

- random exp: some activity that results in an outcome.
- Event: set of outcomes to which we assign probability.
(A)
- Sample space: set of all possible outcomes.
(S)
- Event space: collection of subsets of Sample space.
(F)

e.g. Tossing a coin

$$\Omega = \{H, T\} \rightarrow \text{sample space of } T \text{ tosses of coin}$$

$\Omega = \mathbb{R} \rightarrow$ distance through which coin travelled.

$$\Omega = \{1, 2, 3, \dots\} \rightarrow \text{No. of flips.}$$

$$\mathcal{F} = \{\emptyset, \{H\}, \{T\}, \{\emptyset, H\}, \{\emptyset, T\}, \{H, T\}\} = 2^n \text{ power set of } \Omega.$$

→ A set 'S' is said to be countable if we can define a 1-1 mapping from \mathbb{N} to set 'S'.

$$\text{e.g. } S = \{1, 2, \dots\}$$

$$f: \mathbb{N} \rightarrow S \quad f(n) = n$$

$$S = \{0, 1, 2, \dots\}$$

$$f(n) = n - 1, n \in \mathbb{N}$$

$(Q = \frac{p}{q}, q \neq 0, p, q \text{ are integers} \rightarrow \text{Countable})$

→ A collection of sets \mathcal{F} is said to be σ -algebra.

If

(i) $\emptyset \in \mathcal{F}$

(ii) If $A \in \mathcal{F}$, then $A^c \in \mathcal{F}$.

(iii) A_1, A_2, A_3, \dots then $\bigcup_{i=1}^{\infty} A_i \in \mathcal{F}$

e.g. $\Omega = \{1, 2, 3, 4, 5, 6\}$

$\mathcal{F} = \{\emptyset, \phi, \{1, 3, 5\}, \{2, 4, 6\}\}$

• Probability:

A probability 'P' is a mapping from \mathcal{F} to $[0, 1]$

$$P: \mathcal{F} \rightarrow [0, 1]$$

such that

(i) $P(\Omega) = 1$

(ii) If $A_1, A_2, \dots \in \mathcal{F}$, then $A_i \cap A_j = \emptyset$

then

$$P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i)$$

(i) $P(A^c) = 1 - P(A)$

Proof: $A \cap A^c = \emptyset$

$$A_1 = A \quad A_2 = A^c$$

$$P\left(\bigcup_{i=1}^{\infty} A_i\right) = P(A \cup A^c) = P(\Omega) = 1 = P(A) + P(A^c)$$

(iii) $A, B \in \mathcal{F}$ such that $A \subseteq B$ then $P(A) \leq P(B)$

Proof: $B = A \cup (A^c \cap B)$

$$B - A = A^c \cap B$$

$$P(B) = P(A) + P(A^c \cap B)$$

$\underbrace{\hspace{1cm}}_{>0}$

So, $P(B) > P(A)$



(iii) $A, B \in \mathcal{F}$

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

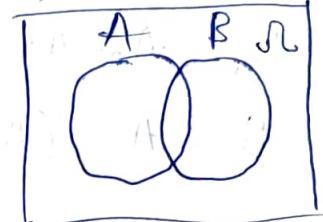
Proof:

$$A \cup B = A \cup (A^c \cap B)$$

$$P(A \cup B) = P(A) + P(A^c \cap B)$$

$$B = (A \cap B) \cup (A^c \cap B)$$

$$P(B) = P(A \cap B) + P(A^c \cap B)$$



$$\underline{P(A \cup B) = P(A) + P(B) - P(A \cap B)}$$

(iv) $P(\emptyset) = 0$

Proof:

$$A^o = \emptyset, i > 1$$

$$P\left(\bigcup_{i=1}^{\infty} A^o_i\right) = P(\emptyset) = \sum_{i=1}^{\infty} P(A^o_i)$$

$$P(\emptyset) = \sum_{i=1}^{\infty} P(\emptyset) \Rightarrow \underline{P(\emptyset) = 0}$$

(v) If A_1, A_2, \dots, A_n are disjoint events

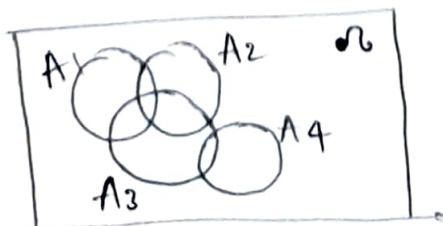
$$P\left(\bigcup_{i=1}^n A^o_i\right) = \sum_{i=1}^n P(A^o_i)$$

(vi) Union bound:

Let A_1, A_2, \dots, A_n be events

$$P\left(\bigcup_{i=1}^n A^o_i\right) \leq \sum_{i=1}^n P(A^o_i)$$

Proof:



$$B_1 = A_1$$

$$B_2 = A_2 - A_1$$

$$B_3 = A_3 - (A_1 \cup A_2)$$

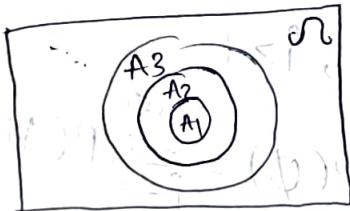
$$B_i^o \subseteq A_i^o$$

$$\text{So, } P(B_i^o) \leq P(A_i^o)$$

$$P\left(\bigcup_{i=1}^n B_i^o\right) = P\left(\bigcup_{i=1}^n A_i^o\right) = \sum_{i=1}^n P(B_i^o) \leq \sum_{i=1}^n P(A_i^o)$$

→ Let A_1, A_2, \dots, A_n be sequence of events

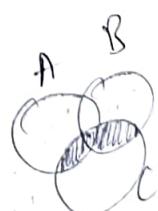
a) if $A_1 \subseteq A_2 \subseteq \dots \subseteq A_n$



$$P\left(\bigcup_{i=1}^n A_i^o\right) = \lim_{n \rightarrow \infty} P(A_n^o)$$

$$\text{b) } P\left(\bigcup_{i=1}^{\infty} A_i^o\right) = \lim_{n \rightarrow \infty} P\left(\bigcup_{i=1}^n A_i^o\right)$$

(Continuity of probability)



$$P(A \cup B \cup C) = P(A) + P(B) + P(C) - P(A \cap B) - P(A \cap C) - P(B \cap C) + P(A \cap B \cap C)$$

$$P(C)$$

* Conditional probability:

If $P(A)$

$f_n(A)$; No. of times event A occurs.

$$P(A) = \frac{f_n(A)}{n}$$

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

chance of A occurring
when B occurs.

$$\bullet P(A \cup B|C) = P(A|C) + P(B|C) - P(A \cap B|C)$$

Proof:

$$\begin{aligned} P(A \cup B|C) &= \frac{P((A \cup B) \cap C)}{P(C)} \\ &= \frac{P(A \cap C) \cup (B \cap C))}{P(C)} \\ &= \frac{P(A \cap C) + P(B \cap C) - P(A \cap B \cap C)}{P(C)} \end{aligned}$$

$$P(A \cup B|C) = \underline{P(A|C) + P(B|C) - P(A \cap B|C)}$$

→ Let $A_1, A_2, A_3, \dots, A_n$ be disjoint events

$$P\left(\bigcup_{i=1}^{\infty} A_i|C\right) = \sum_{i=1}^n P(A_i|C)$$

Independence:

chance of occurrence of one event doesn't alter the chance of occurrence of another event.

$$P(A|B) = P(A)$$

→ $P(A \cap B) = P(A)P(B) \rightarrow$ independent events.

→ Events A_1, A_2, A_3 are statistically independent if

$$(i) P(A_1 \cap A_2 \cap A_3) = P(A_1)P(A_2)P(A_3)$$

$$(ii) P(A_1 \cap A_2) = P(A_1)P(A_2)$$

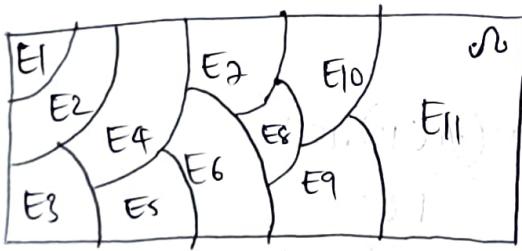
$$P(A_1 \cap A_3) = P(A_1)P(A_3)$$

$$P(A_2 \cap A_3) = P(A_2)P(A_3)$$

→ Let $\{E_i; i=1, 2, \dots, n\}$ be set of disjoint events

The set of events E_i is said to be partition of Ω

if $\bigcup_{i=1}^n E_i = \Omega$



→ Total probability

$$B_i = A \cap E_i$$

$$P(A) = P\left(\bigcup_{i=1}^n B_i\right) = \sum_{i=1}^n P(B_i)$$

$$= \sum_{i=1}^n P(A \cap E_i)$$

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

$$P(A) = \sum_{i=1}^n P(A|E_i)P(E_i)$$

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

$$P(E_i|A) = \frac{P(A|E_i)P(E_i)}{\sum_{i=1}^n P(A|E_i)P(E_i)}$$

eg: Two events A & B $P(A) = \frac{3}{4}$ $P(B) = \frac{1}{3}$

Show that $\frac{1}{12} \leq P(A \cap B) \leq \frac{1}{3}$

Sol:-

$$P(A) + P(B) - P(A \cup B) \leq 1$$

$$A \cap B \subseteq B$$

$$P(A \cup B) = \frac{3}{4} + \frac{1}{3} - P(A \cap B)$$

$$\underline{\quad} \quad P(A \cap B) \leq P(B)$$

$$= \frac{13}{12} - P(A \cap B) \leq 1$$

$$\underline{\quad} \quad P(A \cap B) \leq \frac{1}{3}$$

$$P(A \cap B) \geq \frac{1}{12}$$

$$\underline{\quad} \quad \underline{\quad}$$

$$\underline{\quad} \quad \underline{\quad}$$

Q: Tossing 3 coins (balanced, identical). What is the probability at least one head?

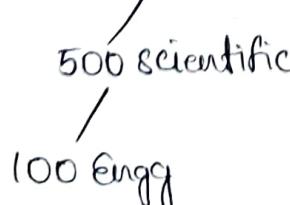
$$P(\text{at least one H}) = 1 - \frac{1}{8} = \underline{\underline{\frac{7}{8}}}$$

Q: Two identical coins (balanced)

$$P\left(\begin{array}{l|l} \text{Both show} \\ \text{head} \end{array} \middle| \begin{array}{l} \text{coin 1 show} \\ \text{head} \end{array}\right) = ? \quad \left(\frac{1}{2}\right)$$

$$P\left(\begin{array}{l|l} \text{Both show} \\ \text{head} \end{array} \middle| \begin{array}{l} \text{at least one} \\ \text{head} \end{array}\right) = \frac{1}{3}$$

Q: Library with 1000 books



(i) Probability that all three are scientific $= \frac{1}{2} \times \frac{1}{2} \times \frac{1}{2} = \frac{1}{8}$

(ii) Probability that all 3 are scientific
in which ^{only} one is Engg. $= 3 \times 0.4 \times 0.4 \times 0.1$

$$= \frac{3 \times 16}{1000}$$

eg:	urn-1	W 2	B 3
	urn-2	4	1
	urn-3	3	4

choose an urn at random and pick a ball from the urn at random. We found ball to be white. What is the probability that it is picked from urn-I?

Sol: $P(\text{Urn-I}/\text{White}) = \frac{P(\text{Urn-I} \cap \text{White})}{P(\text{White})}$

$$= \frac{\frac{1}{3} \times \frac{2}{5}}{\frac{1}{3} \left(\frac{2}{5} + \frac{4}{5} + \frac{3}{3} \right)} = \frac{\frac{2}{15}}{\frac{9}{5}} = \frac{2}{5} \times \frac{5}{9} = \frac{10}{45} = \frac{2}{9}$$

$$\therefore P(\text{Urn-I}/\text{White}) = \frac{2}{9}$$

eg: A, B throw alternatively a pair of dice.
A wins if he throws 6 before B throws 7.
B wins if he throws 7 before A throws 7
If A starts, s.t. the chance of winning (for A) is

Sol: $E_A \text{ throws } 6 = \frac{5}{36} \quad \begin{pmatrix} 1 & 5 \\ 5 & 1 \\ 3 & 3 \\ 2 & 4 \\ 4 & 2 \end{pmatrix}$

 $E_B \text{ throws } 7 = \frac{6}{36} \quad \begin{pmatrix} 1 & 6 \\ 6 & 1 \\ 2 & 5 \\ 5 & 2 \\ 3 & 6 \\ 4 & 3 \end{pmatrix}$
 $E_A^C = \frac{31}{36}$
 $E_B^C = \frac{30}{36}$
 $E_A, E_A^C E_B^C E_A, E_A^C E_B^C E_A^C E_B^C E_A, \dots$
 $\frac{5}{36} + \frac{31}{36} \times \frac{30}{36} \times \frac{5}{36} + \dots$
 $= \frac{30}{61} //$

e.g Given, $P(A) > P(B)$

Show that $P(A/B) > P(B/A)$

Sol:

$$\frac{P(A)}{P(A \cap B)} > \frac{P(B)}{P(A \cap B)} \Rightarrow \frac{1}{P(B/A)} > \frac{1}{P(A/B)}$$

$$\underline{P(A/B) > P(B/A)} \checkmark$$

e.g Train X arrives at a station at random during $(0, T)$ and stops there for ' a ' mins.

Train Y arrives independently during the same interval and stopping for ' b ' mins.

- (i) find probability that X arrives before Y
- (ii) find probability that trains meet.

Eg: An insurance company has equal no. of female and male drivers.

$P(\text{a male driver has an accident in a year}) = \alpha$
independent of other year

$P(\text{a female driver has an accident in a year}) = \beta$

(i) What is probability that selected driver will make a claim? $= \alpha + \beta$

Sol: $P(\text{accident}) = P(\text{accident}/M)P(M) + P(\text{accident}/F)P(F)$
 $= \alpha \cdot \frac{1}{2} + \beta \cdot \frac{1}{2} = \frac{\alpha + \beta}{2}$

(ii) $P(\text{selected driver make a claim in two consecutive years})$

Sol: $P(B) = P(B/M)P(M) + P(B/F)P(F)$
 $= \alpha^2 \cdot \frac{1}{2} + \beta^2 \cdot \frac{1}{2} = \frac{\alpha^2 + \beta^2}{2}$

(iii) Let A_1, A_2 be the events that a randomly chosen driver makes a claim in each of first and second year respectively.

Sol: $P(A_2 | A_1) = \frac{P(A_2 \cap A_1)}{P(A_1)} = \frac{\frac{\alpha^2 + \beta^2}{2}}{\frac{\alpha + \beta}{2}} = \frac{\alpha^2 + \beta^2}{\alpha + \beta}$

$$\begin{aligned} P(A_2 | A_1) - P(A_1) &= \frac{\alpha^2 + \beta^2}{\alpha + \beta} - \frac{\alpha + \beta}{2} \\ &= \frac{(\alpha - \beta)^2}{2(\alpha + \beta)} > 0 \end{aligned}$$

$P(A_2 | A_1) > P(A_1)$ ✓

$$(iv) P(F/C) = \frac{P(F \cap C)}{P(C)} = \frac{P(C/F) \cdot P(F)}{P(C)} \\ = \frac{\frac{B}{\alpha + B}}{\frac{1}{2}} = \frac{B}{\alpha + B} //$$

e.g. Test has 99% accuracy

~~eg.~~ Test has 5% false +ve reading.

$$P(\text{a person has the disease}) = \frac{1}{10,000}$$

One person tested positive (+ve) for the disease.

What is the probability that person has disease?

$$\underline{80\%} \quad P(D) = \frac{1}{10,000}$$

$$P(T \text{ is +ve } | D) = 0.99$$

$$P(T \text{ is +ve } | D^c) = 0.05$$

$$P(D | T \text{ is +ve}) = \frac{P(D \cap T \text{ is +ve})}{P(T \text{ is +ve})}$$

$$P(T \text{ is +ve}) = 0.99 \times \frac{1}{10000} + 0.05 \times \frac{9999}{10000} \\ = \frac{500.94}{10000}$$

$$\frac{P(T \text{ is +ve } | D) P(D)}{P(T \text{ is +ve })} = \frac{0.99 \times \frac{1}{10000}}{\frac{500.94}{10000}}$$

$$= \frac{99}{50094} \approx \underline{\underline{0.002}}$$

e.g. A_1, A_2, \dots, A_n events

$$P\left(\bigcup_{i=1}^n A_i^o\right) = \sum_{i=1}^n P(A_i^o) - \sum_{1 \leq i < j} P(A_i^o \cap A_j^o) \\ + \sum_{1 \leq i < j < k} P(A_i^o \cap A_j^o \cap A_k^o) \\ + \dots + (-1)^n P\left(\bigcap_{i=1}^n A_i^o\right)$$

Sol:-

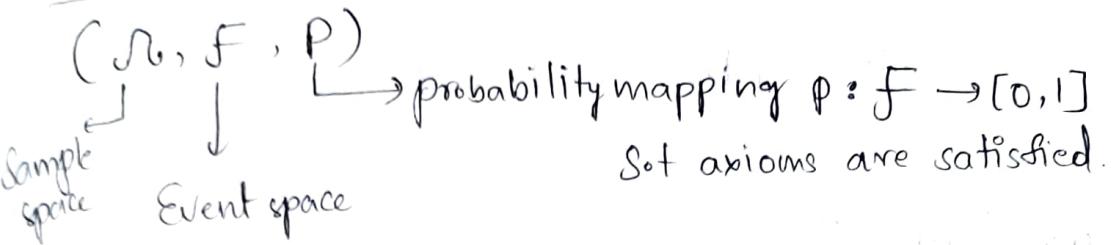
for $n=2 \rightarrow$ statement is true

True for l

for $l \rightarrow l+1$

$$P(A_1 \cup A_2 \cup A_3 \dots \cup A_{l+1}) = P(B) + P(A_{l+1}) \\ - P(B \cap A_{l+1})$$

Probability space:



→ If Ω is finite or countable and $A \in \mathcal{F}$, $\omega \in \Omega$

$$P(\{\omega\}) = P_\omega$$

$$\text{then } P(A) = \sum_{\omega \in A} P_\omega \quad (A = \bigcup_{\omega \in A} \{\omega\})$$

e.g. $\Omega = \{1, 2, 3, 4, 5, 6\}$

$$\text{let } A = \{2, 4, 6\}$$

$$P(A) = P_2 + P_4 + P_6$$

$$= \frac{1}{6} + \frac{1}{6} + \frac{1}{6} = \frac{3}{6} = \frac{1}{2}$$

$P(A) = \frac{1}{2}$

→ Ω : uncountable

$$\Omega = \mathbb{R}$$

$$A = (a, b); a, b \in \mathbb{R}, a < b$$

σ -algebra generated by open intervals

$$(i) \Omega \in \mathcal{F} \qquad (a, b)$$

$$(ii) A \in \mathcal{F} \Rightarrow A^c \in \mathcal{F}$$

$$(iii) A_1, A_2, \dots, A_n \in \mathcal{F} \text{ then } \bigcup_{i=1}^{\infty} A_i \in \mathcal{F}$$

$$\mathcal{F} = \{(a, b), (-\infty, a] \cup [b, \infty)\}$$

include countable unions}

↳ Borel σ -algebra of \mathbb{R}

can be generated by sets of form $(-\infty, c]$, $c \in \mathbb{R}$

$$(a, b) = \{(-\infty, a] \cup [b, \infty)\}^c$$

$$\{b\} = \bigcap_{n=1}^{\infty} \left(b - \frac{1}{n}, b + \frac{1}{n}\right)$$

Random Variables:

A random variable X is a mapping $\Omega \rightarrow \mathbb{R}$ ($X: \Omega \rightarrow \mathbb{R}$) such that

$$\{\omega \in \Omega, X(\omega) \leq c, c \in \mathbb{R}\} \in \mathcal{F}$$

$$X^{-1}((-\infty, c]) \in \mathcal{F}$$

Based on range of X , we classify random variables into

(i) Discrete:

If the range of X is finite or countable then the random variable X is called Discrete Random Variable.

e.g. $\Omega = \{1, 2, 3, 4, 5, 6\}$

$$X(i) = i, i = 1, 2, \dots, 6$$

(ii) Continuous:

→ If the range of X is continuous (Infinite) then X is called continuous Random Variable.

