

I. Continuous Distributions:

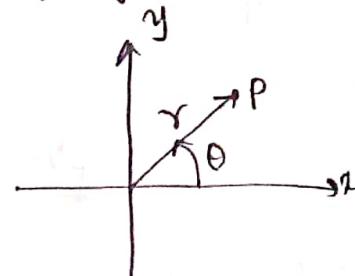
$$1) \text{ Given; } I = \int_{-\infty}^{+\infty} e^{-x^2/2} dx$$

$$I^2 = \int_{-\infty}^{+\infty} e^{-x^2/2} dx \int_{-\infty}^{+\infty} e^{-y^2/2} dy = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} e^{-\frac{(x^2+y^2)}{2}} dx dy$$

Evaluating Double Integral I^2 using Change of variables to polar coordinates.

$$x = r \cos \theta, y = r \sin \theta$$

$$\begin{aligned} -\infty < x < +\infty \\ -\infty < y < +\infty \\ 0 \leq \theta \leq 2\pi \\ 0 \leq r < \infty \end{aligned}$$



$|J(r, \theta)|$: - Jacobian determinant

$$|J(r, \theta)| = \begin{vmatrix} \frac{\partial x}{\partial r} & \frac{\partial x}{\partial \theta} \\ \frac{\partial y}{\partial r} & \frac{\partial y}{\partial \theta} \end{vmatrix}$$

$$= \begin{vmatrix} \cos \theta & -r \sin \theta \\ \sin \theta & r \cos \theta \end{vmatrix}$$

$$I^2 = \int_0^\infty \int_0^{2\pi} e^{-r^2/2} \times r d\theta dr$$

$$I^2 = \int_0^\infty e^{-r^2/2} r dr \int_0^{2\pi} d\theta$$

$$\Rightarrow r^2 = 2a$$

$$\Rightarrow dr = \frac{da}{dr} \Rightarrow r dr = da$$

$$\text{Observe } r = \sqrt{2a} \Rightarrow \text{range of } r = [0, \sqrt{2a}]$$

$$\text{range of } \theta = [0, 2\pi]$$

$$I^2 = (2\pi) \int_0^\infty e^{-a} da = 2\pi \left[\frac{-e^{-a}}{-1} \right]_0^\infty$$

$$I^2 = 2\pi [0 - (-1)] = 2\pi$$

$$\therefore \text{We get } I = \int_{-\infty}^{+\infty} e^{-x^2/2} dx = \sqrt{2\pi}$$

Hence Proved

② Given;

Lifetime of a Computer chip (T) $\sim N(\mu, \sigma^2)$ Normal
Where

Mean (μ) = 4.4×10^6 hours.

Standard Dev (σ) = 3×10^5 hours

→ Client requires that atleast 90% of Procured chips has a life time of 4×10^6 hours.

* Do given some large amount of chips; client will be wishing that; If he chose a chip; it should have $T \geq 4 \times 10^6$. 90% of the times he drew a chip from bunch.

So, let us evaluate $P(T \geq 4 \times 10^6)$

$$\therefore P(T \geq 4 \times 10^6) = 1 - P(T < 4 \times 10^6)$$

$$P(T < 4 \times 10^6) = P(T \leq 4 \times 10^6) - P(T = 4 \times 10^6)$$

$$\therefore P(T < 4 \times 10^6) = P(T \leq 4 \times 10^6) \quad (\because \text{Prob. of a point in continuous dist} = 0)$$

$$P(T < 4 \times 10^6) = P\left(\frac{T-\mu}{\sigma} \leq \frac{4 \times 10^6 - \mu}{\sigma}\right)$$

We know; if $X \sim N(\mu, \sigma^2)$

$$\frac{X-\mu}{\sigma} \sim N(0, 1)$$

Standard Normal

$$\therefore \text{let } Z = \frac{T-\mu}{\sigma}$$

2) Now;

$$P(T < 4 \times 10^6) = P\left(Z \leq \frac{4 \times 10^6 - \mu}{\sigma}\right)$$

$$= P\left(Z \leq \frac{4 \times 10^6 - 4 \cdot 4 \times 10^6}{3 \times 10^5}\right)$$

$$= P\left(Z \leq \frac{-0.4 \times 10^6}{3}\right)$$

$$P(T < 4 \times 10^6) = P\left(Z \leq -\frac{4}{3}\right)$$

$\underbrace{\hspace{10em}}$ CDF of Standard Normal Distribution

$$= \Phi\left(-\frac{4}{3}\right)$$

$$P(T < 4 \times 10^6) = 0.0912 \quad (\text{From Table})$$

$$\therefore P(T \geq 4 \times 10^6) = 1 - 0.0912 = 0.9088$$

So, we saw that; In random; A chip taken will have a life time greater than 4×10^6 hrs with probability 0.9088. Hence; On an average we can expect that atleast 90% of total chips produced has a life time of 4×10^6 hrs.

Hence; Particular Client should procure from the chip manufacturer.

