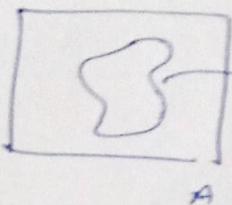


Ex:



find an exp. to find area of figure.

$$P(z \in S) = \iint_{A^2} \frac{1}{A^2} dx dy$$

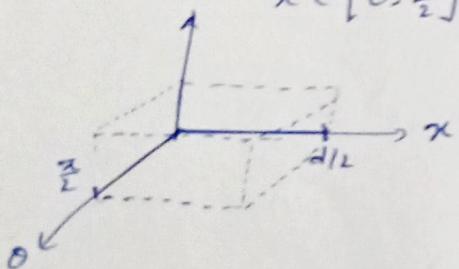
$$P(z \in S) = \frac{|S|}{A^2} \Rightarrow |S| = P(z \in S) \cdot A^2$$

we find $P(z \in S)$ by large no. of trials.

Ex: Buffon's Needle

$$\text{we have } \theta \in [0, \frac{\pi}{2}]$$

$$x \in [0, \frac{d}{2}]$$



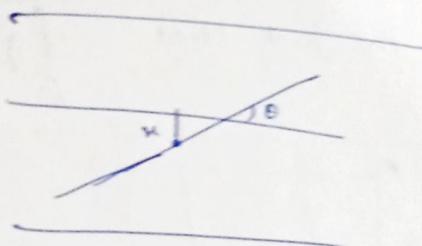
$$f_{x,\theta}(x, \theta) = \frac{4}{\pi d} \quad (\text{uniform distribution})$$

for intersection, $x < \frac{l}{2} \sin \theta$

$$P[x < \frac{l}{2} \sin \theta] = \int_0^{\pi/2} \int_0^{\frac{l}{2} \sin \theta} \frac{4}{\pi d} \cdot dx d\theta$$

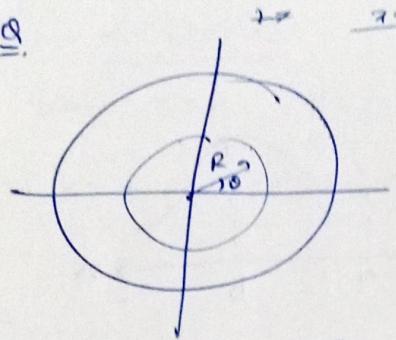
$$= \int_0^{\pi/2} \frac{4x}{\pi d} \Big|_0^{\frac{l}{2} \sin \theta} d\theta$$

$$P[\text{intersection}] = \frac{2l}{\pi d} [1 - 0] = \frac{2l}{\pi d}$$



$$\left\{ \begin{array}{l} \theta > \sin^{-1}\left(\frac{x}{l/2}\right) \\ \frac{x}{l/2} < \sin \theta \\ x < \frac{l}{2} \sin \theta \end{array} \right.$$

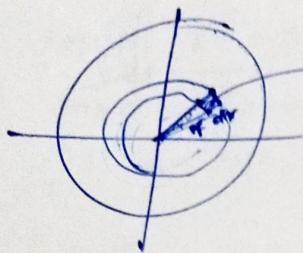
Q.



$$f_R(r < R) = \frac{\pi r^2}{\pi R^2}$$

$$f_R(r) = \frac{r^2}{R^2}$$

$$P[R \in [r, r+dr], \theta \in [\phi, \phi + d\theta]] = \frac{r d\theta \cdot dr}{\pi A^2}$$



$$\text{area} = (r d\theta) \cdot dr$$

or more precisely, $\frac{d\theta}{2\pi} [\pi(r+dr)^2 - \pi r^2]$

$$\text{area} = \frac{d\theta}{2\pi} (\pi r^2 + \pi (dr)^2 + 2\pi r dr - \pi r^2)$$

$$\text{area} = r d\theta dr$$

$$\frac{r dr d\theta}{\pi A^2} = f_{R,\theta}(r, \theta) \cdot dr \cdot d\theta$$

$$\Rightarrow f_{R,\theta}(r, \theta) = \frac{r}{\pi A^2} = \left(\frac{2r}{A^2}\right) \cdot \left(\frac{1}{2\pi}\right)$$

$$f_R(r) \quad f_\theta(\theta)$$

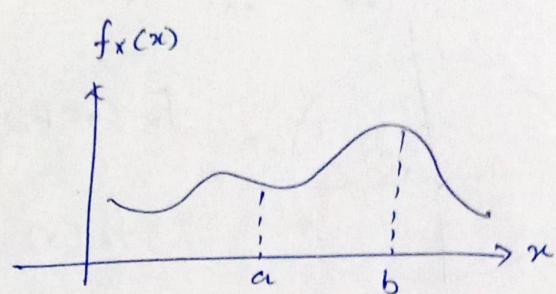
Conditional Dist.

Let $A = \{x \in [a, b]\}$.

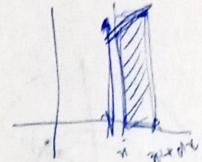
$$P[X \in B | A] = \frac{P[X \in A \cap B]}{P[X \in A]}$$

$$P[X \in B | A] = \frac{\int_{A \cap B} f_x(x) dx}{\int_A f_x(x) dx}$$

$$\text{Let } B = \{x, x+dx\}. \Rightarrow P[X \in B | A] = f_{X|A}(x) \cdot dx$$



$$\int_{A \cap B} f_x(x) dx$$

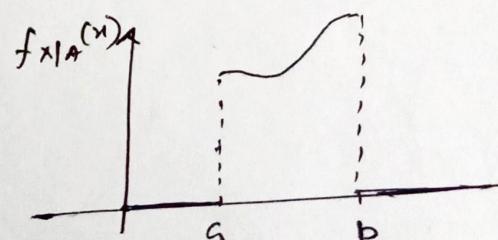
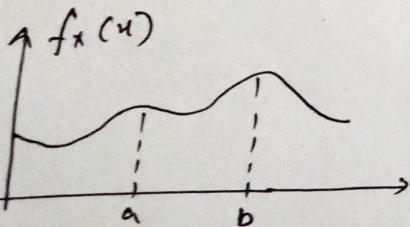


$$\text{but as calculated prev. } P[X \in B | A] = \int_{A \cap B} f_x(x) dx / \int_A f_x(x) dx$$

$$\Rightarrow f_{X|A}(x) dx = \frac{f_x(x) dx}{\int_A f_x(x) dx}$$

$$\Rightarrow f_{X|A}(x) = \boxed{\frac{f_x(x)}{\int_a^b f_x(x) dx}}$$

graphically, $f_{X|A}(x)$ is just a scaled up version of f_x from a to b



where the scaling factor is $\left[\int_A f_x(x) dx \right]^{-1}$

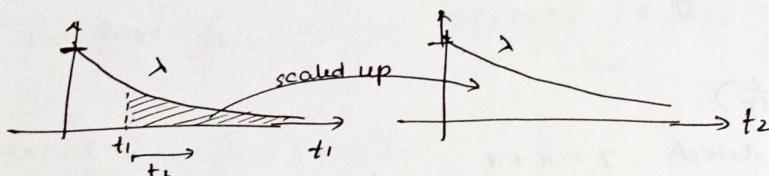
Ex: $X \sim \text{Exp}(\lambda)$

Given $X > t_1$, $X > t_1 + t_2 = ?$

$$\begin{aligned} P[X > t_1 + t_2 | X > t_1] &= \frac{P[X > t_1 + t_2 \text{ and } X > t_1]}{P[X > t_1]} \\ &= \frac{\exp(-\lambda(t_1 + t_2))}{\exp(-\lambda t_1)} = \exp(-\lambda t_2). \end{aligned}$$

Result, $P[X > t_1 + t_2 | X > t_1]$ is independent of t_1

⇒ No matter how much we wait initially, the distribution is always exponential with same λ parameter.



