

M.Sc. MATHEMATICS

MAL-523

METHODS OF APPLIED MATHEMATICS

DIRECTORATE OF DISTANCE EDUCATION

GURU JAMBHESHWAR UNIVERSITY OF

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MAL-523
METHODS OF APPLIED MATHEMATICS
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LESSON-1

FOURIER TRANSFORMS

Integral Transform: The integral transform of a function $f(t)$ is defined by the equation

$$g(s) = \int_a^b f(t) k(s, t) dt, \text{ where } k(s, t) \text{ is a known function of } s \text{ and } t, \text{ called the kernel of the}$$

transform; s is called the parameter of the transform and $f(t)$ is called inverse transform of $g(s)$.

Some of the well known transforms are given as under:

(1) Laplace transform:-

$$\text{When } k(s, t) = e^{-st}, \text{ we have Laplace transform of } f(t) \text{ as: } g(s) = \int_0^{\infty} f(t) e^{-st} dt$$

we can also write

$$L[f(t)] = g(s) \text{ or } F(s) \text{ or } \bar{f}(s)$$

(2) Fourier transform:-

when $k(s, t) = \frac{1}{\sqrt{2\pi}} e^{-ist}$, we have the Fourier transform of $f(t)$ as

$$F[f(t)] = g(s) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-ist} dt$$

(3) Mellin transform:-

When $k(s, t) = t^{s-1}$, we have Mellin transform of $f(t)$ as: $M[f(t)] = g(s) = \int_0^{\infty} f(t) t^{s-1} dt$

(4) Hankel transform (Fourier-Bessel):-

When $k(s, t) = t J_n(st)$, we have Hankel transform of $f(t)$ as: $g(s) = \int_0^{\infty} f(t) t J_n(st) dt$

Fourier Transform:- If $f(t)$ be a function defined on $(-\infty, \infty)$ and f be piecewise continuous in each finite partial interval and absolutely integrable in $(-\infty, \infty)$, i.e., $f(t)$ be a function s. t.

$$\int_{-\infty}^{\infty} |f(t)| dt < \infty$$

then the function

$$\bar{f}(s) = F[f(t)] = F(s) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-ist} dt$$

is called Fourier transform (F.T.) of $f(t)$.

Then $F^{-1}[F(s)] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} F(s) e^{ist} ds = f(t)$ is called inverse Fourier Transform of $F(s)$.

Remarks:

(i) If $F(s) = \frac{1}{2\pi} \int_{-\infty}^{\infty} f(t) e^{-ist} dt$, then

$$F^{-1}[F(s)] = \int_{-\infty}^{\infty} F(s) e^{ist} ds$$

(ii) If $F(s) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-ist} dt$, then

$$F^{-1}[F(s)] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} F(s) e^{ist} ds$$

(iii) If $F(s) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{ist} dt$, then

$$f(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} F(s) e^{-ist} ds$$

Fourier cosine and sine transform

$F_c(s) = \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \cos st dt$ is called Fourier cosine transform (FCT) and $F_s(s) =$

$\sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \sin st dt$ is called Fourier sine transform (FST) of $f(t)$.

The functions $f_c(t) = \sqrt{\frac{2}{\pi}} \int_0^{\infty} F_c(s) \cos st ds$

$$f_s(t) = \sqrt{\frac{2}{\pi}} \int_0^{\infty} F_s(s) \sin st ds$$

are called the Inverse Fourier cosine & inverse Fourier sine transform of $F_c(s)$ and $F_s(s)$, respectively.

Properties of Fourier Transform

(1) Linearity Property

If $f_1(t)$ and $f_2(t)$ are functions with Fourier Transform $F_1(s)$ and $F_2(s)$, respectively and C_1 & C_2 are constant, then Fourier Transform of $C_1 f_1(t) + C_2 f_2(t)$ is

$$\begin{aligned} F[C_1 f_1(t) + C_2 f_2(t)] &= C_1 F[f_1(t)] + C_2 F[f_2(t)] \\ &= C_1 F_1(s) + C_2 F_2(s) \end{aligned}$$

Proof: By definition

$$\begin{aligned} \text{L.H.S.} &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-ist} [C_1 f_1(t) + C_2 f_2(t)] dt \\ &= \frac{C_1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-ist} f_1(t) dt + \frac{C_2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-ist} f_2(t) dt \\ &= C_1 F[f_1(t)] + C_2 F[f_2(t)] \\ &= C_1 F_1(s) + C_2 F_2(s) \end{aligned}$$

(2) Change of scale property or similarity theorem

If 'a' is a real constant and $F(s) = F[f(t)]$ then

$$F[f(at)] = \frac{1}{|a|} F\left(\frac{s}{a}\right)$$

Proof : For $a > 0$,

$$F[f(at)] = \int_{-\infty}^{\infty} f(at) e^{-ist} dt$$

$$\text{Put } at = x \Rightarrow dt = \frac{1}{a} dx$$

$$\begin{aligned} \therefore F[f(at)] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(x) e^{-i\left(\frac{s}{a}\right)x} \frac{1}{a} dx \\ &= \frac{1}{a} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-i\left(\frac{s}{a}\right)t} dt \end{aligned}$$

$$\Rightarrow F[f(at)] = \frac{1}{a} F\left(\frac{s}{a}\right)$$

$$\text{For } a < 0 \text{ :- } F[f(at)] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(at) e^{-ist} dt$$

Put $at = x \Rightarrow dt = \frac{dx}{a}$

$$\begin{aligned}\therefore F[f(at)] &= \frac{1}{a} \cdot \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(x) e^{-i\frac{s}{a}x} dx \\ &= \frac{-1}{a} \cdot \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-i\frac{s}{a}t} dt\end{aligned}$$

$$\Rightarrow F[f(at)] = \frac{-1}{a} F\left(\frac{s}{a}\right)$$

$$\text{Hence, } F[f(at)] = \frac{1}{|a|} F\left(\frac{s}{a}\right)$$

Particular case:- If $a = -1$, then

$$F[f(-t)] = F(-s)$$

(3) First shifting Property

If $F[f(t)] = F(s)$, then

$$F[f(t - u)] = e^{-ius} F[f(t)] = e^{-ius} F(s)$$

Proof :- $F[f(t - u)] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t - u) e^{-ist} dt$

Put $t - u = v \Rightarrow dt = dv$

$$\begin{aligned}\Theta \quad F[f(t - u)] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(v) e^{-is(v+u)} dv \\ &= e^{-isu} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(v) e^{-isv} dv \\ &= e^{-isu} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-ist} dt \\ &= e^{-isu} F[f(t)].\end{aligned}$$

(4). Second shifting property

If $F(s) = F[f(t)]$, then

$$F[f(t)e^{iat}] = F(s - a)$$

$$\begin{aligned}
 \text{Proof :- } F[f(t) e^{iat}] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{iat} e^{-ist} dt \\
 &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-i(s-a)t} dt = F(s-a)
 \end{aligned}$$

(5) Symmetry property

If $F(s) = F[f(t)]$, then $F[F(t)] = f(-s)$

Proof : We know that

$$\sqrt{2\pi} f(t) = \int_{-\infty}^{\infty} F(s) e^{ist} ds$$

changing t to $-t$, we have

$$\sqrt{2\pi} f(-t) = \int_{-\infty}^{\infty} F(s) e^{-ist} ds$$

Interchanging t & s , we get

$$\sqrt{2\pi} f(-s) = \int_{-\infty}^{\infty} F(t) e^{-ist} dt$$

$$\Rightarrow f(-s) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} F(t) e^{-ist} dt$$

$$\Rightarrow f(-s) = F[F(t)]$$

Example. 1. Find Fourier transform of $f(t) = \begin{cases} e^{-\alpha t} & , & t \geq 0, \alpha > 0 \\ 0 & , & t < 0 \end{cases} \dots(1)$

Solution :- By definition, $F(s) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-ist} dt$

$$\Rightarrow F(s) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^0 f(t) e^{-ist} dt + \frac{1}{\sqrt{2\pi}} \int_0^{\infty} e^{-\alpha t} e^{-ist} dt$$

$$= \frac{1}{\sqrt{2\pi}} \int_0^{\infty} e^{-(\alpha+is)t} dt \quad [\text{using (1)}]$$

$$\Rightarrow F(s) = \frac{1}{\sqrt{2\pi}} \left[\frac{e^{-(\alpha+is)t}}{-(\alpha+is)} \right]_0^{\infty}$$

$$= \frac{1}{\sqrt{2\pi}} \left[0 + \frac{1}{\alpha + is} \right] = \frac{\alpha - is}{\sqrt{2\pi}(\alpha^2 + s^2)}$$

Example.2. $f(t) = \begin{cases} 1 & , & |t| \leq a \\ 0 & , & |t| > a \end{cases}$

Solution $F(s) = \frac{1}{\sqrt{2\pi}} \left[\int_{-\infty}^{-a} f(t)e^{-ist} dt + \int_{-a}^a f(t)e^{-ist} dt + \int_a^{\infty} f(t)e^{-ist} dt \right]$

$$= I_1 + I_2 + I_3$$

Let $I_1 = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{-a} f(t)e^{-ist} dt$

Put $t = -u \Rightarrow dt = -du$

$$\therefore I_1 = \frac{1}{\sqrt{2\pi}} \int_{\infty}^a f(-u)e^{isu} (-du)$$

$$= \frac{1}{\sqrt{2\pi}} \int_a^{\infty} f(-u)e^{isu} du = 0$$

Similarly $I_3 = \int_a^{\infty} f(t)e^{-ist} dt = 0$

$$\therefore I_2 = \frac{1}{\sqrt{2\pi}} \int_{-a}^a f(t)e^{-ist} dt$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-a}^a 1 \cdot e^{-ist} dt \quad [\Theta f(t) = 1]$$

$$= \frac{1}{\sqrt{2\pi}} \left[\frac{e^{-ist}}{-is} \right]_{-a}^a = \frac{-1}{\sqrt{2\pi}} is [e^{-ias} - e^{ias}]$$

$$\Rightarrow I_2 = \frac{1}{\sqrt{2\pi}} \left(\frac{e^{ias} - e^{-ias}}{is} \right)$$

$$= \frac{1}{\sqrt{2\pi}} \cdot \frac{2 \sin as}{is} = \sqrt{\frac{2}{\pi}} \left(\frac{\sin as}{s} \right), s \neq 0$$

when $s = 0$,

$$F(s) = \sqrt{\frac{2}{\pi}} \frac{a \cos as}{(1)} \text{ as } s \rightarrow 0 \text{ [By L-Hospital rule]}$$

$$= \sqrt{\frac{2}{\pi}} a.$$

Example. 3 :- $f(t) = \begin{cases} t, & |t| \leq a \\ 0, & |t| > a \end{cases}$... (1)

Solution :- $F(s) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-ist} dt$

$$= \frac{1}{\sqrt{2\pi}} \left[\int_{-a}^{-a} f(t) e^{-ist} dt + \int_{-a}^a f(t) e^{-ist} dt + \int_a^{\infty} f(t) e^{-ist} dt \right]$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-a}^a t e^{-ist} dt \quad [\text{using (1)}]$$

$$= \frac{1}{\sqrt{2\pi}} \left[\left(t \frac{e^{-ist}}{-is} \right)_{-a}^a - \int_{-a}^a (1) \frac{e^{-ist}}{-is} dt \right]$$

$$= \frac{1}{\sqrt{2\pi}} \left[\frac{a}{-is} e^{-ias} + \frac{a}{-is} e^{ias} + \frac{1}{is(-is)} (e^{-ias} - e^{ias}) \right]$$

$$= \frac{1}{\sqrt{2\pi}} \left[\frac{a}{-is} (e^{ias} + e^{-ias}) - \frac{1}{s^2} (e^{ias} - e^{-ias}) \right]$$

$$\Rightarrow F(s) = \frac{1}{\sqrt{2\pi}} \left[\frac{2a \cos as}{-is} - \frac{1}{s^2} \sin as \right]$$

$$= \frac{2}{s^2 \sqrt{2\pi}} [i as \cos as - \sin as]$$

$$\Rightarrow F(s) = \frac{\sqrt{2}}{\sqrt{\pi}} \frac{i}{s^2} [as \cos as - \sin as]$$

Example. 4. If $F(s) = F[f(t)]$. Find F.T. of $f(t) \cos at$

Solution :- We know that

$$\cos at = \frac{1}{2} (e^{iat} + e^{-iat})$$

$$\text{Then } F[f(t) \cos at] = \frac{1}{2} F[f(t) e^{iat}] + \frac{1}{2} F[f(t) e^{-iat}]$$

or prove by definition [By linearity property]

$$\Rightarrow F[f(t) \cos at] = \frac{1}{2} F(s-a) + \frac{1}{2} F(s+a) \quad [\text{By using shifting property}]$$

Example. 5. If $F_s(s)$ and $F_c(s)$ are FST and FCT of $f(t)$ respectively, then

$$F_s[f(t) \cos at] = \frac{1}{2} [F_s(s+a) + F_s(s-a)]$$

$$F_c[f(t) \cos at] = \frac{1}{2} [F_c(s+a) + F_c(s-a)]$$

$$F_s[f(t) \sin at] = \frac{1}{2} [F_c(s-a) - F_c(s+a)]$$

$$F_c[f(t) \sin at] = \frac{1}{2} [F_s(s+a) - F_s(s-a)]$$

Solution :- (i) By definition of FST,

$$\begin{aligned} F_s[f(t) \cos at] &= \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \cos at \sin st \, dt \\ &= \frac{1}{2} \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) 2 \cos at \sin st \, dt \end{aligned}$$

Using $2 \sin A \cos B = \sin(A+B) + \sin(A-B)$,

$$\begin{aligned} \Rightarrow F_s[f(t) \cos at] &= \frac{1}{\sqrt{2\pi}} \int_0^{\infty} f(t) [\sin(s+a)t + \sin(s-a)t] \, dt \\ &= \frac{1}{2} \left[\sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \sin(s+a)t \, dt + \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \sin(s-a)t \, dt \right] \\ &= \frac{1}{2} [F_s(s+a) + F_s(s-a)] \end{aligned}$$

(ii) By definition FCT,

$$\begin{aligned} F_c[f(t) \cos at] &= \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \cos at \cos st \, dt \\ &= \frac{1}{2} \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) [\cos(s+a)t + \cos(s-a)t] \, dt \end{aligned}$$

$$\begin{aligned}
&= \frac{1}{2} \left[\sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \cos(s+a)t \, dt + \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \cos(s-a)t \, dt \right] \\
&= \frac{1}{2} [F_c(s+a) + F_c(s-a)]
\end{aligned}$$

(iii) By definition of FST,

$$\begin{aligned}
F_s[f(t) \sin at] &= \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \sin at \sin st \, dt \\
&= \frac{1}{2} \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) [\cos(s-a)t - \cos(s+a)t] \, dt \\
&\quad [\Theta \, 2 \sin A \sin B = \cos(A-B) - \cos(A+B)] \\
&= \frac{1}{2} \left[\sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \cos(s-a)t \, dt - \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \cos(s+a)t \, dt \right] \\
&= \frac{1}{2} [F_c(s-a) - F_c(s+a)]
\end{aligned}$$

(iv) By definition of FCT,

$$\begin{aligned}
F_c[f(t) \sin at] &= \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \sin at \cos st \, dt \\
&= \frac{1}{2} \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) [\sin(s+a)t - \sin(s-a)t] \, dt \\
&\quad [\text{using } 2 \cos A \sin B = \sin(A+B) - \sin(A-B)] \\
&= \frac{1}{2} \left[\sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \sin(s+a)t \, dt - \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \sin(s-a)t \, dt \right] \\
&= \frac{1}{2} [F_s(s+a) - F_s(s-a)].
\end{aligned}$$

Example. 6. Find Fourier sine & cosine transform of e^{-at} , $a > 0$.

$$\text{Let } \int_0^{\infty} e^{-at} \cos st \, dt = I_1 \quad \dots(1)$$

$$\int_0^{\infty} e^{-at} \sin st \, dt = I_2 \quad \dots(2)$$

Integrating (1) by parts

$$\begin{aligned} I_1 &= \left[-\frac{1}{a} e^{-at} \cos st \right]_0^{\infty} - \int_0^{\infty} e^{-at} \sin st \, dt \\ &= \frac{1}{a} - \frac{s}{a} \int_0^{\infty} e^{-at} \sin st \, dt \\ &= \frac{1}{a} - \frac{s}{a} I_2 \end{aligned} \quad \dots(3)$$

Integrating (2) by parts, we have

$$\begin{aligned} I_2 &= \frac{s}{a} I_1 \\ \left[\Theta \quad I_2 &= \left[\frac{-1}{a} e^{-at} \sin st \right]_0^{\infty} + \frac{s}{a} \int_0^{\infty} e^{-at} \cos st \, dt \right] \end{aligned} \quad \dots(4)$$

solving (3) and (4) for I_1 & I_2 ,

$$\begin{aligned} I_1 &= \frac{1}{a} - \frac{s}{a} \cdot \frac{s}{a} I_1 \\ \Rightarrow \quad I_1 \left(1 + \frac{s^2}{a^2} \right) &= \frac{1}{a} \quad \Rightarrow \quad I_1 = \frac{1}{a} \cdot \frac{a^2}{s^2 + a^2} \\ \Rightarrow \quad I_1 &= \frac{a}{s^2 + a^2} \end{aligned}$$

$$\text{and } I_2 = \frac{s}{a} \cdot \frac{a}{s^2 + a^2} = \frac{s}{s^2 + a^2}$$

$$\text{Hence } F_c[e^{-at}] = \sqrt{\frac{2}{\pi}} I_1 = \sqrt{\frac{2}{\pi}} \frac{a}{s^2 + a^2} \quad \dots(5)$$

$$\text{and } F_s[e^{-at}] = \sqrt{\frac{2}{\pi}} I_2 = \sqrt{\frac{2}{\pi}} \frac{s}{s^2 + a^2} \quad \dots(6)$$

Extensions :- Differentiating both sides of (5) w.r.t. 'a', we find

$$F_c[-t e^{-at}] = \sqrt{\frac{2}{\pi}} \left[\frac{(s^2 + a^2)1 - a \cdot 2a}{(s^2 + a^2)^2} \right]$$

$$\Rightarrow -F_c[t e^{-at}] = \sqrt{\frac{2}{\pi}} \left[\frac{-a^2 + s^2}{(s^2 + a^2)^2} \right]$$

$$\Rightarrow F_c[t e^{-at}] = \sqrt{\frac{2}{\pi}} \left[\frac{a^2 - s^2}{(s^2 + a^2)^2} \right]$$

Differentiating both sides of (6) w.r.t. 'a', we get

$$F_s[-t e^{-at}] = \sqrt{\frac{2}{\pi}} \left[\frac{(s^2 + a^2)0 - s \cdot 2a}{(s^2 + a^2)^2} \right]$$

$$\Rightarrow -F_s[t e^{-at}] = -\sqrt{\frac{2}{\pi}} \frac{2as}{(s^2 + a^2)^2}$$

$$\Rightarrow F_s[t e^{-at}] = \sqrt{\frac{2}{\pi}} \frac{2as}{(s^2 + a^2)^2}.$$

Put a = 1 in (5), (6), we get

$$F_s[e^{-t}] = \sqrt{\frac{2}{\pi}} \frac{s^2}{s^2 + 1} = \sqrt{\frac{2}{\pi}} \frac{s}{s^2 + 1}$$

$$F_c[e^{-t}] = \sqrt{\frac{2}{\pi}} \cdot \frac{1}{s^2 + 1}$$

Results:

$$\int e^{at} \cos \beta t \, dt = \frac{e^{at}}{\alpha^2 + \beta^2} (\alpha \cos \beta t + \beta \sin \beta t)$$

$$\int e^{at} \sin \beta t \, dt = \frac{e^{at}}{\alpha^2 + \beta^2} (\alpha \sin \beta t - \beta \cos \beta t)$$

Example. 7 :- Find F. T. of $f(t) = e^{-t^2/2}$

Solution :- By definition, $F\left[e^{-\frac{t^2}{2}}\right] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{t^2}{2}} e^{-ist} \, dt$

$$\begin{aligned} \Rightarrow F[e^{-t^2/2}] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(t+is)^2} \cdot e^{-\frac{s^2}{2}} \, dt \\ &= \frac{e^{-s^2/2}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}(t+is)^2} \, dt \end{aligned}$$

$$\text{Put } \frac{1}{\sqrt{2}}(t + is) = y \Rightarrow dt = \sqrt{2} dy$$

$$\begin{aligned} \Rightarrow F[e^{-t^2/2}] &= \frac{e^{-s^2/2}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-y^2} \cdot \sqrt{2} dy \\ &= \frac{e^{-s^2/2}}{\sqrt{\pi}} \int_{-\infty}^{\infty} e^{-y^2} dy = \frac{e^{-s^2/2}}{\sqrt{\pi}} \cdot \sqrt{\pi} \end{aligned}$$

$$\Rightarrow F[e^{-t^2/2}] = e^{-s^2/2}, \quad F_c[e^{-t^2/2}] = e^{-s^2/2}$$

Example. 8. Find Fourier cosine transform of $f(t) = e^{-t^2}$

$$\text{Solution :- } F_c[e^{-t^2}] = \sqrt{\frac{2}{\pi}} \int_0^{\infty} e^{-t^2} \cos st dt = I \quad \dots(1)$$

Differentiating w.r.t. 's', we get

$$\begin{aligned} \frac{dI}{ds} &= -\sqrt{\frac{2}{\pi}} \int_0^{\infty} t e^{-t^2} \sin st dt \\ &= \frac{1}{2} \sqrt{\frac{2}{\pi}} \int_0^{\infty} (-2te^{-t^2}) \sin st dt \end{aligned}$$

Integrating by parts,

$$\begin{aligned} \frac{dI}{ds} &= \frac{1}{2} \sqrt{\frac{2}{\pi}} \left[\sin ste^{-t^2} \Big|_0^{\infty} - s \int_0^{\infty} \cos st \cdot e^{-t^2} dt \right] \\ &= -\frac{s}{2} \sqrt{\frac{2}{\pi}} \int_0^{\infty} e^{-t^2} \cos st dt \end{aligned}$$

$$\Rightarrow \frac{dI}{ds} = -\frac{s}{2} I \quad [\text{using (1)}]$$

$$\Rightarrow \frac{dI}{I} = -\frac{s}{2} ds$$

$$\text{Integrating, } \log I = -\frac{s^2}{4} + \log A$$

$$\Rightarrow I = A e^{-s^2/4} \quad \dots(2)$$

when $s = 0$, from (1), $I = \sqrt{\frac{2}{\pi}} \int_0^{\infty} e^{-t^2} dt$

$$\Rightarrow I = \sqrt{\frac{2}{\pi}} \cdot \frac{\sqrt{\pi}}{2} = \frac{1}{\sqrt{2}} \quad \dots(3)$$

Also when $s = 0$, from (2) $\Rightarrow I = A \quad \dots(4)$

$\therefore$ from (3) & (4), we get $A = \frac{1}{\sqrt{2}}$

$\therefore$ (2) gives $I = \frac{1}{\sqrt{2}} e^{-s^2/4}$

Extension :- $F_c [e^{-a^2 t^2}] = \frac{1}{\sqrt{2}} \cdot \frac{1}{a} e^{-\frac{1}{4} \left(\frac{s}{a}\right)^2}$

$$\Rightarrow F_c [e^{-a^2 t^2}] = \frac{1}{a\sqrt{2}} e^{-\frac{s^2}{4a^2}} \text{ [using change of scale probability } F[f(at)] = \frac{1}{|a|} F\left(\frac{s}{a}\right)]$$

If $a = \frac{1}{\sqrt{2}}$, we have

$$F_c [e^{-t^2/2}] = e^{-s^2/2}$$

Self-reciprocal function:

A function $f(t)$ with the property that $F[f(t)] = f(s)$ is said to be self-reciprocal under Fourier transform, e.g. the function $e^{-t^2/2}$ is self-reciprocal function under F.T. The function $e^{-t^2/2}$ is also self reciprocal under F.C.T.

To prove :- $F_c [e^{-t^2/2}] = e^{-s^2/2}$

Let $F_c [e^{-t^2/2}] = e^{-s^2/2}$

$$\Rightarrow \sqrt{\frac{2}{\pi}} \int_0^{\infty} e^{-t^2/2} \cos st dt = e^{-s^2/2}$$

Differentiating w.r.t. 's' on both sides, we get

$$F_s [t e^{-t^2/2}] = s e^{-s^2/2}$$

Hence the function $t e^{-t^2/2}$ is self-reciprocal function under Fourier Sine Transform.

Example. :- We know that if $f(t) = \begin{cases} 1, & |t| \leq a \\ 0, & |t| > a \end{cases}$

$$\text{Then } F(s) = \sqrt{\frac{2}{\pi}} \frac{\sin sa}{s}, s \neq 0 \quad \dots(1)$$

$$\text{By definition of F. T., } F(s) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-ist} dt$$

$$\text{then } f(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} F(s) e^{-st} ds$$

Put $F(s)$ from (1), we get

$$f(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \sqrt{\frac{2\pi}{\pi}} \frac{\sin sa}{s} e^{ist} ds$$

$$\Rightarrow f(t) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{\sin sa}{s} e^{ist} ds = \begin{cases} 1, & |t| < a \\ 0, & |t| > a \end{cases}$$

$$\begin{aligned} \text{L.H.S.} &= \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{\sin sa}{s} [\cos st + i \sin st] ds \\ &= \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{\sin sa}{s} \cos st ds + \frac{i}{\pi} \int_{-\infty}^{\infty} \frac{\sin sa}{s} \sin st ds \end{aligned}$$

Since integrand in second integral is an odd function, so the integral is zero

$$\Rightarrow \text{L.H.S.} = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{\sin sa}{s} \cos st ds$$

$$\Rightarrow \int_{-\infty}^{\infty} \frac{\sin sa}{s} \cos st ds = \begin{cases} \pi, & |t| < a \\ 0, & |t| > a \\ \pi/2, & |t| = a \end{cases}$$

$$\text{or } \int_0^{\infty} \frac{\sin sa \cos st}{s} ds = \begin{cases} \pi/2, & |t| < a \\ 0, & |t| > a \\ \pi/4, & |t| = a \end{cases} \quad \dots(2)$$

$$\text{Evaluate } \int_0^{\infty} \frac{\sin s}{s} ds$$

Solution : Put $t = 0$, $a = 1$ in (2), we get

$$\int_0^{\infty} \frac{\sin s}{s} ds = \frac{\pi}{2} \text{ when } |t| < a.$$

Relation between Laplace Transform and Fourier Transform

Consider the function

$$f(t) = \begin{cases} e^{-xt} \phi(t), & t > 0 \\ 0, & t < 0 \end{cases}$$

Taking F.T. of $f(t)$,

$$\begin{aligned} F[f(t)] = F(s) &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-ist} f(t) dt \\ &= \frac{1}{\sqrt{2\pi}} \int_0^{\infty} e^{-ist} e^{-xt} \phi(t) dt \\ &= \frac{1}{\sqrt{2\pi}} \int_0^{\infty} e^{-(x+is)t} \phi(t) dt \\ &= \frac{1}{\sqrt{2\pi}} \int_0^{\infty} e^{-pt} \phi(t) dt \text{ where } p = x + i \end{aligned}$$

$$\Rightarrow F[f(t)] = \frac{1}{\sqrt{2\pi}} L[\phi(t)]$$

F.T. of Derivatives

If $F[f(t)] = F(s)$ & $f(t) \rightarrow 0$ as $t \rightarrow \pm \infty$, then

$$F[f'(t)] = is F[f(t)] = is F(s)$$

Proof :- By definition,

$$\begin{aligned} F[f'(t)] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f'(t) e^{-ist} dt \\ &= \frac{1}{\sqrt{2\pi}} \left[e^{-ist} f(t) \right]_{-\infty}^{\infty} - \frac{1}{\sqrt{2\pi}} (-is) \int_{-\infty}^{\infty} f(t) e^{-ist} dt \\ &= is \cdot \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-ist} dt \quad [\Theta f(t) \rightarrow 0 \text{ as } t \rightarrow \pm \infty] \end{aligned}$$

$$\Rightarrow F[f'(t)] = is F[f(t)] = is F(s)$$

Now

$$F[f''(t)] = is F[f'(t)] = (is)^2 F[f(t)]$$

In general, we have

$$\begin{aligned} F[f^{(n)}(t)] &= is F[f^{(n-1)}(t)] \\ &= (is)^n F[f(t)] = (is)^n F(s) \end{aligned}$$

Find Fourier sine & cosine transform of $f'(t)$, $f''(t)$.

Derivation :- By definition

$$\begin{aligned} F_c[f'(t)] &= \sqrt{\frac{2}{\pi}} \int_0^\infty f'(t) \cos st \, dt \\ &= \sqrt{\frac{2}{\pi}} [\cos st f(t)]_0^\infty + s \sqrt{\frac{2}{\pi}} \int_0^\infty f(t) \sin st \, dt \end{aligned}$$

Assuming $f(t) \rightarrow 0$ as $t \rightarrow \infty$,

$$\Rightarrow F_c[f'(t)] = -\sqrt{\frac{2}{\pi}} f(0) + s F_s[f(t)] \quad \dots(1)$$

$$\begin{aligned} F_s[f'(t)] &= \sqrt{\frac{2}{\pi}} \int_0^\infty f'(t) \sin st \, dt \\ &= \sqrt{\frac{2}{\pi}} [\sin st f(t)]_0^\infty - s \sqrt{\frac{2}{\pi}} \int_0^\infty f(t) \cos st \, dt \end{aligned}$$

Assuming $f(t) \rightarrow 0$ as $t \rightarrow \infty$,

$$\Rightarrow F_s[f'(t)] = -s \sqrt{\frac{2}{\pi}} \int_0^\infty f(t) \cos st \, dt$$

$$\Rightarrow F_s[f'(t)] = -s F_c[f(t)] \quad \dots(2)$$

Now

$$F_c[f''(t)] = -\sqrt{\frac{2}{\pi}} f'(0) + s F_s[f'(t)] \quad (\text{using (1)})$$

$$= -f'(0) \sqrt{\frac{2}{\pi}} + s[-s F_c[f(t)]] \quad [\text{By using (2)}]$$

$$\Rightarrow F_c[f''(t)] = -f'(0) \sqrt{\frac{2}{\pi}} - s^2 F_c[f(t)] \quad \dots(3)$$

$$\text{and } F_s[f''(t)] = -s F_c[f'(t)] \quad [\text{using (2)}]$$

$$= -s \left\{ -\sqrt{\frac{2}{\pi}} f(0) + s F_s[f(t)] \right\} \quad [\text{using (1)}]$$

$$\Rightarrow F_s[f''(t)] = \sqrt{\frac{2}{\pi}} s f(0) - s^2 F_s[f(t)] \quad \dots(4)$$

Theorem:- If $F[f(t)] = F(s)$, then

$$\frac{d^n}{ds^n} F[f(t)] = (-i)^n F[t^n f(t)], n = 1, 2, 3$$

Proof:- By definition,

$$F[f(t)] = F(s) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-ist} dt$$

Differentiate w.r.t. 's' under integral sign, we get

$$\begin{aligned} \frac{d}{ds} F(s) &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) \frac{\partial}{\partial s} (e^{-ist}) dt \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) (-i t) e^{-ist} dt \end{aligned}$$

$$\Rightarrow \frac{d}{ds} F(s) = (-i) \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} t f(t) e^{-ist} dt$$

$$\Rightarrow \frac{d}{ds} F(s) = (-i) F[t f(t)]$$

$$\text{Now } \frac{d^2}{ds^2} F(s) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} (-i t)^2 f(t) e^{-ist} dt$$

$$= (-i)^2 \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} t^2 f(t) e^{-ist} dt$$

$$\Rightarrow \frac{d^2}{ds^2} F(s) = (-i)^2 F[t^2 f(t)]$$

Generalising the result, we have

$$\frac{d^n}{ds^n} F[f(t)] = (-i)^n F[t^n f(t)], n = 1, 2, \dots$$

Theorem :- If $F[f(t)] = F(s)$

and $\int_{-\infty}^{\infty} f(t)dt = F(0) = 0$

then $F\left[\int_{-\infty}^t f(x)dx\right] = \frac{1}{is} F(s)$

Proof : Consider $\phi(t) = \int_{-\infty}^t f(x)dx$

Then $\phi'(t) = f(t)$

Hence if $F[\phi(t)] = \Phi(s)$,

then $F[\phi'(t)] = F[f(t)] = is \Phi(s)$

$\Rightarrow \Phi(s) = \frac{1}{is} F[f(t)]$

$\Rightarrow \Phi(s) = \frac{F(s)}{is}$

$\Rightarrow F[\phi(t)] = \frac{F(s)}{is}$

$\Rightarrow F\left[\int_{-\infty}^t f(x)dx\right] = \frac{1}{is} F(s)$

Convolution :- Let $f_1(t)$ and $f_2(t)$ be two given functions, the convolution of $f_1(t)$ & $f_2(t)$ is defined by the function

$$\begin{aligned} f(t) &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_1(x) f_2(t-x)dx \\ &= f_1(t) * f_2(t) \end{aligned}$$

Special case :-

$$f_1(t) = 0 \text{ for } t < 0$$

$$f_2(t) = 0 \text{ for } t < 0$$

Then

$$f(t) = f_1(t) * f_2(t) = \frac{1}{\sqrt{2\pi}} \int_0^t f_1(x) f_2(t-x) dx$$

Proof :- $f(t) = \frac{1}{\sqrt{2\pi}} \left[\int_{-\infty}^0 f_1(x)f_2(t-x)dx + \int_0^t f_1(x)f_2(t-x)dx + \int_t^{\infty} f_1(x)f_2(t-x)dx \right]$

...(1)

Now $I_1 = 0$ $[\Theta f_1(t) = 0 \text{ for } t < 0]$... (2)

$$\text{and } I_3 = \frac{1}{\sqrt{2\pi}} \int_t^\infty f_1(x) f_2(t-x) dx$$

Now when $t < 0 \Rightarrow f_2(t) = 0$

$\therefore$ when $t-x < 0 \Rightarrow f_2(t-x) = 0$

$\Rightarrow f_2(t-x) = 0$ for $t < x$ or $x > t$

So $I_3 = 0$ $[\Theta f_2(t-x) = 0 \text{ for } x > t]$... (3)

Using (2) & (3) in (1), we get $f(t) = \frac{1}{\sqrt{2\pi}} \int_1^t f_1(x) f_2(t-x) dx$

Commutative Property:

$$f_1(t) * f_2(t) = f_2(t) * f_1(t)$$

Proof :- By definition,

$$f_1 * f_2 = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^\infty f_1(x) f_2(t-x) dx$$

put $t-x = y \Rightarrow dx = -dy$

when $x = -\infty, y = \infty$

and when $x = \infty, y = -\infty$

$$\Rightarrow f_1 * f_2 = \frac{1}{\sqrt{2\pi}} \int_{\infty}^{-\infty} f_1(t-y) f_2(y) (-dy)$$

$$\Rightarrow f_1 * f_2 = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_2(y) f_1(t-y) dy = f_2 * f_1$$

Associativity property

$$(f_1 * f_2) * f_3 = f_1 * (f_2 * f_3) \quad \dots (1)$$

Take $g(t) = f_1 * f_2$

$$h(t) = f_2 * f_3$$

Then (1) becomes, $g(t) * f_3 = f_1 * h(t)$

Convolution Theorem (or Faltung Theorem) on Fourier Transforms

$$\text{If } F[f_1(t)] = F_1(s)$$

$$F[f_2(t)] = F_2(s) \text{ i.e.}$$

$$F[f_1(t) * f_2(t)] = F_1(s) F_2(s)$$

where

$$f_1(t) * f_2(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_1(x) f_2(t-x) dx$$

Proof :- We have by definition of F.T.,

$$\begin{aligned} F[f_1(t) * f_2(t)] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} [f_1(t) * f_2(t)] e^{-ist} dt \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \left[\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_1(x) f_2(t-x) dx \right] e^{-ist} dt \end{aligned}$$

[By using definition of convolution]

changing the order of integration, we get

$$\begin{aligned} F[f_1(t) * f_2(t)] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_1(x) \left[\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_2(t-x) e^{-ist} dt \right] dx \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_1(x) \left[\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_2(t-x) e^{-is(t-x)} e^{-isx} dt \right] dx \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_1(x) \left[\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_2(y) e^{-isy} dy \right] e^{-isx} dx \end{aligned}$$

[By putting $t-x = y \Rightarrow dt = dy$]

$$\begin{aligned} \Rightarrow F[f_1(t) * f_2(t)] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_1(x) e^{-isx} F_2(s) dx \\ &= F_2(s) \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_1(x) e^{-isx} dx \end{aligned}$$

$$\Rightarrow F[f_1(t) * f_2(t)] = F_1(s) F_2(s)$$

* The convolution can be used to obtain the Fourier transform of the product of two functions.

By definition of F.T., we have

$$F[f_1(t) f_2(t)] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_1(x) f_2(x) e^{-isx} dx$$

By using inverse F.T. of $f_2(x)$, we get

$$\begin{aligned} F[f_1(t) f_2(t)] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_1(x) \left[\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} F_2(s') e^{is'x} ds' \right] e^{-isx} dx \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} ds' F_2(s') \left[\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f_1(x) e^{-i(s-s')x} dx \right] \end{aligned}$$

$$\begin{aligned} \Rightarrow F[f_1(t) f_2(t)] &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} F_2(s') F_1(s-s') ds' \\ &= F_2(s) * F_1(s) \quad [\text{By using definition of convolution}] \end{aligned}$$

$$\Rightarrow F[f_1(t) f_2(t)] = F_2 * F_1$$

$$\Rightarrow F[f_1(t) f_2(t)] = F_1 * F_2$$

$$\text{If } F(z) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-izt} dt$$

$$\text{Then inverse function } f(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} F(z) e^{-izt} dz$$

Example :- Find F.T. of $f(t) = e^{-|t|}$ and verify the inverse transform.

Sol. Now $|t| = t$ for $t > 0$

$$|t| = -t \text{ for } t < 0$$

So

$$f(t) = \begin{cases} e^t & , \quad t < 0 \\ e^{-t} & , \quad t > 0 \end{cases}$$

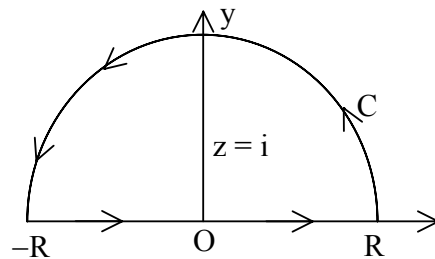
$$\begin{aligned} \therefore F(z) &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t) e^{-izt} dt \\ &= \frac{1}{\sqrt{2\pi}} \left[\int_{-\infty}^0 e^{t(1-iz)} dt + \int_0^{\infty} e^{-t(1+iz)} dt \right] \end{aligned}$$

$$= \frac{1}{\sqrt{2\pi}} \left[\frac{1}{1-iz} + \frac{1}{1+iz} \right] = \frac{1}{\sqrt{2\pi}} \frac{2}{1+z^2}$$

We can invert the transform using contour integration (Residue theorem). First consider $t > 0$, then

$$\begin{aligned} f(t) &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \frac{2}{1+z^2} e^{izt} dz = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{e^{izt}}{1+z^2} dz \\ &= \frac{1}{\pi} \lim_{R \rightarrow \infty} \oint_C \frac{e^{izt}}{1+z^2} dz \end{aligned}$$

where c is the contour shown in figure.

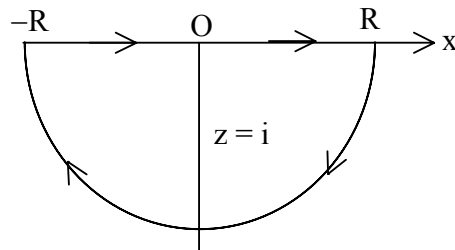


There is a simple pole at $z = i$ and $\text{Res}(z = i) = \lim_{z \rightarrow i} \frac{(z-i)e^{izt}}{(z-i)(z+i)} = \frac{1}{2i} e^{-t}$

Therefore by Residue theorem,

$$\frac{1}{\pi} \int_{-\infty}^{\infty} \frac{e^{izt}}{1+z^2} dz = \frac{1}{\pi} 2\pi i \left(\frac{e^{-t}}{2i} \right) = e^{-t}$$

Consider $t < 0$, then we choose the contour with a semi-circular arc lying below the x-axis where c is the contour shown in figure.



Therefore there is a simple pole at $z = -i$.

$$\text{Res}(z = -) = \lim_{z \rightarrow -i} \frac{(z+i)e^{izt}}{(z+i)(z-i)} = \frac{e^t}{-2i}$$

But in this case contour is in clockwise direction, hence the desired result is

$$\frac{1}{\pi} \int_{-\infty}^{\infty} \frac{e^{izt}}{1+z^2} dz = \frac{-1}{\pi} 2\pi i \left(\frac{-e^t}{2i} \right) = e^t$$

At $t = 0$, we can evaluate directly

$$\begin{aligned} \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{1}{1+z^2} dz &= \frac{1}{\pi} \left(\tan^{-1} z \right)_{-\infty}^{\infty} = \frac{1}{\pi} \left[\frac{\pi}{2} - \left(-\frac{\pi}{2} \right) \right] \\ &= 1 \end{aligned}$$

Example : Find F.T. of $f(t) = \begin{cases} \sin wt, & 0 < t < \infty \\ 0, & \text{otherwise} \end{cases}$

or $f(t) = \sin wt H(t)$

where

$$H(t) = \begin{cases} 1, & t > 0 \\ 0, & t < 0 \end{cases}$$

is a unit step function or Heaviside's unit step function.

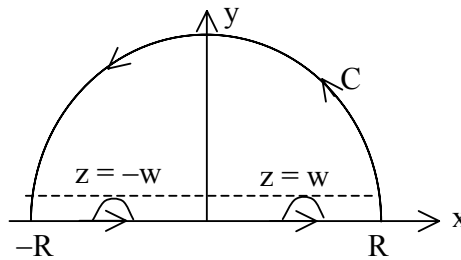
$$\begin{aligned} \text{Sol. Now } F(z) &= \frac{1}{\sqrt{2\pi}} \int_0^{\infty} \sin wt e^{-izt} dt \\ &= \frac{1}{\sqrt{2\pi}} \int_0^{\infty} \left[\frac{e^{iwt} - e^{-iwt}}{2i} \right] e^{-izt} dt \\ &= \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{2i} \int_0^{\infty} [e^{it(w-z)} - e^{it(w+z)}] dt \\ &= \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{2i} \left[\frac{e^{-it(w-z)}}{-i(-w+z)} - \frac{e^{-it(w+z)}}{-i(w+z)} \right]_0^{\infty} \\ &= \frac{1}{\sqrt{2\pi}} \cdot \frac{1}{2i} \left[\frac{1}{i(z-w)} - \frac{1}{i(w+z)} \right] \\ &= \frac{-1}{2i^2 \sqrt{2\pi}} \left[\frac{-1}{z-w} + \frac{1}{z+w} \right] = \frac{1}{2\sqrt{2\pi}} \left[\frac{-z-w+z-w}{z^2-w^2} \right] \\ &= \frac{-1}{\sqrt{2\pi}} \left(\frac{w}{z^2-w^2} \right) \end{aligned}$$

Here $F(z) = \frac{-w}{\sqrt{2\pi}(z^2 - w^2)}$ is analytic in z -plane except at $z = \pm w$

$$\text{If } t > 0 :- f(t) = \frac{-1}{2\pi} \lim_{R \rightarrow \infty} \oint_C \frac{we^{izt}}{z^2 - w^2} dz$$

where c is contour.

There are two simple pole $z = w$ & $z = -w$ inside c .



$$\text{where } f(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} F(z)e^{izt} dz$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \frac{-w}{\sqrt{2\pi}(z^2 - w^2)} e^{izt} dz$$

$$\Rightarrow f(t) = \frac{-1}{2\pi} \int_{-\infty}^{\infty} \frac{we^{izt}}{z^2 - w^2} dz$$

$$\therefore \frac{-1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \frac{we^{izt}}{z^2 - w^2} dz = \frac{-1}{2\pi} \lim_{R \rightarrow \infty} \oint_C \frac{we^{izt}}{z^2 - w^2} dz$$

$$\begin{aligned} \text{Res}(z = w) &= \lim_{z \rightarrow w} (z - w) \frac{we^{izt}}{(z - w)(z + w)} = \frac{we^{iwt}}{2w} \\ &= \frac{e^{iwt}}{2} \end{aligned}$$

$$\begin{aligned} \text{Res}(z = -w) &= \lim_{z \rightarrow -w} (z + w) \frac{we^{izt}}{(z - w)(z + w)} = \frac{we^{-iwt}}{-2w} \\ &= -\frac{1}{2} e^{-iwt} \end{aligned}$$

Therefore by Residue theorem,

$$\begin{aligned}\frac{-1}{2\pi} \lim_{R \rightarrow \infty} \oint_C \frac{w e^{izt}}{z^2 - w^2} dz &= \frac{-1}{2\pi} (2\pi i) \text{ (Sum of residue)} \\ &= -i \left[\frac{e^{iwt} - e^{-iwt}}{2} \right]\end{aligned}$$

$$\Rightarrow f(t) = -i(i \sin wt) = \sin wt$$

If $t < 0$, we choose the contour with a semi-circular arc below x-axis & since there are **no poles** inside the contour, the result is zero.

LESSON-2

APPLICATIONS OF FOURIER TRANSFORMS

Solution of Ordinary Differential Equation

Consider the nth order differential equation

$$A_n \frac{d^n y}{dt^n} + a_{n-1} \frac{d^{n-1} y}{dt^{n-1}} + \dots + a_1 \frac{dy}{dt} + ay = f(t)$$

Taking F.T. of both sides,

$$[a_n (i s)^n + a_{n-1} (i s)^{n-1} + \dots + a_1 (i s) + a] F[y(t)] = F[f(t)]$$

$$\text{Let } F[f(t)] = G(s)$$

$$F[y(t)] = Y(s)$$

$$P(i s) = a_n (i s)^n + a_{n-1} (i s)^{n-1} + \dots + a_1 (i s) + a$$

is a polynomial in (i s).

$$\text{Then we have } Y(s) = \frac{G(s)}{P(is)}$$

Taking inverse F.T., we have the solution is given by

$$y(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} Y(s) e^{ist} ds$$

Example:- Solve using F.T. technique

$$\frac{d^2 y}{dt^2} + 3 \frac{dy}{dt} + 2y = e^{-|t|} \quad \dots(1)$$

Solution :- Taking F.T. on both sides,

$$[(i z)^2 + 3(i z) + 2] F[y(t)] = F[e^{-|t|}]$$

$$\Rightarrow P(i z) F[y(t)] = \frac{1}{\sqrt{2\pi}} \frac{2}{1 + z^2}$$

$$\Rightarrow Y(z) = \frac{1}{\sqrt{2\pi}} \frac{2}{(1 + z^2) \cdot \frac{1}{P(iz)}} \text{ where } Y(z) = F[y(t)]$$

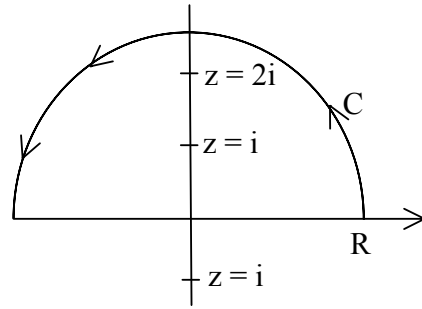
$$\begin{aligned} \Rightarrow y(t) &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \frac{2}{\sqrt{2\pi} (1 + z^2) [(iz)^2 + 3iz + 2]} e^{izt} dz \\ &= \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{e^{izt} dz}{(z^2 + 1)(-z^2 + 3iz + 2)} \end{aligned}$$

$$\begin{aligned}
&= \frac{-1}{\pi} \int_{-\infty}^{\infty} \frac{e^{izt} dz}{(z^2 + 1)(z^2 - 3iz - 2)} \\
&= \frac{-1}{\pi} \int_{-\infty}^{\infty} \frac{e^{izt} dz}{(z-1)(z+1)(z-i)(z-2i)} \\
&= \frac{-1}{\pi} \int_{-\infty}^{\infty} \frac{e^{izt} dz}{(z+i)(z-i)^2(z-2i)}
\end{aligned}$$

For $t > 0$

The singularity within the contour are a simple pole at $z = 2i$ and a double pole at $z = i$.

$$\begin{aligned}
\therefore \text{Res. } (z = 2i) &= \lim_{z \rightarrow 2i} \frac{(z-2i)e^{izt}}{(z+i)(z-i)^2(z-2i)} \\
&= \lim_{z \rightarrow 2i} \frac{e^{izt}}{(z+i)(z-i)^2} \\
&= \frac{e^{-2t}}{3i \cdot i^2} = \frac{1}{3i} e^{-2t}
\end{aligned}$$



$$\begin{aligned}
\text{Res. } (z = i) &= \lim_{z \rightarrow i} \frac{d}{dz} \frac{(z-i)^2 e^{izt}}{(z+i)(z-i)^2(z-2i)} \\
&= \lim_{z \rightarrow i} \frac{d}{dz} \frac{e^{izt}}{(z+i)(z-2i)}
\end{aligned}$$

$$\begin{aligned}
\Rightarrow \text{Res. } (z = i) &= \lim_{z \rightarrow i} \frac{(z+i)(z-2i)e^{izt}(it) - e^{izt}(2z+i-2i)}{[(z+i)(z-2i)]^2} \\
&= \lim_{z \rightarrow i} \frac{(z+i)(z-2i)(it)e^{izt} - e^{izt}(2z-i)}{(z+i)^2(z-2i)^2} \\
&= \frac{2i(-i)(it)e^{-t} - e^{-t}i}{4i^2(-i)^2} \\
&= \frac{2ite^{-t} - ie^{-t}}{4(-1)(-1)} = \frac{2ite^{-t} - ie^{-t}}{4} \\
\therefore y(t) &= \frac{-1}{\pi} \cdot 2\pi i \left[\frac{+i}{3(1)} e^{-2t} + \frac{2ite^{-t} - ie^{-t}}{4} \right]
\end{aligned}$$

$$\begin{aligned}
&= -2i \left[\frac{4ie^{-2t} + 6ite^{-t} - 3ie^{-t}}{12} \right] \\
&= \frac{-i}{6} [6ite^{-t} - 3ie^{-t} + 4ie^{-2t}] \\
&= \frac{1}{6} (6te^{-t} - 3e^{-t} + 4e^{-2t}) \\
&= \frac{2}{3} e^{-2t} + te^{-t} - \frac{1}{2} e^{-t} \quad \dots(2)
\end{aligned}$$

Verification :- Put (2) in L.H.S. of DE. (1) we get

$$\begin{aligned}
\text{L.H.S.} &= \frac{d^2y}{dt^2} + \frac{3dy}{dt} + 2y = \frac{d}{dt} \left[\frac{2}{3} e^{-2t} (-2) + e^{-t} - te^{-t} + \frac{1}{2} e^{-t} \right] \\
&\quad + 3 \left[\frac{-4}{3} e^{-2t} + e^{-t} - te^{-t} + \frac{1}{2} e^{-t} \right] + \frac{4}{3} e^{-2t} + 2te^{-t} - e^{-t} \\
\text{L.H.S.} &= \frac{-4}{3} e^{-2t} (-2) - \frac{3}{2} e^{-t} - e^{-t} + te^{-t} - 4e^{-2t} + \frac{9}{2} e^{-t} - 3te^{-t} \\
&\quad + \frac{4}{3} e^{-2t} + 2te^{-t} - e^{-t} = 2e^{-t} - e^{-t} = e^{-t}
\end{aligned}$$

For $t < 0$

$$\begin{aligned}
\text{Res. } (z = -i) &= \lim_{z \rightarrow -i} \frac{(z+i)e^{izt}}{(z+i)(z-i)^2(z-2i)} \\
&= \frac{e^t}{(-2i)^2(-3i)} = \frac{e^t}{4(-1)(-3i)} = \frac{e^t}{12i}
\end{aligned}$$

$$\text{So } y(t) = \frac{-1}{\pi} (-2\pi i) \frac{e^t}{12i} = \frac{e^t}{6} \quad \dots(3)$$

Verification :- Put (3) in L.H.S. of (1),

$$\begin{aligned}
\text{L.H.S.} &= \frac{d^2y}{dt^2} + \frac{3dy}{dt} + 2y = \frac{d}{dt} \left[\frac{e^t}{6} \right] + 3 \frac{e^t}{6} + \frac{2e^t}{6} \\
&= \frac{e^t}{6} + \frac{3e^t}{6} + \frac{2e^t}{6} = \frac{6e^t}{6} = e^t. \text{ Hence verified.}
\end{aligned}$$

Example:- Solve using F.T. techniques

$$\frac{d^2 y}{dt^2} + \frac{3dy}{dt} + 2y = H(t) \sin wt \quad (1)$$

Solution :- Then we have on taking F.T. on both sides,

$$[(i z)^2 + 3 i z + 2] F[y(t)] = \frac{1}{\sqrt{2\pi}} \frac{w}{w^2 - z^2}$$

$$\text{Then } y(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \left(\frac{w}{w^2 - z^2} \right) \frac{e^{izt} dz}{(-z^2 + 3iz + 2)}$$

$$\begin{aligned} \Rightarrow y(t) &= \frac{w}{2\pi} \int_{-\infty}^{\infty} \frac{e^{izt} dt}{(z^2 - w^2)(z^2 - 3iz - 2)} \\ &= \frac{w}{2\pi} \int_{-\infty}^{\infty} \frac{e^{izt} dt}{(z^2 - w^2)(z - i)(z - 2i)} \end{aligned}$$

For $t > 0$

In this case singularity are at $z = \pm w$, $z = 2i$, $z = i$ and all these lies inside the upper half plane.

$$\begin{aligned} \text{Res. } (z = 2i) &= \lim_{z \rightarrow 2i} \left[\frac{(z - 2i) e^{izt}}{(z - w)(z + w)(z - i)(z - 2i)} \right] \\ &= \frac{e^{-2t}}{(2i - w)(2i + w)i} = \frac{e^{-2t}}{-(4 + w^2)i^2} = \frac{ie^{-2t}}{w^2 + 4} \end{aligned}$$

$$\begin{aligned} \text{Res. } (z = i) &= \lim_{z \rightarrow i} \left[\frac{(z - i) e^{izt}}{(zi - w)(z - 2i)(z^2 - w^2)} \right] \\ &= \frac{e^{-t}}{-i(-1 - w^2)} = \frac{e^{-t}i}{(-1 - w^2)} = \frac{e^{-t}}{i(w^2 + 1)} \end{aligned}$$

$$\begin{aligned} \text{Res. } (z = w) &= \lim_{z \rightarrow w} \frac{(z - w) e^{izt}}{(z - w)(z + w)(z - i)(z - 2i)} \\ &= \frac{e^{iwt}}{2w(w - i)(w - 2i)} = \frac{e^{iwt}}{2w(w^2 - 3iw - 2)} \end{aligned}$$

$$\text{Res. } (z = -w) = \lim_{z \rightarrow -w} \frac{(z + w) e^{izt}}{(z - w)(z + w)(z - i)(z - 2i)}$$

$$\begin{aligned}
&= \frac{e^{-iwt}}{(-2w)(-w-i)(-w-2i)} = \frac{e^{-iwt}}{-2w(w+i)(w+2i)} \\
\Rightarrow \text{Res. } (z = -w) &= \frac{e^{-iwt}}{-2w(w^2 + 3iw - 2)} = \frac{-e^{-iwt}}{2w(w^2 + 3iw - 2)} \\
\therefore y(t) &= \frac{w}{2\pi} \cdot 2\pi i \left[\frac{ie^{-2t}}{w^2 + 4} + \frac{ie^{-t}}{-(w^2 + 1)} + \frac{e^{iwt}}{2w(w-i)(w-2i)} - \frac{e^{-iwt}}{2w(w+i)(w+2i)} \right] \\
&= \frac{-we^{-2t}}{w^2 + 4} + \frac{we^{-t}}{w^2 + 1} + \frac{i}{2} \frac{e^{iwt}}{(w-i)(w-2i)} - \frac{i}{2} \frac{e^{-iwt}}{(w+i)(w+2i)}
\end{aligned}$$

For verification :-

$$\begin{aligned}
y'(t) &= \frac{2we^{-2t}}{w^2 + 4} - \frac{we^{-t}}{w^2 + 1} - \frac{we^{-iwt}}{2(w-i)(w-2i)} - \frac{we^{-iwt}}{2(w+i)(w+2i)} \\
\Rightarrow y''(t) &= \frac{-4we^{-2t}}{w^2 + 4} + \frac{we^{-t}}{w^2 + 1} - \frac{iw^2e^{iwt}}{2(w-i)(w-2i)} + \frac{iw^2e^{-iwt}}{2(w+i)(w+2i)}
\end{aligned}$$

Then

$$\begin{aligned}
y'' + 3y' + 2y &= \frac{-4we^{-2t}}{w^2 + 4} + \frac{we^{-t}}{w^2 + 1} + \frac{iw^2e^{-iwt}}{2(w+i)(w+2i)} \\
&\quad + \frac{-iw^2e^{iwt}}{2(w-i)(w-2i)} + \frac{6we^{-2t}}{w^2 + 4} - \frac{3we^{-t}}{w^2 + 1} - \frac{3we^{iwt}}{2(w-i)(w-2i)} \\
&\quad - \frac{3we^{-iwt}}{2(w+i)(w+2i)} - \frac{2we^{-2t}}{w^2 + 4} + \frac{2we^{-t}}{w^2 + 1} + \frac{2ie^{iwt}}{2(w-i)(w-2i)} - \frac{wie^{-iwt}}{2(w+i)(w+2i)} \\
\Rightarrow y'' + 3y' + 2y &= \frac{e^{-iwt}}{2(w+i)(w+2i)} [iw^2 - 3w - 2i] \\
&\quad + \frac{e^{iwt}}{2(w-i)(w-2i)} [-iw^2 - 3w + 2i] \\
&= \frac{ie^{-iwt}}{2(w+i)(w+2i)} (w^2 + 3iw - 2) - \frac{ie^{iwt}(w^2 - 3iw - 2)}{2(w-i)(w-2i)} \\
&= \frac{-i}{2} (e^{iwt} - e^{-iwt}) = -i^2 \left(\frac{e^{iwt} - e^{-iwt}}{2i} \right)
\end{aligned}$$

$$\Rightarrow y'' + 3y' + 2y = H(t) \sin wt$$

Hence $y'' + 3y' + 2y = \sin wt$. $H(t)$ is verified for $t > 0$.

for $t < 0$, there is no pole inside the lower half plane so residue = 0.

$$\therefore y(t) = 0$$

$$\therefore y'' + 3y' + 2y = H(t) \sin wt \text{ is verified.}$$

For $t < 0$.

$$\therefore \text{for } t < 0, H(t) = 0$$

So R.H.S. of (1) is zero.