- ③ In a batch of 100 chips ; Probability that there are atleast 4 chips whose lifetimes are less than 3.8×10^6 hrs:-

First; Let us evaluate;

Probability that a given chip has lifetime less than 3.8×10^6

$$\text{ie;} P(T < 3.8 \times 10^6) = P(T \leq 3.8 \times 10^6) - P(T = 3.8 \times 10^6)$$

$$\Rightarrow P(T < 3.8 \times 10^6) = P(T \leq 3.8 \times 10^6)$$

$$= P\left(\frac{T-\mu}{\sigma} \leq \frac{3.8 \times 10^6 - \mu}{\sigma}\right)$$

$$= P\left(Z \leq \frac{3.8 \times 10^6 - 4.4 \times 10^6}{3 \times 10^5}\right)$$

$$= P\left(Z \leq -\frac{0.6 \times 10^6}{3}\right)$$

$$= P(Z \leq -2)$$

We Know;

$$Z = \frac{T-\mu}{\sigma} \sim N(0, 1) \rightarrow \text{Standard Normal Dist.}$$

$$\therefore P(T < 3.8 \times 10^6) = P(Z \leq -2) \rightarrow \text{CDF}$$

$$= \Phi(-2)$$

$$= 0.02275$$

Let us denote $P(T < 3.8 \times 10^6)$ for a Given Chip by $'P'$

$$\therefore P = 0.02275 \quad (\text{success})$$

Now;

P (Out of 100 chips atleast 4 chips has lifetimes less than 3.8×10^6 hrs)

$\Rightarrow P$ (Out of 100 chips atleast 4 chips has success (P))

$= 1 - P$ (out of 100 chips; less than 4 chips has success)

$$= 1 - \left[{}^{100}C_0 (P)^0 (1-P)^{100} + {}^{100}C_1 P^1 (1-P)^{99} \right. \\ \left. + {}^{100}C_2 P^2 (1-P)^{98} + {}^{100}C_3 P^3 (1-P)^{97} \right]$$

where

$$P = 0.02275$$

This is the prob. that a batch of 100 chips will contain atleast 4 chips whose lifetimes are less than 3.8×10^6 hrs.

a) Given;

System can function for a random amount of time

X.

$$\& f_X(x) = \begin{cases} Cx e^{-2x/2} & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases}$$

PDF

We need; Prob. that System functions for atleast 5 months!

$$P(X \geq 5) = \int_5^{\infty} f_X(x) dx$$

Since

$$5 < x < 8$$

$$\Rightarrow f_X(x) = Cx e^{-2x/2}$$

$$P(X \geq 5) = \int_5^{\infty} Cx^2 e^{-2x/2} dx$$

$$= C \int_5^{\infty} x^2 e^{-2x/2} dx$$

ILATE

$$\Rightarrow C \left[x \int_5^{\infty} e^{-2x/2} dx - \left(1 \times \int_5^{\infty} e^{-2x/2} dx \right) \right]$$

$$\Rightarrow C \left[x \times \left(-2 e^{-2x/2} \right) \Big|_5^{\infty} + 2 \int_5^{\infty} e^{-2x/2} dx \right]$$

$$\Rightarrow C \left[-2x e^{-2x/2} \Big|_5^{\infty} + 2 \times \left(-2 e^{-2x/2} \right) \Big|_5^{\infty} \right]$$

$$\Rightarrow P(X \geq 5) = C \left[-2x e^{-x/2} \Big|_5^\infty + -4e^{-x/2} \Big|_5^\infty \right] \\ = C \left[\cancel{\left(-2x e^{-x/2} \Big|_\infty^0 \right)} - \cancel{\left(-2 \times 5 \times e^{-2.5} \right)} + \cancel{\left(-4e^{-x/2} \Big|_\infty^0 \right)} \right. \\ \left. - \left(-4e^{-2.5} \right) \right]$$

$$P(X \geq 5) = C \left[10e^{-2.5} + 4e^{-2.5} \right]$$

$$\boxed{P(X \geq 5) = C \times 14e^{-2.5}}$$

Let us find value of C .

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

$$\Rightarrow \int_{-\infty}^0 0 dx + \int_0^{\infty} C x e^{-x/2} dx = 1$$

$$\Rightarrow C \left[\int_0^{\infty} x e^{-x/2} dx \right] = 1$$

$$\Rightarrow C \left[\cancel{-2x e^{-x/2} \Big|_0^\infty} + \cancel{-4e^{-x/2} \Big|_0^\infty} \right] = 1$$

$$\Rightarrow C \left[\cancel{-4e^{-x/2} \Big|_\infty^0} - \left(-4e^{-x/2} \Big|_0 \right) \right] = 1$$

$$\Rightarrow C [4e^0] = 1 \Rightarrow \boxed{C = \frac{1}{4}}$$

$$\therefore P(X \geq 5) = \frac{14}{14} e^{-2.5} = 3.5 e^{-2.5}$$

∴ Probability that system functions for atleast 5 months is $\boxed{3.5 e^{-2.5}}$

(5) Let 'x' be Discrete/Continuous R.V :-

We need to prove that :-

$$E(X) = \int_0^{\infty} P(X > x) dx - \int_0^{\infty} P(X < -x) dx$$

Take the R.H.S part :-

$$\text{RHS: } \int_0^{\infty} P(X > x) dx - \int_0^{\infty} P(X < -x) dx$$

$\downarrow \alpha \quad \downarrow \beta$

$$\alpha = \int_0^{\infty} P(X > x) dx$$

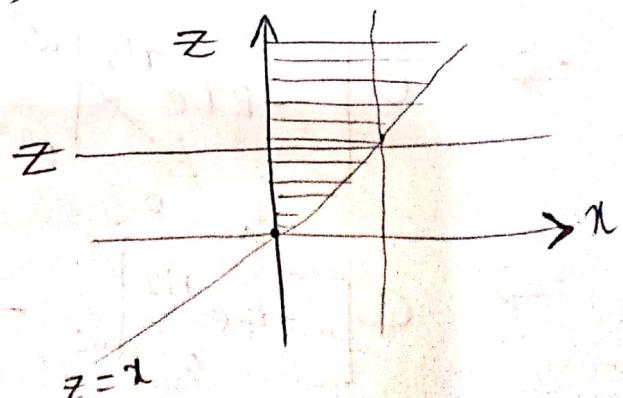
$$\alpha = \int_0^{\infty} \left(\int_x^{\infty} f_X(z) dz \right) dx \quad \text{Here};$$