Why this occurs with exponential R.V?

for. $P[X > t_1]$ to cancel out, Numerator must be $P[X > t_1] \cdot P[X > t_2]$.

$$\Rightarrow P[X > t_1 + t_2] = P[X > t_1] \cdot P[X > t_2].$$

Let $P[X > a]$ be a function = $S(a)$,

$$\Rightarrow S(t_1 + t_2) = S(t_1) * S(t_2).$$

$$\Rightarrow S(2) = S(1)^2$$

$$\Rightarrow S(1) = S\left(\frac{1}{2}\right)^2$$

$$\Rightarrow S(3) = S\left(\frac{3}{2}\right)^2 \text{ or if } t_1 = t_2 = \frac{k}{2}$$

$$S(k) = S\left(\frac{k}{2}\right)^2$$

$$\text{or } S(\underbrace{1+1+1+\dots+1}_a) = \underbrace{S(1) \cdot S(1) \dots S(1)}_{a \text{ times}}$$

$$S(a) = S(1)^a \quad \text{or} \quad y = k^x$$

$$\log_e y = n \cdot \log_e k$$

$$\log_e y = k_1 \cdot x$$

$e^{k_1 x} = y$

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

given $y=y$, find $f_{x|y}(x)=?$

$$P[x \in [x, x+dx] \mid y \in [y, y+dy]] = \frac{P[x \in [x, x+dx], y \in [y, y+dy]]}{P[y \in [y, y+dy]]}$$
$$= \frac{P[x \in [x, x+dx]}{P[y \in [y, y+dy]]}.$$

$$\Rightarrow f_{x|y}(x)dx = \frac{f_{x,y}(x,y) \cdot dx \cdot dy}{f_y(y) \cdot dy}$$

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

PDF of $X|Y$ when $y=y$.

Ex: Speed $x \sim \exp(\frac{1}{50})$.

for $x=y$, Radar detects $y=x+e \sim N(0, 0.1x)$.

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

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

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

$$f_{y|x}(y) = \frac{1}{\sqrt{2\pi 0.1x}} e^{-\frac{(y-x)^2}{2(0.1x)}}$$

$$f_{y|x}(y) = \frac{1}{\sqrt{2\pi 0.1x}} e^{-\frac{y^2 - 2xy + x^2}{0.02x}}$$

$$f_x(x) = \exp\left(-\frac{1}{50}\right) \frac{1}{50} e^{-\frac{x}{50}}$$

$$f_{x,y}(x,y) = \frac{\frac{1}{\sqrt{2\pi 0.1x}} e^{-\frac{(y-x)^2}{0.02x}}}{\frac{1}{50} e^{-\frac{x}{50}}} + x$$

$$\text{For } x = x, \quad Y \sim N(x, 0.1x),$$

$$f_{Y|X}(y) = N(x, 0.1x)$$

↑ mean ↑ σ

$$f_{Y|X}(y) = \frac{1}{\sqrt{2\pi} 0.1x} \exp\left(-\frac{(y-x)^2}{2(0.1x)^2}\right).$$

$$f_X(u) = \frac{1}{50} \exp\left(-\frac{1}{50} \cdot u\right).$$

$$f_{X,Y}(u, y) = \frac{f_{Y|X}(y)}{f_X(u)}$$

Now find $E[X]$ given $Y=y$.

$$\text{we find } f_{X|Y}(x). \quad E[X|Y] = \int_{-\infty}^{\infty} x f_{X|Y}(x) dx. \rightarrow \text{conditional expectation.}$$

$$\frac{f_{X|Y}(x)}{f_Y(y)} = f_{X,Y}(x,y).$$

checking if this condition holds.

$$\int_{-\infty}^{\infty} E[X|Y] f_Y(y) dy = \int_{-\infty}^{\infty} \cancel{x} \cdot f_X(x) dx = E[X]. ?$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x \cdot f_{X|Y}(x) f_Y(y) dx dy$$

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

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

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

$$= E[X].$$

Let $y = \sum_{i=1}^n x_i$ x_i are iid, or id

$$E[y] = \sum_n E[y|N=n] \cdot P[N=n].$$

also we know that $E[y|N=n] = n \cdot E[x]$

$$E[y] = E[x] \cdot \sum_n P[N=n]$$

$$\boxed{E[y] = E[x] E[N]} \quad \text{Wald's equality}$$

Finding variance of y

$$\text{var}[y] = E[y^2] - E[y]^2$$

Finding $E[y^2]$.

$$E[y^2|N=n] = ? \quad y = \sum_{i=1}^n x_i$$

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

$$\begin{aligned} E[y^2|N=n] &= E[(x_1 + x_2 + \dots + x_n)^2 | N=n] \\ &= E[n^2 x_i^2 | N=n] \\ &= n^2 E[x_i^2 | N=n] \end{aligned}$$

$$E[y^2|N=n] = E[x^2] - \underbrace{n(n-1) E[x]^2}_{(\text{only if } x_i \text{ are independent})}$$

Now similarly.

$$\text{var}(y) = \sum_n P[N=n] \cdot \text{var}(y|N=n)$$

$$\text{var}(y^2)$$

$$E[y^2] = \sum_n P[N=n] \cdot E[y^2|N=n].$$

$$E[y^2] = \sum_n P[N=n] \cdot (n E[x^2] - n(n-1) E[x]^2).$$

Independence

X and Y are independent if

$$\boxed{f_{x,y}(x,y) = f_x(x) \cdot f_y(y).}$$

Prove

$$P[X \in A, Y \in B] = P[X \in A] \cdot P[Y \in B].$$

$$\begin{aligned} \text{LHS} &= \int_{X \in A} \int_{Y \in B} f_{x,y}(x,y) \\ &= \int_A \int_B f_x(x) \cdot f_y(y) dx dy = \int_A f_x(x) \int_B f_y(y) dy \cdot dx \\ &= \int_A f_x(x) \cdot P[Y \in B] \cdot dx \\ &= P[Y \in B] \cdot \int_A f_x(x) \cdot dx \\ &= P[Y \in B] \cdot P[X \in A]. \end{aligned}$$

Hence Proved.

$$\text{Now let } A = [-\infty, x], B = [-\infty, y].$$

$$\text{then } P[X \in A, Y \in B] = 1$$

$$f_{x,y}(x,y) = F_{x,y}(x,y).$$

$$\text{LHS} = P[X \in A, Y \in B] = F_{x,y}(x,y) = F_x(x) \cdot F_y(y)$$

$$\boxed{F_{x,y}(x,y) = F_x(x) \cdot F_y(y)}$$

Suppose we are given $f_x(x)$ & $F_x(x)$ of a r.v. X .

We want to generate x s.t. it follows \rightarrow

Let us define $y \sim U[0,1]$

$$\Rightarrow X = F^{-1}(y).$$

For x .