And equal to L.H.S. Hence verify the result.

Example: Find FST of $\frac{e^{-at}}{t}$

Solution :- The sine transform of function $f(t) = \frac{e^{-at}}{t}$

$$\begin{aligned} I = F_s[f(t)] &= \sqrt{\frac{2}{\pi}} \int_0^{\infty} f(t) \sin st \, dt \\ &= \sqrt{\frac{2}{\pi}} \int_0^{\infty} \frac{e^{-at}}{t} \sin st \, dt \end{aligned} \quad \dots(1)$$

Differentiation w.r.t. s , we get

$$\begin{aligned} \frac{dI}{ds} &= \frac{d}{ds} F_s(f(t)) = \sqrt{\frac{2}{\pi}} \int_0^{\infty} \frac{e^{-at}}{t} \cdot t \cos st \, dt = \sqrt{\frac{2}{\pi}} \int_0^{\infty} e^{-at} \cos st \, dt \\ &= \sqrt{\frac{2}{\pi}} \left[\frac{e^{-at}}{a^2 + s^2} (-a \cos st + s \sin st) \right]_0^{\infty} \end{aligned}$$

$$\Rightarrow \frac{d}{ds} F_s[f(t)] = \sqrt{\frac{2}{\pi}} \cdot \frac{a}{a^2 + s^2} = \frac{dI}{ds}$$

Integrating we get,

$$\begin{aligned} \int \frac{d}{ds} F_s[f(t)] &= \sqrt{\frac{2}{\pi}} \int \frac{a}{a^2 + s^2} \, ds \\ \Rightarrow I = F_s[f(t)] &= \sqrt{\frac{2}{\pi}} \tan^{-1} \left(\frac{s}{a} \right) + A \end{aligned} \quad \dots(2)$$

where A is constant of integration. For $s = 0$, we get from (2),

$$I = \sqrt{\frac{2}{\pi}} (0) + A \Rightarrow I = A \quad \dots(3)$$

$$\text{when } s = 0, \text{ from (1), } I = \sqrt{\frac{2}{\pi}} \int_0^{\infty} (0) dt = 0 \quad \dots(4)$$

from (3) & (4), we get

$$A = 0$$

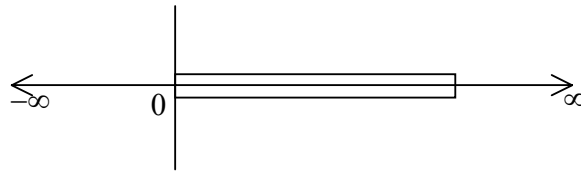
Hence the required FST of given function is

$$F_s \left[\frac{e^{-at}}{t} \right] = \sqrt{\frac{2}{\pi}} \tan^{-1} \left(\frac{s}{a} \right).$$

Solution of partial differential equations (boundary value problems)

Example: - Determine the distribution of temperature in the semi-infinite medium, $x \geq 0$ when the end $x = 0$ is maintained at zero temperature & the initial distribution of temperature is $f(x)$.

Solution :-



Heat equation is given by

$$\frac{\partial u(x, t)}{\partial t} = c^2 \frac{\partial^2 u(x, t)}{\partial x^2}, \quad x > 0, t > 0 \quad \dots(1)$$

where $u(x, t)$ is the distribution of temperature at any point x and time t . We want to determine the solution of (1) subject to initial condition $u(x, 0) = f(x)$... (2)

and the boundary condition $u(0, t) = 0$... (3)

Since $(u)_{x=0}$ is given, we apply F.S.T.

Denote $F_s[u(x, t)] = \bar{u}_s(s, t) = \bar{u}_s$ and $F_c[u(x, t)] = \bar{u}_c$

Taking FST of both sides of (1), we get

$$\sqrt{\frac{2}{\pi}} \int_0^{\infty} \frac{\partial u}{\partial t} \sin st \, dx = c^2 \sqrt{\frac{2}{\pi}} \int_0^{\infty} \frac{\partial^2 u}{\partial x^2} \sin sx \, dx$$

$$\Rightarrow \sqrt{\frac{2}{\pi}} \frac{d}{dt} \int_0^\infty u \sin s x \, dx = c^2 \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial^2 u}{\partial x^2} \sin s x \, dx$$

$$\begin{aligned} \Rightarrow \sqrt{\frac{2}{\pi}} \frac{d}{dt} \int_0^\infty u \sin s x \, dx &= \frac{d}{dt} F_s[u(x, t)] \\ &= c^2 \left\{ \sqrt{\frac{2}{\pi}} \left[\frac{\partial u}{\partial x} \sin s x \right]_0^\infty - \sqrt{\frac{2}{\pi}} s \int_0^\infty \frac{\partial u}{\partial x} \cos s x \, dx \right\} \end{aligned}$$

$$\begin{aligned} \Rightarrow \frac{d}{dt} \bar{u}_s &= 0 - c^2 s \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial u}{\partial x} \cos s x \, dx \text{ if } \frac{\partial u}{\partial x} \rightarrow 0 \text{ as } x \rightarrow \infty \\ &= -c^2 s \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial u}{\partial x} \cos s x \, dx \\ &= -c^2 s \sqrt{\frac{2}{\pi}} [u(x, t) \cos s x]_0^\infty - c^2 s^2 \sqrt{\frac{2}{\pi}} \int_0^\infty u \sin s x \, dx \end{aligned}$$

$$\frac{d}{dt} \bar{u}_s = c^2 \sqrt{\frac{2}{\pi}} s u(0, t) - c^2 s^2 \bar{u}_s; \text{ assuming } u \rightarrow 0 \text{ as } x \rightarrow \infty$$

$$\Rightarrow \frac{d\bar{u}_s}{dt} = c^2 \left[\sqrt{\frac{2}{\pi}} s u(0, t) - s^2 \bar{u}_s \right]$$

By using (3), $u(0, t) = 0$, we get

$$\Rightarrow \frac{d}{dt} \bar{u}_s + c^2 s^2 \bar{u}_s = 0 \quad \dots(4)$$

Also taking FST of (2), we get

$$F_s[u(x, 0)] = F_s[f(x)]$$

$$\Rightarrow \bar{u}_s(s, 0) = \bar{f}_s(s) \quad \dots(5)$$

from (4), we have $(D + C^2 s^2) \bar{u}_s = 0$

Auxiliary equation is $m + c^2 s^2 = 0$

$$\Rightarrow m = -c^2 s^2$$

Solution of (4) is

$$\bar{u}_s(s, t) = \bar{u}_s = A e^{-c^2 s^2 t} \quad \dots(*)$$

To find A, we use (5), from (*), we have $\bar{u}_s(s, 0) = A$

$$\Rightarrow A = \bar{f}_s(s) \quad [\text{using (5)}]$$

Hence solution is

$$\bar{u}_s(s, t) = \bar{f}_s(s) e^{-c^2 s^2 t}$$

Taking inverse FST, we get

$$F_s^{-1}[\bar{u}_s(s, t)] = F_s^{-1}[\bar{f}_s(s) e^{-c^2 s^2 t}]$$

$$\Rightarrow u(x, t) = \sqrt{\frac{2}{\pi}} \int_0^\infty \bar{u}_s \sin sx \, ds$$

$$\Rightarrow u(x, t) = \sqrt{\frac{2}{\pi}} \int_0^\infty \bar{f}_s(s) e^{-c^2 s^2 t} \sin sx \, ds$$

This is the required solution of PDE.

Example:- The temperature u in the semi-infinite rod $0 \leq x < \infty$ (or $x \geq 0$) is determined by equation

$$\frac{\partial u}{\partial t} = K \frac{\partial^2 u}{\partial x^2} \quad \dots(1)$$

subject to conditions

$$(i) \quad u = 0 \text{ when } t = 0, x \geq 0$$

$$\text{i.e. } u(x, 0) = 0$$

$$(ii) \quad \frac{\partial u}{\partial x} = -\mu \text{ (a constant) when } x = 0, t > 0$$

$$\text{i.e. } \frac{\partial u}{\partial x}(0, t) = -\mu$$

$$\text{or } u_x(0, t) = -\mu$$

Solution :- Since $\left(\frac{\partial u}{\partial x}\right)_{x=0}$ is given,

So taking Fourier cosine transform of both sides of (1),

$$\sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial u}{\partial t} \cos sx \, dx = K \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial^2 u}{\partial x^2} \cos sx \, dx$$

$$\Rightarrow \frac{d}{dt} \bar{u}_c(s, t) = K \sqrt{\frac{2}{\pi}} \left[\frac{\partial u}{\partial x} \cos sx \right]_0^\infty + K s \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial u}{\partial x} \sin sx \, dx$$

$$\Rightarrow \frac{d}{dt} \bar{u}_c = -K \sqrt{\frac{2}{\pi}} \left(\frac{\partial u}{\partial x} \right)_{x=0} + Ks \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial u}{\partial x} \sin sx \, dx$$

$$\left[\text{By assuming } \frac{\partial u}{\partial x} \rightarrow 0 \text{ as } x \rightarrow \infty \right]$$

$$\begin{aligned} \Rightarrow \frac{d}{dt} \bar{u}_c &= K \sqrt{\frac{2}{\pi}} \mu + Ks \sqrt{\frac{2}{\pi}} [u \sin sx]_0^\infty - Ks \sqrt{\frac{2}{\pi}} \int_0^\infty u s \cos sx \, dx \\ &= K \sqrt{\frac{2}{\pi}} \mu - Ks^2 \bar{u}_c \text{ if } u \rightarrow 0 \text{ as } x \rightarrow \infty \end{aligned}$$

$$\Rightarrow \frac{d}{dt} \bar{u}_c + Ks^2 \bar{u}_c = K \mu \sqrt{\frac{2}{\pi}} \quad \dots(2)$$

$$\bar{u}_c = \sqrt{\frac{2}{\pi}} \frac{\mu}{s^2} (1 - e^{-Ks^2 t})$$

$$u(x, t) = \frac{2\mu}{\pi} \int_0^\infty \frac{\cos sx}{s^2} (1 - e^{-Ks^2 t}) \, ds$$

This is linear DE of 1st order.

$$\text{I.F. } e^{\int Ks^2 dt} = e^{s^2 kt}$$

$$\text{Solution of (2) is } \bar{u}_c \cdot e^{s^2 kt} = \int K \mu \sqrt{\frac{2}{\pi}} e^{s^2 kt} \, dt + A$$

$$\Rightarrow \bar{u}_c e^{s^2 kt} = A + K \mu \sqrt{\frac{2}{\pi}} \frac{e^{s^2 kt}}{s^2 k} = A + \frac{\mu}{s^2} \sqrt{\frac{2}{\pi}} e^{s^2 kt}$$

$$\Rightarrow \bar{u}_c = A e^{-s^2 kt} + \sqrt{\frac{2}{\pi}} \frac{\mu}{s^2} \quad \dots(3)$$

$$\text{Put } t = 0 \Rightarrow \bar{u}_c(s, 0) = A + \sqrt{\frac{2}{\pi}} \frac{\mu}{s^2} \quad \dots(4)$$

from condition (i),

$$\bar{u}_c(s, 0) = \int_0^\infty u(x, 0) \cos sx \, dx = 0 \quad \dots(5)$$

$$(4), (5) \Rightarrow A = -\sqrt{\frac{2}{\pi}} \frac{\mu}{s^2}$$

$$\therefore (3) \Rightarrow \bar{u}_c = \sqrt{\frac{2}{\pi}} \frac{\mu}{s^2} (1 - e^{-k^2 s t})$$

Finite Fourier Transform :-

Finite Fourier Since Transform :- Let $f(x)$ denote a function that is sectionally continuous over some finite interval $(0, \lambda)$ of the variable x . The finite fourier sine transform of $f(x)$ on the interval is defined as

$$f_s(s) = \int_0^\lambda f(x) \sin \frac{s\pi x}{\lambda} dx \text{ where } s \text{ is an integer}$$

Inversion formula for sine transform

$$f(x) = \frac{2}{\lambda} \sum_{s=1}^{\infty} f_s(s) \sin \frac{s\pi x}{\lambda} \text{ for the interval } (0, \lambda).$$

If $(0, \pi)$ is the interval for $f_s(s)$,

$$f(x) = \frac{2}{\pi} \sum_{s=1}^{\infty} f_s(s) \sin sx$$

Finite FCT :- Let $f(x)$ denote a function that is sectionally continuous over some finite interval $(0, \lambda)$ of the variable x . The finite Fourier cosine transform of $f(x)$ on the interval is defined as

$$f_c(s) = \int_0^\lambda f(x) \cos \frac{s\pi x}{\lambda} dx \text{ where } s \text{ is an integer,}$$

If $(0, \pi)$ is the interval,

$$f_c(s) = \int_0^\pi f(x) \cos sx \, dx$$

Inversion formula for FCT

$$f(x) = \frac{1}{\lambda} f_c(0) + \frac{2}{\lambda} \sum_{s=1}^{\infty} f_c(s) \cos \frac{s\pi x}{\lambda}$$

$$\text{where } f_c(0) = \int_0^\lambda f(x) \, dx$$

If $f(x) = 1$, $(0, \pi)$, then

$$f_s(s) = \int_0^\pi \sin sx \, dx = \left(\frac{-\cos sx}{s} \right)_0^\pi$$

$$= \frac{1}{s} [-\cos s\pi + \cos 0] = \frac{1}{s} [1 - (-1)^2]$$

$$\text{and } f_c(s) = \int_0^\pi \cos sx \, dx = \left(\frac{\sin sx}{s} \right)_0^\pi = 0 \text{ if } s = 1, 2, 3, \dots$$

If $s = 0$, then

$$f_c(s) = \int_0^\pi 1 \cdot dx = \pi$$

Find Finite FST and finite FCT of $\frac{\partial u}{\partial x}$, $\frac{\partial^2 u}{\partial x^2}$, $u(x, t)$ for $0 < x < \lambda$, $t > 0$.

Solution :- By definition, finite FST of $\frac{\partial u}{\partial x}$ is

$$\begin{aligned} f_s(s) &= \int_0^\lambda \frac{\partial u}{\partial x} \sin \frac{s\pi x}{\lambda} \, dx \\ &= \sin \frac{s\pi x}{\lambda} u(x, t) \Big|_0^\lambda - \frac{s\pi}{\lambda} \int_0^\lambda u(x, t) \cos \frac{s\pi x}{\lambda} \, dx \end{aligned}$$

$$\Rightarrow f_s(s) = F_s \left[\frac{\partial u}{\partial x} \right] = -\frac{s\pi}{\lambda} \int_0^\lambda u(x, t) \cos \frac{s\pi x}{\lambda} \, dx$$

$$\Rightarrow f_s(s) = F_s \left[\frac{\partial u}{\partial x} \right] = -\frac{s\pi}{\lambda} F_c[u(x, t)] \quad \dots(1)$$

$$\begin{aligned} F_c \left[\frac{\partial u}{\partial x} \right] &= \int_0^\lambda \frac{\partial u}{\partial x} \cos \frac{s\pi x}{\lambda} \, dx = \cos \frac{s\pi x}{\lambda} u(x, t) \Big|_0^\lambda + \int_0^\lambda \frac{s\pi}{\lambda} u(x, t) \sin \frac{s\pi x}{\lambda} \, dx \\ &= \frac{s\pi}{\lambda} F_s[u(x, t)] - [u(0, t) - u(\lambda, t) \cos s\pi] \quad \dots(2) \end{aligned}$$

To calculate the finite FST & finite FCT of $\frac{\partial^2 u}{\partial x^2}$,

Replace u by $\frac{\partial u}{\partial x}$ in (1) and (2), we get

$$F_s \left[\frac{\partial^2 u}{\partial x^2} \right] = -\frac{s\pi}{\lambda} F_c \left[\frac{\partial u}{\partial x} \right]$$

$$\begin{aligned}
&= \frac{-s\pi}{\lambda} \left[\frac{s\pi}{\lambda} F_s(u) \right] + \frac{s\pi}{\lambda} \{u(0, t) - u(\lambda, t) \cos s\pi\} \\
&= \frac{-s^2\pi^2}{\lambda^2} F_s[u] + \frac{s\pi}{\lambda} [u(0, t) - u(\lambda, t) \cos s\pi] \quad \dots(3)
\end{aligned}$$

$$\begin{aligned}
\text{Similarly } F_c \left[\frac{\partial^2 u}{\partial x^2} \right] &= \frac{s\pi}{\lambda} F_s \left[\frac{\partial u}{\partial x} \right] - [u_x(0, t) - u_x(\lambda, t) \cos s\pi] \\
&= \frac{s\pi}{\lambda} \left(\frac{-s\pi}{\lambda} \right) F_c[u(x, t)] - \{u_x(0, t) - u_x(\lambda, t) \cos s\pi\} \\
&= \frac{-s^2\pi^2}{\lambda^2} F_c[u] - \{u_x(0, t) - u_x(\lambda, t) \cos s\pi\} \quad \dots(4)
\end{aligned}$$

Example:- Use finite Fourier transform to solve

$$\frac{\partial u}{\partial t} = \frac{\partial^2 u}{\partial x^2} \quad \dots(1)$$

$$u(0, t) = 0, u(4, t) = 0$$

$$u(x, 0) = 2x \text{ when } 0 < x < 4, t > 0.$$

Solution :- $(u)_{x=0}$ is given, we apply FST.

Here $\lambda = 4$.

Taking Finite FST of (1), we get

$$\int_0^4 \frac{\partial u}{\partial t} \sin\left(\frac{s\pi x}{4}\right) dx = \int_0^4 \frac{\partial^2 u}{\partial x^2} \sin\left(\frac{s\pi x}{4}\right) dx$$

Writing $\bar{u}_s = F_s[u(x, t)]$, we get

$$\frac{d}{dt} \bar{u}_s = \frac{-s^2\pi^2}{16} \bar{u}_s + \frac{s\pi}{4} (0, -0)$$

[Using equation (3) in previous article and given condition]

$$\Rightarrow \frac{d}{dt} \bar{u}_s + \frac{s^2\pi^2}{16} \bar{u}_s = 0$$

$$\Rightarrow \bar{u}_s(s, t) = E e^{\frac{-s^2\pi^2 t}{16}} \quad \dots(*)$$

To find A, we will take finite FST of $u(x, 0) = 2x$, we get

$$\begin{aligned}
\bar{u}_s(s,0) &= \int_0^4 2x \sin\left(\frac{s\pi x}{4}\right) dx \\
&= 2 \left[x \left(-\cos \frac{s\pi x}{4} \right) \cdot \frac{4}{s\pi} \right]_0^4 + 2 \cdot \frac{4}{s\pi} \int_0^4 \cos \frac{s\pi x}{4} dx \\
&= 2(-1)^{s+1} \frac{16}{s\pi} + \frac{8}{s\pi} \left[\sin\left(\frac{s\pi x}{4}\right) \cdot \frac{4}{s\pi} \right]_0^4 \\
&= 2(-1)^{s+1} \cdot \frac{16}{s\pi} + \frac{8}{s\pi} (0) \\
&= (-1)^{s+1} \frac{32}{s\pi} = -\frac{32}{s\pi} \cos s\pi
\end{aligned}$$

from (*), $\bar{u}_s(s, 0) = A$

$$\therefore A = -\frac{32}{s\pi} \cos s\pi$$

$$\text{Hence } \bar{u}_s(s, t) = -\frac{32}{s\pi} \cos s\pi e^{\frac{-s^2\pi^2}{16}t}$$

Taking Inverse Finite Fourier sine transform, we get

$$\begin{aligned}
u(x, t) &= \frac{2}{4} \sum_{s=1}^{\infty} \left(-\frac{32}{s\pi} \cos s\pi \right) e^{\frac{-s^2\pi^2}{16}t} \sin\left(\frac{s\pi x}{4}\right) \\
\therefore u(x, t) &= \frac{-16}{\pi} \sum_{s=1}^{\infty} \frac{\cos s\pi}{s} \sin\left(\frac{s\pi x}{4}\right) e^{\frac{-s^2\pi^2}{16}t}
\end{aligned}$$

Example :- Solve the equation

$$\frac{\partial u}{\partial t} = 2 \frac{\partial^2 u}{\partial x^2} \quad \dots(1)$$

subject to conditions

- (i) $u(0, t) = 0$
- (ii) $u(x, 0) = e^{-x}$
- (iii) $u(x, t)$ is bounded when $x > 0, t > 0$

Solution :- Since $(u)_{x=0}$ is given, so taking FST, we get

$$\begin{aligned}
& \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial u}{\partial t} \sin sx \, dx = \sqrt{\frac{2}{\pi}} \int_0^\infty 2 \frac{\partial^2 u}{\partial x^2} \sin sx \, dx \\
\Rightarrow & \sqrt{\frac{2}{\pi}} \frac{d}{dt} \int_0^\infty u \sin sx \, dx = \sqrt{\frac{2}{\pi}} \int_0^\infty 2 \frac{\partial^2 u}{\partial x^2} \sin sx \, dx \\
\Rightarrow & \frac{d}{dt} \sqrt{\frac{2}{\pi}} \int_0^\infty u \sin sx \, dx = 2 \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial^2 u}{\partial x^2} \sin sx \, dx \\
\Rightarrow & \frac{d}{dt} \bar{u}_s = 2 \sqrt{\frac{2}{\pi}} \left[\left(\sin sx \frac{\partial u}{\partial x} \right)_0^\infty - s \int_0^\infty \cos sx \frac{\partial u}{\partial x} dx \right] \\
& = 2 \sqrt{\frac{2}{\pi}} (0) - 2 \sqrt{\frac{2}{\pi}} s \int_0^\infty \cos sx \frac{\partial u}{\partial x} dx \\
& \left[\text{assuming } \frac{\partial u}{\partial x} \rightarrow 0 \text{ as } x \rightarrow \infty \right] \\
\Rightarrow & \frac{d}{dt} \bar{u}_s = 2 \sqrt{\frac{2}{\pi}} \left[-s(u(x, t) \cos sx)_0^\infty - s^2 \int_0^\infty \sin sx u(x, t) dx \right] \\
& = 2 \sqrt{\frac{2}{\pi}} \left[-s^2 \int_0^\infty u(x, t) \sin sx dx \right] \quad [\text{assuming } u(x, t) \rightarrow 0 \text{ as } x \rightarrow \infty] \\
& = -2s^2 \sqrt{\frac{2}{\pi}} \int_0^\infty u(x, t) \sin sx \, dx \\
\Rightarrow & \frac{d}{dt} \bar{u}_s = -2s^2 \bar{u}_s \\
\Rightarrow & \frac{d}{dt} \bar{u}_s + 2s^2 \bar{u}_s = 0 \quad \dots(2)
\end{aligned}$$

A.E. is $D + 2s^2 = 0$

Solution is $\bar{u}_s(s, t) = A e^{-2s^2 t}$...(3)

To find A, taking FST of condition

(ii) $u(x, 0) = e^{-x}$

Taking FST, we get

$$\begin{aligned}\bar{u}_s(s,0) &= \sqrt{\frac{2}{\pi}} \int_0^{\infty} e^{-sx} \sin sx \, dx \\ &= \sqrt{\frac{2}{\pi}} \frac{s}{1+s^2} \text{ at } t=0\end{aligned}\quad \dots(4)$$

$$\left[\Theta \text{ using } \int e^{ax} \sin bx \, dx = \frac{e^{ax}}{a^2 + b^2} (a \sin bx - b \cos bx) \text{ taking } a = -1, b = s \right]$$

and then taking lim, we get $\sqrt{\frac{2}{\pi}} \frac{s}{1+s^2}$

Putting $t = 0$ in (3), we get

$$\bar{u}_s(s,0) = A \quad \dots(5)$$

from (4) and (5), we get

$$A = \sqrt{\frac{2}{\pi}} \left(\frac{s}{1+s^2} \right)$$

Putting value of A in (3), we get

$$\bar{u}_s(s,t) = \sqrt{\frac{2}{\pi}} \left(\frac{s}{1+s^2} \right) e^{-2s^2t}$$

Taking inverse FST, we get

$$\begin{aligned}u(x,t) &= \sqrt{\frac{2}{\pi}} \int_0^{\infty} \sqrt{\frac{2}{\pi}} \left(\frac{s}{1+s^2} \right) e^{-2s^2t} \sin sx \, ds \\ &= \frac{2}{\pi} \int_0^{\infty} \frac{s}{1+s^2} e^{-2s^2t} \sin sx \, ds \text{ which is required solution.}\end{aligned}$$

Example: Solve the equation

$$\frac{\partial u}{\partial t} = \frac{\partial^2 u}{\partial x^2} \quad \dots(1)$$

subject to conditions

$$(i) \quad u_x(0,t) = 0$$

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

(iii) $u(x, t)$ is bounded

Solution :- Since $(u_x)_{x=0}$ is given, so taking FCT of (1), we get

$$\begin{aligned} \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial u}{\partial t} \cos sx \, dx &= \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial^2 u}{\partial x^2} \cos sx \, dx \\ \Rightarrow \sqrt{\frac{2}{\pi}} \frac{d}{dt} \int_0^\infty u \cos sx \, dx &= \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial^2 u}{\partial x^2} \cos sx \, dx \\ \Rightarrow \frac{d}{dt} \bar{u}_c &= \sqrt{\frac{2}{\pi}} \left[\left(\frac{\partial u}{\partial x} \cos sx \right)_0^\infty + s \int_0^\infty \sin sx \frac{\partial u}{\partial x} \, dx \right] \end{aligned}$$

$[\Theta \, u \rightarrow 0 \text{ as } x \rightarrow \infty \Rightarrow u_x = 0 \text{ as } x \rightarrow \infty \text{ and also } u_x(0, t) = 0]$

$$\frac{d}{dt} \bar{u}_c \sqrt{\frac{2}{\pi}} [(0 - 0) + s [\sin sx u(x, t)]_0^\infty - s^2 \int_0^\infty u(x, t) \cos sx \, dx]$$

$$\begin{aligned} \Rightarrow \frac{d}{dt} \bar{u}_c &= \sqrt{\frac{2}{\pi}} (-s^2) \int_0^\infty \cos sx \, u(x, t) \, dx \\ &= (-s^2) \sqrt{\frac{2}{\pi}} \int_0^\infty u(x, t) \cos sx \, dx \end{aligned}$$

$$\Rightarrow \frac{d}{dt} \bar{u}_c = -s^2 \bar{u}_c$$

$$\Rightarrow \frac{d}{dt} \bar{u}_c + s^2 \bar{u}_c = 0 \quad \dots(2)$$

A.E. is $D + s^2 = 0$

$$\therefore \text{ solution is } \bar{u}_c(s, t) = A e^{-s^2 t} \quad \dots(3)$$

Now to find A, taking FCT of condition (ii)

$$\begin{aligned} \bar{u}_c(s, 0) &= \sqrt{\frac{2}{\pi}} \int_0^\infty u(x, 0) \cos sx \, dx \\ &= \sqrt{\frac{2}{\pi}} \int_0^1 x \cos sx \, dx \quad [\Theta \, u(x, 0) = 0, x > 1] \\ &= \sqrt{\frac{2}{\pi}} \left[\left[x \frac{\sin sx}{s} \right]_0^1 - \int_0^1 \frac{\sin sx}{s} \, dx \right] \end{aligned}$$

$$\begin{aligned}
&= \sqrt{\frac{2}{\pi}} \left\{ \frac{\sin s}{s} + \left[\frac{\cos sx}{s^2} \right]_0^1 \right\} \\
&= \sqrt{\frac{2}{\pi}} \left[\frac{\sin s}{s} + \frac{\cos s - 1}{s^2} \right] \text{ at } t = 0 \quad \dots(4)
\end{aligned}$$

Putting $t = 0$ in (3), we get

$$\bar{u}_c(s, 0) = A \Rightarrow A = \sqrt{\frac{2}{\pi}} \left[\frac{\sin s}{s} + \frac{\cos s - 1}{s^2} \right]$$

from (3) and (4), we get

$$\bar{u}_c(s, t) = \sqrt{\frac{2}{\pi}} \left[\frac{\sin s}{s} + \frac{\cos s - 1}{s^2} \right] e^{-s^2 t}$$

Taking inverse FCT, we get

$$\begin{aligned}
u(x, t) &= \sqrt{\frac{2}{\pi}} \int_0^\infty \bar{u}_c(s, t) \cos sx \, ds \\
\Rightarrow u(x, t) &= \frac{2}{\pi} \int_0^\infty \left(\frac{\sin s}{s} + \frac{\cos s - 1}{s^2} \right) e^{-s^2 t} \cos sx \, ds
\end{aligned}$$

which is required solution.

Example:- Solve the equation

$$\frac{\partial u}{\partial t} = \frac{\partial^2 u}{\partial x^2}, \quad x > 0, y > 0 \quad \dots(1)$$

Subject to condition

- (i) $u(0, t) = 0$
- (ii) $u(x, 0) = \begin{cases} 1, & 0 < x < 1 \\ 0, & x \geq 1 \end{cases} \text{ when } t = 0$
- (iii) $u(x, t)$ is bounded.

Solution :- Since $(u)_{x=0}$ is given, so taking FST of (1), we get

$$\begin{aligned}
\sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial u}{\partial t} \sin sx \, dx &= \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial^2 u}{\partial x^2} \sin sx \, dx \\
\Rightarrow \sqrt{\frac{2}{\pi}} \frac{d}{dt} \int_0^\infty u \sin sx \, dx &= \sqrt{\frac{2}{\pi}} \int_0^\infty \frac{\partial^2 u}{\partial x^2} \sin sx \, dx
\end{aligned}$$

$$\begin{aligned}
\Rightarrow \quad \frac{d}{dt} \sqrt{\frac{2}{\pi}} \int_0^\infty u \sin sx \, dx &= \sqrt{\frac{2}{\pi}} \left[\sin sx \frac{\partial u}{\partial x} \right]_0^\infty - \sqrt{\frac{2}{\pi}} \int_0^\infty s \cos sx \frac{\partial u}{\partial x} \, dx \\
\Rightarrow \quad \frac{d}{dt} \bar{u}_s &= (0) - \sqrt{\frac{2}{\pi}} s \int_0^\infty \frac{\partial u}{\partial x} \cos sx \, dx \quad \left[\text{assuming } \frac{\partial u}{\partial x} \rightarrow 0 \text{ as } x \rightarrow \infty \right] \\
&= -s \sqrt{\frac{2}{\pi}} [\cos sx \cdot u(x, t)]_0^\infty + s \sqrt{\frac{2}{\pi}} \int_0^\infty (-s \sin sx) u(x, t) \, dx \\
\Rightarrow \quad \frac{d}{dt} \bar{u}_s &= s \sqrt{\frac{2}{\pi}} u(0, t) - s^2 \sqrt{\frac{2}{\pi}} \int_0^\infty u \sin sx \, dx \\
&= 0 - s^2 \bar{u}_s \quad [\Theta u(0, t) = 0 \text{ given}] \\
\Rightarrow \quad \frac{d}{dt} \bar{u}_s + s^2 \bar{u}_s &= 0 \quad \dots(2)
\end{aligned}$$

A.E. is $D + s^2 = 0$

$$\therefore \text{Solution is } \bar{u}_s(s, t) = A e^{-s^2 t} \quad \dots(3)$$

To find A, we take FST of condition (ii),

$$\begin{aligned}
\bar{u}_s(s, 0) &= \sqrt{\frac{2}{\pi}} \int_0^\infty u(x, 0) \sin sx \, dx \\
&= \sqrt{\frac{2}{\pi}} \int_0^1 (1) \sin sx \, dx \quad [\Theta u(x, 0) = 0 \text{ for } x \geq 1] \\
&= \sqrt{\frac{2}{\pi}} \left[\frac{-\cos sx}{s} \right]_0^1 \\
\Rightarrow \quad \bar{u}_s(s, 0) &= \sqrt{\frac{2}{\pi}} \left[-\frac{\cos s}{s} + \frac{1}{s} \right] = \sqrt{\frac{2}{\pi}} \left(\frac{1 - \cos s}{s} \right) \quad \dots(4)
\end{aligned}$$

$$\text{From (3), we have } \bar{u}_s(s, 0) = A \quad \dots(5)$$

$$A = \sqrt{\frac{2}{\pi}} \left(\frac{1 - \cos s}{s} \right)$$

$$\therefore (3) \Rightarrow \bar{u}_s(s, t) = \sqrt{\frac{2}{\pi}} \left(\frac{1 - \cos s}{s} \right) e^{-s^2 t}$$

Taking inverse FST, we get

$$u(x, t) = \sqrt{\frac{2}{\pi}} \int_0^{\infty} \sqrt{\frac{2}{\pi}} \left(\frac{1 - \cos s}{s} \right) e^{-s^2 t} \sin sx \, ds$$

$$\Rightarrow \quad u(x, t) = \frac{2}{\pi} \int_0^{\infty} \left(\frac{1 - \cos s}{s} \right) \sin sx \, e^{-s^2 t} ds$$

which is required solution.

LESSON 3

CURVILINEAR CO-ORDINATES

Transformation of coordinates

Let the rectangular coordinates (x, y, z) of any point be expressed as functions of (u_1, u_2, u_3) so that

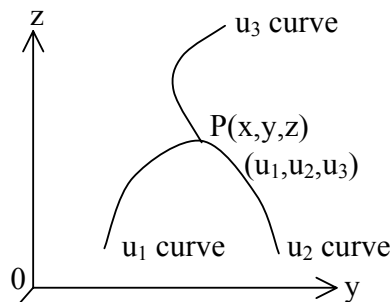
$$\left. \begin{aligned} x &= x(u_1, u_2, u_3) \\ y &= y(u_1, u_2, u_3) \\ z &= z(u_1, u_2, u_3) \end{aligned} \right\} \dots(1)$$

Suppose (1) can be solved for u_1, u_2, u_3 in terms of x, y, z i.e.

$$\left. \begin{aligned} u_1 &= u_1(x, y, z) \\ u_2 &= u_2(x, y, z) \\ u_3 &= u_3(x, y, z) \end{aligned} \right\} \dots(2)$$

Here correspondence between (x, y, z) and (u_1, u_2, u_3) is **unique** i.e. if to each point $P(x, y, z)$ of some region R , there corresponds one & only one triad (u_1, u_2, u_3) , then u_1, u_2, u_3 are said to be **curvilinear coordinates** of the point P .

The set of equations (1) & (2) define a transformation of co-ordinates.



Co-ordinate surfaces and curves:-

The surfaces

$$u_1 = c_1, \quad u_2 = c_2, \quad u_3 = c_3$$

where c_1, c_2, c_3 are constants i.e. surfaces whose equations are

$$u_1 = u_1(x, y, z) = c_1$$

$$u_2 = u_2(x, y, z) = c_2$$

$$u_3 = u_3(x, y, z) = c_3$$

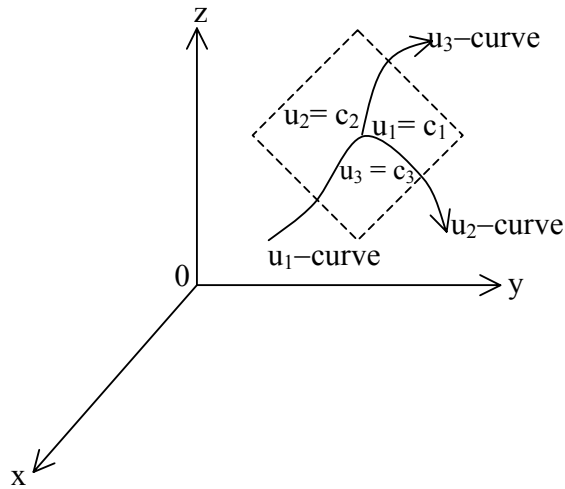
are called **co-ordinate surfaces** and each pair of these surfaces intersect in curves called **co-ordinate curves** or lines.

So $u_1 = c_1$ and $u_2 = c_2$ gives u_3 -curve

Similarly $u_2 = c_2$ and $u_3 = c_3$ gives u_1 - curve

and $u_1 = c_1$ and $u_3 = c_3$ gives u_2 - curve

So if $u_2 = c_2$ and $u_3 = c_3$ and if u_1 is the only variables then point P describe a curve known as u_1 curve which is a function of u_1 .



Orthogonal Curvilinear Co-ordinates

If the three co-ordinate surfaces intersect at right angles (orthogonal), the curvilinear co-ordinate system is called orthogonal i.e. co-ordinates (u_1, u_2, u_3) are said to be orthogonal curvilinear co-ordinates.

Then u_1, u_2, u_3 co-ordinate curves of a curvilinear system are analogous to the x, y, z - coordinates axes of rectangular system.

Unit vectors in curvilinear system

$$\text{Let } \vec{r} = x \hat{i} + y \hat{j} + z \hat{k}$$

be position vector of P, then (1) can be written as

$$\vec{r} = \vec{r}(u_1, u_2, u_3)$$

A tangent vector to the u_1 -curve at P (for which u_2 & u_3 are constant) is $\frac{\partial \vec{r}}{\partial u_1}$

Then, A unit tangent vector in this direction is

$$\hat{e}_1 = \frac{\partial \mathbf{r} / \partial u_1}{\left| \frac{\partial \mathbf{r}}{\partial u_1} \right|}$$

or $\frac{\partial \mathbf{r}}{\partial u_1} = \hat{e}_1 \left| \frac{\partial \mathbf{r}}{\partial u_1} \right|$

$$\Rightarrow \frac{\partial \mathbf{r}}{\partial u_1} = h_1 \hat{e}_1 \text{ where } h_1 = \left| \frac{\partial \mathbf{r}}{\partial u_1} \right|$$

Similarly if $\hat{e}_2$ and $\hat{e}_3$ are unit tangent vectors to the u_2 – & u_3 – curves at P respectively, then

$$\frac{\partial \mathbf{r}}{\partial u_2} = h_2 \hat{e}_2, \quad \frac{\partial \mathbf{r}}{\partial u_3} = h_3 \hat{e}_3$$

where $h_2 = \left| \frac{\partial \mathbf{r}}{\partial u_2} \right|, h_3 = \left| \frac{\partial \mathbf{r}}{\partial u_3} \right|$

The quantities h_1, h_2, h_3 are called **scale factors**.

Also, condition for the orthogonality of co-ordinate surfaces are

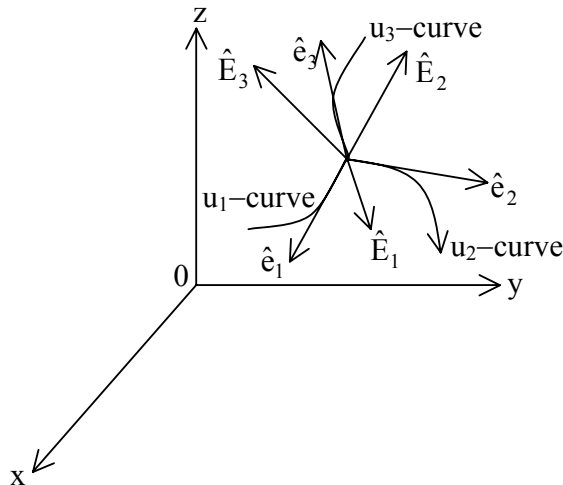
$$\frac{\partial \mathbf{r}}{\partial u_1} \cdot \frac{\partial \mathbf{r}}{\partial u_2} = 0, \quad \frac{\partial \mathbf{r}}{\partial u_2} \cdot \frac{\partial \mathbf{r}}{\partial u_3} = 0, \quad \frac{\partial \mathbf{r}}{\partial u_3} \cdot \frac{\partial \mathbf{r}}{\partial u_1} = 0$$

Also the vectors $\nabla u_1, \nabla u_2, \nabla u_3$ at P are directed along the normal to the co-ordinate surfaces

$u_1 = c_1, u_2 = c_2, u_3 = c_3$ respectively.

So unit-vectors in these directions are given by

$$\hat{E}_1 = \frac{\nabla u_1}{|\nabla u_1|}, \quad \hat{E}_2 = \frac{\nabla u_2}{|\nabla u_2|}, \quad \hat{E}_3 = \frac{\nabla u_3}{|\nabla u_3|}$$



Thus, at each point P of a curvilinear system, there are, in general, two sets of unit vectors $\hat{e}_1, \hat{e}_2, \hat{e}_3$ tangent to the coordinate curves and $\hat{E}_1, \hat{E}_2, \hat{E}_3$ normal to the co-ordinate surfaces.

The sets become identical if & only if the curvilinear coordinate system is orthogonal.

Arc length and Volume element

From $\mathbf{r} = \mathbf{r}(u_1, u_2, u_3)$

$$\begin{aligned} \Rightarrow \quad d\mathbf{r} &= \frac{\partial \mathbf{r}}{\partial u_1} du_1 + \frac{\partial \mathbf{r}}{\partial u_2} du_2 + \frac{\partial \mathbf{r}}{\partial u_3} du_3 \\ &= h_1 du_1 \hat{e}_1 + h_2 du_2 \hat{e}_2 + h_3 du_3 \hat{e}_3 \end{aligned} \quad \dots(1)$$

Then, the differential of arc length ds is determined from

$$(ds)^2 = d\mathbf{r} \cdot d\mathbf{r}$$

For orthogonal system,

$$\hat{e}_1 \cdot \hat{e}_2 = \hat{e}_2 \cdot \hat{e}_3 = \hat{e}_3 \cdot \hat{e}_1 = 0$$

$$\text{or} \quad \frac{\partial \mathbf{r}}{\partial u_1} \cdot \frac{\partial \mathbf{r}}{\partial u_2} = \frac{\partial \mathbf{r}}{\partial u_2} \cdot \frac{\partial \mathbf{r}}{\partial u_3} = \frac{\partial \mathbf{r}}{\partial u_3} \cdot \frac{\partial \mathbf{r}}{\partial u_1} = 0 \quad \dots(2)$$

using (*)

$$\begin{aligned} \text{and } (ds)^2 &= \left(\frac{\partial \mathbf{r}}{\partial u_1} \cdot \frac{\partial \mathbf{r}}{\partial u_1} \right) (du_1)^2 \\ &\quad + \left(\frac{\partial \mathbf{r}}{\partial u_2} \cdot \frac{\partial \mathbf{r}}{\partial u_2} \right) (du_2)^2 \\ &\quad + \left(\frac{\partial \mathbf{r}}{\partial u_3} \cdot \frac{\partial \mathbf{r}}{\partial u_3} \right) (du_3)^2 + 2 \frac{\partial \mathbf{r}}{\partial u_1} \cdot \frac{\partial \mathbf{r}}{\partial u_2} du_1 du_2 \\ &\quad + 2 \frac{\partial \mathbf{r}}{\partial u_2} \cdot \frac{\partial \mathbf{r}}{\partial u_3} du_2 du_3 + 2 \frac{\partial \mathbf{r}}{\partial u_3} \cdot \frac{\partial \mathbf{r}}{\partial u_1} du_1 du_3 \\ \Rightarrow \quad (ds)^2 &= \left(\frac{\partial \mathbf{r}}{\partial u_1} \cdot \frac{\partial \mathbf{r}}{\partial u_1} \right) (du_1)^2 + \left(\frac{\partial \mathbf{r}}{\partial u_2} \cdot \frac{\partial \mathbf{r}}{\partial u_2} \right) (du_2)^2 + \left(\frac{\partial \mathbf{r}}{\partial u_3} \cdot \frac{\partial \mathbf{r}}{\partial u_3} \right) (du_3)^2 \\ &= \left(\frac{\partial \mathbf{r}}{\partial u_1} \right)^2 (du_1)^2 + \left(\frac{\partial \mathbf{r}}{\partial u_2} \right)^2 (du_2)^2 + \left(\frac{\partial \mathbf{r}}{\partial u_3} \right)^2 (du_3)^2 \quad [\text{using (2)}] \end{aligned}$$

$$\Rightarrow (ds)^2 = h_1^2 (du_1)^2 + h_2^2 (du_2)^2 + h_3^2 (du_3)^2$$

$$\text{where } h_1 = \left| \frac{\partial \mathbf{r}}{\partial u_1} \right| = \frac{1}{|\nabla u_1|}$$

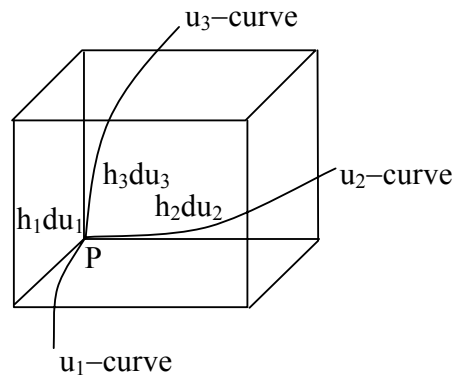
$$h_2 = \left| \frac{\partial \mathbf{r}}{\partial u_2} \right| = \frac{1}{|\nabla u_2|}$$

$$h_3 = \left| \frac{\partial \mathbf{r}}{\partial u_3} \right| = \frac{1}{|\nabla u_3|}$$

Now if $\mathbf{r} = \mathbf{r}(x, y, z)$

$$\text{Then } \frac{\partial \mathbf{r}}{\partial u_1} = \frac{\partial u_1}{\partial x} \hat{i} + \frac{\partial u_1}{\partial y} \hat{j} + \frac{\partial u_1}{\partial z} \hat{k} = \nabla u_1$$

$$\Rightarrow \frac{\partial \mathbf{r}}{\partial u_1} = \frac{1}{\nabla u_1}$$



Length along u_1 -curve

For this u_2 & u_3 are constant.

$$u_2 = c, u_3 = c$$

$$\Rightarrow du_2 = 0, du_3 = 0$$

If $ds_1 \rightarrow$ differential of length along u_1 -curve $(ds_1)^2 = h_1^2 (du_1)^2$

$$\Rightarrow ds_1 = h_1 du_1$$

Similarly length along u_2 -curve is

$$ds_2 = h_2 du_2$$

and length along u_3 -curve is

$$ds_3 = h_3 du_3$$

The volume element

For an orthogonal curvilinear coordinate system is given by

$$dV = |(h_1 du_1 \hat{e}_1) \cdot (h_2 du_2 \hat{e}_2) \cdot (h_3 du_3 \hat{e}_3)| \quad [\Theta \text{ volume} = |\hat{a} \cdot (\hat{b} \times \hat{c})|]$$

$$\Rightarrow dv = h_1 h_2 h_3 du_1 du_2 du_3$$

Differential operators in terms of orthogonal curvilinear coordinates (u_1, u_2, u_3)

GRADIENT

Let $\phi \rightarrow$ scalar point function

and $\vec{f} = f_1 \hat{a} + f_2 \hat{b} + f_3 \hat{c}$

$$= f_1 \hat{e}_1 + f_2 \hat{e}_2 + f_3 \hat{e}_3$$

i.e. $\phi = \phi(u_1, u_2, u_3)$

$$= \phi[u_1(x, y, z), u_2(x, y, z), u_3(x, y, z)]$$

$$\Rightarrow \frac{\partial \phi}{\partial x} = \frac{\partial \phi}{\partial u_1} \frac{\partial u_1}{\partial x} + \frac{\partial \phi}{\partial u_2} \frac{\partial u_2}{\partial x} + \frac{\partial \phi}{\partial u_3} \frac{\partial u_3}{\partial x} \quad \dots(1)$$

$$\frac{\partial \phi}{\partial y} = \frac{\partial \phi}{\partial u_1} \frac{\partial u_1}{\partial y} + \frac{\partial \phi}{\partial u_2} \frac{\partial u_2}{\partial y} + \frac{\partial \phi}{\partial u_3} \frac{\partial u_3}{\partial y} \quad \dots(2)$$

$$\frac{\partial \phi}{\partial z} = \frac{\partial \phi}{\partial u_1} \frac{\partial u_1}{\partial z} + \frac{\partial \phi}{\partial u_2} \frac{\partial u_2}{\partial z} + \frac{\partial \phi}{\partial u_3} \frac{\partial u_3}{\partial z} \quad \dots(3)$$

Operating $\hat{i} \times (1) + \hat{j} \times (2) + \hat{k} \times (3)$, we get

$$\nabla \phi = \text{grad } \phi = \frac{\partial \phi}{\partial u_1} \nabla u_1 + \frac{\partial \phi}{\partial u_2} \nabla u_2 + \frac{\partial \phi}{\partial u_3} \nabla u_3$$

But $\hat{e}_1 = h_1 \nabla u_1, \hat{e}_2 = h_2 \nabla u_2, \hat{e}_3 = h_3 \nabla u_3$

$$\Rightarrow \text{grad } \phi = \nabla \phi = \frac{\hat{e}_1}{h_1} \frac{\partial \phi}{\partial u_1} + \frac{\hat{e}_2}{h_2} \frac{\partial \phi}{\partial u_2} + \frac{\hat{e}_3}{h_3} \frac{\partial \phi}{\partial u_3}$$

Example:- If (u_1, u_2, u_3) are orthogonal coordinate then prove that

(i) $|\nabla u_p| = h_p^{-1}, p = 1, 2, 3$

(ii) $\hat{e}_p = \hat{E}_p$

Proof :- (i) let $\phi = u_1$, then

$$\nabla u_1 = \frac{1}{h_1} \frac{\partial u_1}{\partial u_1} \hat{e}_1 = \frac{\hat{e}_1}{h_1}$$

$$|\nabla u_1| = \frac{|\hat{e}_1|}{|h_1|} = \frac{1}{h_1} = h_1^{-1}$$

Similarly $\phi = u_2$, then

$$\nabla u_2 = \frac{1}{h_2} \frac{\partial u_2}{\partial u_2} \hat{e}_2 = \frac{\hat{e}_2}{h_2}$$

$$\Rightarrow |\nabla u_2| = \frac{|\hat{e}_2|}{|h_2|} = \frac{1}{h_2} = h_2^{-1}$$

Similarly if $\phi = u_3$, then $|\nabla u_3| = h_3^{-1}$

$$(ii) \quad \text{By definition, } \hat{E}_p = \frac{\nabla u_p}{|\nabla u_p|}$$

$$\Rightarrow \hat{E}_p = h_p \nabla u_p = \hat{e}_p$$

Results :-

$$I. \operatorname{div}(\phi \hat{f}) = \nabla \cdot (\phi \hat{f}) = \phi \operatorname{div} \hat{f} + \hat{f} \cdot \operatorname{Grad} \phi$$

$$= \phi \nabla \cdot \hat{f} + \hat{f} \cdot \nabla \phi$$

$$II. \operatorname{div}(\hat{f} \times \hat{g}) = \nabla \cdot (\hat{f} \times \hat{g}) = \operatorname{curl} \hat{f} \cdot \hat{g} - \operatorname{curl} \hat{g} \cdot \hat{f}$$

$$III. \operatorname{Curl} \operatorname{grad} \phi = \nabla \times \nabla \phi = 0$$

$$\operatorname{div} \operatorname{curl} \hat{f} = \nabla \cdot \nabla \times \hat{f} = 0$$

$$IV. \operatorname{Curl}(\phi \hat{f}) = \nabla \times (\phi \hat{f}) = \operatorname{grad} \phi \times \hat{f} + \phi \operatorname{Curl} \hat{f}$$

DIVERGENCE

Consider a vector function

$$\hat{f}(u_1, u_2, u_3) = f_1 \hat{e}_1 + f_2 \hat{e}_2 + f_3 \hat{e}_3$$

where (u_1, u_2, u_3) are orthogonal curvilinear coordinates.

$$\hat{f} = f_1(\hat{e}_2 \times \hat{e}_3) + f_2(\hat{e}_3 \times \hat{e}_1) + f_3(\hat{e}_1 \times \hat{e}_2)$$

$$\text{using } \hat{e}_1 = h_1 \nabla u_1$$

$$\hat{e}_2 = h_2 \nabla u_2$$

$$\hat{e}_3 = h_3 \nabla u_3$$

$$\hat{f} = f_1 h_2 h_3 (\nabla u_2 \times \nabla u_3) + f_2 h_3 h_1 (\nabla u_3 \times \nabla u_1) + f_3 h_1 h_2 (\nabla u_1 \times \nabla u_2)$$

$$\begin{aligned}
\therefore \quad \text{div } \mathbf{f} &= \nabla \cdot \overset{\text{P}}{\mathbf{f}} = \nabla \cdot [f_1 h_2 h_3 (\nabla \mathbf{u}_2 \times \nabla \mathbf{u}_3)] \\
&\quad + \nabla \cdot [f_2 h_3 h_1 (\nabla \mathbf{u}_3 \times \nabla \mathbf{u}_1)] \\
&\quad + \nabla \cdot [f_3 h_1 h_2 (\nabla \mathbf{u}_1 \times \nabla \mathbf{u}_2)] \quad \dots (*)
\end{aligned}$$

Taking first art,

$$\begin{aligned}
&\nabla \cdot [f_1 h_2 h_3 (\nabla \mathbf{u}_2 \times \nabla \mathbf{u}_3)] = f_1 h_2 h_3 \nabla \cdot (\nabla \mathbf{u}_2 \times \nabla \mathbf{u}_3) + (\nabla \mathbf{u}_2 \times \nabla \mathbf{u}_3) \cdot \nabla (f_1 h_2 h_3) \\
&[\text{By using } \nabla \cdot (\phi \overset{\text{P}}{\mathbf{f}}) = \phi \nabla \cdot \overset{\text{P}}{\mathbf{f}} + \overset{\text{P}}{\mathbf{f}} \cdot \nabla \phi] \\
\Rightarrow \quad &\nabla \cdot [f_1 h_2 h_3 (\nabla \mathbf{u}_2 \times \nabla \mathbf{u}_3)] = f_1 h_2 h_3 \nabla \cdot (\nabla \mathbf{u}_2 \times \nabla \mathbf{u}_3) + (\nabla \mathbf{u}_2 \times \nabla \mathbf{u}_3) \cdot \nabla (f_1 h_2 h_3) \quad \dots (1)
\end{aligned}$$

$$\begin{aligned}
\Rightarrow \quad &\nabla \cdot (\nabla \mathbf{u}_2 \times \nabla \mathbf{u}_3) = \text{curl } \nabla \mathbf{u}_2 \cdot \nabla \mathbf{u}_3 - \text{curl } \nabla \mathbf{u}_3 \cdot \nabla \mathbf{u}_2 \\
&= (\text{curl grad } \mathbf{u}_2) \cdot (\nabla \mathbf{u}_3) - (\text{curl grad } \mathbf{u}_3) \cdot \nabla \mathbf{u}_2 \\
&= 0 - 0 = 0
\end{aligned}$$