→ A random variable X is continuous if it's CDF $F_X(x)$ is continuous.

Cumulative Distribution function (CDF):

CDF of X is defined as

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

$$= P\{\omega \in \Omega : X(\omega) \leq x\}$$

→ If X is discrete

$$X \in \{x_1, x_2, \dots\}$$

$$P(X=x_i^o) = P\{\omega \in \Omega : X(\omega) = x_i^o\}$$

$$= p_i^o$$

$$P(X=x_i^o) = p_i^o$$

↳ Probability mass function (pmf)

$$P(X(-\infty, c]) = \sum_{x_i^o \leq c} p_i^o$$

Probability mass function (pmf):

$$P(X=x_i^o) = p_i^o \quad X \in \{x_1, x_2, \dots\}$$

(i) $p_i^o > 0$ for all i

(ii) $\sum_i p_i^o = 1$

Expectation or mean:

$$E(X) = \sum_i x_i^o p_i^o$$

(i) Bernoulli distribution

$$X = \begin{cases} 0 & \text{with probability } 1-p \\ 1 & \text{with probability } p \end{cases}$$

$$E[X] = 0(1-p) + 1(p)$$

$$= p$$

(ii) Binomial distribution

$X \in \{1, 2, 3, \dots, n\}$

$$P(X=k) = \binom{n}{k} p^k (1-p)^{n-k}$$

$$E[X] = \sum_{k=0}^n k \binom{n}{k} p^k (1-p)^{n-k}$$

$$= \sum_{k=0}^n k \cdot \frac{n!}{k!(n-k)!} p^k (1-p)^{n-k}$$

$$= \sum_{k=0}^n \frac{n!}{(k-1)!(n-k)!} p^k (1-p)^{n-k}$$

$$= np \sum_{k=0}^n \frac{(n-1)!}{(k-1)!(n-k)!} p^{k-1} (1-p)^{n-k}$$

= (1)

$$\therefore \underline{E[X] = np}$$

(iii) Poisson distribution:

$X = \{0, 1, 2, \dots\}$

λ is parameter of distribution

$$P(X=k) = \bar{e}^\lambda \frac{\lambda^k}{k!} \quad k=0, 1, 2, \dots$$

$$E[X] = \sum_{k=0}^{\infty} k P(X=k) = \sum_{k=1}^{\infty} k \cdot \bar{e}^\lambda \frac{\lambda^k}{k!}$$

$$= \lambda \cdot \sum_{k=1}^{\infty} \frac{\bar{e}^\lambda \cdot \lambda^{k-1}}{(k-1)!} = \lambda //$$

(iv) Geometric distribution:

$$X \in \{1, 2, 3, \dots\}$$

$$P(X=k) = p(1-p)^{k-1}$$

$$\mathbb{E}[X] = \sum_{k=1}^{\infty} k p (1-p)^{k-1}$$

$$= p \sum_{k=1}^{\infty} k (1-p)^{k-1}$$

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

$$\frac{q = 1-p}{\sum_{k=1}^{\infty} k \cdot q^{k-1}} = \sum_{k=0}^{\infty} \frac{d}{dq} [q^k]$$

$$= \frac{d}{dq} \left[\frac{1}{1-q} \right] = \frac{1}{(1-q)^2}$$

$$\sum_{k=1}^{\infty} k \cdot (1-p)^{k-1} = \frac{1}{(1-(1-p))^2}$$

• Continuous Random Variables:

CDF

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

$$x_1 \leq x_2$$

$$\{ \omega \in \Omega : X(\omega) \leq x_1 \} \subseteq \{ \omega \in \Omega : X(\omega) \leq x_2 \}$$

→ Properties:

$$(i) F_X(\infty) = 1, F_X(-\infty) = 0$$

$$\{ \omega : X(\omega) \leq \infty \} = \Omega$$

$$\{ \omega : X(\omega) \leq -\infty \} = \emptyset$$

$$(ii) \text{ If } x_1 \leq x_2$$

$$F_X(x_1) \leq F_X(x_2)$$

monotonically non-decreasing function.

(iii) The function $F_X(x)$ is continuous from the right

$$A_n = (-\infty, x + \frac{1}{n}]$$

$$A_1 \supseteq A_2 \supseteq A_3 \dots$$

$$\bigcap_{n=1}^{\infty} A_n = (-\infty, x] = A$$

$$\lim_{n \rightarrow \infty} P(A_n) = P(A)$$

$$\lim_{n \rightarrow \infty} F_X\left(x + \frac{1}{n}\right) = F_X(x)$$

$$P(x_1 < X \leq x_2) = F_X(x_2) - F_X(x_1)$$

$$X \in (x_1, x_2]$$

$$x_1 < X \leq x_2 = (-\infty, x_2] - (-\infty, x_1]$$

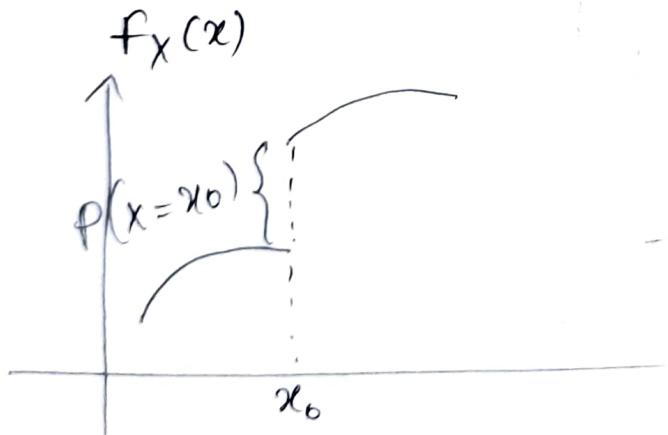
$$(iv) P(X=x) = f_X(x) - F_X(x^-)$$

$$f_X(x^-) = \lim_{\epsilon \rightarrow 0} f_X(x-\epsilon)$$

If X is continuous, $f_X(x)$ is continuous

$$f_X(x^-) = f_X(x)$$

$$\underline{P(X=x)=0} \quad f_X(x) \in [0,1]$$



$P(X=x_0)$ = The height of the jump.

◦ CDF of Discrete R.V:

$$x \in \{0, 1\}$$

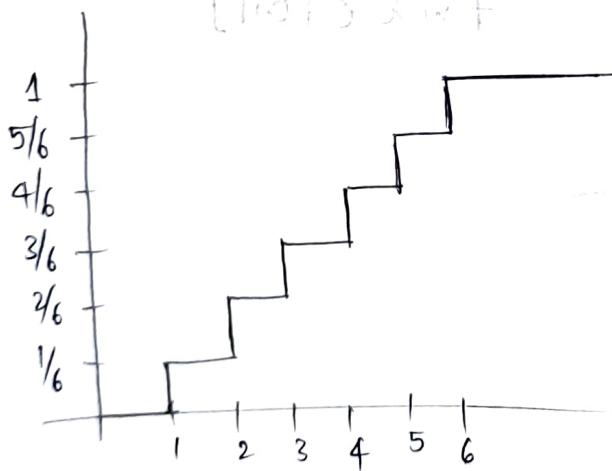
$$F(x) = \begin{cases} 0 & \text{w.p } 1-p \\ 1 & \text{w.p } p \end{cases}$$

→ Properties:

- (i) $F_X(\infty) = 1$, $F_X(-\infty) = 0$
- (ii) $F_X(x)$ is monotonically non-decreasing.
- (iii) $F_X(x)$ is right continuous.

$$X = \{1, 2, 3, 4, 5, 6\}$$

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



Probability density function (PDF):

The PDF of a random variable 'x' is a function $f_X(x)$ such that,

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

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

\Rightarrow

Properties:

(i) $f_X(x) \geq 0$

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

(iii) $P(x_1 < X \leq x_2) = F_X(x_2) - F_X(x_1)$

$$= \int_{-\infty}^{x_2} f_X(x) dx - \int_{-\infty}^{x_1} f_X(x) dx$$

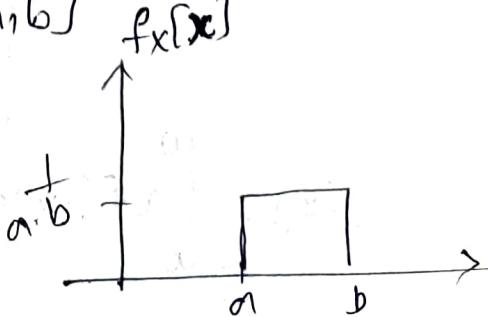
$$= \int_{x_1}^{x_2} f_X(x) dx$$

Expectation/mean of X:

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

e.g. (i) Uniform distribution $U[a, b]$

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



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

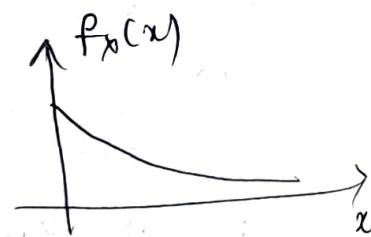
$$= \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \leq x \leq b \\ 1 & x > b \end{cases}$$

$$\mathbb{E}[x] = \frac{a+b}{2}$$

$$\begin{aligned} \int_a^b \frac{x}{b-a} dx &= \frac{b^2 - a^2}{2(b-a)} \\ &= \frac{b+a}{2} // \end{aligned}$$

(ii) Exponential distribution:

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x} & x > 0 \\ 0 & \text{otherwise} \end{cases}$$



λ -parameter of distribution.

$$\begin{aligned} \int_{-\infty}^{\infty} f_X(x) dx &= \int_{-\infty}^{0} 0 dx + \int_{0}^{\infty} \lambda e^{-\lambda x} dx \\ &= \left[\frac{x e^{-\lambda x}}{-\lambda} \right]_{0}^{\infty} = \frac{-\lambda x}{e} \Big|_0^{\infty} \\ &= 1 // \end{aligned}$$

$$f_X(x) = \begin{cases} 0 & x < 0 \\ 1 - e^{-\lambda x} & x \geq 0 \end{cases}$$

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

$$\mathbb{E}[X] = \lambda \left\{ \frac{x e^{\lambda x}}{-\lambda} \Big|_0 - \frac{e^{\lambda x}}{\lambda^2} \Big|_0 \right\} = \frac{1}{\lambda}$$

$$= -\lambda x \Big[\frac{1}{\lambda} + \frac{1}{\lambda^2} \Big]$$

(iii) Gaussian or Normal distribution: $\mu \rightarrow \text{mean.}$

$$(\mu, \sigma^2)$$

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



If, $\mu = 0, \sigma^2 = 1 \rightarrow \text{standard normal distribution}$

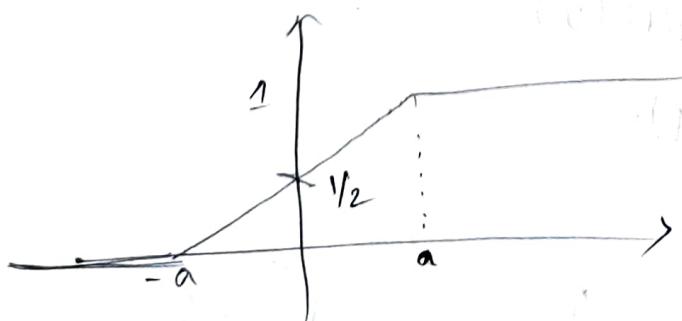
$$f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}$$

Problems:

1. $f_X(x) = \begin{cases} 0 & x < -a \\ \frac{1}{2} \left(\frac{x}{a} + 1 \right) & -a \leq x \leq a \\ 1 & x > a \end{cases}$

Verify that $f_X(x)$ is a valid CDF or not?

Sol: $f_X(\infty) = 1 \quad f_X(-\infty) =$



2.

$$f(x) = \begin{cases} x & 0 < x \leq 1 \\ 2-x & 1 < x \leq 2 \\ 0 & x > 2 \end{cases}$$

find it's CDF?

Sol:

$$F_x(x) = \int_{-\infty}^x f_x(t) dt$$

$$f_x(x) = 0 \text{ for } x \leq 0$$

$$x \in (0, 1] \quad F_x(x) = \int_{-\infty}^x x dt = \frac{x^2}{2}$$

$$1 < x \leq 2 \quad F_x(x) = \int_0^1 t dt + \int_1^x (2-t) dt$$

$$= \frac{1}{2} + \left(2t - \frac{t^2}{2} \right) \Big|_0^x$$

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

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

$$F_x(x) = 0 \text{ for } x > 2$$

3. A continuous r.v. X has the pdf

$$f_x(x) = k(1+x), \quad 2 \leq x \leq 5$$

find $P(X \leq 4)$.

Sol:

$$\int_2^5 k(1+x) dx = 1$$

$$k \left[x + \frac{x^2}{2} \right]_2^5 = 1$$

$$k \left[5 + \frac{25}{2} - (2+2) \right] = 1$$

$$k = 2/27$$

$$P(X \leq 4) = \int_{-\infty}^4 f_X(x) dx = P(X \leq 4)$$

$P(X = 4) = 0$ if X is a continuous random variable.

$$P(X = a) = F_X(a) - F_X(a^-) = 0 //$$

$$\rightarrow P(X < 4) = \int_{-\infty}^4 f_X(x) dx = \int_{-\infty}^4 \frac{2}{27}(1+x) dx$$

$$= \frac{2}{27} \left(x + \frac{x^2}{2} \right) \Big|_0^4$$

$$= \frac{2}{27} (4 + 8 - (0 + 0)) = \underline{\underline{\frac{16}{27}}}$$

$$= \underline{\underline{\frac{16}{27}}} //$$

	x	-2	-1	0	1	2	3
	$P(x)$	0.1	k	0.2	$2k$	0.3	$8k$

$$\text{find } P(X < 2), P(-2 < X < 2)$$

$$P(x) = 1 = 0.6 + 6k$$

$$0.4 = 6k \rightarrow \boxed{k = \frac{1}{15}}$$

$$P(X < 2) = 0.5 //$$

$$P(-2 < X < 2) = 0.4 //$$

$$\text{Mean} = 1.07 = \underline{x P(x)}$$

5. A telephone call occurs at random in interval $[0, T]$.

$$P(t_1 \leq t \leq t_2) = \frac{t_2 - t_1}{T}$$

Define $X = t$ the time at which call occurs,
find CDF of X .

Sol: $f_X(x) = P(X \leq x) = \frac{x}{T}, x \leq T$

$$f_X(x) = 1, x > T$$

6. $f(x) = C e^{-\delta|x|}$, find C such that $f(x)$ is a valid pdf.

Sol: $\int_{-\infty}^{\infty} f(x) dx = 1$

$$\int_{-\infty}^0 C e^{\delta(x)} dx + \int_0^{\infty} C e^{-\delta x} dx$$

$$C \left(\frac{e^{\delta x}}{\delta} \right) \Big|_{-\infty}^0 + C \left(\frac{-e^{-\delta x}}{\delta} \right) \Big|_0^{\infty}$$

$$C \left(\frac{1}{\delta} - 0 \right) + C \left(0 + \frac{1}{\delta} \right) = \left(\frac{2C}{\delta} \right) = 1$$

$$\boxed{C = \frac{\delta}{2}}$$

$f(x) = \frac{D}{x^2 + 1}$ find D s.t. $f(x)$ is a valid pdf

sol

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

$$D \times \left[\frac{1}{6} \tan^{-1}\left(\frac{x}{6}\right) \right]_{-\infty}^{+\infty} = 1$$

$$\frac{D}{6} \left[\frac{\pi}{2} + \left(\frac{-\pi}{2} \right) \right] = 1$$

$$\boxed{D = 6/\pi}$$

Variance:

$$\text{Var}(x) = E[(x-\mu)^2] = \int_{-\infty}^{\infty} (x-\mu)^2 f(x) dx$$

\downarrow

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

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

μ, σ^2 are parameters
 $\downarrow \quad \downarrow$
mean variance $\left[\begin{array}{l} (\frac{\partial}{\partial \mu}) \text{ Not } L \times A \\ (\frac{\partial}{\partial \sigma^2}) \end{array} \right]$

$$\int_{-\infty}^{\infty} f_X(x) dx = 1 = \left[-\frac{(x-\mu)^2}{2\sigma^2} \right]_0^{\infty}$$

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

$$\left[\begin{array}{l} \frac{x-\mu}{\sigma} = t \\ dt = \frac{dx}{\sigma} \end{array} \right] \int_{-\infty}^{\infty} e^{-t^2/2} dt = (x)_{\text{std}}$$

$$S = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt$$

$$S = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx \quad S = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-y^2/2} dy$$

$$S^2 = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{2\pi} e^{-\frac{(x^2+y^2)}{2}} dx dy$$

$$x = r \cos \theta$$

$$y = r \sin \theta$$

$$dx dy = |J| dr d\theta$$

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

$$S^2 = \int_0^{2\pi} \int_0^\infty \frac{1}{2\pi} e^{-r^2/2} r dr d\theta$$

$$= \left(\int_0^{2\pi} d\theta \right) \left(\int_0^\infty \frac{1}{2\pi} e^{-r^2/2} r dr \right)$$

$$= 2\pi \times \frac{1}{2\pi} \int_0^\infty e^{-r^2/2} r dr$$

$$S^2 = \int_0^\infty e^{-r^2/2} r dr = \int_0^\infty e^{-t} dt = e^{-t} \Big|_0^\infty = 0 - (-1)$$

$\left(\frac{r^2}{2} = t \Rightarrow r dr = dt \right) = 1/2$

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} x f_x(x) dx = \int_{-\infty}^{\infty} \frac{x}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

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

$$= \int_{-\infty}^{\infty} \frac{t}{\sqrt{2\pi\sigma^2}} e^{-\frac{t^2}{2\sigma^2}} + \downarrow \mu$$

• Conditional distribution:

$A, B, P(B) \neq 0$

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

$A : \{\omega \in \Omega : X(\omega) \leq x\}$

$$f_X(x|B) = P(X \leq x|B) = \frac{P(X \leq x \cap B)}{P(B)}$$

$$(i) 0 \leq f_X(x|B) \leq 1$$

$$(ii) f_X(x^+|B) = f_X(x|B)$$

$$(iii) f_X(x_1|B) \leq f_X(x_2|B), x_1 < x_2$$

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

$B = \{X \leq b\}$

$$f_X(x|B) = \frac{P(X \leq x \cap X \leq b)}{P(X \leq b)}$$

$$f_X(x|B) = \begin{cases} \frac{F_X(x)}{F_X(b)} & x < b \\ 1 & x \geq b \end{cases}$$

$$f_X(x|B) = \begin{cases} \frac{f_X(x)}{\int_{-\infty}^b f_X(x) dx} & x < b \\ 0 & x \geq b \end{cases}$$

$$B = \{ b_1 < x \leq b_2 \}$$

$$f_X(x|B) = \frac{P(\{x \leq x\} \cap \{b_1 < x \leq b_2\})}{P(B)}$$

$$= \begin{cases} \frac{F_X(x) - F_X(b_1)}{F_X(b_2) - F_X(b_1)} & b_1 < x < b_2 \\ 0 & x < b_1 \\ 1 & x > b_2 \end{cases}$$

$$f_X(x|B) = \begin{cases} \frac{f_X(x)}{f_X(b_2) - f_X(b_1)} & b_1 < x < b_2 \\ 0 & \text{otherwise.} \end{cases}$$

• Memoryless property:

$$P(X > m+t | X > t) = P(X > m)$$

(i) Exponential distribution:

$$f_X(x) = \lambda e^{-\lambda x}, x \geq 0$$

$$F_X(x) = \begin{cases} 1 - e^{-\lambda x}, & x \geq 0 \\ 0 & \text{otherwise.} \end{cases}$$

$$\begin{aligned} P(X > t) &= 1 - P(X \leq t) \\ &= e^{-\lambda t} \end{aligned}$$

$$\frac{P(X > m+t)}{P(X > t)} = \frac{P(X > m+t \cap X > t)}{P(X > t)}$$

$$= \frac{P(X > m+t)}{P(X > t)}$$

$$\begin{aligned} P(X > m+t | X > t) &= \frac{e^{-\lambda(m+t)}}{e^{-\lambda t}} = e^{-\lambda m} \\ &= P(X > m) \end{aligned}$$

(ii) Geometric distribution:

$$P(X = i) = p(1-p)^{i-1} \quad i = 1, 2, \dots$$

$$P(X > n) = \sum_{i=n+1}^{\infty} p(1-p)^{i-1}$$

$$= p(1-p)^n + p(1-p)^{n+1} + \dots$$

$$= p(1-p)^n [1 + (1-p) + (1-p)^2 + \dots]$$

$$= p(1-p)^n \times \frac{1}{1 - (1-p)}$$

$$\therefore P(X > n) = \frac{p(1-p)^n}{p} = (1-p)^n$$

$$\therefore P(X > m+n) = (1-p)^{m+n}$$

$$\begin{aligned} P(X > m+n | X > n) &= \frac{P(X > m+n)}{P(n)} \\ &= \frac{(1-p)^{m+n}}{(1-p)^n} \\ &= (1-p)^m \end{aligned}$$

$$\boxed{\therefore P(X > m+n | X > n) = P(X > m)}$$

$$f_x(x|A)$$

Let A_1, A_2, \dots, A_n be partitions of Ω

$$\bigcup_{i=1}^n A_i = \Omega, \quad A_i \cap A_j = \emptyset, \quad i \neq j$$

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

$$= P(X \leq x | A_1) P(A_1) + \dots + (P(X \leq x | A_n) P(A_n))$$

$$f_x(x) = f_x(x | A_1) P(A_1) + \dots + f_x(x | A_n) P(A_n)$$

$$\underline{f_x(x) = f_x(x | A_1) P(A_1) + \dots + f_x(x | A_n) P(A_n)}$$

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

$$P(A | X=x) = \lim_{\Delta \rightarrow 0} P(A | x \leq X \leq x+\Delta)$$

$$= \lim_{\Delta \rightarrow 0} \frac{P(x \leq X \leq x+\Delta | A) P(A)}{P(x \leq X \leq x+\Delta)}$$

$$= \lim_{\Delta \rightarrow 0} \frac{(F_X(x+\Delta | A) - F_X(x | A)) P(A)}{\left(\frac{f_X(x+\Delta) - f_X(x)}{\Delta} \right)}$$

$$P(A | X=x) = \frac{f_x(x | A)}{f_x(x)} P(A)$$

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

$$\int_{-\infty}^{\infty} P(A | X=x) f_x(x) dx = \int_{-\infty}^{\infty} f_x(x | A) P(A) dx \\ = P(A)$$

$$f_x(x | A) = \frac{P(A | X=x) f_x(x)}{\int_{-\infty}^{\infty} P(A | X=x) f_x(x) dx}$$

Baye's Rule

Asymptotic Approximations:

Eg: A fair coin tossed 1000 times. Find

- probability that heads will show 500 times
- probability that heads will show 510 times

Solt $P(\text{Head}) = P(\text{Tail}) = \frac{1}{2}$

$$\left. \begin{array}{l} \text{(i)} \quad 1000 \times {}_{500}^C \left(\frac{1}{2}\right)^{500} \left(\frac{1}{2}\right)^{500} \\ \text{(ii)} \quad 1000 \times {}_{510}^C \left(\frac{1}{2}\right)^{510} \left(\frac{1}{2}\right)^{490} \end{array} \right\} \text{Binomial Distribution.}$$

De Moivre-Laplace Theorem (Normal Approx):

If k is in the \sqrt{npq} neighborhood of np

then, $\binom{n}{k} p^k q^{n-k} \approx \frac{1}{\sqrt{2\pi npq}} e^{-\frac{(k-np)^2}{2npq}}$, $p+q=1$

$$\xrightarrow{\lambda} \frac{np - \sqrt{npq}}{\sqrt{npq}} \quad \lambda \quad \frac{np + \sqrt{npq}}{\sqrt{npq}}$$

⇒ For the above example problem,

$$\text{(i)} \quad \binom{1000}{500} \left(\frac{1}{2}\right)^{500} \left(\frac{1}{2}\right)^{500} \approx \frac{1}{\sqrt{2\pi \times 1000 \times \frac{1}{2} \times \frac{1}{2}}} e^{-\frac{(500-500)^2}{2 \times 1000 \times \frac{1}{2} \times \frac{1}{2}}}$$

$$\sqrt{npq} = \sqrt{1000 \times \frac{1}{2} \times \frac{1}{2}} \approx 15$$

$$\approx \frac{1}{\sqrt{\pi} \times 500}$$

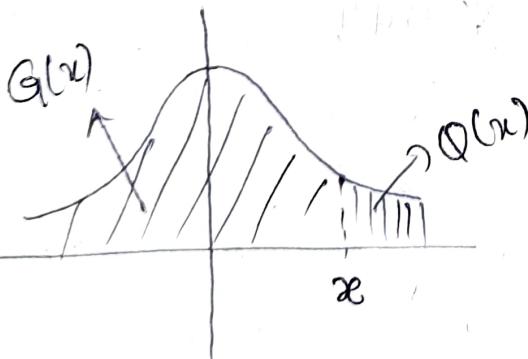
k lies in

$$(485, 515)$$

$$\begin{aligned}
 \text{(ii)} & \left(\frac{1000}{510} \right) \left(\frac{1}{2} \right)^{510} \left(\frac{1}{2} \right)^{490} \approx \frac{1}{\sqrt{2\pi \times 1000 \times \frac{1}{2} \times \frac{1}{2}}} e^{-\frac{(510-500)^2}{2 \times 1000 \times \frac{1}{2} \times \frac{1}{2}}} \\
 & \approx \frac{1}{\sqrt{\pi \times 500}} e^{-\frac{100}{500}} \\
 & \approx \frac{1}{\sqrt{\pi \times 500}} e^{-0.2}
 \end{aligned}$$

$$\begin{aligned}
 P(K_1 \leq X \leq K_2) &= \sum_{k=k_1}^{k_2} \binom{n}{k} p^k q^{n-k} \\
 &\approx \int_{K_1}^{K_2} \frac{1}{\sqrt{2\pi npq}} e^{-\frac{(x-np)^2}{2npq}} dx
 \end{aligned}$$

$$\Rightarrow \text{Error function: } \operatorname{erf}(x) = \frac{1}{\sqrt{2\pi}} \int_0^x e^{-y^2/2} dy$$



density of standard
 or normal function
 $(\mu=0, \sigma^2=1)$

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-y^2/2} dy \quad G(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-y^2/2} dy$$

$$\text{(I)} \quad Q(x) + G(x) = 1$$

$$\text{(II)} \quad \operatorname{erf}(x) = G(x) - \frac{1}{2}$$

$$\text{(III)} \quad G(-x) = 1 - G(x)$$

Eg: A fair coin is tossed 10,000 times. What is the probability that the no. of heads is in b/w 4900 and 5100?

Sol:-

$$n = 10000 \quad k_1 = 4900 \quad k_2 = 5100$$

$$p = q = \frac{1}{2} \quad np = 5000 \quad \sqrt{npq} = \sqrt{2500} = \underline{\underline{50}}$$

$$npq > 1$$

$$x_1 = -2 \quad x_2 = 2$$

$$\begin{aligned} P(k_1 \leq x \leq k_2) &\approx G(2) - G(-2) \\ &= 2G(2) - 1 \\ &= \underline{\underline{0.9545}} \end{aligned}$$

(*) $x_1 = \frac{k_1 - np}{\sqrt{npq}} \quad x_2 = \frac{k_2 - np}{\sqrt{npq}}$

$$P(k_1 \leq x \leq k_2) \approx G(x_2) - G(x_1)$$

Poisson Approximation:

eg: A system contains 1000 components. Each component fails independently of the others and the probability of its failure in one month 10^{-3} . What is the probability that the system will function at the end of one month?

Sol: $k = \text{no. of components failed in one month}$

$$\begin{aligned} P(k=0) &= \binom{1000}{0} p^0 (1-p)^{1000} \quad \lambda = np = 1 \\ &= (0.999)^{1000} \quad P(k=0) \approx \bar{e}^1 \cdot \frac{1^0}{0!} \\ &= \bar{e}^1 \\ &= 0.367 \end{aligned}$$

Poisson theorem:

$n \rightarrow \infty, p \rightarrow 0$ such that $np \rightarrow \lambda$

then $\binom{n}{k} p^k (1-p)^{n-k} \xrightarrow[n \rightarrow \infty]{p \rightarrow 0} e^{-\lambda} \cdot \frac{\lambda^k}{k!}$

$k = 0, 1, 2, \dots$

Proof:

$$= \frac{n!}{(n-k)! (k!)} p^k (1-p)^{n-k}$$

$$= \frac{n(n-1) \dots (n-(k-1))}{(n-k)!} \cancel{(n-k)!} \quad p^k (1-p)^{n-k}$$

$$= \frac{n(n-1) \dots (n-k+1)}{n^k} \cdot \frac{(np)^k}{k!} \left(1 - \frac{np}{n}\right)^{n-k}$$

$$= \frac{\cancel{(1-\frac{1}{n})(1-\frac{2}{n}) \dots (1-\frac{k-1}{n})}}{\cancel{(1-\frac{\lambda}{n})^k}} \cdot \frac{\lambda^k}{k!} \left(1 - \frac{\lambda}{n}\right)^n$$

$$= \frac{\lambda^k}{k!} \cdot \bar{e}^\lambda //$$

Eg: An order of 8000 parts is received. The probability that a part is defective equals 10^{-3} . What is the probability that more than 5 parts are defective.

Solt:

$$P(K > 5) = 1 - P(K \leq 5)$$

$$= 1 - \sum_{K=0}^{5} \binom{3000}{K} (P)^K (1-P)^{8000-K}$$

$$P(K > 5) = 1 - \sum_{K=0}^{5} \binom{3000}{K} (10^{-3})^K (0.999)^{3000-K}$$

$$(\lambda = np = 3000 \times 10^{-3} = 3)$$

$$P(K > 5) = 1 - \sum_{K=0}^{5} \frac{3^K}{K!} e^{-3}$$

$$= 1 - e^{-3} \left[\frac{3^0}{0!} + \frac{3^1}{1!} + \frac{3^2}{2!} + \frac{3^3}{3!} + \frac{3^4}{4!} + \frac{3^5}{5!} \right]$$

$$= 1 - e^{-3} \left[1 + 3 + 4.5 + 4.5 + 3.375 + 2.025 \right]$$

$$= 1 - e^{-3} [18.4]$$

$$= 1 - 0.916$$

$$\therefore P(K > 5) = \underline{\underline{0.084}}$$

e.g. An insurance company has issued policies to 1,00,000 people for a premium of \$500/person. In the event of causality, the probability of which is assumed to be 0.001, the company pays \$200,000/causality.

(a) What is the probability that company will suffer a loss?

$$K > \frac{250}{\cancel{500} \times 1,00,000} \Rightarrow K > 250$$

↓
Company suffers loss.

$$P(K > 250) = \sum_{K=250}^{1,00,000} \binom{100000}{K} p^K (1-p)^{n-K}$$

$$\left(\lambda = np = 10^5 \times 10^{-3} \right)$$

$$\lambda = 10^2$$

$$P(K > 250) = \sum_{K=250}^{1,00,000} e^{-\lambda} \cdot \frac{\lambda^K}{K!}$$

$$\frac{n=250}{\lambda=100} \quad \Delta = \frac{\lambda}{n} e^{1-\frac{\lambda}{n}}$$

$$= \frac{100}{250} e^{1-\frac{100}{250}}$$

$$(A) \underset{250}{\approx} 0$$

$$\Delta = 0.4 e^{0.6} = 0.7288$$

Because the upper bound and lower bound of $P(K > n)$ are close to zero

$$\underline{P(K > 250) \approx 0}$$

$$\frac{\bar{e}^\lambda \cdot \lambda^n}{n!} < \sum_{k=n}^{\infty} \frac{\bar{e}^\lambda \cdot \lambda^k}{k!}$$

$$= \bar{e}^\lambda \cdot \left[\frac{\lambda^n}{n!} + \frac{\lambda^{n+1}}{(n+1)!} + \dots \right]$$

$$= \bar{e}^\lambda \cdot \frac{\lambda^n}{n!} \left[1 + \frac{\lambda}{n+1} + \frac{\lambda^2}{(n+1)(n+2)} + \dots \right]$$

$$= \bar{e}^\lambda \cdot \frac{\lambda^n}{n!} \left[1 + \frac{\lambda}{n+1} + \frac{\lambda^2}{(n+1)^2} + \frac{\lambda^3}{(n+1)^3} + \dots \right]$$

$$= \bar{e}^\lambda \cdot \frac{\lambda^n}{n!} \left[\frac{1}{1 - \frac{\lambda}{n+1}} \right]$$

$$\boxed{\frac{\bar{e}^\lambda \cdot \lambda^n}{n!} < p(k \geq n) < \frac{\bar{e}^\lambda \cdot \lambda^n}{n!} \left[\frac{1}{1 - \frac{\lambda}{n+1}} \right]}$$

Stirling's formula:

$$n! = \sqrt{2\pi n} \cdot n^n \cdot e^{-n}$$

Substituting $n!$ value in above equation,

$$\frac{\bar{e}^\lambda \cdot \lambda^n}{\sqrt{2\pi n} \cdot n^n \cdot e^{-n}} < p(k \geq n) < \frac{\bar{e}^\lambda \cdot \lambda^n}{\sqrt{2\pi n} \cdot n^n \cdot e^{-n}} \left(\frac{1}{1 - \frac{\lambda}{n+1}} \right)$$

$$\left(\frac{\lambda}{n}\right)^n \cdot \frac{e^{n-\lambda}}{\sqrt{2\pi n}} < P(K \geq n) < \frac{e^\lambda \cdot \lambda^n}{\sqrt{2\pi n} \cdot n^n \cdot e^n} \left(\frac{1}{1 - \frac{\lambda}{n+1}}\right)$$

$$\left(\frac{\lambda}{n}\right)^n \cdot \frac{\left(\frac{1-\lambda}{n}\right)^n}{\sqrt{2\pi n}} < P(K \geq n) < \left(\frac{\lambda}{n}\right)^n \cdot \frac{\left(\frac{1-\lambda}{n}\right)^n}{\sqrt{2\pi n}} \left(\frac{1}{1 - \frac{\lambda}{n+1}}\right)$$

$\rightarrow \Delta = \frac{1}{n} e^{\frac{1-\lambda}{n}}$ with this def of Δ , we can write the above inequality as ,

$$\frac{\Delta^n}{\sqrt{2\pi n}} < P(K \geq n) < \frac{\Delta^n}{\sqrt{2\pi n}} \left(\frac{1}{1 - \frac{\lambda}{n+1}}\right)$$

functions of One Random Variable:

Let X be a continuous random variable with CDF $F_X(x)$.

$g(x)$ be real valued function $g: \mathbb{R} \rightarrow \mathbb{R}$

$X: \Omega \rightarrow \mathbb{R}$ range of X . ($R(X) \subseteq \mathbb{R}$)

Let $Y = g(X)$

$Y: \Omega \rightarrow \mathbb{R} \mid Y(\omega) = g(X(\omega))$

Y is a random variable if

$$\{ \omega \in \Omega : Y(\omega) \leq y \} \in \mathcal{F}, \forall y \in \mathbb{R}$$

CDF of Y , $F_Y(y) = P(Y \leq y) = P(g(X) \leq y)$

If $g(\cdot)$ is a Borel function (measurable function)

then Y is a random variable - continuous function

→ We need to find $F_Y(y)$ in terms of F_X , $g(\cdot)$

$$F_Y(y) = P(Y \leq y) = P(g(X) \leq y)$$

$$\downarrow \quad \quad \quad \{ \omega \in \Omega : g(X(\omega)) \leq y \}$$

$$g(X) \leq y$$

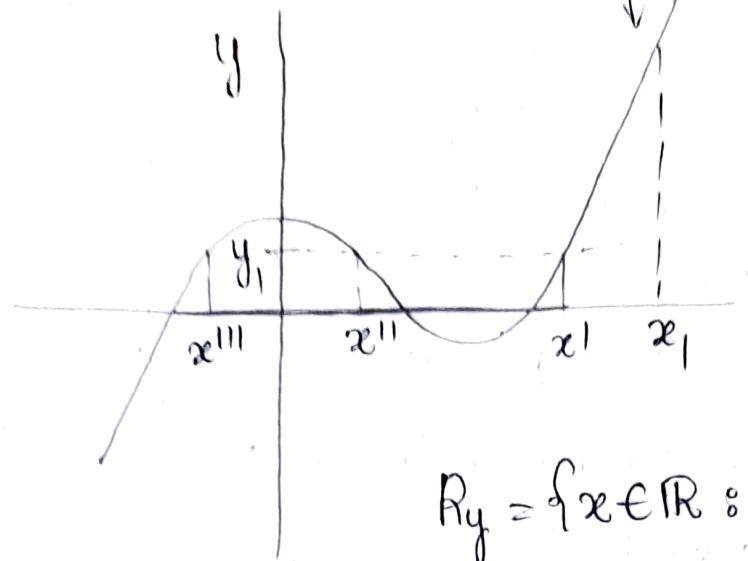
$$R_y = \{ x \in \mathbb{R} : g(x) \leq y \}$$

$$f_Y(y) = P_X(R_y)$$

$$P\{ \omega \in \Omega : X(\omega) \in R_y \}$$

using CDF of X .

eq:



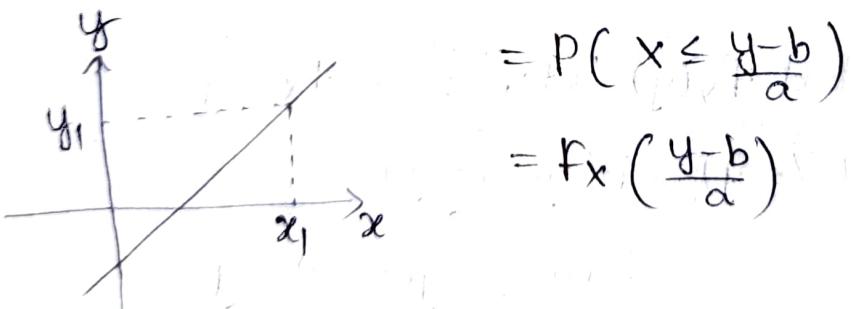
$$R_{y_1} = \{x \in \mathbb{R} : x \leq x_1\}$$

$$R_{y_1} = \{x'' \leq x \leq x'\} \cup \{x \leq x'''\}$$

$$\begin{aligned} f_y(y_1) &= P(R_{y_1}) = P(x'' \leq x \leq x') + P(x \leq x''') \\ &= f_x(x') - f_x(x'') + F_x(x''') \end{aligned}$$

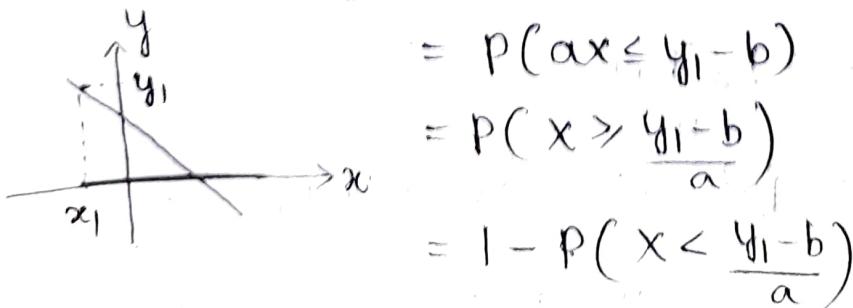
eq: (i) $a > 0$

$$P(ax+b \leq y) = P(ax \leq y-b)$$



(ii) $a < 0$

$$P(Y \leq y_1) = P(ax+b \leq y_1)$$



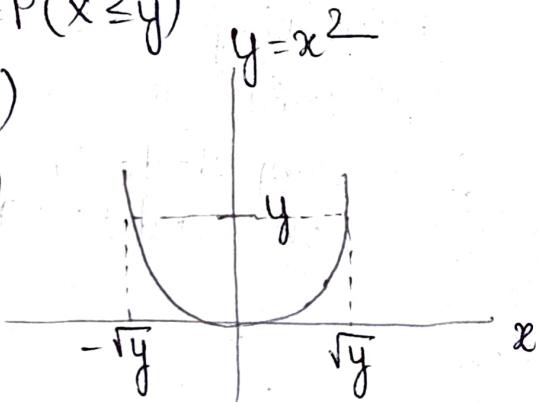
$$f_y(y) = \begin{cases} f_x\left(\frac{y-b}{a}\right), & a > 0 \\ 1 - f_x\left(\frac{y-b}{a}\right), & a < 0 \end{cases}$$

$$\boxed{f_x(x) = \frac{1}{|a|} f_x\left(\frac{y-b}{a}\right)} \rightarrow \text{PDF expression}$$

e.g.: $g(x) = x^2$, $Y = X^2$

$$\begin{aligned} f_y(y) &= P(Y \leq y) = P(X^2 \leq y) \\ &= P(-\sqrt{y} \leq X \leq \sqrt{y}) \end{aligned}$$

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

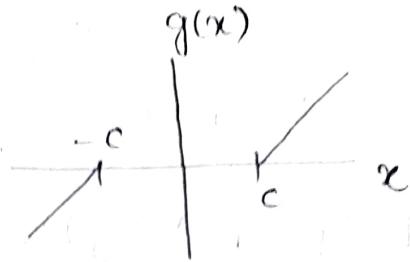


$$f_y(y) = \begin{cases} f_x(\sqrt{y}) - f_x(-\sqrt{y}), & y \geq 0 \\ 0, & y < 0 \end{cases}$$

$$f_y(y) = \frac{1}{2\sqrt{y}} f_x(\sqrt{y}) + \frac{1}{2\sqrt{y}} f_x(-\sqrt{y}), \quad y > 0$$

eg: $g(x) = \begin{cases} x - c & , x > c \\ 0 & , -c < x < c \\ x + c & , x < -c \end{cases}$

$$Y = g(X)$$



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

$$\begin{aligned} y > 0, \quad f_Y(y) &= P(-c \leq X \leq c) \cup P(X + c \leq y) \\ &= f_X(c) - f_X(-c) + f_X(y - c) \end{aligned}$$

$$\begin{aligned} y > 0, \quad f_Y(y) &= P(X - c \leq y) \\ &= P(X \leq y + c) \\ &= f_X(y + c) \end{aligned}$$

$$\begin{aligned} y < 0, \quad f_Y(y) &= P(X + c \leq y) \\ &= P(X \leq y - c) \\ &= f_X(y - c) \end{aligned}$$

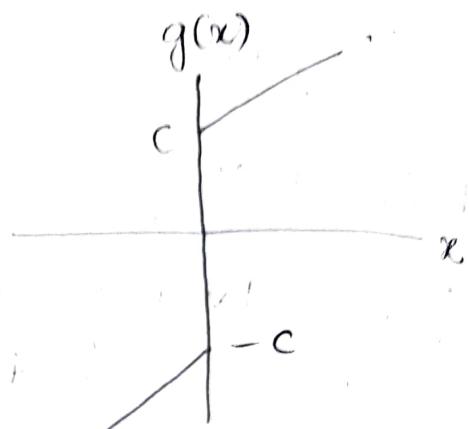
$$f_Y(y) = \begin{cases} f_X(y + c) & , y > 0 \\ f_X(c) - f_X(-c) \\ + f_X(y - c) & , y = 0 \\ f_X(y - c) & , y < 0 \end{cases}$$

Eg:

$$g(x) = \begin{cases} x+c & , x \geq 0 \\ x-c & , x < 0 \end{cases}$$

$$Y = g(X)$$

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



$$y \in (-c, c), f_Y(y) = P(Y \leq y)$$

$$= P(X - c \leq y)$$

$$g(x) \leq y, x \leq 0$$

$$P(Y \leq y) = P(X \leq 0) = F_X(0)$$

$$y > c, g(x) \leq y$$

$$f_Y(y) = P(Y \leq y) = P(X + c \leq y)$$

$$= P(X \leq y - c)$$

$$= F_X(y - c)$$

$$y \leq -c, g(x) \leq y$$

$$f_Y(y) = P(Y \leq y) = P(X - c \leq y)$$

$$= P(X \leq y + c)$$

$$= F_X(y + c)$$

Fundamental Theorem :- $y = g(x)$

To find $f_y(y)$ for a specific y , solve the equation $y = g(x)$,

Let $x_1, x_2, x_3, \dots, x_n$ be the real roots of $y = g(x)$.

Then, PDF is given by,

$$\frac{f_y(y)}{\text{(PDF)}} = \frac{f_x(x_1)}{|g'(x_1)|} + \frac{f_x(x_2)}{|g'(x_2)|} + \dots + \frac{f_x(x_n)}{|g'(x_n)|},$$

$g'(x)$ is the derivative of $g(x)$

eg: $y = x^2$

$$x_1 = \sqrt{y} \quad g'(x) = 2x$$

$$x_2 = -\sqrt{y}$$

$$\begin{aligned} f_y(y) &= \frac{f_x(x_1)}{|g'(x_1)|} + \frac{f_x(x_2)}{|g'(x_2)|} \\ &= \frac{f_x(\sqrt{y})}{2\sqrt{y}} + \frac{f_x(-\sqrt{y})}{2\sqrt{y}} \end{aligned}$$

$$f_y(y) = \frac{1}{2\sqrt{y}} (f_x(\sqrt{y}) + f_x(-\sqrt{y}))$$

$$\text{eg: } Y = \frac{1}{X} , g(x) = \frac{1}{x} , g'(x) = -\frac{1}{x^2}$$

$$Y = g(x) \Rightarrow x_1 = \frac{1}{y}$$

$$f_Y(y) = \frac{f_X(x_1)}{|g'(x_1)|}$$

$$f_Y(y) = \frac{f_X(1/y)}{\left(-\frac{1}{y^2}\right)_{|x_1=1/y}}$$

$$f_Y(y) = \frac{1}{y^2} f_X(1/y)$$

$$f_X(x) = \frac{\alpha/\kappa}{x^2 + \alpha^2} ; \text{ cauchy density with parameter } \alpha$$

$$(Y = 1/x) \quad f_Y(y) = \frac{\alpha/\kappa}{1 + \alpha^2 y^2} = \frac{1/\alpha \kappa}{y^2 + 1/\alpha^2} ; \text{ cauchy density with parameter } 1/\alpha$$

$$\rightarrow f_Y(y) = \frac{1}{y^2} \left[\frac{\alpha/\kappa}{1/y^2 + \alpha^2} \right] \\ = \frac{1}{y^2} \left[\frac{\alpha/\kappa \times y^2}{1 + \alpha^2 y^2} \right]$$

$$f_Y(y) = \frac{\alpha/\kappa}{1 + \alpha^2 y^2}$$

$$\text{eg: } Y = \sqrt{X}, g(x) = \sqrt{x} \quad g'(x) = \frac{1}{2\sqrt{x}}$$

$$Y = g(x) \Rightarrow x_1 = y^2$$

$$y > 0, f_Y(y) = \frac{f_X(x_1)}{|g'(x_1)|}$$

$$= \frac{f_X(y^2)}{\left| \frac{1}{2y} \right|}, \quad U(x) = \begin{cases} 1, & x > 0 \\ 0, & x \leq 0 \end{cases}$$

$$f_Y(y) = 2y f_X(y^2) U(y)$$

• Chi-square density: n-degrees of freedom,

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

$$Y = \sqrt{X}$$

$$\Gamma(\alpha) = \int_0^\infty t^{\alpha-1} e^{-t} dt$$

$$f_Y(y) = 2y f_X(y^2) U(y)$$

$$= 2y \cdot \frac{1}{2^{n/2} \Gamma(\frac{n}{2})} y^{n-2} e^{-y^2} U(y)$$

$$f_Y(y) = 2 \cdot \frac{1}{2^{n/2} \Gamma(\frac{n}{2})} y^{n-1} e^{-y^2} U(y)$$

\hookrightarrow chi-density with n-degrees of freedom

$$n = 3:$$

$$f_Y(y) = \sqrt{2/n} y^2 e^{-y^2/2} \rightarrow \text{Maxwell density}$$

$$n = 2:$$

$$f_Y(y) = y e^{-y^2/2} U(y) \rightarrow \text{Rayleigh density}$$

$$\text{eq: } Y = a \sin(x + \theta), a > 0$$

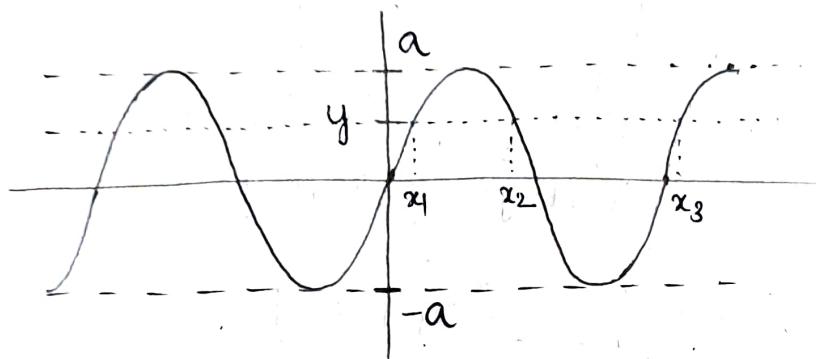
$$g(x) = a \sin(x + \theta)$$

$$|y| > a, f_y(y) = 0$$

$$|y| \leq a \rightarrow x_1 = \sin^{-1}\left(\frac{y}{a}\right) - \theta$$

$$x_2 = \pi - x_1$$

$$x_3 = 2\pi + x_1$$



x_1, x_2, \dots are roots of $y = g(x)$

$$g(x) = a \cos(x + \theta) = \sqrt{a^2 - y^2}$$

$$x_n = \sin^{-1}\left(\frac{y}{a}\right) - \theta$$

$$\sin(x_n + \theta) = y/a$$

$$\sin^2(x_n + \theta) + \cos^2(x_n + \theta) = 1$$

$$\frac{y^2}{a^2} + \cos^2(x_n + \theta) = 1$$

$$\cos(x_n + \theta) = \sqrt{1 - \frac{y^2}{a^2}}$$

$$a \cos(x_n + \theta) = \sqrt{a^2 - y^2}$$

$$f_y(y) = \sum_{n=-\infty}^{\infty} \frac{f_x(x_n)}{\sqrt{a^2 - y^2}} ; |y| < a$$

$$f_X(x) = \begin{cases} \frac{2x}{\pi^2}, & 0 \leq x \leq \pi \\ 0 & \text{else} \end{cases}$$

$$f_Y(y) = \sum_{n=-\infty}^{\infty} \frac{f_X(x_n)}{\sqrt{a^2 - y^2}}$$

$$= \frac{1}{\sqrt{1-y^2}} f_X(x_1) + \frac{1}{\sqrt{1-y^2}} f_X(x_2)$$

$$= \frac{2x_1}{\pi^2 \sqrt{1-y^2}} + \frac{2x_2}{\pi^2 \sqrt{1-y^2}}$$

$$= \frac{2}{\pi^2 \sqrt{1-y^2}} [x_1 + x_2]$$

$$= \frac{2}{\pi^2 \sqrt{1-y^2}} [x_1 + \pi - x_1]$$

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

$$f_Y(y) = \begin{cases} \frac{2}{\pi \sqrt{1-y^2}}, & 0 \leq y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

EC252

02/02/2022

$Y = g(X)$, X is a r.v with CDF $F_X(x)$

We can choose g appropriately so that
 Y is a uniform random variable for any r.v ' X '.

choose $g(x) = F_X(x)$

then $Y = F_X(x)$

$$f_Y(y) = P(Y \leq y) = P(F_X(x) \leq y)$$

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

$$= P(x \leq F_X^{-1}(y))$$

$$= f_X(F_X^{-1}(y))$$

$$= y$$

$X \sim U(0,1]$ $Y = g(x)$

By appropriately choosing g , we can obtain
the r.v ' Y ' with a given $f_Y(y)$

$$g(x) = f_Y^{-1}(x)$$

$$f_Y(y) = P(Y \leq y) = P(g(x) \leq y)$$

$$= P(F_Y^{-1}(x) \leq y)$$

$$= P(x \leq F_Y^{-1}(y))$$

$$= f_Y(y)$$

$U \sim \text{Unif}[0,1]$

$$f_U(u) = 1, \quad 0 \leq u \leq 1$$

$$F_U(u) = \begin{cases} u & 0 \leq u \leq 1 \\ 1 & \text{if } u > 1 \\ 0 & u < 0 \end{cases}$$

$$X \sim f_X(x) \quad Y \sim f_Y(y)$$

$$g = ? \text{ so that } Y = g(X)$$

↓
U
↓
Y

$$U = g_1(X) \quad g_1(X) = f_X(x)$$

$$Y = g_2(U) \quad g_2^{-1}(x) = f_Y^{-1}(x)$$

$$Y = g_2(g_1(X)) = (g_2 \circ g_1)(X)$$

$$= \underline{f_Y^{-1}(f_X(x))}$$

- Mean and Variance:

$$\mathbb{E}[X] = \int_{-\infty}^{\infty} x f_X(x) dx \rightarrow \text{continuous}$$

$$\mathbb{E}[X] = \sum_x x P(X=x) \rightarrow \text{discrete}$$

$$Y = g(X)$$

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

\Rightarrow Mean / Expectation

$$\mathbb{E}[g(X)] = \sum_x g(x) P(X=x)$$

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

for continuous r.v

($\mu \rightarrow \text{mean}$)

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

$$\text{for discrete r.v } \sigma_x^2 = \sum_{x} (x-\mu)^2 p(x=x)$$

$$Y = ax + b$$

$$\mathbb{E}[Y] = a\mathbb{E}[X] + b$$

$$-(x-\mu)^2 / 2\sigma^2$$

example $f_x(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

$$\text{Var}(x) = ?$$

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

$$= 2 \int_0^{\infty} \frac{(x-\mu)^2}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

$$x-\mu = t$$

$$= 2 \int_0^{\infty} \frac{t^2}{\sqrt{2\pi\sigma^2}} e^{-\frac{t^2}{2\sigma^2}} dt$$

Eg:

$$X = \begin{cases} 0 & \text{with probability } p \\ 1 & \text{with probability } 1-p \end{cases}$$

$$\mathbb{E}[X] = 0(1-p) + 1(p)$$

$$= p$$

$$\text{Var}(X) = \sum_{x=0}^1 (x-p)^2 p(x=x)$$

$$= p^2 p(x=0) + (1-p)^2 p(x=1)$$

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

$$= p(1-p)(p+1-p)$$

$$\underline{\text{Var}(X) = p(1-p)}$$

• Moments:

nth moment of a r.v. $X = \mathbb{E}[X^n]$

$\mathbb{E}[X^2]$: second moment

→ Central moments

the nth central moment $\mu_n = \mathbb{E}[(X-\mu)^n]$

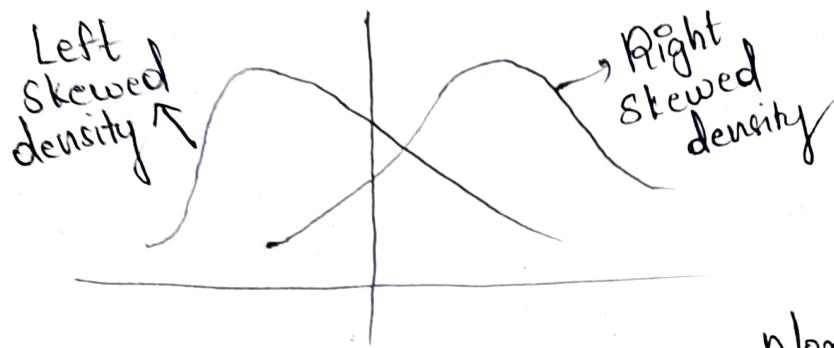
$$\mu_1 = 0 \quad \mathbb{E}[X-\mu] = \mathbb{E}[X] - \mathbb{E}[\mu] = \mu - \mu = 0$$

$$\mu_2 = \text{Var}(X) \quad \mathbb{E}[(X-\mu)^2] = \text{Var}(X)$$

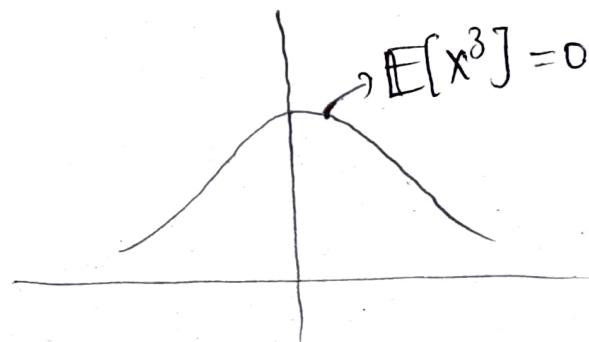
$$\begin{aligned} \text{Var}(X) &= \mathbb{E}[(X-\mu)^2] = \mathbb{E}[X^2 - 2\mu X + \mu^2] \\ &= \mathbb{E}[X^2] - 2\mu \underbrace{\mathbb{E}[X]}_{\mu} + \mu^2 \\ &= \mathbb{E}[X^2] - 2\mu^2 + \mu^2 \end{aligned}$$

$$\boxed{\mathbb{E}[X^2] = \text{Var}(X) + \mu^2}$$

$\mathbb{E}[X^3]$: skewness



Normal distribution



e.g.: $X \sim N(0,1)$ $Y = ax + b$

find mean and variance of Y .