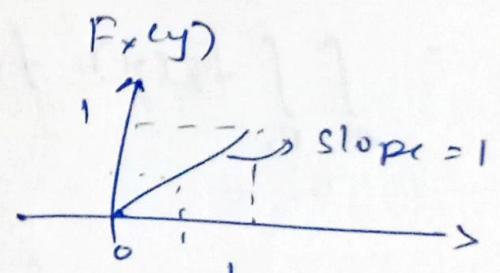
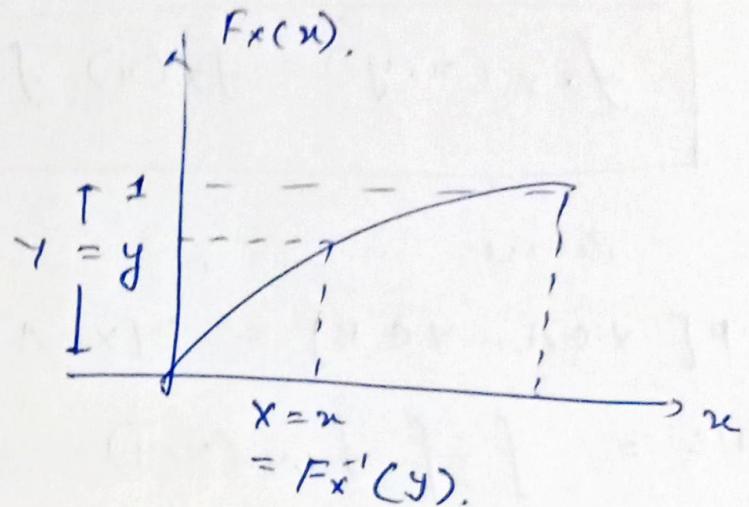
Let the event

$$A := (X \leq x) \Rightarrow F_x[x] \leq F_x(x)$$

$$A \Rightarrow F_x(F_x^{-1}(y)) \leq F_x(x)$$

$$A := (Y \leq F_x(x)).$$

$$\Rightarrow P[X \leq x] = P[A] = \int_0^{F_x(x)} 1 \cdot dy = F_x(x) - 0 = \boxed{F_x(x)}$$



* For +ve R.V.
for $x \geq 0$,

$$\begin{aligned}
 E[x] &= \int_0^\infty x \cdot f_x(x) dx \\
 \int_0^\infty \text{P}[x > x] dx &= \int_0^\infty \left[\int_x^\infty f_x(y) dy \right] dx \\
 &= \int_0^\infty \int_x^\infty f_x(y) dy \cdot dx \quad \} \rightarrow f_{(x,y)} | y > x \} \\
 &= \int_0^\infty f_x(y) \int_0^y dx \cdot dy \\
 &= \int_0^\infty f_x(y) \cdot y dy \\
 &= E[x].
 \end{aligned}$$

$$E[x] = \int_0^\infty \text{P}[x > x] dx \quad \text{for } x \geq 0$$

↓ CDF

* COVARIANCE

$$\begin{aligned}
 \text{cov}[x, y] &= E[(x - E[x])(y - E[y])] \\
 &= E[xy] - E[x] \cdot E[y]
 \end{aligned}$$

$$\begin{aligned}
 E[(x - E[x])(y - E[y])] &= E[xy - xE(y) - yE(x) + E(x)E(y)] \\
 &= E[xy] + E[x]E[y] - E[y]E[x] - E[y]E[x] \\
 &= E[xy] - E[x]E[y].
 \end{aligned}$$

Let $x = \sim U[-1, 1]$.

$$\begin{aligned}
 y &= x^2 & P_x \\
 E[x] &= 0 & E[y] = E[x^2] = \sum x^2 P(x) = \frac{2}{3} \\
 E[y] &= \frac{2}{3}
 \end{aligned}$$

$$\int_{-1}^1 k dx = 1 \Rightarrow 2k = 1 \Rightarrow k = \frac{1}{2}$$

$$E[x^2] = \int_{-1}^1 x^2 \cdot \frac{1}{2} dx = \left[\frac{x^3}{6} \right]_{-1}^1 = \frac{2}{6} = \frac{1}{3}.$$

$$E[x^3] = \int_{-1}^1 x^3 \cdot \frac{1}{2} dx = 0. \quad \text{cos } E[xy] = 0, E[y] = \frac{2}{3}, E[x^2] = \frac{1}{3}$$

- * If X and Y are independent, $\text{cov}(X, Y) = 0$
- * but uncorrelation ($\text{cov} = 0$) does not imply independence

Correlation Coefficient / Pearson correlation

$$\boxed{\rho_{XY} = \frac{\text{cov}(X, Y)}{\sqrt{\text{var}(X) \cdot \text{var}(Y)}}} \quad |\rho_{XY}| \leq 1.$$

Properties of Covariance

i) $\text{cov}(X, Y) = \text{var}(Y)$

$$\text{cov}(X, aY + b) = E[X(aY + b)] - E[X](aE[Y] + b)$$

$$= aE[XY] + bE[X] - bE[X] = aE[X] \cdot E[Y] \\ - a(E[XY] - E[X]E[Y])$$

$$\boxed{\text{cov}(X, aY + b) = a \cdot \text{cov}(X, Y)}$$

ii) $\text{cov}(X, Y + Z) = E[XY + XZ] - E[X](E[Y] + E[Z])$

$$= E[XY] - E[X] \cdot E[Y] + E[XZ] = E[Y] \cdot E[Z]$$

$$\boxed{\text{cov}(X, Y + Z) = \text{cov}(X, Y) + \text{cov}(X, Z)}$$

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

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

$$\boxed{\text{var}(X+Y) = \text{var}(X) + \text{var}(Y) + 2 \cdot \text{cov}(X, Y)}$$

by mathematical induction, we can show,

$$\boxed{\text{var}\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n \text{var}[X_i] + \sum_{i \neq j} \text{cov}(X_i, X_j)}$$

v) $E[XY]^2 \leq E[X^2] \cdot E[Y^2]$.

Let us find $E[(X-tY)^2] \geq 0$

$$\Rightarrow E[X^2] + t^2 E[Y^2] - 2t E[XY] \geq 0$$

Let $t = \frac{E[YY]}{E[Y^2]} \Rightarrow E[X^2] + \frac{E[XY]^2}{E[Y^2]} - 2 \frac{E[XY]}{E[Y^2]} \geq 0$

$$\mathbb{E}[Y^2]$$

Now $\text{Cov}(XY)^2 \leq \text{Var}(X) \cdot \text{Var}(Y) = ?$

$$\begin{aligned} \mathbb{E}[XY]^2 + \mathbb{E}[X]^2 \mathbb{E}[Y]^2 - 2 \mathbb{E}[XY] \cdot \mathbb{E}[X] \cdot \mathbb{E}[Y] &\leq (\mathbb{E}[X] - \mathbb{E}[X]^2) \\ &\quad \underbrace{(\mathbb{E}[Y] - \mathbb{E}[Y]^2)}_{\mathbb{E}[X^2] \mathbb{E}[Y^2]} \\ &= \mathbb{E}[X^2] \mathbb{E}[Y^2] - \mathbb{E}[X]^2 \mathbb{E}[Y^2] \\ &= \mathbb{E}[Y^2] \mathbb{E}[X^2]. \end{aligned}$$

$$\mathbb{E}[XY]^2 = ? \quad \mathbb{E}[XY] = t(X) t(Y) \leq$$

$$\begin{aligned} \mathbb{E}[XY]^2 &= \text{Cov}(XY)^2 + 2 \mathbb{E}[XY] \mathbb{E}[X] \cdot \mathbb{E}[Y] - \mathbb{E}[X]^2 \mathbb{E}[Y]^2 \quad \text{or} \\ &\leq \mathbb{E}[X^2] \mathbb{E}[Y^2] \end{aligned}$$

$$\text{Cov}(XY)^2 \leq 2 [\mathbb{E}[X^2] \mathbb{E}[Y^2] - \mathbb{E}[XY] \mathbb{E}[X] \cdot \mathbb{E}[Y]].$$

$$\Rightarrow \boxed{\text{Cov}(XY)^2 \leq \text{Var}(X) \cdot \text{Var}(Y)}$$

$$\text{Since } \frac{\text{Cov}(X,Y)^2}{\text{Var}(X) \cdot \text{Var}(Y)} \leq 1 \Rightarrow \boxed{\rho^2 \leq 1} \quad \text{or} \quad \boxed{|\rho| \leq 1}$$