$\therefore$ from (1), we get

$$\begin{aligned}
&\nabla \cdot [f_1 h_2 h_3 (\nabla \mathbf{u}_2 \times \nabla \mathbf{u}_3)] = (\nabla \mathbf{u}_2 \times \nabla \mathbf{u}_3) \cdot \nabla (f_1 h_2 h_3) \\
&= (\nabla \mathbf{u}_2 \times \nabla \mathbf{u}_3) \cdot \left[\frac{\partial}{\partial u_1} (f_1 h_2 h_3) \nabla \mathbf{u}_1 + \frac{\partial}{\partial u_2} (f_1 h_2 h_3) \nabla \mathbf{u}_2 \right. \\
&\quad \left. + \frac{\partial}{\partial u_3} (f_1 h_2 h_3) \nabla \mathbf{u}_3 \right] \\
&= \frac{\hat{\mathbf{e}}_2 \times \hat{\mathbf{e}}_3}{h_2 h_3} \left[\frac{\partial}{\partial u_1} (f_1 h_2 h_3) \frac{\hat{\mathbf{e}}_1}{h_1} + \frac{\partial}{\partial u_2} (f_1 h_2 h_3) \frac{\hat{\mathbf{e}}_2}{h_2} + \frac{\partial}{\partial u_3} (f_1 h_2 h_3) \frac{\hat{\mathbf{e}}_3}{h_3} \right] \\
&\left[\Theta \quad \nabla \mathbf{u}_1 = \frac{\hat{\mathbf{e}}_1}{h_1}, \nabla \mathbf{u}_2 = \frac{\hat{\mathbf{e}}_2}{h_2}, \nabla \mathbf{u}_3 = \frac{\hat{\mathbf{e}}_3}{h_3} \right] \\
&= \frac{\hat{\mathbf{e}}_1}{h_2 h_3} \left[\frac{\partial}{\partial u_1} (f_1 h_2 h_3) \frac{\hat{\mathbf{e}}_1}{h_1} + \frac{\partial}{\partial u_2} (f_1 h_2 h_3) \frac{\hat{\mathbf{e}}_2}{h_2} + \frac{\partial}{\partial u_3} (f_1 h_2 h_3) \frac{\hat{\mathbf{e}}_3}{h_3} \right] \\
&= \frac{1}{h_1 h_2 h_3} \frac{\partial}{\partial u_1} (f_1 h_2 h_3)
\end{aligned}$$

$$\Rightarrow \quad \nabla \cdot [f_1 h_2 h_3 (\nabla \mathbf{u}_2 \times \nabla \mathbf{u}_3)] = \frac{1}{h_1 h_2 h_3} \cdot \frac{\partial}{\partial u_1} (f_1 h_2 h_3)$$

$$\text{Similarly } \nabla \cdot [f_2 h_3 h_1 (\nabla \mathbf{u}_3 \times \nabla \mathbf{u}_1)] = \frac{1}{h_1 h_2 h_3} \frac{\partial}{\partial u_2} (f_2 h_3 h_1)$$

$$\text{and } \nabla \cdot [f_3 h_1 h_2 (\nabla u_1 \times \Delta u_2)] = \frac{1}{h_1 h_2 h_3} \frac{\partial}{\partial u_3} (f_3 h_1 h_2)$$

So from (*), we get

$$\therefore \nabla \cdot \vec{f} = \frac{1}{h_1 h_2 h_3} \left[\frac{\partial}{\partial u_1} (f_1 h_2 h_3) + \frac{\partial}{\partial u_2} (f_2 h_3 h_1) + \frac{\partial}{\partial u_3} (f_3 h_1 h_2) \right]$$

CURL

Consider $\vec{f} = f_1 \hat{e}_1 + f_2 \hat{e}_2 + f_3 \hat{e}_3$

$$\Rightarrow \vec{f} = f_1 h_1 \nabla u_1 + f_2 h_2 \nabla u_2 + f_3 h_3 \nabla u_3 \quad [\Theta h_1 \nabla u_1 = \hat{e}_1]$$

$$\begin{aligned} \text{then Curl } \vec{f} &= \nabla \times \vec{f} = \nabla \times (h_1 f_1 \Delta u_1) \\ &\quad + \nabla \times (h_2 f_2 \Delta u_2) \\ &\quad + \nabla \times (h_3 f_3 \Delta u_3) \end{aligned} \quad \dots(1)$$

Taking the first art, we have by using property

$$\text{Curl } (\phi \vec{F}) = \nabla \phi \times \vec{F} + \phi \nabla \times \vec{F}$$

we get

$$\begin{aligned} \nabla \times (h_1 f_1 \nabla u_1) &= \nabla (h_1 f_1) \times \nabla u_1 + h_1 f_1 (\nabla \times \nabla u_1) \\ &= \nabla (h_1 f_1) \times \Delta u_1 \quad [\Theta \Delta \times \Delta u_1 = \text{curl grad } u_1 = 0] \\ \Rightarrow \nabla \times (h_1 f_1 \nabla u_1) &= \left[\frac{\partial}{\partial u_1} (f_1 h_1) \nabla u_1 + \frac{\partial}{\partial u_2} (f_1 h_1) \nabla u_2 + \frac{\partial}{\partial u_3} (f_1 h_1) \nabla u_3 \times \nabla u_1 \right] \\ &\quad [\Theta \text{ By definition of gradient of a function}] \end{aligned}$$

$$\Rightarrow \nabla \times [h_1 f_1 \nabla u_1] = \left[\frac{\partial}{\partial u_1} (f_1 h_1) \frac{\hat{e}_1}{h_1} + (f_1 h_1) \frac{\hat{e}_2}{h_2} + \frac{\partial}{\partial u_3} (f_1 h_1) \frac{\hat{e}_3}{h_3} \times \frac{\hat{e}_1}{h_1} \right]$$

$$\Rightarrow \nabla \times (h_1 f_1 \nabla u_1) = \frac{\hat{e}_2}{h_1 h_3} \frac{\partial}{\partial u_3} (f_1 h_1) - \frac{\hat{e}_3}{h_2 h_1} \frac{\partial}{\partial u_2} (f_1 h_1)$$

$$\text{Similarly } \nabla \times (h_1 f_2 \nabla u_2) = \frac{\hat{e}_3}{h_2 h_1} \frac{\partial}{\partial u_1} (f_2 h_2) - \frac{\hat{e}_1}{h_3 h_2} \frac{\partial}{\partial u_3} (f_2 h_2)$$

$$\text{and } \nabla \times (h_3 f_3 \nabla u_3) = \frac{\hat{e}_1}{h_3 h_2} \frac{\partial}{\partial u_2} (f_3 h_3) - \frac{\hat{e}_2}{h_1 h_3} \frac{\partial}{\partial u_1} (f_3 h_3)$$

$\therefore$ from (1),

$$\begin{aligned}
\text{Curl } \vec{f} &= \frac{\hat{e}_1}{h_2 h_3} \left[\frac{\partial}{\partial u_2} (f_3 h_3) - \frac{\partial}{\partial u_3} (f_2 h_2) \right] \\
&+ \frac{\hat{e}_2}{h_3 h_1} \left[\frac{\partial}{\partial u_3} (f_1 h_1) - \frac{\partial}{\partial u_1} (f_3 h_3) \right] \\
&+ \frac{\hat{e}_3}{h_1 h_2} \left[\frac{\partial}{\partial u_1} (f_2 h_2) - \frac{\partial}{\partial u_2} (f_1 h_1) \right] \\
&= \frac{1}{h_1 h_2 h_3} \begin{vmatrix} h_1 \hat{e}_1 & h_2 \hat{e}_2 & h_3 \hat{e}_3 \\ \frac{\partial}{\partial u_1} & \frac{\partial}{\partial u_2} & \frac{\partial}{\partial u_3} \\ h_1 f_1 & h_2 f_2 & h_3 f_3 \end{vmatrix}
\end{aligned}$$

LAPLACIAN OF SCALAR POINT FUNCTION ($\nabla^2 \phi$)

Now

$$\begin{aligned}
\nabla^2 \phi &= \nabla \cdot (\nabla \phi) \\
\Rightarrow \nabla^2 \phi &= \nabla \cdot \left[\frac{\partial \phi}{\partial u_1} \nabla u_1 + \frac{\partial \phi}{\partial u_2} \nabla u_2 + \frac{\partial \phi}{\partial u_3} \nabla u_3 \right] \\
&= \nabla \cdot \left[\frac{1}{h_1} \frac{\partial \phi}{\partial u_1} \hat{e}_1 + \frac{1}{h_2} \frac{\partial \phi}{\partial u_2} \hat{e}_2 + \frac{1}{h_3} \frac{\partial \phi}{\partial u_3} \hat{e}_3 \right]
\end{aligned}$$

We know that

$$\nabla \cdot \vec{f} = \frac{1}{h_2 h_1 h_3} \left[\frac{\partial}{\partial u_1} (f_1 h_2 h_3) + \frac{\partial}{\partial u_2} (f_2 h_3 h_1) + \frac{\partial}{\partial u_3} (f_3 h_1 h_2) \right]$$

Here put $f_1 = \frac{1}{h_1} \frac{\partial \phi}{\partial u_1}$,

$$f_2 = \frac{1}{h_2} \frac{\partial \phi}{\partial u_2}, \quad f_3 = \frac{1}{h_3} \frac{\partial \phi}{\partial u_3}$$

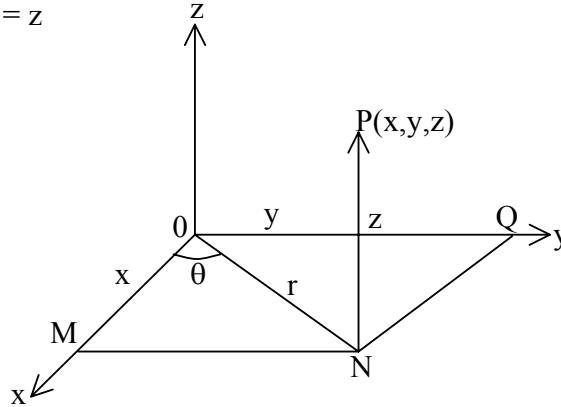
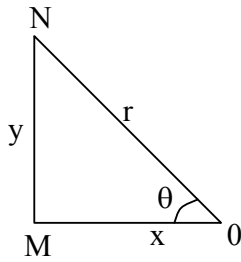
Therefore

$$\nabla^2 \phi = \frac{1}{h_1 h_2 h_3} \left[\frac{\partial}{\partial u_1} \left(\frac{h_2 h_3}{h_1} \frac{\partial \phi}{\partial u_1} \right) + \frac{\partial}{\partial u_2} \left(\frac{h_3 h_1}{h_2} \frac{\partial \phi}{\partial u_2} \right) + \frac{\partial}{\partial u_3} \left(\frac{h_1 h_2}{h_3} \frac{\partial \phi}{\partial u_3} \right) \right]$$

CYLINDRICAL POLAR COORDINATES (r, θ, z)

Let P is a point having Cartesian co-ordinates (x, y, z)

$$OM = x, \quad MN = y (= OQ), \quad PN = z$$



$$x = OM = ON \cos \theta$$

$$\Rightarrow x = r \cos \theta \quad \dots(1)$$

$$\& \quad y = MN = N \sin \theta$$

$$\Rightarrow y = r \sin \theta \quad \dots(2)$$

$$\text{and} \quad z = z \quad \dots(3)$$

so we have,

$$r = \sqrt{x^2 + y^2}$$

$$\text{and} \quad \theta = \tan^{-1} \frac{y}{x}$$

Determine the transformation from cylindrical to rectangular coordinates :- Operating equation

$(1)^2 + (2)^2$, we get

$$r^2 = x^2 + y^2 \Rightarrow r = \sqrt{x^2 + y^2}$$

$$(2)/(1) \Rightarrow \frac{y}{x} = \tan \theta \quad \Rightarrow \theta = \tan^{-1} \left(\frac{y}{x} \right)$$

$$\text{and} \quad z = z.$$

$$(ds)^2 = (dx)^2 + (dy)^2 + (dz)^2 \quad \dots(4)$$

$$\text{Now} \quad dx = \cos \theta \, dr - r \sin \theta \, d\theta$$

$$dy = \sin \theta \, dr + r \cos \theta \, d\theta$$

$$dz = dz$$

$$\therefore (4) \Rightarrow$$

$$\begin{aligned} \therefore (ds)^2 &= (dr \cos \theta - r \sin \theta d\theta)^2 + (\sin \theta dr + r \cos \theta d\theta)^2 + (dz)^2 \\ &= (dr)^2 (\sin^2 \theta + \cos^2 \theta) + (r d\theta)^2 (\sin^2 \theta + \cos^2 \theta) + (dz)^2 \end{aligned}$$

$$\Rightarrow (ds)^2 = (dr)^2 + (rd\theta)^2 + (dz)^2$$

$$\text{Comparing it with } (ds)^2 = h_1^2 (du_1)^2 + h_2^2 (du_2)^2 + h_3^2 (du_3)^2$$

We get,

$$h_1 = 1, h_2 = r, h_3 = 1, u_1 = r, u_2 = \theta, u_3 = z$$

$$\text{Take } \hat{e}_1 = \hat{e}_r, \hat{e}_2 = \hat{e}_\theta, \hat{e}_3 = \hat{e}_z$$

Using these, we have

$$\text{grad } \Phi = \frac{\partial \Phi}{\partial r} \hat{e}_r + \frac{1}{r} \frac{\partial \Phi}{\partial \theta} \hat{e}_\theta + \frac{\partial \Phi}{\partial z} \hat{e}_z$$

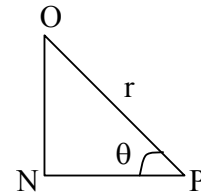
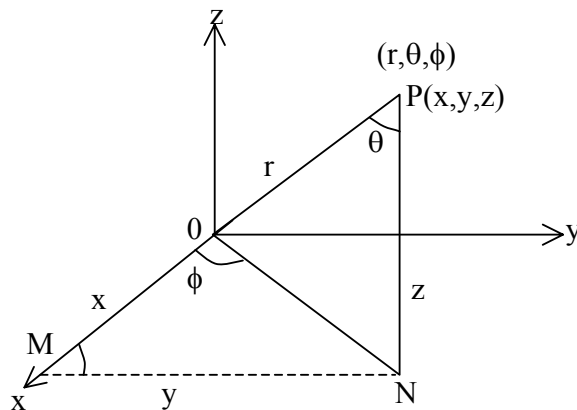
where Φ is a scalar point function

$$\text{div } \vec{f} = \frac{1}{r} \left[\frac{\partial}{\partial r} (f_1 r) + \frac{\partial}{\partial \theta} (f_2) + \frac{\partial}{\partial z} (f_3 r) \right]$$

$$\text{Curl } \vec{f} = \frac{1}{r} \begin{vmatrix} \hat{e}_r & r\hat{e}_\theta & \hat{e}_z \\ \frac{\partial}{\partial r} & \frac{\partial}{\partial \theta} & \frac{\partial}{\partial z} \\ f_1 & f_2 r & f_3 \end{vmatrix}$$

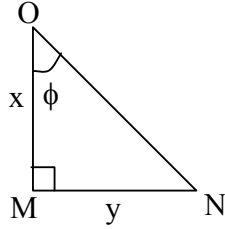
$$\begin{aligned} \nabla^2 \Phi &= \frac{1}{r} \left[\frac{\partial}{\partial r} \left(r \frac{\partial \Phi}{\partial r} \right) + \frac{\partial}{\partial \theta} \left(\frac{1}{r} \frac{\partial \Phi}{\partial \theta} \right) + \frac{\partial}{\partial z} \left(r \frac{\partial \Phi}{\partial z} \right) \right] \\ &= \frac{\partial^2 \Phi}{\partial r^2} + \frac{1}{r} \frac{\partial \Phi}{\partial r} + \frac{1}{r^2} \frac{\partial^2 \Phi}{\partial \theta^2} + \frac{\partial^2 \Phi}{\partial z^2} \end{aligned}$$

SPHERICAL POLAR COORDINATES (r, θ, ϕ)



$$OM = x, MN = y, \quad PN = z, \quad OP = r \quad z = PN = r \cos \theta \quad ON = r \sin \theta$$

In ΔOMN , $x = OM = ON \cos \phi$



$$\Rightarrow x = r \sin \theta \cos \phi$$

$$y = MN = ON \sin \phi \Rightarrow y = r \sin \theta \sin \phi$$

$$\text{Now } (ds)^2 = (dx)^2 + (dy)^2 + (dz)^2 \quad \dots(1)$$

$$dx = \sin \theta \cos \phi dr + r \cos \theta \cos \phi d\theta - r \sin \theta \sin \phi d\phi$$

$$dy = \sin \theta \sin \phi dr + r \cos \theta \sin \phi d\theta + r \sin \theta \cos \phi d\phi$$

$$dz = \cos \theta dr - r \sin \theta d\theta \quad \dots(2)$$

Put the value of (2) in (1) and collecting the coefficients of $(dr)^2$, $(d\theta)^2$, $(d\phi)^2$, we get

$$(ds)^2 = (dr)^2 (1) + (d\theta)^2 (r^2) + (d\phi)^2 (r^2 \sin^2 \theta)$$

Comparing it with,

$$(ds)^2 = h_1^2 (du_1)^2 + h_2^2 (du_2)^2 + h_3^2 (du_3)^2$$

we get

$$h_1 = 1, h_2 = r, h_3 = r \sin \theta$$

$$u_1 = r, u_2 = \theta, u_3 = \phi$$

$$\hat{e}_1 = \hat{e}_r, \hat{e}_2 = \hat{e}_\theta, \hat{e}_3 = \hat{e}_\phi$$

$$\text{So grad } \Phi = \hat{e}_r \frac{\partial \Phi}{\partial r} + \frac{\hat{e}_\theta}{r} \frac{\partial \Phi}{\partial \theta} + \frac{\hat{e}_\phi}{r \sin \theta} \frac{\partial \Phi}{\partial \phi}$$

$$\text{div } \vec{f} = \frac{1}{r^2 \sin \theta} \left[\frac{\partial}{\partial r} (f_1 r^2 \sin \theta) + \frac{\partial}{\partial \theta} (f_2 r \sin \theta) + \frac{\partial}{\partial \phi} (f_3 r) \right]$$

$$\text{Curl } \vec{f} = \frac{1}{r^2 \sin \theta} \left[\frac{\partial}{\partial r} \left(\frac{r^2 \sin \theta}{(1)} \frac{\partial \Phi}{\partial r} \right) \right]$$

$$\text{Curl } \vec{f} = \frac{1}{r^2 \sin \theta} \vec{f} = \frac{1}{r} \begin{vmatrix} \hat{e}_r & r\hat{e}_\theta & r \sin \theta \hat{e}_\phi \\ \frac{\partial}{\partial r} & \frac{\partial}{\partial \theta} & \frac{\partial}{\partial \phi} \\ f_1 & f_2 r & f_3 r \sin \theta \end{vmatrix}$$

$$\nabla^2 \Phi = \frac{1}{r^2 \sin \theta} \left[\frac{\partial}{\partial r} \left(r^2 \sin \theta \frac{\partial \Phi}{\partial r} \right) + \frac{\partial}{\partial \theta} \left(\sin \theta \frac{\partial \Phi}{\partial \theta} \right) + \frac{\partial}{\partial \phi} \left(\frac{1}{\sin \theta} \frac{\partial \Phi}{\partial \phi} \right) \right]$$

$$= \frac{\partial^2 \Phi}{\partial r^2} + \frac{2}{r} \frac{\partial \Phi}{\partial r} + \frac{1}{r^2} \frac{\partial^2 \Phi}{\partial \theta^2} + \frac{\cos \theta}{r^2 \sin \theta} \frac{\partial \Phi}{\partial \theta} + \frac{1}{r^2 \sin^2 \theta} \frac{\partial^2 \Phi}{\partial \phi^2}$$

Example:- Prove that cylindrical coordinate system is orthogonal.

Solution :- The position vector of any point in cylindrical coordinate is

$$\vec{r} = x \hat{i} + y \hat{j} + z \hat{k}$$

$$\therefore \vec{r} = r \cos \theta \hat{i} + r \sin \theta \hat{j} + z \hat{k}$$

$$\vec{r} = \vec{r}(s) \frac{\partial x}{\partial s}, \frac{\partial y}{\partial s}, \frac{\partial z}{\partial s} \text{ are unit vector}$$

The tangent vector to the r , θ and z curves are given by

$$\frac{\partial \vec{r}}{\partial r}, \frac{\partial \vec{r}}{\partial \theta}, \frac{\partial \vec{r}}{\partial z} \text{ respectively.}$$

$$\text{where } \frac{\partial \vec{r}}{\partial r} = \cos \theta \hat{i} + \sin \theta \hat{j}$$

$$\frac{\partial \vec{r}}{\partial \theta} = -r \sin \theta \hat{i} + r \cos \theta \hat{j}$$

$$\frac{\partial \vec{r}}{\partial z} = \hat{k}$$

Therefore the unit-vector in these tangent directions are

$$\hat{e}_1 = \hat{e}_r = \frac{\partial \vec{r}}{\partial r} \left| \frac{\partial \vec{r}}{\partial r} \right|$$

$$\Rightarrow \hat{e}_r = \frac{\cos \theta \hat{i} + \sin \theta \hat{j}}{\sqrt{\cos^2 \theta + \sin^2 \theta}} = \cos \theta \hat{i} + \sin \theta \hat{j}$$

$$\hat{e}_2 = \hat{e}_\theta = \frac{\partial \vec{r} / \partial \theta}{\left| \frac{\partial \vec{r}}{\partial \theta} \right|} = \frac{-r \sin \theta \hat{i} + r \cos \theta \hat{j}}{\sqrt{r^2 \sin^2 \theta + r^2 \cos^2 \theta}}$$

$$\Rightarrow \hat{e}_\theta = \frac{-r \sin \theta \hat{i} + r \cos \theta \hat{j}}{r} = -\sin \theta \hat{i} + \cos \theta \hat{j}$$

$$\hat{e}_3 = \hat{e}_z = \frac{\partial \mathbf{R} / \partial z}{|\partial \mathbf{R} / \partial z|} = \hat{k}$$

$$\text{Now } \hat{e}_r \cdot \hat{e}_\theta = (\cos \theta \hat{i} + \sin \theta \hat{j}) \cdot (-\sin \theta \hat{i} + \cos \theta \hat{j})$$

$$= -\cos \theta \sin \theta + \sin \theta \cos \theta = 0$$

$$\hat{e}_r \cdot \hat{e}_z = (\cos \theta \hat{i} + \sin \theta \hat{j}) \cdot \hat{k} = 0$$

$$\hat{e}_\theta \cdot \hat{e}_z = (-\sin \theta \hat{i} + \cos \theta \hat{j}) \cdot \hat{k} = 0$$

$$\begin{aligned} \hat{e}_r \cdot \hat{e}_r &= (\cos \theta \hat{i} + \sin \theta \hat{j}) \cdot (\cos \theta \hat{i} + \sin \theta \hat{j}) \\ &= \cos^2 \theta + \sin^2 \theta = 1 \end{aligned}$$

$$\begin{aligned} \hat{e}_\theta \cdot \hat{e}_\theta &= (-\sin \theta \hat{i} + \cos \theta \hat{j}) \cdot (-\sin \theta \hat{i} + \cos \theta \hat{j}) \\ &= \sin^2 \theta + \cos^2 \theta = 1 \end{aligned}$$

$$\hat{e}_z \cdot \hat{e}_z = \hat{k} \cdot \hat{k} = 1$$

This shows that $\hat{e}_r, \hat{e}_\theta, \hat{e}_z$ are mutually $\perp_r$ and therefore the coordinate system is orthogonal.

Example:- (a) Find the unit vectors $\hat{e}_r, \hat{e}_\theta, \hat{e}_\phi$ of a spherical co-ordinate system in terms of $\hat{i}, \hat{j}, \hat{k}$.

Solution :- The position vector of any point in spherical coordinate is

$$\begin{aligned} \mathbf{R} &= x \hat{i} + y \hat{j} + z \hat{k} \\ &= (r \sin \theta \cos \phi) \hat{i} + (r \sin \theta \sin \phi) \hat{j} + (r \cos \theta) \hat{k} \end{aligned}$$

We want to find $\frac{\partial \mathbf{R}}{\partial r}, \frac{\partial \mathbf{R}}{\partial \theta}, \frac{\partial \mathbf{R}}{\partial \phi}$

$$\text{Now } \frac{\partial \mathbf{R}}{\partial r} = \sin \theta \cos \phi \hat{i} + \sin \theta \sin \phi \hat{j} + \cos \theta \hat{k}$$

$$\text{So } \hat{e}_r = \frac{\partial \mathbf{R} / \partial r}{|\partial \mathbf{R} / \partial r|} = \frac{\sin \theta \cos \phi \hat{i} + \sin \theta \sin \phi \hat{j} + \cos \theta \hat{k}}{\sqrt{\sin^2 \theta (\cos^2 \phi + \sin^2 \phi) + \cos^2 \theta}}$$

$$\Rightarrow \hat{e}_r = \sin \theta \cos \phi \hat{i} + \sin \theta \sin \phi \hat{j} + \cos \theta \hat{k}$$

$$\text{Also } \frac{\partial \mathbf{R}}{\partial \theta} = r \cos \theta \cos \phi \hat{i} + r \cos \theta \sin \phi \hat{j} - r \sin \theta \hat{k}$$

$$\begin{aligned}\text{So } \hat{e}_\theta &= \frac{\frac{\partial \mathbf{R}}{\partial \theta}}{\left| \frac{\partial \mathbf{R}}{\partial \theta} \right|} = \frac{r \cos \theta \cos \phi \hat{i} + r \cos \theta \sin \phi \hat{j} - r \sin \theta \hat{k}}{\sqrt{r^2 \cos^2 \theta (\cos^2 \phi + \sin^2 \phi) + r^2 \sin^2 \theta}} \\ &= \frac{r \cos \theta \cos \phi \hat{i} + r \cos \theta \sin \phi \hat{j} - r \sin \theta \hat{k}}{r}\end{aligned}$$

$$\Rightarrow \hat{e}_\theta = \cos \theta \cos \phi \hat{i} + \cos \theta \sin \phi \hat{j} - \sin \theta \hat{k}$$

$$\text{Also } \frac{\partial \mathbf{R}}{\partial \phi} = -r \sin \theta \sin \phi \hat{i} + r \sin \theta \cos \phi \hat{j} + \theta \hat{k}$$

$$\begin{aligned}\text{So } \hat{e}_\phi &= \frac{\frac{\partial \mathbf{R}}{\partial \phi}}{\left| \frac{\partial \mathbf{R}}{\partial \phi} \right|} = \frac{-r \sin \theta \sin \phi \hat{i} + r \sin \theta \cos \phi \hat{j} + \theta \hat{k}}{\sqrt{r^2 \sin^2 \theta (\sin^2 \phi + \cos^2 \phi)}} \\ &= \frac{-r \sin \theta \sin \phi \hat{i} + r \sin \theta \cos \phi \hat{j}}{r \sin \theta}\end{aligned}$$

$$\Rightarrow \hat{e}_\phi = -\sin \phi \hat{i} + \cos \phi \hat{j}$$

Example:- Prove that a spherical coordinate system is orthogonal.

Solution :- $\hat{e}_r \cdot \hat{e}_\theta = (\sin \theta \cos \phi \hat{i} + \sin \theta \sin \phi \hat{j} + \cos \theta \hat{k}) \cdot$

$$(\cos \theta \cos \phi \hat{i} + \cos \theta \sin \phi \hat{j} - \sin \theta \hat{k})$$

$$= \cos^2 \phi \sin \theta \cos \theta + \sin^2 \phi \sin \theta \cos \theta - \sin \theta \cos \theta$$

$$= \sin \theta \cos \theta (\sin^2 \phi + \cos^2 \phi) - \sin \theta \cos \theta$$

$$\Rightarrow \hat{e}_r \cdot \hat{e}_\theta = 0$$

$$\hat{e}_\theta \cdot \hat{e}_\phi = (\cos \theta \cos \phi \hat{i} + \cos \theta \sin \phi \hat{j} - \sin \theta \hat{k}) \cdot (-\sin \phi \hat{i} + \cos \phi \hat{j})$$

$$= -\sin \phi \cos \phi \cos \theta + \cos \theta \cos \phi \sin \phi - 0$$

$$\Rightarrow \hat{e}_\theta \cdot \hat{e}_\phi = 0$$

$$\text{Also } \hat{e}_\phi \cdot \hat{e}_r = (-\sin \phi \hat{i} + \cos \phi \hat{j}) \cdot (\sin \theta \cos \phi \hat{i} + \sin \theta \sin \phi \hat{j} + \cos \theta \hat{k})$$

$$= -\sin \theta \sin \phi \cos \phi + \sin \theta \sin \phi \cos \phi + 0$$

$$\Rightarrow \hat{e}_\phi \cdot \hat{e}_r = 0$$

$$\text{and } \hat{e}_r \cdot \hat{e}_r = (\sin \theta \cos \phi \hat{i} + \sin \theta \sin \phi \hat{j} + \cos \theta \hat{k}) \cdot (\sin \theta \cos \phi \hat{i}$$

$$+ \sin \theta \sin \phi \hat{j} + \cos \theta \hat{k})$$

$$= \cos^2 \phi \sin^2 \theta + \sin^2 \phi \sin^2 \theta + \cos^2 \theta$$

$$= \sin^2\theta(\cos^2\phi + \sin^2\phi) + \cos^2\theta$$

$$\Rightarrow \hat{e}_r \cdot \hat{e}_r = 1$$

$$\text{and } \hat{e}_\theta \cdot \hat{e}_\theta = (\cos\theta \cos\phi \hat{i} + \cos\theta \sin\phi \hat{j} - \sin\theta \hat{k})$$

$$(\cos\theta \cos\phi \hat{i} + \cos\theta \sin\phi \hat{j} - \sin\theta \hat{k})$$

$$= \cos^2\phi \cos^2\theta + \cos^2\theta \sin^2\phi + \sin^2\theta$$

$$= \cos^2\theta (\sin^2\phi + \cos^2\phi) + \sin^2\theta$$

$$\Rightarrow \hat{e}_\theta \cdot \hat{e}_\theta = 1$$

$$\text{and } \hat{e}_\phi \cdot \hat{e}_\phi = (-\sin\phi \hat{i} + \cos\phi \hat{j}) \cdot (-\sin\phi \hat{i} + \cos\phi \hat{j})$$

$$= \sin^2\phi + \cos^2\phi = 1$$

$$\Rightarrow \hat{e}_\phi \cdot \hat{e}_\phi = 1$$

This shows that $\hat{e}_r, \hat{e}_\theta, \hat{e}_\phi$ are mutually and therefore the coordinate system is orthogonal.

Example:- Represent the vector $\vec{A} = 2y \hat{i} - z \hat{j} + 3x \hat{k}$... (1)

in spherical coordinates

Solution :- Here $x = r \sin\theta \cos\phi$

$$y = r \sin\theta \sin\phi$$

$$z = r \cos\theta \quad \dots (2)$$

$$\text{and } \hat{e}_r = \sin\theta \cos\phi \hat{i} + \sin\theta \sin\phi \hat{j} + \cos\theta \hat{k}$$

$$\hat{e}_\theta = \cos\theta \cos\phi \hat{i} + \cos\theta \sin\phi \hat{j} - \sin\theta \hat{k}$$

$$\hat{e}_\phi = -\sin\phi \hat{i} + \cos\phi \hat{j} \quad \dots (3)$$

Solving (3), we get

$$\hat{i} = \hat{e}_r \sin\theta \cos\phi + \hat{e}_\theta \cos\theta \cos\phi - \hat{e}_\phi \sin\phi$$

$$\hat{j} = \hat{e}_r \sin\theta \sin\phi + \hat{e}_\theta \sin\phi \cos\theta + \hat{e}_\phi \cos\phi$$

$$\hat{k} = \hat{e}_r \cos\theta - \hat{e}_\theta \sin\theta \quad \dots (4)$$

Put (2) & (4) in (1), we get

$$\begin{aligned} \vec{A} &= 2r \sin\theta \sin\phi (\hat{e}_r \sin\theta \cos\phi + \hat{e}_\theta \cos\theta \cos\phi - \hat{e}_\phi \sin\phi) \\ &\quad - r \cos\theta (\hat{e}_r \sin\theta \sin\phi + \hat{e}_\theta \sin\phi \cos\theta + \hat{e}_\phi \cos\phi) \end{aligned}$$

$$\begin{aligned}
& + 3 r \sin \theta \cos \phi (\hat{e}_r \cos \theta - \hat{e}_\theta \sin \theta) \\
\Rightarrow \quad \vec{A} &= \hat{e}_r (2r \sin^2 \theta \cos^2 \phi - r \sin \theta \cos \theta \sin \phi + 3 r \sin \theta \cos \phi \cos \theta) \\
& + \hat{e}_\theta (2r \sin \theta \cos \theta \sin \phi \cos \phi - r \cos^2 \theta \sin \phi - 3r \sin^2 \theta \cos \phi) \\
& + \hat{e}_\phi (-2r \sin \theta \sin \phi - r \cos \theta \cos \phi) \\
\Rightarrow \quad \vec{A} &= \hat{e}_r 2r \sin \theta (\sin \theta \cos^2 \phi + \cos \theta \sin \phi) \\
& + \hat{e}_\theta r (2 \sin \theta \cos \theta \sin \phi \cos \phi - r \cos^2 \theta \sin \phi - 3r \sin^2 \theta \cos \phi) \\
& - \hat{e}_\phi r (2 \sin \theta \sin^2 \phi + \cos \theta \cos \phi) \\
\Rightarrow \quad \vec{A} &= A_r \hat{e}_r + A_\theta \hat{e}_\theta + A_\phi \hat{e}_\phi
\end{aligned}$$

Example :- Prove that for cylindrical coordinate system (r, θ, z) ,

$$\frac{d}{dt} \hat{e}_r = \dot{\theta} \hat{e}_\theta$$

$$\frac{d}{dt} \hat{e}_\theta = -\dot{\theta} \hat{e}_r$$

Solution :- We have $\hat{e}_r = \cos \theta \hat{i} + \sin \theta \hat{j}$... (1)

$$\hat{e}_\theta = -\sin \theta \hat{i} + \cos \theta \hat{j} \quad \dots (2)$$

$$\therefore \frac{d}{dt} \hat{e}_r = (-\sin \theta) \hat{i} + (\cos \theta) \hat{j}$$

$$\Rightarrow \frac{d}{dt} \hat{e}_r = (-\sin \theta \hat{i} + \cos \theta \hat{j}) \dot{\theta} = \dot{\theta} \hat{e}_\theta \quad [\text{using (2)}]$$

$$\text{Also } \frac{d}{dt} \hat{e}_\theta = (-\cos \theta) \hat{i} + (-\sin \theta) \hat{j}$$

$$= -(\cos \theta \hat{i} + \sin \theta \hat{j}) \dot{\theta}$$

$$\Rightarrow \frac{d}{dt} \hat{e}_\theta = -\dot{\theta} \hat{e}_r \quad [\text{using (1)}]$$

Example:- Express the velocity $\vec{v}$ and acceleration $\vec{a}$ of a particle in cylindrical coordinates.

Solution :- Position vector of a particle P in rectangular coordinates

$$\vec{r} = x \hat{i} + y \hat{j} + z \hat{k}$$

vector $\vec{r}$ in cylindrical coordinate system is

$$\vec{r} = r \cos \theta (\cos \theta \hat{e}_r - \sin \theta \hat{e}_\theta)$$

$$+ r \sin \theta (\sin \theta \hat{e}_r + \cos \theta \hat{e}_\theta) + z \hat{e}_z$$

$$\Rightarrow \vec{r} = r \cos^2 \theta \hat{e}_r - r \cos \theta \sin \theta \hat{e}_\theta + r \sin^2 \theta \hat{e}_r + r \sin \theta \cos \theta \hat{e}_\theta + z \hat{e}_z$$

$$\Rightarrow \vec{r} = r \hat{e}_r + z \hat{e}_z$$

$$\text{Then velocity } \vec{v} = \frac{d\vec{r}}{dt}$$

$$\Rightarrow \vec{v} = \frac{dr}{dt} \hat{e}_r + r \frac{d}{dt} \hat{e}_r + \frac{dz}{dt} \hat{e}_z + z \frac{d}{dt} \hat{e}_z$$

$$\vec{v} = \dot{r} \hat{e}_r + r \dot{\theta} \hat{e}_\theta + \dot{z} \hat{e}_z \quad \left[\theta \frac{d}{dt} \hat{e}_z = 0 \right] \quad \dots(1)$$

$$\text{Differentiating (1) again, we obtain acceleration } \vec{a} = \frac{d\vec{v}}{dt} = \frac{d^2\vec{r}}{dt^2}$$

$$\Rightarrow \vec{a} = \frac{d}{dt} (\dot{r} \hat{e}_r + r \dot{\theta} \hat{e}_\theta + \dot{z} \hat{e}_z)$$

$$= \ddot{r} \hat{e}_r + \dot{r} \frac{d}{dt} \hat{e}_r + \dot{r} \dot{\theta} \hat{e}_r + r \ddot{\theta} \hat{e}_\theta + r \dot{\theta} \frac{d}{dt} \hat{e}_\theta + \ddot{z} \hat{e}_z + \dot{z} \frac{d}{dt} \hat{e}_z$$

$$\text{using } \frac{d}{dt} \hat{e}_r = \dot{\theta} \hat{e}_\theta, \quad \frac{d}{dt} \hat{e}_\theta = -\dot{\theta} \hat{e}_r, \quad \frac{d}{dt} \hat{e}_z = 0,$$

we get

$$\vec{a} = \ddot{r} \hat{e}_r + \dot{r} \dot{\theta} \hat{e}_\theta + \dot{r} \dot{\theta} \hat{e}_\theta + r \ddot{\theta} \hat{e}_\theta + r \dot{\theta} (-\dot{\theta} \hat{e}_r) + \ddot{z} \hat{e}_z$$

$$\Rightarrow \vec{a} = (\ddot{r} - r \dot{\theta}^2) \hat{e}_r + (r \ddot{\theta} + 2\dot{r} \dot{\theta}) \hat{e}_\theta + \ddot{z} \hat{e}_z$$

Example: - Prove that in spherical coordinates (r, θ, ϕ)

$$\frac{d}{dt} \hat{e}_r = \hat{e}_\theta \dot{\theta} + \sin \theta \dot{\phi} \hat{e}_\phi$$

$$\frac{d}{dt} \hat{e}_\theta = \hat{e}_\phi \dot{\phi} - \hat{e}_r \dot{\theta}$$

$$\frac{d}{dt} \hat{e}_\phi = \hat{e}_r \dot{\theta} - \sin \theta \dot{\phi} \hat{e}_\theta \quad \dots(*)$$

$$\text{Proof: - Now } \hat{e}_r = \sin \theta \cos \phi \hat{i} + \sin \theta \sin \phi \hat{j} + \cos \theta \hat{k} \quad \dots(1)$$

$$\begin{aligned} \therefore \frac{d}{dt} \hat{e}_r &= \cos \theta \cos \phi \dot{\theta} \hat{i} + \sin \theta (-\sin \phi) \dot{\theta} \hat{i} \\ &\quad + \cos \theta \cos \phi \hat{i} \sin \theta \cos \phi \dot{\theta} \hat{j} - (\sin \theta) \dot{\theta} \hat{k} \end{aligned}$$

$$= \hat{k}(\cos\theta \cos\phi \hat{i} + \cos\theta \sin\phi \hat{j} - \sin\theta \hat{k}) \\ + \sin\theta \hat{\phi}(-\sin\phi \hat{i} + \cos\phi \hat{j}) \quad \dots(2)$$

$$\text{using } \hat{e}_\theta = \cos\theta \cos\phi \hat{i} + \cos\theta \sin\phi \hat{j} - \sin\theta \hat{k} \quad \dots(3)$$

$$\hat{e}_\phi = -\sin\phi \hat{i} + \cos\phi \hat{j} \quad \dots(4)$$

Put (3) & (4) in (2), we get

$$\frac{d}{dt}\hat{e}_r = \hat{e}_\theta + \sin\theta \hat{\phi} \hat{e}_\phi$$

Also from (3),

$$\begin{aligned} \frac{d}{dt}\hat{e}_\theta &= -\sin\theta \cos\phi \hat{i} - \cos\theta \sin\phi \hat{j} \\ &\quad - \sin\theta \sin\phi \hat{k} - \cos\theta \sin\phi \hat{j} - \cos\theta \hat{k} \\ &= \hat{\phi}(\sin\theta \cos\phi \hat{i} + \sin\theta \sin\phi \hat{j} + \cos\theta \hat{k}) + \cos\theta \hat{\phi}(-\sin\phi \hat{i} + \cos\phi \hat{j}) \\ \Rightarrow \frac{d}{dt}\hat{e}_\theta &= -\hat{e}_r + \cos\theta \hat{e}_\phi \end{aligned}$$

$$\text{Also from (4), } \frac{d}{dt}\hat{e}_\phi = -\cos\phi \hat{i} - \sin\phi \hat{j} - \sin\phi \hat{j} \quad \dots(5)$$

Taking R.H.S of equation (*)

$$\begin{aligned} \text{R.H.S} &= -\sin\theta \hat{\phi} \hat{e}_r - \cos\theta \hat{\phi} \hat{e}_\theta \\ &= -\sin\theta \hat{\phi}(\sin\theta \cos\phi \hat{i} + \sin\theta \sin\phi \hat{j} + \cos\theta \hat{k}) \\ &\quad - \cos\theta \hat{\phi}(\cos\theta \cos\phi \hat{i} + \cos\theta \sin\phi \hat{j} - \sin\theta \hat{k}) \quad [\text{using (1) \& (3)}] \\ &= -\sin^2\theta \cos\phi \hat{i} - \sin^2\theta \sin\phi \hat{j} - \sin\theta \cos\theta \hat{k} \\ &\quad - \cos^2\theta \cos\phi \hat{i} - \cos^2\theta \sin\phi \hat{j} + \sin\theta \cos\theta \hat{k} \\ &= -\hat{i} \cos\phi (\sin^2\theta + \cos^2\theta) - \hat{j} \sin\phi (\sin^2\theta + \cos^2\theta) \\ &= -\hat{\phi} \cos\phi \hat{i} - \sin\phi \hat{j} = \text{L.H.S.} \quad [\text{from (5)}] \end{aligned}$$

$$\Rightarrow \text{L.H.S.} = \text{R.H.S.}$$

$$\text{So } \frac{d}{dt}\hat{e}_\phi = -\sin\theta \hat{\phi} \hat{e}_r - \cos\theta \hat{\phi} \hat{e}_\theta$$

Example:- Express the velocity $\vec{v}$ and acceleration $\vec{a}$ of a particle in spherical coordinates.

Solution : Position vector of a particle P in rectangular coordinates

$\rho = x\hat{i} + y\hat{j} + z\hat{k}$ vector $\mathbf{r}$ in spherical coordinate system is

$$\begin{aligned}\mathbf{r} &= r \cos \phi \sin \theta (\hat{e}_r \sin \theta \cos \phi + \hat{e}_\theta \cos \theta \cos \phi - \hat{e}_\phi \sin \phi) \\ &+ r \sin \theta \sin \phi (\hat{e}_r \sin \theta \sin \phi + \hat{e}_\theta \cos \theta \sin \phi + \hat{e}_\phi \cos \phi) \\ &+ r \cos \theta (\hat{e}_r \cos \theta - \hat{e}_\theta \sin \theta)\end{aligned}$$

$$\begin{aligned}\Rightarrow \mathbf{r} &= r \hat{e}_r (\sin^2 \theta \cos^2 \phi + \sin^2 \theta \sin^2 \phi + \cos^2 \theta) \\ &+ r \hat{e}_\theta (\sin \theta \cos \theta \cos^2 \phi + \sin \theta \sin^2 \phi \cos \theta - \cos \theta \sin \theta) \\ &+ r \hat{e}_\phi (-\cos \phi \sin \theta \sin \phi + \sin \theta \sin \phi \cos \phi)\end{aligned}$$

$$\begin{aligned}\Rightarrow \mathbf{r} &= r \hat{e}_r [\sin^2 \theta (\sin^2 \phi + \cos^2 \phi) + \cos^2 \theta] \\ &+ r \hat{e}_\theta [\sin \theta \cos \theta (\sin^2 \phi + \cos^2 \phi) - \cos \theta \sin \theta] \\ &= r \hat{e}_r (\sin^2 \theta + \cos^2 \theta) + r \hat{e}_\theta (\sin \theta \cos \theta - \sin \theta \cos \theta)\end{aligned}$$

$$\Rightarrow \mathbf{r} = r \hat{e}_r (1) = r \hat{e}_r$$

Then velocity $\mathbf{v}$ is $\mathbf{v} = \frac{d\mathbf{r}}{dt} = \frac{d}{dt}(r \hat{e}_r)$

$$\begin{aligned}\Rightarrow \mathbf{v} &= \frac{dr}{dt} \hat{e}_r + r \frac{d}{dt}(\hat{e}_r) \\ &= \dot{r} \hat{e}_r + r(\dot{\theta} \hat{e}_\theta + \sin \theta \dot{\phi} \hat{e}_\phi) \quad [\text{from previous eg.}] \\ &= \dot{r} \hat{e}_r + r \dot{\theta} \hat{e}_\theta + r \sin \theta \dot{\phi} \hat{e}_\phi \quad \dots(1)\end{aligned}$$

Differentiating (1) again, we obtain acceleration

$$\begin{aligned}\mathbf{a} &= \frac{d\mathbf{v}}{dt} = \frac{d^2\mathbf{r}}{dt^2} \\ \Rightarrow \mathbf{a} &= \frac{d}{dt}(\dot{r} \hat{e}_r + r \dot{\theta} \hat{e}_\theta + r \sin \theta \dot{\phi} \hat{e}_\phi) \\ &= \ddot{r} \hat{e}_r + \dot{r} \frac{d}{dt}(\hat{e}_r) + \dot{r} \dot{\theta} \hat{e}_\theta + r \ddot{\theta} \hat{e}_\theta + r \dot{\theta} \frac{d}{dt}(\hat{e}_\theta) \\ &\quad + r \sin \theta \dot{\phi} \hat{e}_\phi + r \cos \theta \dot{\phi} \hat{e}_\phi + r \sin \theta \dot{\phi} \frac{d}{dt}(\hat{e}_\phi) + r \sin \theta \dot{\phi} \frac{d}{dt}(\hat{e}_\phi) \\ &= \ddot{r} \hat{e}_r + \dot{r}(\dot{\theta} \hat{e}_\theta + \sin \theta \dot{\phi} \hat{e}_\phi) + \dot{r} \dot{\theta} \hat{e}_\theta + r \ddot{\theta} \hat{e}_\theta \\ &\quad + r \dot{\theta}(-\dot{\theta} \hat{e}_r + \cos \theta \dot{\phi} \hat{e}_\phi) + r \sin \theta \dot{\phi} \hat{e}_\phi\end{aligned}$$

$$\begin{aligned}
& + r \cos \theta \frac{d}{dt} \hat{e}_\phi + r \sin \theta \frac{d}{dt} \hat{e}_\phi \\
& + r \sin \theta \frac{d}{dt} (-\sin \theta \hat{e}_r - \cos \theta \hat{e}_\theta) \\
\Rightarrow \quad \vec{a} = \hat{e}_r \left(\frac{d^2 r}{dt^2} - r \sin^2 \theta \right) \\
& + \hat{e}_\theta \left[2r \frac{d\theta}{dt} + r \frac{d^2 \theta}{dt^2} - r \sin \theta \cos \theta \frac{d^2 \phi}{dt^2} \right] \\
& + \hat{e}_\phi \left[2r \frac{d\phi}{dt} \sin \theta + 2r \frac{d\phi}{dt} \cos \theta + r \sin \theta \frac{d^2 \phi}{dt^2} \right] \\
\Rightarrow \quad \vec{a} = \hat{e}_r \left(\frac{d^2 r}{dt^2} - r \sin^2 \theta \frac{d^2 \phi}{dt^2} \right) \\
& + \hat{e}_\theta \left[\frac{1}{r} \frac{d}{dt} (r^2 \frac{d\theta}{dt}) - r \sin \theta \cos \theta \frac{d^2 \phi}{dt^2} \right] \\
& + \hat{e}_\phi \left[\frac{1}{r \sin \theta} \frac{d}{dt} (r^2 \sin^2 \theta \frac{d\phi}{dt}) \right] \quad \dots(2)
\end{aligned}$$

$$\begin{aligned}
\left[\ominus \frac{1}{r} \frac{d}{dt} (r^2 \frac{d\theta}{dt}) = \frac{1}{r} (r^2 \frac{d^2 \theta}{dt^2} + 2r \frac{d\theta}{dt} \frac{d\theta}{dt}) = r \frac{d^2 \theta}{dt^2} + 2 \frac{d\theta}{dt} \frac{d\theta}{dt} \right. \\
= \frac{1}{r \sin \theta} [r^2 \sin^2 \theta \frac{d^2 \phi}{dt^2} + 2r \frac{d\phi}{dt} \sin^2 \theta + \frac{d}{dt} (r^2 \sin^2 \theta \frac{d\phi}{dt})] \\
\left. = r \sin \theta \frac{d^2 \phi}{dt^2} + 2 \frac{d\phi}{dt} \sin \theta + 2r \frac{d\phi}{dt} \cos \theta \right]
\end{aligned}$$

So (2) is required expression for acceleration of a particle in spherical coordinate.

Example : $\frac{d}{dt} \hat{e}_\phi = \hat{e}_\phi = -\sin \theta \hat{e}_r - \cos \theta \hat{e}_\theta$

Solution :- Now $\hat{e}_\phi = -\sin \phi \hat{i} + \cos \phi \hat{j}$

$$\Rightarrow \quad \frac{d}{dt} \hat{e}_\phi = -\cos \phi \hat{i} - \sin \phi \hat{j} \quad \dots(5)$$

Put values of $\hat{i}$ and $\hat{j}$ in(5), we get

$$\begin{aligned}
\frac{d}{dt} \hat{e}_\phi &= -\cos \phi (\hat{e}_r \sin \theta \cos \phi + \hat{e}_\phi \cos \theta \cos \phi - \hat{e}_\phi \sin \phi) \\
&\quad - \sin \phi (\hat{e}_r \sin \theta \sin \phi + \hat{e}_\theta \cos \theta \sin \phi + \hat{e}_\phi \cos \phi) \\
&= -\sin \theta \hat{e}_r (\cos^2 \phi + \sin^2 \phi) - \cos \theta \hat{e}_\theta (\cos^2 \phi + \sin^2 \phi) \\
&\quad + \hat{e}_\phi \cos \phi \sin \phi - \hat{e}_\phi \cos \phi \sin \phi
\end{aligned}$$

$$= -\sin\theta \hat{\phi} \hat{e}_r - \cos\theta \hat{\phi} \hat{e}_\theta. \text{ Hence Proved.}$$

Example:- Represent the vector $\vec{A} = z\hat{i} - 2x\hat{j} + y\hat{k}$ in cylindrical coordinates.

Solution :- In cylindrical coordinates,

$$x = r \cos \theta, \quad y = r \sin \theta, \quad z = z \quad \dots(1)$$

$$\text{and} \quad \hat{e}_r = \cos \theta \hat{i} + \sin \theta \hat{j}$$

$$\hat{e}_\theta = -\sin \theta \hat{i} + \cos \theta \hat{j} \quad \dots(2)$$

$$\hat{e}_z = \hat{k} \quad \dots(3)$$

The position vector of a particle P in rectangular coordinates is

$$\vec{A} = z\hat{i} + (-2x)\hat{j} + y\hat{k}$$

$$\Rightarrow \vec{A} = z\hat{i} - 2r \cos \theta \hat{j} + r \sin \theta \hat{k} \quad \dots(4)$$

Solve (2) for $\hat{i}$ and $\hat{j}$, we get on operating $\hat{e}_r \times \sin \theta + \hat{e}_\theta \times \cos \theta$

$$= \cos \theta \sin \theta \hat{i} + \sin^2 \theta \hat{j} - \sin \theta \cos \theta \hat{i} + \cos^2 \theta \hat{j}$$

$$\Rightarrow \hat{e}_r \sin \theta + \hat{e}_\theta \cos \theta = (\sin^2 \theta + \cos^2 \theta) \hat{j} = \hat{j} \quad \dots(5)$$

Similarly $\hat{e}_r \cos \theta - \hat{e}_\theta \sin \theta = \cos^2 \theta \hat{i} + \sin \theta \cos \theta \hat{j}$

$$- (-\sin^2 \theta \hat{i} + \cos \theta \sin \theta \hat{j})$$

$$\Rightarrow \hat{e}_r \cos \theta - \hat{e}_\theta \sin \theta = (\sin^2 \theta + \cos^2 \theta) \hat{i} + \sin \theta \cos \theta \hat{j} - \sin \theta \cos \theta \hat{j}$$

$$\Rightarrow \hat{e}_r \cos \theta - \hat{e}_\theta \sin \theta = \hat{i} \quad \dots(6)$$

Put the value of $\hat{i}, \hat{j}, \hat{k}$ from (3), (5), (6) in equation (4), we get

$$\vec{A} = z(\hat{e}_r \cos \theta - \hat{e}_\theta \sin \theta) - 2r \cos \theta (\hat{e}_r \sin \theta + \hat{e}_\theta \cos \theta) + r \sin \theta \hat{e}_z$$

$$= \hat{e}_r (z \cos \theta - 2r \cos \theta \sin \theta)$$

$$- \hat{e}_\theta (z \sin \theta + 2r \cos^2 \theta) + \hat{e}_z (r \sin \theta)$$

$$\Rightarrow \vec{A} = A_r \hat{e}_r + A_\theta \hat{e}_\theta + A_z \hat{e}_z \quad \dots(1)$$

where

$$A_r = z \cos \theta - 2r \cos \theta \sin \theta$$

$$A_\theta = -z \sin \theta - 2r \cos \theta \sin \theta$$

$$A_z = r \sin \theta$$

Equation (1) is required vector $\vec{A}$ in cylindrical coordinates.