$$\mathbb{E}[Y] = \mathbb{E}[ax+b] = a\mathbb{E}[x] + b = \underline{\underline{b}}$$

$$\begin{aligned}\text{Var}(Y) &= \mathbb{E}[(Y-b)^2] \\ &= \mathbb{E}[(ax+b-b)^2] \\ &= \mathbb{E}[a^2x^2] \\ &= a^2\mathbb{E}[x^2] \\ &= a^2\mathbb{E}[x^2] \\ &= a^2 \times 1\end{aligned}$$

$$\underline{\underline{\text{Var}(Y) = a^2}}$$

Characteristic function of R.V. X:

characteristic fn of X

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

characteristic fn $\phi_x(\omega) \xrightarrow{FT}$ pdf $f_x(x)$

Moment generating fn $\Psi_x(s) = \mathbb{E}[e^{sx}]$

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

(Laplace-Transform)

$$\frac{d^n}{ds^n} (\Psi_x(s)) = \frac{d^n}{ds^n} \mathbb{E}[e^{sx}]$$

$$= \frac{d^{n-1}}{ds^{n-1}} \left[\mathbb{E}[x e^{sx}] \right]$$

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

e.g. $y = ax + b$

Given characteristic fn $\phi_x(\omega)$ of X, find $\phi_y(\omega)$

$$\text{Solt: } \phi_y(\omega) = \mathbb{E}[e^{j\omega y}] = \mathbb{E}[e^{j\omega(ax+b)}]$$

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

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

$$\therefore \phi_y(\omega) = e^{j\omega b} \phi_x(\omega a)$$

Eg: Compute the moments of $X \sim N(0, \sigma^2)$ from definition

$$\mathbb{E}[X^n] = \int_{-\infty}^{\infty} x^n \frac{1}{\sqrt{2\pi\sigma^2}} e^{-x^2/2\sigma^2} dx$$

If n is odd $\therefore \mathbb{E}[X^n] = 0$

n is even \therefore

$$\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-x^2/2\sigma^2} dx = 1$$

$$\int_{-\infty}^{\infty} e^{-x^2/2\sigma^2} dx = \sqrt{2\pi\sigma^2}$$

$$\text{Let } d = \frac{1}{2\sigma^2}$$

$$\int_{-\infty}^{\infty} e^{-dx^2} dx = \sqrt{\frac{\pi}{d}}$$

Differentiate ' k ' times,

$$\int_{-\infty}^{\infty} x^{2k} e^{-dx^2} dx = \sqrt{\pi} \frac{d^k}{d\alpha^k} \left(\frac{1}{\sqrt{d}}\right)$$

$$\int_{-\infty}^{\infty} (-x)^{2k} e^{-dx^2} dx = \sqrt{\pi} \frac{d^k}{d\alpha^k} \left(\alpha^{-1/2}\right)$$

$$= \sqrt{\pi} \frac{(-1)^k (1)(3)(5) \dots (2k-1)}{2^k} \alpha^{-\frac{(2k+1)}{2}}$$

$$= \sqrt{\pi} \frac{(1 \times 3 \times 5 \times \dots \times (2k-1))}{2^k} \cdot \frac{1}{\sqrt{\alpha^{2k+1}}}$$

$$\int_{-\infty}^{\infty} x^{2k} e^{-\alpha x^2} dx = \sqrt{\pi} \frac{(1 \times 3 \times 5 \dots \times (2k-1))}{2^k} \cdot \frac{1}{\sqrt{\alpha^{2k+1}}}$$

$$(\alpha) = \frac{1}{(2\sigma^2)^{2k+1}}$$

$$= \sqrt{\pi} \frac{(1 \times 3 \times 5 \dots \times (2k-1))}{2^k} \cdot \sqrt{2} \cdot \sigma^{2k+1}$$

$$= \sqrt{\pi} \frac{(1 \times 3 \times 5 \dots \times (2k-1))}{2^k} \cdot \cancel{x} \cdot \sqrt{2} \cdot \sigma^{2k} \cdot \sqrt{\sigma^2}$$

$$= \sqrt{2\pi\sigma^2} (1 \times 3 \times 5 \dots \times (2k-1)) \times \sigma^{2k}$$

$$n=2k$$

$$\mathbb{E}[x^n] = (1 \times 3 \times 5 \times \dots \times (n-1)) \sigma^n$$

$$\mathbb{E}[x^n] = \begin{cases} 0 & \text{if } n \text{ is odd} \\ (1 \times 3 \times 5 \dots \times (n-1)) \sigma^n & \text{if } n \text{ is even} \end{cases}$$

$$\text{Eq. S.T } \phi_x(\omega) = \exp\left\{\int \mu \omega - \frac{1}{2} \sigma^2 \omega^2\right\}$$

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

$$\text{Let } Y = \frac{X-\mu}{\sigma}, \quad Y \sim N(0, 1)$$

Sol:

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

$$\Psi_y(s) = \int_{-\infty}^{\infty} e^{sy} \cdot \frac{e^{-y^2/2}}{\sqrt{2\pi}} dy$$

$$\begin{aligned} sy - \frac{y^2}{2} &= \frac{sy - y^2}{2} = \frac{2sy - y^2 + s^2 - s^2}{2} \\ &= -\frac{(y-s)^2 + s^2}{2} \end{aligned}$$

$$\begin{aligned} \Psi_y(s) &= \int_{-\infty}^{\infty} e^{-\frac{(y-s)^2 + s^2}{2}} \frac{e^{s^2/2}}{\sqrt{2\pi}} dy \\ &= e^{s^2/2} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{(y-s)^2}{2}} dy \\ &\sim \mathcal{N}(s, 1) \end{aligned}$$

$$\underline{\Psi_y(s) = e^{s^2/2}}$$

$$\phi_y(\omega) = e^{\frac{(j\omega)^2/2}{-s^2/2}} = e^{-\omega^2/2}$$

$$X = \sigma Y + \mu$$

$$\begin{aligned} \phi_x(\omega) &= E[e^{j\omega X}] \\ &= E[e^{j\omega(\sigma Y + \mu)}] \\ &= e^{j\omega\mu} E[e^{j\omega\sigma Y}] = e^{j\omega\mu} \phi_y(\omega\sigma) \\ &= e^{j\omega\mu} \cdot \frac{1}{e^{-\sigma^2\omega^2/2}} \end{aligned}$$

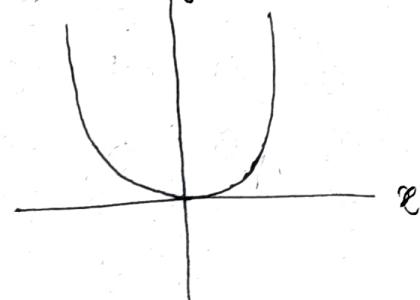
Problems:

1. Let x be a random variable between $(-2c, 2c)$

$$y = g(x) \quad g(x) = x^2$$

find and sketch, $f_y(y)$ and $f_y(y)$

$$f_x(x) = \begin{cases} \frac{1}{4c}, & -2c < x < 2c \\ 0, & \text{else} \end{cases}$$



roots of $g(x) = y$

$$x_1 = \sqrt{y}, \quad x_2 = -\sqrt{y}$$

$$f_y(y) = \frac{f_x(x_1)}{|g'(x_1)|} + \frac{f_x(x_2)}{|g'(x_2)|} \quad \text{for } 0 < y < 4c^2$$

$$f_y(y) = \begin{cases} \frac{1}{4c} + \frac{1}{4c} & 0 < y < 4c^2 \\ 0 & y \geq 4c^2 \end{cases}$$

$$f_y(y) = \frac{1}{4c\sqrt{y}}, \quad 0 < y < 4c^2$$

$$f_y(y) = \begin{cases} \frac{\sqrt{y}}{2c}, & 0 < y < 4c^2 \\ 0, & y \geq 4c^2 \end{cases}$$

$$2. f_X(x) = 2e^{-2x} U(x)$$

$$U(x) = \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{else} \end{cases}$$

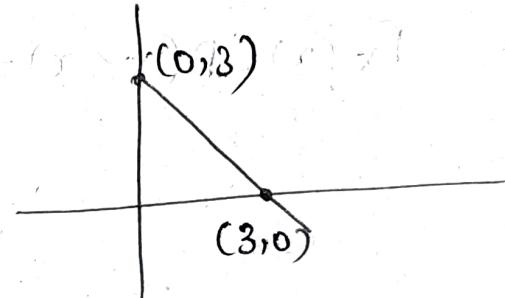
$y = -4x + 3$ find $f_Y(y)$ and $F_Y(y)$

$$x \geq 0$$

$$f_Y(y) = 0 \quad y > 3$$

$$g(x) = y$$

$$x_1 = \frac{y-3}{-4}$$



$$f_Y(y) = \frac{f_X(x_1)}{|g'(x_1)|} = \frac{2e^{-\frac{1}{2}(\frac{y-3}{4})^2}}{4}$$

$$f_Y(y) = \begin{cases} \frac{1}{2} e^{\left(\frac{y-3}{2}\right)^2}, & y \leq 3 \\ 0, & y > 3 \end{cases}$$

$$f_Y(y) = \begin{cases} e^{\left(\frac{y-3}{2}\right)^2}, & y \leq 3 \\ 0, & y > 3 \end{cases}$$

3. U is a uniform random variable between $(0, 1)$

$$X = (U - 0.5)^+ = \max\{0, U - 0.5\}$$

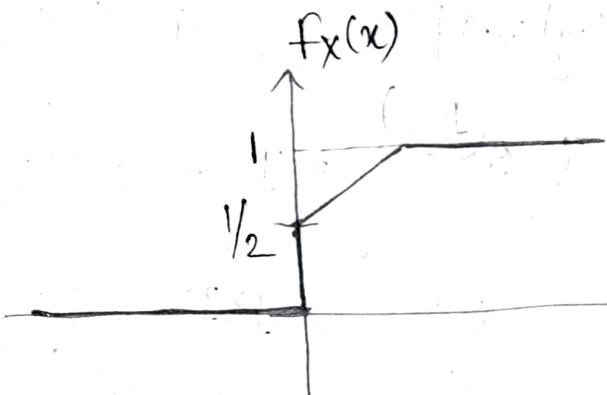
$$= \begin{cases} U - 0.5 & , U \geq 0.5 \\ 0 & , U < 0.5 \end{cases}$$

(i) find and sketch CDF, $F_X(x)$

$$F_X(x) = P(X \leq x) = \begin{cases} 0 & \text{if } x < 0 \\ \frac{1}{2} & \text{if } x = 0 \\ P(U - 0.5 \leq x) & \text{if } x > 0, \\ & x \leq 0.5 \\ 1 & \text{if } x > 0.5 \end{cases}$$

$$0 < x < 0.5$$

$$P(U - 0.5 \leq x) = P(U \leq x + 0.5) = 0.5 + x$$



(ii) find characteristic fn $\phi_X(\omega)$

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

$$\phi_X(x) = \begin{cases} \frac{1}{2} \delta(0) + 1 & \text{if } x \in (0, 0.5) \\ 0 & \text{else} \end{cases}$$

4. X is a random variable with pdf,

$$f_X(x) = \begin{cases} 2x & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

$$(i) P(X > 0.4 | X \leq 0.8)$$

(ii) $Y = -\ln(x)$ find Pdf, CDF of Y .

soln (i)

$$\Rightarrow P(X > 0.4 | X \leq 0.8) = \frac{P(0.4 \leq X \leq 0.8)}{P(X \leq 0.8)}$$

$$= \frac{\int_{0.4}^{0.8} 2x dx}{0.8}$$

$$= \frac{\int_0^{0.8} f_X(x) dx}{0.8}$$

$$= \frac{x^2 \Big|_{0.4}^{0.8}}{x^2 \Big|_0^{0.8}} = \frac{0.64 - 0.16}{0.64}$$

$$P(X > 0.4 | X \leq 0.8) = \frac{0.48}{0.64} = \frac{3}{4} = 0.75$$

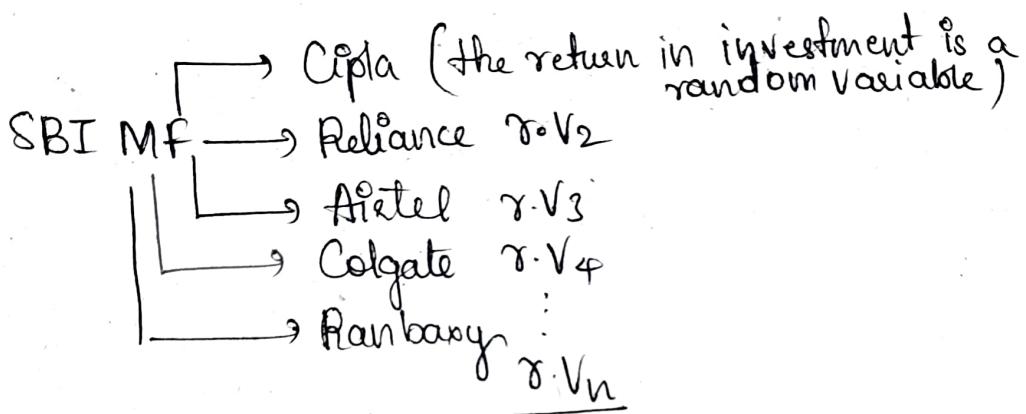
$$(ii) Y = -\ln(x) \quad x_1 = e^{-y}$$

$$f_Y(y) = \frac{f_X(x_1)}{|g'(x_1)|}, \quad y > 0$$

$$= \frac{2e^{-y}}{1/e^{-y}} = 2e^{-2y}, \quad y > 0$$

Multiple Random Variables:

Assume that you have invested ' x ' in MF.
The returns is ' y '.



The random variables may have dependency.

• Joint Discrete Random variables:

Let x, y be discrete r.v. such that

$$P_x(x) = P(x=x)$$

Joint PMF of x and y is defined as

$$\begin{aligned} P_{x,y}(x,y) &= P(x=x, y=y) \\ &= P((x=x) \text{ and } (y=y)) \end{aligned}$$

$$x \in \mathcal{X} = \{x_1, x_2, \dots\}$$

$$y \in \mathcal{Y} = \{y_1, y_2, \dots\}$$

$$(i) P(\Omega) = 1$$

$$\sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} P_{x,y}(x,y) = 1$$

$$P_{xy}(x,y) > 0$$

$$(ii) A = \{ (x_i^o, y_j^o) ; i^o = 1, \dots, k \\ j^o = 1, \dots, l \}$$

$$P((x, y) \in A) = \sum_{x_i^o, y_j^o} P_{xy}(x_i^o, y_j^o)$$

• Marginal PMFs:

$$P_{xy}(x, y) = P(x=x, y=y)$$

$$P(x=x) = P(x=x, y=y_1) + P(x=x, y=y_2) \\ + \dots \quad (\text{law of total probability})$$

↓
Marginal PMF of r.v 'x'

$$= \sum_{y_j^o \in y} P_{xy}(x, y_j^o)$$

$$P(y=y) = \sum_{x_i^o \in x} P_{xy}(x_i^o, y)$$

↓
Marginal PMF of r.v 'y'.

Eg:

	$y=0$	$y=1$	$y=2$
$x=0$	$\frac{1}{6}$	$\frac{1}{4}$	$\frac{1}{8}$
$x=1$	$\frac{1}{8}$	$\frac{1}{6}$	$\frac{1}{6}$

$$P(x,y) = \begin{bmatrix} \frac{1}{6} & \frac{1}{4} & \frac{1}{8} \\ \frac{1}{8} & \frac{1}{6} & \frac{1}{6} \end{bmatrix}$$

$$\underset{(x,y)}{\sum} P_{xy}(x,y) = 1$$

$$\begin{aligned} \underset{(x,y)}{\sum} P_{xy}(x,y) &= 3 \times \frac{1}{6} + 2 \times \frac{1}{8} + \frac{1}{9} \\ &= \frac{1}{2} + \frac{1}{4} + \frac{1}{9} \\ &= 1 \end{aligned}$$

Marginal PMF's:

$$\begin{aligned} P(x=0) &= P(x=0, y=0) + P(x=0, y=1) \\ &\quad + P(x=0, y=2) \\ &= \frac{1}{6} + \frac{1}{4} + \frac{1}{8} = \underline{\underline{\frac{13}{24}}} \end{aligned}$$

$$P(x=1) = \frac{1}{8} + \frac{1}{6} + \frac{1}{6} = \frac{1}{8} + \frac{1}{3} = \underline{\underline{\frac{11}{24}}}$$

$$\begin{aligned} P(y=0) &= P(x=0, y=0) + P(x=1, y=0) \\ &= \frac{1}{6} + \frac{1}{8} = \underline{\underline{\frac{7}{24}}} \end{aligned}$$

$$P(y=1) = \frac{1}{4} + \frac{1}{6} = \underline{\underline{\frac{10}{24}}} \quad P(y=2) = \frac{1}{8} + \frac{1}{6} = \underline{\underline{\frac{7}{24}}}$$

$$P(X=0, Y \leq 1) = P(X=0, Y=0) + P(X=0, Y=1)$$

$$= \frac{1}{6} + \frac{1}{4} = \underline{\underline{\frac{10}{24}}}$$

• Conditional PMF:

from above example,

$$P(Y=1 | X=0) = \frac{P(X=0, Y=1)}{P(X=0)} = \frac{1/4}{13/24} = \frac{6}{13}$$

$$P(Y \in B | X \in A) = \frac{P(X \in A, Y \in B)}{P(X \in A)}$$

⇒ We say that the r.v 'X' and 'Y' are independent

$$\text{If } P_{XY}(x,y) = P_X(x=x) \cdot P_Y(y=y) \text{ if } x, y \in \mathcal{X} \times \mathcal{Y}$$

If X, Y are independent

$$P(Y \in B | X \in A) = P(Y \in B)$$

from above example,

$$P(X=0, Y=0) = 1/6$$

$$P(X=0)P(Y=0) = \frac{13}{24} \times \frac{7}{24} = \frac{91}{576} \neq \frac{1}{6}$$

So, 'X' and 'Y' are not independent.

eg:

	$y=0$	$y=1$
$x=0$	$\frac{1}{4}$	$\frac{1}{4}$
$x=1$	$\frac{1}{4}$	$\frac{1}{4}$

$$P(x=0) = \frac{1}{4} + \frac{1}{4} = \frac{1}{2}$$

$$P(x=1) = \frac{1}{4} + \frac{1}{4} = \frac{1}{2}$$

$$P(y=0) = \frac{1}{4} + \frac{1}{4} = \frac{1}{2}$$

$$P(y=1) = \frac{1}{4} + \frac{1}{4} = \frac{1}{2}$$

$$P(x=0, y=0) = \frac{1}{4}$$

$$P(x=0) \cdot P(y=0) = \frac{1}{2} \times \frac{1}{2} = \frac{1}{4} = P(x=0, y=0)$$

So, 'x' and 'y' are independent.

eg:

	$y=0$	$y=1$
$x=0$	$\frac{1}{4}$	$\frac{1}{4}$
$x=1$	0	$\frac{1}{2}$

$$P(x=0) = \frac{1}{2} \quad P(y=0) = \frac{1}{4}$$

$$P(x=1) = \frac{1}{2} \quad P(y=1) = \frac{3}{4}$$

$$P(x=0, y=0) = \frac{1}{4}$$

$$P(x=0) \cdot P(y=0) = \frac{1}{2} \cdot \frac{1}{4} = \frac{1}{8} \neq \frac{1}{4}$$

So, 'x' and 'y' are not independent.