Fair coin tossed N times.

$$X := \text{no. of heads}, \quad \text{Cov}(X,Y) = ?$$

$$Y := \text{no. of tails.}$$

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

$$X: \text{Bin}(n,p)$$

$$Y: \text{Bin}(n,q)$$

$$\text{Cov}(X,Y) = \mathbb{E}[XY] - \mathbb{E}[X] \cdot \mathbb{E}[Y], \quad | \quad \begin{aligned} \mathbb{E}[X] &= np \\ \mathbb{E}[Y] &= nq = n(1-p) = n - \mathbb{E}[X]. \end{aligned}$$

$$X+Y = n$$

$$\Rightarrow \text{Var}(X+Y) = \text{Var}(n) = 0 = \text{Var}(X) + \text{Var}(Y) + 2 \text{Cov}(X,Y)$$

$$\text{Cov}(X,Y) = \frac{-\text{Var}(X) - \text{Var}(Y)}{2} = \frac{-npq \times 2}{2} = -npq$$

$$\rho = \frac{\text{Cov}(X,Y)}{\sqrt{\text{Var}(X) \text{Var}(Y)}} = \frac{-npq}{npq} = -1$$

Since correlation coefficient is -1

X and Y are perfectly negatively correlated.

$$E[E[X|Y]] = E[X].$$

$$\text{Var}(X) = E[\text{Var}(X|Y)] + \text{Var}[E(X|Y)]$$

: coin toss for n times

X : # heads.

$$P = P(H) \sim U[0,1]$$

$$\begin{cases} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{cases} \sim \mathcal{N}(0, \frac{1}{n})$$

$$E[X] = 1 \quad E[X|P] = np$$

$$E[E[X|P]] = E[n \cdot P] = nE[P] = \frac{n}{2} = E[X]$$

$$\text{Var}(X|P) = npq = n(p-q)$$

$$\begin{aligned} E[\text{Var}(X|P)] &= nE[P \cdot Q] = nE[P] - nE[P^2] \\ &= n \cdot \frac{1}{2} - n \cdot \frac{1}{3} = \frac{n}{6} \end{aligned} \quad \text{--- (1)}$$

$$E[Y|P] = n \cdot P.$$

$$\begin{aligned} \text{Var}(E[X|P]) &= n^2 \text{Var}(P) \\ &= n^2 \cdot \frac{1}{12} = \frac{n^2}{12} \end{aligned} \quad \text{--- (ii)}$$

$$\Rightarrow \text{Var}(X) = \frac{n}{6} + \frac{n^2}{12}$$

$$\text{Now let } P(H) \sim \frac{\mu \exp(-\mu x)}{1 - \exp(-\mu x)}.$$

Now find $\text{Var}(X)$, $E[X]$.

for $\bar{P} = E[P]$, fixed

find $\text{Var}(X)$, $E[X]$

for this.

part a

$$\text{Let } \bar{p} = E[P].$$

$$E[X] = \bar{p}N$$

$$\text{Var}(X) = \bar{p}(1-\bar{p}) \cdot N.$$

$$\begin{aligned}\bar{p} &= \int_0^1 x \cdot \frac{\mu e^{-\mu x}}{1-e^{-\mu}} dx \\ &= \frac{\mu}{1-e^{-\mu}} \int_0^1 x \cdot e^{-\mu x} dx \\ &= \frac{\mu}{1-e^{-\mu}} \left[\frac{x \cdot e^{-\mu x}}{-\mu} - \int \frac{e^{-\mu x}}{-\mu} dx \right] \\ &= \frac{\mu}{1-e^{-\mu}} \left[\frac{x \cdot [e^{-\mu x}]}{-\mu} \Big|_0^1 + \frac{1}{\mu} \frac{[e^{-\mu x}]}{-\mu} \Big|_0^1 \right] \\ &= \frac{-\mu}{1-e^{-\mu}} \left[\frac{e^{-\mu}}{\mu} + \frac{(e^{-\mu}-1)}{\mu^2} \right] \\ &= \frac{1}{1-e^{-\mu}} \left[\frac{e^{-\mu}}{1} + \frac{e^{-\mu}-1}{\mu} \right] \\ \bar{p} &= \frac{\mu e^{-\mu} + e^{-\mu} - 1}{\mu (1 - e^{-\mu})}.\end{aligned}$$

part b

$$E[X] = \sum_n (E[X|P])$$

$$E[X|P] = nP.$$

$$\begin{aligned}E[E[X|P]] &= E[nP] = nE[P] \\ &= n(\bar{p}).\end{aligned}$$

Moment Generating Function (MGF)

$$M_X(s) = \mathbb{E}[e^{sx}]$$

* for discrete X:

$$M_X(s) = \sum_x e^{sx} P_X(x=x) = \sum_{k=-\infty}^{\infty} e^{sk} P_X(x=k)$$

* for continuous X:

$$M_X(s) = \int_{\text{dom}(x)} e^{sx} f_X(x) dx$$

$$e^{sx} = 1 + sx + \frac{(sx)^2}{2!} + \frac{(sx)^3}{3!} + \dots$$

$$\mathbb{E}[se^{sx}] = 1 + s\mathbb{E}[x] + \frac{s^2}{2!}\mathbb{E}[x^2] + \frac{s^3}{3!}\mathbb{E}[x^3] + \dots$$

Now to find the 3rd moment of X's expectation,

we diff. the eqn 3 times wrt s and put s=0.

$$\Rightarrow \boxed{\frac{d^n M_X(s)}{ds^n} \Big|_{s=0} = \mathbb{E}[x^n]}$$

Eg: $x \sim Exp(\lambda)$
MGF = ?

$$\begin{aligned} M_X(s) &= \mathbb{E}[e^{sx}] = \lambda \mu \int_0^\infty e^{sx} e^{-\mu x} dx \\ &= \mu \int_0^\infty e^{x(s-\mu)} dx \\ &= \mu \left[\frac{e^{x(s-\mu)}}{s-\mu} \right]_0^\infty = \mu \frac{0 - 1}{s-\mu} = \frac{\mu}{\mu-s}. \end{aligned}$$

$$\boxed{M_X(s) = \frac{\mu}{\mu-s}} \quad \text{with } \boxed{s < \mu}$$

for $s < \mu$

$$M_X(s) = \frac{\mu}{\mu - s}$$

$$\left. \begin{array}{l} E[X] = \frac{1}{\mu} \\ E[X^2] = \frac{2}{\mu^2} \end{array} \right\} \quad E[f(x)] \Rightarrow \mu - (\mu - s)^{-1}$$

$$E[X] = -\mu(\mu - s)^{-2} = \frac{-\mu(-1)}{(\mu - s)^2} \Rightarrow \frac{1}{\mu}$$

$$E[X^2] = \frac{\mu(-2)(-1)}{(\mu - s)^3} = \frac{2\mu}{(\mu - s)^3} \Rightarrow \frac{2}{\mu^2}$$

$$E[X^3] = \frac{2\mu(-3)(-1)}{(\mu - s)^4} \Rightarrow \frac{6\mu}{\mu^4} \Rightarrow \frac{6}{\mu^3}$$

Let $X \sim \text{Poisson}(\lambda)$.