Example:- Represent the vector $\vec{A} = z\hat{i} - 2x\hat{j} + y\hat{k}$ in spherical coordinates (r, θ, ϕ)

Solution :- In spherical coordinates,

$$\begin{aligned}x &= r \sin\theta \cos\phi \\y &= r \sin\theta \sin\phi \\z &= r \cos\theta\end{aligned}\quad \dots(2)$$

and

$$\begin{aligned}\hat{e}_r &= \sin\theta \cos\phi \hat{i} + \sin\theta \sin\phi \hat{j} + \cos\theta \hat{k} \\ \hat{e}_\theta &= \cos\theta \cos\phi \hat{i} + \cos\theta \sin\phi \hat{j} - \sin\theta \hat{k} \\ \hat{e}_\phi &= -\sin\phi \hat{i} + \cos\phi \hat{j}\end{aligned}\quad \dots(3)$$

Solving system (3) for $\hat{i}, \hat{j}, \hat{k}$ by Cramer's rule, for this we have

$$\begin{aligned}D &= \begin{vmatrix} \sin\theta \cos\phi & \sin\theta \sin\phi & \cos\theta \\ \cos\theta \cos\phi & \cos\theta \sin\phi & -\sin\theta \\ -\sin\phi & \cos\phi & 0 \end{vmatrix} \\ &= \sin\theta \cos\phi(\sin\theta \cos\phi) + \sin\theta \sin\phi(\sin\theta \sin\phi) \\ &\quad + \cos\theta(\cos\theta \cos^2\phi + \cos\theta \sin^2\phi) \\ &= \sin^2\theta \cos^2\phi + \sin^2\theta \sin^2\phi + \cos^2\theta (\cos^2\phi + \sin^2\phi) \\ &= \sin^2\theta(\cos^2\phi + \sin^2\phi) + \cos^2\theta (1) \\ &= \sin^2\theta + \cos^2\theta = 1\end{aligned}$$

$$\Rightarrow D = 1$$

and

$$\begin{aligned}D_1 &= \begin{vmatrix} \hat{e}_r & \sin\theta \sin\phi & \cos\theta \\ \hat{e}_\theta & \cos\theta \sin\phi & -\sin\theta \\ \hat{e}_\phi & \cos\phi & 0 \end{vmatrix} \\ &= \hat{e}_r(\sin\theta \cos\phi) + \sin\theta \sin\phi(-\sin\theta \hat{e}_\phi) \\ &\quad + \cos\theta(\hat{e}_\theta \cos\phi - \hat{e}_\phi \cos\theta \sin\phi) \\ &= \hat{e}_r \sin\theta \cos\phi + \hat{e}_\theta \cos\theta \cos\phi - \hat{e}_\phi \sin\phi(\sin^2\theta + \cos^2\theta)\end{aligned}$$

$$\Rightarrow D_1 = \hat{e}_r \sin\theta \cos\phi + \hat{e}_\theta \cos\theta \cos\phi - \hat{e}_\phi \sin\phi$$

$$\begin{aligned}
D_2 &= \begin{vmatrix} \sin \theta \cos \varphi & \hat{e}_r & \cos \theta \\ \cos \theta \cos \varphi & \hat{e}_\theta & -\sin \theta \\ -\sin \varphi & \hat{e}_\varphi & 0 \end{vmatrix} \\
&= \sin \theta \cos \varphi (\sin \theta \hat{e}_\varphi) + \hat{e}_r (\sin \theta \sin \varphi - 0) \\
&\quad + \cos \theta (\hat{e}_\varphi \cos \theta \cos \varphi + \hat{e}_\theta \sin \varphi) \\
&= \sin \theta \sin \varphi \hat{e}_r + \cos \theta \sin \varphi \hat{e}_\theta + \cos \varphi \hat{e}_\varphi (\sin^2 \theta + \cos^2 \theta)
\end{aligned}$$

$$\Rightarrow D_2 = \hat{e}_r \sin \theta \sin \varphi + \hat{e}_\theta \cos \theta \sin \varphi + \cos \varphi \hat{e}_\varphi$$

$$\begin{aligned}
D_3 &= \begin{vmatrix} \sin \theta \cos \varphi & \sin \theta \sin \varphi & \hat{e}_r \\ \cos \theta \cos \varphi & \cos \theta \sin \varphi & \hat{e}_\theta \\ -\sin \varphi & \cos \varphi & \hat{e}_\varphi \end{vmatrix} \\
&= \sin \theta \cos \varphi (\cos \theta \sin \varphi \hat{e}_\varphi - \cos \varphi \hat{e}_\theta) \\
&\quad + \sin \theta \sin \varphi (-\sin \varphi \hat{e}_\theta - \hat{e}_\varphi \cos \theta \cos \varphi) \\
&\quad + \hat{e}_r (\cos \theta \cos^2 \varphi + \cos \theta \sin^2 \varphi) \\
&= \hat{e}_r \cos \theta (\sin^2 \varphi + \cos^2 \varphi) + \\
&\quad \hat{e}_\theta (-\sin \theta \cos^2 \varphi - \sin \theta \sin^2 \varphi) \\
&\quad + \hat{e}_\varphi (\sin \theta \cos \theta \sin \varphi \cos \varphi - \sin \theta \cos \theta \sin \varphi \cos \varphi)
\end{aligned}$$

$$\Rightarrow D_3 = \hat{e}_r \cos \theta - \sin \theta \hat{e}_\theta$$

$$\text{Then } \hat{i} = \frac{D_1}{D} = \hat{e}_r \sin \theta \cos \varphi + \hat{e}_\theta \cos \theta \cos \varphi - \hat{e}_\varphi \sin \varphi$$

$$\hat{j} = \frac{D_2}{D} = \hat{e}_r \sin \theta \sin \varphi + \hat{e}_\theta \cos \theta \sin \varphi + \cos \varphi \hat{e}_\varphi$$

$$\hat{k} = \frac{D_3}{D} = \hat{e}_r \cos \theta - \hat{e}_\theta \sin \theta$$

from (1), (2) and (4), we get

$$\begin{aligned}
&\rho(r \cos \theta) (\hat{e}_r \sin \theta \cos \varphi + \hat{e}_\theta \cos \theta \cos \varphi - \hat{e}_\varphi \sin \varphi) \\
&\quad - 2r \sin \theta \cos \varphi (\hat{e}_r \sin \theta \sin \varphi + \hat{e}_\theta \cos \theta \sin \varphi + \hat{e}_\varphi \cos \varphi) \\
&\quad + r \sin \theta \sin \varphi (\hat{e}_r \cos \theta - \hat{e}_\theta \sin \theta)
\end{aligned}$$

$$\begin{aligned}
\Rightarrow \quad \vec{A} &= r \hat{e}_r (\cos\theta \sin\theta \cos\phi - 2 \sin^2\theta \cos\phi \sin\phi + \sin\theta \cos\theta \sin\phi) \\
&\quad + r \hat{e}_\theta (\cos^2\theta \cos\phi - 2 \sin\theta \cos\theta \sin\phi \cos\phi) \\
&\quad + r \hat{e}_\phi (-\cos\theta \sin\phi - 2 \sin\theta \cos^2\phi) \\
&= r \hat{e}_r [\sin\theta \cos\theta (\cos\phi + \sin\phi) - 2 \sin^2\theta \cos\phi \sin\phi] \\
&\quad + r \hat{e}_\theta (\cos^2\theta \cos\phi - 2 \sin\theta \cos\theta \sin\phi \cos\phi) \\
&\quad + r \hat{e}_\phi (-\cos\theta \sin\phi - 2 \sin\theta \cos^2\phi) \\
\Rightarrow \quad \vec{A} &= A_r \hat{e}_r + A_\theta \hat{e}_\theta + A_\phi \hat{e}_\phi
\end{aligned}$$

which is required expression.

Example:- Find the square of the element of arc length in cylindrical & spherical coordinates

Solution:- In cylindrical coordinates,

$$x = r \cos\theta, y = r \sin\theta, z = z$$

$$\text{Now } (ds)^2 = (dx)^2 + (dy)^2 + (dz)^2 \quad \dots(1)$$

$$\text{as } dx = dr \cos\theta - r \sin\theta d\theta$$

$$dy = dr \sin\theta + r \cos\theta d\theta \quad \dots(2)$$

$$dz = dz$$

Put (2) in (1), we get

$$\begin{aligned}
(ds)^2 &= (\cos\theta dr - r \sin\theta d\theta)^2 \\
&\quad + (\sin\theta dr + r \cos\theta d\theta)^2 + (dz)^2 \\
&= (dr)^2 (\sin^2\theta + \cos^2\theta) + (d\theta)^2 (r^2 \sin^2\theta + r^2 \cos^2\theta) \\
&\quad - 2r \sin\theta \cos\theta dr d\theta + 2r \sin\theta \cos\theta dr d\theta + (dz)^2
\end{aligned}$$

$$\Rightarrow (ds)^2 = (dr)^2 + r^2 (d\theta)^2 + (dz)^2 = h_1^2 (dr)^2 + h_2^2 (d\theta)^2 + h_3^2 (dz)^2$$

In spherical coordinates (r, θ, ϕ)

$$x = r \sin\theta \cos\phi, y = r \sin\theta \sin\phi, z = r \cos\theta \quad \dots(1)$$

$$\text{as } (ds)^2 = (dx)^2 + (dy)^2 + (dz)^2$$

using (1), we get

$$(ds)^2 = (dr)^2 + r^2 (d\theta)^2 + r^2 \sin^2\theta (d\phi)^2$$

Comparing it with,

$$(ds)^2 = h_1^2 (du_1)^2 + h_2^2 (du_2)^2 + h_3^2 (du_3)^2, \text{ we get}$$

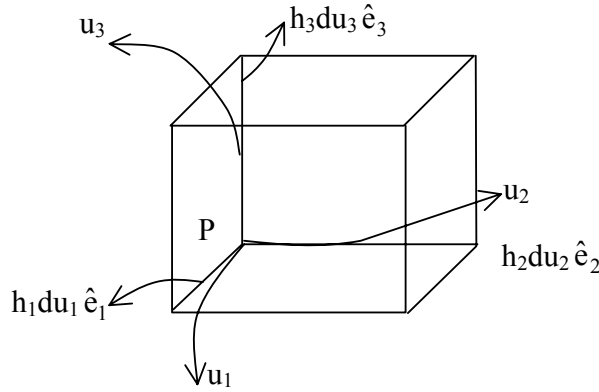
$$h_1 = 1, h_2 = r_1, h_3 = r \sin \theta$$

$$u_1 = r, u_2 = \theta, u_3 = \phi$$

$$\text{we get } (ds)^2 = h_1^2 (dr)^2 + h_2^2 (d\theta)^2 + h_3^2 (d\phi)^2$$

Example : - Find expression for the elements of area in orthogonal curvilinear coordinates.

Solution: -



Now area element is given by

$$\begin{aligned} dA_1 &= |h_2 du_2 \hat{e}_2 \times h_3 du_3 \hat{e}_3| \\ &= h_2 h_3 |\hat{e}_2 \times \hat{e}_3| du_2 du_3 = h_2 h_3 |\hat{e}_1| du_2 du_3 \\ &= h_2 h_3 du_2 du_3 \end{aligned}$$

$$[\Theta | \hat{e}_1 | = 1]$$

$$\begin{aligned} dA_2 &= |h_3 du_3 \hat{e}_3 \times h_1 du_1 \hat{e}_1| \\ &= h_3 h_1 |\hat{e}_3 \times \hat{e}_1| du_3 du_1 = |\hat{e}_2| du_3 du_1 \end{aligned}$$

$$[\Theta | \hat{e}_2 | = 1]$$

$$\begin{aligned} dA_3 &= |h_1 du_1 \hat{e}_1 \times h_2 du_2 \hat{e}_2| \\ &= h_1 h_2 |\hat{e}_1 \times \hat{e}_2| du_1 du_2 \\ &= h_1 h_2 |\hat{e}_3| du_1 du_2 = h_1 h_2 du_1 du_2 \end{aligned}$$

$$[\Theta | \hat{e}_3 | = 1]$$

Example:- Find the volume element dv in cylindrical & spherical coordinate system.

Solution: - We know that volume element dV in orthogonal curvilinear coordinates is

$$dV = h_1 h_2 h_3 du_1 du_2 du_3 \quad \dots(1)$$

In cylindrical coordinates (r, θ, ϕ)

$$h_1 = 1, h_2 = r, h_3 = 1$$

$$u_1 = r, u_2 = \theta, u_3 = z$$

$$\text{So (1)} \Rightarrow dV = r dr d\theta dz$$

In spherical coordinates (r, θ, ϕ)

$$h_1 = 1, h_2 = r, h_3 = r \sin \theta$$

$$u_1 = r, u_2 = \theta, u_3 = \phi$$

$$\therefore \text{So (1)} \Rightarrow dV r^2 \sin^2 \theta dr d\theta d\phi$$

Example:- If u_1, u_2, u_3 are general coordinates, show that $\frac{\partial \mathcal{F}}{\partial u_1}, \frac{\partial \mathcal{F}}{\partial u_2}, \frac{\partial \mathcal{F}}{\partial u_3}$ & $\nabla u_1, \nabla u_2, \nabla u_3$ are

reciprocal system of vectors.

Solution:- We know that if $\phi = \phi(x, y, z)$

$$\begin{aligned} d\phi &= \frac{\partial \phi}{\partial x} dx + \frac{\partial \phi}{\partial y} dy + \frac{\partial \phi}{\partial z} dz \\ &= \left(\frac{\partial \phi}{\partial x} \hat{i} + \frac{\partial \phi}{\partial y} \hat{j} + \frac{\partial \phi}{\partial z} \hat{k} \right) \cdot (dx \hat{i} + dy \hat{j} + dz \hat{k}) \end{aligned}$$

$$\Rightarrow d\phi = \nabla \phi \cdot d\mathcal{F}$$

Replacing ϕ with ∇u_p , we get

$$du_p = \nabla u_p \cdot d\mathcal{F} \quad \dots(1)$$

$$\Rightarrow du_1 = \nabla u_1 \cdot d\mathcal{F}$$

$$du_2 = \nabla u_2 \cdot d\mathcal{F}$$

$$du_3 = \nabla u_3 \cdot d\mathcal{F}$$

Now $\mathcal{F} = \mathcal{F}(u_1, u_2, u_3)$

$$\Rightarrow d\mathcal{F} = \frac{\partial \mathcal{F}}{\partial u_1} du_1 + \frac{\partial \mathcal{F}}{\partial u_2} du_2 + \frac{\partial \mathcal{F}}{\partial u_3} du_3 \quad \dots(2)$$

Taking dot product with ∇u_1 , we get

$$\nabla u_1 \cdot d\mathcal{F} = \left(\nabla u_1 \cdot \frac{\partial \mathcal{F}}{\partial u_1} \right) du_1 + \left(\nabla u_1 \cdot \frac{\partial \mathcal{F}}{\partial u_2} \right) du_2 + \left(\nabla u_1 \cdot \frac{\partial \mathcal{F}}{\partial u_3} \right) du_3 \quad \dots(3)$$

$$\Rightarrow du_1 = \left(\nabla u_1 \cdot \frac{\partial \mathcal{F}}{\partial u_1} \right) du_1 + \left(\nabla u_1 \cdot \frac{\partial \mathcal{F}}{\partial u_2} \right) du_2 + \left(\nabla u_1 \cdot \frac{\partial \mathcal{F}}{\partial u_3} \right) du_3 \quad [\text{using (1)}]$$

Comparing like coefficients on both sides,

$$\nabla u_1 \cdot \frac{\partial \mathcal{F}}{\partial u_1} = 1, \quad \nabla u_1 \cdot \frac{\partial \mathcal{F}}{\partial u_2} = 0, \quad \nabla u_1 \cdot \frac{\partial \mathcal{F}}{\partial u_3} = 0$$

Similarly taking dot product of (2) with ∇u_2 and ∇u_3 , we get

$$\nabla u_2 \cdot \frac{\partial f^p}{\partial u_2} = 1, \nabla u_2 \cdot \frac{\partial f^p}{\partial u_1} = 0 \quad \nabla u_2 \cdot \frac{\partial f^p}{\partial u_3} = 0$$

$$\nabla u_3 \cdot \frac{\partial f^p}{\partial u_3} = 1,$$

So we get the required result i.e.

$$\nabla u_p \cdot \frac{\partial f^p}{\partial u_q} = \begin{cases} 1 & \text{if } p = q \\ 0 & \text{if } p \neq q \end{cases}$$

Where $(p, q) = (1, 2, 3)$

Example: - Prove that $\hat{e}_1 = h_2 h_3 \nabla u_2 \times \nabla u_3$ with similar equation for $\hat{e}_2$ and $\hat{e}_3$ where u_1, u_2, u_3 are orthogonal coordinates.

Solution: - We know that

$$\nabla u_1 = \frac{\hat{e}_1}{h_1}, \quad \nabla u_2 = \frac{\hat{e}_2}{h_2}, \quad \nabla u_3 = \frac{\hat{e}_3}{h_3}$$

$$\text{Then } \nabla u_2 \times \nabla u_3 = \frac{\hat{e}_2 \times \hat{e}_3}{h_2 h_3} = \frac{\hat{e}_1}{h_2 h_3}$$

$$\Rightarrow \hat{e}_1 = h_2 h_3 \nabla u_2 \times \nabla u_3$$

$$\text{Similarly } \nabla u_3 \times \nabla u_1 = \frac{\hat{e}_3 \times \hat{e}_1}{h_3 h_1} = \frac{\hat{e}_2}{h_3 h_1}$$

$$\Rightarrow \hat{e}_2 = h_3 h_1 \nabla u_3 \times \nabla u_1$$

$$\text{and } \nabla u_1 \times \nabla u_2 = \frac{\hat{e}_1 \times \hat{e}_2}{h_1 h_2} = \frac{\hat{e}_3}{h_1 h_2}$$

$$\Rightarrow \hat{e}_3 = h_1 h_2 \nabla u_1 \times \nabla u_2 \quad \text{Hence proved.}$$

Example: - If u_1, u_2, u_3 are orthogonal curvilinear coordinates, show that the jacobian of x, y, z w.r.t. u_1, u_2, u_3 is

$$J\left(\frac{x, y, z}{u_1 u_2 u_3}\right) = \frac{\partial(x, y, z)}{\partial(u_1, u_2, u_3)} = \begin{vmatrix} \frac{\partial x}{\partial u_1} & \frac{\partial y}{\partial u_1} & \frac{\partial z}{\partial u_1} \\ \frac{\partial x}{\partial u_2} & \frac{\partial y}{\partial u_2} & \frac{\partial z}{\partial u_2} \\ \frac{\partial x}{\partial u_3} & \frac{\partial y}{\partial u_3} & \frac{\partial z}{\partial u_3} \end{vmatrix}$$

$$= h_1 h_2 h_3$$

Proof: - we know that $\vec{A} = A_1 \hat{i} + A_2 \hat{j} + A_3 \hat{k}$

$$\vec{B} = (B_1, B_2, B_3), \quad \vec{C} = (C_1, C_2, C_3)$$

Then

$$\begin{aligned} \vec{A} \cdot (\vec{B} \times \vec{C}) &= \vec{A} \cdot \begin{vmatrix} \hat{i} & \hat{j} & \hat{k} \\ B_1 & B_2 & B_3 \\ C_1 & C_2 & C_3 \end{vmatrix} \\ &= (A_1 \hat{i} + A_2 \hat{j} + A_3 \hat{k}) \cdot [\hat{i} (B_2 C_3 - B_3 C_2) + \hat{j} (B_3 C_1 - B_1 C_3) + \hat{k} (B_1 C_2 - B_2 C_1)] \\ \Rightarrow \vec{A} \cdot (\vec{B} \times \vec{C}) &= A_1 (B_2 C_3 - B_3 C_2) + A_2 (B_3 C_1 - B_1 C_3) + A_3 (B_1 C_2 - B_2 C_1) \\ \Rightarrow \vec{A} \cdot (\vec{B} \times \vec{C}) &= \begin{vmatrix} A_1 & A_2 & A_3 \\ B_1 & B_2 & B_3 \\ C_1 & C_2 & C_3 \end{vmatrix} \end{aligned}$$

Therefore

$$\begin{aligned} \begin{vmatrix} \frac{\partial x}{\partial u_1} & \frac{\partial y}{\partial u_1} & \frac{\partial z}{\partial u_1} \\ \frac{\partial x}{\partial u_2} & \frac{\partial y}{\partial u_2} & \frac{\partial z}{\partial u_2} \\ \frac{\partial x}{\partial u_3} & \frac{\partial y}{\partial u_3} & \frac{\partial z}{\partial u_3} \end{vmatrix} &= \left(\frac{\partial x}{\partial u_1} \hat{i} + \frac{\partial y}{\partial u_1} \hat{j} + \frac{\partial z}{\partial u_1} \hat{k} \right) \left[\left(\frac{\partial x}{\partial u_2} \hat{i} + \frac{\partial y}{\partial u_2} \hat{j} + \frac{\partial z}{\partial u_2} \hat{k} \right) \right. \\ &\quad \left. \times \left(\frac{\partial x}{\partial u_3} \hat{i} + \frac{\partial y}{\partial u_3} \hat{j} + \frac{\partial z}{\partial u_3} \hat{k} \right) \right] \\ &= \left(\frac{\partial \vec{r}}{\partial u_1} \right) \cdot \left(\frac{\partial \vec{r}}{\partial u_2} \times \frac{\partial \vec{r}}{\partial u_3} \right) \\ &= h_1 \vec{e}_1 \cdot (h_2 \vec{e}_2 \times h_3 \vec{e}_3) \\ &= h_1 \vec{e}_1 \cdot h_2 h_3 (\vec{e}_2 \times \vec{e}_3) = h_1 \vec{e}_1 \cdot h_2 h_3 \vec{e}_1 \end{aligned}$$

$$\begin{aligned}
&= h_1 h_2 h_3 \xi_1^\nu \xi_1^\nu \\
&= h_1 h_2 h_3 \xi_1^\nu \xi_1^\nu \\
&= h_1 h_2 h_3 \quad [\Theta \quad \xi_1^\nu \xi_1^\nu = 1]
\end{aligned}$$

Hence proved.

Contravariant Components of $\vec{A}$ and covariant components of $\vec{A}$

$\vec{A}$ in terms of unit base vectors $\hat{e}_1, \hat{e}_2, \hat{e}_3$ or $\hat{E}_1, \hat{E}_2, \hat{E}_3$ can be written as

$$\vec{A} = A_1 \hat{e}_1 + A_2 \hat{e}_2 + A_3 \hat{e}_3 = a_1 \hat{E}_1 + a_2 \hat{E}_2 + a_3 \hat{E}_3$$

Where A_1, A_2, A_3 & a_1, a_2, a_3 are components of $\vec{A}$ in each that $\frac{\partial \vec{r}}{\partial u_1}, \frac{\partial \vec{r}}{\partial u_2}, \frac{\partial \vec{r}}{\partial u_3}$ and $\nabla u_1, \nabla u_2,$

∇u_3 constitute reciprocal system of vectors. We can also represent $\vec{A}$ in terms of base vectors $\frac{\partial \vec{r}}{\partial u_1}, \frac{\partial \vec{r}}{\partial u_2}, \frac{\partial \vec{r}}{\partial u_3}$ or $\nabla u_1, \nabla u_2, \nabla u_3$ which are called **unitary base vectors** & are not unit vectors.

In general,

$$\begin{aligned}
\vec{A} &= C_1 \frac{\partial \vec{r}}{\partial u_1} + C_2 \frac{\partial \vec{r}}{\partial u_2} + C_3 \frac{\partial \vec{r}}{\partial u_3} \\
\Rightarrow \vec{A} &= C_1 \alpha_1 + C_2 \alpha_2 + C_3 \alpha_3 \quad \text{where } \alpha_p = \frac{\partial \vec{r}}{\partial u_p}, p = 1, 2, 3
\end{aligned}$$

$$\begin{aligned}
&\& \vec{A} = C_1 \nabla u_1 + C_2 \nabla u_2 + C_3 \nabla u_3 \\
&= C_1 \beta_1 + C_2 \beta_2 + C_3 \beta_3 \quad \text{where } \beta_p = \nabla u_p, p = 1, 2, 3
\end{aligned}$$

where C_1, C_2, C_3 are called **contravariant component** of $\vec{A}$ and $\alpha_1, \alpha_2, \alpha_3$ are called **covariant components of $\vec{A}$** .

Example: - Let $\vec{A}$ be a given vector defined w.r.t. two general curvilinear coordinates system (u_1, u_2, u_3) & $(\bar{u}_1, \bar{u}_2, \bar{u}_3)$. Find the relation between the contravariant components of the vector in the two coordinate system.

(Find relation between C_p and $\bar{C}_p$)

Solution: - Suppose the transformation equation from rectangular (x, y, z) system to the two general curvilinear coordinations systems (u_1, u_2, u_3) and $(\bar{u}_1, \bar{u}_2, \bar{u}_3)$ are given by

$$x = x_1(u_1, u_2, u_3), \quad y = y_1(u_1, u_2, u_3), \quad z = z_1(u_1, u_2, u_3)$$

$$x = x_2(\bar{u}_1, \bar{u}_2, \bar{u}_3), \quad y = y_2(\bar{u}_1, \bar{u}_2, \bar{u}_3), \quad z = z_2(\bar{u}_1, \bar{u}_2, \bar{u}_3) \quad \dots(1)$$

Then

A transformation directly from (u_1, u_2, u_3) system to $(\bar{u}_1, \bar{u}_2, \bar{u}_3)$ system is defined by

$$u_1 = u_1(\bar{u}_1, \bar{u}_2, \bar{u}_3), \quad u_2 = u_2(\bar{u}_1, \bar{u}_2, \bar{u}_3), \quad u_3 = u_3(\bar{u}_1, \bar{u}_2, \bar{u}_3) \quad \dots(i)$$

$$\bar{u}_1 = \bar{u}_1(u_1, u_2, u_3), \quad \bar{u}_2 = \bar{u}_2(u_1, u_2, u_3), \quad \bar{u}_3 = \bar{u}_3(u_1, u_2, u_3) \quad \dots(2)$$

Let $\mathbf{r} = x\hat{i} + y\hat{j} + z\hat{k}$

Then use (1)

$$\mathbf{r} = \mathbf{r}(u_1, u_2, u_3), \quad \mathbf{r} = \mathbf{r}(\bar{u}_1, \bar{u}_2, \bar{u}_3)$$

$$\begin{aligned} d\mathbf{r} &= \frac{\partial \mathbf{r}}{\partial u_1} du_1 + \frac{\partial \mathbf{r}}{\partial u_2} du_2 + \frac{\partial \mathbf{r}}{\partial u_3} du_3 \\ &= \alpha_1 du_1 + \alpha_2 du_2 + \alpha_3 du_3 \end{aligned} \quad \dots(3)$$

$$\begin{aligned} \& \quad d\mathbf{r} &= \frac{\partial \mathbf{r}}{\partial \bar{u}_1} d\bar{u}_1 + \frac{\partial \mathbf{r}}{\partial \bar{u}_2} d\bar{u}_2 + \frac{\partial \mathbf{r}}{\partial \bar{u}_3} d\bar{u}_3 \\ &= \bar{\alpha}_1 d\bar{u}_1 + \bar{\alpha}_2 d\bar{u}_2 + \bar{\alpha}_3 d\bar{u}_3 \end{aligned} \quad \dots(4)$$

where $\alpha_p = \frac{\partial \mathbf{r}}{\partial u_p}, \quad \bar{\alpha}_p = \frac{\partial \mathbf{r}}{\partial \bar{u}_p}, \quad p = 1, 2, 3$

from (3) & (4), we get

$$\alpha_1 du_1 + \alpha_2 du_2 + \alpha_3 du_3 = \bar{\alpha}_1 d\bar{u}_1 + \bar{\alpha}_2 d\bar{u}_2 + \bar{\alpha}_3 d\bar{u}_3 \quad \dots(5)$$

from 2(i) since $u_p = u_p(\bar{u}_1, \bar{u}_2, \bar{u}_3)$

$$\begin{aligned} \Rightarrow \quad du_1 &= \frac{\partial u_1}{\partial \bar{u}_1} d\bar{u}_1 + \frac{\partial u_1}{\partial \bar{u}_2} d\bar{u}_2 + \frac{\partial u_1}{\partial \bar{u}_3} d\bar{u}_3 \\ du_2 &= \frac{\partial u_2}{\partial \bar{u}_1} d\bar{u}_1 + \frac{\partial u_2}{\partial \bar{u}_2} d\bar{u}_2 + \frac{\partial u_2}{\partial \bar{u}_3} d\bar{u}_3 \\ du_3 &= \frac{\partial u_3}{\partial \bar{u}_1} d\bar{u}_1 + \frac{\partial u_3}{\partial \bar{u}_2} d\bar{u}_2 + \frac{\partial u_3}{\partial \bar{u}_3} d\bar{u}_3 \end{aligned}$$

using these in L.H.S of (5) and equating coefficient of $d\bar{u}_1, d\bar{u}_2, d\bar{u}_3$, we get

$$\alpha_1 du_1 + \alpha_2 du_2 + \alpha_3 du_3 = \left(\frac{\partial u_1}{\partial \bar{u}_1} d\bar{u}_1 + \frac{\partial u_1}{\partial \bar{u}_2} d\bar{u}_2 + \frac{\partial u_1}{\partial \bar{u}_3} d\bar{u}_3 \right) \bar{\alpha}_1$$

$$\begin{aligned}
& + \left(\frac{\partial u_2}{\partial \bar{u}_1} d\bar{u}_1 + \frac{\partial u_2}{\partial \bar{u}_2} d\bar{u}_2 + \frac{\partial u_{21}}{\partial \bar{u}_3} d\bar{u}_3 \right) \rho_2 \\
& + \left(\frac{\partial u_3}{\partial \bar{u}_1} d\bar{u}_1 + \frac{\partial u_3}{\partial \bar{u}_2} d\bar{u}_2 + \frac{\partial u_3}{\partial \bar{u}_3} d\bar{u}_3 \right) \rho_3 \\
& = \rho_1 d\bar{u}_1 + \rho_2 d\bar{u}_2 + \rho_3 d\bar{u}_3
\end{aligned}$$

We get $\frac{\rho}{\alpha_1} = \rho_1 \frac{\partial u_1}{\partial \bar{u}_1} + \rho_2 \frac{\partial u_2}{\partial \bar{u}_1} + \rho_3 \frac{\partial u_3}{\partial \bar{u}_1}$

$$\frac{\rho}{\alpha_2} = \rho_1 \frac{\partial u_1}{\partial \bar{u}_2} + \rho_2 \frac{\partial u_2}{\partial \bar{u}_2} + \rho_3 \frac{\partial u_3}{\partial \bar{u}_2}$$

$$\frac{\rho}{\alpha_3} = \rho_1 \frac{\partial u_1}{\partial \bar{u}_3} + \rho_2 \frac{\partial u_2}{\partial \bar{u}_3} + \rho_3 \frac{\partial u_3}{\partial \bar{u}_3} \quad \dots(6)$$

Also $\overset{\rho}{A} = \rho_1 C_1 + \rho_2 C_2 + \rho_3 C_3$
 $= \frac{\rho}{\alpha_1} \bar{C}_1 + \frac{\rho}{\alpha_2} \bar{C}_2 + \frac{\rho}{\alpha_3} \bar{C}_3 \quad \dots(7)$

where C_1, C_2, C_3 and $\bar{C}_1, \bar{C}_2, \bar{C}_3$ are contravariant components of $\overset{\rho}{A}$ in the two systems (u_1, u_2, u_3) and $(\bar{u}_1, \bar{u}_2, \bar{u}_3)$. Substituting (6) in (7),

$$\begin{aligned}
C_1 \rho_1 + C_2 \rho_2 + C_3 \rho_3 &= \rho_1 \left(\rho_1 \frac{\partial u_1}{\partial \bar{u}_1} + \rho_2 \frac{\partial u_2}{\partial \bar{u}_1} + \rho_3 \frac{\partial u_3}{\partial \bar{u}_1} \right) \\
&+ \rho_2 \left(\rho_1 \frac{\partial u_1}{\partial \bar{u}_2} + \rho_2 \frac{\partial u_2}{\partial \bar{u}_2} + \rho_3 \frac{\partial u_3}{\partial \bar{u}_2} \right) \\
&+ \rho_3 \left(\rho_1 \frac{\partial u_1}{\partial \bar{u}_3} + \rho_2 \frac{\partial u_2}{\partial \bar{u}_3} + \rho_3 \frac{\partial u_3}{\partial \bar{u}_3} \right) \\
&= \rho_1 \left(\rho_1 \frac{\partial u_1}{\partial \bar{u}_1} + \bar{C}_2 \frac{\partial u_1}{\partial \bar{u}_2} + \bar{C}_3 \frac{\partial u_1}{\partial \bar{u}_3} \right) \\
&+ \rho_2 \left(\rho_1 \frac{\partial u_2}{\partial \bar{u}_1} + \bar{C}_2 \frac{\partial u_2}{\partial \bar{u}_2} + \bar{C}_3 \frac{\partial u_2}{\partial \bar{u}_3} \right) \\
&+ \rho_3 \left(\rho_1 \frac{\partial u_3}{\partial \bar{u}_1} + \bar{C}_2 \frac{\partial u_3}{\partial \bar{u}_2} + \bar{C}_3 \frac{\partial u_3}{\partial \bar{u}_3} \right)
\end{aligned}$$

Equating coefficients of ρ_1, ρ_2, ρ_3 , we get

$$\begin{aligned}
C_1 &= \bar{C}_1 \frac{\partial u_1}{\partial \bar{u}_1} + \bar{C}_2 \frac{\partial u_1}{\partial \bar{u}_2} + \bar{C}_3 \frac{\partial u_1}{\partial \bar{u}_3} \\
C_2 &= \bar{C}_1 \frac{\partial u_2}{\partial \bar{u}_1} + \bar{C}_2 \frac{\partial u_2}{\partial \bar{u}_2} + \bar{C}_3 \frac{\partial u_2}{\partial \bar{u}_3} \\
C_3 &= \bar{C}_1 \frac{\partial u_3}{\partial \bar{u}_1} + \bar{C}_2 \frac{\partial u_3}{\partial \bar{u}_2} + \bar{C}_3 \frac{\partial u_3}{\partial \bar{u}_3} \quad \dots(8)
\end{aligned}$$

$$\text{or } C_p = \bar{C}_1 \frac{\partial u_p}{\partial \bar{u}_1} + \bar{C}_2 \frac{\partial u_p}{\partial \bar{u}_2} + \bar{C}_3 \frac{\partial u_p}{\partial \bar{u}_3}, p = 1, 2, 3 \quad \dots(9)$$

$$\text{or } C_p = \sum_{q=1}^3 \bar{C}_q \frac{\partial u_p}{\partial \bar{u}_q}, p = 1, 2, 3 \quad \dots(10)$$

Similarly by interchanging the coordinates,

We can get

$$\bar{C}_p = \sum_{q=1}^3 C_q \frac{\partial \bar{u}_p}{\partial u_q}, p = 1, 2, 3 \quad \dots(11)$$

Equation (8), (9), (10), (11) gives the relation between contravariant components of vector in two coordinates systems.

Example: - Let $\vec{A}$ be given vector defined w.r.t. two curvilinear coordinates system (u_1, u_2, u_3) and $(\bar{u}_1, \bar{u}_2, \bar{u}_3)$. Find the relation between the covariant components of the vectors in the two coordinate system.

Solution: - Let the covariant component of $\vec{A}$ in the system (u_1, u_2, u_3) and $(\bar{u}_1, \bar{u}_2, \bar{u}_3)$ are C_1, C_2, C_3 and $\bar{C}_1, \bar{C}_2, \bar{C}_3$ respectively

$$\therefore \vec{A} = C_1 \nabla u_1 + C_2 \nabla u_2 + C_3 \nabla u_3 = \bar{C}_1 \nabla \bar{u}_1 + \bar{C}_2 \nabla \bar{u}_2 + \bar{C}_3 \nabla \bar{u}_3 \quad \dots(1)$$

Since $\bar{u}_p = \bar{u}_p(u_1, u_2, u_3)$, $p=1, 2, 3$

$$\begin{aligned}
\frac{\partial \bar{u}_p}{\partial x} &= \frac{\partial \bar{u}_p}{\partial u_1} \frac{\partial u_1}{\partial x} + \frac{\partial \bar{u}_p}{\partial u_2} \frac{\partial u_2}{\partial x} + \frac{\partial \bar{u}_p}{\partial u_3} \frac{\partial u_3}{\partial x} \\
\frac{\partial \bar{u}_p}{\partial y} &= \frac{\partial \bar{u}_p}{\partial u_1} \frac{\partial u_1}{\partial y} + \frac{\partial \bar{u}_p}{\partial u_2} \frac{\partial u_2}{\partial y} + \frac{\partial \bar{u}_p}{\partial u_3} \frac{\partial u_3}{\partial y} \\
\frac{\partial \bar{u}_p}{\partial z} &= \frac{\partial \bar{u}_p}{\partial u_1} \frac{\partial u_1}{\partial z} + \frac{\partial \bar{u}_p}{\partial u_2} \frac{\partial u_2}{\partial z} + \frac{\partial \bar{u}_p}{\partial u_3} \frac{\partial u_3}{\partial z} \quad \dots(2)
\end{aligned}$$

$$\begin{aligned}
\text{Also } C_1 \nabla u_1 + C_2 \nabla u_2 + C_3 \nabla u_3 &= C_1 \left(\frac{\partial u_1}{\partial x} \hat{i} + \frac{\partial u_1}{\partial y} \hat{j} + \frac{\partial u_1}{\partial z} \hat{k} \right) \\
&+ C_2 \left(\frac{\partial u_2}{\partial x} \hat{i} + \frac{\partial u_2}{\partial y} \hat{j} + \frac{\partial u_2}{\partial z} \hat{k} \right) \\
&+ C_3 \left(\frac{\partial u_3}{\partial x} \hat{i} + \frac{\partial u_3}{\partial y} \hat{j} + \frac{\partial u_3}{\partial z} \hat{k} \right) \\
&= \left(C_1 \frac{\partial u_1}{\partial x} + C_2 \frac{\partial u_2}{\partial x} + C_3 \frac{\partial u_3}{\partial x} \right) \hat{i} \\
&+ \left(C_1 \frac{\partial u_1}{\partial y} + C_2 \frac{\partial u_2}{\partial y} + C_3 \frac{\partial u_3}{\partial y} \right) \hat{j} \\
&+ \left(C_1 \frac{\partial u_1}{\partial z} + C_2 \frac{\partial u_2}{\partial z} + C_3 \frac{\partial u_3}{\partial z} \right) \hat{k} \quad \dots(3)
\end{aligned}$$

$$\begin{aligned}
\text{and } \bar{C}_1 \nabla \bar{u}_1 + \bar{C}_2 \nabla \bar{u}_2 + \bar{C}_3 \nabla \bar{u}_3 &= \left(\bar{C}_1 \frac{\partial \bar{u}_1}{\partial x} + \bar{C}_2 \frac{\partial \bar{u}_2}{\partial x} + \bar{C}_3 \frac{\partial \bar{u}_3}{\partial x} \right) \hat{i} \\
&+ \left(\bar{C}_1 \frac{\partial \bar{u}_1}{\partial y} + \bar{C}_2 \frac{\partial \bar{u}_2}{\partial y} + \bar{C}_3 \frac{\partial \bar{u}_3}{\partial y} \right) \hat{j} \\
&+ \left(\bar{C}_1 \frac{\partial \bar{u}_1}{\partial z} + \bar{C}_2 \frac{\partial \bar{u}_2}{\partial z} + \bar{C}_3 \frac{\partial \bar{u}_3}{\partial z} \right) \hat{k} \quad \dots(4)
\end{aligned}$$

Equating coefficients of $\hat{i}, \hat{j}, \hat{k}$ in (3) & (4),

We get

$$\begin{aligned}
C_1 \frac{\partial u_1}{\partial x} + C_2 \frac{\partial u_2}{\partial x} + C_3 \frac{\partial u_3}{\partial x} &= \bar{C}_1 \frac{\partial \bar{u}_1}{\partial x} + \bar{C}_2 \frac{\partial \bar{u}_2}{\partial x} + \bar{C}_3 \frac{\partial \bar{u}_3}{\partial x} \\
C_1 \frac{\partial u_1}{\partial y} + C_2 \frac{\partial u_2}{\partial y} + C_3 \frac{\partial u_3}{\partial y} &= \bar{C}_1 \frac{\partial \bar{u}_1}{\partial y} + \bar{C}_2 \frac{\partial \bar{u}_2}{\partial y} + \bar{C}_3 \frac{\partial \bar{u}_3}{\partial y} \\
C_1 \frac{\partial u_1}{\partial z} + C_2 \frac{\partial u_2}{\partial z} + C_3 \frac{\partial u_3}{\partial z} &= \bar{C}_1 \frac{\partial \bar{u}_1}{\partial z} + \bar{C}_2 \frac{\partial \bar{u}_2}{\partial z} + \bar{C}_3 \frac{\partial \bar{u}_3}{\partial z} \quad \dots(5)
\end{aligned}$$

Substituting equation (2) with $p = 1, 2, 3$ on R.H.S in the corresponding equation of (5) and

equating coefficients of $\frac{\partial u_1}{\partial x}, \frac{\partial u_2}{\partial x}, \frac{\partial u_3}{\partial x}$ or $\frac{\partial u_1}{\partial y}, \frac{\partial u_2}{\partial y}, \frac{\partial u_3}{\partial y}$ or $\frac{\partial u_1}{\partial z}, \frac{\partial u_2}{\partial z}, \frac{\partial u_3}{\partial z}$ on each side,

We can get,

Taking first equation of (5),

$$\begin{aligned} C_1 \frac{\partial u_1}{\partial x} + C_2 \frac{\partial u_2}{\partial x} + C_3 \frac{\partial u_3}{\partial x} &= \bar{C}_1 \left[\frac{\partial \bar{u}_1}{\partial u_1} \frac{\partial u_1}{\partial x} + \frac{\partial \bar{u}_1}{\partial u_2} \frac{\partial u_2}{\partial x} + \frac{\partial \bar{u}_1}{\partial u_3} \frac{\partial u_3}{\partial x} \right] \\ &+ \bar{C}_2 \left[\frac{\partial \bar{u}_2}{\partial u_1} \frac{\partial u_1}{\partial x} + \frac{\partial \bar{u}_2}{\partial u_2} \frac{\partial u_2}{\partial x} + \frac{\partial \bar{u}_2}{\partial u_3} \frac{\partial u_3}{\partial x} \right] \\ &+ \bar{C}_3 \left[\frac{\partial \bar{u}_3}{\partial u_1} \frac{\partial u_1}{\partial x} + \frac{\partial \bar{u}_3}{\partial u_2} \frac{\partial u_2}{\partial x} + \frac{\partial \bar{u}_3}{\partial u_3} \frac{\partial u_3}{\partial x} \right] \end{aligned}$$

Here equating coefficients of $\frac{\partial u_1}{\partial x}, \frac{\partial u_2}{\partial x}, \frac{\partial u_3}{\partial x}$

We get

$$\begin{aligned} C_1 &= \bar{C}_1 \frac{\partial \bar{u}_1}{\partial u_1} + \bar{C}_2 \frac{\partial \bar{u}_2}{\partial u_1} + \bar{C}_3 \frac{\partial \bar{u}_3}{\partial u_1} \\ C_2 &= \bar{C}_1 \frac{\partial \bar{u}_1}{\partial u_2} + \bar{C}_2 \frac{\partial \bar{u}_2}{\partial u_2} + \bar{C}_3 \frac{\partial \bar{u}_3}{\partial u_2} \\ C_3 &= \bar{C}_1 \frac{\partial \bar{u}_1}{\partial u_3} + \bar{C}_2 \frac{\partial \bar{u}_2}{\partial u_3} + \bar{C}_3 \frac{\partial \bar{u}_3}{\partial u_3} \end{aligned} \quad \dots(6)$$

or $C_p = \bar{C}_1 \frac{\partial \bar{u}_1}{\partial u_p} + \bar{C}_2 \frac{\partial \bar{u}_2}{\partial u_p} + \bar{C}_3 \frac{\partial \bar{u}_3}{\partial u_p}, p = 1, 2, 3$

or $C_q = \sum_{p=1}^3 \bar{C}_p \frac{\partial \bar{u}_q}{\partial u_p}, p = 1, 2, 3$

Similarly, we can show that

$$\bar{C}_p = \sum_{q=1}^3 C_q \frac{\partial u_q}{\partial u_p}, p = 1, 2, 3 \quad \dots(7)$$

Equation (6) and (7) are required relation.

Example: - Show that square of element of arc length in general curvilinear coordinate can be

$$ds^2 = \sum_{p=1}^3 \sum_{q=1}^3 g_{pq} du_p du_q$$

Solution: - $(ds)^2 = d\mathbf{r} \cdot d\mathbf{r} = d\mathbf{r}^T d\mathbf{r} = \left(\frac{\partial \mathbf{r}}{\partial u_1} du_1 + \frac{\partial \mathbf{r}}{\partial u_2} du_2 + \frac{\partial \mathbf{r}}{\partial u_3} du_3 \right)$

$$\left(\frac{\partial f}{\partial u_1} du_1 + \frac{\partial f}{\partial u_2} du_2 + \frac{\partial f}{\partial u_3} du_3 \right)$$

$$(ds)^2 = (\bar{u}_1 du_1 + \bar{u}_2 du_2 + \bar{u}_3 du_3) \cdot (\bar{u}_1 du_1 + \bar{u}_2 du_2 + \bar{u}_3 du_3)$$

where $\bar{u}_p = \frac{\partial f}{\partial u_p}$

$$= \bar{u}_1 \cdot \bar{u}_1 du_1^2 + \bar{u}_1 \cdot \bar{u}_2 du_1 du_2 + \bar{u}_1 \cdot \bar{u}_3 du_1 du_3$$

$$+ \bar{u}_2 \cdot \bar{u}_1 du_2 du_1 + \bar{u}_2 \cdot \bar{u}_2 du_2^2 + \bar{u}_2 \cdot \bar{u}_3 du_2 du_3$$

$$+ \bar{u}_3 \cdot \bar{u}_1 du_3 du_1 + \bar{u}_3 \cdot \bar{u}_2 du_3 du_2 + \bar{u}_3 \cdot \bar{u}_3 du_3^2$$

$$(ds)^2 = \sum_{p=1}^3 \sum_{q=1}^3 g_{pq} du_p du_q, \quad g_{pq} = \bar{u}_p \cdot \bar{u}_q$$

This is called **fundamental quadratic form** or **Metric form**. The quantities g_{pq} are called **metric coefficients** and these are symmetric i.e. $g_{pq} = g_{qp}$

If $g_{pq} = 0$ $p \neq q$, the coordinate system is orthogonal.

and in this case $g_{11} = h_1^2$, $g_{22} = h_2^2$, $g_{33} = h_3^2$

Here also

$$\bar{u}_1 = \frac{\partial f}{\partial u_1} = h_1 \hat{e}_1, \bar{u}_2 = \frac{\partial f}{\partial u_2} = h_2 \hat{e}_2, \bar{u}_3 = \frac{\partial f}{\partial u_3} = h_3 \hat{e}_3$$

Example: - (a) Prove that in general coordinate (u_1, u_2, u_3)

$$g = \begin{vmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \end{vmatrix} = \left(\frac{\partial f}{\partial u_1} \cdot \frac{\partial f}{\partial u_2} \cdot \frac{\partial f}{\partial u_3} \right)^2$$

where g_{pq} are coefficients of $du_p du_q$ in ds^2

Solution: - we know that

$$g_{pq} = \bar{u}_p \cdot \bar{u}_q = \frac{\partial f}{\partial u_p} \cdot \frac{\partial f}{\partial u_q}$$

$$= \frac{\partial x}{\partial u_p} \frac{\partial x}{\partial u_q} + \frac{\partial y}{\partial u_p} \frac{\partial y}{\partial u_q} + \frac{\partial z}{\partial u_p} \frac{\partial z}{\partial u_q}, \quad p = 1, 2, 3$$

$$\begin{aligned}
\left(\frac{\partial \mathbf{f}}{\partial u_1} \cdot \frac{\partial \mathbf{f}}{\partial u_2} \cdot \frac{\partial \mathbf{f}}{\partial u_3} \right)^2 &= \begin{vmatrix} \frac{\partial x}{\partial u_1} & \frac{\partial y}{\partial u_1} & \frac{\partial z}{\partial u_1} \\ \frac{\partial x}{\partial u_2} & \frac{\partial y}{\partial u_2} & \frac{\partial z}{\partial u_2} \\ \frac{\partial x}{\partial u_3} & \frac{\partial y}{\partial u_3} & \frac{\partial z}{\partial u_3} \end{vmatrix} \begin{vmatrix} \frac{\partial x}{\partial u_1} & \frac{\partial y}{\partial u_1} & \frac{\partial z}{\partial u_1} \\ \frac{\partial x}{\partial u_2} & \frac{\partial y}{\partial u_2} & \frac{\partial z}{\partial u_2} \\ \frac{\partial x}{\partial u_3} & \frac{\partial y}{\partial u_3} & \frac{\partial z}{\partial u_3} \end{vmatrix} \\
&= \begin{vmatrix} \frac{\partial x}{\partial u_1} & \frac{\partial y}{\partial u_1} & \frac{\partial z}{\partial u_1} \\ \frac{\partial x}{\partial u_2} & \frac{\partial y}{\partial u_2} & \frac{\partial z}{\partial u_2} \\ \frac{\partial x}{\partial u_3} & \frac{\partial y}{\partial u_3} & \frac{\partial z}{\partial u_3} \end{vmatrix} \begin{vmatrix} \frac{\partial x}{\partial u_1} & \frac{\partial x}{\partial u_2} & \frac{\partial x}{\partial u_3} \\ \frac{\partial y}{\partial u_1} & \frac{\partial y}{\partial u_2} & \frac{\partial y}{\partial u_3} \\ \frac{\partial z}{\partial u_1} & \frac{\partial z}{\partial u_2} & \frac{\partial z}{\partial u_3} \end{vmatrix} \\
&= \begin{vmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \end{vmatrix} = g
\end{aligned}$$

Example (b) show that the volume element in general coordinate is $\sqrt{g} \, du_1 \, du_2 \, du_3$.

Solution: - The volume element is given by

$$\begin{aligned}
dV &= \left| \left(\frac{\partial \mathbf{f}}{\partial u_1} du_1 \right) \cdot \left(\frac{\partial \mathbf{f}}{\partial u_2} du_2 \right) \times \left(\frac{\partial \mathbf{f}}{\partial u_3} du_3 \right) \right| \\
&= \left| \frac{\partial \mathbf{f}}{\partial u_1} \cdot \frac{\partial \mathbf{f}}{\partial u_2} \times \frac{\partial \mathbf{f}}{\partial u_3} \right| du_1 du_2 du_3 \\
&= \sqrt{g} \, du_1 \, du_2 \, du_3
\end{aligned}$$

LESSON 4 RANDOM VARIABLE AND MATHEMATICAL EXPECTATION

Sample space

The set points representing the possible outcomes of an experiment is called the sample space of the experiment.

Example: - (1) In tossing one coin, the sample space is $S = \{H, T\}$

(2) Two coins are tossed,

$$S = \{HH, HT, TH, TT\}$$

(3) In throw a dice,

$$S = \{(1, 1), (1, 2), (1, 3), (1, 4), (1, 5), (1, 6)$$

$$(2, 1), (2, 2), (2, 3), (2, 4), (2, 5), (2, 6)$$

$$M$$

$$(6, 1), (6, 2), (6, 3), (6, 4), (6, 5), (6, 6)$$

Total outcome = 36

Random Variable

A random variable is a real valued function defined on a sample space. When an experiment is performed, several outcomes are possible corresponding to each outcome, a number can be associated.

Example: - If two coins are tossed, the possible outcomes are TT, TH, HT, HH

Let $X \rightarrow$ denotes the number of heads

The number associated with the outcome are : TT, TH, HT, HH

No. of heads, $X : 0, 1, 1, 2$

The variable X is said to be random variable.

and may be defined as

“ Let S be the sample space associated with a given experiment. A real valued function defined on S & taking values in $R(-\infty, \infty)$ (real no.) is called a **random variable** (or chance variable or Stochastic variable or variate).

Discrete and Continuous Sample Space

A sample space that consists of a finite number or an infinite sequence, of points is called a **discrete sample space** and that consists of one or more intervals of points is called a continuous sample space.

Discrete and Continuous Random Variable

A random variable defined on a discrete sample space is called **discrete r.v.** or If a r.v. takes at most a countable no. values, it is called Discrete r.v.

A r.v. is said to be **Continuous** if it can take all possible values between certain limits or certain interval.

Example: -

- 1) If X represents the sum of points on two dice, X is a discrete r.v.
- 2) If X represents the height or weight of students in a class, then it is a continuous r.v.
- 3) If X represents the amount of rainfall, it is a continuous r.v.

Density function (d.f) or probability density function(p.d.f)

A function associated with discrete r.v.

X s.t. $f(x) = \text{prob}[X = x]$ is called density function of X .

Example: - In tossing two coins,

Outcomes = {HH, TH, HT, TT}

$$X = [0, 1, 2]$$

$$f(0) = P[X = 0] = \frac{1}{4}$$

$$f(1) = P[X = 1] = 2/4 = 1/2$$

$$f(2) = P[X = 2] = 1/4$$

Example: - In throwing two dice, the sample space of sum of points on two dice is

$$S = [1, 2, 3, \dots, 12]$$

$$f(2) = P[X = 2] = (1, 1) = \frac{1}{36} = f(12) (6,6)$$

$$f(3) = \frac{2}{36} = f(11) \quad [\Theta \quad (2, 1), (1, 2)]$$

$$f(4) = f(10) = \frac{3}{36}$$

$$f(5) = f(9) = \frac{4}{36}$$

$$f(6) = f(8) = \frac{5}{36}$$

$$f(7) = P[X = 7] = \frac{6}{36}$$

Also $\sum f(x_i) = 1$

$$X = x_i = 2, 3, \dots, 12$$

Distribution function

For a r.v. X , the function $F(x) = P(X \leq x)$ is called the distribution function of X or **Cumulative distribution**.

Since $F(x) = P(X \leq x)$, then $f(x)$ the p.d.f.

We have

$$F(x) = \sum_{t \leq x} f(t)$$

If $P(X \leq 2)$, then

$$\sum_{x \leq 2} f(x) = f(0) + f(1) + f(2)$$

Example: - A r.v. X has the following distribution

$X : 0$	1	2	3	4	5	6	7	8
$f(x) : k$	3k	5k	8k	9k	11k	12k	14k	17k

(1) Find k , As $\sum f(x) = 1$

$$\Rightarrow k + 3k + \dots + 17k = 1$$

$$\Rightarrow 80k = 1 \quad \Rightarrow \quad k = \frac{1}{80}$$

(2) Find $P(X < 2)$

$$P(X = 0) + P(X = 1) = P(0) + P(1)$$

$$= k + 3k = 4k = \frac{4}{80} = \frac{1}{20}$$

$$P(X < 3) = P(0) + P(1) + P(2) = \frac{9}{80}$$

$$(3) \quad P(X \geq 3) = P(3) + P(4) + \dots + P(8) = \frac{71}{80}$$

$$\text{Also } P(X \geq 3) = 1 - P(X < 3) = 1 - \frac{9}{80} = \frac{71}{80}$$

$$(4) \quad P(0 < X < 5) = P(1) + P(2) + P(3) + P(4) = 25/80$$

Distribution function F(x) is obtained

$$F(x) : \quad \frac{1}{80} \quad \frac{4}{80} \quad \frac{9}{80} \quad \frac{17}{80} \quad \frac{26}{80} \quad \frac{37}{80} \quad \frac{49}{80} \quad \frac{63}{80} \quad \frac{80}{80} = 1$$

Joint density function

Let X, Y be two r.v. , Joint d.f. gives the probability that X will assume Y will taken a value y

$$\text{i.e. } f(x, y) = P(X = x, Y = y)$$

Example: - 52 cards and 2 cards are drawn

X → no. of spade in the 1st draw

Y → no. of spade in the 2nd draw

Without replacing the 1st card drawn.

$$f(0, 0) = P[X = 0, Y = 0] = \frac{39}{52} \times \frac{38}{51}$$

$$f(0, 1) = P[X = 0, Y = 1] = \frac{39}{52} \times \frac{13}{51}$$

Y \ X	0	1	Total
0	19/34	13/68	51/68
1	13/68	1/17	17/68
Total	51/68	17/68	1

$$f(1, 0) = P[X = 1, Y = 0] = \frac{13}{52} \times \frac{39}{51}$$

$$f(1, 1) = P[X = 1, Y = 1] = \frac{13}{52} \times \frac{12}{51}$$

Let A & B be two events, then

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

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

Conditional density function

$f(y/x)$ is defined as

$$f(y/x) = P[Y = y | X = x]$$

gives distribution of Y when X is fixed

$$f(y/x) = \frac{f(x, y)}{f(x)}$$

and $f(x/y) = \frac{f(x, y)}{f(y)}$

Marginal density function

Here $f(x, y) = f(y/x) \cdot f(x)$... (1)

Conditional density Y = y when X = x is fixed.

$$\sum_y f(y/x) = 1$$

Summing over all possible values of y on both sides of (1), we get

$$\sum_y f(x, y) = \sum_y f(y/x) f(x)$$

$$\Rightarrow \sum_y f(x, y) = f(x)$$

This $f(x)$ is known as Marginal density function of X.

Similarly $g(y) = \sum_x f(x, y)$

This gives Marginal function of Y.

Example: - 2 white & 4 black balls find probability of having two white balls.

$$X, Y = \begin{cases} 0 & \text{for black ball} \\ 1 & \text{for white ball} \end{cases}$$

Solution: - $f(0, 0) = f(0) f(0/0)$

$$= \frac{4}{6} \cdot \frac{3}{5} = \frac{6}{15}$$

$$f(0, 1) = f(0) f(1/0) = \frac{4}{6} \cdot \frac{2}{5}$$

$$f(1,0) = f(1) f(0/1) = \frac{2}{6} \cdot \frac{4}{5}$$

$$f(1, 1) = f(1) f(1/1) = \frac{2}{6} \cdot \frac{1}{5}$$

Marginal density function of X is

$$f(x) = \sum_y f(x, Y)$$

$$\Rightarrow f(0) = \sum_y f(0, y) = f(0, 0) + f(0, 1)$$

$$\Rightarrow f(0) = \frac{6}{15} + \frac{4}{15} = \frac{10}{15} = \frac{2}{3}$$

$$\& f(1) = \sum_y f(1, y)$$

$$f(1, 0) + f(1, 1) = \frac{8}{30} + \frac{2}{30} = \frac{10}{30}$$

$$f(1) = \frac{1}{3} \quad \dots(2)$$

The conditional density function of Y for fixed x can be obtained from (1),

$$f(y/x) = \frac{f(x, y)}{f(x)}$$

$$\therefore f(0/1) = \frac{f(1,0)}{f(1)} = \frac{4/15}{1/3} = \frac{4}{5} \quad [\text{using (1)}]$$

$$f(1/1) = \frac{f(1,1)}{f(1)} = \frac{1/15}{1/3} = \frac{1}{5}$$

Continuous r.v. :- $-\infty < X < \infty$

Density function

A d.f. for a continuous r.v. X is a function f(x) that possesses the following properties

$$(i) f(x) \geq 0$$

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

$$(iii) \int_a^b f(x) dx = P[a < X < b] \text{ where } a < b$$

Distribution function

$$F(x) = \int_{-\infty}^{\infty} f(x) \, dx = P[X \leq x]$$

Provided integral exists.

