{B} \quad \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} 2\sigma_x a_x z e^{-2\gamma_2} dz$$

$$= \frac{2\sigma_x a_x}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z (-e^{-2\gamma_2}) dz$$

$$= \frac{2\sigma_x a_x}{\sqrt{2\pi}} (0)$$

$$= 0$$

$$\textcircled{C} \quad \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} a_x^2 e^{-2\gamma_2} dz$$

$$\frac{a_x^2}{\sqrt{2\pi}} \text{ (1)}$$

$$= a_x^2$$

$$E(x^2) = \sigma_x^2 + 0 + a_x^2$$

$$\boxed{E(x^2) = \sigma_x^2 + a_x^2}$$

Variance of random variable 'x' :-

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

$$= \sigma_x^2 + a_x^2 - (a_x)^2$$

$$\therefore \boxed{\text{Var}(x) = \sigma_x^2}$$

(20)

Moment generating function :-

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

$$= \int_{-\infty}^{\infty} e^{tx} f_x(x) dx$$

$$= \int_{-\infty}^{\infty} e^{tx} \frac{1}{\sqrt{2\pi\sigma_x^2}} e^{-\frac{(x-\mu)^2}{2\sigma_x^2}} dx$$

$$\text{let } \frac{x-\mu}{\sigma_x} = z \Rightarrow x = \sigma_x z + \mu$$

$$dx = \sigma_x dz$$

$$M_X(t) = \int_{-\infty}^{\infty} e^{t(\sigma_x z + \mu)} \frac{1}{\sqrt{2\pi}} e^{-z^2/2} dz$$

$$= \frac{1}{\sqrt{2\pi}} \cdot \int_{-\infty}^{\infty} e^{t\sigma_x z - z^2/2} e^{\mu t} dz$$

$$= \frac{e^{\mu t}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{z^2 - 2z\sigma_x t - \sigma_x^2 t^2/2} dz$$

$$= \frac{e^{\mu t}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{(z - \sigma_x t)^2 - \sigma_x^2 t^2/2} dz$$

$$= \frac{e^{\mu t}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{\left(z^2 - 2z\sigma_x t + \frac{\sigma_x^2 t^2}{2}\right) - \frac{\sigma_x^2 t^2}{2}} dz$$

$$= \frac{e^{\mu t}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(z - \sigma_x t)^2}{2}} \cdot \frac{e^{\sigma_x^2 t^2}}{\sqrt{\pi}} dz$$

$$= \text{Ans} \cdot \frac{e^{\mu t - \sigma_x^2 t^2/2}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(z - \sigma_x t)^2}{2}} dz$$

$$N_X(t) = e^{\mu t - \frac{\sigma_x^2 t^2}{2}} \quad (1)$$

$$\boxed{M_X(t) = \frac{e^{\mu t - \sigma_x^2 t^2/2}}{\sqrt{2\pi}}}$$

Characteristic function :-

$$\phi_X(w) = E[e^{jwX}]$$

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

$$= \int_{-\infty}^{\infty} e^{jwX} \frac{1}{\sqrt{2\pi\sigma_x^2}} e^{-\frac{(x-\mu)^2}{2\sigma_x^2}} dx$$

$$\text{let } \frac{x-\mu}{\sigma_x} = z \Rightarrow X = \sigma_x z + \mu$$

$$dx = \sigma_x dz$$

$$= \int_{-\infty}^{\infty} e^{jw(\sigma_x z + \mu)} \times \frac{1}{\sqrt{2\pi\sigma_x^2}} e^{-z^2/2} dz$$

$$= \frac{e^{jw\mu}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{jw\sigma_x z - z^2}{2}} dz$$

$$= \frac{e^{jw\mu}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(z^2 - 2z\sigma_x jw)}{2}} dz$$

$$= \frac{e^{jw\mu}}{\sqrt{2\pi}}$$

$$\boxed{M_X(t) = \frac{e^{jw\mu}}{\sqrt{2\pi}}}$$

UNIT-III.

"Operations on single random variable's" problems

(3.26)

①

A random variable "x" has possible values $x_i = i^y$, $i=1, 2, 3, 4, 5$, which occur with probabilities 0.4, 0.25, 0.15, 0.1 and 0.1 respectively. Find

(i) probability density function (ii) distribution function (iii) Mean value of x.

Sol: Given that $x_i = i^y$

$i=1, 2, 3, 4, 5, \dots$

The assigned values of random variable "x" are

$$x_1 = 1^y = 1$$

$$x_2 = 2^y = 4$$

$$x_3 = 3^y = 9$$

$$x_4 = 4^y = 16$$

$$x_5 = 5^y = 25$$

\therefore The probabilities of assigned values are.

$$P(x=x_1) = 0.4$$

$$P(x=x_2) = 0.25$$

$$P(x=x_3) = 0.15$$

$$P(x=x_4) = 0.1$$

$$P(x=x_5) = 0.1$$

The density function is

$x=x$	1	4	9	16	25
$P(x=x)$	0.4	0.25	0.15	0.1	0.1

Here the assigned values are finite. Hence the random variable "x" is

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

Here $N=5$

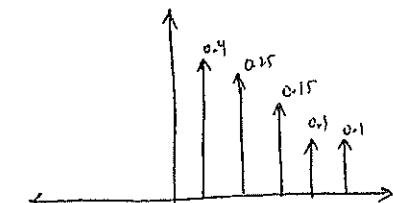
$$= \sum_{i=1}^5 P(x=x_i) \delta(x-x_i)$$

$$= P(x=x_1) \delta(x-x_1) + P(x=x_2) \delta(x-x_2) + P(x=x_3) \delta(x-x_3) + P(x=x_4) \\ + P(x=x_5) \delta(x-x_5).$$

$$= 0.4 \delta(x-1) + 0.25 \delta(x-4) + 0.15 \delta(x-9) + 0.1 \delta(x-16) + 0.1 \delta(x-25).$$

$$\therefore f_x(x) = 0.4 \delta(x-1) + 0.25 \delta(x-4) + 0.15 \delta(x-9) + 0.1 \delta(x-16) + 0.1 \delta(x-25).$$

The plot of density function is



The distribution function is given by

$$F_x(x) = \sum_{i=1}^N P(x=x_i) U(x-x_i)$$

Here $N=5$

$$F_x(x) = \sum_{i=1}^5 P(x=x_i) U(x-x_i)$$

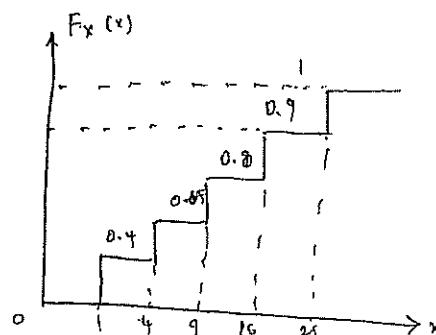
$$= P(x=x_1) U(x-1) + P(x=x_2) U(x-4) + P(x=x_3) U(x-9) + P(x=x_4) U(x-16) \\ + P(x=x_5) U(x-25).$$

$$F_x(x) = 0.4 U(x-1) + 0.25 U(x-4) + 0.15 U(x-9) + 0.1 U(x-16) + 0.1 U(x-25).$$

$$F_x(x) = 0.4 U(x-1) + 0.25 U(x-4) + 0.15 U(x-9) + 0.1 U(x-16) + 0.1 U(x-25)$$

The plot of distribution function is

(3.29)



Mean of 'x' is

$$\bar{x} = H_1^1 = \mu = m_1 = E[x]$$

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

$$= \sum_{i=1}^5 x_i P(x=x_i).$$

$$= x_1 P(x=x_1) + x_2 P(x=x_2) + x_3 P(x=x_3) + x_4 P(x=x_4) + x_5 P(x=x_5)$$

$$= 1(0.4) + 4(0.15) + 9(0.15) + 16(0.1) + 20(0.1)$$

$$\boxed{\bar{x} = 6.85}$$

② A random variable "X" (say "x") has the following probability function

x	-2	-1	0	1	2	3
P(x)	0.1	k	0.2	2k	0.3	k

(i) find value of "k" (ii) Mean of 'x', (iii) Variance of 'x'.

Sol: (i) We know that the sum of probabilities = 1

$$\sum_{\text{all } x} p(x) = 1$$

$$0.1 + k + 0.2 + 2k + 0.3 + k = 1$$

$\boxed{K=0.1}$

x	-2	-1	0	1	2	3
p(x)	0.1	0.1	0.2	0.2	0.3	0.1

(ii) mean of 'x'.

$$\bar{x} = H_1^1 = \mu = m_1 = E[x]$$

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

$$= \sum_{i=1}^6 x_i p(x_i)$$

$$= (-2)(0.1) + (-1)(0.1) + 0 + 1(0.2) + 2(0.3) + 3(0.1)$$

$$= 0.8$$

$$\boxed{\bar{x} = H_1^1 = 0.8}$$

(iii) the mean square value of 'x' is $H_2^1 = \sum_{\text{all } x} x^2 p(x)$

$$H_2^1 = (4)(0.1) + (1)(0.1) + 1(0.2) + 4(0.3) + 9(0.1)$$

$$\boxed{H_2^1 = 2.8}$$

Variance of 'x' is $\sigma_x^2 = \mu_2 - (H_1^1)^2$

$$= 2.8 - (0.8)^2$$

$$= 2.8 - 0.64$$

$$\boxed{\sigma_x^2 = 2.14}$$

Let 'x' be the random variable defined by the density function, is

$$f_x(x) = \frac{\pi}{16} \cos\left(\frac{\pi x}{8}\right), -4 \leq x \leq 4$$

= 0 else where, find $E[3x]$, $E(x^2)$.

SOL

Given that $f_x(x) = \frac{\pi}{16} \cos\left(\frac{\pi x}{8}\right)$: $-4 \leq x \leq 4$
 $= 0$; elsewhere.

(1.19)

Here the random variable x is continuous random variable
 for continuous random variable $E[x] = \int_{-\infty}^{\infty} x \cdot f_x(x) dx$

$$\begin{aligned} \text{i)} E[3x] &= \int_{-\infty}^{\infty} 3x \cdot f_x(x) dx \\ &= 3 \int_{-4}^{4} x \cdot \cos\left(\frac{\pi x}{8}\right) \frac{\pi}{16} dx \\ &= \frac{3\pi}{16} \int_{-4}^{4} x \cdot \cos\left(\frac{\pi x}{8}\right) dx \end{aligned}$$

$$\text{let } g(x) = x \cos\left(\frac{\pi x}{8}\right).$$

$$g'(x) = -x \cos\left(\frac{\pi x}{8}\right).$$

$$= -x \cos\left(\frac{\pi x}{8}\right).$$

$$= -g(x)$$

$\therefore g(x)$ is odd function

for odd function, $\int_a^a g(x) dx = 0$.

$$\therefore E[3x] = 3(0)$$

$$= 0$$

$$\begin{aligned} E[x^2] &= \int_{-\infty}^{\infty} x^2 \cdot f_x(x) dx \\ &= \int_{-4}^{4} x^2 \cdot \frac{\pi}{16} \cos\left(\frac{\pi x}{8}\right) dx \\ &= \frac{\pi}{16} \int_{-4}^{4} x^2 \cos\left(\frac{\pi x}{8}\right) dx \end{aligned}$$

$$\begin{aligned} &= \frac{\pi}{16} \int_{-4}^{4} x^2 \cos\left(\frac{\pi x}{8}\right) dx \\ &= \frac{\pi}{16} \left[x^2 \cdot \left(\frac{\sin(\pi x/8)}{\pi/8} \right) \Big|_{-4}^4 - \int_{-4}^{4} 2x \cdot \frac{\sin(\pi x/8)}{\pi/8} dx \right] \\ &= \frac{\pi}{16} \left[\left[16 \cdot \frac{\sin(\pi/2)}{\pi/8} - 16 \cdot \frac{\sin(-\pi/2)}{\pi/8} \right] - \frac{16}{\pi} \int_{-4}^{4} x \cdot \sin\left(\frac{\pi x}{8}\right) dx \right] \\ &= \frac{\pi}{16} \cdot \left[16 \cdot \frac{8}{\pi} + 16 \cdot \frac{8}{\pi} \right] - \frac{16}{\pi} \int_{-4}^{4} x \cdot \sin\left(\frac{\pi x}{8}\right) dx \\ &= \frac{16}{\pi} \left(16 \right) - \int_{-4}^{4} x \cdot \sin\left(\frac{\pi x}{8}\right) dx \\ &= 16 - \int_{-4}^{4} x \cdot \sin\left(\frac{\pi x}{8}\right) dx \\ &= 16 - \left[x \left(\frac{-\cos(\pi x/8)}{\pi/8} \right) \Big|_{-4}^4 - \int_{-4}^{4} 1 \cdot \frac{-\cos(\pi x/8)}{\pi/8} dx \right] \\ &= 16 - \left[-4 \cdot \frac{\cos(\pi/2)}{\pi/8} - 4 \cdot \frac{\cos(-\pi/2)}{\pi/8} \right] + \frac{8}{\pi} \cdot \int_{-4}^{4} \cos\left(\frac{\pi x}{8}\right) dx \\ &= 16 - \left[0 + \frac{8}{\pi} \int_{-4}^{4} \cos\left(\frac{\pi x}{8}\right) dx \right] \end{aligned}$$

$$\begin{aligned} &= 16 - \frac{8}{\pi} \left(\frac{\sin(\pi x/8)}{\pi/8} \right) \Big|_{-4}^4 \\ &= 16 - \frac{8}{\pi} \left[\frac{8}{\pi} (2) \right] \end{aligned}$$

$$\boxed{E[x^2] = 16 - \frac{128}{\pi^2}}$$

The density function of random variable of x is $g(x) = 5e^{-x}$; $0 \leq x \leq$
 $= 0$; otherwise
 find $E(x)$, $E(x-1)^2$; $E(\beta x-1)$

(14)

Solt
Given that $f(x) = 5e^{-x}$; $x \geq 0$
= 0 ; elsewhere.

Here the random variable 'x' follows continuous distribution function

$$\begin{aligned} E[x] &= \int_{-\infty}^{\infty} x \cdot g(x) dx \\ &= \int_0^{\infty} x \cdot 5e^{-x} dx \\ &= 5 \int_0^{\infty} x e^{-x} dx \\ &= 5 \left[x \left(\frac{e^{-x}}{-1} \right)_0^{\infty} + \int_0^{\infty} (1) e^{-x} dx \right] \\ &= 5 \left[0 + \left(\frac{e^{-x}}{-1} \right)_0^{\infty} \right] \\ &= 5 \left[-e^0 + e^0 \right] \end{aligned}$$

$$\boxed{E[x] = 5}$$

$$\begin{aligned} E[x^2] &= \int_{-\infty}^{\infty} x^2 \cdot g(x) dx \\ &= \int_0^{\infty} x^2 \cdot 5e^{-x} dx \\ &= 5 \int_0^{\infty} x^2 e^{-x} dx \\ &= 5 \left[x^2 \left(\frac{e^{-x}}{-1} \right)_0^{\infty} + \int_0^{\infty} 2x e^{-x} dx \right] \\ &= 5 \left[0 + 2 \int_0^{\infty} x e^{-x} dx \right] \\ &= 5 + \left[0 + \left[2 \int_0^{\infty} 5x e^{-x} dx \right] \right] \\ &= 5 + \frac{2 \times 5}{1-e^{-5}} = 10 \end{aligned}$$

(3.29)

$$\begin{aligned} E[(x-1)^2] &= E[x^2 + 1 - 2x] \\ &= E(x^2) + E(1) - 2E(x) \\ &= 10 - 2(5) + 1 \\ &= 10 - 10 + 1 \\ &= 1 \\ \boxed{\therefore E[(x-1)^2] = 1} \end{aligned}$$

$$\begin{aligned} E[(x-1)^2] &= \int_0^{\infty} (x-1)^2 \cdot 5e^{-x} dx \\ &= \int_0^{\infty} (x^2 + 1 - 2x) \cdot 5e^{-x} dx \\ &= \int_0^{\infty} x^2 g(x) dx - 2 \int_0^{\infty} x \cdot g(x) dx + \int_0^{\infty} g(x) dx \\ &= 10 - 2(5) + \int_0^{\infty} 5e^{-x} dx \\ &= 10 - 10 + 5 \left(\frac{e^{-x}}{-1} \right)_0^{\infty} \\ &= 5(e^{\infty} - e^0) \\ &= 5 \end{aligned}$$

Note! The theorems on expectation and variance can be applicable when the density function is valid density function

$$\begin{aligned} E[(x-1)] &= \int_0^{\infty} (x-1) \cdot 5e^{-x} dx \Rightarrow 3 \cdot \int_0^{\infty} x \cdot g(x) dx - \int_0^{\infty} g(x) dx \\ &= 3(5) - 5 \\ &= 15 - 5 \\ &= 10 \\ \boxed{E[(x-1)] = 10} \end{aligned}$$

Q: For a random variable $y = \cos \pi x$, where x is a random variable follows uniform distribution over the interval $(-y_1, y_2)$. find the mean and mean square value of y .