$$f_{x \in \mathbb{C}} P_x(x=k) = e^{-\lambda} \frac{\lambda^k}{k!}$$

$$\Rightarrow E[e^{sx}] = \sum_{k=0}^{\infty} e^{sk} e^{-\lambda} \frac{\lambda^k}{k!} = \sum_{k=0}^{\infty} e^{-\lambda} \frac{(e^s \lambda)^k}{k!} = e^{-\lambda} e^{s\lambda} = e^{\lambda(e^s - 1)}$$

$$\therefore M_X(s) = e^{\lambda(e^s - 1)}$$

$$E[X] = e^{\lambda(e^s - 1)} \cdot \lambda e^s = \lambda \cdot 1 = \lambda$$

$$E[X^2] = \frac{d}{ds} [\lambda \cdot e^{\lambda(e^s - \lambda + s)}] = \lambda \cdot e^{\lambda(e^s - \lambda + s)} \cdot [\lambda e^s + 1]$$

$$E[X^2] = \lambda e^{-s} \cdot [\lambda e^s + 1]$$

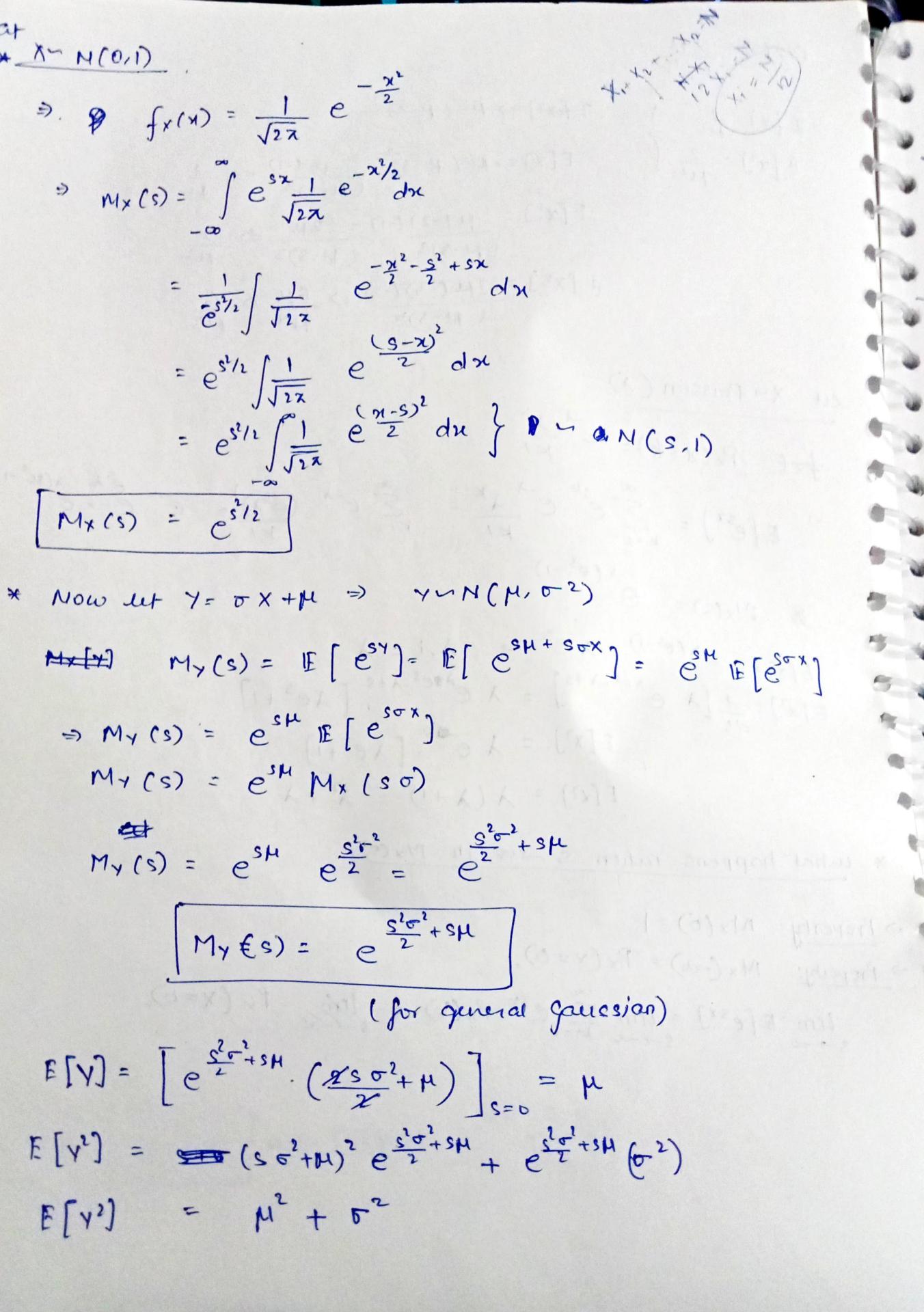
$$E[X^2] = \lambda(\lambda + 1) = \lambda^2 + \lambda$$

* what happens when $s \rightarrow \infty$ in $M_X(s)$.

Property: $M_X(0) = 1$

Property: $M_X(-\infty) = P_X(X=0)$.

$$\lim_{s \rightarrow -\infty} E[e^{sx}] = \lim_{s \rightarrow -\infty} \sum_{k=0}^{\infty} e^{sk} P_X(k) = \lim_{s \rightarrow -\infty} P_X(X=0).$$



Property: If $M_X(s) = M_Y(s)$ then $F_X(s) = F_Y(s)$
OR $f_X(s) = f_Y(s)$

To obtain PDF/PMF from MGF, we write MGF in the form of polynomial and s^k coeff corresponds to $P(X=k)$
 \hookrightarrow check.

Given $X \sim \text{Geometric}(P)$.

$$M_X(s) = \frac{ps}{1-(1-p)e^s} \stackrel{\textcircled{a}}{=} pe^s [1 + (1-p)e^s + (1-p)^2 e^{2s} + \dots]$$

$$M_X(s) \stackrel{\textcircled{b}}{=} [pe^s + p(1-p)e^{2s} + p(1-p)^2 e^{3s} + \dots]$$

$\uparrow \quad \uparrow \quad \uparrow$
 $P(X=1) \quad P(X=2) \quad P(X=3) \dots$

In general: $P[X=k] = \text{coeff of } s^k = p(1-p)^{k-1}$

Let X and Y be independent

\Rightarrow let $Z = X+Y$.

$$M_Z(s) = E[e^{s(X+Y)}] = E[e^{sX} \cdot e^{sY}]$$

since X, Y are independent

$$e^{sX}, e^{sY} \text{ are independent} \Rightarrow E[e^{sX} \cdot e^{sY}] = E[e^{sX}] \cdot E[e^{sY}]$$

$$\boxed{M_Z(s) = M_X(s) \cdot M_Y(s)}$$

Now if X , and Y are iids, then

$$\boxed{M_Z(s) = (M_X(s))^2}$$

similarly, by mathematical induction, this result is valid for n iid/i random variables

$$X \sim \text{Poisson}(\lambda_1) \\ Y \sim \text{Poisson}(\lambda_2) \quad \Rightarrow \quad Z = X + Y.$$

$$M_X(s) = e^{\lambda_1(e^s - 1)}$$

$$M_Y(s) = e^{\lambda_2(e^s - 1)}$$

$$M_Z(s) = [e^{(e^s - 1)(\lambda_1 + \lambda_2)}] \Rightarrow \text{Poisson}(\lambda_1 + \lambda_2), = Z.$$

$$\boxed{\begin{array}{c} Z = X + Y \\ \downarrow \quad \downarrow \quad \downarrow \\ \text{Poi}(\lambda_1 + \lambda_2) \quad \text{Poi}(\lambda_1) \quad \text{Poi}(\lambda_2) \end{array}}$$

* Sum of independent Poisson R.V.
is another Poisson R.V. with parameters
sum of individual parameters