Marginal density function

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

$$f(y) = \int_{-\infty}^{\infty} f(x, y) \, dx \rightarrow \text{Marginal density function of } Y.$$

Independent Random Variable

Two r.v. X and Y are said to be independent if $f(x, y) = f(x) f(y)$

Example: - Let the joint d.f. $f(x, y)$ of r.v.'s X and Y be

$$f(x, y) = \begin{cases} k(xy + e^x) & , \quad 0 < x, y < 1 \\ 0 & , \quad \text{otherwise} \end{cases}$$

- 1) Determine k
- 2) Examine whether X & Y are independent.

Solution: - 1) For d.f. $\iint f(x, y) \, dx \, dy = 1$

$$\therefore k \int_0^1 \int_0^1 (xy + e^x) \, dx \, dy = 1$$

$$\Rightarrow k \int_0^1 \left(\frac{x^2}{2} y + e^x \right) \Big|_0^1 \, dy = 1$$

$$\Rightarrow k \int_0^1 \left(\frac{y}{2} + e - 1 \right) \, dy = 1$$

$$\Rightarrow k \left[\frac{y^2}{4} + ey - y \right]_0^1 = 1$$

$$\Rightarrow k \left[\frac{1}{4} + e - 1 \right] = 1$$

$$\Rightarrow k \left(e - \frac{3}{4} \right) = 1$$

$$\Rightarrow k = \frac{4}{4e - 3}$$

$$(2) \quad f(x) = \int_0^1 f(x, y) \, dy$$

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

check whether $f(x, y) = f(x) f(y)$

$$\text{Now } f(x) = \int_0^1 k(xy + e^x) \, dy$$

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

$$= k \left[\frac{x}{2} + e^x \right]$$

$$f(y) = k \int_0^1 (xy + e^x) \, dx$$

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

$$= k \left[\frac{y}{2} + e - 1 \right]$$

So $f(x, y) \neq f(x) f(y)$ so they are not independent.

Example: - $f(x, y) = \begin{cases} 2 & , \quad 0 < x < 1, 0 < y < x \\ 0 & , \quad \text{otherwise} \end{cases}$

1) Find marginal d.f. of X and Y

2) Find conditional d.f. of Y given $X = x$

Find conditional d.f. of X given $Y = y$

3) Check whether X&Y are independent or not?

Solution: -(1)
$$f(x) = \int_0^x f(x, y) dy$$

$$= \int_0^x 2 dy = (2y)_0^x = 2x, 0 < x < 1$$

$$f(y) = \int_y^1 f(x, y) dx = 2 \int_y^1 dx = (2x)_y^1$$

$$= 2(1 - y), 0 < y < 1$$

So $f(x, y) \neq f(x) f(y)$

$\Rightarrow$ X and Y are not independent.

(2)
$$f(Y/X = x) = \frac{f(x, y)}{f(x)} = \frac{2}{2x} = \frac{1}{x}, \quad 0 < x < 1$$

$$f(X/Y = y) = \frac{f(x, y)}{f(y)} = \frac{2}{2(1 - y)} = \frac{1}{1 - y}, \quad 0 < y < 1$$

Example: - A continuous r.v. X has p.d.f. $f(x) = 3x^2$, $0 \leq x \leq 1$. Find a and b s.t.

(1) $P(X \leq a) = P(X \geq a)$

(2) $P(X \leq b) = 0.05$

Solution: - Since $P(X \leq a) = P(X > a)$

So, each must be equal to $\frac{1}{2}$ because total probability is always one i.e. $\int_0^a + \int_a^1 = 1$

$$P(X \leq a) = \frac{1}{2} \Rightarrow \int_0^a f(x) dx = \frac{1}{2}$$

$$\Rightarrow 3 \int_0^a x^2 dx = \frac{1}{2} \Rightarrow a = \left(\frac{x^3}{3} \right)_0^a = \frac{1}{2}$$

$$\Rightarrow a^3 = \frac{1}{2} \Rightarrow a = \left(\frac{1}{2} \right)^{1/3}$$

Also
$$\int_a^1 f(x) dx = \int_a^1 3x^2 dx = \frac{1}{2}$$

$$\Rightarrow 3 \left(\frac{x^3}{3} \right)_a^1 = \frac{1}{2} \Rightarrow 1 - a^3 = \frac{1}{2}$$

$$\Rightarrow a^3 = \frac{1}{2} \Rightarrow a = \left(\frac{1}{2} \right)^{1/3}$$

$$(2) \quad P(X > b) = 0.05 \Rightarrow \int_b^1 f(x) \, dx = 0.05$$

$$\Rightarrow 3 \int_b^1 x^2 \, dx = 0.5 \quad \Rightarrow \quad 3 \left(\frac{x^3}{3} \right)_b^1 = 0.05$$

$$\Rightarrow (1 - b^3) = \frac{1}{20} \quad \Rightarrow \quad b^3 = \frac{19}{20}$$

$$\Rightarrow b = \left(\frac{19}{20} \right)^{1/3}$$

Example: - If X be a continuous r. v. with

$$f(x) = \begin{cases} ax & , \quad 0 \leq x \leq 1 \\ a & , \quad 1 \leq x \leq 2 \\ -ax + 3a, & 2 \leq x \leq 3 \\ 0 & , \quad \text{elsewhere} \end{cases}$$

(1) Find constant a

(2) Find $P(X \leq 1.5)$

$$\textbf{Solution:} - (1) \quad \int_{-\infty}^0 f(x) \, dx + \int_0^1 f(x) \, dx + \int_1^2 f(x) \, dx + \int_2^3 f(x) \, dx + \int_3^{\infty} f(x) \, dx = 1$$

$$\Rightarrow 0 + \int_0^1 f(x) \, dx + \int_1^2 f(x) \, dx + \int_2^3 f(x) \, dx + 0 = 1$$

$$\Rightarrow \int_0^1 ax \, dx + \int_1^2 a \, dx + \int_2^3 (3a - ax) \, dx = 1$$

$$\Rightarrow a \left(\frac{x^2}{2} \right)_0^1 + a(x)_1^2 + a \left(3x - \frac{x^2}{2} \right)_2^3 = 1$$

$$\Rightarrow \frac{a}{2} + a + a + \left(9 - \frac{9}{2} - 6 + 2\right) = 1$$

$$\Rightarrow \frac{3a}{2} + \frac{a}{2} = 1$$

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

$$\begin{aligned} (2) \text{ Now } P(X \leq 1.5) &= \int_{-\infty}^{1.5} f(x) dx \\ &= \int_{-\infty}^0 f dx + \int_0^1 f(x) dx + \int_1^{1.5} f(x) dx \\ &= 0 + \int_0^1 ax dx + \int_1^{3/2} a dx \\ &= a \left(\frac{1}{2} \right) + a(x)_1^{3/2} = \frac{a}{2} + a \left(\frac{3}{2} - 1 \right) \end{aligned}$$

Example: - From the given bivariate probability distribution

- (1) Obtain marginal distribution of X & Y.
- (2) The conditional distribution of X given Y = 2

$\begin{array}{c} y \\ \backslash \\ x \end{array}$	-1	0	1	$\sum_x f(x, y) = f(y)$
0	1/15	2/15	1/15	4/15
1	3/15	2/15	1/15	6/15
2	2/15	1/15	2/15	5/15
$f(x) = \sum_y f(x, y)$	6/15	5/15	4/15	

Solution: (1) Marginal distribution of X

From above table $f(x) = \sum_y f(x, y)$

Therefore $f(-1) = P(X = -1) = 6/15$

$$f(0) = P(X = 0) = 5/15$$

$$f(1) = P(X = 1) = 4/15$$

Marginal distribution of Y

From above table $f(y) = \sum_x f(x, y)$

Therefore $P(Y = 0) = 4/15$

$$P(Y = 1) = 6/15$$

$$P(Y = 2) = 5/15$$

(2) Conditional distribution of X given Y = 2, we get

$$P(X = x/Y = 2) = \frac{P(X = x, Y = 2)}{P(Y = 2)}$$

For X = -1, $P(X = -1/Y = 2) = \frac{2/15}{5/15} = \frac{2}{5}$

Similarly $P(X = 0/Y = 2) = \frac{1/15}{5/15} = \frac{1}{5}$

$$P(X = 1/Y = 2) = \frac{2/15}{5/15} = \frac{2}{5}$$

MATHEMATICAL EXPECTATION:-

Let X be a r.v. with p.d.f. $f(x)$, then its mathematical expectation (or its mean value) is defined as

$$E(X) = \sum x f(x)$$

It X assumes values $x_1, x_2, \dots, x_n, \dots$

With probabilities $f(x_1), f(x_2), \dots, f(x_n), \dots$

then $E(X) = \sum_{i=1}^{\infty} x_i f(x_i)$

Also $E(X) = \text{Mean of distribution}$ and $\sum f(x_i) = 1$

The expected value or Mathematical expectation of the function $g(x)$ of discrete r.v. X, whose p.d.f. is $f(x)$ is given by

$$E[g(X)] = \sum_{i=1}^{\infty} g(x_i) f(x_i)$$

and $f(x_i) = P(X = x_i)$

Example: - When 3 coins are tossed and

$X \rightarrow$ represents the number of heads is a r. v., then total outcomes are

$$\{HHH, HTH, HHT, THH, THT, TTH, HTT, TTT\}$$

Here X can take values $X = 0, 1, 2, 3$

with $f(x) = \frac{1}{8}, \frac{3}{8}, \frac{3}{8}, \frac{1}{8}$

Then $E(X) = \sum xf(x) = 0 \cdot \frac{1}{8} + 1 \cdot \frac{3}{8} + 2 \cdot \frac{3}{8} + 3 \cdot \frac{1}{8}$

$$= \frac{12}{8} = \frac{3}{2} \times 1 \text{ Rs.} = \text{Rs. } 1.50$$

If $g(x) = x^2$

Then $g(x) = 0^2, 1^2, 2^2, 3^2$

$\therefore E[g(x)] = \sum g(x_i)f(x_i)$

$$= 0^2 \times \frac{1}{8} + 1^2 \times \frac{3}{8} + 2^2 \times \frac{3}{8} + 3^2 \times \frac{1}{8}$$

$$= \frac{3}{8} + \frac{12}{8} + \frac{9}{8} = \text{Rs. } 3.0$$

Mathematical Expectation for Continuous r.v.

Let X be a continuous r.v. with p.d.f. $f(x)$, then its mathematical expectation is

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

For function $g(x)$, $E[g(x)] = \int_{-\infty}^{\infty} g(x)f(x) dx$

Theorem: - If C is a finite real number & if $E(X)$ exists, then

Proof: - for continuous r.v.

$$\text{Let } E(CX) = \int_{-\infty}^{\infty} C x f(x) dx$$

$$= C \int_{-\infty}^{\infty} x f(x) dx = C E(X)$$

for discrete r.v.;

$$\begin{aligned} E(CX) &= \sum Cx f(x) = C \sum x f(x) \\ &= CE(X) \end{aligned}$$

Result: - $E[a + CX] = E(a) + CE(X) = a + CE(X)$

Proof: - Now $E(a) = \sum af(x) = a \sum f(x)$

$$= a.1 = a \quad \dots (1)$$

for continuous r.v., $E(a) = \int_{-\infty}^{\infty} af(x) dx$

$$\Rightarrow E(a) = a \int_{-\infty}^{\infty} f(x) dx = a.1 = a$$

Now By definition, $E[a + CX] = \sum (a + Cx)f(x)$

$$\begin{aligned} \Rightarrow E[a + CX] &= \sum [af(x) + Cxf(x)] = \sum af(x) + \sum Cxf(x) \\ &= \sum af(x) + CE(X) = E(a) + CE(X) \end{aligned}$$

$$\Rightarrow E(a + CX) = a + CE(X) \quad \dots \text{using (1)}$$

Theorem: - The expectation of the sum of two r.v.'s is equal to the sum of their expectations, i.e., $E(X + Y) = E(X) + E(Y)$

Proof: - For discrete case

Let X & Y be two discrete r.v., $f(x_i, y_j)$ is the joint p.d.f. of X and Y. then $(X + Y)$ is also a r.v.

$$f(x_i, y_j) = P(X = x_i, Y = y_j)$$

Now by definition,

$$\begin{aligned} E(X + Y) &= \sum_i \sum_j (x_i + y_j) f(x_i, y_j) \\ &= \sum_i \sum_j x_i f(x_i, y_j) + \sum_i \sum_j y_j f(x_i, y_j) \\ &= \sum_i x_i \sum_j f(x_i, y_j) + \sum_j y_j \sum_i f(x_i, y_j) \\ &= \sum_i x_i f(x_i) + \sum_j y_j f(y_j) \end{aligned}$$

$$\Rightarrow E(X + Y) = E(X) + E(Y)$$

For continuous r.v.

$$E(X + Y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x + y) f(x, y) dx dy$$

$$\begin{aligned}
&= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xf(x, y) dx dy + \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} yf(x, y) dx dy \\
&= \int_{-\infty}^{\infty} x \left[\int_{-\infty}^{\infty} f(x, y) dy \right] dx + \int_{-\infty}^{\infty} y \left[\int_{-\infty}^{\infty} f(x, y) dx \right] dy \\
&= \int_{-\infty}^{\infty} xf(x) dx + \int_{-\infty}^{\infty} yf(y) dy
\end{aligned}$$

$$\Rightarrow E(X + Y) = E(X) + E(Y)$$

In general,

$$E(X_1 + X_2 + \dots + X_n) = E(X_1) + E(X_2) + \dots + E(X_n)$$

Theorem: - If $Y = a_1X_1 + a_2X_2 + \dots + a_nX_n$, where a 's are constants, then

$$E(Y) = a_1E(X_1) + a_2E(X_2) + \dots + a_nE(X_n)$$

Proof: - As $E(Y) = E(a_1X_1 + a_2X_2 + \dots + a_nX_n)$

$$= E(a_1X_1) + E(a_2X_2) + \dots + E(a_nX_n)$$

$$= a_1E(X_1) + a_2E(X_2) + \dots + a_nE(X_n)$$

$$[\Theta E(aX) = aE(X)]$$

Theorem: - If X is a continuous r.v. and a and b are constants, then

$E(aX$

$+ b) = a E(X) + b$, provided all expectation exists.

Proof: - By definition, we have

$$\begin{aligned}
E(aX + B) &= \int_{-\infty}^{\infty} (ax + b) f(x) dx \\
&= \int_{-\infty}^{\infty} axf(x) dx + \int_{-\infty}^{\infty} b f(x) dx \\
&= a \int_{-\infty}^{\infty} xf(x) dx + b \int_{-\infty}^{\infty} f(x) dx
\end{aligned}$$

$$\Rightarrow E(aX + b) = aE(X) + b \quad \left[\Theta \int_{-\infty}^{\infty} f(x) dx = 1 \right]$$

Case1: - If $b = 0$, $E(aX) = aE(X)$

Case2: - If $a = 1$, $b = -\bar{X} = -E(X)$, we get $E(X - \bar{X}) = 0$

Example: - If $f(x, y) = e^{-(x+y)}$ is the joint p.d.f. of r.v. X and Y , then find

$$P = (1 < X < 2, 0 < Y < 2)$$

Solution: - First we check for:-

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

$$\text{L.H.S} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-(x+y)} dx dy = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-x} e^{-y} dx dy$$

$$= \int_{-\infty}^{\infty} \left[-e^{-x} e^{-y} \right]_{-\infty}^{\infty} dy$$

$$= \int_{-\infty}^{\infty} P(1 < X < 2, 0 < Y < 2)$$

$$= \int_1^2 \int_0^2 e^{-(x+y)} dy dx$$

$$= \int_1^2 \int_0^2 e^{-x} e^{-y} dy dx$$

$$= \int_1^2 e^{-x} dx \int_0^2 e^{-y} dy = (1 - e^{-2}) \int_1^2 e^{-x} dx$$

$$= (1 - e^{-2}) (e^{-1} - e^{-2}) = \left(1 - \frac{1}{e^2}\right) \left(\frac{1}{e} - \frac{1}{e^2}\right)$$

$$= \left(\frac{e^2 - 1}{e^2}\right) \left(\frac{e - 1}{e^2}\right)$$

$$= \frac{(e^2 - 1)(e - 1)}{e^4} = \frac{(e^3 - e^2 - e + 1)}{e^4}$$

Example: - Let $f(x_1, x_2) = \begin{cases} C(x_1 x_2 + e^{x_1}), & 0 < (x_1, x_2) < 1 \\ 0, & \text{otherwise} \end{cases}$

- (i) Determine C
- (ii) Examine whether X_1 and X_2 are independent or not.

Solution: - For density function $F(x_1, x_2)$ we must have

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

$$\Rightarrow C \int_0^1 \left[\frac{x_1^2 x_2}{2} + e^{x_1} \right]_{x_2=0}^{x_2=1} dx_2 = 1$$

$$\Rightarrow C \int_0^1 \left[\frac{1}{2} x_2 + e - 1 \right] dx_2 = 1$$

$$\Rightarrow C \left[\frac{1}{2} \times \frac{x_2^2}{2} + e x_2 - x_2 \right]_0^1 = 1$$

$$\Rightarrow C \left[\frac{1}{4} + e - 1 \right] = 1$$

$$\Rightarrow C [1 + 4e - 4] = 4$$

$$\text{or } C = \frac{4}{4e - 3}$$

Theorem: - Show that the expectation of the product of independent r.v. is equal to product of their expectations. i.e. $E(XY) = E(X).E(Y)$

Proof: - Let X and Y are two independent random variables, then

$$X: x_1, x_2, \dots, x_n$$

With d.f: $f(x_1), f(x_2), \dots, f(x_n)$

and $Y: y_1, y_2, \dots, y_m$

with d.f: $f(y_1), f(y_2), \dots, f(y_m)$

$$\therefore E(X) = \sum_{i=1}^n x_i f(x_i), \quad E(Y) = \sum_{j=1}^m y_j f(y_j)$$

Let $f(x_i, y_j)$ is the joint p.d.f. of X & Y .

and Since X & Y are independent, so

$$f(x_i, y_j) = f(x_i) f(y_j)$$

$$\text{Now } E(XY) = \sum_{i=1}^n \sum_{j=1}^m x_i y_j f(x_i, y_j)$$

$$= \sum_{i=1}^n \sum_{j=1}^m x_i y_j f(x_i) f(y_j)$$

$$= \sum_i x_i f(x_i) \sum_j y_j f(y_j)$$

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

Similarly for continuous r.v.: $f(x, y) = f(x) f(y)$, since X and Y are independent.

$$\text{Now } E(XY) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f(x, y) dx dy$$

$$E(XY) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f(x) f(y) dx dy$$

$$= \int_{-\infty}^{\infty} x f(x) dx \int_{-\infty}^{\infty} y f(y) dy = E(X) E(Y)$$

In general, we get

$$E(X_1 X_2 X_3 \dots X_n) = E(X_1) E(X_2) \dots E(X_n)$$

Example: - Let X represents the number on the face of dice then

X:	1	2	3	4	5	6
f(x):	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$	$\frac{1}{6}$

$$\text{Now } E(X) = \sum x f(x)$$

$$= \frac{1}{6} (1 + 2 + \dots + 6) = \frac{21}{6} = \frac{7}{2}$$

And when X is sum of points when two dies are thrown, i.e.

X:	2	3	4	5	6	7	8	9	10	11	12
f(x):	$\frac{1}{36}$	$\frac{2}{36}$	$\frac{3}{36}$	$\frac{4}{36}$	$\frac{5}{36}$	$\frac{6}{36}$	$\frac{5}{36}$	$\frac{4}{36}$	$\frac{2}{36}$	$\frac{2}{36}$	$\frac{1}{36}$

$$\therefore E(X) = \sum x f(x) = \frac{1}{36} [2 + 6 + 12 + 20 + 30 + 42 + 40 + 36 + 30 + 22 + 12]$$

$$\Rightarrow E(X) = \frac{1}{36} \cdot 252 = 7$$

Example: - Let X be the profit that a person makes in a business. He may earn Rs. 2800 with a probability 0.5, he may lose Rs 5500 with probability 0.3 and he may neither earn nor lose with a probability 0.2. Calculate $E(X)$

Solution: - Here $P(X = 2800) = 0.5$

$$P(X = -5500) = 0.3$$

$$P(X = 0) = 0.2$$

$$\begin{aligned}\text{Then } E(X) &= \sum xf(x) \\ &= 2800(0.5) + (-5500)(0.3) + (0)(0.2) \\ &= 1400 - 1650 = -250, \text{ he may lose Rs 250.}\end{aligned}$$

Example: - A and B in turns throw an ordinary dice for a price of Rs. 44. The first to throw a “six” wins. If A has first throw, what is his expectation?. Also calculate B’s expectation

Solution: - The problem of getting a “six” on dice is $p(x) = \frac{1}{6}$

A has 1st throw, so he can win in the 1st, 3rd, 5th

Hence A’ chance (probability) of winning is

$$\begin{aligned}&= \frac{1}{6} + \frac{5}{6} \times \frac{5}{6} \times \frac{1}{6} + \frac{5}{6} \times \frac{5}{6} \times \frac{5}{6} \times \frac{1}{6} + \dots \\ &= \frac{1}{6} \left[1 + \left(\frac{5}{6}\right)^2 + \left(\frac{5}{6}\right)^4 + \dots \right] \\ &= \frac{1}{6} \cdot \frac{1}{1 - \left(\frac{5}{6}\right)^2} = \frac{1}{6} \cdot \frac{36}{11} = \frac{6}{11}\end{aligned}$$

$$\therefore \text{Amount of A} = 44 \times \frac{6}{11} = \text{Rs. 24}$$

Similarly B can win in 2nd, 4th, 6th,

Hence B’(chance) of winning are

$$\begin{aligned}&= \frac{5}{6} \cdot \frac{1}{6} + \frac{5}{6} \cdot \frac{5}{6} \cdot \frac{1}{6} + \dots \\ &= \frac{5}{6} \cdot \frac{1}{6} \left[1 + \left(\frac{5}{6}\right)^2 + \dots \right]\end{aligned}$$

$$= \frac{1}{6} \cdot \frac{5}{6} \cdot \frac{36}{11} = \frac{5}{11}$$

$$\therefore \text{Amount of B} = \frac{5}{11} \times 49 = \text{Rs. } 20$$

Example: - A bag contains a coin of value M and a number of other coins whose aggregate value is m. a person draws one at a time till he draws the coin M, find the value of his expectation.

Solution: - Let there be K other coins each of value m/K, so that their aggregate value is m. he may draw the coin M at 1st draw or 2nd or 3rd or.....or (K+1)th draw with probability

$$\frac{1}{K+1}, \frac{1}{K+1}, \frac{1}{K+1}, \dots$$

$$\Theta \quad \frac{1}{K+1}, \left[1 - \frac{1}{K-1}\right] \frac{1}{K}, \left[1 - \frac{1}{K+1}\right] \left[1 - \frac{1}{K}\right] \frac{1}{K-1}, \dots$$

$$= \frac{1}{K+1}, \frac{1}{K+1}, \frac{1}{K+1}, \dots$$

The corresponding amount drawn X is

$$M, \frac{m}{K} + M, \frac{2m}{K} + M, \dots, \frac{(k-1)m}{K} + M, \frac{Km}{K} + M$$

$$\therefore E(X) = \frac{1}{K+1} \left[M + \frac{m}{K} + M + \frac{2m}{K} + M + \dots + \frac{Km}{K} + M \right]$$

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

$$= M + \frac{1}{K+1} \cdot \frac{m}{K} \frac{K(K+1)}{2} = M + \frac{m}{2}$$

LESSON 5 MOMENTS AND MOMENT GENERATING FUNCTIONS

Moments: - Let X is a r. v., then $E[X^r]$, if exists is called the r^{th} moment of X about origin and is denoted by μ'_r

$$\text{i.e } \mu'_r = E[X^r] \quad \dots (1)$$

and about some point 'a', it is defined as

$$\mu'_r(a) = E[(X - a)^r]$$

and r^{th} moment about mean is

$$\mu_r = E[(X - E(X))^r] = E[(X - \mu)^r] \quad \dots (2)$$

Moments about Mean are called Central Moments.

In case of discrete r.v.:-

$$\mu'_r = E[X^r] = \sum x^r f(x)$$

$$\& \quad \mu_r = E[(X - \mu)^r] = \sum_{i=1}^n (x_i - \mu)^r f(x_i)$$

Where $\mu = E(X)$

and $f(x_i) = P(X = x_i)$

when $r = 1$ from (1), we get

$$\mu'_1 = E(X) = \sum xf(x) = \text{Mean}$$

and from (2),

$$\mu_1 = E(X - \mu) = E(X) - E(\mu)$$

$$\Rightarrow \mu_1 = \mu - \mu = 0 \quad [\ominus E(\mu) = \mu, E(X) = \mu]$$

Moments about Mean (μ_r) in terms of moments about any point 'a':-

Let $X \rightarrow$ r. v.,

$$E(X) = \bar{X} = \mu$$

$$\text{then } \mu_r = E[X - \mu]^r = E[X - a - \mu + a]^r$$

$$\Rightarrow \mu^r = E(X - a - d)^r$$

Where $d = \mu - a$

$$\text{or } \mu_r = E[(X - a)^r - {}^rC_1 d(X - a)^{r-1} + \dots + {}^rC_{r-1}(-1)^{r-1}d^{r-1}(X - a) + d^r(-1)^r]$$

$$\Rightarrow \mu_r = \mu'_r(a) - {}^rC_1 d \mu'_{r-1}(a) + \dots + {}^rC_{r-1}(-1)^{r-1}d^{r-1}E(X - a) + d^r(-1)^r$$

Now $\mu_1 = 0$ $[\mu_1 = \mu'_1(a) - d = \mu'_1(a) - \mu'_1(a) = 0]$

and $\mu_2 = \mu'_2(a) - 2d \mu'_1(a) + d^2$

$\Rightarrow \mu_2 = \mu'_2 - \mu_1'^2$ $[\Theta d = E(X) - a = E(X - a), d = \mu'_1(a)]$

This μ_2 is called Variance. Similarly,

$$\mu_3 = \mu'_3 - 3\mu'_2\mu'_1 + 2\mu_1'^3$$

and $\mu_4 = \mu'_4 - 4\mu'_3 + 6\mu'_2\mu_1'^2 - 3\mu_1'^4$

If X is a continuous r.v.

$$\mu'_r = \int_{-\infty}^{\infty} (x - a)^r f(x) dx$$

$$\mu_r = \int_{-\infty}^{\infty} (x - \mu)^r f(x) dx$$

and $E(X) = \mu'_1 \rightarrow \text{Mean}$

Also $\mu_2 = E(X - \mu)^2$. This $E(X - \mu)^2$ is called Variance and is denoted by σ^2 .

Covariance between X and Y

$$\begin{aligned} \text{Cov}(X, Y) &= E[(X - \bar{X})(Y - \bar{Y})] \\ &= E[(X - E(X))(Y - E(y))] \end{aligned}$$

Example: - Find $E(X)$, $E(X^2)$, $E(X - E(X))^2$ from the following:-

X:	8	12	16	20	2
f(x):	$\frac{1}{8}$	$\frac{1}{6}$	$\frac{3}{8}$	$\frac{1}{4}$	$\frac{1}{12}$

Solution: - $E(X) = \sum xf(x)$

$$= 8 \times \frac{1}{8} + 12 \times \frac{1}{6} + \dots + 24 \times \frac{1}{12}$$

$\Rightarrow E(X) = 16 = \text{Mean}$

and $E(X^2) = \sum x^2 f(x) = 64 \times \frac{1}{8} + 144 \times \frac{1}{6} + 256 \times \frac{3}{8} + \dots + 576 \times \frac{1}{12}$

$\Rightarrow E(X^2) = 276$

$$\mu_2 = E[X - E(X)]^2 = E(X^2) - [E(X)]^2 \quad [\Theta \mu_2 = \mu'_2 - \mu_1'^2]$$

$$\Rightarrow \mu_2 = 276 - (16)^2 = 20$$

This $\mu_2 = 20$ is the variance.

Example: - Find $E(X)$, $E(X^2)$, $E(X - E(X))^2$

X:	2	3	4	5	6	7	8	9	10	11	12
f(x):	$\frac{1}{36}$	$\frac{2}{36}$	$\frac{3}{36}$	$\frac{4}{36}$	$\frac{5}{36}$	$\frac{6}{36}$	$\frac{5}{36}$	$\frac{4}{36}$	$\frac{2}{36}$	$\frac{2}{36}$	$\frac{1}{36}$

$$\text{Solution: - } E(X) = \sum xf(x) = \frac{1}{36} [2+6+12+20+30+42+40+36+30+22+12]$$

$$= 7 = \text{Mean}$$

$$E(X^2) = \sum Ex^2f(X) = \frac{1}{36} [4+18+48+10+30+5+49+64+81+100+121+144]$$

$$= \frac{1}{36} (1974) = \frac{329}{6}$$

$$\mu_2 = E[X - E(X)]^2 = E(X^2) - [E(X)]^2$$

$$= \frac{1974}{36} - 49 = \frac{329}{6} - 49$$

$$= \frac{329 - 294}{6} = \frac{35}{6}$$

Let m represents median, then

$$P(X < m) = P(X > m)$$

In this eg, $m = 7$

$$\text{mode} = 7$$

Also mean = 7

So it is a very good distribution.

Example: - For distribution,

$$f(x) = \begin{cases} \frac{1}{16}(3-x^2) & , \quad -3 < x \leq -1 \\ \frac{1}{16}(6-2x^2) & , \quad -1 < x \leq 1 \\ \frac{1}{16}(3-x)^2 & , \quad 1 < x \leq 3 \\ 0 & , \quad \text{otherwise} \end{cases}$$

Check whether it represents a probability distribution or not. Also find its mean and variance.

Solution: - First we prove that

$$\int_{-\infty}^{\infty} f(x) dx = 1 \quad \text{or} \quad \int_{-3}^3 f(x) dx = 1$$

$$\text{Now} \quad \int_{-\infty}^{\infty} f dx = \left(\int_{-\infty}^{-3} + \int_{-3}^{-1} + \int_{-1}^1 + \int_1^3 + \int_3^{\infty} \right) f dx$$

$$\Rightarrow \quad \int_{-\infty}^{\infty} f(dx) = \int_{-3}^{-1} \frac{1}{16} (3+x^2) dx + \int_{-1}^1 \frac{1}{16} (6-2x^2) dx + \int_1^3 \frac{1}{16} (3-x^2) dx$$

$$= \frac{1}{16} \left[\frac{(3+x)^3}{3} \right]_{-3}^{-1} + \frac{1}{16} \left[x^6 - \frac{2x^3}{3} \right]_{-1}^1 + \frac{1}{16} \left[\frac{(3-x)^3}{-3} \right]_1^3$$

$$= \frac{1}{48} [8-0] + \frac{1}{16} \left[6 - \frac{2}{3} + 6 - \frac{2}{3} \right] - \frac{1}{48} [0-8]$$

$$= \frac{1}{6} + \frac{1}{16} \left(12 - \frac{4}{3} \right) + \frac{1}{6}$$

$$\Rightarrow \quad \int_{-\infty}^{\infty} f(x) dx = \frac{1}{3} + \frac{1}{16} \cdot \frac{32}{3} = \frac{1}{3} + \frac{2}{3} = 1$$

$$\text{Also Mean} = E(X) = \int_{-\infty}^{\infty} xf(x) dx$$

$$\Rightarrow \quad E(X) = \int_{-3}^3 xf(x) dx$$

$$= \int_{-3}^{-1} \frac{x}{16} (3+x)^2 dx + \int_{-1}^1 \frac{x}{16} (6-2x^2) dx + \int_1^3 \frac{x}{16} (3-x)^2 dx$$

$$= \frac{1}{16} \left[x \frac{(3+x)^3}{3} \right]_{-3}^{-1} - \int_{-3}^{-1} \frac{1}{16} (1) \frac{(3+x)^3}{3} dx + 0$$

$$+ \frac{1}{16} \left\{ \left[\frac{x(3-x)^3}{-3} \right]_1^3 - \int_1^3 (1) \frac{(3-x)^3}{-3} dx \right\}$$

[Integrand in second integral is an odd function of x, so its value is zero]

$$\begin{aligned}
&= \frac{1}{48} [(-1)8 + 0] - \frac{1}{48} \left[\frac{(3+x)^4}{4} \right]_{-3}^{-1} - \frac{1}{48} [0 - 1,8] + \frac{1}{48} \left[\frac{(3-x)^4}{-4} \right]_1^3 \\
&= -\frac{1}{6} - \frac{1}{48} \cdot \frac{1}{4} (16 - 0) + \frac{1}{6} - \frac{1}{48} \cdot \frac{1}{4} (0 - 16)
\end{aligned}$$

$$\Rightarrow E(X) = -\frac{1}{48} \cdot \frac{1}{4} \cdot 16 + \frac{1}{48} \cdot \frac{1}{4} \cdot 16 = -\frac{1}{12} + \frac{1}{12} = 0$$

$$\text{Also Variance} = V(X) = E(X - E(X))^2 = E(X^2) - [E(X)]^2$$

Now

$$\begin{aligned}
E(X^2) &= \int_{-3}^3 x^2 f(x) dx \\
&= \int_{-3}^{-1} \frac{x^2}{16} (3+x)^2 dx + \int_{-1}^1 \frac{x^2}{16} (6-2x^2) dx + \int_1^3 \frac{x^2}{16} (3-x)^2 dx \\
\Rightarrow E(X^2) &= \int_{-3}^{-1} \frac{x^2}{16} (9+x^2+6x) dx + \int_{-1}^1 \frac{1}{16} (6x^2-2x^4) dx + \int_1^3 \frac{x^2}{16} (9+x^2-6x) dx \\
&= \frac{1}{16} \left[\frac{9x^3}{3} + \frac{x^5}{5} + \frac{6x^4}{4} \right]_{-3}^{-1} + \frac{1}{16} \left[\frac{6x^3}{3} - \frac{2x^5}{5} \right]_{-1}^1 \\
&\quad + \frac{1}{16} \left[\frac{9x^3}{3} + \frac{x^5}{5} - \frac{6x^4}{4} \right]_1^3 \\
&= \frac{1}{16} \left(-3 - \frac{1}{5} + \frac{3}{2} + 81 + \frac{243}{5} - \frac{3}{2} \times 81 \right) + \frac{1}{16} \left(2 - \frac{2}{5} + 2 - \frac{2}{5} \right) \\
&\quad + \frac{1}{16} \left[81 + \frac{243}{5} - \frac{3}{2} \times 81 - 3 - \frac{1}{5} \times 81 \right] \\
&= 2 \cdot \frac{1}{16} \left[-3 - \frac{1}{5} + \frac{3}{2} + 81 + \frac{243}{5} - \frac{243}{2} \right] + \frac{1}{16} \left(4 - \frac{4}{5} \right) \\
&= \frac{1}{8} \left[78 - \frac{240}{2} + \frac{242}{5} \right] + \frac{1}{16} \cdot \frac{16}{5} \\
&= \frac{1}{8} \left[-42 + \frac{242}{5} \right] + \frac{1}{5}
\end{aligned}$$

$$\Rightarrow E(X^2) = \frac{1}{8} \cdot \frac{32}{5} + \frac{1}{5} = \frac{4}{5} + \frac{1}{5} = 1$$

$$\begin{aligned}\text{Hence Variance} &= E(X^2) - [E(X)]^2 \\ &= 1 - 0^2 = 1\end{aligned}$$

Example: - Show that the value of $\text{cov}(X, Y)$ for probability distribution

$$f(x, y) = \begin{cases} \frac{1}{9}e^{-y/3}, & 0 \leq x \leq y \leq \infty \\ 0, & \text{otherwise} \end{cases} \quad \text{is 9.}$$

Solution: - We Know that $\text{Cov.}(X, Y) = E(XY) - E(X) E(Y)$

Thus we have to find $E(X)$, $E(Y)$ and $E(XY)$

$$\text{But } E(X) = \int_{-\infty}^{\infty} xf(x)dx$$

$$E(Y) = \int_{-\infty}^{\infty} yf(y)dy$$

$\therefore$ First we have to find $f(x)$ and $f(y)$.

Now marginal density function of X is given by

$$\begin{aligned}g(x) &= \int_{-\infty}^{\infty} f(x, y)dy = \int_{-\infty}^{\infty} f(x, y)dy + \int_x^{\infty} f(x, y)dy \\ &= \int_x^{\infty} \frac{1}{9}e^{-y/3}dy = \left[\frac{1}{9}e^{-y/3}(-3) \right]_x^{\infty}\end{aligned}$$

$$\Rightarrow g(x) = \frac{1}{3}e^{-x/3}, 0 \leq x \leq \infty$$

Similarly Marginal density function of Y will be

$$h(y) = \int_0^y \frac{1}{9}e^{-y/3}dx = \frac{y}{9}e^{-y/3}, 0 \leq y \leq \infty$$

$$\begin{aligned}\therefore E(X) &= \int_0^{\infty} xf(x)dx \\ &= \int_0^{\infty} x \cdot \frac{1}{3}e^{-x/3}dx = \frac{1}{3} \int_0^{\infty} x e^{-x/3} dx\end{aligned}$$

$$\begin{aligned}
&= \frac{1}{3} \left[\left[x e^{-x/3} (-3) \right]_0^\infty + 3 \int_0^\infty e^{-x/3} dx \right] \\
&= \frac{1}{3} \left[0 + 3 \left[e^{-x/3} (-3) \right]_0^\infty \right] = 3 \quad \dots (1)
\end{aligned}$$

$$\begin{aligned}
E(Y) &= \int_0^\infty y h(y) dy = \frac{1}{9} \int_0^\infty y^2 e^{-y/3} dy \\
&= \frac{1}{9} \left[\left\{ y^2 e^{-y/3} (-3) \right\}_0^\infty + 6 \int_0^\infty y e^{-y/3} dy \right] \\
&= \frac{2}{3} \left[\left[y e^{-y/3} (-3) \right]_0^\infty + 3 \int_0^\infty e^{-y/3} dy \right] \\
&= \frac{2}{3} \times 3 \left[e^{-y/3} (-3) \right]_0^\infty = 2 \times 3 = 6 \quad \dots (2)
\end{aligned}$$

$$\begin{aligned}
E(XY) &= \int_{x=0}^\infty \int_{y=x}^\infty xy f(x, y) dx dy \\
&= \int_{x=0}^\infty \int_{y=x}^\infty xy \cdot \frac{1}{9} e^{-y/3} dx dy \\
&= \frac{1}{9} \int_{x=0}^\infty x \left[\int_{y=x}^\infty y e^{-y/3} dy \right] dx \\
&= \frac{1}{9} \int_{x=0}^\infty x \left\{ \left[y e^{-y/3} (-3) \right]_x^\infty + 3 \int_x^\infty e^{-y/3} dy \right\} dx \\
&= \frac{1}{9} \int_{x=0}^\infty x \left(3x e^{-x/3} + 3(3) e^{-x/3} \right) dx \\
&= \frac{1}{9} \int_0^\infty \left[3x^2 e^{-x/3} + 9e^{-x/3} x \right] dx \\
&= \frac{1}{3} \left[\int_0^\infty x^2 e^{-x/3} dx + 3 \int_0^\infty e^{-x/3} x dx \right] \\
&= \frac{1}{3} [54 + 3 \times 9]
\end{aligned}$$

$$= \frac{54+27}{3} = \frac{81}{3} = 27$$

$$\begin{aligned}\therefore \text{Cov}(X, Y) &= E(XY) - E(X)E(Y) \\ &= 27 - 3 \times 6 = 27 - 18 = 9\end{aligned}$$

Hence proved

Example: - If $f(x) = \frac{1}{a} \left[1 - \frac{|x-b|}{a} \right], |x-b| < a$. Find mean and variance.

Solution: - $f(x) = \frac{1}{a} \left[1 - \frac{|x-b|}{a} \right]$

Now $|x-b| < a \Rightarrow -a < x-b < a$

$\Rightarrow b-a < x < b+a$

$\therefore f(x) = \frac{1}{a} \left[1 + \frac{(x-b)}{a} \right]$ for $b-a < x < b$ $\therefore |x-b| = -(x-b)$ for $(b-a) < x < b$

Similarly

$f(x) = \frac{1}{a} \left[1 - \frac{(x-b)}{a} \right]$ for $b < x < b+a$ as $|x-b| = x-b$ for $b < x < b+a$

$$\begin{aligned}\therefore \text{Mean} = E(X) &= \int_{-\infty}^{\infty} xf(x) dx \\ &= \int_{b-a}^b x \cdot \frac{1}{a} \left[1 + \frac{(x-b)}{a} \right] dx + \int_b^{b+a} x \cdot \frac{1}{a} \left[1 - \frac{(x-b)}{a} \right] dx \\ &= \frac{1}{a} \int_{b-a}^b \left(x + \frac{x^2 - bx}{a} \right) dx + \frac{1}{a} \int_b^{b+a} \left(x - \frac{x^2}{a} + \frac{bx}{a} \right) dx \\ &= \frac{1}{a} \left[\frac{x^2}{2} + \frac{x^3}{3a} - \frac{bx^2}{2a} \right]_{b-a}^b + \frac{1}{a} \left[\frac{x^2}{2} - \frac{x^3}{3a} + \frac{bx^2}{2a} \right]_{b+a}^b \\ &= \frac{1}{a} \frac{b^2}{2} + \frac{b^3}{3a^2} - \frac{b^3}{2a^2} - \left(\frac{b^2 + a^2 - 2ab}{2a} \right) - \frac{(b-a)^2}{3a^2} + \frac{b}{2a^2} (b-a)^2 \\ &\quad + \frac{1}{a} \left(\frac{b^2 + a^2 + 2ab}{2} \right) - \frac{(b+a)^3}{3a^2} + \frac{b(b+a)^2}{2a^2} - \frac{b^2}{2a} + \frac{b^3}{3a^2} - \frac{b^3}{2a^2}\end{aligned}$$

$$\begin{aligned}
&= \frac{b^2}{2a} + \frac{b^3}{3a^2} - \frac{b^3}{2a^2} - \frac{b^2}{2a} - \frac{a^2}{2a} + \frac{2ab}{2a} + \frac{b^2}{2a} + \frac{a^2}{2a} + \frac{2ab}{2a} \\
&\quad + \frac{(-b^3 + a^3 + 3ab^2 - 3a^2b)}{3a^2} + \frac{b^3 + a^2b - 2ab^2}{2a^2} \\
&\quad + \frac{(-b^3 - a^3 - 3ab^2 - 3a^2b)}{3a^2} + \frac{b^3 + a^2b + 2ab^2}{2a^2} \\
&\quad - \frac{b^2}{2a} + \frac{b^3}{3a^2} - \frac{b^3}{2a^2} = b
\end{aligned}$$

$$\text{Variance} = V(X) = E[X - E(X)]^2$$

$$\begin{aligned}
&= E(X - b)^2 = \int_{-\infty}^{\infty} (x - b)^2 f(x) dx \\
&= \int_{b-a}^b (x - b)^2 \cdot \frac{1}{a} \left(\frac{1+x-b}{a} \right) dx + \int_b^{b+a} (x - b)^2 \frac{1}{a} \left[1 - \frac{(a-b)}{a} \right] dx \\
&= \frac{1}{a} \int_{b-a}^b \left[(x - b)^2 + \frac{(x - b)^3}{a} \right] dx + \frac{1}{a} \int_b^{b+a} \left[(x - b)^2 - \frac{(x - b)^3}{a} \right] dx \\
&= \frac{1}{a} \left[\frac{(x - b)^3}{3} + \frac{(x - b)^4}{4a} \right]_{b-a}^b + \frac{1}{a} \left[\frac{(x - b)^3}{3} - \frac{(x - b)^4}{4a} \right]_b^{b+a} \\
&= \frac{1}{a} \cdot \frac{a^3}{3} - \frac{a^4}{4a^2} + \frac{a^3}{3a} - \frac{a^4}{4a^2} \\
&= \frac{2a^3}{3a} - \frac{a^4}{2a^2} = \frac{2a^2}{3} - \frac{a^2}{2} = \frac{a^2}{6}
\end{aligned}$$

Example: - Find mean and Variance for the following distribution

$$f(x) = \begin{cases} \frac{(x-1)^3}{4}, & 1 \leq x \leq 3 \\ 0, & \text{otherwise} \end{cases}$$

Solution: - Check for $\int_{-\infty}^{\infty} f(x) dx = 1$

$$\text{As mean} = E(X) = \int_{-\infty}^{\infty} xf(x) dx = \int_1^3 \frac{(x-1)^3}{4} \cdot x dx$$

$$= \frac{1}{4} \int_1^3 (x^4 - x - 3x^3 + 3x^2) dx = \frac{13}{5}$$

$$\text{Variance} = V(X) = E[X - E(X)]^2 = E\left(X - \frac{13}{6}\right)^2$$

$$= \int_{-\infty}^{\infty} \left(x - \frac{13}{5}\right)^2 f(x) dx$$

$$= \frac{1}{4} \int_1^3 \left(x - \frac{13}{5}\right)^2 \frac{(x-1)^3}{4} dx$$

$$= \frac{1}{4} \left\{ \left[\left(x - \frac{13}{5}\right)^2 \frac{(x-1)^4}{4} \right]_1^3 - \frac{1}{2} \int_1^2 \left(x - \frac{13}{5}\right) (x-1)^4 dx \right\}$$

$$= \frac{1}{4} \left\{ 4 \times \frac{4}{25} - \frac{1}{2} \left[\left(x - \frac{13}{5}\right) \frac{(x-1)^5}{5} \right]_1^3 + \frac{1}{2} \times \frac{1}{5} \left[\frac{(x-1)^6}{6} \right]_1^3 \right\}$$

$$= \frac{4}{25} - \frac{4}{5} \times \frac{2}{5} + \frac{4}{15}$$

$$= \frac{4}{25} - \frac{8}{25} + \frac{4}{15} = -\frac{4}{25} + \frac{4}{15} = \frac{8}{75}$$

Theorem: - If X is a r.v., then $V(aX + b) = a^2 V(X)$, where a and b are constants.

Proof: - Let $Y = aX + b$, then

$$E(Y) = aE(X) + b$$

$$\text{Then } V(aX + b) = V(Y) = E[Y - E(Y)]^2$$

$$= E[aX + b - aE(X) - b]^2$$

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

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

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

Cor(i) If $b = 0$, then $V(ax) = a^2 V(X)$

(ii) If $a = 0$, then $V(b) = 0$

(iii) If $a = 1$, then $V(X + b) = V(X)$.

Theorem: - Prove that $V(X \pm Y) = V(X) \pm V(Y) \pm 2 \text{Cov}(X, Y)$ and $V(X \pm Y) = V(X) + V(Y)$ provided X and Y are independent r.v.

$$\begin{aligned}
 \text{Proof: } - V(X + Y) &= E[(X + Y) - E(X + Y)]^2 \\
 &= E[(X + Y) - E(X) - E(Y)]^2 \\
 &= E[\{X - E(X)\} + \{Y - E(Y)\}]^2 \\
 &= E[X - E(X)]^2 + E[Y - E(Y)]^2 + 2E[(X - E(X))[Y - E(Y)]] \\
 &= E[X - E(X)]^2 + E[Y - E(Y)]^2 + 2E[\{X - E(X)\}\{Y - E(Y)\}] \\
 &= V(X) + V(Y) + 2 \text{cov}(X, Y)
 \end{aligned}$$

Similarly $V(X - Y) = V(X) + V(Y) - 2\text{cov}(X, Y)$

$$V(X \pm Y) = V(X) + V(Y) \pm 2\text{cov}(X, Y)$$

If X and Y are independent, then $\text{cov}(X, Y) = 0$

$$\begin{aligned}
 \therefore V(X \pm Y) &= V(X) + V(Y) \pm 2.0 \\
 &= V(X) + V(Y).
 \end{aligned}$$

Covariance: - If X and Y are two r.v., then cov between them is defined as

$$\begin{aligned}
 \text{Cov}(X, Y) &= E[(X - E(X))[Y - E(Y)]] \\
 &= E[XY - XE(Y) - YE(X) + E(X)E(Y)] \\
 &= E(XY) - E(X)E(Y) - E(Y)E(X) + E(X)E(Y) \\
 &= E(XY) - E(X)E(Y)
 \end{aligned}$$

We can also express it as

$$\begin{aligned}
 \text{Cov}(X, Y) &= E[(X - E(X))[Y - E(Y)]] \\
 &= \sum_i \sum_j (x_i - \bar{X})(y_j - \bar{Y})f(x_i, y_j) \text{ for discrete case} \\
 \text{Cov}(X, Y) &= E[XY - \bar{X}Y - X\bar{Y} + \bar{X}\bar{Y}] \\
 &= E(XY) - \bar{X}E(Y) - \bar{Y}E(X) + \bar{X}\bar{Y} \\
 &= E(XY) - \bar{X}\bar{Y} - \bar{Y}\bar{X} + \bar{X}\bar{Y} \\
 &= E(XY) - \bar{X}\bar{Y}
 \end{aligned}$$

If X and Y are independent r.v., then

$$\begin{aligned}
 E(XY) &= E(X)E(Y) \\
 \text{Cov}(X, Y) &= E(X)E(Y) - \bar{X}\bar{Y} = \bar{X}\bar{Y} - \bar{X}\bar{Y} = 0
 \end{aligned}$$

$\Rightarrow \text{Cov}(X, Y) = 0$ if X and Y are independent.

Remark

$$\begin{aligned} \text{i) } \text{Cov}(ax, by) &= E[(aX - E(ax))(bY - E(bY))] \\ &= E[(aX - aE(X))(bY - bE(Y))] \\ &= E[a[X - E(X)] \cdot b[Y - E(Y)]] \\ &= ab[E(X - E(X))(Y - E(Y))] \\ &= ab \text{Cov}(X, Y) \end{aligned}$$

$\Rightarrow$ Covariance is not independent of change of scale.

$$\begin{aligned} \text{ii) } \text{Cov}(X + a, Y + b) &= E[\{(X + a) - E(X + a)\} \{Y + b - E(Y + b)\}] \\ &= E[\{(X + a) - E(X) - a\} \{Y + b - E(Y) - b\}] \\ &= E[\{X - E(X)\} \{Y - E(Y)\}] \\ &= \text{Cov}(X, Y) \end{aligned}$$

Thus $\text{Cov}(X, Y)$ is independent of change of origin but is not independent of change of scale.

MEAN DERIVATION FOR CONTINUOUS CASE

$$E[|X - a|] = \int_{-\infty}^{\infty} |x - a| f(x) dx$$

$$\text{Variance} = \sigma_x^2 = E[X - E(X)]^2 = \int_{-\infty}^{\infty} (x - \bar{X})^2 f(x) dx$$

Absolute moment

Let X be r. v. with p.d.f $f(x)$, then its r^{th} absolute moment about any point a is given by

$$E[|X - a|^r] = \int_{-\infty}^{\infty} |x - a|^r f(x) dx$$

$$\begin{aligned} \text{For Variance i.e. } \mu_2 &= E[X - E(X)]^2 \\ &= E[X^2 - 2XE(X) + E^2(X)] \\ &= E(X^2) - 2E(X)E(X) + E^2(X) \quad [\ominus E(X) = \mu_1] \\ \mu_2 &= E(X^2) - 2[E(X)]^2 + E^2(X) \\ &= E(X^2) - [E(X)]^2 \\ \mu_2 &= \mu_2' - \mu_1^2 \end{aligned}$$

Effect of change of origin & scale on moment

$$U = \frac{X - a}{h}$$

$$\text{Now } E[U] = \bar{U} = E\left(\frac{X - a}{h}\right) = \frac{1}{h} [E(X) - E(a)]$$

$$\bar{U} = \frac{1}{h} (\bar{X} - a) \Rightarrow \bar{X} = a + h\bar{U}$$

$$\begin{aligned} \text{Then } \mu_r &= E[X - \bar{X}]^r = E[a + hU - a - h\bar{U}]^r \\ &= E[h^r(U - \bar{U})^r] = h^r E[U - \bar{U}]^r \end{aligned}$$

Where $E[U - \bar{U}]^r = r^{\text{th}}$ moment of U about mean

MOMENT GENERATING FUNCTION (M.G.F)

M.G.F of a r.v. X with p.d.f. $f(x)$ is given by

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

where t is real number.

Then $M_X(t)$ is known as Moment generating function about origin.

Now, M.G.F about Mean is given by

$$M_{X-\mu}(t) = E[e^{t(X-\mu)}]$$

If X is a discrete r.v.: -

MGF about origin is given by

$$M_X(t) = E[e^{tX}] = \sum_{x=0}^{\infty} e^{tx} f(x) \quad \dots (1)$$

$$\begin{aligned} \text{or } M_X(t) &= E\left[1 + \frac{tX}{1!} + \frac{t^2X^2}{2!} + \dots + \frac{t^rX^r}{r!} + \dots\right] \\ &= 1 + \frac{t}{1!} E(X) + \frac{t^2}{2!} E(X^2) + \dots + \frac{t^r}{r!} E(X^r) + \dots \end{aligned}$$

$$M_X(t) = 1 + t\mu'_1 + \frac{t^2}{2!}\mu'_2 + \dots + \frac{t^r}{r!}\mu'_r + \dots$$

where μ'_r = coefficient of $\frac{t^r}{r!}$ in $M_X(t)$, is the r^{th} moment about origin.

The moments can also be obtained from the M.G.F through following relations:

$$\mu'_r = \frac{d^r}{dt^r} M_X(t) \Big/_{t=0}$$

$$\mu'_1 = \frac{d}{dt} M_X(t) \Big/_{t=0}$$

$$\mu'_2 = \frac{d^2}{dt^2} M_X(t) \Big/_{t=0} \quad \text{etc.}$$

when X is continuous r.v., then MGF about origin is given by

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

& MGF about mean is given by

$$M_X(t) = \int_{-\infty}^{\infty} e^{t(x-\mu)} f(x) dx$$

and MGF about any point 'a' is

$$M_X(t) = \int_{-\infty}^{\infty} e^{t(x-a)} f(x) dx$$

$$\text{As } M_X(t) = \sum_x e^{tx} f(x) = \sum_x f(x) \left[1 + \frac{tx}{1!} + \frac{t^2 x^2}{2!} + \dots + \frac{t^r x^r}{r!} \right]$$

$$\therefore \frac{d}{dt} M_X(t) = \sum_{x=0}^{\infty} f(x) \left[x + \frac{2tx^2}{2!} + \frac{3t^2 x^3}{3!} + \dots + \frac{rt^{r-1} x^{r-1}}{r} + \dots \right]$$

$$\therefore \frac{d}{dt} M_X(t) = \sum_{x=0}^{\infty} xf(x) = \sum_{x=1}^{\infty} xf(x) = \mu'_1 = 1^{\text{st}} \text{ moment about origin.}$$

Example: - Let x be a r.v. with p.d.f

$$f(x) = \begin{cases} x & , \quad 0 \leq x \leq 1 \\ 2-x & , \quad 1 \leq x \leq 2 \\ 0 & , \quad \text{otherwise} \end{cases}$$

Find MGF for this distribution. Also determine mean & variance.