So; By using Fubini's theorem;

For interchanging the limits;

Now; We can write;

$$\boxed{0 < z < \infty \\ 0 < x < z}$$



$$\therefore \alpha = \int_0^{\infty} \left(\int_{-\infty}^{\infty} f_X(z) dz \right) dx = \int_0^{\infty} \left(\int_0^z f_X(z) dx \right) dz$$

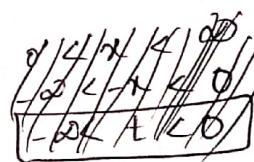
$$\alpha = \int_0^{\infty} \left(f_X(z) \cdot \int_0^z dx \right) dz = \int_0^{\infty} f_X(z) \cdot z dz$$

$$\boxed{\therefore \alpha = \int_0^{\infty} z \cdot f_X(z) dz}$$

~~NOW; $\beta = \int_0^{\infty} P(X < -x) dx$~~ let $-x = t$
 ~~$dx = dt$~~

$$\beta = \int_{-\infty}^0 P(X < t) (-dt)$$

$$\beta = - \int_{-\infty}^0 P(X < t) dt$$



~~NOW; $\beta = \int_0^{\infty} P(X < -x) dx$~~

let $-x = t \quad 0 < x < \infty$

$-dx = dt \quad 0 < t < -\infty$

$$\therefore \beta = \int_0^{-\infty} P(X < t) (-dt) = - \int_0^{-\infty} P(X < t) dt$$

$$\beta = \int_{-\infty}^0 P(X < t) dt$$

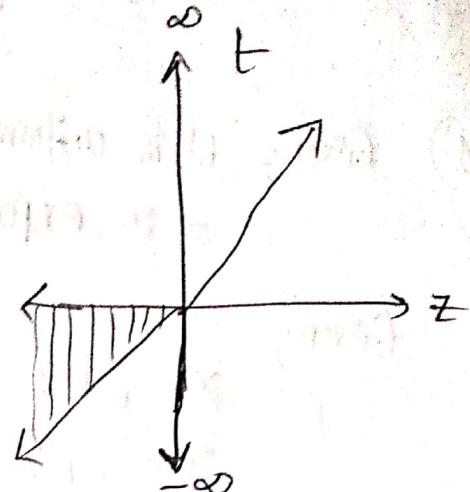
$$\beta = \int_{-\infty}^0 \int_{-\infty}^t f_X(z) dz dt$$

⑤ We have;

$$\beta = \int_{-\infty}^0 \int_{-\infty}^t f_X(z) dz dt$$

Again; By using
Fubini's theorem,

$$\begin{aligned} -\infty < z < t \\ -\infty < t < 0 \end{aligned}$$



$$\beta = \int_{-\infty}^0 \int_{-\infty}^t f_X(z) dz dt = \int_{-\infty}^0 \left(\int_z^0 f_X(z) dz \right) dt$$

$$\beta = \int_{-\infty}^0 \left(f_X(z) \int_z^0 dt \right) dz = \int_{-\infty}^0 f_X(z) (-z) dz$$

$$\boxed{\beta = - \int_{-\infty}^0 z f_X(z) dz}$$

Now; R.H.S :- A - B

$$\Rightarrow \int_{-\infty}^{\infty} z \cdot f_X(z) dz + \int_{-\infty}^0 z \cdot f_X(z) dz$$

$$\Rightarrow \int_{-\infty}^0 z \cdot f_X(z) dz + \int_0^{\infty} z \cdot f_X(z) dz$$

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

$$\Rightarrow Q[X] \Rightarrow \boxed{RHS = LHS}$$

Hence;

$$\boxed{E[X] = \int_{-\infty}^{\infty} P(X > z) dz - \int_{-\infty}^{\infty} P(X < -z) dz}$$

⑥ The PDF of X (the life-time in hrs of elect. Device)

$$f_X(x) = \begin{cases} 10/x^2 & \text{if } x \geq 10 \\ 0 & \text{if } x \leq 10 \end{cases}$$

a) $P(X > 20) = \int_{20}^{\infty} f_X(x) dx$

$$= \int_{20}^{\infty} \frac{10}{x^2} dx$$

$$= 10 \int_{20}^{\infty} \frac{dx}{x^2} = 10 \int_{20}^{\infty} x^{-2} dx$$

$$= 10 \left[\frac{x^{-2+1}}{-2+1} \right]_{20}^{\infty} = 10 \left[\frac{x^{-1}}{-1} \right]_{20}^{\infty}$$

$$= -10 \left[\frac{1}{x} \right]_{20}^{\infty}$$

$$= -10 \left[\frac{1}{\infty} - \frac{1}{20} \right] \Rightarrow \boxed{\frac{1}{2}}$$

$$\therefore P(X > 20) = 1/2$$

b) We know; CDF of ' X ' is defined as

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

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

if $x \leq 10$;

$$[-\infty < t < x \leq 10]$$

$$\Rightarrow t \leq 10$$

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

Hence; if $x \leq 10$; $F_X(x) = 0$

if $x > 10$;

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

$$= \int_{10}^x f_X(t) dt$$

$$F_X(x) = \int_{10}^x \frac{1}{t^2} dt$$

$$F_X(x) = 10 \left[\frac{-1}{t} \right]_{10}^x = -10 \left[\frac{1}{x} - \frac{1}{10} \right]$$

$$F_X(x) = 1 - \frac{10}{x}$$

$$\therefore \text{CDF of } X = \begin{cases} 0 & \text{if } x \leq 10 \\ 1 - \frac{10}{x} & \text{if } x > 10 \end{cases}$$

c) Let us assume that '6' devices given are independent of each other.