Q10

Sol: Given that the random variable y is $\cos \pi x$

Here, x is a random variable which follows uniform distribution over the interval $(-y_1, y_2)$

We know that, the random variable x is follows uniform density function over the interval (a, b) . Then the density function of

$$f_x(x) = \begin{cases} \frac{1}{b-a} & ; a \leq x \leq b \\ 0 & ; \text{elsewhere} \end{cases}$$

$$\therefore f_x(x) = \frac{1}{y_2 - y_1} = \frac{1}{y_2 - (-y_1)} = \frac{1}{y_1 + y_2}$$

$$\therefore f_x(x) = \begin{cases} 1 & ; -y_1 \leq x \leq y_2 \\ 0 & ; \text{elsewhere.} \end{cases}$$

mean of y is $= E[y]$

$$\begin{aligned} &= E[\cos \pi x] \\ &= \int_{-\infty}^{\infty} \cos(\pi x) f_x(x) dx \\ &= \int_{-y_1}^{y_2} \cos(\pi x) \cdot 1 dx \\ &= \left(\frac{\sin \pi x}{\pi} \right) \Big|_{-y_1}^{y_2} = \frac{\sin \pi y_2}{\pi} + \frac{\sin \pi (-y_1)}{\pi} \end{aligned}$$

$$\boxed{E[y] = \frac{2}{\pi}}$$

mean square value of y is $= E[y^2]$

$$\begin{aligned} &= E[\cos^2 \pi x] \\ &= E\left[\frac{1 + \cos 2\pi x}{2} \right] \\ &= \frac{1}{2} + \frac{1}{2} E[\cos(2\pi x)] \\ &= \frac{1}{2} + \frac{1}{2} \int_{-\infty}^{\infty} \cos 2\pi x dx \\ &= \frac{1}{2} + \frac{1}{2} \int_{-y_1}^{y_2} \cos 2\pi x dx \\ &= \frac{1}{2} + \frac{1}{2} \left(\frac{\sin 2\pi x}{2\pi} \right) \Big|_{-y_1}^{y_2} \\ &= \frac{1}{2} + \frac{1}{2} \left[\frac{\sin \pi}{2\pi} + \frac{\sin \pi}{2\pi} \right] \\ &= \frac{1}{2} + \frac{1}{2} (0) = \frac{1}{2} = 0.5 \\ \boxed{E[y^2] = 0.5}. \end{aligned}$$

Q: If the given function $f_x(x) = \frac{1}{2} \cos x ; -\frac{\pi}{2} \leq x \leq \frac{\pi}{2}$ is the density

$= 0 ; \text{otherwise}$
function of a random variable x , then find the mean value of the functions. (i) $g(x) = 4x^2$ (ii) $g(x) = 4x^4$

Sol:

$$f_x(x) = \frac{1}{2} \cos x ; -\frac{\pi}{2} \leq x \leq \frac{\pi}{2}$$

$$= 0 ; \text{otherwise.}$$

Given that
Here, x is a continuous random variable is

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

$$(i) \quad g(x) = 4x^2$$

$$\therefore \text{Mean of } g(x) = E[g(x)] = E[4x^2]$$

$$= \int_{-\infty}^{\infty} 4x^2 \cdot f_x(x) dx$$

$$= \int_{-\pi/2}^{\pi/2} 4x^2 \cdot \frac{1}{2} \cos x dx$$

$$= 2 \int_{-\pi/2}^{\pi/2} \cos x \cdot (x)^2 dx$$

$$= 2 \left[x^2 \cdot (\sin x) \Big|_{-\pi/2}^{\pi/2} - \int_{-\pi/2}^{\pi/2} 2x \sin x dx \right]$$

$$= 2 \left[\frac{\pi^2}{4} + \frac{\pi^2}{4} \right] - 2 \left[\int_{-\pi/2}^{\pi/2} x \sin x dx \right]$$

$$= \cancel{\frac{\pi^2}{2}} - 2 \left[x \cdot (-\cos x) \Big|_{-\pi/2}^{\pi/2} + \int_{-\pi/2}^{\pi/2} \cos x dx \right]$$

$$= \cancel{\frac{\pi^2}{2}} - 2 \left[\frac{\pi^2}{2} \right]$$

$$= 2 \left(\frac{\pi^2}{2} - 2 \cdot (\ln 2) \right)$$

$$= 2 \left[\frac{\pi^2}{2} - 2 \cdot (i+1) \right]$$

$$\boxed{E[g(x)] = \left[\frac{\pi^2}{2} - 8 \right]}$$

(ii)

$$E[g(x)] = E[4x^4]$$

$$= \int_{-\infty}^{\infty} 4x^4 \cdot f_x(x) dx$$

$$= \int_{-\pi/2}^{\pi/2} 4x^4 \cdot \frac{1}{2} \cos x dx$$

$$= 2 \int_{-\pi/2}^{\pi/2} x^4 \cos x dx$$

(3.41)

$$= 2 \left[x^4 (\sin x) \Big|_{-\pi/2}^{\pi/2} - \int_{-\pi/2}^{\pi/2} 4x^3 \sin x dx \right]$$

$$= 2 \left[(\frac{\pi}{2})^4 + \frac{\pi^4}{8} - 4 \int_{-\pi/2}^{\pi/2} x^3 \sin x dx \right]$$

$$= 2 \left[\frac{2\pi^4}{16} - 4 \left[x^3 (-\cos x) \Big|_{-\pi/2}^{\pi/2} + \int_{-\pi/2}^{\pi/2} 3x^2 \cos x dx \right] \right]$$

$$= 2 \left[\frac{\pi^4}{8} - 12 \left[\int_{-\pi/2}^{\pi/2} x^2 \cos x dx \right] \right]$$

$$= 2 \left[\frac{\pi^4}{8} - 12 \left[x^2 (\sin x) \Big|_{-\pi/2}^{\pi/2} - \int_{-\pi/2}^{\pi/2} 2x \cdot \sin x dx \right] \right]$$

$$= 2 \left[\frac{\pi^4}{8} - 12 \left[\frac{\pi^2}{4} + \frac{\pi^2}{4} \right] - 2 \int_{-\pi/2}^{\pi/2} x \sin x dx \right]$$

$$= 2 \left[\frac{\pi^4}{8} - 12 \left[\frac{2\pi^2}{2} \right] - 2 \left[x \cdot (-\cos x) \Big|_{-\pi/2}^{\pi/2} + \int_{-\pi/2}^{\pi/2} \cos x dx \right] \right]$$

$$= 2 \left[\frac{\pi^4}{8} - 12 \left[\frac{\pi^2}{2} \right] - 2 \left[0 + (\ln 2) \right] \right]$$

$$= 2 \left[\frac{\pi^4}{8} - 12 \left[\frac{\pi^2}{2} - 0 + (4) \right] \right]$$

$$= \cancel{\frac{\pi^4}{8}} - \frac{12\pi^2}{2} - 48$$

$$\boxed{E[g(x)] = \frac{\pi^4}{4} - 12\pi^2 - 96}$$

⑦ Find the expected value of the function $g(x) = x^r$, where x is a random variable defined by the density function $f_x(x) = a \cdot e^{-ax} u(x)$, where 'a' is a constant.

Sol: Given that $g(x) = x$.
Here, "X" is a random variable
the density function of "X" is

$$f_X(x) = a \cdot e^{-ax} \cdot u(x)$$

Here, $u(x) = 1$, $x \geq 0$

$$= 0, x < 0$$

$$\therefore f_X(x) = a \cdot e^{-ax}, x \geq 0 \\ = 0, x < 0$$

A. Mean of $g(x)$ is $= E(g(x))$

$$= E(x) \\ = \int_{-\infty}^{\infty} x \cdot f_X(x) dx \\ = \int_{-\infty}^{\infty} x \cdot a \cdot e^{-ax} dx \\ = a \int_{0}^{\infty} x \cdot e^{-ax} dx \\ = a \cdot \left[x \left(\frac{e^{-ax}}{-a} \right) \Big|_0^\infty - \frac{2x}{(-a)^2} + \frac{2}{(-a)^3} \Big|_0^\infty \right] \\ = a \left[\left(-\frac{e^{ax}}{a} \right) \Big|_0^\infty - \left[0 - \frac{2(0)}{a^2} + \frac{2}{-a^3} \right] \right] \\ = \frac{a \cdot 2}{a^2}$$

$$E(g(x)) = \frac{2}{a^2}$$

- ⑧ In an experiment throwing a die, find the expected value of no. of points on the die.
- Given: The experiment is throwing a die

(Q42)

Let us consider random variable 'X'. That denotes no. of points on a die.
 \therefore the assign values of "X" are 1, 2, 3, 4, 5, and 6.
 \therefore the probability of assign values are

$$P(X=1) = \frac{1}{6}$$

$$P(X=2) = \frac{1}{6}$$

$$P(X=3) = \frac{1}{6}$$

$$P(X=4) = \frac{1}{6}$$

$$P(X=5) = \frac{1}{6}$$

$$P(X=6) = \frac{1}{6}$$

B. The PDF is.

X=x	1	2	3	4	5	6
P(X=x)	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$

$$\text{Mean of } X = \sum_{\text{all } x} x \cdot P(X=x).$$

$$E(X) = 1 \cdot \frac{1}{6} + 2 \cdot \frac{1}{6} + 3 \cdot \frac{1}{6} + 4 \cdot \frac{1}{6} + 5 \cdot \frac{1}{6} + 6 \cdot \frac{1}{6} \\ = \frac{21}{6}$$

$$\boxed{E(X) = 3.5}$$

- ⑨ In an experiment two dice are thrown simultaneously find the expected value of no. of points on them.

Sol: Given the experiment is two dice are thrown the sample space

$$\text{of experiment} = \{(1,1), (1,2), (1,3), (1,4), (1,5), (1,6), (2,1), (2,2), (2,3), (2,4), (2,5), (2,6), (3,1), (3,2), (3,3), (3,4), (3,5), (3,6), (4,1), (4,2), (4,3), (4,4), (4,5), (4,6), (5,1), (5,2), (5,3), (5,4), (5,5), (5,6), (6,1), (6,2), (6,3), (6,4), (6,5), (6,6)\}$$

Let us consider random variable X and that denotes the no. of points on dies when two dies are thrown.

(S-13)

The assign values of "X" are, 2, 3, 4, 5, 6, ... 12.

\therefore The PDF is

$X=x$	2	3	4	5	6	7	8	9	10	11	12
$P(X=x)$	$2/36$	$3/36$	$4/36$	$5/36$	$6/36$	$7/36$	$8/36$	$9/36$	$10/36$	$11/36$	$12/36$

$$\text{Mean of } X = E[X] = \sum_{\text{all } x} x \cdot P(X=x).$$

$$= 2 \cdot 2/36 + 3 \cdot 3/36 + 4 \cdot 4/36 + 5 \cdot 5/36 + 6 \cdot 6/36 + 7 \cdot 7/36 + 8 \cdot 8/36 + 9 \cdot 9/36 + 10 \cdot 10/36 \\ + 11 \cdot 11/36 + 12 \cdot 12/36$$

$$= 7.$$

$\therefore \text{Mean of } X = 7$

(10) Define a function $g(x)$ of random variable X by $g(x) = 1 ; x > x_0$
 $= 0 ; x \leq x_0$

where, x_0 is a real number's show that $E[g(x)] = 1 - F_X(x_0)$

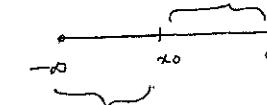
Sol: Let us consider random variable X with density function

$f_X(x)$, from $-\infty$ to ∞

$$\text{Given } g(x) = 1 ; x > x_0 \\ = 0 ; x \leq x_0$$

$$\text{Mean of } g(x) = E[g(x)] = \int_{-\infty}^{\infty} g(x) \cdot f_X(x) dx \\ = \int_{x_0}^{\infty} 1 \cdot f_X(x) dx \\ = \int_{x_0}^{\infty} f_X(x) dx$$

We know that



$$= \int_{-\infty}^{x_0} f_X(x) dx + \int_{x_0}^{\infty} f_X(x) dx = 1$$

$$= \int_{x_0}^{\infty} f_X(x) dx = 1 - \int_{-\infty}^{x_0} f_X(x) dx \rightarrow ①$$

from the definition of distribution function

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

\therefore eq ① becomes

$$E[g(x)] = 1 - F_X(x_0)$$

(11) A random variable "X" has a density function is $f_X(x) = \frac{3}{32}(x^2 + 8x - 12)$, $2 \leq x \leq 6$.
 find mo, M_1 , M_2 , H_2 , $H_n = M_n = E[X^n]$.
 $= 0$; elsewhere

NOTE: the moment about origin are also denoted by M_n

Sol: Given the density function of a random variable is

$$f_X(x) = \frac{3}{32}(-x^2 + 8x - 12), 2 \leq x \leq 6$$

$$= 0 ; \text{ elsewhere.}$$

$$H_0 = E[X^0]$$

$$= E[1]$$

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

$$= \int_2^6 \frac{3}{32}(-x^2 + 8x - 12) dx$$

$$= \frac{3}{32} \left(\frac{-x^3}{3} + \frac{8x^2}{2} - 12x \right)_2^6$$

$$= \frac{3}{32} \left[\left[-\frac{x^3}{3} + \frac{8x^2}{2} - 12x \right] - \left[-\frac{2^3}{3} + \frac{8 \cdot 2^2}{2} - 12 \cdot 2 \right] \right]$$

(344)

= 1.

$$\begin{aligned} M_1 &= E(X) = \int_{-\infty}^{\infty} x \cdot f_X(x) dx \\ &= \int_2^6 x \cdot \frac{3}{32} (-x^2 + 8x - 12) dx \\ &= \frac{3}{32} \int_2^6 (-x^3 + 8x^2 - 12x) dx \\ &= \frac{3}{32} \left[-\frac{x^4}{4} + \frac{8x^3}{3} - \frac{12x^2}{2} \right]_2^6 \\ &= \frac{3}{32} \left[\left[-\frac{1^4}{4} + \frac{8 \cdot 1^3}{3} - 12 \cdot 1^2 \right] - \left[-\frac{2^4}{4} + \frac{8 \cdot 2^3}{3} - 12 \cdot 2^2 \right] \right] \end{aligned}$$

=

$$\begin{aligned} M_2' &= m_2 = E(X^2) = \int_{-\infty}^{\infty} x^2 \cdot f_X(x) dx \\ &= \int_2^6 x^2 \cdot \frac{3}{32} (-x^2 + 8x - 12) dx \\ &= \frac{3}{32} \int_2^6 (-x^4 + 8x^3 - 12x^2) dx \\ &= \frac{3}{32} \left(-\frac{x^5}{5} + \frac{8x^4}{4} - \frac{12x^3}{3} \right)_2^6 \\ &= \frac{3}{32} \left[\left[-\frac{6^5}{5} + \frac{6^4 \cdot 2}{4} - 4 \cdot 2^3 \right] - \left[-\frac{2^5}{5} + 2^4 - 12 \cdot 2^2 \right] \right] \\ &= 16.8 \end{aligned}$$

M_2 = second moment about mean = $E[(X - M_1)^2]$

$$= M_2' - (M_1)^2$$

$$= m_2 - (M_1)^2 \quad \dots \quad \boxed{M_1 = 1}$$

Q A random variable "X" has $\bar{x} = -3$, $\bar{x}^2 = 11$ and $\sigma_x^2 = 2$. for new random variable $Y = 2X + 3$; find $E(Y)$, \bar{Y} and σ_Y^2

Ans:

Given $\bar{x} = -3$; $M_1 = E(X)$

$$\bar{x}^2 = 11; M_2' = E(X^2)$$

$$\text{We know that } \sigma_x^2 = M_2' - (M_1)^2 = 11 - 9 = 2$$

$$\sigma_x^2 = 2 \rightarrow ①$$

As per problem $\sigma_x^2 = 2$.

i) the given random variable "X" has valid density function

The new random variable $Y = 2X + 3$

$$\bar{Y} = E(Y)$$

$$= E(2X + 3)$$

$$= 2E(X) + E(3)$$

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

$$= -9.$$

$$\bar{Y}^2 = E(Y^2)$$

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

$$= E(4X^2 + 12X + 9)$$

$$= 4E(X^2) + E(9) - 12E(X)$$

$$= 4(11) + 9 - 12(-3)$$

$$= 44 + 9 + 36$$

$$\boxed{\bar{Y}^2 = 89}$$

ii) $\sigma_Y^2 = M_2' - (M_1)^2$

$$= E(Y^2) - (E(Y))^2$$

$$= \frac{89 - 81}{8 \cdot 1}$$

(15) The exponential density function is given by $f(x) = \frac{1}{b} e^{-\frac{(x-a)}{b}}$; $x > a$
 $= 0$; $x \leq a$
 find out the variance, skew and coefficient of skewness?