* Similarly for Gaussian

$$M_Z(s) = M_X(s) \cdot M_Y(s) \\ = e^{\frac{s^2 \sigma_1^2}{2} + s\mu_1} \cdot e^{\frac{s^2 \sigma_2^2}{2} + s\mu_2} \\ M_Z(s) = e^{\frac{s^2}{2}(\sigma_1^2 + \sigma_2^2) + s(\mu_1 + \mu_2)} \Rightarrow Z \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2)$$

This will also hold for N number of Gauss. R.V.

$$\text{if } Z = X_1 + X_2 + \dots + X_N.$$

$$X_i \sim \text{Normal}(\mu_i, \sigma_i^2).$$

$$\Rightarrow Z \sim \text{Normal}(\sum \mu_i, \sum \sigma_i^2)$$

* To find MGF of Binomial R.V. iids

use the fact that Bino-R.V. = sum of infinite Bernoulli R.V

*** Let N also be a R.V.

$$Z = X_1 + X_2 + \dots + X_N$$

and all X_i are i.i.d.s.

$$M_{\text{AF}}(z) = M_Z(z) = [M_X(s)]^N$$
$$M_{Z|n}(s) = M_X(s)^n$$
$$M_Z(s) = \sum_{n=0}^{\infty} M_X(s)^n \cdot P[N=n]$$
$$= \sum_{n=0}^{\infty} e^{n \log M_X(s)} \cdot P[N=n]$$
$$\boxed{M_Z(s) = M_N(\log M_X(s))}$$

$$M_N(s) = E(e^{sT})$$
$$= \sum_{n=0}^{\infty} e^{ns} P[N=n]$$

Let $T_i \sim \text{Exp}(\mu)$
 $N \sim \text{Geo}(p)$.

$T = \sum T_i$ T_i are iid.

$$\Rightarrow M_T(s) = M_N(\log M_{T_i}(s))$$

$$M_{T_i}(s) = \frac{pe^s}{1-(1-p)e^s}$$

$$M_{T_i}(s) = \frac{\mu}{\mu-s} = k(s)$$

$$M_T(s) = \frac{p e^{\log k}}{1-(1-p)e^{\log k}} = \frac{pk}{1-(1-p)k} = \frac{pk}{\frac{\mu-s}{\mu-s} - \frac{(1-p)\mu}{\mu-s}}$$

$$M_T(s) = \frac{p\mu}{\mu-s-\mu+pm} = \frac{p\mu}{pm-s}$$

$$\boxed{M_T(s) = \frac{p\mu}{pm-s}} \Rightarrow \underline{M_T(s) = T \sim \text{Exp}(pm)}$$

- * sum of geometric no. of exponential R.V. is again exponential R.V.
- * sum of N exponential R.V. is not an expo. R.V.

Now we can find $\text{Var}(T) = \frac{1}{p^2\mu^2}$

Function of RV

$$Y = g(X).$$

- * $F_Y(y) = P[Y \leq y] = P[X \in R_Y] \rightarrow$ $R_Y \neq \emptyset$ otherwise $f_Y(y) = 0$
- * R_Y is defined as $\{x : g(x) \leq y\} + \mathbb{R}_y$ where \mathbb{R}_y is defined as
- * R_Y should be ~~sum~~ union of countable set

$$Y \leq y \Leftrightarrow g(x) \leq y$$

$\{x : x \leq g^{-1}(y)\} + \mathbb{R}_y$ (when invertible)

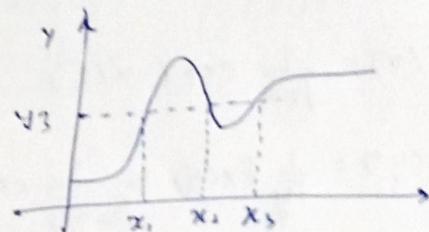
or better $\{x : g(x) \leq y\} = R_Y$

$$Y \leq y_3 \Rightarrow \begin{cases} x \leq x_1 \\ \text{or} \\ x_2 \leq x \leq x_3 \end{cases}$$

$$F_Y(y_3) = P[X \leq x_1] + P[x_2 \leq X \leq y_3]$$

$$F_Y(y_3) = F_X(x_1) + F_X(y_3) - F_X(x_2)$$

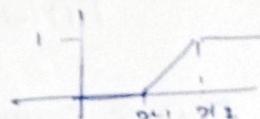
$$R_{Y_3} = \{x \in \mathbb{R} \mid x \leq x_1 \text{ or } x_2 \leq x \leq x_3\}$$



$\frac{1}{x_1, x_2}$

$$F_Y(y) = \sum_{x: g(x) \leq y} P_x(x).$$

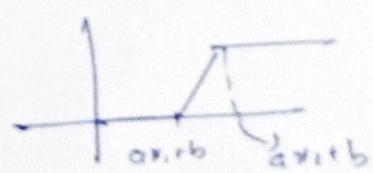
$$\begin{aligned} \text{Let } y &= ax + b & Y \leq y &\Rightarrow x \leq \frac{y-b}{a} \\ \Rightarrow F_Y(y) &= P_x\left(\frac{y-b}{a}\right) \end{aligned}$$



$$X = [x_1, x_2].$$

$$Y = ax + b$$

$$\begin{aligned} F_Y(y) &= P_x\left(\frac{y-b}{a}\right) \\ &= \frac{\frac{y-b}{a} - x_1}{x_2 - x_1} = \frac{y - (ax_1 + b)}{(ax_2 + b) - (ax_1 + b)} \end{aligned}$$



④.

$$Y = X^2$$

$$F_Y(y) = P\{X \in (-\infty, y]\}$$

$$F_Y(y) = F_X(\sqrt{y}) - F_X(-\sqrt{y})$$

$$\Rightarrow f_Y(y) = \frac{1}{2\sqrt{y}} [f_X(\sqrt{y}) + f_X(-\sqrt{y})]$$

$$\Rightarrow \frac{1}{2\sqrt{y}} f_X(\sqrt{y}) + \frac{1}{2\sqrt{y}} f_X(-\sqrt{y}).$$

thus, if $X \sim N(0, 1)$

$$\Rightarrow f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

$$f_Y(y) = \frac{1}{\sqrt{y}} f_X(y) = \frac{1}{\sqrt{2\pi y}} e^{-y^2/2} \text{ for } y \geq 0$$

[chi-square with degree of freedom 1].

* chi square with DDF k

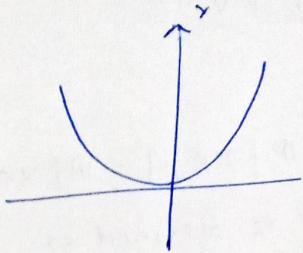
$$X(k) \\ f_X(x) = \frac{1}{\Gamma(k/2)} 2^{k/2} x^{k/2-1} e^{-x/2}$$