Eq°

x \ y	y_1	y_2	y_3
x_1	$\frac{1}{12}$	$\frac{1}{6}$	0
x_2	0	$\frac{1}{9}$	$\frac{1}{5}$
x_3	$\frac{1}{18}$	$\frac{1}{4}$	$\frac{2}{15}$

$$P[x_1] = \frac{1}{12} + \frac{1}{6} = \frac{3}{12} = \underline{\underline{\frac{1}{4}}}$$

$$P[x_2] = \frac{1}{9} + \frac{1}{5} = \underline{\underline{\frac{14}{45}}}$$

$$P[x_3] = \frac{1}{18} + \frac{1}{4} + \frac{2}{15} = \frac{10 + 45 + 24}{180} = \underline{\underline{\frac{79}{180}}}$$

$$P[y_1] = \frac{1}{12} + \frac{1}{18} = \frac{3 + 2}{36} = \underline{\underline{\frac{5}{36}}}$$

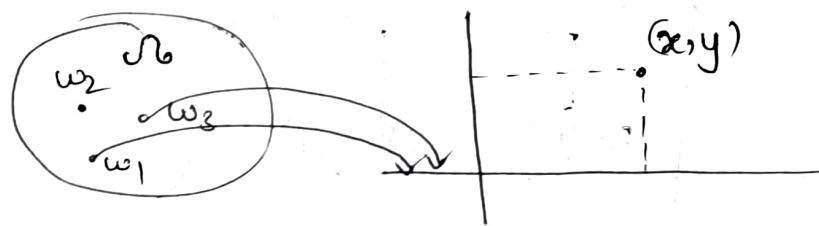
$$P[y_2] = \frac{1}{6} + \frac{1}{9} + \frac{1}{4} = \frac{6 + 4 + 9}{36} = \underline{\underline{\frac{19}{36}}}$$

$$P[y_3] = 0 + \frac{1}{5} + \frac{2}{15} = \underline{\underline{\frac{1}{3}}}$$

$$P[y=y_3 / x=x_2] = \frac{P[x=x_2, y=y_3]}{P[x=x_2]} = \frac{\frac{1}{5}}{\frac{14}{45}} = \underline{\underline{\frac{9}{14}}}$$

$$P[x=x_2 / y=y_1] = \frac{P[x=x_2, y=y_1]}{P[y=y_1]} = \underline{\underline{0}}$$

Let X and Y be continuous random variables



$$F_X(x) = P(\{\omega \in \Omega : X(\omega) \leq x\})$$

Joint CDF,

$$F_{XY}(x, y) = P(\{\omega \in \Omega : X(\omega) \leq x, Y(\omega) \leq y\})$$

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

Properties:

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

$$\rightarrow F_{XY}(\infty, \infty) = 1$$

$$\rightarrow F_{XY}(-\infty, -\infty) = 0$$

$$(ii) F_{XY}(-\infty, y) = P(X \leq -\infty, Y \leq y)$$

$$= 0 //$$

$$(iii) F_{XY}(x, -\infty) = P(X \leq x, Y \leq -\infty)$$

$$= 0 //$$

$$(iv) F_{XY}(\infty, y) = P(X \leq \infty, Y \leq y)$$

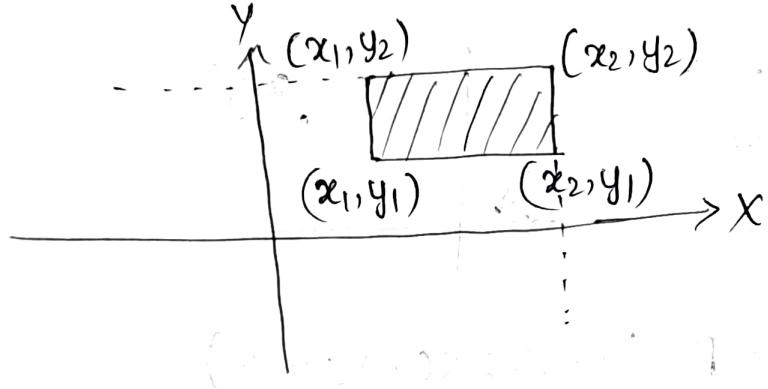
$$= P(Y \leq y) = \underline{f_Y(y)}$$

$$(v) F_{XY}(x, \infty) = P(X \leq x, Y \leq \infty)$$

$$= P(X \leq x) = \underline{f_X(x)}$$

$f_X(x)$ and $f_Y(y)$ are marginal CDFs

(Vii) $P(x_1 < x \leq x_2, y_1 < y \leq y_2)$



$$P((x_1 < x \leq x_2), (y_1 < y \leq y_2)) = f_{xy}(x_2, y_2) - f_{xy}(x_2, y_1) - f_{xy}(x_1, y_2) + f_{xy}(x_1, y_1)$$

(Viii) $f_{xy}(x, y)$ is non-decreasing in terms of x & y .

(Ix) $f_{xy}(x, y)$ is right-continuous

→ The joint pdf of x, y denoted by $f_{xy}(x, y)$, is a function such that,

$$f_{xy}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{xy}(\theta_x, \theta_y) d\theta_y d\theta_x$$

$$\boxed{f_{xy}(x, y) = \frac{\partial^2}{\partial x \partial y} f_{xy}(x, y)}$$

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

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

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

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

$$\text{iv) } P(x_1 < x \leq x_2, y_1 < y \leq y_2) \\ = \int_{x_1}^{x_2} \int_{y_1}^{y_2} f_{xy}(x, y) dy dx$$

L, area of f_{xy} under
the rectangle.

Conditional distribution:

$$f_{x|y}(x|M) = \frac{P(x \leq x \cap M)}{P(M)}, \quad M = \{y \leq y\}$$

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

$$f_{x|y}(x | y - \Delta y \leq y \leq y + \Delta y) \\ = \frac{P(x \leq x \cap y - \Delta y \leq y \leq y + \Delta y)}{P(f_x(y + \Delta y) - F_x(y - \Delta y))}$$

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

→ The random variables x and y are said to be independent if $f_{xy}(x,y) = f_x(x) \cdot f_y(y)$

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

Joint distribution and its properties.

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

Properties:

1. $F_{X,Y}(-\infty, -\infty) = 0$, $F_{X,Y}(-\infty, y) = 0$, $F_{X,Y}(x, -\infty) = 0$
2. $F_{X,Y}(\infty, \infty) = 1$
3. $0 \leq F_{X,Y}(x,y) \leq 1$
4. $F_{X,Y}(x,y)$ is nondecreasing function of both x and y
5. $P(x_1 < X \leq x_2, y_1 < Y \leq y_2)$
 $= F_{X,Y}(x_2, y_2) + F_{X,Y}(x_1, y_1) - F_{X,Y}(x_1, y_2) - F_{X,Y}(x_2, y_1)$
6. $F_{X,Y}(x, \infty) = f_X(x)$, $F_{X,Y}(\infty, y) = f_Y(y)$

Joint density f_{X,Y}:

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

Properties of pdf.

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

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

$$f_{X,Y}(x,y) = \int_{-\infty}^y \int_{-\infty}^x f_{XY}(\theta_1, \theta_2) d\theta_2 d\theta_1$$

$$f_X(x) = \int_{-\infty}^x \int_{-\infty}^y f_{X,Y}(\theta_1, \theta_2) d\theta_2 d\theta_1$$

$$f_Y(y) = \int_{-\infty}^y \int_{-\infty}^x f_{X,Y}(\theta_1, \theta_2) d\theta_1 d\theta_2$$

$$P(\gamma_1 < X \leq \gamma_2, \gamma_1 < Y \leq \gamma_2) = \int_{\gamma_1}^{\gamma_2} \int_{\gamma_1}^{\gamma_2} f_{X,Y}(x,y) dx dy$$

$$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy \rightarrow \text{Marginal P.d.f. of } x$$

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

Conditional distributions and density

Joint Conditioning:

$$B = \{y - \Delta y \leq Y \leq y + \Delta y\}$$

$$f_X(x | y - \Delta y \leq Y \leq y + \Delta y) = \frac{\int_{y-\Delta y}^{y+\Delta y} \int_{-\infty}^x f_{X,Y}(\theta_1, \theta_2) d\theta_2 d\theta_1}{\int_{y-\Delta y}^{y+\Delta y} f_Y(y) dy}$$

If Δy is very small, we can write the above equation as

$$F_x(z/y - \Delta y, z/y \leq y + \Delta y) =$$

$$\frac{\int_{-\infty}^y f_{x,y}(z, s) ds}{f_y(y) 2\Delta y}$$

Then in the limit $\Delta y \rightarrow 0$

$$F_x(z/y = y) = \frac{\int_{-\infty}^y f_{x,y}(z, s) ds}{f_y(y)} \quad \text{for every } y \text{ such that } f_y(y) \neq 0$$

Differentiating we get

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

(similarly)

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

Internal Conditioning:

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

$$F_X\left(\frac{x}{y_a} < Y \leq y_b\right) = \frac{f_{XY}(x/y_b) - f_{XY}(x/y_a)}{F_Y(y_b) - F_Y(y_a)}$$

$$= \frac{\int_{y_a}^{y_b} \int_{-\infty}^x p_{X,Y}(0,y) dy dx}{\int_{y_a}^{y_b} \int_{-\infty}^{\infty} p_{X,Y}(0,y) dy dx}$$

X and Y are statistically independent

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

$$F_{X,Y}(x,y) = F_X(x)F_Y(y)$$

Problem-1:

$$F_{X,Y}(x,y) = U(x)U(y) \left[1 - e^{-ax} - e^{-ay} + e^{-a(x+y)} \right]$$

where $U(\cdot)$ is the unit step fn, $a > 0$.

Find marginal CDFs.

Find joint pdf and marginal pdf's.

Marginal CDF's

$$F_X(x, \infty) = F_X(x)$$

$$f_X(x) = F_{XY}(x; \infty)$$

$$= u(x) \left[1 - e^{-ax} \right]$$

$$f_Y(y) = f_{XY}(\infty; y)$$

$$= u(y) \left[1 - e^{-ay} \right]$$

$$f_{XY}(x,y) = \frac{\partial^2 F_{XY}(x,y)}{\partial x \partial y} \rightarrow \text{Joint PDF}$$

$$= \frac{\partial}{\partial y} \left[ae^{ay} - a e^{-a(x+y)} \right]$$

$$= ae^{-a(x+y)}, x>0, y>0$$

$$f_X(x) = \frac{d}{dx} F_X(x) \text{ (by) } = \int_{-\infty}^{\infty} f_{XY}(x,y) dy$$

$$= ae^{-ax}$$

$$f_Y(y) = \frac{d}{dy} f_Y(y) = \int_{-\infty}^{\infty} f_{XY}(x,y) dx = ae^{-ay}$$

Q] Find the constant 'b' such that the following are valid joint density functions.

$$(a) f_{XY}(x,y) = \begin{cases} bxy(1-y), & 0 < x < 0.5 \\ & 0 < y < 1 \\ 0 & \text{else.} \end{cases}$$

$$\int_{-\infty}^{\infty} \int_0^b b\alpha(1-y) dx dy = 1$$

$$b \left[\int_0^1 \frac{x^2}{2} - \frac{x^2}{2} y \Big|_0^{y_2} dy \right] = 1$$

$$\cancel{b} (y_2) \times \frac{1}{2} \left[y - \frac{y^2}{2} \right]_0^{y_2} = \frac{1}{b}$$

$$\frac{1}{8} \left[\frac{1}{2} \right] = \frac{1}{b} \Rightarrow b = 16$$

Formulae

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

Joint pdf with $b = 16$:

Marginal $f_{X,Y}(x,y) = 16x(1-y)$

~~$\int_{-\infty}^{\infty} f_{X,Y}(x) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy = \int_0^1 16(x-y) dy$~~

$$16x \left[\frac{1}{2} \right] = 8x$$

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

$$\int_0^2 \int_{-1}^1 b(x^2 + 4y^2) dx dy = 1.$$

$$2 \int_0^2 \int_0^1 (x^2 + 4y^2) dx dy = 1/b$$

$$2 \int_0^2 \left[\frac{x^3}{3} + 4y^3 \right]_0^1 dy = 1/b$$

$$\int_0^2 (x^3 + 4y^3) dy = \frac{1}{2b}$$

$$\left. \frac{1}{3}y + \frac{4}{3}y^3 \right|_0^2 = \frac{1}{2b}$$

$$\frac{2}{3} + \frac{32}{3} = \frac{1}{2b} \Rightarrow \frac{34}{3} = \frac{1}{2b}$$

Marginaly

$$f_Y(y) = \int_{-1}^1 \frac{3}{68} (x^2 + 4y^2) dx$$

$$= \frac{3(2)}{68} \left[\frac{x^3}{3} + 4xy^2 \right]_0^1 = \frac{3}{34} \left[\frac{1}{3} + 4y^2 \right]$$

$$b = \frac{3}{68}$$

$$f_X(x) = \int_0^x \frac{3}{68} \left[2^y + \frac{4}{3} y^3 \right] dy$$

$$= \frac{3}{68} \left[2^y \frac{y^2}{2} + \frac{4}{3} \frac{y^4}{4} \right]_0^x$$

\rightarrow Independent

EC252:problems:

$$\textcircled{1} \quad f_{x,y}(x,y) = \begin{cases} \frac{1}{8}(6-x-y), & 0 \leq x \leq 2, 2 \leq y \leq 4 \\ 0 & \text{otherwise} \end{cases}$$

find \textcircled{a} $P(X < 1, Y < 3) = ?$

$$\int_0^1 \int_2^3 \frac{1}{8}(6-x-y) dy dx$$

$$\int_0^1 \left[\frac{1}{8}(6y - xy - \frac{y^2}{2}) \right]_2^3 dx$$

$$\int_0^1 \frac{1}{8}(6-x-\frac{5}{2}) dx$$

$$\frac{1}{8} \int_0^1 \left[\frac{7}{2}x - x^2 \right] dx = \frac{1}{8} \left[\frac{7}{2}x - \frac{x^2}{2} \right]_0^1 = \frac{1}{8} \left[\frac{7}{2} - \frac{1}{2} \right] = \frac{1}{8} \times \frac{6}{2} = \underline{\underline{\frac{3}{8}}}$$

$$\textcircled{b} \quad P(X < 1 | Y < 3) = \frac{P(X < 1, Y < 3)}{P(Y < 3)} = \frac{3/8}{\dots}$$

$$\int_0^2 \int_2^3 \frac{1}{8}(6-x-y) dy dx$$

$$\frac{1}{8} \int_0^2 \left(\frac{7}{2}x - x^2 \right) dx = \frac{1}{8} \left[\frac{7}{2}x - \frac{x^2}{2} \right]_0^2 = \frac{1}{8} [7 - 2] = \underline{\underline{\frac{5}{8}}}$$

$$\therefore P(X < 1 | Y < 3) = \frac{3/8}{5/8} = \underline{\underline{\frac{3}{5}}}$$

(2) The joint pdf of random variables x and y is

$$f_{xy}(x,y) = A e^{-(x+y)}, \quad x > 0, y > 0$$

(a) find 'A' such that $f_{xy}(x,y)$ is a valid pdf

(b) find $f_x(x), f_y(y)$.

Sol: $\int_0^\infty \int_0^\infty f_{xy}(x,y) dy dx = 1$

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

$$\int_0^\infty A e^{-y} (-e^{-x}) \Big|_0^\infty dy = 1$$

$$\int_0^\infty A e^{-y} (+1) dy = \cancel{A} 1$$

$$\int_0^\infty A e^{-y} dy = 1$$

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

$$A[0+1] = 1$$

$$\therefore A = 1$$

$$f_x(x) = \int_0^\infty e^{-(x+y)} dy = e^{-x} (-e^{-y}) \Big|_0^\infty = e^{-x} (0+1) = e^{-x} //$$

$$f_y(y) = \int_0^\infty e^{-(x+y)} dx = e^{-y} (-e^{-x}) \Big|_0^\infty = e^{-y} (0+1) = e^{-y} //$$

Both marginal pdf's are independent.