Solution: - First we shall prove that given distribution is probability distribution or not

i.e. $\int_{-\infty}^{\infty} f(x) dx = 1$ or not

Now
$$\begin{aligned}\int_{-\infty}^{\infty} f(x) dx &= \left(\int_{-\infty}^0 + \int_0^1 + \int_1^2 + \int_2^{\infty} \right) f(x) dx \\ &= 0 + \int_0^1 x dx + \int_1^2 (2-x) dx + 0 \\ &= \left[\frac{x^2}{2} \right]_0^1 + \left[2x - \frac{x^2}{2} \right]_1^2 \\ &= \frac{1}{2} - 0 + 4 - 2 - 2 + \frac{1}{2}\end{aligned}$$

$\Rightarrow \int_{-\infty}^{\infty} f(x) dx = \frac{1}{2} + \frac{1}{2} = 1$

$\Rightarrow$ Given distribution is a probability distribution

Mean = $E(X) = \int_0^1 xf(x) dx + \int_1^2 xf(x) dx$

$$\begin{aligned}&= \int_0^1 x \cdot x dx + \int_1^2 x(2-x) dx \\ &= \left[\frac{x^3}{3} \right]_0^1 + \left[\frac{2x^2}{2} - \frac{x^3}{3} \right]_1^2 \\ &= \frac{1}{3} + 4 - \frac{8}{3} - 1 - \frac{1}{3} = \frac{2}{3} + 3 - \frac{8}{3} = 1\end{aligned}$$

$\Rightarrow E(X^2) = \int_0^1 x^2 f(x) dx + \int_1^2 x^2 f(x) dx$

$$\begin{aligned}&= \int_0^1 x^2 \cdot x dx + \int_1^2 x^2(2-x) dx \\ &= \left[\frac{x^4}{4} \right]_0^1 + \left[\frac{2x^3}{3} - \frac{x^4}{4} \right]_1^2\end{aligned}$$

$$\begin{aligned}
&= \frac{1}{4} + \frac{2}{3}(8) - 4 - \frac{2}{3} + \frac{1}{4} \\
&= \frac{1}{2} - 4 + \frac{14}{3} = \frac{3 - 24 + 28}{6} = \frac{7}{6}
\end{aligned}$$

$$\therefore \text{Variance} = \frac{7}{6} - 1^2 = \frac{1}{6}$$

$$\begin{aligned}
\text{Now } M_X(t) &= E[e^{tx}] = \int_{-\infty}^{\infty} e^{tx} f(x) dx \\
&= \int_0^1 e^{tx} x dx + \int_1^2 (2-x) e^{tx} dx \\
&= \left[x \frac{e^{tx}}{t} \right]_0^1 - \int_0^1 (1) \frac{e^{tx}}{t} dx + \left[(2-x) \frac{e^{tx}}{t} \right]_1^2 - \int_1^2 (-1) \frac{e^{tx}}{t} dx \\
&= (1) \frac{e^t}{t} - \frac{1}{t^2} [e^{tx}]_0^1 + \left[0 - 1 \cdot \frac{e^t}{t} \right] + \frac{1}{t^2} [e^{tx}]_1^2 \\
&= \frac{e^t}{t} - \frac{1}{t^2} [e^t - 1] - \frac{e^t}{t} + \frac{1}{t^2} [e^{2t} - e^t] \\
&= -\frac{1}{t^2} e^t + \frac{1}{t^2} + \frac{e^{2t}}{t^2} - \frac{e^t}{t^2} \\
&= \frac{1}{t^2} + \frac{e^{2t}}{t^2} - \frac{2e^t}{t^2} = \frac{1}{t^2} [e^{2t} - 2e^t + 1] \\
M_X(t) &= \left(\frac{e^t - 1}{t} \right)^2
\end{aligned}$$

$$\text{Now } \mu'_1 = \frac{d}{dt} M_X(t) \Big|_{t=0}$$

$$\left[\Theta \mu'_r = \frac{d^r}{dt^r} M_X(t) \Big|_{t=0} \right]$$

$$\mu'_2 = \frac{d}{dt} M_X(t) \Big|_{t=0}$$

$$\text{then variance, } \mu_2 = \mu'_2 - \mu_1'^2$$

$$\begin{aligned}
\text{also } M_X(t) &= \frac{1}{t^2} \left[\left(1 + 2t + \frac{(2t)^2}{2!} + \frac{(2t)^3}{3!} + \frac{(2t)^4}{4!} + \dots \right) - 2 \left(1 + t + \frac{t^2}{2!} + \frac{t^3}{3!} + \dots \right) + 1 \right] \\
&= \frac{1}{t^2} \left[(4-2) \frac{t^2}{2!} + (8-2) \frac{t^3}{3!} + (16-2) \frac{t^4}{4!} + \dots \right] \\
&= \frac{1}{t^2} \left[\frac{2t^2}{2} + \frac{6t^3}{6} + \frac{7t^4}{12} + \dots \right]
\end{aligned}$$

$$M_X(t) = \left[1 + \frac{t}{1!} + \left(\frac{7}{6} \right) \frac{t^2}{2!} + \dots \right]$$

$$\mu'_1 = \text{coefficient of } \frac{t}{1!} \rightarrow \text{Mean}$$

$$\mu'_2 = \text{coefficient of } \frac{t^2}{2!} = \frac{7}{6}$$

$$\therefore \text{Variance} = \mu'_2 - \mu_1'^2 = \frac{7}{6} - 1^2 = \frac{1}{6}$$

Property: - (1) $M_{cX}(t) = M_X(Ct)$

Proof: - By definition,

$$M_{cX}(t) = E[e^{te^{cX}}] = E[e^{(ct)X}]$$

$$M_{cX}(t) = M_X(ct)$$

(2) MGF of the sum of a number of independent r. v. is equal to the product of their respective MGF's i.e.

$$M_{X_1+X_2+\dots+X_n}(t) = M_{X_1}(t) \cdot M_{X_2}(t) \cdot \dots \cdot M_{X_n}(t)$$

Proof: - By definition,

$$\begin{aligned}
M_{X_1+X_2+\dots+X_n}(t) &= E[e^{t(X_1+X_2+\dots+X_n)}] \\
&= E[e^{tX_1} \cdot e^{tX_2} \cdot \dots \cdot e^{tX_n}]
\end{aligned}$$

If $X_1, X_2, \dots, X_n$ are independent r.v., then function $e^{tX_1}, e^{tX_2}, \dots, e^{tX_n}$ are also independent.

$$\begin{aligned}
\therefore M_{X_1+X_2+\dots+X_n}(t) &= E[e^{tX_1}] E[e^{tX_2}] \cdot \dots \cdot E[e^{tX_n}] \\
&= M_{X_1}(t) \cdot M_{X_2}(t) \cdot \dots \cdot M_{X_n}(t)
\end{aligned}$$

(3) Effect of change of origin and scale on M.G.F

Let us transform X to the new variable U by changing both the origin and scale in X as follows: -

Proof: - If X is a r.v., then

$$U = \frac{X - a}{h} \Rightarrow X = a + hU \quad \text{where } a \text{ \& } h \text{ are constants}$$

$$\begin{aligned} \text{Now } M_X(t) &= E[e^{tX}] = E[e^{t(a+hU)}] \\ &= E[e^{at}, e^{thU}] \\ &= e^{at} E[e^{(th)U}] \end{aligned}$$

where $M_X(t)$ is the m.g.f. of X about origin.

$$\Rightarrow M_X(t) = e^{at} M_U(th)$$

$$\Rightarrow M_U(th) = e^{-at} M_X(t)$$

$$\text{Put } th = t' \Rightarrow t = \frac{t'}{h}$$

$$\text{then } M_U(t') = e^{\frac{-at'}{h}} M_X\left(\frac{t'}{h}\right) = \text{M.G.F of } U \text{ (about origin)}$$

Standard normal variate

If X is a r.v., then the variable Z defined by

$$Z = \frac{X - \mu}{\sigma} \text{ is called standard normal variate}$$

where μ, σ are Mean & standard derivation, respectively

$$\text{Also } E(Z) = 0$$

$$\text{Variance } (Z) = 1$$

$$\text{Now } E(Z) = E\left(\frac{X - \mu}{\sigma}\right) = \frac{1}{\sigma} E(X - \mu)$$

$$E(Z) = \frac{1}{\sigma} [E(X) - \mu] = \frac{1}{\sigma} [\mu - \mu] = 0$$

$$\text{and } V(Z) = E\left(\frac{X - \mu}{\sigma}\right)^2 = \frac{1}{\sigma^2} [E(X - \mu)^2]$$

$$\Rightarrow V(Z) = \frac{1}{\sigma^2} \cdot \sigma^2 = 1 \quad [\Theta \sigma^2 = E(X - \mu)^2]$$

If $X \sim N(\mu, \sigma^2)$, then $Z \sim N(0, 1)$

The m.g.f of standard variate Z is $M_Z(t) = e^{-\mu t/\sigma} M_X\left(\frac{t}{\sigma}\right)$

Example: - Let X is a discrete r.v.

$$P(X = r) = pq^{r-1}, r = 1, 2, \dots$$

where p is the probability of success in one trial and q is the probability of failure in one trial.

Then find MGF, Mean & variance.

Solution: - $M_X(t) = E[e^{tX}]$

$$= \sum_{r=1}^{\infty} e^{tr} pq^{r-1}$$

$$\Rightarrow M_X(t) = \frac{p}{q} \sum_{r=1}^{\infty} e^{tr} q^r = \frac{p}{q} (qe^t) \sum_{r=1}^{\infty} (qe^t)^{r-1}$$

$$= \frac{p}{q} \cdot qe^t [1 + qe^t + (qe^t)^2 + \dots]$$

$$\Rightarrow M_X(t) = pe^t \frac{1}{(1 - qe^t)} \quad [\text{sum of G.P}]$$

$$\text{Now } \mu'_1 = \left. \frac{d}{dt} M_X(t) \right|_{t=0} = \left. \frac{(1 - qe^t) \cdot pe^t - pe^t \cdot (-qe^t)}{(1 - qe^t)^2} \right|_{t=0}$$

$$= \left. \frac{pe^t - pqe^{2t} + PQE^{2T}}{(1 - qe^t)^2} \right|_{t=0}$$

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

$$\Rightarrow \mu'_1 = \frac{p}{(1 - q)^2} = \frac{p}{p^2} \quad [\ominus 1 - q = p]$$

$$\Rightarrow \mu'_1 = \frac{1}{p} = \text{Mean}$$

$$\text{and } \mu'_2 = \left. \frac{d^2}{dt^2} M_X(t) \right|_{t=0}$$

$$= \left. \frac{d}{dt} \left(\frac{pe^t}{(1 - qe^t)^2} \right) \right|_{t=0}$$

$$= \frac{(1-qe^t)pe^t - pe^t \cdot 2(1-qe^t)(-qe^t)}{(1-qe^t)^4} \Bigg/_{t=0}$$

$$= \frac{(1-qe^t)pe^t + 2pqe^{2t}}{(1-qe^t)^3} \Bigg/_{t=0}$$

$$= \frac{pe^t + pqe^{2t}}{(1-qe^t)^3} \Bigg/_{t=0}$$

$$= \frac{p + pq}{(1-q)^3} = \frac{p(1+q)}{p^3} = \frac{1+q}{p^2}$$

$$\therefore \text{Variance, } \mu_2 = \mu'_2 - \mu_1'^2$$

$$\Rightarrow \mu_2 = \frac{1+q}{p^2} - \frac{1}{p^2} = \frac{q}{p^2}$$

CUMULANT GENERATING FUNCTION AND CUMULANTS

The logarithm of m.g.f about origin of a r.v. X is called second m'g.f or cumulant generating function (c.g.f.)

$$\text{i.e. } K_X(t) = \log M_X(t) = \sum_r K_r \frac{t^r}{r!}$$

$$\text{and } K_r = \text{coefficient of } \frac{t^r}{r!} \text{ in } K_X(t)$$

This K_r is known as r^{th} cumulant

$$\text{Now } K(t) = \log M_X(t) = \log[E(e^{tx})]$$

$$= \log \left[E \left(1 + tX + \frac{t^2 X^2}{2!} + \dots + \frac{t^r X^r}{r!} + \dots \right) \right]$$

$$= \log \left[1 + \left(\mu'_1 t + \mu'_2 \frac{t^2}{2!} + \dots + \mu'_r \frac{t^r}{r!} \right) \right]$$

$$\Rightarrow K_X(t) = \left[\left(\mu'_1 t + \mu'_2 \frac{t^2}{2!} + \dots + \mu'_r \frac{t^r}{r!} + \dots \right) - \frac{1}{2} \left(\mu'_1 + \mu'_2 \frac{t^2}{2!} + \dots + \mu'_r + \frac{t^r}{r!} + \dots \right) \right]$$

$$+ \frac{1}{3} \left(\mu'_1 t + \mu'_2 \frac{t^2}{2!} + \dots + \mu'_r \frac{t^r}{r!} + \dots \right)^3 - \frac{1}{4} \left(\mu'_1 t + \mu'_2 \frac{t^2}{2!} + \dots + \mu'_r \frac{t^r}{r!} \right)^4 + \dots \quad \dots(1)$$

$$\text{Now } K_X(t) = K_1 t + K_2 \frac{t^2}{2!} + K_3 \frac{t^3}{3!} + K_4 \frac{t^4}{4!} + \dots \quad \dots(2)$$

Equating coefficients of like terms in equation (1), (2) we get

$$K_1 = \text{coefficient of } \frac{t}{1!} = \mu'_1 = \text{Mean}$$

$$K_2 = \mu'_2 - \mu_1' = \mu_2 = (\text{variance})$$

$$K_3 = \mu'_3 - 3\mu'_2\mu'_1 + 2\mu_1'^3 = \mu_3$$

$$\frac{K_4}{4!} = \frac{\mu_4^1}{4!} - \frac{1}{2} \left(\frac{\mu_2'^2}{4} + \frac{2\mu_1'\mu_3'}{3!} \right) + \frac{1}{3} \frac{3\mu_1'^2\mu_2'}{2} - \frac{\mu_1'^4}{4}$$

$$\Rightarrow K_4 = \mu_4' - 3\mu_2'^2 - 4\mu_1'\mu_3' + 12\mu_1'^2\mu_2' - 6\mu_1'^4 \\ = (\mu_4' - 4\mu_3'\mu_1' + 6\mu_2'\mu_1'^2 - 3\mu_1'^4) - 3(\mu_2'^2 - 2\mu_2'\mu_1'^2 + \mu_1'^4)$$

$$\Rightarrow K_4 = \mu_4 - 3K_2^2 = \mu_4 - 3\mu_2^2$$

$$\text{Also } K_r = \frac{d^r}{dt^r} K_X(t)$$

Characteristic function

Characteristic function of a variable X is defined as $\phi_X(t) = E[e^{itX}]$

If X is continuous r. v., then

$$\phi_X(t) = \int e^{itx} f(x) dx$$

If X is discrete r. v, then

$$\phi_X(t) = \sum e^{itx} f(x)$$

LESSON 6

THEORETICAL DISCRETE DISTRIBUTIONS

BINOMIAL DISTRIBUTION

Let n represent the number of trials in an event.

$x \rightarrow$ consecutive successes

$(n-x) \rightarrow$ failure

then $ppp\dots pqq\dots q = p^x q^{n-x}$

But x successes in n trials can occur in nC_x ways.

$\therefore$ Probability of x successes in any order in n trials = ${}^nC_x p^x q^{n-x}$, here n and p are called parameters.

Therefore, probability density function for a Binomial distribution is

$$P(X = x) = B(n, p; x) \\ = f(x) = {}^nC_x p^x q^{n-x}, x = 0, 1, 2, \dots, n$$

Also $p + q = 1$ and $\sum f(x) = 1$

Moments about origin of Binomial distribution

The r^{th} moment of the Binomial distance about origin is

$$\mu'_r = E[X^r] = \sum_{x=0}^n x^r f(x)$$

$$\Rightarrow \mu'_r = \sum_{x=0}^n x^r {}^nC_x p^x q^{n-x}$$

when $r = 1$, 1st moment, $\mu'_1 = \sum_{x=0}^n x {}^nC_x p^x q^{n-x}$

$$\begin{aligned} \Rightarrow \mu'_1 &= \sum_{x=0}^n \frac{x \cdot \underline{n}}{\underline{n-x} \cdot \underline{x}} p^x q^{n-x} \\ &= \sum_{x=1}^n \frac{\underline{n}}{\underline{n-x} \cdot \underline{x-1}} p^x q^{n-x} \\ &= np \sum_{x=1}^n \frac{\underline{n-1}}{\underline{n-x} \cdot \underline{x-1}} p^{x-1} q^{n-x} \\ &= np \sum_{x=1}^n \frac{\underline{n-1}}{\underline{(n-1)-(x-1)} \cdot \underline{x-1}} p^{x-1} q^{(n-1)-(x-1)} \end{aligned}$$

$$\begin{aligned}
&= np \sum_{x=1}^n {}^{n-1}C_{x-1} p^{x-1} q^{(n-1)-(x-1)} \\
&= np (q + p)^{n-1} \quad \left[\sum f(x) = (q + p)^n = 1 \right]
\end{aligned}$$

$$\Rightarrow \mu'_1 = np = \text{Mean}$$

Now Second moment about origin is $\mu'_2 = E(X^2) = \sum x^2 f(x)$

$$\begin{aligned}
\mu'_2 &= \sum_{x=0}^n [x(x-1) + x] {}^nC_x p^x q^{n-x} \\
&= \sum_{x=0}^n x(x-1) {}^nC_x p^x q^{n-x} + \sum_{x=0}^n x {}^nC_x p^x q^{n-x} \\
&= \sum_{x=2}^n x(x-1) {}^nC_x p^x q^{n-x} + \sum_{x=1}^n x {}^nC_x p^x q^{n-x} \\
&= \sum_{x=2}^n \frac{x(x-1) \underline{n}}{x(x-1) \underline{x-2} \underline{n-x}} p^x q^{n-x} + np \\
\Rightarrow \mu'_2 &= \sum_{x=2}^n \frac{n(n-1) \underline{n-2}}{\underline{x-2} \underline{n-x}} p^x q^{n-x} + np \\
&= n(n-1)p^2 \sum_{x=2}^n \frac{\underline{n-2}}{\underline{x-2} \underline{(n-2)-(x-2)}} p^{x-2} q^{(n-2)-(x-2)} + np \\
&= n(n-1)p^2 \sum_{x=2}^n {}^{n-2}C_{x-2} p^{x-2} q^{(n-2)-(x-2)} + np \\
&= n(n-1)p^2 (1) + np \\
\Rightarrow \mu'_2 &= n(n-1)p^2 + np
\end{aligned}$$

Also variance, $\mu_2 = \mu'_2 - \mu'^2_1$

$$\begin{aligned}
\Rightarrow \mu_2 &= n(n-1)p^2 + np - n^2p^2 \\
&= n^2p^2 - np^2 + np - n^2p^2
\end{aligned}$$

$$\Rightarrow \mu_2 = np(1 - p) = npq$$

So, variance = npq

Also variance $\leq$ Mean

i.e. $npq \leq np$ as $q \leq 1$

and variance = Mean if $q = 1$

$$\text{Now } \mu'_3 = E(X^3) = \sum_{x=0}^n x^3 f(x)$$

$$\text{As } x^3 = x(x-1)(x-2) + 3x(x-1) + x$$

$$\begin{aligned} \text{So } \mu'_3 &= \sum_{x=0}^n [x(x-1)(x-2) + 3x(x-1) + x] f(x) \\ &= \sum_{x=0}^n x(x-1)(x-2) {}^nC_x p^x q^{n-x} + 3 \sum_{x=0}^n x(x-1) {}^nC_x p^x q^{n-x} \\ &\quad + \sum_{x=0}^n x {}^nC_x p^x q^{n-x} \\ &= \sum_{x=3}^n x(x-1)(x-2) {}^nC_x p^x q^{n-x} + 3 \sum_{x=2}^n x(x-1) {}^nC_x p^x q^{n-x} \\ &\quad + \sum_{x=1}^n x {}^nC_x p^x q^{n-x} \\ &= \sum_{x=3}^n x(x-1)(x-2) \frac{\underline{n}}{x(x-1)(x-2) \underline{x-3} \underline{n-x}} p^x q^{n-x} \\ &\quad + 3n(n-1)p^2 + np \\ &= n(n-1)(n-2) \sum_{x=3}^n \frac{\underline{n-3}}{\underline{x-3} \underline{(n-3)-(x-3)}} p^x q^{n-x} + 3n(n-1)p^2 + np \\ \mu'_3 &= n(n-1)(n-2)p^3 \sum_{x=3}^n {}^{n-3}C_{x-3} p^{x-3} q^{(n-3)-(x-3)} + 3n(n-1)p^2 + np \\ \Rightarrow \mu'_3 &= n(n-1)(n-2)p^3 + 3n(n-1)p^2 + np \end{aligned}$$

Also 3rd moment about mean is

$$\begin{aligned} \mu_3 &= \mu'_3 - 3\mu'_2\mu'_1 + 2\mu_1'^3 \\ &= n(n-1)(n-2)p^3 + 3n(n-1)p^2 + np - 3[n(n-1)p^2 + np] np + 2n^3 p^3 \\ &= (n^2-n)(n-2)p^3 + 3n^2p^2 - 3np^2 + np - 3n^3p^3 + 3n^2p^3 - 3n^2p^2 + 2n^3p^3 \\ &= n^3p^3 - n^2p^3 - 2n^2p^3 + 2np^3 - 3np^2 + np - n^3p^3 + 3n^2p^3 \\ &= np + 2np^3 - 3np^2 \\ &= np(1-3p+2p^2) = np(p-1)(2p-1) \end{aligned}$$

$$= np(-q)(2p-p-q) = npq(q-p)$$

$$\mu'_4 = \sum_{x=0}^n x^4 {}^nC_x p^x q^{n-x}$$

$$\text{Now } x^4 = x(x-1)(x-2)(x-3) + 6x(x-1)(x-2) + 7x(x-1) + x$$

$$\text{So } \mu'_4 = n(n-1)(n-2)(n-3)p^4 + 6n(n-1)(n-2)p^3 + 7n(n-1)p^2 + np$$

$$\text{and } \mu_4 = \mu'_4 - 4\mu'_3\mu'_1 + 6\mu'_2\mu'_1 - 3\mu_1^4$$

$$\Rightarrow \mu_4 = npq[1 + 3(n-2)pq]$$

Moment generating function (M.G.F) about origin for a Binomial distribution

$$M_X(t) = E[e^{tx}] = \sum e^{tx} f(x)$$

$$= \sum_{x=0}^n e^{tx} {}^nC_x p^x q^{n-x}$$

$$= \sum_{x=0}^n {}^nC_x q^{n-x} (pe^t)^x \quad [\Theta e^{tx} = (e^t)^x]$$

$$M_X(t) = (q + pe^t)^n$$

$$\text{Now } \mu'_r = \left. \frac{d^r}{dt^r} M_X(t) \right|_{t=0}$$

$$\Rightarrow \mu'_1 = \left. \frac{d}{dt} M_X(t) \right|_{t=0}$$

$$\begin{aligned} \mu'_1 &= \left. \frac{d}{dt} (q + pe^t)^n \right|_{t=0} \\ &= \left. n(q + pe^t)^{n-1} pe^t \right|_{t=0} \end{aligned}$$

$$= np (q + p)^{n-1} = np$$

$$\begin{aligned} \text{Also } \mu'_2 &= \left. \frac{d^2}{dt^2} M_X(t) \right|_{t=0} \\ &= \left. \frac{d}{dt} \left[n(q + pe^t)^{n-1} pe^t \right] \right|_{t=0} \end{aligned}$$

$$\begin{aligned}
&= np \frac{d}{dt} \left[e^t (q + pe^t)^{n-1} \right] \Bigg|_{t=0} \\
&= np [e^t (q + pe^t)^{n-1} + 1 (n-1)(q + pe^t)^{n-2} pe^t] \Big|_{t=0} \\
&= np [1 (q + p)^{n-1} + 1(n-1)(q+p)^{n-2} p] \\
&= np [1 + (n-1)p] = np + n(n-1)p^2
\end{aligned}$$

Pearson's Coefficients

$$\beta_1 = \frac{\mu_3^2}{\mu_2^3}, \quad \beta_2 = \frac{\mu_4}{\mu_2^2}, \quad \alpha_1 = \sqrt{\beta_1}, \quad \alpha_2 = \beta_2 - 3$$

$$\beta_1 = \frac{(1-2p)^2}{npq}, \quad \beta_2 = 3 + \frac{(1-6pq)}{npq}$$

$$\alpha_1 = \frac{1-2p}{\sqrt{npq}}, \quad \alpha_2 = \frac{1-6pq}{npq}$$

Characteristic function

$$\phi_X(t) = E[e^{itx}] = (q + pe^{it})^n$$

Cumulants

Cumulant generating function (c.g.f) of a Binomial distribution is

$$\begin{aligned}
K_X(t) &= \log M_X(t) \\
&= \log (q + pe^t)^n = n \log (q + pe^t) \\
&= n \log \left[q + p \left(1 + t + \frac{t^2}{2!} + \frac{t^3}{3!} + \dots \right) \right] \\
&= n \log \left[(q + p) + p \left(t + \frac{t^2}{2!} + \frac{t^3}{3!} + \dots \right) \right] \\
&= n \log \left[1 + p \left(t + \frac{t^2}{2!} + \frac{t^3}{3!} + \dots \right) \right]
\end{aligned}$$

using $\log(1+x) = x - \frac{x^2}{2} + \frac{x^3}{3} - \dots$, we get

$$K_X(t) = n \left[p \left(t + \frac{t^2}{2!} + \frac{t^3}{3!} + \dots \right) - \frac{p^2}{2} \left(t + \frac{t^2}{2!} + \frac{t^3}{3!} + \dots \right)^2 + \frac{p^3}{3} \left(t + \frac{t^2}{2!} + \dots \right)^3 - \dots \right]$$

The r^{th} cumulant is

$$K_r = \text{coefficient of } \frac{t^r}{r!} \text{ in } K_X(t) = \left. \frac{d^r}{dt^r} K_X(t) \right|_{t=0}$$

So $K_1 = np = \mu'_1$

$$K_2 = np - np^2 = \text{coefficient of } \frac{t^2}{2!}$$

$$\Rightarrow K_2 = np(1-p) = npq = \mu_2 \quad [\Theta p + q = 1]$$

$$\& \quad \frac{K_3}{3!} = \frac{np}{3!} - \frac{np^2}{2} \frac{2}{2!} + \frac{np^3}{3}$$

$$\begin{aligned} \Rightarrow K_3 &= np - 3np^2 + 2p^3n = np(1-3p+2p^2) \\ &= np(p-1)(2p-1) \\ &= np(-q)[2p-p-q] \\ &= npq(q-p) = \mu_3 \end{aligned}$$

Example: - p = probability of getting a head = $\frac{1}{2}$

q = probability of not getting a head = $\frac{1}{2}$

The probability of getting x heads in a random throw of 10 coins is

$$p(x) = \binom{10}{x} \left(\frac{1}{2}\right)^x \left(\frac{1}{2}\right)^{10-x} = \binom{10}{x} \left(\frac{1}{2}\right)^{10}; x = 0, 1, 2, \dots, 10$$

$\therefore$ Probability of getting at least 7 heads is

$$\begin{aligned} P(X \geq 7) &= p(7) + p(8) + p(9) + p(10) \\ &= \left(\frac{1}{2}\right)^{10} \left\{ \binom{10}{7} + \binom{10}{8} + \binom{10}{9} + \binom{10}{10} \right\} \\ &= \frac{120 + 45 + 10 + 1}{1024} = \frac{176}{1024} \end{aligned}$$

Recurrence Relation

$$\mu_{r+1} = pq[nr \mu_{r-1} + \frac{d}{dp} \mu_r]$$

where μ_r is the r^{th} moment about mean.

$$\text{Now, } \mu_r = E[(X-np)^r] = \sum_{x=0}^n (x-np)^r {}^nC_x p^x q^{n-x}$$

Differentiating w.r.t.p, we get

$$\begin{aligned} \frac{d\mu_r}{dp} &= \sum_{x=0}^n \left[({}^nC_x p^x q^{n-x})r(x-np)^{r-1}(-n) + (x-np)^r {}^nC_x \frac{d}{dp}(p^x q^{n-x}) \right] \\ &= -nr \sum_{x=0}^n (x-np)^{r-1} {}^nC_x p^x q^{n-x} \\ &\quad + \sum_{x=0}^n (x-np)^r {}^nC_x \left[q^{n-x} x p^{x-1} + p^x (n-x) q^{n-x-1} (-1) \right] \\ &\quad \left[\Theta p=1-q, q=1-p \therefore \frac{dq}{dp} = -1 \right] \\ &= -nr \sum_{x=0}^n (x-np)^{r-1} f(x) + \sum_{x=0}^n (x-np)^r {}^nC_x p^x q^{n-x} \left[\frac{x}{p} - \frac{n-x}{q} \right] \\ &= -nr \mu_{r-1} + \sum_{x=0}^n (x-np)^r {}^nC_x p^x q^{n-x} \frac{(x-np)}{pq} \\ &\quad \left[\therefore \frac{x}{p} - \frac{(n-x)}{q} = \frac{xq-np+xp}{pq} = \frac{x(p+q)-np}{pq} = \frac{x-np}{pq} \right] \\ \Rightarrow \frac{d\mu_r}{dp} &= -nr \mu_{r-1} + \sum_{x=0}^n \frac{(x-np)^{r+1}}{pq} {}^nC_x p^x q^{n-x} \\ &= -nr \mu_{r-1} + \frac{1}{pq} \mu_{r+1} \end{aligned}$$

M.G.F about its Mean

$$M_{X-np}(t) = [qe^{-pt} + pe^{qt}]^n$$

Now by definition $M_{X-np}(t) = \sum_{x=0}^n e^{(x-np)t} f(x)$

$$\begin{aligned} \Rightarrow M_{X-np}(t) &= \sum_{x=0}^n e^{(x-np)t} {}^n C_x p^x q^{n-x} \\ &= \sum_{x=0}^n e^{xt} e^{-npt} {}^n C_x p^x q^{n-x} \\ &= e^{-npt} \sum_{x=0}^n {}^n C_x q^{n-x} (pe^t)^x \\ &= e^{-npt} (q + pe^t)^n \\ &= (e^{-pt})^n (q + pe^t)^n \\ &= [qe^{-pt} + pe^{qt}]^n \end{aligned}$$

$$\Rightarrow M_{X-np}(t) = [qe^{-pt} + pe^{qt}]^n \quad [\Theta p + q = 1]$$

$$\begin{aligned} M_{X-np}(t) &= \left[q \left(1 - pt + \frac{p^2 t^2}{2!} - \frac{p^3 t^3}{3!} + \dots \right) + p \left(1 + qt + \frac{q^2 t^2}{2!} + \frac{q^3 t^3}{3!} + \dots \right) \right]^n \\ &= \left[(p+q) + pq(p+q) \frac{t^2}{2!} + pq(q^2 - p^2) \frac{t^3}{3!} + \dots \right]^n \end{aligned}$$

As $p + q = 1$, we have

$$\begin{aligned} M_{X-np}(t) &= \left[1 + \left(pq \frac{t^2}{2!} + pq(q-p) \frac{t^3}{3!} + \dots \right) \right]^n \\ &= 1 + n \left[pq \frac{t^2}{2!} + pq(q-p) \frac{t^3}{3!} + \dots \right] \\ &\quad + \frac{n(n-1)}{2!} \left[pq \frac{t^2}{2!} + pq(q-p) \frac{t^3}{3!} + \dots \right]^2 + \dots \\ &= 1 + npq \frac{t^2}{2!} + npq(q-p) \frac{t^3}{3!} + \dots \end{aligned}$$

$$\therefore \mu_1 = 0$$

$$\mu_2 = \text{coefficient of } \frac{t^2}{2!} = npq$$

$$\mu_3 = \text{coefficient of } \frac{t^3}{3!} = npq(q - p)$$

Example: - In 8 throw of a dice, 5 or 6 is considered as success. Find the mean number of successes and S.D.

Solution: - Here $n = 8$, $p = \frac{2}{6} = \frac{1}{3}$, $q = \frac{2}{3}$

$$\therefore \text{Mean} = np = 8 \times \frac{1}{3} = \frac{8}{3}$$

$$\text{and SD} = \sqrt{npq} = \sqrt{\frac{8}{3} \times \frac{2}{3}} = \frac{4}{3}$$

Example: - 6 dice are thrown 729 times. How many times do you expect at least 3 dice to show five or six?

Solution: - $n = 6$, $N = 729$

$$p = \frac{2}{6} = \frac{1}{3}, x = 3, q = \frac{2}{3}$$

$$\therefore P(X \geq 3) = f(3) + f(4) + f(5) + f(6) \quad \dots(1)$$

$$\text{Now } f(x) = {}^nC_x p^x q^{n-x}$$

$$\begin{aligned} \therefore (1) \Rightarrow P(X \geq 3) &= \sum_{x=3}^6 {}^nC_x p^x q^{n-x} \\ &= {}^6C_3 \left(\frac{1}{3}\right)^3 \left(\frac{2}{3}\right)^3 + {}^6C_4 \left(\frac{1}{3}\right)^4 \left(\frac{2}{3}\right)^2 + {}^6C_5 \left(\frac{1}{3}\right)^5 \left(\frac{2}{3}\right) + \left(\frac{1}{3}\right)^6 = \frac{233}{729} \end{aligned}$$

No. of times, at least 3 dice will show

$$\begin{aligned} 5 \text{ or } 6 &= NP(X \geq 3) = 729 \times \frac{233}{729} \\ &= 233 \end{aligned}$$

Fitting of Binomial distribution

By fitting of Binomial distribution we mean to find out the theoretical or expected frequencies for all values of $X = 0, 1, 2, \dots, n$

The frequency $F(x)$ for $X = x$ is

$$F(x) = N f(x) = N \sum_{x=0}^n {}^n C_x p^x q^{n-x}$$

for $x = 0$

$$F(0) = Nq^n \quad \dots(1)$$

Also
$$\frac{f(x)}{f(x-1)} = \frac{{}^n C_x p^x q^{n-x}}{{}^n C_{x-1} p^{x-1} q^{n-x+1}}$$

$$\frac{Nf(x)}{Nf(x-1)} = \frac{n-x+1}{x} \cdot \frac{p}{q}$$

$$\Rightarrow \frac{F(x)}{F(x-1)} = \left(\frac{n-x+1}{x} \right) \frac{p}{q}$$

$$\Rightarrow F(x) = \left(\frac{n-x+1}{x} \right) \cdot \frac{p}{q} F(x-1) \quad \dots(2)$$

where $x = 1, 2, \dots, n$

POISSON DISTRIBUTION

Poisson distribution can be obtained from Binomial distribution under three conditions

- (i) no. of trials is large i.e. $n \rightarrow \infty$
- (ii) probability of success is very small i.e. $p \rightarrow 0$
- (iii) the mean no. of successes is finite, i.e. $np = m(\text{say})$

In case of Binomial distribution,

$$f(x) = {}^n C_x p^x q^{n-x}, \quad x = 0, 1, 2, \dots, n$$

Taking limit case of $f(x)$ in Binomial distribution, we get $f(x)$ for Poisson distribution,

$$f(x) = \frac{m^x e^{-m}}{x!}, \quad x = 0, 1, 2, 3, \dots$$

Now $n \rightarrow \infty, p \rightarrow 0, np = m$

i.e. $p = \frac{m}{n}, q = 1 - \frac{m}{n}$ as $n \rightarrow \infty$

Probability of x successes in Binomial distance is

$$f(x) = {}^n C_x p^x q^{n-x}$$

Probability of x successes in Poisson distance is

$$\begin{aligned}
f(x) &= \lim_{n \rightarrow \infty} {}^nC_x p^x q^{n-x} \\
&= \lim_{n \rightarrow \infty} {}^nC_x \left(\frac{m}{n}\right)^x \left(1 - \frac{m}{n}\right)^{n-x} \\
&= \lim_{n \rightarrow \infty} \frac{n!}{x!(n-x)!} \left(\frac{m}{n}\right)^x \left(1 - \frac{m}{n}\right)^{n-x} \\
&= \lim_{n \rightarrow \infty} \frac{m^x}{\underline{x}} \frac{n(n-1)(n-2)\dots(n-x+1)}{\underline{n-x} (n^x)} \left(1 - \frac{m}{n}\right)^{n-x} \\
&= \lim_{n \rightarrow \infty} \frac{m^x}{\underline{x}} \frac{n(n-1)(n-2)\dots(n-x+1)}{n^x} \left(1 - \frac{m}{n}\right)^n \left(1 - \frac{m}{n}\right)^{-x} \\
&= \lim_{n \rightarrow \infty} \frac{m^x}{\underline{x}} \left(\frac{n}{n}\right) \left(\frac{n-1}{n}\right) \left(\frac{n-2}{n}\right) \dots \left(\frac{n-x+1}{n}\right) \left(1 - \frac{m}{n}\right)^n \left(1 - \frac{m}{n}\right)^{-x} \\
&= \lim_{n \rightarrow \infty} \frac{m^x}{\underline{x}} 1 \left(1 - \frac{1}{n}\right) \left(1 - \frac{2}{n}\right) \dots \left(1 - \frac{x-1}{n}\right) \left(1 - \frac{m}{n}\right)^n \left(1 - \frac{m}{n}\right)^{-x} \\
&= \lim_{n \rightarrow \infty} \frac{m^x}{\underline{x}} \left(1 - \frac{m}{n}\right)^n \quad [\Theta \text{ Rest of the terms tends to unity as } n \rightarrow \infty] \\
&= \lim_{n \rightarrow \infty} \frac{m^x}{\underline{x}} \left(1 - \frac{m}{n}\right)^n \quad (1)
\end{aligned}$$

Now

$$\begin{aligned}
\lim_{n \rightarrow \infty} \left(1 - \frac{m}{n}\right)^n &= \lim_{n \rightarrow \infty} \left(1 - n \cdot \frac{m}{n} + \frac{n(n-1)}{2!} \frac{m^2}{n^2} - \frac{n(n-1)(n-2)}{3!} \frac{m^3}{n^3} + \dots\right) \\
&= \lim_{n \rightarrow \infty} \left(1 - m + \frac{m^2}{2!} - \frac{m^3}{3!} + \dots\right) \\
&= e^{-m}
\end{aligned}$$

∴ from (1)

$$f(x) = \frac{m^x}{\underline{x}} e^{-m}, \quad x = 0, 1, 2, \dots$$

Moments of Poisson distribution

$$\mu'_r = E[X^r] = r^{\text{th}} \text{ moment about origin}$$

$$\begin{aligned}
\therefore \mu'_1 &= E[X] = \sum_{x=0}^{\infty} x f(x) \\
&= \sum_{x=0}^{\infty} x e^{-m} \frac{m^x}{x!} = \sum_{x=0}^{\infty} \frac{x e^{-m} m^x}{x!} \\
&= \sum_{x=1}^{\infty} \frac{e^{-m} m^x}{(x-1)!} \\
&= m e^{-m} \sum_{x=1}^{\infty} \frac{m^{x-1}}{(x-1)!} \\
&= m e^{-m} \left[1 + \frac{m}{1!} + \frac{m^2}{2!} + \dots \right]
\end{aligned}$$

$$\Rightarrow \mu'_1 = m e^{-m} e^m = m$$

$$\Rightarrow \mu'_1 = m = \text{Mean}$$

$$\begin{aligned}
\text{Now } \mu'_2 &= E(X^2) = \sum_{x=0}^{\infty} x^2 e^{-m} \frac{m^x}{x!} \\
&= \sum_{x=0}^{\infty} \left[\frac{x(x-1) + x}{x!} \right] e^{-m} m^x \\
&= e^{-m} \left[\sum_{x=0}^{\infty} \frac{x(x-1)}{x!} m^x + \sum_{x=0}^{\infty} \frac{x m^x}{x!} \right] \\
&= e^{-m} \sum_{x=2}^{\infty} \frac{m^x}{(x-2)!} + e^{-m} \sum_{x=1}^{\infty} \frac{m^x}{(x-1)!} \\
&= m^2 e^{-m} \sum_{x=2}^{\infty} \frac{m^{x-2}}{(x-2)!} + m \\
&= m^2 e^{-m} e^m + m
\end{aligned}$$

$$\Rightarrow \mu'_2 = m^2 + m$$

$$\therefore \text{Variance, } \mu_2 = \mu'_2 - \mu'^2_1$$

$$\Rightarrow \mu_2 = m^2 + m - m^2 = m \Rightarrow \mu_2 = m$$

$$\text{So mean} = \text{Variance}$$

Moment generating function about origin

M.G.F about origin is by definition

$$\begin{aligned}
 M_X(t) &= E[e^{tx}] = \sum_{x=0}^{\infty} e^{tx} f(x) \\
 &= \sum_{x=0}^{\infty} e^{tx} \frac{e^{-m} m^x}{x!} = e^{-m} \sum_{x=0}^{\infty} \frac{(me^t)^x}{x!} \\
 &= e^{-m} \left[1 + me^t + \frac{(me^t)^2}{2!} + \dots \right] \\
 &= e^{-m} \cdot e^{me^t}
 \end{aligned}$$

$$\Rightarrow M_X(t) = e^{m(e^t-1)} \quad \dots(1)$$

Moment generating function about mean

$$\begin{aligned}
 M_{X-m}(t) &= \sum_{x=0}^{\infty} e^{t(x-m)} f(x) \\
 &= \sum_{x=0}^{\infty} e^{t(x-m)} \frac{e^{-m} m^x}{x!} \\
 &= \sum_{x=0}^{\infty} e^{tx} e^{-mt} e^{-m} \frac{m^x}{x!} \\
 &= e^{-(1+t)m} \sum_{x=0}^{\infty} \frac{(me^t)^x}{x!} \\
 &= e^{-m(1+t)} e^{me^t} = e^{m(e^t-t-1)} \quad \dots(2) \\
 &= e^{m \left(1+t+\frac{t^2}{2!}+\frac{t^3}{3!}+\dots \right) - t-1} = e^{m \left(\frac{t^2}{2!}+\frac{t^3}{3!}+\dots \right)}
 \end{aligned}$$

Now $\mu'_r = \frac{d^r}{dt^r} M_X(t) \Big|_{t=0}$

$$\begin{aligned}
\therefore \mu'_1 &= \left. \frac{d}{dt} M_X(t) \right|_{t=0} \\
&= \left. \frac{d}{dt} e^{m(e^t-1)} \right|_{t=0} \\
&= e^{m(e^t-1)} m e^t \Big|_{t=0}
\end{aligned}$$

$$\mu'_1 = m$$

$$\begin{aligned}
\text{and } \mu'_2 &= \left. \frac{d^2}{dt^2} M_X(t) \right|_{t=0} \\
&= \left. \frac{d}{dt} \left[m e^t e^{m(e^t-1)} \right] \right|_{t=0} \\
&= m \left[e^t m(e^t-1) + e^t e^{m(e^t-1)} m e^t \right] \Big|_{t=0} \\
&= m[1 \cdot e^0 + 1 \cdot 1 \cdot m \cdot 1] \\
&= m(1 + m) = m^2 + m
\end{aligned}$$

Characteristic function

$$\phi_X(t) = e^{m(e^{it}-1)} = E[e^{itx}]$$

Cumulant generating function about origin

$$\begin{aligned}
K_X(t) &= \log M_X(t) = \log e^{m(e^t-1)} \\
&= m(e^t - 1) \\
\Rightarrow K_X(t) &= m \left[t + \frac{t^2}{2!} + \frac{t^3}{3!} + \dots \right]
\end{aligned}$$

The r^{th} cumulant is

$$K_r = \text{coefficient of } \frac{t^r}{r!} \text{ in } K_X(t)$$

$$\therefore K_1 = m, K_2 = m, K_3 = m, \dots$$

$$\text{i.e. } K_r = m, \text{ for } r=1, 2, 3, \dots$$

All cumulants are equal for Poisson distribution

Recurrence Relation for Moments

$$\mu_{r+1} = m[r\mu_{r-1} + \frac{d\mu_r}{dm}]$$

Now r^{th} central moment by definition is

$$\begin{aligned}\mu_r &= E[(X - m)^r] \\ &= \sum_{x=0}^{\infty} (x - m)^r f(x) = \sum_{x=0}^{\infty} (x - m)^r \frac{e^{-m} m^x}{\lfloor x \rfloor} \\ \therefore \frac{d\mu_r}{dm} &= \sum_{x=0}^{\infty} \left[r(x - m)^{r-1} (-1) e^{-m} \frac{m^x}{\lfloor x \rfloor} \right] + \sum_{x=0}^{\infty} \left[(x - m)^r e^{-m} (-1) \frac{m^x}{\lfloor x \rfloor} \right] \\ &\quad + \sum_{x=0}^{\infty} (x - m)^r e^{-m} x \frac{m^{x-1}}{\lfloor x \rfloor} \\ &= -r \sum_{x=0}^{\infty} (x - m)^{r-1} \frac{e^{-m} m^x}{\lfloor x \rfloor} + \sum_{x=0}^{\infty} (x - m)^r \frac{e^{-m} m^x}{\lfloor x \rfloor} \left[\frac{x}{m} - 1 \right] \\ &= -r \sum_{x=0}^{\infty} (x - m)^{r-1} \frac{e^{-m} m^x}{\lfloor x \rfloor} + \sum_{x=0}^{\infty} (x - m)^r \frac{e^{-m} m^x}{\lfloor x \rfloor} \left(\frac{x - m}{m} \right) \\ &= -r \mu_{r-1} + \frac{1}{m} \sum_{x=0}^{\infty} (x - m)^{r+1} \frac{e^{-m} m^x}{\lfloor x \rfloor} \\ \Rightarrow \frac{d\mu_r}{dm} &= -r\mu_{r-1} + \frac{1}{m} \mu_{r+1} \\ \Rightarrow \frac{d\mu_r}{dm} + r\mu_{r-1} &= \frac{1}{m} \mu_{r+1} \\ \Rightarrow \mu_{r+1} &= m[r\mu_{r-1} + \frac{d\mu_r}{dm}]\end{aligned}$$

Recurrence relation or Fitting of Poisson distribution

$$\begin{aligned}f(x) &= \frac{e^{-m} m^x}{\lfloor x \rfloor} \\ f(x+1) &= \frac{e^{-m} m^{x+1}}{\lfloor x+1 \rfloor} \\ \therefore \frac{f(x+1)}{f(x)} &= \frac{m}{x+1}\end{aligned}$$

$$\Rightarrow f(x+1) = \frac{mf(x)}{x+1} \quad \dots(1)$$

Now $Nf(x) = F(x)$

$$\therefore F(0) = Nf(0) = Ne^{-m}$$

$$\therefore (1) \Rightarrow Nf(x+1) = \left(\frac{m}{x+1}\right) f(x)N$$

$$\Rightarrow F(x+1) = \frac{m}{x+1} F(x), x = 0, 1, 2, \dots \quad \dots(2)$$

Put $x = 0$ in (2), we get

$$F(1) = m F(0) = m Ne^{-m}$$

$$F(2) = \frac{m}{2} F(1) = \frac{m^2}{2} Ne^{-m}$$

$$F(3) = \frac{m}{3} F(2) = \frac{m^3}{6} Ne^{-m}, \dots$$

Additive Property of Poisson variate

If X_1, X_2 are two independent Poisson variates with parameters m_1, m_2 . Then their sum $X_1 + X_2$ is also a Poisson variate with Parameter $(m_1 + m_2)$

i.e. $X_1 + X_2 \sim P(m_1 + m_2; x)$

Proof: - If X is a Poisson variable, then

$$f(x) = \frac{e^{-m} m^x}{x!}, x = 0, 1, 2, \dots$$

$$\& M_{X_1}(t) = e^{m_1(e^t-1)}$$

$$M_{X_2}(t) = e^{m_2(e^t-1)}$$

“The MGF of sum of two independent r.v. is equal to the product of their MGF.”

By using this result, we have

$$\begin{aligned} M_{X_1+X_2}(t) &= M_{X_1}(t) \cdot M_{X_2}(t) \\ &= e^{m_1(e^t-1)} \cdot e^{m_2(e^t-1)} \\ &= e^{(e^t-1)(m_1+m_2)} \end{aligned}$$

This is the MGF of Poisson variate $X_1 + X_2$ with parameter $(m_1 + m_2)$.

Example: - Show that in a Poisson distribution with unit mean, deviation about mean is $\frac{2}{e}$ times the standard deviation.

Solution: - Here mean = 1

$$\text{Variance} = \text{SD} = 1 \quad [\text{In Poisson distribution mean} = \text{variance}]$$

$$\therefore \text{M.D} = \text{Mean Deviation} = E[|X-1|]$$

$$\begin{aligned} &= \sum_{x=0}^{\infty} \frac{|x-1|e^{-1}}{x!} \\ &= e^{-1} \sum_{x=0}^{\infty} \frac{|x-1|}{x!} \\ &= \frac{1}{e} \left[1 + \frac{1}{2!} + \frac{2}{3!} + \frac{3}{4!} + \dots \right] \end{aligned}$$

Now general term of the series

$$\frac{1}{2!} + \frac{2}{3!} + \frac{3}{4!} + \dots \text{is}$$

$$\begin{aligned} \text{General term} &= \frac{n}{(n+1)!} = \frac{n+1-1}{(n+1)!} \\ &= \frac{1}{n!} - \frac{1}{(n+1)!} \end{aligned}$$

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

$$\begin{aligned} \text{M.D} &= \frac{1}{e} \left[1 + \left(1 - \frac{1}{2!} \right) + \left(\frac{1}{2!} - \frac{1}{3!} \right) + \left(\frac{1}{3!} - \frac{1}{4!} \right) + \dots \right] \\ &= \frac{1}{e} (1 + 1) = \frac{2}{e} \times 1 = \frac{2}{e} \times \text{S.D.} \end{aligned}$$

M.G.F about mean

M.G.F about mean for Binomial distribution is

$$\begin{aligned} M_{X-np}(t) &= E[e^{t(X-np)}] \\ &= [qe^{-pt} + pe^{(1-p)t}]^n = [qe^{-pt} + pe^{qt}]^n \\ &= e^{-npt} [q + pe^t]^n \end{aligned}$$

$$\begin{aligned}
\therefore \log M_{X-np}(t) &= -npt + n \log \left[q \left(1 + \frac{pe^t}{q} \right) \right] \\
&= -npt + n \log q + n \log \left(1 + \frac{pe^t}{q} \right)
\end{aligned}$$

Put $np = m$, we get

$$\begin{aligned}
\text{Log } M_{X-np}(t) &= -mt + n \log \left(1 - \frac{m}{n} \right) + n \log \left[1 + \frac{me^t}{n \left(1 - \frac{m}{n} \right)} \right] \\
&= -mt + n \left[-\frac{m}{n} - \frac{m^2}{2n^2} - \frac{m^3}{3n^3} \dots \right] + n \left[\frac{me^t}{n \left(1 - \frac{m}{n} \right)} - \frac{1}{2} \left\{ \frac{me^t}{n \left(1 - \frac{m}{n} \right)} \right\}^2 \right. \\
&\quad \left. + \frac{1}{3} \left\{ \frac{me^t}{n \left(1 - \frac{m}{n} \right)} \right\}^3 \right] \\
&= -mt - m + \frac{me^t}{\left(1 - \frac{m}{n} \right)} - \frac{1}{2n} \left\{ \frac{me^t}{1 - \frac{m}{n}} \right\}^2 - \frac{m^2}{2n} + o\left(\frac{1}{n^2} \right) \\
&= -mt - m + \frac{me^t}{1 - \frac{m}{n}} + o\left(\frac{1}{n} \right)
\end{aligned}$$

As $n \rightarrow \infty$, we have

$$\lim_{n \rightarrow \infty} \log M_{X-np}(t) = -mt - m + me^t$$

$$\Rightarrow \lim_{n \rightarrow \infty} M_{X-np}(t) = e^{me^t - mt - m}$$

$$= e^{m(e^t - t - 1)}$$

= M.G.F about mean of Poisson distance

Example: - If X is a Poisson variate s.t. $P(X = 1) = P(X = 2)$, find $P(X = 4)$.

Solution: - Probability of x successes in Poisson distribution is

$$P(X = x) = f(x) = \frac{e^{-m} m^x}{x!}$$

$$\therefore P(X = 1) = \frac{e^{-m} m}{1!} = e^{-m} m \quad \dots(1)$$

$$P(X = 2) = \frac{e^{-m} m^2}{2!} = \frac{m^2}{2} e^{-m} \quad \dots(2)$$

Since $P(X = 1) = P(X = 2)$

$\therefore$ from (1) & (2), we get

$$m e^{-m} = \frac{m^2}{2} e^{-m} \Rightarrow m = 2$$

Therefore for $X = 4$

$$\begin{aligned} P(X = 4) &= \frac{e^{-m} m^4}{4!} = \frac{e^{-2} (2)^4}{24} \\ &= \frac{16}{24} e^{-2} = 0.09 \end{aligned}$$

Let $e^{-2} = a$

$$\Rightarrow \log_{10} a = -2 \log_{10} e$$

$$\begin{aligned} \Rightarrow \log_{10} a &= -2(0.4343) = -0.8686 \\ &= T.1314 \end{aligned}$$

$$\Rightarrow a = \text{antilog}(T.1314) = 0.1353$$

Example: -Six coins are tossed, 6400 times, using Poisson distribution, what is the probability of getting six heads x times?

Solution: - When a coin is tossed, probability of getting head is $= \frac{1}{2}$

When 6 coins are tossed, probability of getting 6 heads $= \left(\frac{1}{2}\right)^6 = \frac{1}{64} = p(\text{say})$

$$\text{Mean} = np = 6400 \times \frac{1}{64} = 100 \text{ (Mean)}$$

$$\Rightarrow m = 100$$

Probability of getting six heads x times

$$= \frac{e^{-m} m^x}{x!} \text{ with } m = 100$$

$$= \frac{e^{-100} (100)^x}{x!}$$

Example: - After correcting 50 pages of the proof of a book, the proof reader finds that there are on the average 2 errors of 5 pages. How many pages would one expect to find with 0, 1, 2, 3 & 4 errors in 1000 pages of first print of the book?

Solution: - Now Mean = $\frac{2}{5} = 0.4 = M$ (say)

$X \rightarrow$ Poisson distance,

$$f(x) = P(X = x) = \frac{e^{-m} m^x}{x!}$$

$$= \frac{e^{-0.4} (0.4)^x}{x!}$$

Expected number of pages with 1000 pages is

$$1000 f(x) = \frac{1000 e^{-0.4} (0.4)^x}{x!}$$

Now we want to find $f(0)$, $f(1)$, $f(2)$, $f(3)$, $f(4)$ by using Recurrence Relation,

$$f(x+1) = \frac{m}{x+1} f(x)$$

$X = x$	$f(x)$	Expected number of pages $= 1000 f(x)$
0	$f(0) = e^{-0.4} = 0.6703$	$670.3 \approx 670$
1	$f(1) = \frac{0.4}{0+1} f(0) = 0.4 \times 0.6703$ $= 0.26812$	$268.12 \approx 268$
2	$f(2) = \frac{0.4}{1+1} f(1) = 0.053624$	$53.62 \approx 54$

$$3 \quad f(3) = \frac{0.4}{2+1} f(2) = 0.0071298 \quad 7.1298 \approx 7$$

$$4 \quad f(4) = \frac{0.4}{3+1} f(3) = 0.0007129 \quad \approx 1$$

Example: - In a certain factory making blades, there is a small chance $\frac{1}{500}$ for any blade to be defective. The blades are supplied in packets of 10. Use Poisson distribution to calculate the approximate. Number of packets containing no defective, one defective & 2 defective blades respectively in a consignment of 10000 packets.

$$(e^{-0.02} = 0.9802)$$

Solution: - Let $p \rightarrow$ probability of blade being defective = $\frac{1}{500}$

$$n = 10$$

$$\therefore \text{Mean} = m = np = \frac{1}{50} = 0.02$$

Number of packets containing x defective blades,

$$\begin{aligned} F(x) &= \frac{N e^{-m} m^x}{x!} \\ &= \frac{10000 \times e^{-0.02} (0.02)^x}{x!} \\ &= \frac{10000 \times 0.9802 (0.02)^x}{x!} \end{aligned}$$

$$F(x) = \frac{9802 (0.02)^x}{x!}$$

X

0

1

F(x)

$$F(0) = \frac{9802 (0.02)^0}{0!} = 9802$$

$$F(1) = \frac{9802 (0.02)^1}{1!} = 196$$

2

$$F(2) = \frac{9802(0.02)^2}{\underline{2}}$$

Mode of Poisson distribution

Let the most probable values of r.v. X be r i.e. r is mode.

Then $P(X = r)$ should be greater than $P(X = r + 1)$ and $P(X = r - 1)$

i.e

$$\begin{aligned} & \frac{e^{-m}m^{r-1}}{\underline{r-1}} < \frac{e^{-m}m^r}{\underline{r}} > \frac{e^{-m}m^{r+1}}{\underline{r+1}} \\ \Rightarrow & \frac{m^{r-1}}{\underline{r-1}} < \frac{m.m^{r-1}}{r\underline{r-1}} > \frac{m^{r-1}m^2}{(r+1)r\underline{r-1}} \\ \Rightarrow & 1 < \frac{m}{r} > \frac{m^2}{r(r+1)} \\ \Rightarrow & r(r+1) < m(r+1) > m^2 \\ \Rightarrow & r < m \quad \& \quad (r+1) > m \\ \Rightarrow & r < m \quad \& \quad r > m-1 \\ \Rightarrow & m-1 < r < m \end{aligned}$$

Thus if m is an **integer**, there shall be two modes m and (m-1).

If m is not an integer, then mode is the integral value between (m-1) & m.

Example: - A Poisson distance a double mode at $X = 3$ and $X = 4$, what is the probability that X will have one or the other of these two values.