$P(\text{out of 6, atleast 3 will func^n for at least 15 hours})$

$$= P(\text{out of 6, 3 func^n for atleast 15 hrs})$$

$$+ P(\text{"", 4 func^n " " " " })$$

$$+ P(\text{"", 5 func^n " " " " " })$$

$$+ P(\text{"", 6 func^n " " " " " })$$

Let us find first;

$$\begin{aligned} P(X \geq 15) &= 1 - P(X < 15) \\ &= 1 - P(X \leq 15) \\ &= 1 - F_X(15) \\ &= 1 - \left(1 - \frac{10}{15}\right) \end{aligned}$$

$$P(X \geq 15) = \frac{10}{15} = \frac{2}{3}$$

$$\therefore P_{req} = {}^6C_3 \left(\frac{2}{3}\right)^3 \left(\frac{1}{3}\right)^3$$

$$+ {}^6C_4 \left(\frac{2}{3}\right)^4 \left(\frac{1}{3}\right)^2$$

$$+ {}^6C_5 \left(\frac{2}{3}\right)^5 \left(\frac{1}{3}\right)$$

$$+ {}^6C_6 \left(\frac{2}{3}\right)^6 \left(\frac{1}{3}\right)^0$$

Probability
that of
6 devices;
atleast
3 will

funcⁿ for
atleast 15 hrs

(using notes for assumption)

$${}^6C_3 \times \frac{8}{36} + {}^6C_2 \frac{16}{36}$$

$$+ 6 \times \frac{32}{36} + \frac{64}{36} \Rightarrow$$

0.89986

* We took an assumption that devices are independent of each other

$$\text{⑦ } X \sim N(\mu, \sigma^2) \quad \mu = 10 \\ \sigma^2 = 36$$

We know; from 68-95-99 Rule;

$$P(10 - 6 \leq X \leq 10 + 6) = P(4 \leq X \leq 16) = 0.68$$

$$P(10 - 2\sigma \leq X \leq 10 + 2\sigma) = P(-2 \leq X \leq 12) = 0.95$$

$$P(10 - 3\sigma \leq X \leq 10 + 3\sigma) = P(-8 \leq X \leq 28) = 0.99$$

$$a) P(X > 5) = 1 - P(X \leq 5)$$

$$= 1 - P\left(\frac{X-\mu}{\sigma} \leq \frac{5-\mu}{\sigma}\right)$$

$$= 1 - P\left(\frac{X-\mu}{\sigma} \leq \frac{5-10}{6}\right)$$

We have
 $\mu = 10$
 $\sigma = 6$

$$= 1 - P\left(\frac{X-\mu}{\sigma} \leq \frac{-5}{6}\right)$$

We know; $\frac{X-\mu}{\sigma} = Z \rightarrow$ a Standard Normal.

$$P(X > 5) = 1 - \Phi\left(\frac{-5}{6}\right)$$

$$b) P(4 < X < 16) = P(4 \leq X \leq 16) \quad (\because \text{Prob. of single point in cont. R.V} = 0)$$

$$= 0.68$$

(from 68-95-99 Rule)

$$\begin{aligned}
 c) P(X < 8) &= P(X \leq 8) \\
 &= P\left(\frac{X-\mu}{\sigma} \leq \frac{8-\mu}{\sigma}\right) \\
 &= P\left(\frac{X-10}{6} \leq \frac{8-10}{6}\right) \\
 &= P(Z \leq -\frac{2}{3}) \quad Z \sim N(0, 1)
 \end{aligned}$$

$$\begin{aligned}
 d) P(X < 20) &= P\left(\frac{X-\mu}{\sigma} \leq \frac{20-10}{6}\right) \\
 &= P\left(\frac{X-10}{6} \leq \frac{10}{6}\right) \\
 &= P(Z \leq \frac{5}{3}) \quad Z \sim N(0, 1) \\
 &= \boxed{\phi(5/3)} \Rightarrow \phi(1.66)
 \end{aligned}$$

$$\begin{aligned}
 b) P(4 < X < 16) &= P(X < 16) - P(X < 4) \\
 &= P(X \leq 16) - P(X \leq 4) \\
 &= P\left(\frac{X-\mu}{\sigma} < \frac{16-10}{6}\right) - P\left(\frac{X-\mu}{\sigma} < \frac{4-10}{6}\right) \\
 &= P(Z < 1) - P(Z < -1) \\
 &= \boxed{\phi(1) - \phi(-1)}
 \end{aligned}$$

II) Derived Distributions :-

1) Given; U is uniform on $[0, 2\pi]$
 Z is expn with $\lambda = 1$ U & Z are indep

Given;

$$X = \sqrt{UZ} \cos U$$

$$Y = \sqrt{UZ} \sin U$$

We know; since, U is uniform on $[0, 2\pi]$; $f_U(u) = \frac{1}{2\pi}$

Z is expn with $\lambda = 1$;

$$f_Z(z) = \lambda e^{-\lambda z} = e^{-z}$$

Since; U & Z are independent R.V's;

$$\begin{aligned} f_{U,Z}(u,z) &= f_U(u) \cdot f_Z(z) \\ &= \frac{e^{-z}}{2\pi}. \end{aligned}$$