Soln
 Given that $f(x) = \frac{1}{b} e^{-\frac{(x-a)}{b}}$, $x > a$
 $= 0$; $x \leq a$

We know that, $E[x] = \mu_1 = a + b$

$$E[x^2] = \mu_2 = (a+b)^2 + b^2$$

Variance $\sigma_x^2 = b^2$

Skew = $\mu_3 = 3\text{rd moment about mean}$

$$\mu_3 = E[(x - \mu_1)^3]$$

$$= E[x^3 - 3x^2\mu_1 + 3x\mu_1^2 - (\mu_1)^3]$$

$$= \mu_3 - 3\mu_1 E[x^2] + 3\mu_1^2 E[x] - (\mu_1)^3$$

$$= \mu_3 - 3\mu_1^2 \mu_2 + 3(\mu_1)^3 - (\mu_1)^3$$

$$= \mu_3 - 3\mu_1^2 \mu_2 + 2(\mu_1)^3$$

$$\mu_3 = E[x^3]$$

$$= \int_{-\infty}^{\infty} x^3 \cdot f(x) dx$$

$$= \int_{-\infty}^{\infty} x^3 \cdot \frac{1}{b} e^{-\frac{(x-a)}{b}} dx$$

$$= \frac{e^{a/b}}{b} \int_a^{\infty} x^3 \cdot e^{-\frac{x-b}{b}} dx$$

$$= \frac{e^{a/b}}{b} \left[-e^{-\frac{x-b}{b}} \left(\frac{x^3}{(-1/b)^2} - \frac{3x^2}{(-1/b)^3} + \frac{6x}{(-1/b)^4} - \frac{6}{(-1/b)^5} \right) \right]_a^{\infty}$$

$$= \frac{e^{a/b}}{b} \left[0 - e^{-\frac{a-b}{b}} \left(\frac{a^3}{(-1/b)^2} - \frac{3a^2}{(-1/b)^3} + \frac{6a}{(-1/b)^4} - \frac{6}{(-1/b)^5} \right) \right]$$

$$= \frac{e^{a/b}}{b} \left[-e^{-\frac{a-b}{b}} (-ba^3 - 3a^2b^2 + 6ab^3 - 6b^4) \right]$$

$$= \frac{e^{a/b}}{b} \left[e^{-\frac{a-b}{b}} (6a^3 + 3a^2b^2 + 6ab^3 + 6b^4) \right]$$

$$\mu_3 = a^3 + 3a^2b + 6ab^2 + 6b^3$$

$$\therefore \text{Skew} = \mu_3 = \mu_3 - 3\mu_1^2 \mu_2 + 2(\mu_1)^3$$

$$\mu_3 = (a^3 + 3a^2b + 6ab^2 + 6b^3) - 3(a+b)(a+b)^2 + 2(a+b)^3$$

$$= a^3 + 3a^2b + 6ab^2 + 6b^3 - 3(a+b)[a^2 + b^2 + 2ab + 2(a^2 + 3a^2b + 3ab^2 + b^3)]$$

$$= a^3 + 3a^2b + 6ab^2 + 6b^3 - 3a^3 + 3a^2b^2 + 3a^2b + 2b^3 + 2a^3 + 6a^2b + 6ab^2 + 2b^3$$

$$= 2b^3$$

$$\therefore \text{coefficient of skewness} = d_3 = \frac{\mu_3}{\sigma_x^3}$$

$$\sigma_x^2 = b^2$$

$$\sigma_x = b$$

$$\sigma_x^3 = b^3$$

$$d_3 = \frac{2b^3}{b^3}$$

$$\boxed{d_3 = 2}$$

- (4) The plot for the random variable "X", is given by $f_X(x) = 0.503\sqrt{x}$; find mean of "X", mean of the square of "X", variable variance of "X".
- Sol: Given that $f_X(x) = 0.503\sqrt{x}$; $0 \leq x \leq 2$
 $= 0$; otherwise.

Sol: Given that $f_X(x) = 0.503\sqrt{x}$; $0 \leq x \leq 2$
 $= 0$; otherwise.

mean of $X = H_1 = m_1 = E[X]$

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

$$= \int_0^{\sqrt{2}} x \cdot 0.503 \sqrt{x} dx$$

$$= \int_0^{\sqrt{2}} 0.503 x^{3/2} dx$$

$$= 0.503 \cdot \frac{2}{5} \left(x^{\frac{5}{2}} \right)_0^{\sqrt{2}}$$

$$\boxed{H_1 = 1.128}$$

$$H_2 = E[X^2]$$

$$= 0.503 \int_0^{\sqrt{2}} x^2 \cdot x^{1/2} dx$$

$$= 0.503 \cdot \frac{2}{7} \left(x^{\frac{7}{2}} \right)_0^{\sqrt{2}}$$

$$\boxed{H_2 = 1.625}$$

Variance $= \sigma_X^2 = H_2 - H_1^2$

$$= 1.625 - (1.128)^2$$

$$\boxed{\sigma_X^2 = 0.325}$$

- (5) Given random variable "X" and its density function is

$$f_X(x) = 1 ; 0 \leq x \leq 1
= 0 ; \text{otherwise}$$

(3.46)

Sol: Given that $f_X(x) = 1 ; 0 \leq x \leq 1$
 $= 0$; elsewhere.

$$\begin{aligned}\bar{X} &= E(X) \\ &= \int_{-\infty}^{\infty} x \cdot f_X(x) dx \\ &= \int_0^1 x \cdot 1 dx \\ &= \left(\frac{x^2}{2} \right)_0^1 \\ \boxed{\bar{X}} &= \frac{1}{2}\end{aligned}$$

- (6) Find the expected value of the function $g(x) = x^3$; where "x" is a random variable defined by the density function $f_X(x) = \frac{1}{2} e^{-\frac{1}{2}x} u(x)$

Sol:

Given that $g(x) = x^3$
The density function of the random variable "X" is

$$f_X(x) = \frac{1}{2} e^{-\frac{1}{2}x} u(x) ; x \geq 0$$

$$= 0 ; x < 0.$$

The expected value of the function $g(x)$ is

$$\begin{aligned}&= E[g(x)] \\ &= E(x^3) \\ &= \int_{-\infty}^{\infty} x^3 \cdot f_X(x) dx \\ &= \int_0^{\infty} x^3 \cdot \frac{1}{2} e^{-\frac{1}{2}x} dx \\ &= \frac{1}{2} \int_0^{\infty} x^3 \cdot e^{-\frac{1}{2}x} dx \\ &= \frac{1}{2} \left[\frac{-\frac{1}{2}x \cdot x^3}{(-\frac{1}{2})^1} - \frac{3x^2}{(-\frac{1}{2})^2} + \frac{6x}{(-\frac{1}{2})^3} - \frac{6}{(-\frac{1}{2})^4} \right]_0^{\infty}\end{aligned}$$

$$= y_2 \left(0 - \frac{t^6}{6} \right)$$

(17)

$$= \frac{1}{2} \times 96 \\ = 48$$

$$\boxed{E[g(x)] = 48}$$

- (17) x is a uniform random variable in the interval (x_1, x_2) , find.

The expected value of x .

Sol: Given x is a uniform random variable of the density

function is:

$$f_x(x) = \frac{1}{b-a} ; a \leq x \leq b \\ = 0 ; \text{ elsewhere}$$

As per problem,

$$\text{The density function is } f_x(x) = \frac{1}{x_2-x_1} ; x_1 \leq x \leq x_2 \\ = 0 ; \text{ elsewhere}$$

$$\text{Mean} = E(x) = \int_{-\infty}^{\infty} x \cdot f_x(x) dx \\ = \int_{x_1}^{x_2} x \cdot \left(\frac{1}{x_2-x_1} \right) dx \\ = \frac{1}{x_2-x_1} \int_{x_1}^{x_2} x dx$$

$$= \left(\frac{1}{x_2-x_1} \right) \left(\frac{x^2}{2} \right) \Big|_{x_1}^{x_2}$$

$$= \frac{(x_2^2 - x_1^2)}{2(x_2 - x_1)} = \frac{(x_2 + x_1)(x_2 - x_1)}{2 \cdot (x_2 - x_1)}$$

$$\therefore \text{Mean } M = H_1 = \frac{x_1 + x_2}{2}$$

(18)

Consider the random variable with exponential density $f_x(x) =$

$$f_x(x) = \frac{1}{b} e^{-(x-a)/b} ; x \geq 0 \quad \text{find its characteristic function.} \\ = 0 ; x < a$$

and its first moment.

Sol:

Given the random variable x of exponential density function is

$$f_x(x) = \frac{1}{b} e^{-(x-a)/b} ; x \geq a \\ = 0 ; x < a$$

The first moment about origin = mean

$$E(x) = \int_{-\infty}^{\infty} x \cdot f_x(x) dx \\ = \int_a^{\infty} x \cdot \frac{1}{b} e^{-(x-a)/b} dx \\ = \frac{e^{a/b}}{b} \cdot \int_a^{\infty} x \cdot e^{-x/b} dx \\ = \frac{e^{a/b}}{b} \left[x \left(\frac{-e^{-x/b}}{b} \right) \Big|_a^{\infty} - \int_a^{\infty} (1) \frac{-e^{-x/b}}{b} dx \right]$$

$$= \frac{e^{a/b}}{b} \left[ab \cdot e^{-a/b} + b^2 \cdot e^{-a/b} \right]$$

$$= (a+b)$$

$$\boxed{\text{Mean} = a+b}$$

characteristic function = $E(e^{j\omega x})$

$$\begin{aligned}
 &= \int_{-\infty}^{\infty} e^{j\omega x} f_x(x) dx \\
 &= \int_a^{\infty} e^{j\omega x} \frac{1}{b-a} e^{-(x-a)/b} dx \\
 &= \frac{1}{b-a} e^{a/b} \int_a^{\infty} e^{j\omega x} e^{-x/b} dx \\
 &= \frac{1}{b-a} e^{a/b} \int_a^{\infty} e^{-x/(b-j\omega)} dx \\
 &= \frac{1}{b-a} e^{a/b} \left[\frac{-e^{-x/(b-j\omega)}}{-(b-j\omega)} \right]_a^{\infty} \\
 &= \frac{1}{b-a} e^{a/b} \left[\frac{-e^{-\infty/(b-j\omega)}}{-(b-j\omega)} - \frac{-e^{-a/(b-j\omega)}}{-(b-j\omega)} \right] \\
 &= \frac{1}{b-a} e^{a/b} \left[\frac{-e^{-a/(b-j\omega)}}{(b-j\omega)} \right] \\
 &= \frac{1}{b-a} e^{a/b} \left(e^{-a/b - a/b + j\omega} \right) \\
 &= \frac{1}{b-a} \left(\frac{1}{y_b - j\omega} \right) (e^{j\omega})
 \end{aligned}$$

$$\boxed{\phi_x(\omega) = \frac{1}{b-a} \left(\frac{1}{y_b - j\omega} \right) (e^{j\omega})}$$

(3.48)

$$f_x(x) = \frac{1}{b-a} ; a \leq x \leq b$$

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

$$\begin{aligned}
 \mu_1^1 &= \text{mean} = E[x] = \int_{-\infty}^{\infty} x \cdot f_x(x) dx \\
 &= \int_a^b x \left(\frac{1}{b-a} \right) dx \\
 &= \frac{1}{b-a} \int_a^b x dx \\
 &= \frac{1}{b-a} \left[\frac{x^2}{2} \right]_a^b \\
 &= \left(\frac{1}{b-a} \right) \frac{1}{2} (b^2 - a^2) \\
 &= \frac{(b^2 - a^2)}{2(b-a)} \\
 &= \frac{(b+a)(b-a)}{2(b-a)}
 \end{aligned}$$

$$\boxed{\mu_1^1 = \text{mean} = \frac{a+b}{2}}$$

$$\begin{aligned}
 \mu_2^1 &= E[x^2] = \int_a^b x^2 \cdot f_x(x) dx \\
 &= \int_a^b x^2 \left(\frac{1}{b-a} \right) dx \\
 &= \frac{1}{b-a} \int_a^b x^2 dx \\
 &= \frac{1}{b-a} \left[\frac{x^3}{3} \right]_a^b = \frac{1}{3} \frac{1}{b-a} (b^3 - a^3) \\
 &= \frac{1}{3} \frac{(b-a)(b^2 + ab + a^2)}{(b-a)}
 \end{aligned}$$

$$\boxed{\mu_2^1 = \text{variance} = \frac{a^2 + ab + b^2}{3}}$$

(19) Show that the mean value- and variance of a random variable

having the uniform density function $f_x(x) = \frac{1}{b-a}$; $a \leq x \leq b$, are

$$\bar{x} = E(x) = \frac{a+b}{2} ; \text{ and } \sigma_x^2 = \frac{(b-a)^2}{12}$$

Sol:

Given the uniform density function of a random variable "x" is given by

Variance $\sigma_x^2 = H_2 - (H_1)^2$

$$\begin{aligned}\sigma_x^2 &= \frac{a^2 + ab + b^2}{3} - \frac{a^2 + 2ab + b^2}{4} \\ &= \frac{4a^2 + 4ab + 4b^2 - 3a^2 - 6ab - 3b^2}{12} \\ &= \frac{a^2 + b^2 - 2ab}{12} \\ &= \frac{(a-b)^2}{12} \\ &= \frac{(b-a)^2}{12} \\ \boxed{\sigma_x^2 = \frac{(b-a)^2}{12}}\end{aligned}$$

- (20) prove that the moment generating function of sum of two independent random variable is the product of their moment generating functions. $M_{x+y}(t) = M_x(t) \cdot M_y(t)$.