(3)

$$f_{xy}(x, y) = \begin{cases} C(1+xy), & 0 \leq x \leq 6, 0 \leq y \leq 5 \\ 0 & \text{otherwise} \end{cases}$$

@find 'C'

⑤ $f_{x|y}(x|y=3)$

Solt $\int_0^6 \int_0^5 C(1+xy) dy dx = 1$

$$\int_0^6 C(y + xy^2) \Big|_0^5 dx = 1$$

$$\int_0^6 C(5 + x(25/2)) dx = 1$$

$$C \left(5x + \frac{25}{2} \frac{x^2}{2} \right) \Big|_0^6 = 1$$

$$C \left(30 + \frac{25}{2} \frac{36}{2} \right) = 1$$

$$C = \frac{1}{255}$$

$$f_{x|y}(x|y=3) = \frac{f_{xy}(x, 3)}{f_y(3)} = \frac{\frac{1}{255}(1+3x)}{\int_0^6 \frac{1}{255}(1+xy) dx} \Big|_{y=3}$$

$$= \frac{1+3x}{x + y \frac{x^2}{2}} \Big|_0^6 \Big|_{y=3} = \frac{1+3x}{6+54} = \frac{1+3x}{60}$$

$$= \frac{1+3x}{6+18y} \Big|_{y=3}$$

$$④ f_{XY}(x, y) = A e^{-|x|-2|y|}$$

check whether X and Y are independent or not.

$$\text{Sof} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} A e^{-|x|-2|y|} dx dy = 1$$

$$A \int_{-\infty}^{\infty} e^{-2|y|} dy \int_{-\infty}^{\infty} e^{-|x|} dx = 1$$

$$\begin{aligned} \int_{-\infty}^{\infty} e^{-|x|} &= \int_{-\infty}^0 e^x dx + \int_0^{\infty} e^{-x} dx \\ &= e^x \Big|_{-\infty}^0 - e^{-x} \Big|_0^{\infty} \\ &= 1 - (-1) = 2 \end{aligned}$$

$$\begin{aligned} \int_{-\infty}^{\infty} e^{-2|y|} dy &= \int_{-\infty}^0 e^{2y} dy + \int_0^{\infty} e^{-2y} dy \\ &= \frac{1}{2} [e^{2y}] \Big|_{-\infty}^0 - \frac{1}{2} [\bar{e}^{-2y}] \Big|_0^{\infty} \\ &= \frac{1}{2} [1] - \frac{1}{2} (-1) = 1 \end{aligned}$$

$$A(1)(2) = 1$$

$$\therefore \boxed{A = 1/2}$$

$$f_X(x) = \int_{-\infty}^{\infty} \frac{1}{2} e^{-|x|-2|y|} dy$$

$$= \frac{1}{2} e^{-|x|} \int_{-\infty}^{\infty} e^{-2|y|} dy$$

$$= \frac{1}{2} e^{-|x|}$$

$$f_Y(y) = \int_{-\infty}^{\infty} \frac{1}{2} e^{-|x|-2|y|} dx$$

$$= \frac{1}{2} e^{-2|y|} \int_{-\infty}^{\infty} e^{-|x|} dx$$

$$= e^{-2|y|}$$

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

∴ X and Y are independent

$$⑤ f_{xy}(x, y) = c[1-x-y] \quad 0 \leq x \leq 1-y \quad 0 \leq y \leq 1$$

check whether X & Y are independent.

$$\underline{\underline{\text{Sol}}} \quad \int_0^1 \int_0^{1-y} c[1-x-y] dx dy = 1$$

$$\int_0^1 c \left[x - \frac{x^2}{2} - xy \right]_{0}^{1-y} dy = 1$$

$$c \int_0^1 \left(1-y - \frac{(1-y)^2}{2} - (1-y)y \right) dy = 1$$

$$c \int_0^1 \frac{(1-y)^2}{2} dy = 1$$

$$\frac{c}{2} \int_0^1 1 + y^2 - 2y dy = 1$$

$$\frac{c}{2} \left[y + \frac{y^3}{3} - y^2 \right]_0^1 = 1$$

$$\frac{c}{2} \left[1 + \frac{1}{3} - 1 \right] = 1 \Rightarrow \boxed{C=6}$$

$$f_X(x) = \int_0^1 6(1-x-y) dy = 6 \left[y - xy - \frac{y^2}{2} \right]_0^1 \\ = 6 \left[1-x-\frac{1}{2} \right] \\ = 3-6x \quad (0 \leq x \leq 1-y)$$

$$f_Y(y) = \int_0^{1-y} 6(1-x-y) dx$$

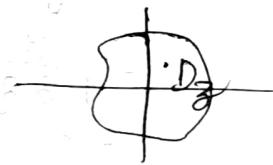
$$= 6 \left(x - \frac{x^2}{2} - xy \right) \Big|_0^{1-y} = 6 \left(1-y - \frac{(1-y)^2}{2} - (1-y)y \right) \\ = 6 \left(\frac{(-y)^2}{2} \right) = \frac{3(1-y)^2}{2} \\ \boxed{0 \leq y \leq 1}$$

02/08/2022

function of two Random Variables:

Let X, Y be random variables with joint pdf $f_{X,Y}(x,y)$ then,

$$Z = g(X, Y)$$



$$f_Z(z) = P(Z \leq z)$$

$$= P(g(X, Y) \leq z) = \iiint_{D_Z} f_{X,Y}(x, y) dx dy$$

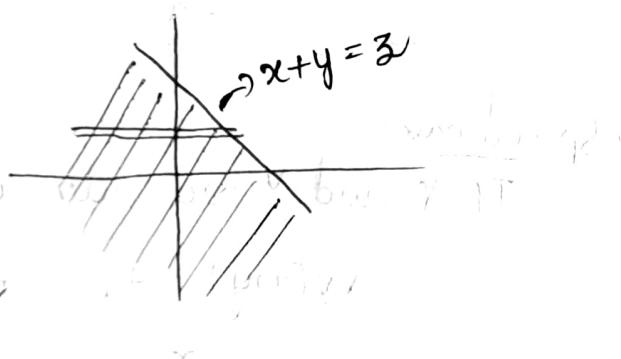
Case - (i) :

e.g. $Z = X + Y$ $f_Z(z) = ?$

$$f_Z(z) = P(Z \leq z)$$

$$= P(X + Y \leq z)$$

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



$$f_Z(z) = \frac{\partial}{\partial z} f_Z(z)$$

• Leibnitz Rule:

$$f_Z(z) = \int_{a(z)}^{b(z)} f(x, z) dx$$

$$\begin{aligned} \frac{dF(z)}{dz} &= \frac{d}{dy} \frac{d}{dz} (b(z)) f(b(z), z) - \frac{d}{dz} (a(z)) f(a(z), z) \\ &\quad + \int_{a(z)}^{b(z)} \frac{\partial}{\partial z} f(x, z) dx \end{aligned}$$

In the previous example,

$$f_z(z) = \frac{d}{dz} (f_Z(z))$$

$$= \int_{-\infty}^{\infty} \frac{d}{dz} \left(\int_{-\infty}^{z-y} f_{xy}(x,y) dy \right)$$

$$= \int_{-\infty}^{\infty} 1 \cdot f_{xy}(z-y, y) dy$$

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

• Special case:

If X and Y are independent, $f_z(z)$ is convolution

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

$$\therefore f_z(z) = \int_{-\infty}^{\infty} f_x(z-y) f_y(y) dy$$

$$\therefore f_z(z) = \int_{-\infty}^{\infty} f_x(x) f_y(z-x) dx$$

e.g. X, Y are IID with uniform distribution on $(0,1)$

Find $f_Z(z)$ of $Z = X + Y$

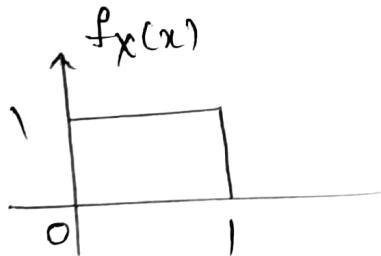
Sol:-

$$f_X(x) = \begin{cases} 1 & 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

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

$$f_Z(z) = \int_{-\infty}^{\infty} f_{X+Y}(z-y) f_X(z-y) f_Y(y) dy$$

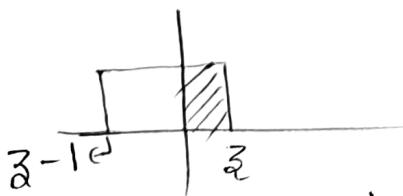
$$f_Z(z) = \begin{cases} z & 0 \leq z \leq 1 \\ 2-z & 1 < z \leq 2 \end{cases}$$



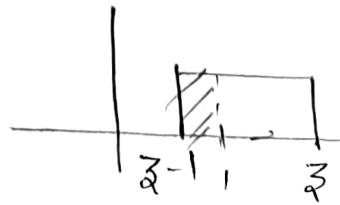
$$\begin{aligned} f_Z(z) &= f_X(x) \otimes f_Y(y) \\ &= \int_0^1 f_X(z-y) \cdot f_Y(y) dy \end{aligned}$$

$$0 < z \leq 1$$

$$1 < z \leq 2$$



$$f_Z(z) = z = \int_0^1 dz$$



$$f_Z(z) = 2 - z$$

e.g. X and Y are two independent random variables with pdf

$$\begin{aligned} f_X(x) &= \lambda e^{-\lambda x} u(x) && \text{Independent and} \\ f_Y(y) &= \lambda e^{-\lambda y} u(y) && \text{Identically distributed} \end{aligned}$$

\downarrow
 $X \neq Y$
But $f_X(x) = f_Y(y)$.

find $f_Z(z)$ for $Z = X + Y$

Solt

$$\begin{aligned} f_Z(z) &= \int_{-\infty}^{\infty} f_X(z-y) f_Y(y) dy \\ &= \int_{-\infty}^{\infty} \lambda e^{-\lambda(z-y)} u(z-y) \lambda e^{-\lambda y} u(y) dy \\ &= \int_0^y \lambda^2 e^{-\lambda z} dy \\ &= \lambda^2 e^{-\lambda z} (y)_0^y \end{aligned}$$

$$\therefore f_Z(z) = \underline{\underline{\lambda^2 y e^{-\lambda z}}}$$

$Z = X - Y$, $f_{XY}(x, y) \longrightarrow \text{Case (ii)}$

$$f_Z(z) = P(X - Y \leq z)$$

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

$$f_Z(z) = \frac{d}{dz} (F_Z(z))$$

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

If X and Y are independent,

$$f_Z(z) = \int_{-\infty}^{\infty} f_X(z+y) \cdot f_Y(y) dy$$

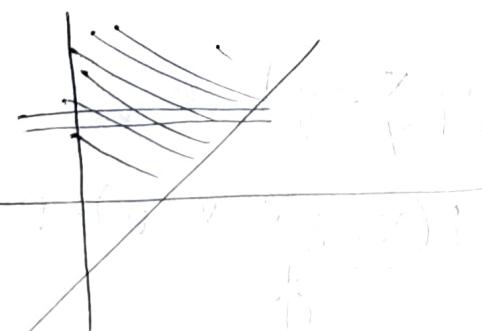
$$= f_X(-z) \otimes f_Y(y)$$

$\rightarrow X \geq 0, Y \geq 0$

$$f_X(x) = 0, x < 0 \quad f_Y(y) = 0, y < 0$$

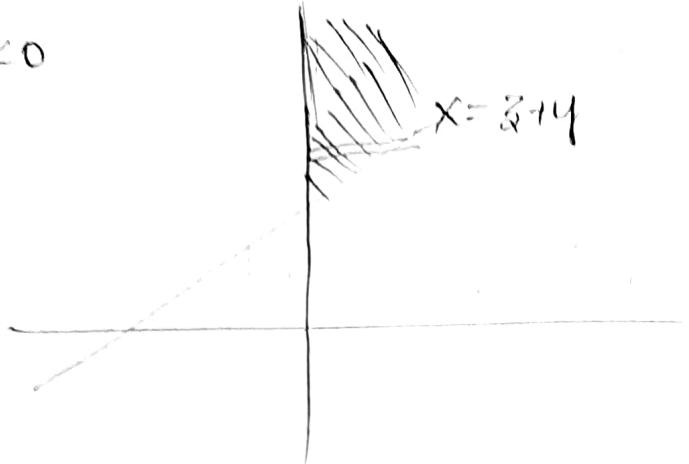
Z can be 've' or 've'

If $Z \geq 0$



$$f_Z(z) = \int_{y=0}^{y=\infty} \int_{x=0}^{z+y} f_{XY}(x, y) dx dy$$

if $z < 0$



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

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

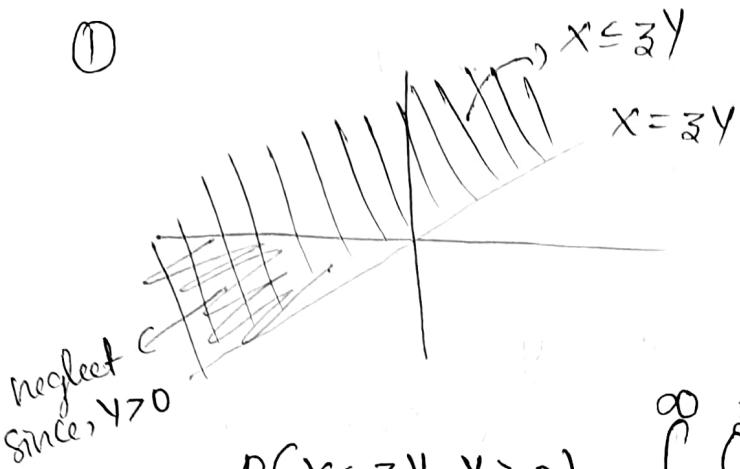
Case - (iii):

$$z = \frac{x}{y} \quad f_{xy}(x,y)$$

$$f_z(z) = P\left(\frac{x}{y} \leq z\right)$$

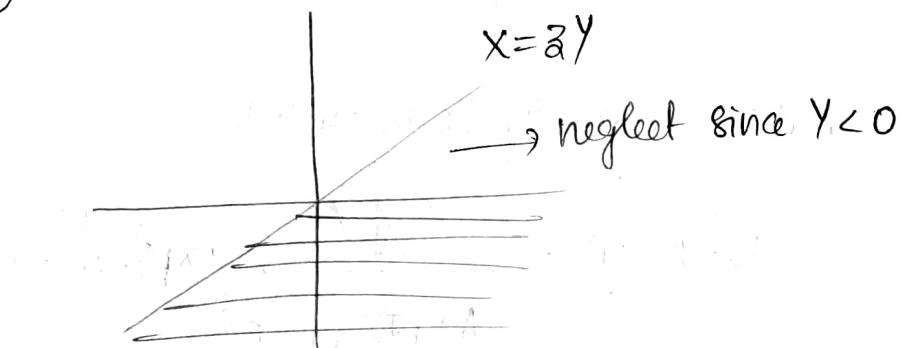
$$= \underbrace{P(x \leq zy, y \geq 0)}_{\textcircled{1}} + \underbrace{P(x \geq zy, y < 0)}_{\textcircled{2}}$$

①



$$P(X \leq 2Y, Y \geq 0) = \int_0^{\infty} \int_{-\infty}^{2y} f_{XY}(x, y) dx dy$$

②



$$P(X \geq 2Y, Y < 0) = \int_{-\infty}^0 \int_{\frac{2y}{2}}^{\infty} f_{XY}(x, y) dx dy$$

$$\begin{aligned} f_Z(z) &= \int_0^{\infty} y f_{XY}(2y, y) dy + \int_{-\infty}^0 -y f_{XY}(x, y) dy \\ &= \int_{-\infty}^{\infty} |y| f_{XY}(2y, y) dy \end{aligned}$$

special case: $f_X(x) = 0, x < 0$
 $f_Y(y) = 0, y < 0$

$$x = 3y$$

$$f_z(z) = \int_{y=0}^{\infty} \int_{x=0}^{3y} f_{xy}(x,y) dx dy$$

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

e.g. x and y are jointly Gaussian R.V's

$$f_{xy}(x,y) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp\left(\frac{-1}{2(1-\rho^2)}\right)$$

$$f_{xy}(x,y) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp\left\{\frac{-1}{2(1-\rho^2)}\left[\frac{x^2}{\sigma_1^2} - 2\rho xy + \frac{y^2}{\sigma_2^2}\right]\right\}$$

$Z = \frac{x}{y}$. Show that Z has Cauchy distribution centered at $\frac{\rho\sigma_1}{\sigma_2}$

Sol:

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

$$= 2 \int_0^{\infty} \frac{y}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp\left\{\frac{-1}{2(1-\rho^2)}\left[\frac{y^2\sigma_1^2}{\sigma_1^2} - \frac{2\rho y z}{\sigma_1\sigma_2} + \frac{y^2}{\sigma_2^2}\right]\right\} dy$$

$$f_z(z) = \frac{2}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \int_0^{\infty} y e^{-y^2/2\sigma_2^2} dy$$

$$\text{where, } \tau_0 = \frac{1 - e^2}{\left[\frac{z^2}{\sigma_1^2} - \frac{2cz}{\sigma_1 \sigma_2} + \frac{1}{\sigma_2^2} \right]}$$

$$\frac{y^2}{2\tau_0} = t$$

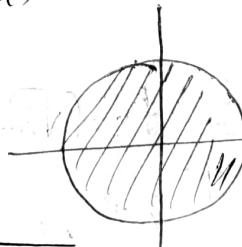
$$y dy = \tau_0 dt$$

$$f_Z(z) = \frac{2\tau_0}{2\pi\sigma_1\sigma_2\sqrt{1-e^2}} \left[\frac{e^{-t}}{t} \right] \Big|_0^\infty$$

$$\boxed{f_Z(z) = \frac{\tau_0}{\pi\sigma_1\sigma_2\sqrt{1-e^2}}}$$

Case-(iv): $Z = X^2 + Y^2$ with $f_{XY}(x,y)$

$$\therefore f_Z(z) = P(X^2 + Y^2 \leq z)$$



$$\therefore f_Z(z) = \int_{-\sqrt{z}}^{\sqrt{z}} \int_{-\sqrt{z-y^2}}^{\sqrt{z-y^2}} f_{XY}(x,y) dx dy$$

$$f_Z(z) = \frac{d}{dz} (f_Z(z))$$

$$\therefore f_Z(z) = \int_{-\sqrt{z}}^{\sqrt{z}} f_{XY}(\sqrt{z-y^2}, y) dy$$

$$\therefore f_z(z) = \int_{-\sqrt{z}}^{\sqrt{z}} \frac{1}{2\sqrt{z-y^2}} \left\{ f_{xy}(\sqrt{z-y^2}, y) + f_{xy}(-\sqrt{z-y^2}, y) \right\} dy$$

Case-(V): $z = \sqrt{x^2 + y^2}$ with pdf $f_{xy}(x, y)$

$$f_z(z) = P(Z \leq z)$$

$$= P(\sqrt{x^2 + y^2} \leq z)$$

$$= P(x^2 + y^2 \leq z^2)$$

$$\therefore f_z(z) = \int_{y=-z}^{+z} \int_{x=-\sqrt{z^2-y^2}}^{+\sqrt{z^2-y^2}} f_{xy}(x, y) dx dy$$

$$f_z(z) = \frac{d}{dz} (f_z(z))$$

$$f_z(z) = \int_{y=-z}^{+z} \frac{z}{2\sqrt{z^2-y^2}} f_{xy}(\sqrt{z^2-y^2}, y) dy + \int_{y=-z}^{+z} \frac{z}{2\sqrt{z^2-y^2}} f_{xy}(-\sqrt{z^2-y^2}, y) dy$$

$$f_z(z) = \int_{-z}^{+z} \frac{z}{\sqrt{z^2-y^2}} [f_{xy}(\sqrt{z^2-y^2}, y) + f_{xy}(-\sqrt{z^2-y^2}, y)] dy$$

case-(vi): $Z = \text{Max}(X, Y)$

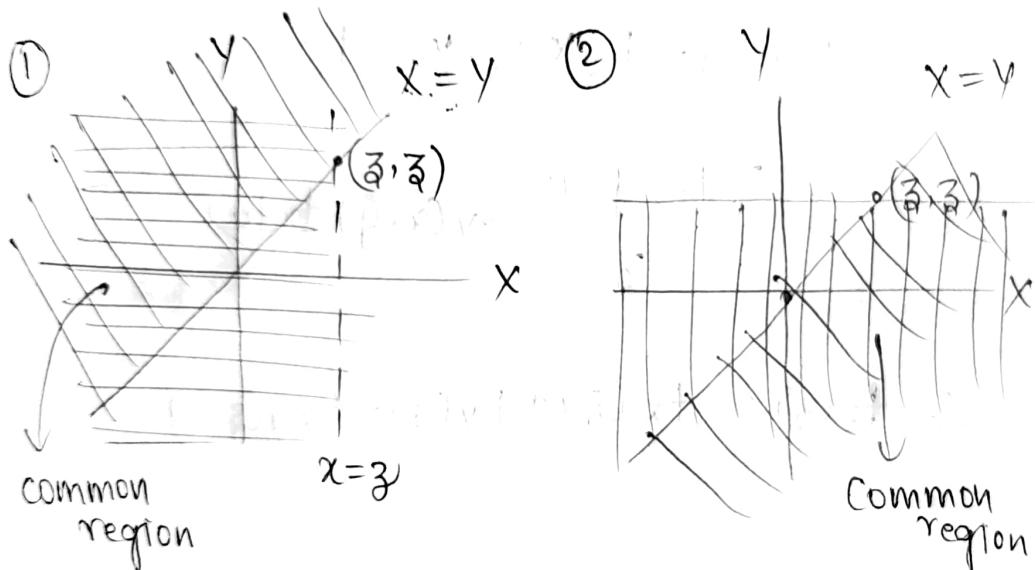
$$Z = \begin{cases} X, & X > Y \\ Y, & X < Y \end{cases}$$

$$f_Z(z) = P(Z \leq z) = P(X \leq z, X > Y) \cup (Y \leq z, Y > X)$$

$$= P[X \leq z, X > Y] + P[Y \leq z, Y > X]$$

①

②



$$f_Z(z) = P(X \leq z, Y \leq z)$$

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

$$\therefore f_Z(z) = \underline{f_{XY}(z, z)}$$

→ If X and Y are independent,

$$F_Z(z) = F_X(z) \cdot F_Y(z)$$

$$\boxed{f_Z(z) = f_X(z) \cdot f_Y(z) + f_X(z) f_Y(z)}$$

Case-VIII: $Z = \min(x, y)$

$$Z = \begin{cases} X, & X \leq Y \\ Y, & X > Y \end{cases}$$

$$f_Z(z) = P(Z \leq z)$$

$$= P[X \leq z, X \leq Y] + P[Y \leq z, X > Y]$$

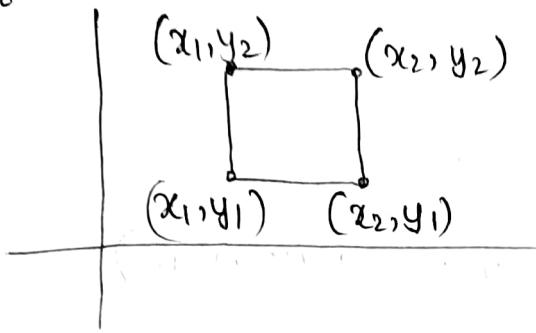
(1) (2)

$$f_Z(z) = 1 - P[X > z, Y > z]$$

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

$$\therefore f_Z(z) = f_X(z) + f_Y(z) - f_{XY}(z, z)$$

NOTE:



$$f_{X,Y}(x_1 \leq X \leq x_2, y_1 \leq Y \leq y_2)$$

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

$$= 1 - F_X(z) - F_Y(z) + f_{X,Y}(z, z)$$

$$[x_1 = z, x_2 = \infty, y_1 = z, y_2 = \infty]$$

eg: X and Y are two iid exponential random variables with parameter λ .