Solution: - $P(X = x) = \frac{e^{-m}m^x}{\underline{x}}$

$$\left. \begin{aligned} \therefore \quad P(X=3) &= \frac{e^{-m}m^3}{\underline{3}} \\ \& \quad P(X=4) &= \frac{e^{-m}m^4}{\underline{4}} \end{aligned} \right\} \dots(1)$$

Since the Poisson distance has a double mode at $X = 3$ and $X = 4$, so

$$\begin{aligned} & P(X = 3) = P(X = 4) \\ \Rightarrow & \frac{e^{-m}m^3}{\underline{3}} = \frac{e^{-m}m^4}{\underline{4}} \end{aligned}$$

$$\Rightarrow m = \frac{4}{3} = 4$$

$$\therefore \text{from (1), } P(X=3) = \frac{e^{-4} 4^3}{3!} = \frac{32}{3} e^{-4}$$

$$\begin{aligned} \& P(X=4) &= \frac{e^{-4} 4^4}{4!} = \frac{e^{-4} \cdot 4 \cdot 4^3}{4 \cdot 3!} \\ &= \frac{e^{-4} \cdot 4^3}{3!} = \frac{32}{3} e^{-4} \end{aligned}$$

$$\begin{aligned} \text{Now } P[(X=3) \cup (X=4)] &= P(X=3) + P(X=4) \\ &= \frac{64}{3} e^{-4} \\ &= \frac{64}{3} (0.0183) = 0.3904 \end{aligned}$$

Example: - If X is a Poisson variate with mean m , show that $\frac{X-m}{\sqrt{m}}$ is a variable with mean **zero** and variance **unity**.

Solution: - We know that

$$\text{Mean} = E(X) = m$$

$$\text{Let } Z = \frac{X-m}{\sqrt{m}}$$

$$\begin{aligned} \text{then } E(Z) &= E\left(\frac{X-m}{\sqrt{m}}\right) = \frac{1}{\sqrt{m}} E(X-m) \\ &= \frac{1}{\sqrt{m}} [E(X) - E(m)] \\ &= \frac{1}{\sqrt{m}} [m - m] = 0 \end{aligned}$$

$$\begin{aligned} \text{and variance} &= E\left(\frac{X-m}{\sqrt{m}}\right)^2 \\ &= \frac{1}{m} E(X-m)^2 = \frac{1}{m} \mu_2 \end{aligned}$$

$$= \frac{1}{m} \cdot m = 1$$

Also find M.G.F of this variable and show that it approaches $e^{\frac{1}{2}t^2}$ as $m \rightarrow \infty$

$$\text{Let } Y = \frac{X - m}{\sqrt{m}}$$

$$\text{then } M_Y(t) = E[e^{tY}] = E\left[e^{t \frac{(X-m)}{\sqrt{m}}}\right]$$

$$= e^{-\frac{mt}{\sqrt{m}}} E\left[e^{\frac{tx}{\sqrt{m}}}\right]$$

$$= e^{-\sqrt{m}t} \sum_{x=0}^{\infty} \frac{e^{-m} m^x}{x!} e^{\frac{tx}{\sqrt{m}}}$$

$$= e^{-\sqrt{m}t} e^{-m} \sum_{x=0}^{\infty} \frac{(me^{t/\sqrt{m}})^x}{x!}$$

$$= e^{-m-\sqrt{m}t} \left[1 + \frac{me^{t/\sqrt{m}}}{1!} + \frac{(me^{t/\sqrt{m}})^2}{2!} + \dots \right]$$

$$= e^{-m-\sqrt{m}t} e^{me^{t/\sqrt{m}}}$$

$$= e^{-m-\sqrt{m}t+m \left(1 + \frac{t}{\sqrt{m}} + \frac{t^2}{2!} + \frac{t^3}{3! m\sqrt{m}} + \dots \right)}$$

$$M_Y(t) = e^{\frac{t^2}{2} + \frac{t^3}{3\sqrt{m}} + \dots}$$

As $m \rightarrow \infty$, $\lim_{m \rightarrow \infty} M_Y(t) = e^{t^2/2}$ which is MGF of standard normal variate (Normal Distribution)?

GEOMETRIC DISTRIBUTION

Suppose we have a series of independent trials or repetitions and on each trial or repetition, the probability of success 'p' remains the same. Then the probability preceding the first success is given by

$$pq^x$$

where $X \rightarrow$ Number of failures preceding the 1st success in series of independent trials.

and $p = P(\text{success in a single trial})$

eg., in tossing a coin, the possible outcomes of experiment are

S, FS, FFS,FF,FS,

$X = 0, 1, 2, \dots, x$

and corresponding probability are

$p, qp, q^2p, \dots, q^x p \dots$

$\therefore$ Probability distribution of X,

$$f(x) = P(X = x) = \begin{cases} pq^x & , \quad x = 0, 1, 2, \dots, \infty \\ 0 & , \quad \text{otherwise} \end{cases}$$

Also $\sum_x f(x) = 1$

Now $\sum_{x=0}^{\infty} f(x) = \sum_{x=0}^{\infty} pq^x$

$$= p + pq + pq^2 + pq^3 + \dots$$

$$= p(1 + q + q^2 + \dots)$$

$$= p \cdot \frac{1}{1-q}$$

$$\left[\text{sum of infinite G.P.} + \frac{a}{1-r} \right]$$

$$= p \cdot \frac{1}{p} = 1$$

Moments of Geometric distribution

$$\mu'_1 = E(X) = \sum_{x=0}^{\infty} xf(x) = \sum_{x=1}^{\infty} xpq^x$$

$$= pq \left(\sum_{x=1}^{\infty} xq^{x-1} \right)$$

$$= pq(1 + 2q + 3q^2 + \dots)$$

$$= pq(1 - q)^{-2}$$

$$\Rightarrow \mu'_1 = pq \cdot \frac{1}{p^2} = \frac{q}{p} \quad \dots(1)$$

$$\Rightarrow \mu'_1 = \text{Mean} = \frac{q}{p}$$

$$\mu'_2 = \sum_{x=0}^{\infty} x^2 f(x) = \sum_{x=0}^{\infty} [x(x-1) + x] pq^x$$

$$= \sum_{x=2}^{\infty} x(x-1) pq^x + \sum_{x=1}^{\infty} x pq^x$$

$$= 2pq^2 \sum_{x=2}^{\infty} \frac{x(x-1)}{2 \cdot 1} q^{x-2} + \frac{q}{p} \quad [\text{from (1)}]$$

$$= 2pq^2(1-q)^{-3} + \frac{q}{p} = \frac{2q^2}{p^2} + \frac{q}{p}$$

which is 2nd moment about origin.

$$\therefore \text{variance, } \mu_2 = \mu'_2 - \mu'_1{}^2$$

$$= \frac{2q^2}{p^2} + \frac{q}{p} - \frac{q^2}{p^2} = \frac{q^2}{p^2} + \frac{q}{p}$$

$$= \frac{q}{p^2}(q + p) = \frac{q}{p^2}$$

MGF about origin

$$\begin{aligned} M_X(t) &= E[e^{tX}] = \sum_{x=0}^{\infty} e^{tx} pq^x \\ &= p \sum_{x=0}^{\infty} (qe^t)^x = p[1 - qe^t]^{-1} \\ &= \frac{p}{1 - qe^t} \end{aligned}$$

Moments from MGF

$$\mu'_1 = \left. \frac{d}{dt} M_X(t) \right|_{t=0} = \left. \frac{p(-1)(-qe^t)}{(1 - qe^t)^2} \right|_{t=0}$$

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

$$\mu'_2 = \frac{d^2}{dt^2} M_X(t) \Big|_{t=0} = \frac{d}{dt} \left[\frac{pqe^t}{(1-qe^t)} \right] \Big|_{t=0}$$

$$= pq \left[\frac{(1-qe^t)^2 e^t - e^t \cdot 2(1-qe^t)(-qe^t)}{(1-qe^t)^4} \right] \Big|_{t=0}$$

$$= pq \left[\frac{(1-qe^t)e^t + 2qe^{2t}}{(1-qe^t)^3} \right] \Big|_{t=0}$$

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

$$= pq \left(\frac{p+2q}{p^3} \right) = \frac{q}{p} + \frac{2q^2}{p^2}$$

$$\mu'_3 = \frac{d^3}{dt^3} M_X(t) \Big|_{t=0}$$

$$= pq \frac{d}{dt} \left[e^t (1-qe^t)^{-2} + 2qe^{2t} (1-qe^t)^{-3} \right] \Big|_{t=0}$$

$$= pq [e^t (1-qe^t)^{-2} + e^t (-2) (1-qe^t)^{-3} (-qe^t) + 2qe^{2t} \cdot 2(1-qe^t)^{-3} + 2qe^{2t} (-3) (1-qe^t)^{-4} (-qe^t)]$$

$$= pq[(1-q)^{-2} + 2q(1-q)^{-3} + 4q(1-q)^{-3} + 6q^2e(1-q)^{-4}]$$

$$\Rightarrow \mu'_3 = \left[\frac{1}{p^2} + \frac{6q}{p^3} + \frac{6q^2}{p^4} \right] pq$$

$$\mu'_3 = \frac{q}{p} + \frac{6q^2}{p^2} + \frac{6q^3}{p^3}$$

$$= \frac{q}{p} + \frac{6q^2}{p^3} (p+q)$$

$$= \frac{q}{p} + \frac{6q^2}{p^3} \cdot 1 = \frac{q}{p} + \frac{6q^2}{p^3}$$

$$\begin{aligned}
\mu'_4 &= \frac{d^4}{dt^4} M_X(t) \Big|_{t=0} \\
&= pq \frac{d}{dt} \left[e^t (1 - qe^t)^{-2} + 2qe^{2t} (1 - qe^t)^{-3} + 4qe^{2t} (1 - qe^t)^{-3} \right. \\
&\quad \left. + 6q^2 e^{3t} (1 - qe^t)^{-4} \right] \Big|_{t=0} \\
&= pq \left[e^t (1 - qe^t)^{-2} + e^t qe^t \cdot 2(1 - qe^t)^{-3} + 4qe^{2t} (1 - qe^t)^{-3} \right. \\
&\quad + 6q^2 e^{3t} (1 - qe^t)^{-4} + 8qe^{2t} (1 - qe^t)^{-3} + 12q^2 e^{3t} (1 - qe^t)^{-4} \\
&\quad \left. + 18q^2 e^{3t} (1 - qe^t)^{-4} + 24q^2 e^{3t} (1 - qe^t)^{-5} (qe^t) \right] \Big|_{t=0} \\
&= pq [(1-q)^{-2} + 2q(1-q)^{-3} + 4q(1-q)^{-3} + 6q^2(1-q)^{-4} + 8q(1-q)^{-3} + \\
&\quad 12q^2(1-q)^{-4} + 18q^2(1-q)^{-4} + 24q^3(1-q)^{-5}] \\
&= pq \left[\frac{1}{p^2} + \frac{14q}{p^3} + \frac{36q^2}{p^4} + \frac{24q^3}{p^5} \right] \\
\mu'_4 &= \frac{q}{p} + \frac{14q^2}{p^2} + \frac{36q^3}{p^3} + \frac{24q^4}{p^4}
\end{aligned}$$

LESSON 7 THEORETICAL CONTINUOUS DISTRIBUTIONS

Uniform or rectangular distribution

A **continuous** r.v. X is said to have continuous uniform (or rectangular) distribution over an interval $[a, b]$ if its p.d.f. is given by

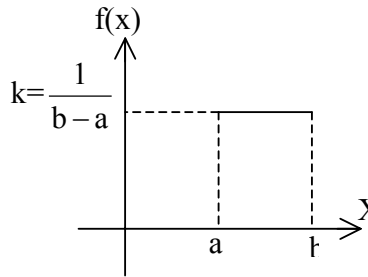
$$f(x) = \begin{cases} K & , \quad a \leq x \leq b \\ 0 & , \quad \text{otherwise} \end{cases}$$

$$\text{also } \int_a^b f(x) \, dx = 1$$

$$\Rightarrow \int_a^b K \, dx = 1 \quad \Rightarrow [Kx]_a^b = 1$$

$$\Rightarrow K(b-a) = 1 \quad \Rightarrow K = \frac{1}{b-a}$$

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



Moments

$$\mu'_r = E[X^r] = \int_a^b x^r f(x) \, dx$$

$$\begin{aligned} \therefore \mu'_r &= \int_a^b x^r \left(\frac{1}{b-a} \right) dx \\ &= \frac{1}{(b-a)} \left(\frac{x^{r+1}}{r+1} \right)_a^b \end{aligned}$$

$$= \frac{1}{(b-a)(r+1)} \left[b^{r+1} - a^{r+1} \right]$$

$$\therefore \mu'_1 = \frac{1}{(b-a)} \left(\frac{b^2 - a^2}{2} \right) = \frac{b+a}{2}$$

$$\Rightarrow \mu'_1 = \text{Mean} = \frac{b+a}{2}$$

$$\begin{aligned} \mu'_2 &= \frac{1}{(b-a).3} (b^3 - a^3) = \frac{(b-a)(b^2 + a^2 + ab)}{3(b-a)} \\ &= \frac{1}{3} (b^2 + a^2 + ab) \end{aligned}$$

$$\text{Variance, } \mu_2 = \mu'_2 - \mu'^2_1$$

$$= \frac{1}{3} (b^2 + a^2 + ab) - \frac{1}{4} (b^2 + a^2 + 2ab)$$

$$= \frac{b^2}{12} + \frac{a^2}{12} - \frac{2ab}{12}$$

$$= \frac{1}{12} (b^2 + a^2 + 2ab) = \frac{(a-b)^2}{12}$$

$$\Rightarrow \mu_2 = \frac{1}{12} (b-a)^2$$

MOMENT GENERATING FUNCTION

$$M_X(t) = \int_a^b e^{tx} \cdot \frac{1}{(b-a)} dx$$

$$\begin{aligned} \Rightarrow M_X(t) &= \frac{1}{(b-a)} \left[\frac{e^{tx}}{t} \right]_a^b \\ &= \frac{1}{t(b-a)} [e^{bt} - e^{at}] \end{aligned}$$

Characteristic function

$$\phi_X(t) = \int_a^b e^{itx} f(x) dx = \frac{e^{ibt} - e^{iat}}{it(b-a)}$$

Mean deviation

$$\begin{aligned} E[|X - \text{Mean}|] &= \int_a^b \left| x - \frac{(a+b)}{2} \right| \cdot \frac{1}{(b-a)} dx \\ &= \frac{1}{(b-a)} \int_a^b \left| x - \left(\frac{a+b}{2} \right) \right| dx \end{aligned} \quad \dots(1)$$

$$\text{Put } t = x - \frac{a+b}{2} \Rightarrow dt = dx$$

$$\text{when } x = a, \quad t = a - \frac{(a+b)}{2} = \frac{a-b}{2}$$

$$\text{when } x = b, \quad t = b - \frac{(a+b)}{2} = \frac{b-a}{2}$$

$$\begin{aligned} \therefore (1) \Rightarrow E[|X - \text{Mean}|] &= \frac{1}{(b-a)} \int_{\left(\frac{b-a}{2}\right)}^{\frac{b-a}{2}} |t| dt \\ &= \frac{2}{(b-a)} \int_0^{b-a/2} t dt = \frac{2}{(b-a)} \left[\frac{t^2}{2} \right]_0^{b-a/2} \\ &= \frac{2}{2(b-a)} \cdot \frac{(b-a)^2}{4} = \frac{b-a}{4} \end{aligned}$$

Example: - Show that for the rectangular distance if $f(x) = \frac{1}{2a}$, $-a < x < a$,

The MGF about origin is $\frac{\sinh at}{at}$.

Also show that moments of even order are given by $\mu_{2n} = \frac{a^{2n}}{2n+1}$

Solution: - By definition,

$$\begin{aligned} M_X(t) &= \int_{-a}^a e^{tx} \cdot \frac{1}{2a} dx = \frac{1}{2at} [e^{tx}]_{-a}^a \\ &= \frac{1}{2at} (e^{at} - e^{-at}) = \frac{1}{2at} \cdot 2 \sinh at \end{aligned}$$

$$\Rightarrow M_X(t) = \frac{\sinh at}{at}$$

$$= \frac{1}{at} \left[at + \frac{(at)^3}{3!} + \frac{(at)^5}{5!} + \dots \right]$$

$$= 1 + \frac{(at)^2}{3!} + \frac{(at)^4}{5!} + \dots \quad \dots(1)$$

Since there are no terms with odd powers of t in $M_X(t)$, all moments of odd order about origin are zero i.e.

$$\mu'_{2n+1}(\text{about origin}) = 0$$

In particular, $\mu'_1 = 0$ i.e. Mean = 0

$$\Rightarrow \mu'_r(\text{about origin}) = \mu_r(\text{about Mean})$$

$$\begin{aligned} \left[\begin{array}{ll} \ominus \mu'_r = E[X^r], & \mu_r = E[(X - \mu)^r] \\ \text{if } \mu = 0 = \text{Mean, then} & \mu_r = E[X^r] = \mu'_r \end{array} \right] \end{aligned}$$

Therefore $\mu_{2n+1} = 0$

The moments of even order are given by

$$\mu'_{2n} = \mu_{2n} = \text{Coefficient of } \frac{t^{2n}}{2n} \text{ in } M_X(t)$$

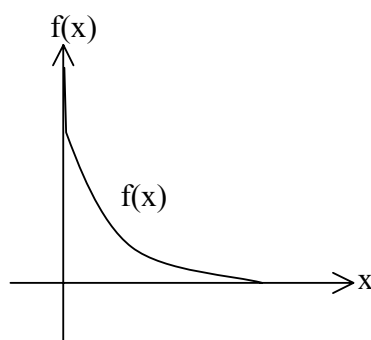
$$\Rightarrow \mu_{2n} = \frac{a^{2n}}{2n+1} \quad [\text{using (1)}]$$

THE EXPONENTIAL DISTRIBUTION

A **continuous** r.v. X assuming **non-negative** values is said to have an exponential distribution with parameter $\theta > 0$ if its p.d.f. is given by

$$f(x) = \begin{cases} \theta e^{-\theta x} & , \quad x \geq 0 \\ 0 & , \quad \text{otherwise} \end{cases}$$

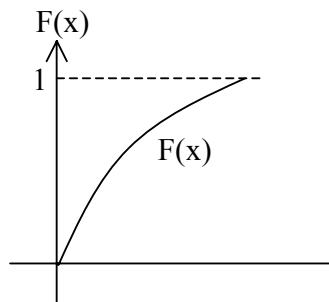
Also $\int_0^{\infty} f(x) \, dx = 1$



F(x) is given by,

$$F(x) = \int_0^x f(x) \, dx = \theta \int_0^x e^{-\theta x} \, dx$$

$$= \begin{cases} 1 - e^{-\theta x}, & x \geq 0 \\ 0, & \text{otherwise} \end{cases}$$



MOMENT GENERATING FUNCTION

$$\begin{aligned} M_X(t) &= E[e^{tx}] = \theta \int_0^{\infty} e^{tx} e^{-\theta x} dx \\ &= \theta \int_0^{\infty} e^{(\theta-t)x} dx \\ &= \theta \left[\frac{e^{-(\theta-t)x}}{-(\theta-t)} \right]_0^{\infty} \\ &= \frac{\theta}{\theta-t}, \quad \theta > t \\ \Rightarrow M_X(t) &= \frac{\theta}{\theta-t} = \frac{\theta}{\theta \left(1 - \frac{t}{\theta}\right)} = \frac{1}{1 - \frac{t}{\theta}} \\ &= \left(1 - \frac{t}{\theta}\right)^{-1} = 1 + \frac{t}{\theta} + \frac{t^2}{\theta^2} + \frac{t^3}{\theta^3} + \dots \dots \dots \quad \dots(1) \\ &= \sum_{r=0}^{\infty} \left(\frac{t}{\theta}\right)^r \end{aligned}$$

$$(1) \Rightarrow M_X(t) = 1 + \frac{t}{\theta} + \frac{\frac{2}{\theta^2}}{\frac{2}{\theta^2}} \frac{t^2}{2} + \frac{\frac{3}{\theta^3}}{\frac{3}{\theta^3}} \frac{t^3}{3} + \dots$$

$$\therefore \mu'_r = E[X^r] = \text{coefficient of } \frac{t^r}{r!} \text{ in } M_X(t)$$

$$= \frac{r!}{\theta^r}, \quad r = 1, 2, 3, \dots$$

$$\therefore \text{Mean} = \mu'_1 = \frac{1}{\theta}$$

$$\mu'_2 = \frac{2}{\theta^2}$$

$$\text{Variance} = \mu_2 = \mu'_2 - \mu_1'^2 = \frac{2}{\theta^2} - \frac{1}{\theta^2} = \frac{1}{\theta^2}$$

Also by definition,

$$\text{Mean} = \int_0^{\infty} x f(x) dx = \int_0^{\infty} x \theta e^{-\theta x} dx$$

$$= \theta \left[\left(x \frac{e^{-\theta x}}{-\theta} \right)_0^{\infty} - \int_0^{\infty} (1) \frac{e^{-\theta x}}{-\theta} dx \right]$$

$$= \theta \left[0 + (-1) \frac{e^{-\theta x}}{\theta^2} \right]_0^{\infty}$$

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

$$E(X^2) = \mu'_2 = \int_0^{\infty} x^2 f(x) dx = \int_0^{\infty} x^2 \cdot \theta e^{-\theta x} dx$$

$$= \theta \left[\left(x^2 \cdot \frac{e^{-\theta x}}{-\theta} \right)_0^{\infty} - \int_0^{\infty} 2x \cdot \frac{e^{-\theta x}}{-\theta} dx \right]$$

$$= \theta \left[0 - 0 + \frac{2}{\theta} \int_0^{\infty} x e^{-\theta x} dx \right]$$

$$= \frac{2}{\theta} \left[\theta \int_0^{\infty} x e^{-\theta x} dx \right] = \frac{2}{\theta} \cdot \frac{1}{\theta} = \frac{2}{\theta^2}$$

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

$$= E\left[X - \frac{1}{\theta}\right]^2 = E(X^2) - \frac{1}{\theta^2}$$

$$= \frac{2}{\theta^2} - \frac{1}{\theta^2} = \frac{1}{\theta^2}$$

Mean Deviation

$$E|X - E(X)| = E\left[\left|X - \frac{1}{\theta}\right|\right]$$

$$= \int_0^{\infty} \left|x - \frac{1}{\theta}\right| \theta e^{-\theta x} dx$$

$$= \frac{\theta}{\theta} \int_0^{\infty} |x\theta - 1| e^{-\theta x} dx = \int_0^{\infty} |x\theta - 1| e^{-\theta x} dx$$

Put $\theta x = y \Rightarrow \theta dx = dy$

when $x = 0 \Rightarrow y = 0$

$x = \infty \Rightarrow y = \infty$

$$\therefore E[|X - E(X)|] = \int_0^{\infty} |y - 1| e^{-y} \frac{dy}{\theta}$$

$$= \frac{1}{\theta} \int_0^{\infty} |y - 1| e^{-y} dy \quad \dots(1)$$

when $|y - 1| = -(y - 1)$ for $y - 1 < 0$

$\Rightarrow |y - 1| = 1 - y, \quad y < 1$

and $|y - 1| = y - 1$ for $y - 1 > 0$

$= y - 1$ for $y > 1$

$$\therefore (1) \quad E[|X - E(X)|] = \frac{1}{\theta} \left[\int_0^1 (1 - y) e^{-y} dy + \int_1^{\infty} (y - 1) e^{-y} dy \right]$$

$$= \frac{1}{\theta} \left[\left((1 - y) \frac{e^{-y}}{-1} \right)_0^1 - \int_0^1 (-1) \frac{e^{-y}}{-1} dy + \left((y - 1) \frac{e^{-y}}{-1} \right)_1^{\infty} \right]$$

$$\begin{aligned}
& - \int_1^{\infty} 1 \cdot \frac{e^{-y}}{-1} dy \Bigg] \\
&= \frac{1}{\theta} \left[-0 + 1 - \left(\frac{e^{-y}}{-1} \right)_0^1 + 0 - 0 + \left(\frac{e^{-y}}{-1} \right)_1^{\infty} \right] \\
&= \frac{1}{\theta} [1 + (e^{-1} - 1) - (0 - e^{-1})] \\
&= \frac{1}{\theta} [e^{-1} + e^{-1}] = \frac{2}{\theta} e^{-1}
\end{aligned}$$

Cumulants

The c.g.f. is

$$\begin{aligned}
K_X(t) &= \log M_X(t) = \log \left(1 - \frac{t}{\theta} \right)^{-1} = -\log \left(1 - \frac{t}{\theta} \right) \\
&= \left[\frac{t}{\theta} + \frac{1}{2} \left(\frac{t}{\theta} \right)^2 + \frac{1}{3} \left(\frac{t}{\theta} \right)^3 + \dots \right] \\
&= \sum_{r=1}^{\infty} \left(\frac{t}{\theta} \right)^r \frac{1}{r} = \sum_{r=1}^{\infty} \frac{t^r}{r} \left(\frac{|r-1|}{\theta^r} \right)
\end{aligned}$$

$$\Rightarrow K_r = \text{coefficient of } \frac{t^r}{r} \text{ in } K_X(t)$$

$$= \frac{|r-1|}{\theta^r}, \quad r = 1, 2, 3, \dots$$

$$\therefore K_1 = \frac{1}{\theta}, \quad K_2 = \frac{1}{\theta^2}$$

$$K_3 = \frac{2}{\theta^3}, \quad K_4 = \frac{6}{\theta^4}$$

Example: - Let X have the probability density function $f(x) = \theta e^{-\theta x}$ for $x > 0$ and zero, otherwise. Prove that if the +ve part of x -axis is divided into intervals of equal length h starting at the origin, then the probabilities that X will lie in successive intervals form a G.P. with common ratio $e^{-\theta h}$.

Solution: - $P(0 \leq X \leq h) = \int_0^h f(x) dx = \int_0^h \theta e^{-\theta x} dx$

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

$$= 1 - e^{-\theta h}$$

$$P(h \leq X \leq 2h) = \int_h^{2h} \theta e^{-\theta x} dx$$

$$= -\frac{\theta}{\theta} [e^{-\theta x}]_h^{2h} = -[e^{-2\theta h} - e^{-\theta h}]$$

$$= e^{-\theta h} (1 - e^{-\theta h})$$

$$P(2h \leq X \leq 3h) = -[e^{-\theta x}]_{2h}^{3h}$$

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

and so on.

Thus the probabilities that X will lie in successive intervals from a G.P. with common ratio $e^{-\theta h}$.

Example: - The r.v. X has the exponential distribution with density function given by

$$f(x) = \begin{cases} 2e^{-2x} & , \quad x > 0 \\ 0 & , \quad x \leq 0 \end{cases}$$

(i) what is the probability that X is not smaller than two?

(ii) Show that $\frac{\text{Mean}}{\text{S.D}} = 1$

(iii) Find its M.G.F

Solution: -(i) Probability that X is not smaller than two

$$P(X \geq 2) = \int_2^{\infty} f(x) dx = 2 \int_2^{\infty} e^{-2x} dx$$

$$= 2 \left[\frac{e^{-2x}}{-2} \right]_2^{\infty} = -1[0 - e^{-4}] = \frac{1}{e^4}$$

(ii) Mean = $\mu'_1 = E(X) = \int_0^{\infty} xf(x) dx$

$$\begin{aligned}
&= 2 \int_0^{\infty} x e^{-2x} dx \\
&= 2 \left[\left(x \frac{e^{-2x}}{-2} \right)_0^{\infty} + \int_0^{\infty} (1) \frac{e^{-2x}}{2} dx \right] \\
&= 2 \left[0 - 0 - \frac{1}{4} (e^{-2x})_0^{\infty} \right] \\
&= 2 \left[-\frac{1}{4} (0 - 1) \right] = 2 \cdot \frac{1}{4} = \frac{1}{2}
\end{aligned}$$

$$\mu'_2 = E(X^2) = \int_0^{\infty} x^2 f(x) dx = 2 \int_0^{\infty} x^2 e^{-2x} dx$$

$$\mu'_2 = 2 \left[\left(x^2 \frac{e^{-2x}}{-2} \right)_0^{\infty} + \int_0^{\infty} 2x \cdot \frac{e^{-2x}}{+2} dx \right] = 2 \left[0 - 0 + \frac{1}{2} \cdot 2 \int_0^{\infty} x e^{-2x} dx \right] = 2 \left[\frac{1}{2}, \frac{1}{2} \right] = \frac{1}{2}$$

$$\text{Variance, } \mu_2 = \mu'_2 - \mu'_1 = \frac{1}{2} - \frac{1}{4} = \frac{1}{4}$$

$$\therefore \text{S.D.} = \sqrt{\mu_2} = \frac{1}{2}$$

$$\therefore \frac{\text{Mean}}{\text{S.D.}} = \frac{1/2}{1/2} = 1$$

$$\text{(iii) M.G.F., } M_X(t) = E[e^{tx}] = \int_0^{\infty} e^{tx} f(x) dx$$

$$\begin{aligned}
&= \int_0^{\infty} e^{tx} (2) e^{-2x} dx = 2 \int_0^{\infty} e^{(t-2)x} dx = 2 \left[\frac{e^{(t-2)x}}{(t-2)} \right]_0^{\infty} \\
&= \frac{2}{(t-2)} [e^{-(2-t)x}]_0^{\infty} = \frac{2}{t-2} [0 - 1] = \frac{-2}{t-2} = \frac{2}{2-t}, \quad 2 > t
\end{aligned}$$

NORMAL DISTRIBUTION

A r.v. X is said to have Normal distribution with parameters μ and σ^2 , called Mean & variance respectively if its density function is given by

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}, \quad -\infty < x < \infty; \sigma > 0; -\infty < \mu < \infty$$

If $Z = \frac{X-\mu}{\sigma} \Rightarrow z = \frac{x-\mu}{\sigma}$

Here Mean = $E(z) = 0$

and variance = $V(Z) = 1 = \text{S.D.}$

then $f(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z^2}, \quad -\infty < z < \infty$

then $f(z)$ is known as Standard Normal distribution.

Now $\int_{-\infty}^{\infty} f(x) dx = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx$

Put $z = \frac{x-\mu}{\sigma} \Rightarrow \sigma dz = dx$

$$\begin{aligned} \therefore \int_{-\infty}^{\infty} f(x) dx &= \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}z^2} \cdot \sigma dz \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}z^2} dz \end{aligned}$$

$$\therefore \int_{-\infty}^{\infty} f(x) dx = \frac{2}{\sqrt{2\pi}} \int_0^{\infty} e^{-\frac{1}{2}z^2} dz \quad [\Theta \text{Integrand is even function of } z]$$

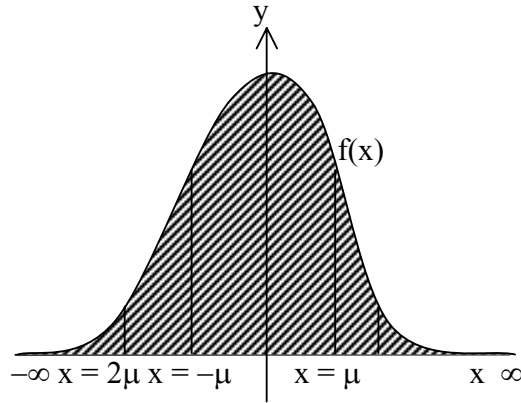
Put $\frac{1}{2}z^2 = t$

$$\Rightarrow z dz = dt \Rightarrow dz = \frac{dt}{z} = \frac{dr}{\sqrt{2t}}$$

$$\therefore \int_{-\infty}^{\infty} f(x) dx = \sqrt{\frac{2}{\pi}} \int_0^{\infty} e^{-t} \frac{dt}{\sqrt{2\pi}} = \frac{1}{\sqrt{\pi}} \int_0^{\infty} e^{-t} e^{-1/2} dt$$

$$= \frac{1}{\sqrt{\pi}} \cdot \Gamma\left(\frac{1}{2}\right) = \frac{\sqrt{\pi}}{\sqrt{\pi}} = 1 \quad \dots(1)$$

$\Rightarrow$ it is a probability density function.



This is called *Normal distribution* or Normal probability curve or *Gaussian distribution*.

This curve is symmetrical w.r.t. y-axis. The area under the curve gives the probability density function, $f(x) = P(0 \leq X \leq x)$ where x is constant.

$$\text{Mean, } \mu'_1 = E(X) = \int_{-\infty}^{\infty} x f(x) dx$$

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

$$\text{Put } z = \frac{x-\mu}{\sigma} \quad \dots(2)$$

$$\Rightarrow x = \mu + \sigma z \Rightarrow dx = \sigma dz$$

$$\begin{aligned} \therefore \mu'_1 &= \int_{-\infty}^{\infty} (\mu + \sigma z) \cdot \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}z^2} \sigma dz \\ &= \frac{\mu}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}z^2} dz + \frac{\sigma}{\sqrt{2\pi}} \int_{-\infty}^{\infty} ze^{-\frac{1}{2}z^2} dz \end{aligned}$$

$$\Rightarrow \mu'_1 = \mu(1) + 0 \quad [\text{from(1)}] \quad [\ominus \text{ integrand } ze^{-\frac{1}{2}z^2} \text{ is an odd function of } z]$$

$$\Rightarrow \mu'_1 = \mu \text{ (Mean)}$$

$$\text{Variance, } \mu_2 = E[(X-\mu)^2]$$

$$\begin{aligned}
&= \int_{-\infty}^{\infty} (x - \mu)^2 \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \\
&= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \sigma^2 z^2 \frac{e^{-\frac{1}{2}z^2}}{\sigma} \cdot \sigma dz \\
&= \frac{2\sigma^2}{\sqrt{2\pi}} \int_0^{\infty} z^2 e^{-\frac{1}{2}z^2} dz
\end{aligned}$$

Put $\frac{z^2}{2} = t \Rightarrow dz = \frac{dt}{\sqrt{2t}}$

$$\begin{aligned}
\mu_2 &= \frac{\sqrt{2}}{\pi} \sigma^2 \int_0^{\infty} 2t e^{-t} \frac{dt}{\sqrt{2t}} \\
&= \frac{2}{\sqrt{\pi}} \sigma^2 \int_0^{\infty} e^{-t} t^{1/2} dt \\
&= \frac{2}{\sqrt{\pi}} \sigma^2 \Gamma\left(\frac{3}{2}\right) = \frac{2}{\sqrt{\pi}} \sigma^2 \cdot \frac{1}{2} \Gamma\left(\frac{1}{2}\right)
\end{aligned}$$

$$\Rightarrow \mu_2 = \frac{\sigma^2}{\sqrt{\pi}} \cdot \sqrt{\pi} = \sigma^2 \quad \Rightarrow \quad \mu_2 = \sigma^2$$

Normal distribution as a limiting case of Binomial distribution

It can be derived under these conditions: -

- (i) n, the number of trials is infinitely large i.e. $n \rightarrow \infty$
- (ii) neither p nor q is very small.

p.d.f. of Binomial distribution is

$$\begin{aligned}
f(x) &= {}^nC_x p^x q^{n-x} \\
&= \frac{n!}{x! (n-x)!} p^x q^{n-x}, \quad x = 0, 1, 2, \dots, n \quad \dots(1)
\end{aligned}$$

$$Z = \frac{X - E(X)}{\sqrt{\text{var}(x)}} \quad \text{i.e.} \quad z = \frac{x - np}{\sqrt{npq}} \quad \dots(2)$$

where $x = 0, 1, 2, \dots, n$

when $x = 0 \Rightarrow z = -\sqrt{\frac{np}{q}}$; As $n \rightarrow \infty, z \rightarrow -\infty$

when $x = n \Rightarrow z = \frac{n - np}{\sqrt{npq}} = \frac{nq}{\sqrt{npq}} = \sqrt{\frac{nq}{p}}$

and As $n \rightarrow \infty, z \rightarrow \infty$

Thus in the limiting case as $n \rightarrow \infty$, z takes values $-\infty$ to ∞ .

Using Stirling's approximation formula,

$$|r| = \sqrt{2\pi} e^{-r} r^{\frac{1}{2}}$$

From (1) as $n \rightarrow \infty$, we get

$$\begin{aligned} \lim_{n \rightarrow \infty} f(x) &= \lim_{n \rightarrow \infty} \frac{\sqrt{2\pi} e^{-n} n^{\frac{n+1}{2}} p^x q^{n-x}}{\sqrt{2\pi} e^{-x} x^{\frac{x+1}{2}} \sqrt{2\pi} e^{-(n-x)} (n-x)^{\frac{n-x+1}{2}}} \\ &= \frac{1}{\sqrt{2\pi}} \lim_{n \rightarrow \infty} \frac{n^{\frac{n+1}{2}} p^x q^{n-x}}{x^{\frac{x+1}{2}} (n-x)^{\frac{n-x+1}{2}}} \\ &= \frac{1}{\sqrt{2\pi}} \lim_{n \rightarrow \infty} \frac{n^{\frac{n+1}{2}} p^x q^{n-x}}{x^{\frac{x+1}{2}} (n-x)^{\frac{n-x+1}{2}}} \cdot \frac{\sqrt{npq}}{\sqrt{npq}} \\ &= \frac{1}{\sqrt{2\pi}} \lim_{n \rightarrow \infty} \frac{n^{n+1} p^{\frac{x+1}{2}} q^{\frac{n-x+1}{2}}}{\sqrt{npq} x^{\frac{x+1}{2}} (n-x)^{\frac{n-x+1}{2}}} \\ &= \frac{1}{\sqrt{2\pi}} \lim_{n \rightarrow \infty} \frac{n^{n+1}}{\sqrt{npq}} \cdot \frac{1}{x^{\frac{x+1}{2}} (n-x)^{\frac{n-x+1}{2}}} \cdot \frac{(nq)^{\frac{n-x+1}{2}}}{n^{\frac{n-x+1}{2}}} \cdot \frac{(np)^{\frac{x+1}{2}}}{n^{\frac{x+1}{2}}} \\ &= \frac{1}{\sqrt{2\pi}} \lim_{n \rightarrow \infty} \frac{1}{\sqrt{npq}} \left(\frac{np}{x} \right)^{\frac{x+1}{2}} \left(\frac{nq}{n-x} \right)^{\frac{n-x+1}{2}} \dots (3) \end{aligned}$$

from (2), $x = np + z\sqrt{npq}$

$$\therefore \frac{n}{np} = 1 + z \frac{\sqrt{npq}}{np} = 1 + z \sqrt{\frac{q}{np}} \quad \dots(4)$$

$$\begin{aligned} \text{and } n-x &= n - np - z \sqrt{npq} \\ &= n(1-p) - z \sqrt{npq} = nq - z \sqrt{npq} \end{aligned}$$

$$\therefore \frac{n-x}{nq} = 1 - z \sqrt{\frac{p}{nq}} \quad \dots(5)$$

Hence probability difference of the distribution is

$$\lim_{n \rightarrow \infty} f(x) dx = \lim_{n \rightarrow \infty} \frac{1}{\sqrt{2\pi} \sqrt{npq}} \cdot \frac{1}{N} dx \quad \dots(6)$$

$$\text{where } N = \left(\frac{x}{np} \right)^{x+\frac{1}{2}} \left(\frac{n-x}{nq} \right)^{n-x+\frac{1}{2}}$$

using (4) & (5), we get

$$\begin{aligned} N &= \left(1 + z \sqrt{\frac{q}{np}} \right)^{\left(np + z\sqrt{npq} + \frac{1}{2} \right)} \left(1 - z \sqrt{\frac{p}{nq}} \right)^{\left(nq - z\sqrt{npq} + \frac{1}{2} \right)} \\ \therefore \log N &= \left(np + z\sqrt{npq} + \frac{1}{2} \right) \log \left(1 + z \sqrt{\frac{q}{np}} \right) + \left(nq - z\sqrt{npq} + \frac{1}{2} \right) \log \left(1 - z \sqrt{\frac{p}{nq}} \right) \\ &= \left(np + z\sqrt{npq} + \frac{1}{2} \right) \left[z \sqrt{\frac{q}{np}} - \frac{1}{2} z^2 \frac{q}{np} + \frac{1}{3} z^3 \frac{q^{3/2}}{(np)^{3/2}} \dots \right] \\ &\quad + \left(nq - z\sqrt{npq} + \frac{1}{2} \right) \left[-z \sqrt{\frac{p}{nq}} - \frac{z^2}{2} \frac{p}{nq} - \frac{z^3}{3} \frac{p^{3/2}}{(nq)^{3/2}} \dots \right] \\ &= z\sqrt{npq} - \frac{z^2}{z} q + \frac{z^3}{3} \frac{q^{3/2}}{\sqrt{nq}} + \dots + z^2 q - \frac{z^3}{2} \frac{q^{3/2}}{\sqrt{np}} + \frac{z}{2} \sqrt{\frac{q}{np}} - \frac{z^2}{4} \frac{q}{np} \\ &\quad + \frac{z^3}{6} \frac{q^{3/2}}{(np)^{3/2}} + \left[-z\sqrt{npq} - \frac{z^2}{2} p - \frac{z^3}{3} \frac{p^{3/2}}{\sqrt{nq}} + z^2 p + \frac{z^3}{2} \frac{p^{3/2}}{\sqrt{nq}} - \frac{3}{2} \sqrt{\frac{p}{nq}} \right] \\ &\quad - \frac{z^2}{4} \frac{p}{nq} - \frac{z^3}{6} \frac{p^{3/2}}{(nq)^{3/2}} + \dots \end{aligned}$$

Collecting the terms in decreasing power of n, we get

$$\begin{aligned}\log N &= \frac{z^2}{2}(p+q) + \frac{1}{\sqrt{n}} \left[\frac{z^3}{3} \left(\frac{-q^{3/2}}{\sqrt{p}} + \frac{p^{3/2}}{\sqrt{q}} \right) + \frac{z}{2} \left(\sqrt{\frac{q}{p}} - \sqrt{\frac{p}{q}} \right) \right] + \dots \\ &= \frac{z^2}{2} + \frac{1}{\sqrt{n}} \left[\left(\frac{z^3}{3} \frac{p^2 - q^2}{\sqrt{pq}} \right) + \frac{3}{2} \left(\frac{q-p}{\sqrt{pq}} \right) \right] + [\text{terms of higher powers } 1/\sqrt{n}] \end{aligned}$$

Taking limit as $n \rightarrow \infty$

$$\lim_{n \rightarrow \infty} \log N = z^{2/2}$$

or $\lim_{n \rightarrow \infty} \log N = z^{2/2} \Rightarrow \lim_{n \rightarrow \infty} \frac{1}{N} = e^{-z^{2/2}}$

Put this value in (6), we get the probability of the distribution of Z is given by

$$\begin{aligned}dP &= \lim_{n \rightarrow \infty} f(x) dx = \lim_{n \rightarrow \infty} \frac{1}{\sqrt{2\pi} \sqrt{npq}} e^{-z^{2/2}} \sqrt{npq} dz \quad [\Theta dz = \frac{dx}{\sqrt{npq}}] \\ &= \frac{1}{\sqrt{2\pi}} e^{-z^{2/2}} dz \end{aligned}$$

Hence probability function of Z is

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-z^{2/2}}, \quad -\infty < z < \infty$$

The probability function of normal distribution with variable X is

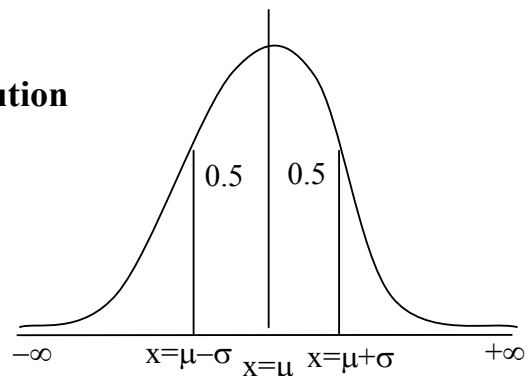
$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma} \right)^2}$$

Some characteristics of Normal distribution

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma} \right)^2}$$

where $-\infty < x < \infty$

and $f(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} z^2}$ where $z = \frac{x-\mu}{\sigma}$



- (1) The curve is Bell shaped & symmetrical about the line $x = \mu$
- (2) Mean, Median & Mode coincides.
- (3) Max. probability occurs at the point $x = \mu$ and is given by

$$[f(x)]_{\max.} = \frac{1}{\sigma\sqrt{2\pi}}$$

(4) $\beta_1 = 0, \beta_2 = 3$

(5) All odd order moments are zero i.e. $\mu_{2n+1} = 0$

(6) Linear combination of independent normal variate is also a normal variate.

(7) Points of inflexion of the curve are given by $x = \mu \pm \sigma$

(8) Mean Derivation is $\frac{4}{5}\sigma$ (approx.)

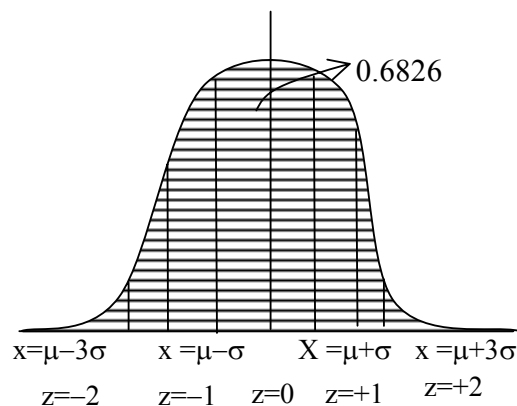
$$= \sqrt{\frac{2}{\pi}}\sigma$$

(9) Area property

$$P(\mu - \sigma < x < \mu + \sigma) = 0.6826$$

$$P(\mu - 2\sigma < x < \mu + 2\sigma) = 0.9544$$

$$P(\mu - 3\sigma < x < \mu + 3\sigma) = 0.9973$$



when $x = \mu - \sigma$, $z = -1$

and $x = \mu + \sigma$, $z = +1$

$$\therefore P(-1 < Z < +1) = 0.6826$$

$$P(-2 < Z < +2) = 0.9544$$

$$P(-3 < Z < +3) = 0.9973$$

also $P(-z < Z < 0) = P(0 < Z < z)$ due to symmetry.

Theorem: - Prove that Mean, Median and Mode coincide.

Proof: - Mode

To calculate Mode, we have

$$f'(x) = 0, f''(x) < 0$$

$$\text{Now } f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \quad \dots(1)$$

$$\therefore \log f(x) = -\log \sigma - \frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2$$

Differentiating w.r.t. x , we get

$$\begin{aligned} \frac{1}{f(x)} f'(x) &= 0 - \frac{2}{2\sigma^2} (x-\mu) = -\frac{1}{\sigma^2} (x-\mu) \\ \Rightarrow f'(x) &= -\frac{f(x)}{\sigma^2} (x-\mu) \quad \dots(2) \end{aligned}$$

$$\text{Now } f'(x) = 0 \Rightarrow x - \mu = 0 \Rightarrow x = \mu$$

$$\begin{aligned} \text{Also } f''(x) &= \frac{-1}{\sigma^2} [1 \cdot f(x) + (x-\mu) f'(x)] \\ &= \frac{-1}{\sigma^2} \left[f(x) - (x-\mu) \frac{f(x)(x-\mu)}{\sigma^2} \right] \quad \text{from(2)} \\ &= \frac{f(x)}{\sigma^2} \left[1 - \frac{(x-\mu)^2}{\sigma^2} \right] \end{aligned}$$

Put $x = \mu$, we get

$$f''(x) = -\frac{1}{\sigma^2} [f(x)]_{x=\mu} = -\frac{1}{\sigma^2} \cdot \frac{1}{\sigma\sqrt{2\pi}} < 0 \quad [\text{By using (1)}]$$

Hence $x = \mu$ is the mode of Normal distribution.

Median

Median is the middle value of variate. Let M be the Median distribution, then

$$\int_{-\infty}^{\infty} f(x) dx + \int_M^{\infty} f(x) dx = 1$$

$$\text{Also } \int_{-\infty}^M f(x) dx = \int_{-\infty}^M f(x) dx$$

$$\text{So we have } \int_{-\infty}^M f(x) dx = \frac{1}{2}$$

$$\Rightarrow \int_{-\infty}^M \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx = \frac{1}{2}$$

$$\Rightarrow \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\mu} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx + \frac{1}{\sigma\sqrt{2\pi}} \int_{\mu}^M e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx = \frac{1}{2}$$

$$\text{or } I_1 + I_2 = \frac{1}{2}$$

$$\text{Now } I_1 = \frac{1}{\sigma\sqrt{2\pi}} \int e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

$$\text{Put } z = \frac{x-\mu}{\sigma}$$

$$\therefore I_1 = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^0 e^{-z^2/2} dz$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^0 e^{-z^2/2} dz$$

$$\Rightarrow I_1 = \frac{1}{\sqrt{2\pi}} \int_0^{\infty} e^{-\frac{1}{2}z^2} dz$$

$$\text{Put } z^2/2 = t \quad \Rightarrow z dz = dt \quad \Rightarrow dz = \frac{dt}{\sqrt{2t}}$$

$$I_1 = \frac{1}{\sqrt{2\pi}} \int_0^{\infty} e^{-t} \frac{1}{\sqrt{2}} t^{-1/2} dt$$

$$= \frac{1}{\sqrt{2\pi}} \Gamma\left(\frac{1}{2}\right) = \frac{1}{2\sqrt{\pi}} \cdot \sqrt{\pi} = \frac{1}{2}$$

$$\Rightarrow I_2 = 0 \Rightarrow \frac{1}{\sigma\sqrt{2\pi}} \int_{\mu}^M e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx = 0$$

$$\Rightarrow M = \mu$$

Hence Mean = Median = Mode

Moment generating function about origin

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

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

Put $z = \frac{x-\mu}{\sigma}$

$\Rightarrow x = \mu + \sigma z$

$dx = \sigma dz$

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

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

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

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

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

Put $z-t\sigma = \mu \Rightarrow dz = d\mu$

$\therefore M_X(t) = \frac{e^{\mu t + \frac{1}{2}t^2\sigma^2}}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}\mu^2} d\mu$

$= e^{\mu t + \frac{1}{2}t^2\sigma^2} (1)$

$= e^{\mu t + \frac{1}{2}t^2\sigma^2}$

$$\left[\Theta \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}z^2} dz = 1 \right]$$

...(1)

Moment generating function about mean

$$\begin{aligned}M_{X-\mu}(t) &= E[e^{t(X-\mu)}] = E[e^{tX} \cdot e^{-\mu t}] \\&= e^{-\mu t} E[e^{tX}] = e^{-\mu t} M_X(t) \\&= e^{-\mu t} e^{\mu t + \frac{1}{2}\sigma^2 t^2} = e^{\frac{1}{2}\sigma^2 t^2}\end{aligned}$$

Also by definition

$$\begin{aligned}M_{X-\mu}(t) &= \int_{-\infty}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{t(x-\mu)} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \\&= e^{-\mu t} \int_{-\infty}^{\infty} \frac{1}{\sigma\sqrt{2\pi}} e^{tx} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \\&= e^{-\mu t} \cdot e^{\mu t + \frac{1}{2}\sigma^2 t^2} = e^{\frac{1}{2}\sigma^2 t^2}\end{aligned}$$

[from(1)]

Moment generating function about any point 'a'

$$M_{X-a}(t) = e^{t(\mu-a) + \frac{1}{2}\sigma^2 t^2}$$

By definition

$$\begin{aligned}M_{X-a}(t) &= E[e^{t(X-a)}] \\&= \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{t(x-a)} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \\&= e^{-at} \cdot \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{tx} \cdot e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \\&= e^{-at} \cdot e^{\mu t + \frac{1}{2}\sigma^2 t^2} = e^{t(\mu-a) + \frac{1}{2}\sigma^2 t^2}\end{aligned}$$

Cumulants

$$\begin{aligned}K_X(t) &= \log M_X(t) = \log \left(e^{\mu t + \frac{1}{2}\sigma^2 t^2} \right) \\&= \mu t + \frac{1}{2}\sigma^2 t^2\end{aligned}$$

The 1st cumulants, K_1 = coefficient of $t = \mu'_1$ (Mean) = μ

The 2nd cumulants, $K_2 = \sigma^2 = \text{variance} = \mu_2$

$$K_r = 0 \quad \text{for } r = 3, 4, \dots$$

$$\text{Thus } \mu_3 = K_3 = 0 \text{ and } \mu_4 = K_4 + 3 K_2^2 = 3\sigma^4 \quad [\Theta K_4 = \mu_4 - K_2^2]$$

$$\text{Now } \beta_1 = \frac{\mu_4}{\mu_2} = \frac{3\sigma^2}{\sigma^4} = 3 \quad (\beta_1 = 0, \beta_2 = 3)$$

Moments from Moment generating function

M.G.F about mean = $e^{\frac{1}{2}\sigma^2 t^2}$

$$= 1 + \frac{1}{2} t^2 \sigma^2 + \frac{\left(\frac{t^2 \sigma^2}{2}\right)^2}{\underline{2}} + \frac{\left(\frac{1}{2} t^2 \sigma^2\right)^3}{\underline{3}} + \dots + \frac{\left(\frac{t^2 \sigma^2}{2}\right)^n}{\underline{n}} + \dots \quad (1)$$

from here,

$$(1), \quad \mu_r = \text{coefficient of } \frac{t^r}{\underline{r}} = \text{rth moment about mean}$$

Since there is no term with odd powers of t in (1), there fore all moments of odd order about Mean vanish.

$$\text{i.e. } \mu_{2n+1} = 0, \quad n = 1, 2, \dots$$

$$\text{and } \mu_{2n} = \text{coefficient of } \frac{t^{2n}}{\underline{2n}} \text{ in (1)} = \frac{\sigma^{2n} \underline{2n}}{2^n \underline{n}}$$

$$\left[\Theta \frac{t^{2n} \sigma^{2n} \underline{2n}}{2^n \underline{n} \underline{2n}} = \left(\frac{\sigma^{2n} \underline{2n}}{2^n \underline{n}} \right) \frac{t^{2n}}{\underline{2n}} \right]$$

$$\begin{aligned} \therefore \mu_{2n} &= \frac{\sigma^{2n}}{2^n \underline{n}} [2n(2n-1)(2n-2)\dots 4.3.2.1] \\ &= \frac{\sigma^{2n}}{2^n \underline{n}} [1.3.5\dots(2n-1)] [2.4.6.(2n-2)2n] \\ &= \frac{\sigma^{2n}}{2^n \underline{n}} [1.3.5\dots(2n-1) 2^n [1.2\dots n]] \\ &= \frac{\sigma^{2n}}{2^n \underline{n}} [1.3.5\dots(2n-1) 2^n \underline{n}] \end{aligned}$$

$$\Rightarrow \mu_{2n} = \sigma^{2n} [1.3.5 \dots (2n-1)]$$

$$\therefore \mu_2 = 1 \cdot \sigma^2 = \sigma^2$$

$$\mu_3 = 0, \quad \mu_4 = 1 \cdot 3 \sigma^4$$

$$\mu_5 = 0, \quad \mu_6 = 1 \cdot 3 \cdot 5 \sigma^6$$

$$\beta_1 = 0, \quad \beta_2 = 3$$

Also μ'_1 = moment about origin

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

So μ_{2n+1} = odd moments about mean

$$= \int_{-\infty}^{\infty} (x - \mu)^{2n+1} f(x) dx$$

and $\mu_{2n} = \int_{-\infty}^{\infty} (x - \mu)^{2n} f(x) dx$ = even order moments about mean

Characteristic Function

$$\phi_X(t) = E[e^{itx}] = e^{i\mu t - \frac{1}{2}t^2\sigma^2}$$

Mean deviation

$$M.D = \int_{-\infty}^{\infty} |x - \mu| f(x) dx$$

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

Put $z = \frac{x - \mu}{\sigma} \Rightarrow dz = \frac{1}{\sigma} dx$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} |\sigma z| \frac{e^{-\frac{1}{2}z^2}}{\sigma} \cdot \sigma dz$$

$$\therefore M.D = \frac{2}{\sqrt{2\pi}} \int_0^{\infty} \sigma z e^{-\frac{1}{2}z^2} dz$$

[$\ominus$ integrand is even function of z]

$$\text{Put } \frac{1}{2} z^2 = t \quad \Rightarrow \quad \frac{1}{2} \cdot 2z \, dz = dt$$

$$\Rightarrow \quad z \, dz = dt$$

$$\begin{aligned} \therefore \quad \text{M.D.} &= \frac{2}{\sqrt{2\pi}} \sigma \int_0^\infty e^{-t} \, dt \\ &= \sqrt{\frac{2}{\pi}} \sigma \left[\frac{e^{-t}}{-1} \right]_0^\infty = \sqrt{\frac{2}{\pi}} \sigma \cdot [0 - 1] = \sqrt{\frac{2}{\pi}} \sigma \\ &= \frac{4}{5} \sigma = 0.8 \sigma \quad \Rightarrow \quad \text{M.D} = \sqrt{\frac{2}{\pi}} \sigma \end{aligned}$$

Points of Inflexion of a Normal Curve

At the points of inflexion,

$$f''(x) = 0, \quad f'''(x) \neq 0$$

$$\text{Now } f''(x) = -\frac{f(x)}{\sigma^2} \left[1 - \frac{(x-\mu)^2}{\sigma^2} \right]$$

$$\text{Put } f''(x) = 0, \quad 1 - \frac{(x-\mu)^2}{\sigma^2} = 0$$

$$\Rightarrow \quad (x-\mu)^2 = \sigma^2 \quad \Rightarrow \quad x-\mu = \pm \sigma$$

$$\Rightarrow \quad x = \mu \pm \sigma$$

$$\begin{aligned} \text{Now } f'''(x) &= -\frac{f'(x)}{\sigma^2} \left[1 - \frac{(x-\mu)^2}{\sigma^2} \right] - \frac{f(x)}{\sigma^2} \left[\frac{-2(x-\mu)}{\sigma^2} \right] \\ &= -\frac{f'(x)}{\sigma^2} \left[1 - \frac{(x-\mu)^2}{\sigma^2} \right] + \frac{2f(x)(x-\mu)}{\sigma^4} \end{aligned}$$

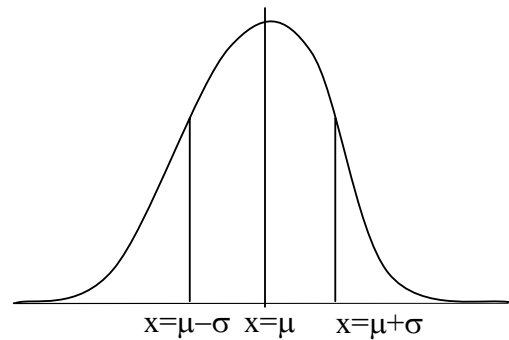
$$\text{At } x = \mu \pm \sigma,$$

$$\begin{aligned} f'''(x) &= \frac{-f'(x)}{\sigma^2} \left[1 - \frac{(\mu + \sigma - \mu)^2}{\sigma^2} \right] + \frac{2f(x)}{\sigma^4} (\mu + \sigma - \mu) \\ \Rightarrow \quad f'''(x) &= \frac{-f'(x)}{\sigma^2} [1 - 1] + \frac{2f(x)}{\sigma^3} \cdot \sigma \\ &= 0 + \frac{2f(x)}{\sigma^3} = \frac{2f(\mu + \sigma)}{\sigma^3} \neq 0 \end{aligned}$$

$$\text{At } x = \mu - \sigma,$$

$$\begin{aligned}
 f'''(x) &= -\frac{f'(x)}{\sigma^2} \left[1 - \frac{(-\sigma)^2}{\sigma^2} \right] + \frac{2f(x)}{\sigma^4} (-\sigma) \\
 &= -\frac{f'(x)}{\sigma^2} (1-1) - \frac{2f(x)}{\sigma^3} = 0 - \frac{2f(x)}{\sigma^3} \\
 \Rightarrow f'''(x) &= \frac{-2f(x)}{\sigma^3} = \frac{-2f(\mu - \sigma)}{\sigma^3} \neq 0 \\
 f'''(x) &= \frac{(\pm\sigma)}{\sigma^4} f(\mu \pm \sigma) \left[3 - \frac{(\pm\sigma)^2}{\sigma^2} \right] \\
 &= \frac{\pm 2f(\mu \pm \sigma)}{\sigma^3} \neq 0
 \end{aligned}$$

The S.D. is the distance of point of inflexion from the axis of symmetry.