Sol: From the definition of moment generating function

$$\begin{aligned}\phi_x(t) &= E[e^{tx}] \\ M_{x+y}(t) &= E[e^{t(x+y)}] \\ &= E[e^{tx+ty}] \\ &= E[e^{tx} \cdot e^{ty}] \\ &= E[e^{tx}] \cdot E[e^{ty}] \\ &= M_x(t) \cdot M_y(t)\end{aligned}$$

$$\boxed{M_{x+y}(t) = M_x(t) \cdot M_y(t)}$$

- (21) Show that any characteristic function $\phi_{X(\omega)}$ satisfies $|\phi_{X(\omega)}| \leq 1$ $\phi_x(0) = 1$; (property of 1st and 2nd of characteristic function)

Sol: we know that $\phi_x(\omega) = \int_{-\infty}^{\infty} e^{j\omega x} \cdot f_x(x) dx$

$$\begin{aligned}|\phi_x(\omega)| &= \left| \int_{-\infty}^{\infty} e^{j\omega x} \cdot f_x(x) dx \right| \\ &= \int_{-\infty}^{\infty} |f_x(x)| dx \quad [\because |e^{j\omega x}| = 1] \\ &\leq \int_{-\infty}^{\infty} 1 dx \quad [\because \int_{-\infty}^{\infty} 1 dx = 1] \\ &= 1\end{aligned}$$

$$|\phi_x(\omega)| \leq 1 \rightarrow \textcircled{1}$$

$$\begin{aligned}|\phi_x(0)| &= \int_{-\infty}^{\infty} e^0 \cdot f_x(x) dx \\ &= \int_{-\infty}^{\infty} f_x(x) dx \\ &= 1\end{aligned}$$

$$\phi_x(0) = 1 \rightarrow \textcircled{2}$$

∴ from eq \textcircled{1} and \textcircled{2}

$$\boxed{|\phi_x(\omega)| \leq |\phi_x(0)| = 1}$$

- (22) find the moment generating function of random variable "x" with $x = y_2$, with probability y_2 , $x = -y_2$, with probability y_2 also findout first 4 moments about origin from moment generating function?

Sol: Given that the random variable "x" has $x = y_2$ with probability y_2

$$\text{i.e. } x = y_2 ; P(x = y_2) = y_2$$

i.e. $x = -y_2$; $P(x = -y_2) = \frac{1}{2}$

∴ The PDF is

$x = y$	$-y_2$	y_2
$P(x = y)$	y_2	y_2

Here the random variable is "x" is discrete random variable

for discrete random variable, the moment generating function is given by

$$H_X(t) = E(e^{tx}) = \sum_{\text{all } x} e^{tx} \cdot f_X(x)$$

$$= \sum_{\text{all } x} e^{tx} \cdot P(x=x).$$

$$= e^{t(y_2)} \cdot P(x=y_2) + e^{t(-y_2)} \cdot P(x=-y_2)$$

$$= e^{ty_2} y_2 + e^{-ty_2} y_2$$

$$H_X(t) = \frac{1}{2} (e^{ty_2} + e^{-ty_2})$$

$$M_X(t) = \frac{1}{2} \left[1 + \frac{(ty_2)}{1!} + \frac{(ty_2)^2}{2!} + \dots + 1 + \frac{(-ty_2)}{1!} + \frac{(-ty_2)^2}{2!} + \dots \right]$$

$$= \frac{1}{2} \left[1 + \frac{t}{2 \cdot 1!} + \frac{t^2}{4 \cdot 2!} + \dots + 1 + \frac{t}{2 \cdot 1!} + \frac{t^2}{4 \cdot 2!} + \dots \right]$$

$$= \frac{1}{2} \left[2 + \frac{t}{1!} \left(\frac{1}{2} - \frac{1}{2} \right) + \frac{t^2}{2!} \left(\frac{1}{4} + \frac{1}{4} \right) + \frac{t^3}{3!} \left(\frac{1}{8} - \frac{1}{8} \right) + \dots \right]$$

$$= \frac{1}{2} \left[2 + \frac{t^2}{2!} \left(\frac{2}{4} \right) \right] + \dots$$

$$\therefore 1 + \frac{t}{1!}(0) + \frac{t^2}{2!}\left(\frac{1}{4}\right) + \frac{t^3}{3!}(0) + \frac{t^4}{4!} y_2 + \dots \rightarrow ①$$

We know that from the definition of moment generating function is

$$M_X(t) = E(e^{tx}) = 1 + \frac{t}{1!} \cdot E(x) + \frac{t^2}{2!} E(x^2) + \dots \rightarrow ②$$

from ① and ②

$$E(x) = 0; E(x^2) = \frac{1}{4}; E(x^3) = 0; E(x^4) = \frac{1}{8}$$

(or)

$$\begin{aligned} M_X(t) &= \frac{1}{2} (e^{ty_2} + e^{-ty_2}) \\ &= \frac{1}{2} e^{ty_2} + \frac{1}{2} e^{-ty_2} \end{aligned}$$

$$\therefore \text{the 1st moment about origin} = H_1 = m_1 = \frac{d}{dt} (H_X(t)) \Big|_{t=0}$$

$$= \frac{d}{dt} \left(\frac{1}{2} e^{ty_2} + \frac{1}{2} e^{-ty_2} \right) \Big|_{t=0}$$

$$= \frac{1}{2} \cdot e^{ty_2} \left(\frac{1}{2} \right) + \frac{1}{2} (e^{ty_2}) (-y_2) \Big|_{t=0}$$

$$= \frac{1}{4} - \frac{y_2}{4}$$

$$= 0.$$

$$\therefore \text{the 2nd moment about origin} = H_2 = m_2 = \frac{d^2}{dt^2} (H_X(t)) \Big|_{t=0}$$

$$\frac{d}{dt} \left[\frac{d}{dt} (H_X(t)) \right] \Big|_{t=0}$$

$$= \frac{d}{dt} \left(\frac{1}{4} e^{ty_2} - \frac{1}{4} e^{-ty_2} \right) \Big|_{t=0}$$

$$= \frac{1}{4} e^{ty_2} \left(\frac{1}{2} \right) - \frac{1}{4} e^{-ty_2} (-y_2) \Big|_{t=0}$$

$$\begin{aligned} &= \frac{y_2 + 1/y_2}{4} \\ &\boxed{H_2 = \frac{y_2 + 1/y_2}{4}} \end{aligned}$$

$$\text{1) } \text{moment about origin} = M_3 = m_3 = \frac{d^3}{dt^3} (H_x(t)) \Big|_{t=0} \quad (2.5)$$

$$= \frac{d}{dt} \left(\frac{d^2}{dt^2} (H_x(t)) \right) \Big|_{t=0}$$

$$= \frac{d}{dt} \left[\left(Y_2 e^{th_2} + Y_1 \bar{e}^{th_2} \right) \Big|_{t=0} \right]$$

$$= \frac{1}{16} e^{th_2} - \frac{1}{16} \bar{e}^{th_2} \Big|_{t=0}$$

$$= \frac{1}{16} - \frac{1}{16}$$

$$= 0$$

$$\text{2) } \text{moment about origin} \cdot M_4 = m_4 = \frac{d^4}{dt^4} (H_x(t)) \Big|_{t=0}$$

$$\frac{d}{dt} \left(\frac{d^3}{dt^3} (H_x(t)) \right) \Big|_{t=0}$$

$$\frac{d}{dt} \left(\frac{1}{16} e^{th_2} + Y_1 \bar{e}^{th_2} \right) \Big|_{t=0}$$

$$\frac{1}{32} e^{th_2} + \frac{1}{32} \bar{e}^{th_2} \Big|_{t=0}$$

$$= \frac{1}{32} + \frac{1}{32}$$

$$= 1/16$$

(2.5) The moment generating function of a random variable \hat{x}'' is

$\frac{1}{2-t}$ find out its mean and variance?

Sol: Given the moment generating function of random variable x is $\frac{2}{2-t}$

$$\therefore M_1 = m_1 = \frac{d}{dt} (m_x(t)) \Big|_{t=0}$$

$$= \frac{d}{dt} \left(\frac{2}{2-t} \right) \Big|_{t=0}$$

$$= \frac{(2-t)(0) - 2(-1)}{(2-t)^2} \Big|_{t=0}$$

$$= \frac{2}{(2-0)^2}$$

$$= \frac{2}{4}$$

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

$$\text{Second moment about origin} = M_2 = m_2 = \frac{d^2}{dt^2} (m_x(t)) \Big|_{t=0}$$

$$\frac{d}{dt} \left(\frac{d}{dt} (m_x(t)) \right) \Big|_{t=0}$$

$$\frac{d}{dt} \left(\frac{2}{(2-t)^2} \right) \Big|_{t=0}$$

$$\frac{(2-t)^2(0) - 2(2-t)(-1)}{(2-t)^3} \Big|_{t=0}$$

$$= \frac{4(2-0)}{(2-0)^3} \Big|_{t=0}$$

$$= \frac{4}{2^3}$$

$$= \frac{4}{8} = \frac{1}{2}$$

$$\text{Variance of } \hat{x}'' = \sigma_{\hat{x}''}^2 = M_2 - (M_1)^2$$

$$= Y_2 - Y_1^2$$

$$= 1/4$$

(24) The moment generating function of random variable "x" having the density function $f_x(x) = e^{-x}$; $x > 0$ find moment generating function of $= 0$ elsewhere.

a variance?

Sol:

$$\text{Given } f_x(x) = e^{-x} \quad ; \quad x > 0 \\ = 0 \quad ; \quad \text{elsewhere}$$

$$\mu_x(t) = E[e^{tx}] \quad M_1^t = E(x) = \frac{d}{dt}(M_x(t)) \Big|_{t=0}$$

$$= \int_0^\infty e^{tx} f_x(x) dx \quad = \frac{d}{dt} \left(\frac{1}{1-t} \right) \Big|_{t=0}$$

$$= \int_0^\infty e^{tx} e^{-x} dx \quad = \frac{-1}{(t-1)^2} \Big|_{t=0}$$

$$= \int_0^\infty e^{x(t-1)} dx \quad \boxed{M_1^t = -1}$$

$$= \left[\frac{e^{x(t-1)}}{t-1} \right]_0^\infty \quad M_2^t = \frac{d^2}{dt^2}(M_x(t)) \Big|_{t=0}$$

$$= 0 + \frac{1}{(t-1)^2} \quad = \frac{2}{(t-1)^3} \Big|_{t=0}$$

$$= \boxed{M_2^t = 2.}$$

$$M_x(t) = \left(\frac{1}{1-t} \right) \Big|_{t=0}$$

$$\boxed{M_x(t) = 1}$$

$$\therefore \text{variance } \sigma_x^2 = M_2^t - (M_1^t)^2$$

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

$$= 2 - 1$$

$$= 1$$

(25) If density function of a continuous random variable is $f_x(x) = \frac{1}{2} e^{-|x|}$, find moment generating function of "x". and its mean and variance.

Sol:-

$$\text{Given that } f_x(x) = \frac{1}{2} e^{-|x|}$$

The moment generating function of random variable "x" is

$$\begin{aligned} M_x(t) &= E[e^{tx}] \\ &= \int_{-\infty}^{\infty} e^{tx} f_x(x) dx \\ &= \int_{-\infty}^{\infty} e^{tx} \frac{1}{2} e^{-|x|} dx \\ &= \frac{1}{2} \left[\int_{-\infty}^0 e^{tx} e^{-x} dx + \int_0^{\infty} e^{tx} e^{-x} dx \right] \\ &= \frac{1}{2} \int_{-\infty}^0 e^{tx+x^2} dx + \frac{1}{2} \int_0^{\infty} e^{tx-x^2} dx \\ &= \frac{1}{2} \int_{-\infty}^0 e^{\left(\frac{(t+1)x}{2}\right)^2} dx + \frac{1}{2} \int_0^{\infty} e^{\left(\frac{(t-1)x}{2}\right)^2} dx \\ &= \frac{1}{2} \left(\frac{e^0 - 1}{\frac{t+1}{2}} \right) + \frac{1}{2} \left(\frac{e^0 - 1}{\frac{t-1}{2}} \right) \\ &= \frac{1}{2} \left[e^0 - \frac{1}{t+1} \right] + \frac{1}{2} \left[\frac{e^0 - 1}{t-1} \right] \\ &= \frac{-1}{2t+2} + \frac{1}{2t-2} \\ &= \frac{-2t+2 + 2t-2}{(2t)^2 - 2^2} = \frac{4}{4t^2 - 4} = \frac{4}{(t^2-1)^2} = \frac{1}{(t^2-1)^2} \\ \boxed{M_x(t) = \frac{1}{(t^2-1)^2}}$$

The mean of random variable "x" is $M_1^t = E(x)$

$$= \int_{-\infty}^{\infty} x \cdot f_x(x) dx \quad (\text{or}) \quad \frac{d}{dt}(M_x(t)) \Big|_{t=0}$$

$$M_1^t = \frac{d}{dt} \left(\frac{1}{(t^2-1)^2} \right) \Big|_{t=0} = \frac{(1-t^2)(0) - 1(-2t)}{(t^2-1)^3} \Big|_{t=0}$$

$$|H_1| = 0$$

$$H_2' = \frac{d}{dt^y} \left(\frac{1}{1-t^y} \right) \Big|_{t=0}$$

$$= \frac{d}{dt} \left[\frac{2t}{(1+t)^2} \right]_{t=0}$$

$$= \frac{(1-t^y)^2 - 2t - 2(1-t^y)(-2t)}{(1-t^y)^4} \Bigg|_{t=0}$$

$$= \frac{2 \cdot (1-t^y)^2 + 8t^y(1-t^y)}{(1-t^y)^4} = \frac{(1-t^y)[2(1-t^y) + 8t^y]}{(1-t^y)^4}$$

$$= \frac{2(1-t^y) + 8t^y}{(1-t^y)^2} \Bigg|_{t=0}$$

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

$$|H_2'| = 2$$

$$\therefore \text{variance } \sigma_x^2 = H_2' - (H_1')^2$$

$$= 2 - 0^2$$

$$= 2 - 0$$

$$= 2$$

$$\sigma_x^2 = 2$$

(26) Show that the distribution function for which the characteristic function \tilde{e}^{itx} has density function $f_X(x) = \frac{1}{\pi(1+x^2)}$; $-\infty < x < \infty$

Sol: Given the characteristic function $\phi_x(t) = \tilde{e}^{itx}$.

We know that, the density function of random variable "x" is inverse fourier transform of its characteristic function

(27)

$$\begin{aligned} \therefore f_X(x) &= \frac{1}{2\pi} \int_{-\infty}^{\infty} \phi_x(t) e^{-jwx} dt \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} \tilde{e}^{itx} e^{-jwx} dt \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{-|t|} e^{-jwx} dt \\ &= \frac{1}{2\pi} \left[\int_{-\infty}^0 e^t \cdot e^{-jwx} dt + \int_0^{\infty} e^{-t} e^{-jwx} dt \right] \\ &= \frac{1}{2\pi} \left[\int_{-\infty}^0 e^{t(1-jw)} dx + \int_0^{\infty} e^{-t(1+jw)} dx \right] \\ &= \frac{1}{2\pi} \left[\left(\frac{e^{t(1-jw)}}{(1-jw)} \right) \Big|_{-\infty}^0 + \left(\frac{-e^{-t(1+jw)}}{(1+jw)} \right) \Big|_0^{\infty} \right] \\ &= \frac{1}{2\pi} \left[\frac{1}{1-jw} + 0 + \frac{1}{1+jw} \right] \\ &= \frac{1}{2\pi} \left(\frac{1}{1-jw} + \frac{1}{1+jw} \right) \\ &= \frac{1}{2\pi} \left(\frac{1+jw + 1-jw}{1+w^2} \right) \\ &= \frac{1}{2\pi} \left(\frac{2}{1+w^2} \right) \end{aligned}$$

$$\boxed{f_X(x) = \frac{1}{\pi(1+x^2)} ; -\infty \leq x \leq \infty}$$

(28)

Find the characteristic function of a random variable "x" with the density function $f_X(x) = \frac{x}{2} ; 0 \leq x \leq 2$
 $= 0 ; \text{elsewhere}$.