We had; Derived Distribution's PDF in multivariable case;

$$f_{Y_1, Y_2, Y_3, \dots, Y_n} = f_{X_1, X_2, \dots, X_n} \left(h_1(y_1, y_2, \dots, y_n), h_2(y_1, y_2, \dots, y_n), \dots, h_n(y_1, y_2, \dots, y_n) \right) \times \left| \det(J_n(y_1, y_2, \dots, y_n)) \right|$$

where;

$$x_1 = h_1(y_1, y_2, \dots, y_n)$$

$$x_2 = h_2(y_1, y_2, \dots, y_n)$$

$$\vdots$$

$$x_n = h_n(y_1, y_2, \dots, y_n)$$

$$\begin{vmatrix} \frac{\partial h_1}{\partial y_1} & \frac{\partial h_1}{\partial y_2} & \cdots & \frac{\partial h_1}{\partial y_n} \\ \frac{\partial h_2}{\partial y_1} & \frac{\partial h_2}{\partial y_2} & \cdots & \frac{\partial h_2}{\partial y_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial h_n}{\partial y_1} & \frac{\partial h_n}{\partial y_2} & \cdots & \frac{\partial h_n}{\partial y_n} \end{vmatrix}$$

Using that formula in our case;

$$f_{U,Z}(u,z) = f_{X,Y}(x,y) \left| \det(J_2(u,z)) \right|$$

We had; $x = \sqrt{2z} \cos u$

$$y = \sqrt{2z} \sin u$$

Now;

$$\det(J_2(u,z)) = \begin{vmatrix} \frac{\partial x}{\partial u} & \frac{\partial x}{\partial z} \\ \frac{\partial y}{\partial u} & \frac{\partial y}{\partial z} \end{vmatrix}$$

$$\det(J_2(u,z)) = \begin{vmatrix} -\sqrt{2z} \sin u & \sqrt{2z} \frac{1}{2\sqrt{z}} \cos u \\ \sqrt{2z} \cos u & \sqrt{2z} \frac{1}{2\sqrt{z}} \sin u \end{vmatrix}$$

$$\det(J_2(u,z)) = -\sin^2 u - \cos^2 u = -1$$

Now; $f_{U,Z}(u,z) = f_{X,Y}(x,y) \left| -1 \right|$

Now; $f_{X,Y}(x,y) = f_{U,Z}(u,z)$

$$f_{X,Y}(x,y) = \frac{e^{-z}}{2\pi}$$

Now; $x = \sqrt{2z} \cos u \rightarrow x^2 = 2z \cos^2 u \quad x^2 + y^2 = 2z$
 $y = \sqrt{2z} \sin u \rightarrow y^2 = 2z \sin^2 u$

$$f_{X,Y}(x,y) = \frac{e^{-\frac{(x^2+y^2)}{2}}}{2\pi}$$

Now;

$$f_{X,Y}(x,y) = \frac{e^{-\frac{(x^2+y^2)}{2}}}{2\pi}$$

$$f_{X,Y}(x,y) = \left(\frac{e^{-x^2/2}}{\sqrt{2\pi}}\right) \cdot \left(\frac{e^{-y^2/2}}{\sqrt{2\pi}}\right)$$

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

where

$$f_X(x) = \frac{e^{-x^2/2}}{\sqrt{2\pi}} \quad \& \quad f_Y(y) = \frac{e^{-y^2/2}}{\sqrt{2\pi}}$$

are normal distributions with $\mu=0$, $\sigma^2=1$

i.e; $f_X(x), f_Y(y) \sim N(0, 1)$

Standard Normal Distributions.

Also;

$$\text{since } f_{X,Y}(x,y) = f_X(x) \cdot f_Y(y);$$

\therefore we can say that X, Y are Independent

Standard Normal Variables

Q2 Given;

' x ' is said to have lognormal dist if $\log x \sim N(\mu, \sigma^2)$
if ' x ' is lognormal with $E[\log x] = \mu$ & $\text{var}[\log x] = \sigma^2$ find $f_x(x)$.

$$\therefore \log x \sim N(\mu, \sigma^2)$$

Let us call ' $\log x$ ' as ' y '

$$\therefore Y \sim N(\mu, \sigma^2)$$

We have;

$$Y = \log x$$

$$\Rightarrow \boxed{x = e^y}$$

We can calculate CDF:-

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

$$= P(e^Y \leq x)$$

$$F_X(x) = P(Y \leq \log x) = F_Y(\log x)$$

We knew;

$$\boxed{f_X(x) = \frac{d}{dx}(F_X(x))}$$

Applying diff on both sides;

$$f_X(x) = f_Y(\log x) \frac{d(\log x)}{dx}$$

$$f_X(x) = f_Y(\log x) \frac{1}{x}$$

We know; $\because Y \sim N(\mu, \sigma^2)$

$$f_Y(y) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y-\mu)^2}{2\sigma^2}}$$

$$\therefore f_X(x) = f_Y(\log x) \times \frac{1}{x}$$

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\log x - \mu)^2}{2\sigma^2}} \times \frac{1}{x}$$

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma x} \exp \left\{ -\frac{(\log x - \mu)^2}{2\sigma^2} \right\}$$

③ Given; V is uniform R.V with $[0, 1]$

$$f_V(u) = 1$$

$$Y = \log(u)$$

Now; $F_Y(y) = P(Y \leq y) = P(\log V \leq y)$

$$= P(V \leq e^y)$$

$$F_Y(y) = F_V(e^y)$$

Difff on both sides;

$$f_Y(y) = f_V(e^y) \cdot \frac{d(e^y)}{dy}$$

$$f_Y(y) = f_V(e^y) \cdot e^y$$

$$f_Y(y) = 1 \cdot e^y = e^y.$$

PDF of Y is e^y

III Other topics :-

① σ_x, σ_y are stand. deviations of R.V's X & Y .