Example: - μ'_1 (about 10) = 40

$$\mu'_4 \text{ (about 50) } = 48$$

Find Mean and S.D.

Solution: - By definition 1st moment about 10,

$$\begin{aligned}
 \mu'_1 &= \int_{-\infty}^{\infty} (x-10)f(x) dx = 40 \\
 \Rightarrow &= \int_{-\infty}^{\infty} xf(x) dx - 10 \int_{-\infty}^{\infty} f(x) dx = 40 \\
 \Rightarrow &= \int_{-\infty}^{\infty} xf(x) dx = 40 + 10 = 50 \quad \left[\Theta \int_{-\infty}^{\infty} f(x) dx = 1 \right] \\
 \therefore \text{ Mean} &= \int_{-\infty}^{\infty} xf(x) dx = 50
 \end{aligned}$$

As Mean is 50.

$$\mu'_4 = 48(4^{\text{th}} \text{ moment about Mean})$$

$$\Rightarrow 3\sigma^4 = 48 \quad \Rightarrow \sigma^4 = 16 = 2^4$$

$$\Rightarrow \sigma = \text{S.D.} = 2$$

Theorem: - If X_1 and X_2 are **independent** normal variates, then $X_1 + X_2$ is also a normal variate.

Proof: - $X_1 \sim N(\mu_1, \sigma_1^2)$

$$X_2 \sim N(\mu_2, \sigma_2^2)$$

$$M_{X_1}(t) = E[e^{tX_1}] = e^{\mu_1 t + \frac{1}{2}\sigma_1^2 t^2}$$

$$M_{X_2}(t) = E[e^{tX_2}] = e^{\mu_2 t + \frac{1}{2}\sigma_2^2 t^2}$$

As X_1 and X_2 are independent,

$$\begin{aligned} \therefore M_{X_1+X_2}(t) &= M_{X_1}(t) \cdot M_{X_2}(t) \\ &= e^{(\mu_1+\mu_2)t + \frac{1}{2}t^2(\sigma_1^2+\sigma_2^2)} \end{aligned}$$

which is the M.G.F of Normal distribution with Mean $\mu_1+\mu_2$ and variance $\sigma_1^2 + \sigma_2^2$

$$\text{i.e. } X_1 + X_2 \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

Theorem: - A linear combination of independent normal variates is also a normal variate. i.e.

if $Y = a_1X_1 + a_2X_2 + \dots + a_nX_n$, then Y is also a normal variate.

Proof: - X_i are independent normal variates.

$$\therefore M_{X_i}(t) = e^{\mu_i t + \frac{1}{2}\sigma_i^2 t^2}$$

$$\text{and } M_{X_i}(a_i t) = e^{\mu_i a_i t + \frac{1}{2}\sigma_i^2 a_i^2 t^2} \quad \dots(1)$$

Now M.G.F of $Y = \sum_{i=1}^n a_i X_i$ is

$$\begin{aligned} M_{\sum a_i X_i}(t) &= M_{a_1 X_1 + a_2 X_2 + \dots + a_n X_n}(t) \\ &= M_{a_1 X_1}(t) M_{a_2 X_2}(t) \dots M_{a_n X_n}(t) && [\text{Since } X_i \text{'s are independent}] \\ &= M_{X_1}(a_1 t) \cdot M_{X_2}(a_2 t) \dots M_{X_n}(a_n t) && [M_{CX}(t) = M_X(Ct)] \\ &= e^{\mu_1 a_1 t + \frac{1}{2}\sigma_1^2 a_1^2 t^2} \cdot e^{\mu_2 a_2 t + \frac{1}{2}\sigma_2^2 a_2^2 t^2} \dots && [\text{from (1)}] \end{aligned}$$

$$= e^{t(\sum a_i \mu_i) + \frac{1}{2} t^2 (\sum a_i^2 \sigma_i^2)}$$

which is M.G.F of Normal distribution with **Mean** = $\sum a_i \mu_i$ and **Variance** = $\sum a_i^2 \sigma_i^2$

Remarks

(1) If we take $a_1 = a_2 = 1, a_3 = a_4 = \dots = 0$,

then $X_1 + X_2 \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$

if we take $a_1 = 1, a_2 = -1, a_3 = a_4 = \dots = 0$,

then $X_1 - X_2 \sim N(\mu_1 - \mu_2, \sigma_1^2 + \sigma_2^2)$

Thus we see that sum as well as the difference of two independent normal variates is also a normal variate.

Note: - If $X_i \sim N(\mu, \sigma^2)$, X_i are identically distributed independent Normal variates, then their mean

$$\bar{X}_i \sim N\left(\mu, \frac{\sigma^2}{n}\right)$$

Taking $a_1 = a_2 = \dots = a_n = \frac{1}{n}$ in the result

$$Y = \sum a_i X_i \sim N\left(\sum a_i \mu_i, \sum a_i^2 \sigma_i^2\right) \quad \dots(1)$$

then $\frac{1}{n}(X_1 + X_2 + \dots + X_n) \sim N\left\{\frac{1}{n} \sum_{i=1}^n \mu_i, \frac{1}{n^2} \sum_{i=1}^n \sigma_i^2\right\}$

$$\Rightarrow \bar{X}_i \sim N\left\{\frac{1}{n} \cdot n\mu, \frac{1}{n^2} n\sigma^2\right\}$$

[As each X_i has mean = μ , variance = σ^2]

$$\Rightarrow \bar{X}_i \sim N\left(\mu, \frac{1}{n} \sigma^2\right)$$

Theorem: - If $X \sim B(n, p)$, then prove that MGF of $\frac{X - np}{\sqrt{npq}}$ tends to $e^{t^2/2}$ as $n \rightarrow \infty$.

Proof: - Let $U = \frac{X - np}{\sqrt{npq}}$

$$f(x) = {}^nC_x p^x q^{n-x}$$

MGF of Binomial distribution is

$$M_X(t) = (q + pe^t)^n$$

$$\therefore M_U(t) = e^{-at/h} M_X\left(\frac{t}{h}\right) \text{ where } U = \frac{X-a}{h}$$

$$M_U(t) = e^{-\frac{npt}{\sqrt{npq}}} \left[q + pe^{\frac{t}{\sqrt{npq}}} \right]^n$$

$$\begin{aligned} \therefore \log M_U(t) &= \frac{-npt}{\sqrt{npq}} + n \log \left[q + pe^{t/\sqrt{npq}} \right] \\ &= \frac{-npt}{\sqrt{npq}} + n \log \left[1 + p \left\{ \frac{t}{\sqrt{npq}} + \frac{t^2}{2npq} + \frac{t^3}{3(npq)^{3/2}} + \dots \right\} \right] \\ &= \frac{t^2}{2q} (1-p) + o(n^{-1/2}) \\ &= \frac{t^2}{2} + o\left(\frac{1}{\sqrt{n}}\right) \end{aligned}$$

$$\text{As } n \rightarrow \infty, \quad \log M_U(t) = t^2/2$$

$$\Rightarrow M_U(t) = e^{t^2/2}$$

Area property

$$\text{If } X \sim N(\mu, \sigma^2)$$

The probability that r.v. X will lie between $X = \mu$ and $X = x_1$ is given by

$$\begin{aligned} P(\mu < X < x_1) &= \int_{\mu}^{x_1} f(x) \, dx \\ &= \frac{1}{\sigma\sqrt{2\pi}} \int_{\mu}^{x_1} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \, dx \end{aligned}$$

$$\text{Put } Z = \frac{X-\mu}{\sigma}, \text{ then } z = \frac{x-\mu}{\sigma}$$

$$\text{If } X = \mu, \text{ then } Z = 0$$

$$\& \text{ when } X = x_1, Z = z_1(\text{say}) \text{ where } z_1 = \frac{x_1 - \mu}{\sigma}$$

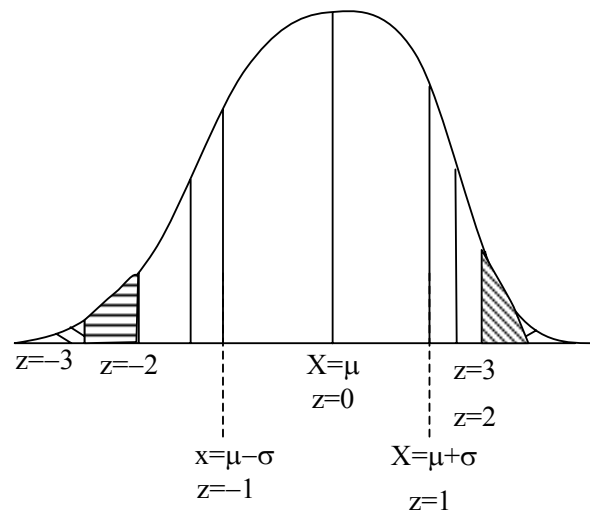
$$\therefore P(\mu < X < x_1) = P(0 < Z < z_1)$$

$$= \frac{1}{\sqrt{2\pi}} \int_0^{z_1} e^{-\frac{1}{2}z^2} dz = \int_0^{z_1} \phi(z) dz$$

where $\phi(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2}$ is the probability function.

The definite integral $\int_0^{z_1} \phi(z) dz$ is known as normal probability Integral & gives the area under

Normal curve between ordinates at $Z = 0$ & $Z = z_1$. These are tabulated for different values of z_1 at interval of 0.01



$$P(\mu - \sigma < X < \mu + \sigma) = P(-1 < Z < 1)$$

$$= \int_{\mu-\sigma}^{\mu+\sigma} f(x) dx = \int_{-1}^1 \phi(z) dz = 2 \int_0^1 \phi(z) dz \quad [\Theta \text{ curve is symmetrical}]$$

$$= 2(0.3413)$$

$$= 0.6826$$

and $P(\mu - 2\sigma < X < \mu + 2\sigma) = P(-2 < Z < 2)$

$$= \int_{-2}^2 \phi(z) dz = 2 \int_0^2 \phi(z) dz$$

$$= 2(0.4772) = 0.9544$$

and $(\mu - 3\sigma < X < \mu + 3\sigma) = P(-3 < Z < 3)$

$$= 2(0.4987) = 0.9974$$

and outside range $\mu \pm 3\sigma$

$$\begin{aligned}
 P(|X-\mu| > 3\sigma) &= P(|Z| > 3) \\
 &= 1 - P(-3 < Z < 3) \\
 &= 1 - 0.9974 = 0.0026
 \end{aligned}$$

Example: - If $X \sim N(12, 16)$

Find (i) $P(X \geq 20)$ (ii) $P(X \leq 20)$ (iii) $P(0 \leq X \leq 12)$

Solution: - (i) Here $\mu = 12, \sigma = 4$

$$Z = \frac{X - \mu}{\sigma} = \frac{X - 12}{4}$$

$$\begin{aligned}
 \therefore P(X \geq 20) &= P(Z \geq 2) \\
 &= 0.5 - P(0 \leq Z < 2) \\
 &= 0.5 - 0.4772 = 0.0228
 \end{aligned}$$

$$\begin{aligned}
 \text{(ii) } P(X \leq 20) &= 1 - P(X \geq 20) \\
 &= 1 - 0.0228 = 0.9772
 \end{aligned}$$

$$\text{(iii) } P(0 \leq X \leq 12) = P(-3 \leq Z \leq 0) = P(0 \leq Z \leq 3) \quad (\text{due to symmmtrical})$$

$$\therefore P(0 \leq X \leq 12) = 0.4987$$

(iv) Find x' when $P(X > x') = 0.24$

$$\text{Solution: - when } X = x', \text{ then } Z = \frac{x' - 12}{4} = z_1 \text{ (say)} \quad \dots(1)$$

$$\begin{aligned}
 \therefore P(Z > z_1) &= 0.24 \\
 P(0 < Z < z_1) &= 0.5 - 0.24 = 0.26
 \end{aligned}$$

From table, $z_1 = 0.71$

$$\therefore (1) \Rightarrow z_1 = \frac{x' - 12}{4} = 0.71$$

$$\Rightarrow x' = 14.84$$

Example: - $X \sim N(\overset{\mu}{30}, \overset{\sigma^2}{25})$

Find (i) $P(26 \leq X \leq 40)$ (ii) $X \geq 45$ (iii) $|X - 30| > 5$

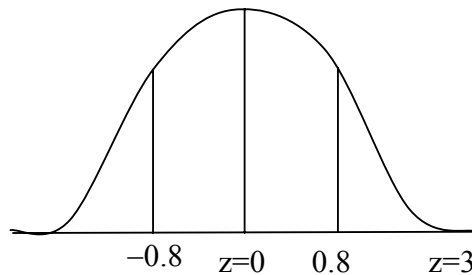
Solution: - Here $\mu = 30, \sigma = 5$

$$(i) \quad \text{when } X = 26, \quad Z = \frac{X - \mu}{\sigma} = \frac{26 - 30}{5} = -0.8$$

& when $X = 40$, $Z = \frac{40-30}{5} = 2.0$

$$\begin{aligned}\therefore P(26 \leq X \leq 40) &= P(-0.8 \leq Z \leq 2) \\ &= P(-0.8 \leq Z < 0.8) + P(0 \leq Z \leq 2) \\ &= P(0 \leq Z \leq 0.8) + P(0 \leq Z < 2) \\ &= 0.2881 + 0.4772\end{aligned}$$

$$P(26 \leq X \leq 40) = 0.7653$$



$$\begin{aligned}\text{(ii) } P(X \geq 45) &= P(Z \geq 3) = 0.5 - P(0 \leq Z \leq 3) \\ &= 0.5 - 0.4987 = 0.0013\end{aligned}$$

$$\text{(iii) } P(|X-30| > 5)$$

Put $|X-30| = |Y| \quad \therefore |Y| \leq 5$

$$\Rightarrow -5 \leq Y \leq 5$$

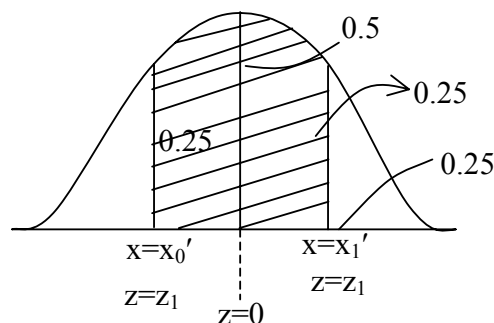
$$\begin{aligned}\therefore P(|X-30| \leq 5) &= P(25 \leq X \leq 35) \\ &= P(-1 \leq Z \leq 1) = 2P(0 \leq Z \leq 1)\end{aligned}$$

$$\begin{aligned}\text{Then } P(|X-30| > 5) &= 1 - P(|X-30| \leq 5) \\ &= 1 - 0.6826 = 0.3174\end{aligned}$$

Example: - $X \sim N(12, 16)$

Find x_0^1 and x_1^1 when $P(x_0^1 \leq X \leq x_1^1) = 0.50$ and $P(X > x_1^1) = 0.25$

Solution: -



when $X = x'_1$, $Z = \frac{x'_1 - 12}{4} = z_1$ (say)

when $X = x'_0$, $Z = \frac{x'_0 - 12}{4} = -z_1$ (from figure)

$$P(X > X'_1) = 0.25 \Rightarrow P(Z > z_1) = 0.25$$

and $[P(Z > z_1) = 0.5 - P(0 \leq Z \leq z_1) = 0.25]$

$$\therefore P(0 < Z < z_1) = 0.5 - P(Z > z_1) = 0.25$$

from table, $z_1 = 0.67$

Hence $\frac{x'_1 - 12}{4} = 0.67$

$$\Rightarrow x'_1 = 0.67 \times 4 + 12 = 14.68$$

and $\frac{x'_0 - 12}{4} = -0.67 \Rightarrow x'_0 = 9.32$

LESSON 8 MULTIPLE AND PARTIAL CORRELATION

INTRODUCTION.

When the value of the one variable is associated with or influenced by other variable, e.g., the age of husband and wife, the height of father and son, the supply and demand of a commodity and so on, Karl Pearson's coefficient of correlation can be used as a measure of linear relationship between them. But sometimes there is correlation between many variables and the value of one variable may be influenced by many others, e.g., the yield of crop per acre say (X_1) depends upon quality of seed (X_2), fertility of soil (X_3), fertilizer used (X_4), irrigation facilities (X_5) etc. Whenever we are interested in studying the joint effect of a group of variable upon a variable not included in that group, our study is that of **multiple correlation and multiple regression**. The correlation and regression between only two variates after eliminating the linear effect of other variates in them is called the **partial correlation and partial regression**.

Yule's Notation:

Let us consider a distribution involving three random variables X_1 , X_2 and X_3 . Then the equation of the plane of regression of X_1 on X_2 and X_3 is

$$X_1 = a + b_{12.3} X_2 + b_{13.2} X_3 \quad (1)$$

Without loss of generality, we can assume the variables X_1 , X_2 , and X_3 have been measured from their respective means, so that

$$E(X_1) = E(X_2) = E(X_3) = 0$$

Hence on taking expectation of both sides in (1), we get $a = 0$

Thus the plane of regression of X_1 , X_2 , and X_3 becomes

$$X_1 = b_{12.3} X_2 + b_{13.2} X_3 \quad (2)$$

The coefficient $b_{12.3}$ and $b_{13.2}$ are known as the **partial regression coefficients** of X_1 on X_2 and of X_1 on X_3 , respectively. The quantity

$$e_{1.23} = b_{12.3} X_2 + b_{13.2} X_3$$

is called the estimate of X_1 as given by the plane of regression (1) and the quantity.

$$X_{1.23} = X_1 - b_{12.3} X_2 - b_{13.2} X_3$$

is called the **error of estimate or residual**.

In the general case of n variable $X_1, X_2, \dots, X_n$ the equation of the plane of regression of X_1 on $X_2, X_3, \dots, X_n$ becomes

$$X_1 = b_{12.34\dots n} X_2 + b_{13.24\dots n} X_3 + \dots + b_{1n.23\dots(n-1)} X_n$$

The error of estimate or residual is given by

$$X_{1.23\dots n} = X_1 - b_{12.34\dots n} X_2 + b_{13.24\dots n} X_3 + \dots + b_{1n.23\dots(n-1)} X_n.$$

The notation used here are due to Yule. The subscripts before the dot (.) are known as **primary subscripts** and those after the dot are called **secondary subscripts**. The order of regression coefficient is determined by the number of secondary subscripts, e.g.,

$$b_{12.3}, b_{12.34}, \dots, b_{12.34\dots n}$$

are the regression coefficients of order 1, 2, ..., (n-2) respectively. Thus in general, a regression coefficient with p -secondary subscripts will be called a regression coefficient of order 'p'. It may be noted that the order in which the secondary subscripts are written is immaterial but the order of the primary subscripts is important, e.g., in $b_{12.34\dots n}$, X_2 is independent while X_1 is dependent variable but in $b_{21.34\dots n}$, X_1 is independent while X_2 is dependent variable. Thus of the two primary subscripts, former refer to dependent variable and the latter to independent variable.

The order of the residual is also determined by the number of secondary subscripts in it, e.g., $X_{1.23}$, $X_{1.234}$, $X_{1.23.....n}$, are the residual of order 2, 3, (n-1) respectively.

Remaks: In the following sequences we shall assume that the variable under consideration has been measured from their respective means.

Plane of regression:

The equation of the plane of regression of X_1 on X_2 and X_3 is

$$X_1 = b_{12.3} X_2 + b_{13.2} X_3 \quad (3)$$

The constants b 's in (3) are determined by the principle of leastsquares, i.e., by minimizing the sum of the squares of the residual, viz.,

$$S = \sum X_{1.23}^2 = \sum (X_1 - b_{12.3} X_2 - b_{13.2} X_3)^2,$$

the summation being extended to the given values (N in number) of the variables.

The normal equation of estimating $b_{12.3}$ and $b_{13.2}$ are

$$\left. \begin{aligned} \frac{\partial S}{\partial b_{12.3}} = 0 &= -2 \sum X_2 (X_1 - b_{12.3} X_2 - b_{13.2} X_3) \\ \frac{\partial S}{\partial b_{13.2}} = 0 &= -2 \sum X_3 (X_1 - b_{12.3} X_2 - b_{13.2} X_3) \end{aligned} \right\} \quad (4)$$

$$\text{i.e., } \sum X_2 X_{1.23} = 0 \text{ and } \sum X_3 X_{1.23} = 0 \quad (5)$$

$$\Rightarrow \left. \begin{aligned} \sum X_1 X_2 - b_{12.3} \sum X_2^2 - b_{13.2} \sum X_2 X_3 \\ \sum X_1 X_3 - b_{12.3} \sum X_2 X_3 - b_{13.2} \sum X_3^2 \end{aligned} \right\} \quad (6)$$

Since X_i 's are measured from their respective means, we have

$$\left. \begin{aligned} \sigma_i^2 &= \frac{1}{N} \sum X_i^2, \quad \text{Cov}(X_i, X_j) = \frac{1}{N} \sum X_i X_j \\ r_{ij} &= \frac{\text{Cov}(X_i, X_j)}{\sigma_i \sigma_j} = \frac{\sum X_i X_j}{N \sigma_i \sigma_j} \end{aligned} \right\} \quad (7)$$

Hence from (6), we get

$$\begin{aligned} r_{12} \sigma_1 \sigma_2 - b_{12.3} \sigma_2^2 - b_{13.2} r_{23} \sigma_2 \sigma_3 &= 0 \\ r_{13} \sigma_1 \sigma_3 - b_{12.3} r_{23} \sigma_2 \sigma_3 - b_{13.2} \sigma_3^2 &= 0 \end{aligned} \quad (8)$$

solving equations (10.30d) for $b_{12.3}$ and $b_{13.2}$, we get

$$b_{12.3} = \frac{\begin{vmatrix} r_{12} \sigma_1 & r_{23} \sigma_3 \\ r_{13} \sigma_1 & \sigma_3 \end{vmatrix}}{\begin{vmatrix} \sigma_2 & r_{23} \sigma_3 \\ r_{23} \sigma_2 & \sigma_3 \end{vmatrix}} = \frac{\sigma_1}{\sigma_2} \frac{\begin{vmatrix} r_{12} & r_{23} \\ r_{13} & 1 \end{vmatrix}}{\begin{vmatrix} 1 & r_{23} \\ r_{23} & 1 \end{vmatrix}} \quad (9)$$

Similarly, we obtain

$$b_{13.2} = \frac{\sigma_1}{\sigma_3} \frac{\begin{vmatrix} 1 & r_{12} \\ r_{23} & r_{13} \end{vmatrix}}{\begin{vmatrix} 1 & r_{23} \\ r_{23} & 1 \end{vmatrix}} \quad (10)$$

If we write

$$\omega = \begin{vmatrix} 1 & r_{12} & r_{13} \\ r_{21} & 1 & r_{23} \\ r_{31} & r_{32} & 1 \end{vmatrix} \quad (11)$$

And ω_{ij} is the cofactor of the element in the i th row and j th column of ω , we have from (9) and (10)

$$b_{12.3} = -\frac{\sigma_1}{\sigma_2} \frac{\omega_{12}}{\omega_{11}} \quad \text{and} \quad b_{13.2} = -\frac{\sigma_1}{\sigma_3} \frac{\omega_{13}}{\omega_{11}} \quad (12)$$

Substituting these values in (3), we get the required equation of the plane of regression of X_1 on X_2 and X_3

$$\begin{aligned} X_1 &= -\frac{\sigma_1}{\sigma_2} \cdot \frac{\omega_{12}}{\omega_{11}} \cdot X_2 - \frac{\sigma_1}{\sigma_3} \frac{\omega_{13}}{\omega_{11}} \cdot X_3 = 0 \\ \Rightarrow \quad \frac{X_1}{\sigma_1} \cdot \omega_{11} + \frac{X_2}{\sigma_2} \cdot \omega_{12} + \frac{X_3}{\sigma_3} \cdot \omega_{13} &= 0 \end{aligned} \quad (13)$$

or Eliminating the coefficient $b_{12.3}$ and $b_{13.2}$ in (3) and (8), the required equation of the plane of regression of X_1 on X_2 and X_3 becomes

$$\begin{vmatrix} X_1 & X_2 & X_3 \\ r_{12}\sigma_1\sigma_2 & \sigma_2^2 & r_{23}\sigma_2\sigma_3 \\ r_{13}\sigma_1\sigma_3 & r_{23}\sigma_2\sigma_3 & \sigma_3^2 \end{vmatrix} = 0$$

Dividing C_1 , C_2 and C_3 by σ_1 , σ_2 and σ_3 respectively and also R_2 and R_3 by σ_2 and σ_3 respectively, we get

$$\begin{vmatrix} \frac{X_1}{\sigma_1} & \frac{X_2}{\sigma_2} & \frac{X_3}{\sigma_3} \\ r_{12} & 1 & r_{23} \\ r_{13} & r_{23} & 1 \end{vmatrix} = 0$$

$$\Rightarrow \quad \frac{X_1}{\sigma_1} \cdot \omega_{11} + \frac{X_2}{\sigma_2} \cdot \omega_{12} + \frac{X_3}{\sigma_3} \cdot \omega_{13} = 0$$

Where ω_{ij} is defined in (11)

Generalization:

In general, the equation of the plane of regression of X_1 on $X_2, X_3, \dots, X_n$ is

$$X_1 = b_{12.34,\dots,n} X_2 + b_{13.24,\dots,n} X_3 + \dots + b_{1n.23,\dots,(n-1)} X_n \quad (14)$$

The sum of the squares of residuals is given by

$$S = \sum X_{1.23.....n}^2$$

$$= \sum (X_1 - b_{12.34.....n} X_2 + b_{13.24.....n} X_3 - \dots \dots b_{1n.23.....(n-1)} X_n$$

Using the principle of least squares, the normal equations for estimating the (n-1), b's are

$$\left. \begin{aligned} \frac{\partial S}{\partial b_{12.34.....n}} &= 0 = -2 \sum X_2 (X_1 - b_{12.34.....n} X_2 - b_{13.24.....n} X_3 - \dots \dots b_{1n.23.....(n-1)} X_n) \\ \frac{\partial S}{\partial b_{13.24.....n}} &= 0 = -2 \sum X_3 (X_1 - b_{12.34.....n} X_2 - b_{13.24.....n} X_3 - \dots \dots b_{1n.23.....(n-1)} X_n) \\ &\cdot \\ &\cdot \\ &\cdot \\ &\cdot \\ \frac{\partial S}{\partial b_{1n.23.....n}} &= 0 = -2 \sum X_n (X_1 - b_{12.34.....n} X_2 - b_{13.24.....n} X_3 - \dots \dots b_{1n.23.....(n-1)} X_n) \end{aligned} \right\} \quad (15)$$

$$\text{i.e., } \sum X_i X_{1.23.....n} = 0, \quad (i = 2, 3, \dots, n) \quad (16)$$

which on simplification after using (7)

$$r_{12} \sigma_1 \sigma_2 = b_{12.34.....n} \sigma_2^2 + b_{13.24.....n} r_{23} \sigma_2 \sigma_3 + \dots \dots b_{1n.23.....(n-1)} r_{2n} \sigma_2 \sigma_n = 0$$

$$r_{13} \sigma_1 \sigma_3 = b_{12.34.....n} r_{23} \sigma_2 \sigma_3 + b_{13.24.....n} \sigma_3^2 + \dots \dots b_{1n.23.....(n-1)} r_{3n} \sigma_3 \sigma_n = 0$$

$$\cdot \qquad \qquad \qquad \cdot \qquad \qquad \qquad \cdot$$

$$\cdot \qquad \qquad \qquad \cdot \qquad \qquad \qquad \cdot$$

$$\cdot \qquad \qquad \qquad \cdot \qquad \qquad \qquad \cdot$$

$$r_{1n} \sigma_1 \sigma_n = b_{12.34.....n} r_{2n} \sigma_2 \sigma_n + b_{13.24.....n} r_{3n} \sigma_3 \sigma_n + \dots \dots b_{1n.23.....(n-1)} \sigma_n^2 = 0 \quad (15)$$

Hence, the elimination of b's between (14) and (15) yields

$$\begin{vmatrix} X_1 & X_2 & X_3 & \dots & X_n \\ r_{12}\sigma_1\sigma_2 & \sigma_2^2 & r_{23}\sigma_2\sigma_3 & \dots & r_{23}\sigma_2\sigma_3 \\ r_{13}\sigma_1\sigma_3 & r_{23}\sigma_2\sigma_3 & \sigma_3^2 & \dots & r_{3n}\sigma_3\sigma_n \\ M & M & M & M & M \\ r_{1n}\sigma_1\sigma_n & r_{2n}\sigma_2\sigma_n & r_{3n}\sigma_3\sigma_n & K & \dots & \sigma_n^2 \end{vmatrix} = 0$$

Dividing $C_1, C_2, \dots, C_n$ by $\sigma_1, \sigma_2, \dots, \sigma_n$ respectively and also $R_2, R_3, \dots, R_n$ by $\sigma_2, \sigma_3, \dots, \sigma_n$ respectively, we get

$$\begin{vmatrix} \frac{X_1}{\sigma_1} & \frac{X_2}{\sigma_2} & \frac{X_3}{\sigma_3} & \dots & \frac{X_n}{\sigma_n} \\ r_{12} & 1 & r_{32} & \dots & r_{2n} \\ r_{13} & r_{23} & 1 & \dots & r_{3n} \\ M & M & M & \dots & M \\ r_{1n} & r_{2n} & r_{3n} & \dots & 1 \end{vmatrix} = 0 \quad (18)$$

If we write

$$\omega = \begin{vmatrix} 1 & r_{12} & r_{13} & \dots & r_{1n} \\ r_{21} & 1 & r_{23} & \dots & r_{2n} \\ r_{31} & r_{32} & 1 & \dots & r_{3n} \\ M & M & M & M & M \\ r_{n1} & r_{n2} & r_{n3} & \dots & 1 \end{vmatrix} \quad (19)$$

And ω_{ij} is the cofactor of the element in the i th row and j th column of ω , we get from (18)

$$\Rightarrow \frac{X_1}{\sigma_1} \cdot \omega_{11} + \frac{X_2}{\sigma_2} \cdot \omega_{12} + \frac{X_3}{\sigma_3} \cdot \omega_{13} + \dots + \frac{X_n}{\sigma_n} \cdot \omega_{1n} = 0 \quad (20)$$

As the required equation of plane of regression of X_1 on $X_2, X_3, \dots, X_n$.

Equation (20) can be re-written as

$$X_1 = -\frac{\sigma_1}{\sigma_2} \cdot \frac{\omega_{12}}{\omega_{11}} X_2 - \frac{\sigma_1}{\sigma_3} \frac{\omega_{13}}{\omega_{11}} X_3 - \dots \dots \dots - \frac{\sigma_1}{\sigma_n} \frac{\omega_{1n}}{\omega_{11}} X_n = 0 \quad (21)$$

Comparing (21) with (14), we get

$$\left. \begin{aligned} b_{12,34} &= -\frac{\sigma_1}{\sigma_2} \frac{\omega_{12}}{\omega_{11}} \\ b_{13,24} &= -\frac{\sigma_1}{\sigma_3} \frac{\omega_{13}}{\omega_{11}} \\ M & \quad M \\ b_{1n,23,\dots,(n-1)} &= -\frac{\sigma_1}{\sigma_n} \frac{\omega_{1n}}{\omega_{11}} \end{aligned} \right\} \quad (22)$$

Properties of residuals

Property 1. The sum of the product of any residual of order zero with any other residual of higher order is zero, provided the subscript of the former occurs among the secondary subscripts of the latter.

The normal equation for estimating b's in trivariate and n-variate distributions are

$$\sum X_2 X_{1,23} = 0, \sum X_3 X_{1,23} = 0$$

And $\sum X_i X_{1,23,\dots,n} = 0$; $i = 2, 3, \dots, n$

respectively. Here X_i , ($i = 1, 2, 3, \dots, n$) can be regarded as a residual of order zero.

Property 2. The sum of the product of any two residual in which all the secondary subscripts of the first occur among the secondary subscripts of the second is unaltered if we omit any or all the secondary subscripts of the first.

e.g. $\sum X_{1,2} X_{1,23} = \sum X_1 X_{1,23}$

also $\sum X_{1,23}^2 = \sum X_1 X_{1,23}$

so $\sum X_{1,23}^2 = \sum X_{1,2} X_{1,23} = \sum X_1 X_{1,23}$

Property 3. The sum of the product of two residuals is zero if all the subscripts (primary as well as secondary) of the one occur among the secondary subscripts of the other, e.g.,

$$\sum X_{1.2} X_{3.12} = 0$$

Variance of the Residuals

Let us consider the plane of regression of X_1 on $X_2, X_3, \dots, X_n$ as.

$$X_1 = b_{12.34\dots n} X_2 + b_{13.24\dots n} X_3 + \dots + b_{1n.23\dots(n-1)} X_n$$

Since all the X_i 's are measured from their respective means, we have

$$E(X_i) = 0; i = 1, 2, 3, \dots, n \Rightarrow E(X_{1.23\dots n}) = 0$$

Hence the variance of the residual is given by

$$\sigma_{1.23\dots n}^2 = \frac{1}{N} \sum [X_{1.23\dots n} - E(X_{1.23\dots n})]^2 = \frac{1}{N} \sum X_{1.23\dots n}^2$$

$$\sigma_{1.23\dots n}^2 = \frac{1}{N} \sum X_{1.23\dots n} X_{1.23\dots n} = \frac{1}{N} \sum X_1 X_{1.23\dots n}$$

$$= \frac{1}{N} \sum X_1 (X_1 - b_{12.34\dots n} X_2 - b_{13.24\dots n} X_3 - \dots - b_{1n.23\dots(n-1)} X_n)$$

$$= \sigma_1^2 - b_{12.34\dots n} r_{12} \sigma_1 \sigma_2 - b_{13.24\dots n} r_{13} \sigma_1 \sigma_3 - \dots - b_{1n.23\dots(n-1)} r_{1n} \sigma_1 \sigma_n$$

$$\Rightarrow \sigma_1^2 - \sigma_{1.23\dots n}^2 = b_{12.34\dots n} r_{12} \sigma_1 \sigma_2 - b_{13.24\dots n} r_{13} \sigma_1 \sigma_3 - \dots - b_{1n.23\dots(n-1)} r_{1n} \sigma_1 \sigma_n$$

Eliminating the b's we get

$$\begin{vmatrix} \sigma_1^2 - \sigma_{1.23\dots n}^2 & r_{12}\sigma_1\sigma & \dots & r_{1n}\sigma_1\sigma_n \\ r_{12}\sigma_1\sigma & \sigma_2^2 & \dots & r_{2n}\sigma_2\sigma_n \\ M & M & M & M \\ r_{1n}\sigma_1\sigma_n & r_{2n}\sigma_2\sigma_n & \dots & \sigma_n^2 \end{vmatrix} = 0$$

Dividing $R_1, R_2, \dots, R_n$ by $\sigma_1, \sigma_2, \dots, \sigma_n$ respectively and also $C_1, C_2, \dots, C_n$ by $\sigma_1, \sigma_2, \dots, \sigma_n$ respectively, we get

$$\begin{vmatrix} 1 - \frac{\sigma_{1.23\dots n}^2}{\sigma_1^2} & r_{12} & \dots & r_{1n} \\ r_{12} & 1 & \dots & r_{2n} \\ M & M & M & M \\ r_{1n} & r_{2n} & \dots & 1 \end{vmatrix} = 0$$

$$\begin{vmatrix} 1 & r_{12} & \dots & r_{1n} \\ r_{12} & 1 & \dots & r_{2n} \\ M & M & M & M \\ r_{1n} & r_{2n} & \dots & 1 \end{vmatrix} - \frac{\sigma_{1.23\dots n}^2}{\sigma_1^2} \begin{vmatrix} r_{12} & \dots & r_{1n} \\ 0 & 1 & \dots & r_{2n} \\ M & M & M & M \\ 0 & r_{2n} & \dots & 1 \end{vmatrix} = 0$$

$$\Rightarrow \omega - \frac{\sigma_{1.23\dots n}^2}{\sigma_1^2} \omega_{11} = 0$$

$$\therefore \sigma_{1.23\dots n}^2 = \sigma_1^2 - \frac{\omega}{\omega_{11}} \quad (23)$$

Remarks: In a tri-variate distribution,

$$\therefore \sigma_{1.23\dots n}^2 = \sigma_1^2 - \frac{\omega}{\omega_{11}} \quad (24)$$

Where ω and ω_{11} are defined in (11)

Coefficient of Multiple Correlation:

In a tri-variate distribution in which each of the variables X_1 , X_2 and X_3 has N observations, the multiple correlation coefficient of X_1 on X_2 and X_3 , usually denoted by $R_{1.23}$, is the simple correlation coefficient between X_1 and the joint effect of X_2 and X_3 on X_1 . In other words $R_{1.23}$ is the correlation coefficient between X_1 and its assumed value as given by the plane of regression of X_1 on X_2 and X_3 i.e.

$$e_{1.23} = b_{12.3} X_2 + b_{13.2} X_3$$

we have,

$$X_{1.23} = X_1 - b_{12.3} X_2 - b_{13.2} X_3 = X_1 - e_{1.23}$$

$$\Rightarrow e_{1.23} = X_1 - X_{1.23}$$

Since X_i 's are measured from their respective means, we have

$$E(X_{1.23}) = 0 \text{ and } E(e_{1.23}) = 0$$

By definition

$$R_{1.23} = \frac{\text{Cov}(X_1, e_{1.23})}{\sqrt{V(X_1)V(e_{1.23})}} \quad (25)$$

$$\begin{aligned} \text{Cov}(X_1, e_{1.23}) &= E[\{X_1 - E(X_1)\} \{e_{1.23} - E(e_{1.23})\}] = E(X_1, e_{1.23}) \\ &= \sigma_1^2 - \sigma_{1.23}^2 \end{aligned}$$

Also

$$V(e_{1.23}) = \sigma_1^2 - \sigma_{1.23}^2$$

$$R_{1.23} = \frac{\sigma_1^2 - \sigma_{1.23}^2}{\sqrt{\sigma_1^2(\sigma_1^2 - \sigma_{1.23}^2)}}$$

$$1 - R_{1.23}^2 = \frac{\sigma_{1.23}^2}{\sigma_1^2} \quad (26)$$

Using (24), we get

$$1 - R_{1.23}^2 = \frac{\omega}{\omega_{11}} \quad (27)$$

$$\text{Where, } \omega = \begin{vmatrix} 1 & r_{12} & r_{13} \\ r_{21} & 1 & r_{23} \\ r_{31} & r_{32} & 1 \end{vmatrix}$$

$$\text{and } \omega_{11} = \begin{vmatrix} 1 & r_{23} \\ r_{32} & 1 \end{vmatrix}$$

Hence from (27), we get

$$R_{1.23}^2 = 1 - \frac{\omega}{\omega_{11}} = \frac{r_{12}^2 + r_{13}^2 - 2r_{12}r_{13}r_{23}}{1 - r_{23}^2}$$

This formula expresses the multiple correlation coefficient in terms of the total correlation coefficients between the pairs of variables

Generalisation:

$$R_{1.23\dots n} = \frac{\sigma_1^2 - \sigma_{1.23\dots n}^2}{\sqrt{\sigma_1^2 (\sigma_1^2 - \sigma_{1.23\dots n}^2)}}$$

$$R_{1.23\dots n}^2 = 1 - \frac{\sigma_{1.23\dots n}^2}{\sigma_1^2}$$

$$R_{1.23\dots n}^2 = 1 - \frac{\omega}{\omega_{11}} \quad (28)$$

Where ω and ω_{11} are defined in (19)

Coefficient of Partial Correlation:

The partial correlation coefficient between X_1 and X_2 , usually denoted by $r_{12.3}$ is given by

$$r_{12.3} = \frac{\text{Cov}(X_{1.3}, X_{2.3})}{\sqrt{\text{Var}(X_{1.3})\text{Var}(X_{2.3})}}$$

We have

$$\begin{aligned}\text{Cov}(X_{1.3}, X_{2.3}) &= \frac{1}{N} \sum X_{1.3} X_{2.3} = \frac{1}{N} \sum X_1 X_{2.3} \\ &= \frac{1}{N} \sum X_1 (X_2 - b_{23} X_3) = \frac{1}{N} \sum X_1 X_2 - b_{23} \sum X_1 X_3 \\ &= r_{12} \sigma_1 \sigma_2 - (r_{23} \sigma_2 r_{13} \sigma_1) / \sigma_3 \\ &= \sigma_1 \sigma_2 (r_{12} - r_{23} r_{13})\end{aligned}$$

$$\begin{aligned}\text{Var}(X_{1.3}) &= \frac{1}{N} \sum X_{1.3}^2 = \frac{1}{N} \sum X_1 X_{2.3} \\ &= \frac{1}{N} \sum X_1 X_{2.3} = \frac{1}{N} \sum X_1 (X_1 - b_{13} X_3) \\ &= \frac{1}{N} \sum X_1^2 - b_{13} \cdot \frac{1}{N} \sum X_1 X_3 \\ &= \sigma_1^2 - r_{13} \frac{\sigma_1}{\sigma_3} r_{13} \sigma_1 \sigma_3 \\ &= \sigma_1^2 (1 - r_{13}^2)\end{aligned}$$

Similarly, we can get $\text{Var}(X_{2.3}) = \sigma_2^2 (1 - r_{23}^2)$

$$\text{Hence, } r_{12.3} = \frac{\sigma_1 \sigma_2 (r_{12} - r_{13} r_{23})}{\sqrt{\sigma_1^2 (1 - r_{13}^2) \sigma_2^2 (1 - r_{23}^2)}} = \frac{(r_{12} - r_{13} r_{23})}{\sqrt{(1 - r_{13}^2)(1 - r_{23}^2)}}$$

Example: From the data relating to the yield of grain (X_1), fertilizer used (X_2) and whether condition (X_3) for 18 crops the following correlation coefficients were obtained:

$$r_{12} = 0.77, \quad r_{13} = 0.72, \quad r_{23} = 0.52$$

Fond the partial correlation coefficient $r_{12.3}$ and multiple correlation coefficient $R_{1.23}$

Solution:

$$r_{1.23} = \frac{(r_{12} - r_{13}r_{23})}{\sqrt{(1 - r_{13}^2)(1 - r_{23}^2)}} = \frac{(0.77 - 0.72 \times 0.52)}{\sqrt{(1 - (0.72)^2)(1 - (0.52)^2)}} = 0.62$$

$$R_{1.23}^2 = \frac{r_{12}^2 + r_{13}^2 - 2r_{12}r_{13}r_{23}}{1 - r_{23}^2} = \frac{(0.77)^2 + (0.72)^2 - 2(0.77)(0.72)(0.52)}{1 - (0.52)^2} = 0.7334$$

$$R_{1.23} = +0.8564$$

Central Limit Theorem

If $X_1, X_2, \dots, X_n$ are independent and identically distributed variables with

$$E(X_i) = \mu_1$$

$$V(X_i) = \sigma_1^2, \quad i = 1, 2, \dots, n$$

Then the sum $S_n = X_1 + X_2 + \dots + X_n$ is asymptotically normal with mean $\mu = n \mu_1$ and variance $\sigma^2 = n \sigma_1^2$

Hence we make the following assumptions

- (i) The variable are independent and identically distributed
- (ii) $E(X_i^2)$ exists for $i = 1, 2, \dots$

Proof: Let $M_1(t)$ denote the M.G.F. of each of the derivation $(X_i - \mu_1)$ and $M(t)$ denote the M.G.F. of the standard variate

$$Z = (S_n - \mu)/\sigma$$

Since $\mu_1' = E(X_i - \mu_1) = 0$, $\mu_2' = E(X_i - \mu_1)^2 = \sigma_1^2$

We have

$$\begin{aligned} M_1(t) &= \left(1 + \mu_1' t + \mu_2' \frac{t^2}{2} + \mu_3' \frac{t^3}{6} + \dots \right) \\ &= \left[1 + \frac{t^2}{2} \sigma_1^2 + O(t^3) \right] \end{aligned} \quad (1)$$

Where $O(t^3)$ contains terms of order t^3 and higher powers of t

We have

$$Z = \frac{S_n - \mu}{\sigma} = \frac{(X_1 + X_2 + \dots + X_n) - n\mu_1}{\sigma} = \sum_{i=1}^n \left(\frac{X_i - \mu_1}{\sigma} \right)$$

And since X_i 's are independent, we get

$$\begin{aligned} M_Z(t) &= M_{\sum_{i=1}^n \left(\frac{X_i - \mu_1}{\sigma} \right)}(t) = M_{\sum_{i=1}^n (X_i - \mu_1)}(\sigma/t) \\ &= \prod_{i=1}^n \{M_{(X_i - \mu_1)}(t/\sigma)\} = [M_1(t/\sigma)]^n = [M_{(X_i - \mu_1)}(t/\sqrt{n}\sigma_1)]^n \\ &= \left[1 + \frac{t^2}{2n} + O(n^{-3/2}) \right]^n \end{aligned} \quad \text{From (1)}$$

For every fixed 't', the term $O(n^{-3/2}) \rightarrow 0$ as $n \rightarrow \infty$. Therefore, as $n \rightarrow \infty$, we get

$$\lim_{n \rightarrow \infty} M_Z(t) = \lim_{n \rightarrow \infty} \left[1 + \frac{t^2}{2n} + O(n^{-n/2}) \right]^n = \exp \left[\frac{t^2}{2} \right] = e^{\frac{t^2}{2}},$$

which is the M.G.F. of standard normal variate

Hence by uniqueness theorem of M.G.F.'s, $Z = (S_n - \mu)/\sigma$ is asymptotically $N(0, 1)$,
or $S_n = X_1 + X_2 + \dots + X_n$ is asymptotically $N(\mu, \sigma^2)$, where $\mu = n \mu_1$ and $\sigma^2 = n \sigma_1^2$

Weak Law of Large Number:

Let $X_1, X_2, \dots, X_n$ be a sequence of random variables and $\mu_1, \mu_2, \dots, \mu_n$

Be their respective expectation and let

$$B_n = \text{Var}(X_1 + X_2 + \dots + X_n) < \infty$$

$$\text{Then } P \left\{ \left| \frac{X_1 + X_2 + \dots + X_n}{n} - \frac{\mu_1 + \mu_2 + \dots + \mu_n}{n} \right| \leq \varepsilon \right\} \geq 1 - \eta$$

For all $n > n_0$, where ε and η are arbitrary small positive numbers, provided

$$\lim_{n \rightarrow \infty} \frac{B_n}{n^2} \rightarrow 0$$

Proof. Using Chebychev's inequality, to the random variable

$(X_1 + X_2 + \dots + X_n)/n$, we get for any $\varepsilon > 0$,

$$P \left\{ \left| \frac{X_1 + X_2 + \dots + X_n}{n} - E \left(\frac{X_1 + X_2 + \dots + X_n}{n} \right) \right| \leq \varepsilon \right\} \geq 1 - \frac{B_n}{n^2 \varepsilon^2}$$

$$\left[\text{Since } \text{Var} \left(\frac{X_1 + X_2 + \dots + X_n}{n} \right) \right] = \frac{1}{n^2} \text{Var}(X_1 + X_2 + \dots + X_n) = \frac{B_n}{n^2}$$

$$\Rightarrow P\left\{\left|\frac{X_1 + X_2 + \dots + X_n}{n} - \left(\frac{\mu_1 + \mu_2 + \dots + \mu_n}{n}\right)\right| < \varepsilon\right\} \geq 1 - \frac{B_n}{n^2 \varepsilon^2}$$

Since ε is arbitrary, we assume $\frac{B_n}{n^2 \varepsilon^2} \rightarrow \infty$, as n becomes indefinitely large. Thus,

having chosen two arbitrary small positive numbers ε and η , number n_0 can be found so that the inequality

$$\frac{B_n}{n^2 \varepsilon^2} < \eta, \text{ is 1}$$

Is true for $n > n_0$. Therefore, we shall have

$$P\left\{\left|\frac{X_1 + X_2 + \dots + X_n}{n} - \frac{\mu_1 + \mu_2 + \dots + \mu_n}{n}\right| \leq \varepsilon\right\} \geq 1 - \eta.$$

Chi-Square Distribution

Definition. If $X \sim N(\mu, \sigma^2)$, then $Z = \frac{X - \mu}{\sigma} \sim N(0, 1)$

And $Z^2 = \left(\frac{X - \mu}{\sigma}\right)^2$, is the chi-square variate with 1 d. f

In general, if $X_i (i=1, 2, \dots, n)$ are n independent normal variates with mean μ_i and variance $\sigma_i^2 (i=1, 2, \dots, n)$, then

$\chi^2 = \sum_{i=1}^n \left(\frac{X_i - \mu_i}{\sigma_i}\right)^2$, is the chi-square variate with n d. f

Chi-square distribution: if $X_i (i=1, 2, \dots, n)$ are independent $N(\mu_i, \sigma_i^2)$, we want the distribution of

$$\chi^2 = \sum_{i=1}^n \left(\frac{X_i - \mu_i}{\sigma_i} \right)^2 = \sum_{i=1}^n U_i^2$$

Where $U_i = \frac{X_i - \mu_i}{\sigma_i}$

Probability density function

$$\begin{aligned} dP(\chi^2) &= \frac{(1/2)^{n/2}}{\Gamma(n/2)} \left[\exp\left(-\frac{1}{2}\chi^2\right) \right] (\chi^2)^{(n/2)-1} d\chi^2 \\ &= \frac{1}{2^{n/2}\Gamma(n/2)} \left[\exp\left(-\frac{\chi^2}{2}\right) \right] (\chi^2)^{(n/2)-1} d\chi^2, \end{aligned} \quad 0 \leq \chi^2 < \infty$$

Which is the required probability distribution function of chi-square distribution with n degree of freedom

Students t distribution

Definition. Let x_i ($i=1, 2, 3, \dots, n$) be a random sample of size n from a normal population with mean μ and variance σ^2 . Then student 's t' is defined by the statistic

$$t = \frac{\bar{x} - \mu}{s} \sqrt{n},$$

where $\bar{x}$ is the sample mean and s^2 is an estimate of population variance of σ^2 . It follows Student t –distribution with $v = (n-1)$ degrees of freedom with probability density function

$$f(t) = \frac{1}{\sqrt{v} B(\frac{1}{2}, \frac{v}{2}) \{1 + \frac{t^2}{v}\}^{\frac{v+1}{2}}} \quad -\infty < t < \infty .$$

Moments

The probability curve of t is symmetrical about $t=0$ and therefore,

$$\text{Mode}=\text{mean}=\text{median}=0$$

All odd order moments are zero i.e. $\mu_{2r+1}=0$

Even order moments are given by

$$\mu_{2r} = \mu_{2r}' = \int_{-\infty}^{\infty} t^{2r} f(t) dt = \frac{2}{\sqrt{v} B(\frac{1}{2}, \frac{v}{2})} \int_0^{\infty} \frac{t^{2r}}{\{1 + \frac{t^2}{v}\}^{\frac{v+1}{2}}} dt$$

$$= \frac{v^r B(\frac{v}{2} - r, r + \frac{1}{2})}{B(\frac{1}{2}, \frac{v}{2})}$$

$$\text{Put } r=1, \text{ then } \mu_2 = \frac{n}{n-2}, \quad n>2,$$

is known as variance.

F –distribution.

If U and V are two independent χ^2 variates with v_1 and v_2 degrees of freedom, respectively, then F –statistic is defined by

$$F = \frac{\left(\frac{U}{v_1}\right)}{\left(\frac{V}{v_2}\right)}, \quad (v_1 > v_2), \quad | \quad \text{as} \quad \begin{matrix} U \sim \chi^2_{v_1} \\ V \sim \chi^2_{v_2} \end{matrix}$$

In other words, F is defined as the ratio of two independent chi-square variates divided by their respective degrees of freedom and it follows Snedecor's F-distribution with (v_1, v_2) degrees of freedom with density function given by

$$f(F) = \frac{\left(\frac{v_1}{v_2}\right)^{\frac{v_1}{2}} F^{\frac{v_1}{2}-1}}{B\left(\frac{v_1}{2}, \frac{v_2}{2}\right) \left\{1 + \frac{v_1}{v_2} F\right\}^{\frac{v_1+v_2}{2}}}, \quad 0 < F < \infty.$$

Moments.

The rth moment about origin is given by

$$\mu_r' = E(F^r) = \int_0^\infty F^r f(F) dF = \int_0^\infty \frac{F^r \left(\frac{v_1}{v_2}\right)^{\frac{v_1}{2}} F^{\frac{v_1}{2}-1}}{B\left(\frac{v_1}{2}, \frac{v_2}{2}\right) \left\{1 + \frac{v_1}{v_2} F\right\}^{\frac{v_1+v_2}{2}}} dF$$

$$\mu_r' = \frac{\left(\frac{v_2}{v_1}\right)^r}{B\left(\frac{v_1}{2}, \frac{v_2}{2}\right)} B\left(r + \frac{v_1}{2}, \frac{v_2}{2} - r\right)$$

Putting $r=1$, we get **mean** = $\mu_1' = \frac{v_2}{v_2 - 2}$

Further $\mu_2' = \frac{v_2^2(v_1 + 2)}{v_2(v_2 - 2)(v_2 - 4)}, \quad v_2 > 4$

Now variance is obtained from $\mu_2 = \mu_2' - \mu_1'^2 = \frac{v_2^2}{(v_2 - 2)} \left[\frac{v_1^2 - 4 - v_1 v_2 + 4v_1}{v_1(v_2 - 4)(v_2 - 2)} \right]$