Sol:

Given the density function of a random variable "x" by

$$f_x(x) = \begin{cases} \frac{x}{2} & ; 0 \leq x \leq 1 \\ 0 & ; \text{elsewhere} \end{cases}$$

The characteristic function of random variable "x" is

$$\begin{aligned}\phi_x(\omega) &= E(e^{j\omega x}) \\ &= \int_{-\infty}^{\infty} e^{j\omega x} \cdot f_x(x) dx \\ &= \int_{-\infty}^{\infty} \frac{x}{2} e^{j\omega x} dx \\ &= \frac{1}{2} \int_{-\infty}^{\infty} x e^{j\omega x} dx \\ &= \frac{1}{2} \left[x \left(\frac{e^{j\omega x}}{j\omega} \right)_0^\infty - \int_0^\infty \frac{e^{j\omega x}}{j\omega} dx \right] \\ &= \frac{1}{2} \left[(k-0) \frac{e^{j\omega 0}}{j\omega} - \frac{1}{j\omega} \left(\frac{e^{j\omega x}}{j\omega} \right)_0^\infty \right] \\ &= \frac{1}{2} \left[\frac{2e^{j\omega}}{j\omega} + \frac{1}{j\omega} (e^{j\omega} - 1) \right] \\ \boxed{\therefore \phi_x(\omega) = \frac{e^{j\omega}}{j\omega} + \frac{2}{j\omega} (e^{j\omega} - 1)}\end{aligned}$$

- ⑧ A random variable "x" has a characteristic function $\phi_x(\omega) = 1 - |\omega| ; |\omega| \leq 1$
 $= 0 ; |\omega| > 1$

find the density function of a random variable "x".

Sol:
Given that $\phi_x(\omega) = 1 - |\omega| ; |\omega| \leq 1$
 $= 0 ; |\omega| > 1$

$$\therefore \phi_x(\omega) = 1 - |\omega| ; -1 \leq |\omega| \leq 1
= 0 ; \text{otherwise.}$$

We know that the density function of a random variable "x" is

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Inverse Fourier transform of its characteristic function

$$\begin{aligned}f_x(x) &= \frac{1}{2\pi} \int_{-\infty}^{\infty} \phi_x(\omega) e^{-j\omega x} d\omega \\ &= \frac{1}{2\pi} \int_{-1}^1 (1 - |\omega|) \cdot e^{-j\omega x} d\omega \\ &= \frac{1}{2\pi} \left[\int_{-1}^0 (1 - (\omega)) \cdot e^{-j\omega x} d\omega + \int_0^1 (1 - \omega) \cdot e^{-j\omega x} d\omega \right] \\ &\stackrel{1}{=} \frac{1}{2\pi} \left[\int_{-1}^0 ((1+\omega) \cdot e^{-j\omega x} d\omega + \int_0^1 (1-\omega) \cdot e^{-j\omega x} d\omega \right] \\ &= \frac{1}{2\pi} \left[- \int_{-1}^0 (1+\omega) \left(\frac{e^{-j\omega x}}{-jx} \right)_1^0 - \int_{-1}^0 \frac{e^{-j\omega x}}{-jx} d\omega \right] + \frac{1}{2\pi} \left[(1-\omega) \left(\frac{e^{-j\omega x}}{-jx} \right)_0^1 + \int_0^1 \frac{e^{-j\omega x}}{-jx} d\omega \right] \\ &= \frac{1}{2\pi} \left[\left(\frac{1}{jx} - 0 \right) - \frac{1}{(jx)} \left(e^{-j\omega x} \right)_1^0 \right] + \frac{1}{2\pi} \left[(0 + \frac{1}{jx}) + \frac{1}{(jx)} \left(e^{-j\omega x} \right)_0^1 \right] \\ &= \frac{1}{2\pi} \left[-\frac{1}{jx} - \left(\frac{1}{(jx)^2} - \frac{e^{-j\omega x}}{(jx)^2} \right) \right] + \frac{1}{2\pi} \left[\frac{1}{jx} + \left(\frac{e^{j\omega x}}{(jx)^2} - \frac{1}{(jx)^2} \right) \right] \\ &= \frac{1}{2\pi} \left[\frac{-1}{jx} - \frac{1}{(jx)^2} + \frac{e^{j\omega x}}{(jx)^2} + \frac{1}{jx} + \frac{e^{-j\omega x}}{(jx)^2} - \frac{1}{(jx)^2} \right] \\ &= \frac{1}{2\pi} \left[-\frac{e^{j\omega x}}{x^2} + \frac{e^{-j\omega x}}{x^2} + \frac{1}{x^2} + \frac{1}{x^2} \right] \\ &= \frac{1}{2\pi} \left[\frac{1}{x^2} \right] (e^{j\omega x} + e^{-j\omega x} + 2) \\ &= \frac{1}{\pi x^2} \left[1 + \left(\frac{e^{j\omega x} + e^{-j\omega x}}{2} \right) \right] \\ &= \frac{1}{\pi x^2} [1 + \cos \omega x] = \underbrace{(1 + \cos x)}_{\pi x^2}\end{aligned}$$

Q) for the Rayleigh density function $f_x(x) = \frac{2}{b} \cdot (x-a) \cdot e^{-(x-a)/b}$, $x \geq a$

$$= 0 \quad ; \quad x < a.$$

Show that $E[x] = a + \sqrt{\frac{\pi b}{4}}$; $\sigma_x^2 = \frac{b(4-\pi)}{4}$. (655)

Sol: Given that $f_x(x) = \frac{2}{b} \cdot (x-a) \cdot e^{-(x-a)/b}$; $x \geq a$

$$= 0 \quad ; \quad x < a$$

let $(x-a) = t$ If $x=a \Rightarrow t=a-a \Rightarrow t=0$

$$\frac{b}{2} = \alpha^2$$

$$\therefore f_x(x) = \frac{t}{\alpha^2} e^{-t^2/2\alpha^2}, \quad t \geq 0$$

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

Mean of random variable "x" is $= E[x]$

$$\begin{aligned} &= \int_{-\infty}^{\infty} x \cdot f_x(x) dx \\ &= \int_0^{\infty} (t+a) \cdot \frac{t}{\alpha^2} e^{-t^2/2\alpha^2} dt \\ &= \int_0^{\infty} \left(\frac{t^2}{\alpha^2} + \frac{at}{\alpha^2} \right) e^{-t^2/2\alpha^2} dt \\ &= \int_0^{\infty} \frac{t^2}{\alpha^2} \cdot e^{-t^2/2\alpha^2} dt + \int_0^{\infty} \frac{at}{\alpha^2} e^{-t^2/2\alpha^2} dt. \rightarrow ① \end{aligned}$$

Let us consider, first term in eq ①.

$$\begin{aligned} \int_0^{\infty} \frac{t^2}{\alpha^2} \cdot e^{-t^2/2\alpha^2} dt &= \int_0^{\infty} t \left(\frac{t}{\alpha^2} e^{-t^2/2\alpha^2} \right) dt \\ &= \int_0^{\infty} t \cdot (-d(e^{-t^2/2\alpha^2})) dt \end{aligned}$$

$$= t \cdot \left[e^{-t^2/2\alpha^2} \right]_0^\infty - \int_0^\infty 1 \cdot (-e^{-t^2/2\alpha^2}) dt$$

$$= 0(a-0) + \int_0^\infty e^{-t^2/2\alpha^2} dt.$$

$$\therefore \int_0^\infty \frac{t^2}{\alpha^2} e^{-t^2/2\alpha^2} dt = \int_0^\infty e^{-t^2/2\alpha^2} dt \rightarrow ②$$

We know that the density function of a normal distribution function is given by

$$f_x(z) = \frac{1}{\sqrt{2\pi\sigma_x^2}} \cdot e^{-z^2/2\sigma_x^2}$$

Let $m=a$

$$f_x(z) = \frac{1}{\sqrt{2\pi\sigma_x^2}} \cdot e^{-z^2/2\sigma_x^2}.$$

We know that gaussian density function is valid density function

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma_x^2}} e^{-z^2/2\sigma_x^2} dz = 1 \rightarrow ③$$

eq ② $\Rightarrow \int_0^\infty \frac{t^2}{\alpha^2} e^{-t^2/2\alpha^2} dt = \int_0^\infty e^{-t^2/2\alpha^2} dt$

$$= \frac{1}{2} \cdot 2 \left(\int_0^\infty e^{-t^2/2\alpha^2} dt \right)$$

$$= \frac{1}{2} \left[\int_{-\infty}^{\infty} e^{-t^2/2\alpha^2} dt \right]$$

$$= \frac{1}{2} \left[\int_{-\infty}^a \frac{1}{\sqrt{2\pi\sigma_x^2}} \cdot e^{-t^2/2\alpha^2} dt \right]$$

$$= \frac{\sqrt{2\pi\sigma_x^2}}{2} \int_{-\infty}^a \frac{1}{\sqrt{2\pi\sigma_x^2}} \cdot e^{-t^2/2\alpha^2} dt$$

$$\therefore \int_0^\infty \frac{t^{\alpha}}{\alpha} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt = \int_0^\infty \sqrt{\frac{\pi \alpha^{\gamma}}{2}} \quad (1)$$

(3.56)

$$= \sqrt{\frac{\pi \alpha^{\gamma}}{2}} \rightarrow ④$$

let us consider . ②nd term . in eq ① is

$$\begin{aligned} \int_0^\infty t \cdot \frac{a}{\alpha^{\gamma}} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt &= a \int_0^\infty t \cdot d(e^{-t^{\gamma}/2\alpha^{\gamma}}) \\ &= a \left[-e^{-t^{\gamma}/2\alpha^{\gamma}} \right]_0^\infty \\ &= a \left(-e^{-\infty} + e^0 \right) \\ &= a. \rightarrow ⑤ \end{aligned}$$

Substitute eq ④ and ⑤ in ①

$$\therefore E(x) = \sqrt{\frac{\pi \alpha^{\gamma}}{2}} + a$$

$$\text{but } \frac{b}{2} = \alpha^{\gamma}$$

$$\Rightarrow E(x) = \sqrt{\frac{\pi(b/2)}{2}} + a$$

$$\therefore E(x) = a + \sqrt{\frac{\pi b}{4}}$$

$$\begin{aligned} \therefore E(x^{\gamma}) &= \int_0^\infty \alpha^{\gamma} \cdot f_x(t) dt \\ &= \int_0^\infty (\alpha + a)^{\gamma} \cdot \frac{t}{\alpha^{\gamma}} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt \\ &= \int_0^\infty (\alpha + a)^{\gamma} \cdot \frac{t}{\alpha^{\gamma}} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt \end{aligned}$$

$$\begin{aligned} &= \int_0^\infty \frac{t^3}{\alpha^{\gamma}} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt + \int_0^\infty \frac{2at^2}{\alpha^{\gamma}} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt + \int_0^\infty a^{\gamma} \frac{t}{\alpha^{\gamma}} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt \\ &= \int_0^\infty \frac{t^3}{\alpha^{\gamma}} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt + 2a \int_0^\infty \frac{t^2}{\alpha^{\gamma}} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt + a^{\gamma} \int_0^\infty \frac{t}{\alpha^{\gamma}} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt \\ E(x^{\gamma}) &= \int_0^\infty \frac{t^3}{\alpha^{\gamma}} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt + 2a \sqrt{\frac{\pi \alpha^{\gamma}}{2}} + a^{\gamma} (1) \rightarrow ⑥ \\ \therefore &= \int_0^\infty \frac{t^3}{\alpha^{\gamma}} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt = \int_0^\infty t^{\gamma} \cdot \frac{t}{\alpha^{\gamma}} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt \\ &= \int_0^\infty t^{\gamma} \cdot d(-e^{-t^{\gamma}/2\alpha^{\gamma}}) dt \\ &= \left[t^{\gamma} \cdot (-e^{-t^{\gamma}/2\alpha^{\gamma}}) \right]_0^\infty + \int_0^\infty 2t^{\gamma} \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt \end{aligned}$$

$$\begin{aligned} &= \left[0 + 2 \int_0^\infty t \cdot e^{-t^{\gamma}/2\alpha^{\gamma}} dt \right]_0^\infty \\ &= 2 \int_0^\infty t \cdot d \left[(-e^{-t^{\gamma}/2\alpha^{\gamma}}), \alpha^{\gamma} \right] dt \\ &= 2 \left[-e^{-t^{\gamma}/2\alpha^{\gamma}} \cdot \alpha^{\gamma} \right]_0^\infty \\ &= 2 \alpha^{\gamma} \end{aligned}$$

$$\therefore E(x^{\gamma}) = 2 \alpha^{\gamma} + \frac{2a \sqrt{\pi \alpha^{\gamma}}}{\sqrt{2}} + a^{\gamma}$$

$$= 2 \cdot \frac{b}{2} + 2a \sqrt{\frac{\pi b}{4}} + a^{\gamma}$$

$$= b + a \sqrt{\pi b} + a^{\gamma}$$

$$\therefore E(x^{\gamma}) = b + a \sqrt{\pi b} + a^{\gamma}$$

$$\text{Therefore } \sigma_x^{\gamma} = H_2 - (H_1)^2 = b + a \sqrt{\pi b} + a^{\gamma} - \left(a + \sqrt{\frac{\pi b}{4}} \right)^2$$

$$\sigma_x^{\gamma} = b + a \sqrt{\pi b} + a^{\gamma} - a^2 - \frac{\pi b}{4} - 2a \sqrt{\pi b}$$

$$\begin{aligned}
 &= b - \frac{\pi b}{4} \\
 &= \frac{4b - \pi b}{4} \\
 &= \frac{b(4-\pi)}{4}
 \end{aligned}$$

(30) The characteristic function of a Laplace-density function is

$$\phi_x(\omega) = \frac{e^{j\omega b}}{1+(b\omega)^2}, \text{ find mean and variance of } r.v. X.$$

Sol: Given, the random variable X follows the Laplace transform

distribution with characteristic function

$$\phi_x(\omega) = \left[\frac{e^{j\omega b}}{1+(b\omega)^2} \right]$$

$$\therefore \text{Mean of } X = E[X] = M_1 = \left(\frac{1}{j} \right) \cdot \frac{d}{d\omega} (\phi_x(\omega)) \Big|_{\omega=0}$$

$$= \left(\frac{1}{j} \right) \cdot \frac{d}{d\omega} \left(\frac{e^{j\omega b}}{1+(b\omega)^2} \right) \Big|_{\omega=0}$$

$$= \left(\frac{1}{j} \right) \left[\frac{(1+(b\omega)^2) e^{j\omega b} (j) - e^{j\omega b} (2bw)}{(1+(b\omega)^2)^2} \right] \Big|_{\omega=0}$$

$$= \left(\frac{1}{j} \right) \left(\frac{j\pi}{1} \right)$$

$$\boxed{E(X) = m}$$

$$E(X^2) = M_2 = \left(\frac{1}{j} \right)^2 \cdot \frac{d^2}{d\omega^2} (\phi_x(\omega)) \Big|_{\omega=0}$$

$$= (-1) \cdot \frac{d}{d\omega} \left[\frac{d}{d\omega} (\phi_x(\omega)) \right] \Big|_{\omega=0}$$

$$= (-1) \frac{d}{d\omega} \left[\frac{(1+(b\omega)^2) j\pi e^{j\omega b} - e^{j\omega b} (2bw)}{(1+(b\omega)^2)^2} \right] \Big|_{\omega=0}$$

$$= \cdot M + 2b^2$$

$$\sigma_X^2 = E(X^2) - (E(X))^2$$

$$= \pi^2 + 2b^2 - \pi^2$$

$$\boxed{\sigma_X^2 = 2b^2}$$

(31) The analog $r.v. X^N$ has a characteristic function $\phi_{X^N}(\omega) = \left(\frac{a}{a-j\omega} \right)^N$ for $a > 0$, and $N = 1, 2, 3, \dots$. Show that $\bar{x} = N/a$; $\bar{X}^N = \frac{N(N+1)}{a^N}$; $\sigma_{X^N}^2 = \frac{N}{a^N}$