$$\text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

a) Given;

$$\text{Var}\left(\frac{X}{\sigma_X} + \frac{Y}{\sigma_Y}\right) \geq 0$$

$$\text{We know; } \text{Var}(Z) = E((Z - E[Z])^2)$$

$$E\left(\left(\left(\frac{X}{\sigma_X} + \frac{Y}{\sigma_Y}\right) - E\left(\frac{X}{\sigma_X} + \frac{Y}{\sigma_Y}\right)\right)^2\right) \geq 0$$

$$\text{We know; } E[aX + bY] = aE[X] + bE[Y] \rightarrow I$$

$$E\left(\left(\left(\frac{X}{\sigma_X} + \frac{Y}{\sigma_Y}\right) - \left(\frac{E[X]}{\sigma_X} + \frac{E[Y]}{\sigma_Y}\right)\right)^2\right) \geq 0$$

$$E\left(\left(\left(\frac{X-E[X]}{\sigma_X}\right) + \left(\frac{Y-E[Y]}{\sigma_Y}\right)\right)^2\right) \geq 0$$

$$E\left[\left(\frac{X-E[X]}{\sigma_X}\right)^2 + \left(\frac{Y-E[Y]}{\sigma_Y}\right)^2 + 2 \frac{(X-E[X])(Y-E[Y])}{\sigma_X \sigma_Y}\right] \geq 0$$

Again using eq I;

$$\left[\left(\frac{1}{\sigma_X}\right)^2 E\left((X-E[X])^2\right) + \left(\frac{1}{\sigma_Y}\right)^2 E\left((Y-E[Y])^2\right) + \frac{2}{\sigma_X \sigma_Y} E\left((X-E[X])(Y-E[Y])\right)\right] \geq 0$$

We know;

$$\sigma_z^2 = E[(z - E[z])^2]$$

$$\Rightarrow \frac{1}{6x^2} \times \cancel{x^2} + \frac{1}{6y^2} \times \cancel{y^2} + \frac{2}{6x^6y} \text{Cov}(X, Y) \geq 0$$
$$\Rightarrow \frac{2 + 2\text{Cov}(X, Y)}{6x^6y} \geq 0$$
$$\Rightarrow 1 + \text{Corr}(X, Y) \geq 0$$
$$\Rightarrow \boxed{\text{Corr}(X, Y) \geq -1}$$

b) We need; $\text{Corr}(X, Y) \leq 1$

We know;

$$\text{Cov}(X, Y) = E[(X - E[X])(Y - E[Y])]$$
$$= E[XY] - E[X] \cdot E[Y]$$

Upon expanding the R.H.S of equation &
using the concept of Max & Min;

We will get $\text{Cov}(X, Y)$ has maxima when $\boxed{X = Y}$

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

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

$$\text{Cov}(X, X) = \sigma_X^2$$

$$\therefore \text{corr}(X, X) = \frac{\text{Cov}(X, X)}{\sigma_X^2} = \frac{\sigma_X^2}{\sigma_X^2} = 1$$

∴ upper limit of $\text{corr}(X, Y)$ is 1

$$\therefore \text{corr}(X, Y) \leq 1$$

from a) part:-

$$[-1 \leq \text{corr}(X, Y) \leq 1]$$

Hence Proved.

c) σ_{X+Y} is the std. dev of $X+Y$;

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

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

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

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

$$+ 2 E[(X - E[X]) \cdot (Y - E[Y])]$$

$$= \sigma_X^2 + \sigma_Y^2 + 2 \text{Cov}(X, Y)$$

$$\sigma_{X+Y}^2 = \sigma_X^2 + \sigma_Y^2 + 2 \text{Cov}(X, Y)$$

we had $\text{corr}(X, Y) \leq 1$

(from Q) $\Rightarrow \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y} \leq 1$

$$\Rightarrow \boxed{\text{Cov}(X, Y) \leq \sigma_x \sigma_y}$$

$$\sigma_{x+y}^2 = \sigma_x^2 + \sigma_y^2 + 2\text{Cov}(X, Y)$$

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

$$\sigma_{x+y}^2 \leq (\sigma_x + \sigma_y)^2$$

$$\Rightarrow \boxed{\sigma_{x+y} \leq \sigma_x + \sigma_y}$$

Hence Proved:

② X & Y are Independent Poisson Random Variables
with rate λ_1 & λ_2

Given; $Z = X + Y$

We need;

$$P_X(k) = \frac{e^{-\lambda_1} \lambda_1^k}{k!}$$

$$P_Z(z) = P(Z = z)$$

* Using result of Convolution in Discrete Random Variable case:-

$$P_Y(k) = \frac{e^{-\lambda_2} \lambda_2^k}{k!}$$

$$P_Z(z) = P(Z = z)$$

$$= \sum_{i=0}^z P(X=i \text{ and } Y=z-i)$$

$$= \sum_{i=0}^z P(X=i) \cdot P(Y=z-i)$$

$$= \sum_{i=0}^z \frac{e^{-\lambda_1} \lambda_1^i}{i!} \cdot \frac{e^{-\lambda_2} \lambda_2^{(z-i)}}{(z-i)!}$$

$$= \sum_{i=0}^z \frac{1}{i!(z-i)!} e^{-(\lambda_1 + \lambda_2)} \cdot \lambda_1^i \lambda_2^{(z-i)}$$

$$= \sum_{i=0}^z \frac{z!}{i!(z-i)!} \frac{e^{-(\lambda_1 + \lambda_2)} \cdot \lambda_1^i \lambda_2^{(z-i)}}{z!}$$

$$P_Z(z) = \sum_{i=0}^z \binom{z}{i} \lambda_1^i \lambda_2^{z-i} \frac{e^{-(\lambda_1 + \lambda_2)}}{z!}$$

$$P_Z(z) = \frac{e^{-(\lambda_1 + \lambda_2)}}{z!} \sum_{i=0}^z \binom{z}{i} \lambda_1^i \lambda_2^{z-i}$$

$$P_Z(z) = \frac{e^{-(\lambda_1 + \lambda_2)}}{z!} (\lambda_1 + \lambda_2)^z$$

$\therefore Z = X+Y$ is also a poisson Random variable with rate $[\lambda_1 + \lambda_2]$