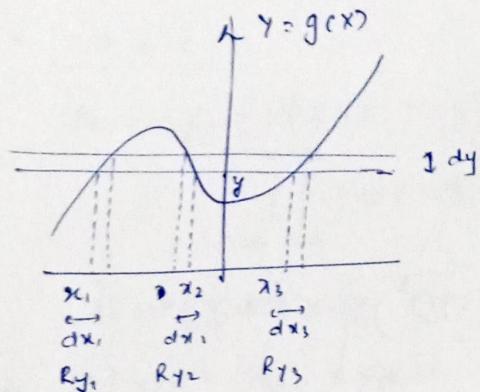
$\Gamma(\cdot)$ \Rightarrow Gamma function

$$\Gamma(m) = (m-1)! \quad \text{for } m = \text{integer}$$

$$\Gamma(1/2) = \sqrt{\pi}$$

$$\Gamma(n+1) = n \cdot \Gamma(n)$$





$$f_y(y) dy = P[y \in [y, y+dy]]$$

$$= P[x \in \cap (R_i)]$$

$$= P[x \in [x_1, x_1 + dx_1]]$$

$$+ P[x \in [x - dx_2, x_2]]$$

$$+ P[x \in [x_3, x_3 + dx_3]].$$

$$f_y(y) dy = f_x(x_1) dx_1 + f_x(x_2) dx_2 + f_x(x_3) dx_3$$

$$\boxed{f_y(y) = \sum_{i=1}^3 \frac{f_x(x_i)}{|g'(x_i)|}}$$

$$|g'(x_i)| \neq 0$$

* $y = x^2 \Rightarrow$ root, $x = \pm\sqrt{y}$
 $\frac{dy}{dx} = g'(x) = 2x \Rightarrow |g'(x)| = 2|x|$

$$f_y(y) = \frac{f_x(\sqrt{y}) + f_x(-\sqrt{y})}{2\sqrt{y}}$$

* $y = ax + b$
 $g'(x) = a \rightarrow f_y(y) = f_x\left(\frac{y-b}{a}\right)$

* $g'(x) = \frac{1}{x^2} \rightarrow f_y(y) = f_x\left(\frac{1}{y}\right) \cancel{\left(\frac{x^2}{y^2}\right)} \left(-\frac{1}{y^2}\right).$
 $= f_x(y) = \frac{f_x(\frac{1}{y})}{y^2}$

\Rightarrow Cauchy Dist:

$$f_x(x) = \frac{\alpha/\pi}{x^2 + \alpha^2} \xrightarrow{x \in (-\infty, \infty)} \text{Cauchy}(\alpha)$$

$$\Rightarrow \text{if } f_y(y) = \alpha \frac{\alpha/\pi}{\alpha^2 + 1/y^2} = \frac{1/\pi\alpha}{y^2 + 1/\alpha^2} = \text{Cauchy}(1/\alpha)$$

Let $y = e^x$

$$f_y(y) = \frac{f_x(\ln y)}{e^{(\ln y)}} = \frac{f_x(\ln y)}{y}$$

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

$$\left[f_y(y) = \frac{1}{y} \cdot \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(\ln y - \mu)^2}{2\sigma^2}\right) \right] \text{ for } y > 0$$

Log Normal distribution

* X, Y be r.v.

$$F_{XY}(x, y) = P[X \leq x, Y \leq y]$$
$$= \int_{-\infty}^y \int_{-\infty}^x f_{XY}(u, v) du dv$$

$$D := \{ -\infty < y < \infty, -\infty < x < \infty \}.$$

$$* P[x_1 < X \leq x_2, Y < y] = \int_{-\infty}^y \int_{x_1}^{x_2} f_{XY}(u, v) du dv = F_{XY}(x_2, y) - F_{XY}(x_1, y)$$

$$\begin{aligned} * P[x_1 < X \leq x_2, y_1 < Y \leq y_2] &= \int_{y_1}^{y_2} \int_{x_1}^{x_2} f_{XY}(u, v) du dv \\ &= \int_{y_1}^{y_2} \int_{x_1}^{x_2} f_{XY}(u, v) du dv \\ &= \int_{y_1}^{y_2} \left[\int_{-\infty}^{x_2} f(u) du - \int_{-\infty}^{x_1} f(u) du \right] dv \\ &= \int_{-\infty}^{y_2} \left[\int_{-\infty}^{x_2} f(u) du - \int_{-\infty}^{x_1} f(u) du \right] dv - \int_{-\infty}^{y_1} \left[\int_{-\infty}^{x_2} f(u) du - \int_{-\infty}^{x_1} f(u) du \right] dv \\ P[x_1 < X \leq x_2, y_1 < Y \leq y_2] &= F_{XY}(x_2, y_2) - F_{XY}(x_1, y_2) - F_{XY}(x_2, y_1) + F_{XY}(x_1, y_1) \end{aligned}$$

Let \mathcal{E} be the event $X < Y$

$$P[\mathcal{E}] = \int_{-\infty}^{\infty} \int_{-\infty}^y f_{XY}(u, v) du dv = \int_{-\infty}^{\infty} \int_{-\infty}^y f_{XY}(u, v) du dv.$$

$$\mathcal{E} := D = \{(x, y) : x < y\}$$

$$D = \{-\infty < y < \infty, -\infty < x < y\}$$

$$(4) \quad z = g(x, y)$$

$$F_z(z) = P[z < z]$$

$$D_z = \{(x, y) \mid g(x, y) < z\}.$$

$$\text{then } F_z(z) = \iint_{D_z} f_{xy}(x, y) dx dy$$

* Leibnitz Integral Rule

$$\text{if } F(\theta) = \int_{a(\theta)}^{b(\theta)} f(x, \theta) dx$$

$$\text{then } \frac{d}{d\theta} F(\theta) = b'(\theta) f(b(\theta), \theta) - a'(\theta) f(a(\theta), \theta) + \int_{a(\theta)}^{b(\theta)} \frac{d}{d\theta} f(x, \theta) dx$$

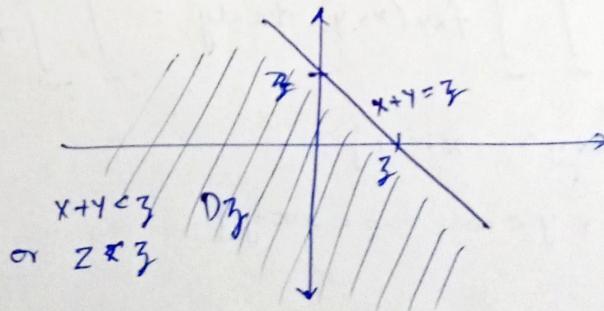
If limits $a(\theta), b(\theta)$ are independent of θ

$$\text{then } \frac{dF(\theta)}{d\theta} = \int_a^b \frac{df(x, \theta)}{d\theta} dx$$

* Sum of 2 R.V.s

$$Z = X + Y$$

$$\text{then } D_z := \{z < z\} = \{(x, y) : x+y < z\}.$$



$$F_z(z) = P[z < z]$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{z-y} f_{xy}(u, v) du dv$$

$$\text{then } f_z(z) = \frac{d}{dz} F_z(z) = \int_{-\infty}^{\infty} \left[\int_{-\infty}^z f_{xy}(u, v) du dv \right] dv$$

$$= \int_{-\infty}^{\infty} \left[1 \cdot f_{xy}(z-y, y) - 0 + \int_{-\infty}^{z-y} \frac{d}{dz} f_{xy}(u, y) du \right] dy$$

$$f_z(z) = \int_{-\infty}^{\infty} f_{xy}(z-y, y) dy$$

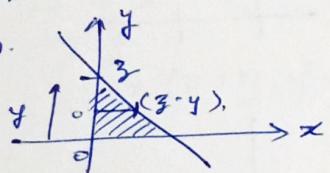
If X and Y are independent, then

$$f_z(z) = \int_{-\infty}^{\infty} f_x(z-y) \cdot f_y(y) dy = [f_x * f_y](z)$$

Result: distribution of sum of 2 independent R.V. is equal to convolution of their individual pdfs.