Sol: Given $\phi_x(\omega) = \left(\frac{a}{a-j\omega} \right)^N = \frac{a^N}{(a-j\omega)^N}$

$$\therefore \text{Mean of } X = E(X) = M_1 = \left(\frac{1}{j} \right) \cdot \frac{d}{d\omega} (\phi_x(\omega)) \Big|_{\omega=0}$$

$$= \left(\frac{1}{j} \right) \cdot \frac{d}{d\omega} \left(\frac{a^N}{(a-j\omega)^N} \right) \Big|_{\omega=0}$$

$$= \frac{a^N}{j} \cdot \frac{d}{d\omega} \left(\frac{1}{(a-j\omega)^N} \right) \Big|_{\omega=0}$$

$$= \frac{a^N}{j} \left[\frac{-N(a-j\omega)^{N-1} (j)}{(a-j\omega)^{2N}} \right] \Big|_{\omega=0}$$

$$= \frac{a^N}{j} \left[\frac{jN(a-j\omega)^{N-1}}{(a-j\omega)^{2N}} \right] \Big|_{\omega=0}$$

$$= \frac{a^N}{j} \left(\frac{jN a^{N-1}}{a^{2N}} \right)$$

$$= \frac{a^N}{j} \cdot jN a^{N-1-2N}$$

$$= N a^{N+N-1-2N}$$

$$H_i^1 = \frac{1}{a^2} N$$

(3.58)

$$\boxed{H_i^1 = m = \frac{N}{a}}$$

$$\begin{aligned}
 \bar{x}^v &= E(x^v) = \left(\frac{1}{j}\right)^v \frac{d^v}{dw^v} \cdot \left[\psi_x(w) \right] \Big|_{w=0} \\
 &= \left(\frac{1}{j}\right)^v \cdot \frac{d}{dw} \left(\frac{\alpha^N j^N \cdot (a-jw)^{N-1}}{(a-jw)^{2N}} \right) \Big|_{w=0} \\
 &= \frac{1}{j^v} \alpha^N j^N \cdot \frac{d}{dw} \cdot \left(\frac{(a-jw)^{v-1}}{(a-jw)^{2N}} \right) \Big|_{w=0} \\
 &= \frac{\alpha^N N}{j^v} \cdot \frac{d}{dw} \left[\frac{1}{(a-jw)^{N+1}} \right] \Big|_{w=0} \\
 &= \frac{\alpha^N N}{j^v} \cdot \left[-\frac{(N+1)}{(a-jw)^{2N+2}} (a-jw)^N (-j) \right] \Big|_{w=0} \\
 &= \frac{\alpha^N N}{j^v} \left[\frac{j(N+1) \alpha^N}{a^{2N+2}} \right] \\
 &= \frac{\alpha^N N \cdot (N+1) \alpha^N}{a^{2N+2}}
 \end{aligned}$$

$$\boxed{\bar{x}^v = \frac{N(N+1)}{\alpha^{2N+2}}}$$

$$E_x^v = E(x^v) - E(x) = \frac{N(N+1)}{\alpha^v} - \frac{N^v}{\alpha^v}$$

$$\boxed{\sigma_x^v = N/a^v}$$

(32) A random variable has . Palt. $f_X(x) = \frac{1}{2^x}$; $x=1,2,3,4 \dots$ find.

the moment generating function ..

Sol: Given $f_X(x) = \frac{1}{2^x}$; $x=1,2,3,4 \dots$

here "X" is a discrete random variable.

i.e. the moment generating function of "X" is

$$\begin{aligned} f_X(x) &= E(e^{tx}) \\ &= \sum_{all\ x} e^{tx} \cdot f_X(x) \\ &= \sum_{x=1}^{\infty} e^{tx} \cdot \frac{1}{2^x} \\ &= \sum_{x=1}^{\infty} \left(\frac{e^t}{2}\right)^x \\ &= \left(\frac{e^t}{2}\right)^1 + \left(\frac{e^t}{2}\right)^2 + \left(\frac{e^t}{2}\right)^3 + \dots \\ &= \left(\frac{e^t}{2}\right) \left[1 + \frac{e^t}{2} + \left(\frac{e^t}{2}\right)^2 + \left(\frac{e^t}{2}\right)^3 + \dots \right] \\ &= \left(\frac{e^t}{2}\right) \left[1 - \frac{e^t}{2} \right]^{-1} \\ &= \frac{e^t}{2} \left[\frac{2 - e^t}{2} \right]^{-1} \\ &= \frac{e^t}{2} \frac{(2 - e^t)^{-1}}{2^{-1}} \\ &= e^t (2 - e^t)^{-1} \\ \boxed{M_X(t) = \frac{e^t}{2 - e^t}} \end{aligned}$$

where "X" is discrete random variable

\therefore the moment generating function of "X" is

$$\begin{aligned} M_X(t) &= E(e^{tx}) \\ &= \sum_{all\ x} e^{tx} f_X(x) \\ &= \sum_{x=0}^{\infty} e^{tx} \frac{2}{3} \left(\frac{1}{3}\right)^x \\ &= \frac{2}{3} \sum_{x=0}^{\infty} \left(\frac{e^t}{3}\right)^x \\ &= \frac{2}{3} \left[\left(\frac{e^t}{3}\right)^0 + \left(\frac{e^t}{3}\right)^1 + \left(\frac{e^t}{3}\right)^2 + \dots \right] \\ &= \frac{2}{3} \left[1 - \frac{e^t}{3} \right]^{-1} \\ &= \frac{2}{3} \left[\frac{3 - e^t}{3} \right]^{-1} \\ &= \frac{2}{3} \frac{(3 - e^t)^{-1}}{3^{-1}} \\ &= 2(3 - e^t)^{-1} \\ \boxed{M_X(t) = 2(3 - e^t)^{-1}} \end{aligned}$$

First moment about origin :-

$$\begin{aligned} M_1 &= E(X) = \left. \frac{d}{dt} [M_X(t)] \right|_{t=0} \\ &= \left. \frac{d}{dt} \left[\frac{2}{3} \left(\frac{2}{3 - e^t} \right) \right] \right|_{t=0} \\ &= \left. \frac{2 - e^t (2) - 2 (0 - e^t)}{(3 - e^t)^2} \right|_{t=0} \\ &= \left. \frac{2 e^t}{(3 - e^t)^2} \right|_{t=0} \\ &= \frac{2 e^0}{(3 - e^0)^2} = \frac{2}{(3 - 1)^2} = \frac{2}{4} = \frac{1}{2} \end{aligned}$$

(33) The probability density function of a random variable is given by

$$f_X(x) = \frac{2}{3} \left(\frac{1}{3}\right)^x, x=0,1,2,\dots \infty ; \text{ find moment generating function and also}$$

find. out 1st & 2nd moment ?

Sol: Given $f_X(x) = \frac{2}{3} \left(\frac{1}{3}\right)^x, x=0,1,2,\dots \infty$

Second moment about origin :-

$$\begin{aligned}
 M_2 = E[X^2] &= \frac{d^2}{dt^2} [M_X(t)] \Big|_{t=0} \\
 &= \frac{d}{dt} \left[\frac{d}{dt} [M_X(t)] \right] \Big|_{t=0} \\
 &= \cdot \frac{d}{dt} \left[\frac{2e^t}{(3-e^t)^2} \right] \Big|_{t=0} \\
 &= \frac{(3-e^t)^2 \cdot 2e^t - 2e^t \cdot 2 \cdot (3-e^t)(-e^t)}{(3-e^t)^4} \Big|_{t=0} \\
 &= \frac{(3-1)^2 \cdot 2e^0 - 2e^0 \cdot 2 \cdot (3-e^0)(-e^0)}{(3-e^0)^4} \\
 &= \frac{4 - 4 \times 2(-1)}{2^4} \\
 &= \frac{16}{16} = 1
 \end{aligned}$$

$$\boxed{M_2 = E[X^2] = 1}$$

(34) Find the characteristic function of r.v. "X" having the density function

$$\begin{aligned}
 f_X(x) &= \frac{1}{2a} ; |x| < a \\
 &= 0 ; \text{elsewhere}
 \end{aligned}$$

Given, that

$$\begin{aligned}
 f_X(x) &= \frac{1}{2a} ; |x| < a \\
 &= 0 ; \text{otherwise}
 \end{aligned}$$

$$\begin{aligned}
 f_X(x) &= \frac{1}{2a} ; -a < x < a \\
 &= 0 ; \text{elsewhere}
 \end{aligned}$$

The characteristic function of "X" is

$$\begin{aligned}
 \phi_X(w) &= E(e^{jwX}) \\
 &= \int_{-\infty}^{\infty} e^{jwX} f_X(x) dx
 \end{aligned}$$

(35)

$$\begin{aligned}
 &= \int_{-a}^a e^{jwX} \cdot \frac{1}{2a} dx \\
 &= \frac{1}{2a} \int_{-a}^a e^{jwX} dx \\
 &= \frac{1}{2a} \left(\frac{e^{jwX}}{jw} \right) \Big|_{-a}^a \\
 &= \frac{1}{2a jw} \left[e^{jwa} - e^{-jwa} \right] \\
 &= \frac{1}{aw} \left[\frac{e^{jwa} - e^{-jwa}}{2j} \right] \\
 &\approx \frac{1}{aw} \sin wa \\
 \phi_X(w) &= \frac{\sin(wa)}{wa}
 \end{aligned}$$

(35)

Find the characteristic function of for $f_X(x) = e^{-|x|}$.

Solve the density function of "X" is $f_X(x) = e^{-|x|}$

$$\begin{aligned}
 \phi_X(w) &= E(e^{jwX}) \\
 &= \int_{-\infty}^{\infty} e^{jwX} \cdot f_X(x) dx \\
 &= \int_{-\infty}^0 e^{jwx} f(x) dx + \int_0^{\infty} e^{jwx} f(x) dx \\
 &= \int_{-\infty}^0 e^{jwx} \cdot e^{-(-x)} dx + \int_0^{\infty} e^{jwx} \cdot e^{-(x)} dx \\
 &= \int_{-\infty}^0 e^{(jw+1)x} dx + \int_0^{\infty} e^{(jw-1)x} dx \\
 &= \left(\frac{e^{x(jw+1)}}{jw+1} \right) \Big|_{-\infty}^0 + \left(\frac{e^{(jw-1)x}}{jw-1} \right) \Big|_0^{\infty} \\
 &= \left[\frac{e^0}{jw+1} + e^{\infty} - \frac{e^0}{jw-1} \right] = \frac{1}{jw+1} - \frac{1}{jw-1}
 \end{aligned}$$

$$\frac{1}{(1+j\omega)} + \frac{1}{(1-j\omega)}$$

$$= \frac{1-j\omega + 1+j\omega}{1+\omega^2} = \frac{2}{1+\omega^2}$$

$$\boxed{\phi_X(\omega) = \frac{2}{1+\omega^2}}$$

- (2) The characteristic function of r.v. is $f_X(x) = a e^{-bx}$, $x \geq 0$. Find the characteristic function and first two moments.

Sol: Given $f_X(x) = a e^{-bx}$, $x \geq 0$
 $= 0$; $x < 0$

The characteristic function of 'x' is

$$\begin{aligned}\phi_X(\omega) &= E(e^{j\omega x}) \\ &= \int_{-\infty}^{\infty} e^{j\omega x} f_X(x) dx \\ &= \int_0^{\infty} e^{j\omega x} a e^{-bx} dx \\ &= a \int_0^{\infty} e^{(j\omega - b)x} dx \\ &= a \int_0^{\infty} \frac{1}{e^{(b-j\omega)x}} dx \\ &= a \left[\frac{-e^{(b-j\omega)x}}{-(b-j\omega)} \right]_0^{\infty} \\ &= a \left[0 + \frac{1}{(b-j\omega)} \right] \\ &= \frac{a}{b-j\omega}\end{aligned}$$

$$\therefore \boxed{\phi_X(\omega) = \frac{a}{b-j\omega}}$$

(36)

first moment about origin :-

The n^{th} moment about origin from characteristic function

$$i.e. m_n = E(x^n) = \left(\frac{1}{j} \right)^n \frac{d^n}{dw^n} (\phi_X(w)) \Big|_{w=0}$$

$$m_1 = E(x) = \frac{1}{j} \cdot \frac{d}{dw} (\phi_X(w)) \Big|_{w=0}$$

$$= \frac{1}{j} \cdot \frac{b-j\omega(0)-a(0-j)}{(b-j\omega)^2} \Big|_{w=0}$$

$$= \frac{1}{j} \cdot \frac{b+aj}{(b-j\omega)^2} \Big|_{w=0}$$

$$= \frac{a}{(b-j\omega)^2} \Big|_{w=0}$$

Second moment about origin :-

$$m_2 = E(x^2) = \left(\frac{1}{j} \right)^2 \frac{d^2}{dw^2} \left[\phi_X(w) \right] \Big|_{w=0}$$

$$= \frac{1}{j^2} \cdot \frac{d}{dw} \left[\frac{d}{dw} (\phi_X(w)) \right] \Big|_{w=0}$$

$$= \frac{1}{j^2} \cdot \frac{d}{dw} \left(\frac{a}{(b-j\omega)^2} \right) \Big|_{w=0}$$

$$= \frac{1}{j^2} \cdot \frac{1}{(b-j\omega)^4} \left[0 + 2abj(b-j\omega) \right] \Big|_{w=0}$$

$$= \frac{2ab}{b^4} = \frac{2a}{b^3}$$

- (37) Let us consider $f_X(x)$ is a density function of 'x' then find density function of $y = ax+b$

Sol:

$$\text{Given } y = ax+b$$

Here 'x' is a random variable with density function $f_X(x)$

Here the transformation is monotonic transformation

w.r.t. for monotonic transformation,

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

$$\text{Here } x = T^{-1}(y) \rightarrow ①$$

$$y = ax + b$$

$$ax + b = y \Rightarrow ax + b = y$$

$$ax = y - b$$

$$x = \left(\frac{y-b}{a} \right)$$

$$x = T^{-1}(y) = \frac{1}{a} \left(\frac{y-b}{a} \right) = y_a$$

$$\frac{dx}{dy} = \frac{d}{dy} \left(\frac{y-b}{a} \right) = \frac{1}{|a|}$$

substitute "x" value and $\left| \frac{dx}{dy} \right|$ in eq. ①

$$f_y(y) = f_x\left(\frac{y-b}{a}\right) \cdot \frac{1}{|a|}$$

This is the required density function of "y"

(38) Let "x" be a continuous random variable with probability density

$$\begin{aligned} f_x(x) &= \frac{x}{12} ; 0 < x < 12 \\ &= 0 ; \text{ otherwise} \end{aligned}$$

Sol:

$$\text{Given } y = 2x - 3$$

Here "x" is a r.v. with density function

$$f_x(x) = \frac{x}{12} ; 0 < x < 12$$

= 0 ; otherwise

$$\text{The limits of "y" are if } x=0 \Rightarrow y=2-3=-1$$

$$\text{If } x=5 \Rightarrow y=10-3=7$$

\therefore The limits of "y" are $-1 \leq y \leq 7$

Here the transformation is monotonic transformation

For Monotonic transformation

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

$$\text{Here } x = T^{-1}(y) \rightarrow ①$$

$$y = 2x - 3$$

$$y+3 = 2x$$

$$x = \frac{y+3}{2} = T^{-1}(y)$$

$$\frac{dx}{dy} = \frac{1}{2} = \frac{1}{12}$$

$$\therefore f_x(x) = f_x\left(\frac{y+3}{2}\right) = \frac{y+3}{2} = \frac{y+3}{12}$$

Sub. x and $\left| \frac{dx}{dy} \right|$ in eq. ①

$$\begin{aligned} f_y(y) &= \frac{y+3}{12} \times \frac{1}{12} = \frac{y+3}{144} ; -1 < y < 7 \\ &= 0 ; \text{ otherwise.} \end{aligned}$$

(39) Given a r.v. having the density function $f_x(x) = 2x ; 0 < x < 1$
find the density function of $y = 8x^3$
 $= 0 ; \text{ otherwise}$

Sol:

$$\text{Given } y = 8x^3$$

Here x is a r.v. with density function $f_x(x) = 2x ; 0 < x < 1$
 $= 0 ; \text{ otherwise}$
the limits of "y" are if $x=0 \text{ then } y=0$

if $x=1 \text{ then } y=8$

∴ the limits of "y" are $0 \leq y \leq 8$

Here given is monotonic transformation.

$$f_y(y) = f_x(x) \left| \frac{dx}{dy} \right| \rightarrow ①$$

$$x = T^{-1}(y)$$

$$y = 8x^3$$

$$x = \frac{y^{1/3}}{\delta}$$

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

$$\frac{dx}{dy} = \frac{1}{2y} \cdot \left(\frac{y^{1/3}}{2}\right) = \frac{1}{2} y^{-1/3} = \frac{1}{2} \frac{1}{y^{2/3}} = \frac{1}{6 \cdot 3\sqrt[3]{4}}$$

$$f_x(x) = f_x\left(\frac{y^{1/3}}{2}\right) = \frac{2 \cdot y^{1/3}}{2} = \frac{y^{1/3}}{2} = 3\sqrt[3]{4}.$$

Sub "x" and $\left|\frac{dx}{dy}\right|$ in eq ①

$$\boxed{f_y(y) = \frac{1}{6} \frac{1}{3\sqrt[3]{4}}, 0 < y < 6}$$

= 0 ; outside

- (40) If "x" is a normal r.v with "0" mean. and variance σ^2 ($N(0, \sigma^2)$) then find the density function of $y = e^x$.