③ Given; X, Y & Z are independent uniform Random variables in $[0,1]$.

$$\text{& } W = X+Y+Z$$

To find PDF of W ;

Let us split this;

$$A = X+Y$$

$$W = A+Z$$

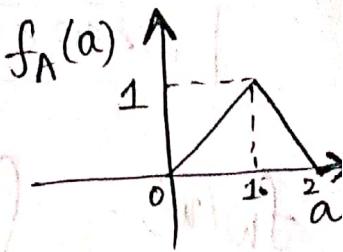
$$\text{Since; } f_X(x) = \begin{cases} 1, & 0 \leq x \leq 1 \\ 0, & \text{else} \end{cases}$$

$$f_Y(y) = \begin{cases} 1, & 0 \leq y \leq 1 \\ 0, & \text{else} \end{cases}$$

We know;

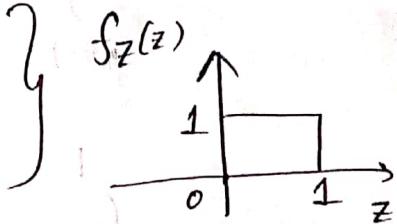
How $A = X+Y$ looks using Convolution.

$$f_A(a) = \begin{cases} a, & 0 \leq a < 1 \\ 2-a, & 1 \leq a < 2 \\ 0, & \text{else} \end{cases}$$



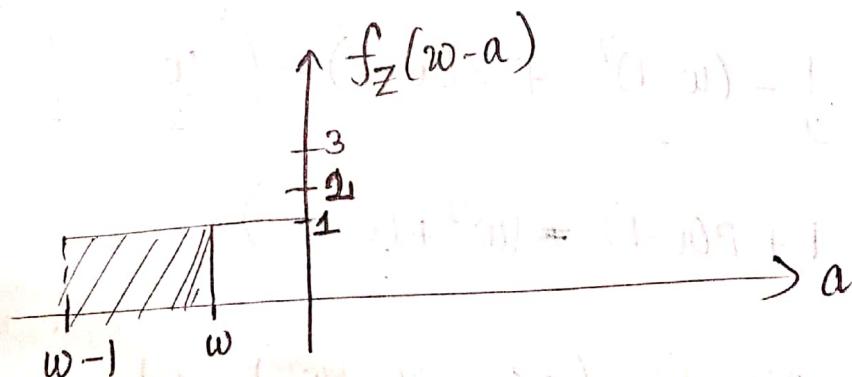
We also have;

$$f_Z(z) = \begin{cases} z, & 0 \leq z \leq 1 \\ 0, & \text{else} \end{cases}$$



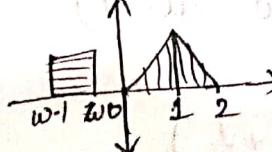
We need $f_W(w)$ where $W = A + Z$.

$$f_W(w) = \int_{-\infty}^{+\infty} f_A(a) \cdot f_Z(w-a) da$$



Case-1 :-

$$\ast [w < 0]$$

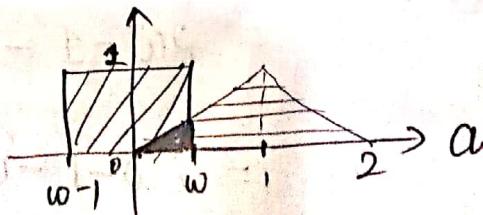


$$f_W(w) = \int_0^w 0 \cdot da = 0$$

(No Overlap)

Case-2 :- P

$$\ast [0 < w < 1]$$



$$f_W(w) = \int_0^w 1 \times da = w$$
$$f_W(w) = \frac{w^2}{2}$$

(9)

Case 3:-

$$1 < w < 2$$

$$f_W(w) = \int_{w-1}^w f_A(a) f_Z(w-a) da$$

$$= \int_{w-1}^1 a(1) da + \int_1^w (2-a) da$$

$$= \frac{a^2}{2} \Big|_{w-1}^1 + 2(w-1) - \frac{a^2}{2} \Big|_1^w$$

$$= \frac{1}{2} - \frac{(w-1)^2}{2} + 2(w-1) = \left(\frac{w^2}{2} - \frac{1}{2} \right)$$

$$= 1 + 2(w-1) \neq \frac{(w^2 + (w-1)^2)}{2}$$

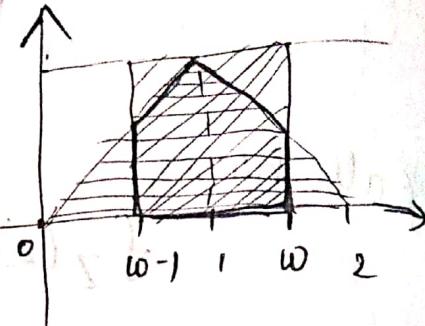
$$= 2(w-1) - \frac{(w^2 + 1 - 2w + w^2)}{2} + 1$$