Now if we had Y and $X \geq 0$,

then,



$$D_3 := \{(x, y) : 0 < y < z, 0 < x < z-y\}$$

$$D_3 := \{(x, y) : x+y \leq z, x \geq 0, y \geq 0\}$$

$$F_z(z) = \int_0^z \int_0^{z-y} f_{xy}(x, y) dx dy = P[Z \leq z]$$

$$f_z(z) = \frac{d}{dz} (F_z(z)) = + \int_0^{z-y} f_{xy}(x, y) dx$$

$$= 1 \cdot \int_0^{z-y} f_{xy}(x, z) dx - 0 + \int_0^z \frac{d}{dz} \int_0^{z-y} f_{xy}(x, y) dx dy$$

$$= \int_0^z \left[1 \cdot f_{xy}(z-y, y) - 0 + \int_0^{z-y} \frac{d}{dz} f_{xy}(x, y) dx \right] dy$$

$$f_z(z) = \int_0^z f_{xy}(z-y, y) dy$$

is the same expression
in the prev. case with
Limits refined to $[0, z]$

$$\text{Es: } \begin{cases} x \sim \exp(\lambda) \\ y \sim \exp(\lambda) \end{cases} \left. \begin{array}{l} \text{independent} \\ \text{Z} = x + y \end{array} \right\} f_Z(z) = ?$$

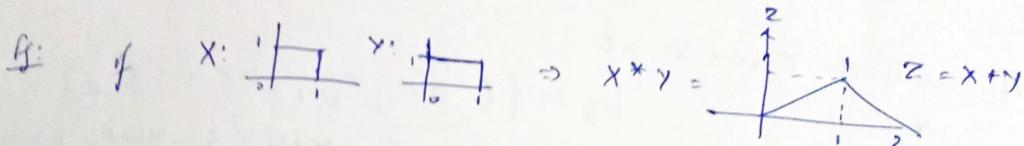
$$f_Z(z) = \int_{-\infty}^{\infty} f_X(x) f_Y(y) dx$$

$$f_Z(z) = \int_0^z f_X(z-y) f_Y(y) dy$$

$$= \int_0^z \lambda e^{-\lambda(z-y)} \cdot \lambda e^{-\lambda y} dy$$

$$= \lambda^2 \int_0^z e^{-\lambda(z-y+y)} dy = \lambda^2 \int_0^z e^{-\lambda z} dy$$

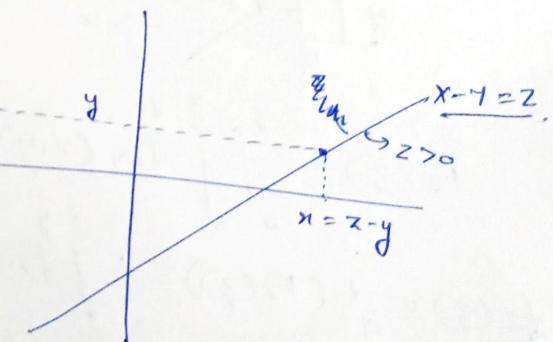
$$f_Z(z) = \lambda^2 e^{-\lambda z} \cdot z$$



$$\textcircled{*} \text{ mit } \underline{Z = X - Y}$$

$$z = x - y$$

$$\mathcal{D}_Z := \{ -\infty < y < \infty, -\infty < x < z+y \}.$$



$$F_Z(z) = \mathbb{P}[Z < z]$$

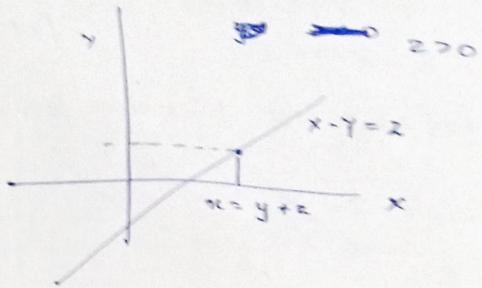
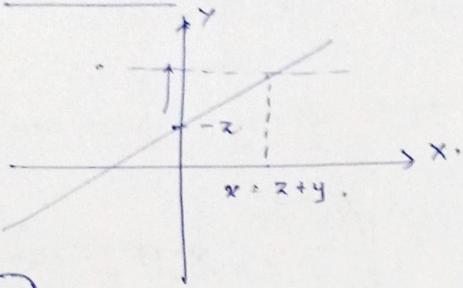
$$= \int_{-\infty}^{\infty} \int_{-\infty}^{z+y} f_{XY}(x, y) dx dy$$

$$\Rightarrow f_Z(z) = \int_{-\infty}^{\infty} \left[\int_{-\infty}^{z+y} f_{XY}(x, y) dx \right] dy$$

$$f_Z(z) = \int_{-\infty}^{\infty} [f_{XY}(z+y, y) \cdot 0 + 0] dy = \int_{-\infty}^{\infty} f_{XY}(z+y, y) dy$$

Now if we assume $x \geq 0$ and $y \geq 0$.

Then 2 cases:



#1

$$D_3 = \{ -z < y < \infty, 0 < x < z+y \}$$

$$F_2(z) = \int_{-z}^{\infty} \int_0^{z+y} f_{xy} dx dy$$

$$\begin{aligned} f_z(3) &= -(-1) \cdot \int_0^{z-z} f_{xy}(x, -z) dx + \int_{-z}^{\infty} \frac{d}{dz} \int_0^{z+y} f_{xy} dx dy \\ &= \int_{-z}^{\infty} [f_{xy}(z+y, y) - 0 + 0] dy \end{aligned}$$

$$f_z(3) = \int_{-z}^{\infty} f_{xy}(z+y, y) dy$$

#2

$$D_2 = \{ 0 < y < \infty, 0 < x < z+y \}$$

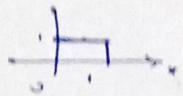
$$F_2(z) = \int_0^{\infty} \int_0^{z+y} f_{xy} dx dy$$

$$\begin{aligned} f_z(3) &= \int_0^{\infty} \frac{d}{dz} \left[\int_0^{z+y} f_{xy}(x, y) dx \right] dy \\ &= \int_0^{\infty} [f_{xy}(z+y, y) - 0 + 0] dy \end{aligned}$$

$$f_z(3) = \int_0^{\infty} f_{xy}(z+y, y) dy$$

$$f_z(2) = \begin{cases} \int_{-z}^{\infty} f_{xy}(z+y, y) dy & z < 0 \\ \int_0^{\infty} f_{xy}(z+y, y) dy & z > 0 \end{cases}$$

$$\begin{aligned} & \left. \begin{aligned} & x \sim U[0,1] \\ & y \sim U[0,1] \end{aligned} \right\} \text{ind.} \quad f_y(y) = 1 \\ \Rightarrow & z = x - y \quad f_x(x) = 1 \end{aligned}$$



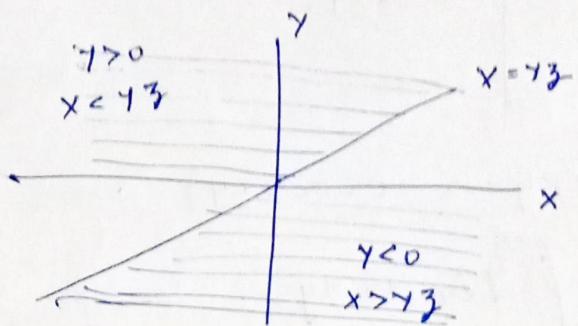
$f_z(z)$ = use previous formula.

Ex: let $Z = \frac{x}{y}$

$$Z < z$$

(DF)

$$\begin{aligned} f_z(z) &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{xy}(x,y) dx dy \\ &+ \int_{-\infty}^{yz} \int_{yz}^{\infty} f_{xy}(x,y) dx dy \end{aligned}$$



PDF:

$$\begin{aligned} f_z(z) &= \int_0^{\infty} \left[y \cdot f(yz, y) - 0 + \int_{-\infty}^{yz} \frac{\partial}{\partial z} f_{xy}(x, y) dx \right] dy \\ &+ \int_{-\infty}^0 \left[0 - y \cdot f(yz, y) + 0 \right] dy \\ &= \int_0^{\infty} y \cdot f(yz, y) dy + \int_{-\infty}^0 -y f(yz, y) dy \\ &= \int_{-\infty}^{\infty} |y| f(yz, y) dy \end{aligned}$$