Sol: $y = e^x$

Here "x" is a gaussian random variable with mean $a_x = 0$.

and variance $\sigma_{x^2} = \sigma^2$

$$\therefore f_x(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-a_x)^2}{2\sigma^2}}$$

$= a_x = 0, ;$

$$f_x(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{x^2}{2\sigma^2}}$$

Here the transformation is monotonic transfer function for monotonic transformation

$$f_y(y) = f_x(x) \left| \frac{dx}{dy} \right| \rightarrow ①$$

$$y = e^x \Rightarrow e^x = y \Rightarrow x = \log y$$

(36)

$$f_x(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$f_y(y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(\log y)^2}{2\sigma^2}} \frac{1}{|y|}$$

$$= \frac{1}{|y| \sqrt{2\pi\sigma^2}} e^{-\frac{(\log y)^2}{2\sigma^2}}$$

(41)

Let $y = ax + b$. show that if $x = N(\mu, \sigma^2)$ then $y = N(a\mu + b, a^2\sigma^2)$

Sol:

$$y = ax + b.$$

Here "x" is a r.v with $N(\mu, \sigma^2)$

$$\therefore f_x(x) = N(\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Here It is a monotonic transferfunction for monotonic transfer function

$$f_y(y) = f_x(x) \left| \frac{dx}{dy} \right| \rightarrow ①$$

$$ax + b = y$$

$$x = \frac{y-b}{a}$$

$$\frac{dx}{dy} = \frac{1}{a} \left(\frac{y-b}{a} \right) = \frac{1}{a} \quad \left| \frac{dx}{dy} \right| = \frac{1}{|a|}$$

$$f_x(x) = f_x\left(\frac{y-b}{a}\right) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(\frac{y-b}{a})^2}{2\sigma^2}}$$

$$f_y(y) = f_y = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(\frac{y-b}{a})^2 - \mu^2}{2\sigma^2}}$$

$$= \frac{1}{|a| \sqrt{2\pi\sigma^2}} e^{-\frac{(\frac{y-b}{a})^2 - \mu^2}{2\sigma^2}}$$

$$= \frac{1}{|a| \sqrt{2\pi\sigma^2}} e^{-\frac{(\frac{y-(b+a\mu)}{a})^2}{2\sigma^2}}$$

$$= N(b+a\mu, a^2\sigma^2)$$

(42) A random variable "x" is uniformly distributed in the interval $(-5, 5)$.

another r.v. $y = e^{x/5}$ is formed find $E(y)$ and $f_y(y)$. (3.64)

Sol: Given. The r.v. is "x" is uniformly distributed over the interval $(-5, 5)$

w.r.t the density function of uniform distribution is

$$f_x(x) = \begin{cases} \frac{1}{b-a} & ; -5 \leq x \leq 5 \\ 0 & ; \text{otherwise} \end{cases}$$

The density function of given r.v "x" is $= \frac{1}{15-(-5)} = \frac{1}{20}$

\therefore mean of $y = E(y) = E(e^{x/5})$

$$\begin{aligned} &= \int_{-\infty}^{\infty} e^{x/5} f_x(x) dx \\ &= \int_{-5}^{15} e^{x/5} \frac{1}{20} dx \\ &= \frac{1}{20} \int_{-5}^{15} e^{x/5} dx \\ &= \frac{1}{20} \left(\frac{e^{x/5}}{-y/5} \right)_{-5}^{15} \\ &= \frac{1}{20} \left(\frac{e^3}{-y/5} - \frac{e^1}{-y/5} \right) \\ &= \frac{1}{20} (5e^3 + 5e^1) \\ &= \frac{1}{4} (e^3 + e) \\ &= 0.667 \end{aligned}$$

Density function of y is $y = e^{x/5}$

The limits of "y" are if $x = -5$; $y = e^{-1} = 0.367$

$$\text{if } x = 15 \Rightarrow y = e^3 = 20.07$$

\therefore The limits of y are $0.367 \leq y \leq 20.07$.

Here the transformation is a monotonic transformation, for monotonic transformation

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

$$y = e^{x/5}$$

$$e^{x/5} = y$$

$$x/5 = \ln(y)$$

$$x = 5 \ln(y)$$

$$\frac{dx}{dy} = \frac{5}{y}$$

$$\left| \frac{dx}{dy} \right| = \frac{5}{y}$$

$$\therefore f_x(x) = f_x(-5 \ln(y))$$

$$= \frac{1}{20}$$

$$\therefore f_y(y) = \frac{1}{20} \cdot \frac{5}{y} = \frac{1}{4y}; 0.367 \leq y \leq 20.07$$

$$= 0; \text{ otherwise}$$

(43) It is given that the r.v "x" is a gaussian with mean of "zero" and variance of "1". The r.v "y" is obtained from "x" with the relation $y = 5x - 6$. Find the PDF of "y".

Sol:

$$\text{Given } y = 5x - 6$$

Here "x" is a gaussian random variable with mean $a_x = 0$ and

Variance $\sigma_x^2 = 1$, $f_x(x) = \frac{1}{\sqrt{2\pi\sigma_x^2}} e^{-(x-a_x)^2/2\sigma_x^2}$

$$a_x = 0; \sigma_x^2 = 1, = \frac{1}{\sqrt{\pi}} e^{-x^2/2}$$

Here the transformation is monotonic transformation for monotonic

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

(3.65)

$$y = 5x - 6$$

$$y+6 = 5x$$

$$x = \frac{y+6}{5}$$

$$\frac{dx}{dy} = \frac{d}{dy} \left(\frac{y+6}{5} \right) = \frac{1}{5} ; \left| \frac{dx}{dy} \right| = \frac{1}{5}$$

$$f_x(x) = f_x \left(\frac{y+6}{5} \right) = \frac{1}{\sqrt{2\pi}} \cdot e^{-\left(\frac{y+6}{5}\right)^2/2}$$

$$= \frac{1}{\sqrt{2\pi}} \cdot e^{-\left(\frac{y+6}{5}\right)^2/50}$$

$$\therefore f_y(y) = \frac{1}{\sqrt{2\pi}} \cdot e^{-\left(\frac{y+6}{5}\right)^2/50} \cdot \frac{1}{5}$$

$$= \frac{1}{15\sqrt{2\pi}} \cdot e^{-\left(\frac{y+6}{5}\right)^2/50}$$

(3.66)
(4.4)

A r.v "x" undergoes the transformation $y = \frac{a}{x}$, where a is a real number. Find the density function of "y"

Sol: Given that $y = \frac{a}{x}$

Here "x" a random variable with density function $f_x(x)$

$$y = \frac{a}{x}$$

$$xy = a$$

$$x = \frac{a}{y}$$

$$\frac{dx}{dy} = -\frac{a}{y^2} \quad \left| \frac{dx}{dy} \right| = \left| -\frac{a}{y^2} \right| = \left| \frac{a}{y^2} \right|$$

$$\therefore \boxed{f_y(y) = \frac{a}{y^2} \cdot f_x\left(\frac{a}{y}\right)}$$

(4.5) The gaussian random variable "x" having mean zero and variance "1" transformed to another random variable "y" by a square law transformation. find the density function "y".

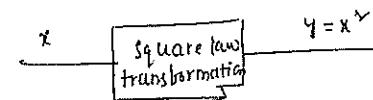
Sol: $y = x^2$. find PDF of "y" if $x \sim N(0,1)$

Given "x" is a r.v. with "0" mean and variance "1"

$$\text{i.e. } E[x] = 0 \quad \text{and } \sigma_x^2 = 1$$

$$f_x(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

The r.v "y" is formed by the square law transformation of "x" i.e



Here the transformation is non monotonic transformation for non monotonic transformation

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

$$\text{Here } x_n = T^{-1}(y_n)$$

$$x^2 = y$$

$$x = \sqrt{y} = \pm \sqrt{y}$$

$$x_1 = \sqrt{y}, \quad x_2 = -\sqrt{y},$$

$$\frac{dx_1}{dy} = \frac{1}{2\sqrt{y}}, \quad \frac{dx_2}{dy} = -\frac{1}{2\sqrt{y}}$$

$$\left| \frac{dx_1}{dy} \right| = \frac{1}{2\sqrt{y}} \quad ; \quad \left| \frac{dx_2}{dy} \right| = \frac{1}{2\sqrt{y}}$$

$$f_x(x_1) = f_x(\sqrt{y}) = \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{\sqrt{y}}{\sqrt{2\pi}}\right)^2} = \frac{1}{\sqrt{2\pi}} e^{-y/2}$$

$$f_x(x_2) = f_x(-\sqrt{y}) = \frac{1}{\sqrt{2\pi}} e^{-\left(\frac{-\sqrt{y}}{\sqrt{2\pi}}\right)^2} = \frac{1}{\sqrt{2\pi}} e^{-y/2}$$

$$\begin{aligned} \therefore f_Y(y) &= \sum_{x=1}^2 f_X(x) \cdot \left| \frac{\partial x}{\partial y} \right| \\ &= f(x_1) \cdot \left| \frac{\partial x_1}{\partial y} \right| + f(x_2) \cdot \left| \frac{\partial x_2}{\partial y} \right| \\ &= \frac{1}{2\sqrt{y}} \times \frac{1}{\sqrt{2\pi}} e^{-y/2} + \frac{1}{\sqrt{2\pi}} \times \frac{1}{2\sqrt{y}} e^{-y/2} \\ &= \frac{1}{\sqrt{2\pi}} \cdot \frac{e^{-y/2}}{\sqrt{y}} \end{aligned}$$

$$f_Y(y) = \frac{1}{\sqrt{2\pi y}} e^{-y/2}$$

(46) A r.v "X" uniformly distributed in the interval $(-\pi/2, \pi/2)$. X is transformed into a new r.v. $Y = T(X) = a \tan X$, where $a > 0$, find the probability density function of "Y".

Solt: Given. $Y = a \tan X$.

Here "X" is a r.v. uniformly distributed over the interval $(-\pi/2, \pi/2)$

$$\begin{aligned} f_X(x) &= \frac{1}{\pi/2 - (-\pi/2)} = \frac{1}{\pi} ; -\pi/2 \leq x \leq \pi/2 \\ &= 0 ; \text{ otherwise} \end{aligned}$$

The range of "Y" are If $x = -\pi/2$ then $y = a \tan(\pi/2) = -\infty$

If $x = \pi/2$ then $y = a \tan(\pi/2) = \infty$

Here the transformation is monotonic transformation

NOTE: (All) the trigonometric functions are monotonic with in a particular interval otherwise it is not a monotonic

For monotonic transformation

$$\begin{aligned} y &= a \tan(x) \\ y &= a \tan(x) \\ \frac{y}{a} &= \tan x \\ x &= \tan^{-1}(y/a) \end{aligned}$$

$$\left| \frac{\partial x}{\partial y} \right| = \left(\frac{1}{a^2 + y^2} \right).$$

$$f_X(x) = f_X(\tan^{-1}(y/a)) = \frac{1}{\pi}$$

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

$$= \frac{1}{\pi} \frac{a}{a^2 + y^2} = \frac{a}{\pi(a^2 + y^2)} ; -\infty \leq y < \infty$$

(47) Let us consider the square-law transmission $y = cx^2$, then find the density function of "Y".

Solt:

Given. $y = cx^2$

Let us consider here "X" is a random variable with density function. of $f_X(x)$

Here the transmission is non monotonic transmission

$$f_Y(y) = \sum_{\text{all } x} f_X(x) \cdot \left| \frac{\partial x}{\partial y} \right|$$

$$y = cx^2$$

$$x^2 = y/c$$

$$x = \pm \sqrt{y/c}$$

$$x_1 = \pm \sqrt{y/c} ; x_2 = -\sqrt{y/c}$$

$$\frac{\partial x_1}{\partial y} = \frac{1}{2\sqrt{y/c}} (1/c) = \frac{1}{2\sqrt{y/c}} \quad \frac{\partial x_2}{\partial y} = \frac{-1}{2\sqrt{y/c}} (1/c) = -\frac{1}{2\sqrt{y/c}}$$

$$\left| \frac{\partial x_1}{\partial y} \right| = \frac{1}{2\sqrt{c}} \quad ; \quad \left| \frac{\partial x_2}{\partial y} \right| = \frac{1}{2\sqrt{c}}$$

(67)

$$\begin{aligned} f_Y(y) &= \sum_{i=1}^2 f_X(x_i) \left(\frac{\partial x_i}{\partial y} \right) \\ &= f_X(x_1) \left(\frac{\partial x_1}{\partial y} \right) + f_X(x_2) \left(\frac{\partial x_2}{\partial y} \right) \\ &= f_X(\sqrt{y/c}) \cdot \frac{1}{2\sqrt{c}} + f_X(-\sqrt{y/c}) \cdot \frac{1}{2\sqrt{c}} \\ &= \frac{1}{2\sqrt{c}} \left[f_X(\sqrt{y/c}) + f_X(-\sqrt{y/c}) \right] \end{aligned}$$

(48) A random variable "x" is uniformly distributed in the interval $(-a, a)$. It is transmitted to a new r.v. "y" by the transformation

$y = cx^2$. find the density function of y and sketch it

Sol: Given the two the new r.v. $y = cx^2$

Here x is a r.v. uniformly selected distributed over the interval $(-a, a)$

$$\therefore f_X(x) = \frac{1}{2a} ; -a \leq x \leq a$$

$$= 0 ; \text{ otherwise}$$

The range of y are if $x = -a$, then $y = ca^2$

If $x = a$, then $y = ca^2$

Here only one interval is existing for finding of other intervals. let us consider the "x" value is equals to the average value of given interval

$$\therefore \text{If } x = \frac{-a+a}{2} = 0 \Rightarrow y = c(0) = 0.$$

\therefore the range of "y" is $0 \leq y \leq ca^2$

$$y = cx^2$$

$$x^2 = y/c$$

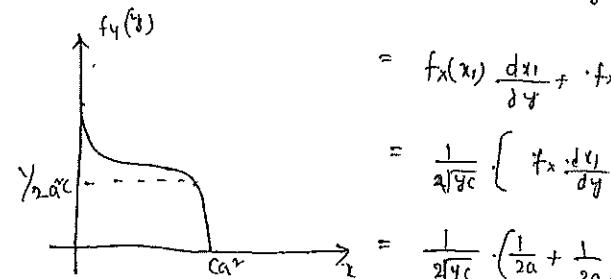
$$x = \pm \sqrt{y/c} \Rightarrow x_1 = \sqrt{y/c} ; x_2 = -\sqrt{y/c}$$

$$\frac{dx_1}{dy} = \frac{1}{2\sqrt{c}} ; \frac{dx_2}{dy} = \frac{-1}{2\sqrt{c}} \quad ; \quad \frac{dx_1}{dy} = \frac{1}{2\sqrt{c}} ; \quad \frac{dx_2}{dy} = \frac{1}{2\sqrt{c}}$$

$$f_Y(y) = \sum_{i=1}^2 f_X(x_i) \left| \left(\frac{dx_i}{dy} \right) \right|$$

$$= f_X(x_1) \frac{dx_1}{dy} + f_X(x_2) \frac{dx_2}{dy}$$

$$= \frac{1}{2\sqrt{c}} \left(f_X \left(\frac{dy}{dx_1} \right) + f_X \left(\frac{dy}{dx_2} \right) \right)$$



$$= \frac{1}{2\sqrt{c}} \cdot \left(\frac{1}{2a} + \frac{1}{2a} \right)$$

$$= \frac{2}{2a} \cdot \frac{1}{2\sqrt{c}}$$

$$f_Y(y) = \frac{1}{2a\sqrt{c}} ; 0 \leq y \leq ca^2$$

= 0 ; elsewhere

(49) A r.v. x is uniformly distributed on $(0, 6)$. If "x" is transformed

to a new r.v. $y = 2(x-3)^2 - 4$, find the density function of "y", f_Y and σ_Y .