$$= 2(w-1) - \frac{(2w^2 - 2w + 1)}{2}$$

$$= 2w-1 - \left(w^2 - w + \frac{1}{2} \right)$$

$$= 2w-1 - w^2 + w - 1/2$$

$$= 3w - w^2 - 3/2$$



④ Case :- 4

$$w > 2$$

$$f_W(w) = \int_{w-1}^2 (1)(2-a)da$$

$$f_W(w) = \int_{w-1}^2 (2-a)da$$

$$= 2 \int_{w-1}^2 da - \int_{w-1}^2 a da$$

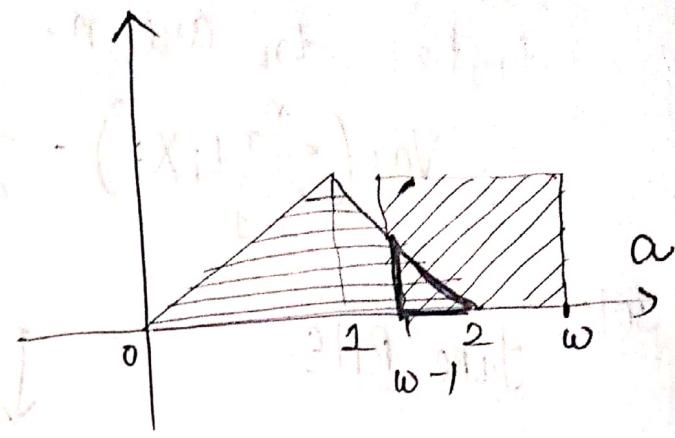
$$= 2(2-(w-1)) - \left(\frac{a^2}{2}\right) \Big|_{w-1}^2$$

$$f_W(w) = 2[3-w] - \frac{1}{2}[4-(w-1)^2]$$

$$f_W(w) = 8-2w - \frac{2+(w-1)^2}{2} = 4-2w + \frac{(w-1)^2}{2}$$

∴ Probability density funcⁿ of $w = X+Y+Z$ is

$$f_W(w) = \begin{cases} 0 & ; w < 0 \\ \frac{w^2}{2} & ; 0 < w < 1 \\ 3w - w^2 - 1.5 & ; 1 < w < 2 \\ 4-2w + \frac{(w-1)^2}{2} & ; w > 2 \end{cases}$$



④ Given,

X_1, X_2, \dots, X_n are n - Random Variables.
 t_1, t_2, \dots, t_n are n - Real numbers.

$$\text{Var}\left(\sum_{i=1}^n t_i X_i\right) = \sum_{i=1}^n \sum_{j=1}^n t_i t_j \text{Cov}(X_i, X_j)$$

Sol:

Take RHS.

$$\text{Var}\left(\sum_{i=1}^n t_i X_i\right) = E\left[\left(\sum_{i=1}^n t_i X_i\right)^2\right] - \left(E\left[\sum_{i=1}^n t_i X_i\right]\right)^2$$

$\underbrace{\qquad\qquad}_{A} - \underbrace{\qquad\qquad}_{B}$

$$A = E\left[\left(\sum_{i=1}^n t_i X_i\right)^2\right] = E\left[\left(\sum_{i=1}^n t_i X_i\right)\left(\sum_{j=1}^n t_j X_j\right)\right]$$

$$A = E\left[\sum_{i=1}^n \sum_{j=1}^n t_i t_j X_i X_j\right]$$

$$A = \sum_{i=1}^n \sum_{j=1}^n t_i t_j E[X_i X_j]$$

↔ linearly
of
Expectations

Now;

$$B = \left(E\left[\sum_{i=1}^n t_i X_i\right]\right)^2$$

$$B = \left(E\left[\sum_{i=1}^n t_i X_i\right]\right) \cdot \left(E\left[\sum_{i=1}^n t_i X_i\right]\right)$$

$$B = \left(\sum_{i=1}^n t_i E[X_i]\right) \cdot \left(\sum_{j=1}^n t_j E[X_j]\right)$$

$$B = \sum_{i=1}^n \sum_{j=1}^n t_i t_j E[x_i] E[x_j]$$

Now;

$$\text{Var}\left(\sum_{i=1}^n t_i x_i\right) = A - B$$

$$= \sum_{i=1}^n \sum_{j=1}^n t_i t_j \left(E[x_i x_j] - E[x_i] E[x_j]\right)$$

$$\text{Var}\left(\sum_{i=1}^n t_i x_i\right) = \sum_{i=1}^n \sum_{j=1}^n t_i t_j \text{Cov}(x_i, x_j)$$

Hence Proved.

⑤ Given; $X = [x_1, x_2, x_3]^T$ is a random vector
with means $\mu = [\mu_1, \mu_2, \mu_3]^T$.

Also;

Σ is covariance matrix of X such that

$$\Sigma_{ij} = \text{Cov}(x_i, x_j)$$

We need to show;

$$\Sigma = E((X-\mu)(X-\mu)^T)$$

(5)

Since we have X, μ

$$X - \mu = \begin{bmatrix} X_1 - \mu_1 \\ X_2 - \mu_2 \\ X_3 - \mu_3 \end{bmatrix}$$

$$(X - \mu)^T = [X_1 - \mu_1, X_2 - \mu_2, X_3 - \mu_3]$$

$$(X - \mu)(X - \mu)^T = \sum_{i=1}^3 \sum_{j=1}^3 (X_i - \mu_i)(X_j - \mu_j)$$

$$E[(X - \mu)(X - \mu)^T] = E\left[\sum_{i=1}^3 \sum_{j=1}^3 (X_i - \mu_i)(X_j - \mu_j)\right]$$

$$= \sum_{i=1}^3 \sum_{j=1}^3 E[(X_i - \mu_i)(X_j - \mu_j)]$$

$$= \sum_{i=1}^3 \sum_{j=1}^3 \text{Cov}(X_i, X_j)$$

Using linearity
of expectation

We are also given that;

$$\text{Cov}(X_i, X_j) = \Sigma_{i,j}$$

So;

$$\Sigma = E[(X - \mu)(X - \mu)^T]$$

Hence Proved.