Sol: Given $y = 2(x-3)^2 - 4$

Here x is a r.v. uniformly distributed over the interval $(0, 6)$

$$f_X(x) = \frac{1}{6} ; 0 \leq x \leq 6$$

$$= 0 ; \text{ otherwise}$$

The range of "y" is. If $x=0 \Rightarrow y=2(0-3)^2-4=14$

$$\text{If } x=6 \Rightarrow y=2(6-3)^2-4=-4$$

$$= \frac{1}{6\sqrt{2}} \int_{-4}^{14} \frac{y}{\sqrt{y+4}} dy$$

$$= 2$$

$$\bar{y^2} = \int_{-4}^{14} y^2 \cdot \frac{1}{\sqrt{y+4}} dy$$

$$= \frac{1}{6\sqrt{2}} \int_{-4}^{14} \frac{y^2}{\sqrt{y+4}} dy$$

$$= 52.8$$

$$\sigma_x^2 = 32.3 - 4$$

$$\boxed{\sigma_y^2 = 28.8}$$

(50) The characteristic function for a gaussian r.v "x" having a mean

value of "0" is $\phi_x(w) = e^{-\frac{\sigma_x^2 w^2}{2}}$ find all moments of "x" using $\phi_x(w)$

Solt:

$$\text{Given } \phi_x(w) = e^{-\frac{\sigma_x^2 w^2}{2}}$$

Here r.v "x" is a gaussian r.v with mean. $\mu_x = 0$.

$$\text{K.F.T } e^x = 1 + \frac{x}{1!} + \frac{x^2}{2!} + \dots$$

$$\begin{aligned} e^{-\frac{\sigma_x^2 w^2}{2}} &= \sum_{k=0}^{\infty} \left(\frac{-\sigma_x^2 w^2}{2} \right)^k \\ &= \sum_{k=0}^{\infty} \frac{(-1)^k \sigma_x^{2k} w^{2k}}{2^k k!} \rightarrow \textcircled{1} \end{aligned}$$

From the definition of characteristic function of $\phi_x(w) =$

$E(e^{jw_x x})$ Here x is a r.v. i.e. continuous

(68)

i.e. the range of "y" is "-4 ≤ y ≤ 14"

$$\text{given. } y = 2((x-3)^2 - 4)$$

$$y+4 = 2(x-3)^2$$

$$(x-3)^2 = \frac{(y+4)}{2}$$

$$(x-3) = \pm \sqrt{\frac{y+4}{2}}$$

$$x = 3 \pm \sqrt{\frac{y+4}{2}} + 3$$

$$\text{If } x_1 = 3 + \sqrt{\frac{y+4}{2}}, \quad x_2 = 3 - \sqrt{\frac{y+4}{2}}$$

$$\frac{dx_1}{dy} = 0 + \frac{1}{2} \sqrt{\frac{y+4}{2}} = \frac{1}{2\sqrt{y+4}}$$

$$\frac{dx_2}{dy} = \frac{-1}{2\sqrt{y+4}} = \frac{-1}{\sqrt{y+4}} = \frac{1}{2\sqrt{2(y+4)}}$$

$$f_x(x_1) = f_x(3 + \sqrt{\frac{y+4}{2}}) = \nu_6$$

$$f_x(x_2) = f_x(3 - \sqrt{\frac{y+4}{2}}) = \nu_6$$

$$\begin{aligned} \therefore f_y(y) &= \sum_{i=1}^2 f_x(x_i) \left(\frac{dx_i}{dy} \right) \\ &= f_x(x_1) \cdot \frac{dx_1}{dy} + f_x(x_2) \cdot \frac{dx_2}{dy} \\ &= \frac{1}{6} \times \frac{1}{2\sqrt{2(y+4)}} + \frac{1}{6} \times \frac{1}{2\sqrt{2(y+4)}} \end{aligned}$$

$$f_y(y) = \frac{1}{6\sqrt{2(y+4)}} ; -4 \leq y \leq 14$$

$$= 0 ; \text{ otherwise}$$

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

$$= \frac{(-1)^{n/2}}{j^n} \cdot \frac{n!}{(n/2)!} \cdot \frac{\sigma_x^n}{2^{n/2}}$$

(370)

The all moments of r.v \bar{x} are $m_n = 0$ if $n = \text{odd}$

$$m_n = \frac{(-1)^{n/2}}{j^n} \cdot \frac{n!}{(n/2)!} \cdot \frac{\sigma_x^n}{2^{n/2}} ; n = \text{even}$$

Here for $n = \text{even}$, $(-1)^{n/2} = j^n$

$$m_n = 0, n = \text{odd}$$

$$= \frac{n!}{(n/2)!} \cdot \frac{\sigma_x^n}{2^{n/2}} ; n = \text{even}$$

(51) Let us consider the moment generating function of a r.v. with "0" mean

b) $M_X(t) = e^{\sigma_x t + \frac{\sigma_x^2 t^2}{2}}$ find the all moments about origin from its moment

generating function!

solt

$$\text{Given } M_X(t) = e^{\sigma_x t + \frac{\sigma_x^2 t^2}{2}}$$

Here random variable " x " is a gaussian r.r. with mean $\mu_x = 0$

$$M_X(t) = 1 + \frac{\mu_x t}{1!} + \frac{\mu_x^2 t^2}{2!} + \dots$$

$$\begin{aligned} e^{\sigma_x t + \frac{\sigma_x^2 t^2}{2}} &= \sum_{k=0}^{\infty} \left(\frac{\sigma_x t + \frac{\sigma_x^2 t^2}{2}}{k!} \right)^k \\ &= \sum_{k=0}^{\infty} \frac{\sigma_x^{2k} t^{2k}}{2^k k!} \end{aligned}$$

from the definition of characteristic function of $\phi_x(\omega)$

i.e. $\phi_x(\omega) = E(e^{j\omega X})$ Here X is g.r.v. is continuous

$$\phi_x(\omega) = \int_{-\infty}^{\infty} e^{j\omega x} f_x(x) dx = \int_{-\infty}^{\infty} \sum_{n=0}^{\infty} \frac{(e^{j\omega x})^n}{n!} f_x(x) dx \rightarrow \textcircled{1}$$

$$\begin{aligned} \phi_x(\omega) &= \int_{-\infty}^{\infty} e^{j\omega x} f_x(x) dx = \int_{-\infty}^{\infty} \sum_{n=0}^{\infty} \frac{(e^{j\omega x})^n}{n!} f_x(x) dx \\ &= \int_{-\infty}^{\infty} \sum_{n=0}^{\infty} \frac{(\omega)^n}{n!} x^n f_x(x) dx = \sum_{n=0}^{\infty} \frac{(\omega)^n}{n!} \int_{-\infty}^{\infty} x^n f_x(x) dx \\ &= \sum_{n=0}^{\infty} \frac{(\omega)^n}{n!} m_n \\ &= \phi_x(\omega) = \sum_{n=0}^{\infty} \frac{(\omega)^n \cdot \omega^n m_n}{n!} \rightarrow \textcircled{2} \end{aligned}$$

equate \textcircled{1} and \textcircled{2}, we get

$$\sum_{n=0}^{\infty} \frac{0^n \cdot \omega^n \cdot m_n}{n!} = \sum_{k=0}^{\infty} \frac{(-1)^k \cdot \sigma_x^{2k} \cdot \omega^{2k}}{2^k k!} \rightarrow \textcircled{3}$$

$$\frac{0^0 m_0 \omega^0}{0!} + \frac{0^1 m_1 \omega^1}{1!} + \dots = - \frac{(-1)^{00} \sigma_x^0 \omega^0}{0!} + \frac{(-1)^1 \sigma_x^2 \omega^2}{2!} + \dots$$

$$m_0 + \frac{0 m_1 \omega^1}{1!} + \frac{0 m_2 \omega^2}{2!} + \dots = 1 + \frac{(-1)^1 \sigma_x^2 \omega^2}{2!}$$

For $n = \text{odd}$ $m_n = 0$.

For $n = \text{even} \Rightarrow n = 2k$

$$\begin{aligned} \text{From eq } \textcircled{3}, \sum_{n=0}^{\infty} \frac{j^n \omega^n m_n}{n!} &= \sum_{n=0}^{\infty} (-1)^{n/2} \frac{\sigma_x^n \omega^n}{2^{n/2} (n/2)!} \\ &\quad \text{for solving of } m_n \text{ we will neglect the summation} \end{aligned}$$

$$\frac{j^n \omega^n m_n}{n!} = \frac{(-1)^{n/2} \sigma_x^n \omega^n}{2^{n/2} (n/2)!}$$

$$m_n = \frac{(-1)^{n/2} \omega^n \cdot \sigma_x^n}{2^{n/2} (n/2)!}$$

$$= \int_{-\infty}^{\infty} \sum_{n=0}^{\infty} \frac{(jt)^n}{n!} x^n f_x(x) dx \quad (3.71)$$

$$= \sum_{n=0}^{\infty} \frac{(jt)^n}{n!} \int_{-\infty}^{\infty} x^n f_x(x) dx \quad [\because m_n = E(x^n) = \int_{-\infty}^{\infty} x^n f_x(x) dx]$$

$$\phi_x(w) = \sum_{n=0}^{\infty} \frac{(jt)^n}{n!} m_n$$

$$\phi_x(w) = \sum_{n=0}^{\infty} \frac{j^n t^n m_n}{n!} \rightarrow (2)$$

from (1) and (2)

$$= \sum_{n=0}^{\infty} \frac{(jt)^n t^n m_n}{n!} = \sum_{k=0}^{\infty} \frac{\sigma_x^{2k} t^{2k}}{2^k k!} \rightarrow (3)$$

$$= \frac{(jt)^0 m_0 t^0}{0!} + \frac{(jt)^1 m_1 t^1}{1!} + \frac{(jt)^2 m_2 t^2}{2!} + \dots$$

$$= \frac{\sigma_x^0 t^0}{0!} + \frac{\sigma_x^2 t^2}{2!} + \frac{\sigma_x^4 t^4}{4!} + \dots$$

$$= m_0 + \frac{j m_1 t^1}{1!} + \frac{j^2 m_2 t^2}{2!} + \frac{j^3 m_3 t^3}{3!} + \dots \rightarrow (4)$$

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

for n odd, $m_n = 0$. (\because from eq(1))

for n even, then n is $2k$

$$k = n/2$$

$$\therefore \text{from eq (3)} \quad \sum_{n=0}^{\infty} \frac{j^n t^n m_n}{n!} = \sum_{k=0}^{\infty} \frac{(j)^{n/2} \sigma_x^n t^n}{2^{n/2} (n/2)!}$$

for solving of m_n , 't' will neglect the summations

$$\frac{j^n t^n m_n}{n!} = \frac{(j)^{n/2} \sigma_x^n t^n}{2^{n/2} (n/2)!}$$

$$\therefore m_n = \frac{(j)^{n/2} t^n \sigma_x^n}{n!} \times \frac{n!}{n}$$

$$m_n = \frac{(j)^{n/2}}{j^n} \cdot \frac{n!}{(n/2)!} \cdot \frac{\sigma_x^n}{2^{n/2}}$$

The all moments of r.v "x" are $m_n = 0$; n odd.

$$m_n = \frac{(j)^{n/2}}{j^n} \cdot \frac{n!}{(n/2)!} \cdot \frac{\sigma_x^n}{2^{n/2}} ; n = \text{even}$$

$$\text{Here, for } n = \text{even} \quad \frac{(-1)^{n/2}}{j^n} = j^n$$

$$m_n = 0 ; \text{ for } n = \text{odd.}$$

$$= \frac{n!}{(n/2)!} \cdot \frac{\sigma_x^n}{2^{n/2}} ; n \text{ is even}$$

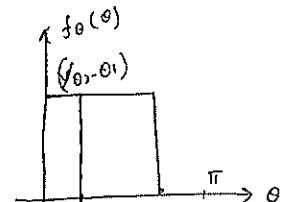
(52) A random variable θ is uniformly distributed over the interval (θ_1, θ_2) where θ_1 and θ_2 are real and satisfy $0 \leq \theta_1 < \theta_2 \leq \pi$. Find and sketch the probability density function of the transformed r.v. $y = \cos \theta$.

Sol:

Given a random variable " θ " is uniformly distributed

$$\therefore f_{\theta}(\theta) = \frac{1}{\theta_2 - \theta_1}$$

$$f_{\theta}(\theta) = \begin{cases} \frac{1}{\theta_2 - \theta_1} & ; \theta_1 < \theta < \theta_2 \\ 0 & ; \text{elsewhere} \end{cases}$$



and also given that

$$y = \cos \theta$$

Here the r.v " θ " varies then y can also varies

$$\text{i.e. } y = y_1 < y < y_2$$

$$y = \cos \theta$$

$\theta = \arccos(y)$

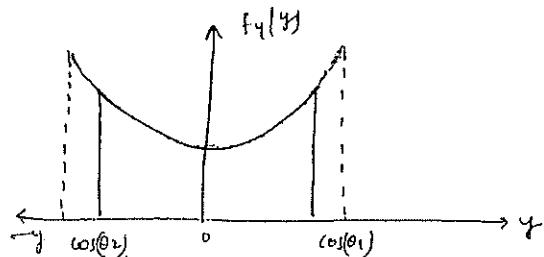
$$\frac{d\theta}{dy} = \frac{d}{dy} (\cos^{-1} y)$$

(3.72)

$$= \frac{1}{\sqrt{1-y^2}}$$

$$\therefore f_y(y) = \frac{1}{\theta_2 - \theta_1} \frac{1}{\sqrt{1-y^2}} ; \quad \theta_2 < y < \theta_1$$

$$= \frac{1}{\theta_2 - \theta_1} \frac{1}{\sqrt{1-y^2}} ; \quad \cos(\theta_2) < y < \cos(\theta_1).$$



prepared by

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(53)

Find the characteristic function of the following probability

$$\text{function } f_x(x) = \frac{\lambda}{\pi(\lambda^2 + x^2)}$$

Sol:

$$\text{Given : p.d.f is } \frac{\lambda}{\pi(\lambda^2 + x^2)}$$

Q. 8. T The characteristic function is the Fourier transform of the density function

$$\text{i.e. } \phi_x(\omega) = \int_{-\infty}^{\infty} f_x(x) e^{j\omega x} dx \\ = \int_{-\infty}^{\infty} \frac{\lambda}{\pi(\lambda^2 + x^2)} e^{j\omega x} dx$$

$$\text{W. R. T } \bar{e}^{\lambda j\omega} | \omega | \xleftrightarrow{\text{FT}} \frac{\lambda}{\pi(\lambda^2 + x^2)}$$

$$\therefore \boxed{\phi_x(\omega) = \bar{e}^{\lambda j\omega}}$$