$$\text{find } Z = \min[X, Y]$$

find pdf of Z :

Sol:

$$f_X(x) = \lambda e^{-\lambda x} U(x)$$

$$f_Y(y) = \lambda e^{-\lambda y} U(y)$$

$$f_Z(z) = f_X(z) + f_Y(z) - \frac{d}{dz} (F_X(z) \cdot F_Y(z))$$

$$= f_X(z) + f_Y(z) - f_X(z) f_Y(z) - f_X(z) f_Y(z)$$

$$= f_X(z) [1 - f_Y(z)] + f_Y(z) [1 - f_X(z)]$$

CDF of exponential r.v is $F_X(x) = 1 - e^{-\lambda x}$, $x > 0$

$$f_Z(z) = [\lambda e^{-\lambda z}] [\bar{e}^{-\lambda z}] + [\lambda \bar{e}^{-\lambda z}] [\bar{e}^{-\lambda z}]$$

$$= 2\lambda e^{-2\lambda z}, z > 0$$

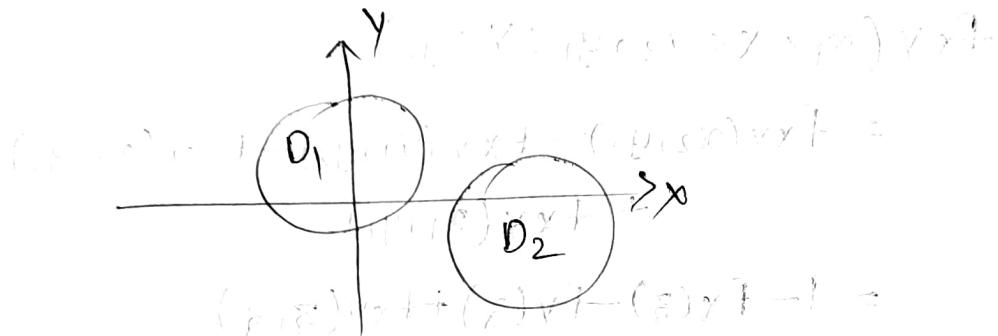
 exponential with parameter 2λ .

$$\textcircled{*} Z = g_1(x, y)$$

$$W = g_2(x, y)$$

$$f_{ZW}(z, w) = P(Z \leq z, W \leq w)$$

$$= P(g_1(x, y) \leq z, g_2(x, y) \leq w)$$

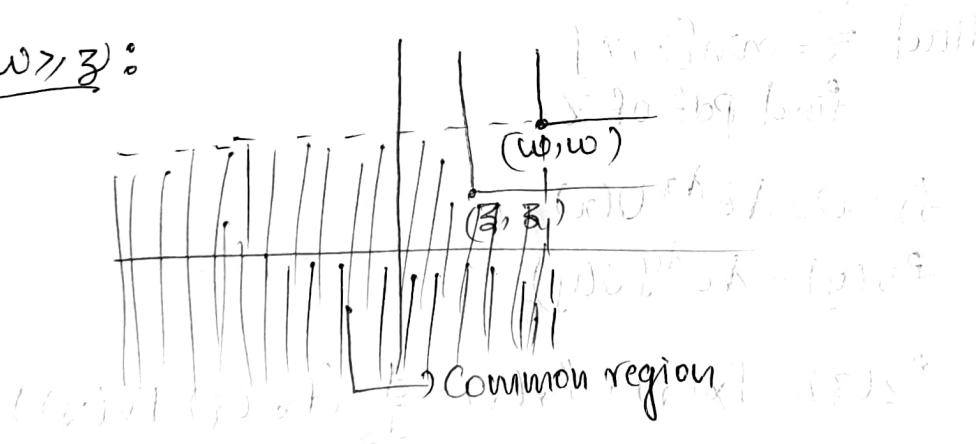


$$\text{eq: } Z = \min(x, y)$$

$$W = \max(x, y)$$

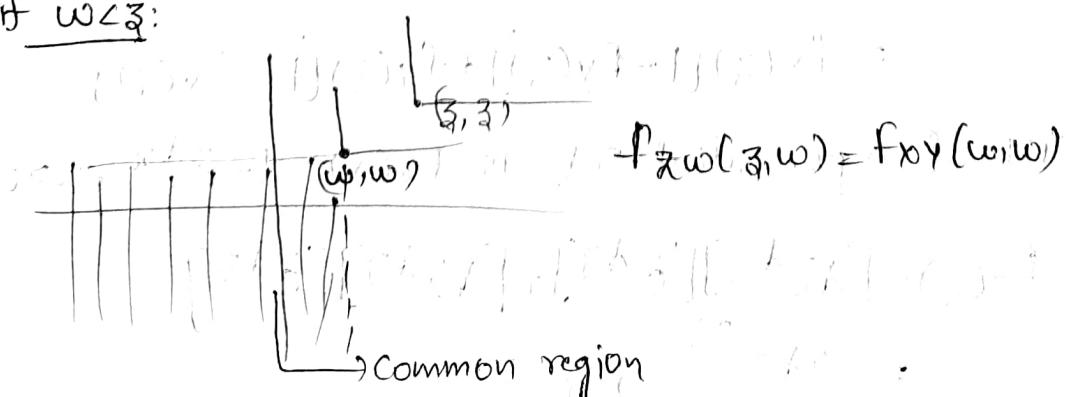
$$f_{ZW}(z, w) = P(Z \leq z, W \leq w)$$

If $w \geq z$:



$$f_{ZW}(z, w) = f_{XY}(z, w) + f_{XY}(w, z) - f_{XY}(z, z)$$

If $w < z$:



$$f_{z\omega}(z, \omega) = \begin{cases} f_{xy}(z, \omega) & z > \omega \\ f_{xy}(z, \omega) + f_{xy}(\omega, z) - f_{xy}(z, z) & z \leq \omega \end{cases}$$

Result 8

$$\begin{aligned} z &= g_1(x, y) \\ w &= g_2(x, y) \end{aligned} \quad \Rightarrow \quad \begin{aligned} x &= h_1(z, \omega) \\ y &= h_2(z, \omega) \end{aligned}$$

$$J_i(z, \omega) = \begin{bmatrix} \frac{\partial h_1}{\partial z} & \frac{\partial h_1}{\partial \omega} \\ \frac{\partial h_2}{\partial z} & \frac{\partial h_2}{\partial \omega} \end{bmatrix} \quad i = 1, 2, \dots, n \quad x = x_i^*, y = y_i^*$$

$$\begin{aligned} f_{z\omega}(z, \omega) &= \sum_i |J(z, \omega)| f_{xy}(x_i^*, y_i^*) \\ &= \sum_i \frac{1}{|J(x, y)|} f_{xy}(x_i^*, y_i^*) \end{aligned}$$

$$J(x, y) = \begin{bmatrix} \frac{\partial g_1}{\partial x} & \frac{\partial g_1}{\partial y} \\ \frac{\partial g_2}{\partial x} & \frac{\partial g_2}{\partial y} \end{bmatrix}$$

$$|J(z, \omega)| = \frac{1}{|J(x, y)|}$$

e.g. X and Y are iid Gaussian R.V's with $\mu=0$, σ^2 Variance.

$$R = \sqrt{x^2 + y^2} \quad \theta = \tan^{-1}\left(\frac{y}{x}\right)$$

find $f_{R\theta}(r, \theta)$

Sol:

$$X = R \cos \theta$$

$$Y = R \sin \theta$$

$$|\mathcal{J}(r, \theta)| = \begin{bmatrix} \cos \theta & -r \sin \theta \\ \sin \theta & r \cos \theta \end{bmatrix} = R / \sqrt{r^2}$$

$$|\mathcal{J}(x, y)| = \begin{bmatrix} \frac{x}{\sqrt{x^2 + y^2}} & \frac{y}{\sqrt{x^2 + y^2}} \\ \frac{-y}{x^2 + y^2} & \frac{x}{x^2 + y^2} \end{bmatrix}$$

$$= \frac{x^2}{(x^2 + y^2)^{3/2}} + \frac{y^2}{(x^2 + y^2)^{3/2}}$$

$$\frac{1}{|\mathcal{J}(x, y)|} = \frac{1}{\sqrt{x^2 + y^2}} = \frac{1}{R}$$

$$\therefore |\mathcal{J}(r, \theta)| = \frac{1}{|\mathcal{J}(x, y)|}$$

$$\begin{aligned} f_{R\theta}(r, \theta) &= r \cdot f_{xy}(r \cos \theta, r \sin \theta) \\ &= r \cdot \left(\frac{1}{\sqrt{2\pi r^2}} \right)^2 \cdot e^{-\frac{r^2}{2r^2}} \end{aligned}$$

$$\therefore f_{R\theta}(r, \theta) = \frac{r}{2\pi r^2} e^{-\frac{r^2}{2r^2}}$$

e.g. X and Y are iid exponential RVs with parameter λ .

$$Z = X+Y$$

$$W = X-Y$$

$$\text{Find } f_{ZW}(z, w)$$

Sol:

$$X = \frac{Z+W}{2}$$

$$Y = \frac{Z-W}{2}$$

$$|J(z, w)| = \begin{vmatrix} 1/2 & 1/2 \\ 1/2 & -1/2 \end{vmatrix} = +1/2$$

$$f_{ZW}(z, w) = \frac{1}{2} f_{XY}\left(\frac{z+w}{2}, \frac{z-w}{2}\right)$$

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

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

$$\therefore f_{ZW}(z, w) = \underline{\frac{1}{2} \lambda^2 e^{-\lambda z}} \quad 0 < w < z < \infty$$

$$\text{Result: } Z = ax + by$$

$$W = cx + dy$$

$$\begin{bmatrix} Z \\ W \end{bmatrix} = \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} X \\ Y \end{bmatrix}$$

↓
linear transformation

$$|J(x, y)| = ad - bc$$

$$|J(z, w)| = |AD - BC|$$

$$X = AZ + BW$$

$$Y = CZ + DW$$

$$f_{ZW}(z, w) = \frac{1}{|ad - bc|} f_{XY}(Az + Bw, Cz + Dw)$$

$$\mathbb{E}[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{XY}(x, y) dx dy$$

$$\mathbb{E}[X+Y] = \mathbb{E}[X] + \mathbb{E}[Y]$$

$$\mathbb{E}[XY] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_{XY}(x, y) dx dy \neq \mathbb{E}[X] \cdot \mathbb{E}[Y]$$

(In general)

If X and Y are independent,

$$\mathbb{E}[XY] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_X(x) \cdot f_Y(y) dx dy$$

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

$$\therefore \underline{\mathbb{E}[XY]} = \underline{\mathbb{E}[X] \cdot \mathbb{E}[Y]}$$

Covariance (C_{xy}):

$$\begin{aligned} C_{xy} &= \mathbb{E}\{(x - \mu_x)(y - \mu_y)\} \\ &= \mathbb{E}[XY - \mu_x Y - \mu_y X + \mu_x \mu_y] \\ &= \mathbb{E}[XY] - \mu_x \mathbb{E}[Y] - \mu_y \mathbb{E}[X] + \mu_x \mu_y \\ &= \mathbb{E}[XY] - \mu_x \mu_y - \cancel{\mu_y \mu_x} + \cancel{\mu_x \mu_y} \\ \therefore C_{xy} &= \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y] \end{aligned}$$

→ R.V's X and Y are said to be Uncorrelated

if $C_{xy} = 0 \Rightarrow \mathbb{E}[XY] = \mathbb{E}[X] \cdot \mathbb{E}[Y]$

→ If X and Y are independent then they are uncorrelated but the converse is not true.

→ Correlation coefficient : (ρ_{xy})

$$\rho_{xy} = \frac{C_{xy}}{\sigma_x \sigma_y}$$

Standard deviation of X , $\sigma_x = \sqrt{\text{Var}(X)} = \sqrt{\mathbb{E}[(X - \mu)^2]}$

$$|\rho_{xy}| \leq 1$$

Proof: $\mathbb{E}[(a(X - \mu_x) + (Y - \mu_y))^2] \geq 0$

$$\begin{aligned} &\mathbb{E}[a^2(X - \mu_x)^2 + 2a(X - \mu_x)(Y - \mu_y) + (Y - \mu_y)^2] \\ &= a^2 \sigma_x^2 + 2a C_{xy} + \sigma_y^2 \end{aligned}$$

$$\Delta \Rightarrow 4C_{xy}^2 - 4\sigma_x^2 \sigma_y^2 \leq 0$$

$$C_{xy}^2 \leq \sigma_x^2 \sigma_y^2$$

$$|C_{xy}| \leq \sigma_x \sigma_y \Rightarrow |\rho_{xy}| \leq 1$$

→ R.V's X and Y are said to be orthogonal,

if $E[XY] = 0$

↓
 X and Y are uncorrelated and $E[X] = 0$

e.g. X and Y are two R.V's that are uniformly distributed between $(0,1)$. Suppose X and Y are independent

$$Z = X+Y ; W = X-Y$$

(i) Are Z and W independent?

(ii) find Covariance of Z and W ($\text{Cov}(Z,W)$)

Sol: $f_{ZW}(z,w) = f_Z(z) \cdot f_W(w)$

$$X \quad f_X(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$Y \quad f_Y(y) = \begin{cases} 1 & \text{if } y > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$Z = X+Y$$

$$X = \frac{Z+W}{2}, Y = \frac{Z-W}{2}$$

$$W = X-Y$$

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

$$J(z,w) = \begin{vmatrix} 1/2 & 1/2 \\ 1/2 & -1/2 \end{vmatrix} = -1/2$$

$$f_{ZW}(z,w) = \frac{1}{2} f_{XY}\left(\frac{z+w}{2}, \frac{z-w}{2}\right)$$

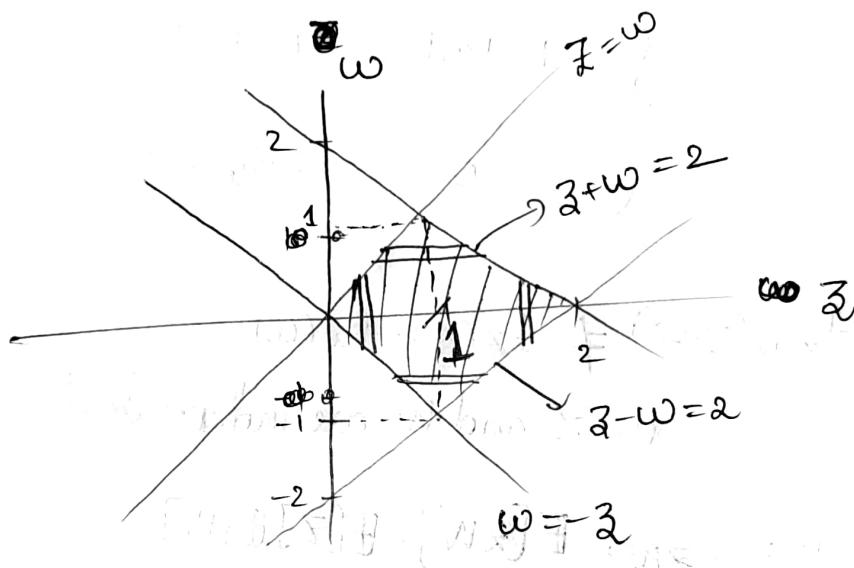
$$= \begin{cases} 1/2 & 0 < z < 2, -1 < w < 1 \\ & 1/w < z, z + w < 2 \\ & z - w < 2 \\ 0 & \text{otherwise} \end{cases}$$

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

$$f_Z(z) = \begin{cases} z, & 0 < z \leq 1 \\ 2-z, & 1 < z \leq 2 \end{cases}$$

$$W = X - Y$$

~~$$f_W(w) = \int_{-\infty}^{\infty} f_X(z+y) \cdot f_Y(y) dy$$~~



$$f_Z(z) = \int_{-\infty}^{\infty} f_{ZW}(z, w) dw$$

$$= \begin{cases} \int_{-z}^z \frac{1}{2} dw & 0 < z < 1 \\ 2-z & 1 < z < 2 \\ z-2 & \end{cases}$$

$$= \begin{cases} z & 0 < z < 1 \\ \frac{1}{2}(4-z) & 1 < z < 2 \end{cases} \Rightarrow \begin{cases} z & 0 < z < 1 \\ 2-z & 1 < z < 2 \end{cases}$$

$$f_{ZW}(z, w) = \int_{-\infty}^{\infty} f_{ZW}(z, w) dz$$

$$= \begin{cases} \int_{|w|}^{2-|w|} \frac{1}{2} dz, & |w| < 1 \\ 0 & \text{otherwise} \end{cases}$$

$$= \begin{cases} 1-|w|, & |w| < 1 \\ 0 & \text{otherwise} \end{cases}$$

$$f_{ZW}(z, w) \neq f_Z(z) \cdot f_W(w)$$

So, Z and W are independent.

$$C(z, w) = C_{ZW} = E[zw] - E[z]E[w]$$

$$\begin{aligned} E[zw] &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} z w f_{ZW}(z, w) dz dw \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{ZW}(z, w) dz dw \end{aligned}$$

$$E[zw] = E[(x+y)(x-y)]$$

$$= E[x^2 - y^2] = E[x^2] - E[y^2]$$

$$= \int_{-\infty}^{\infty} x^2 f_x(x) dx - \int_{-\infty}^{\infty} y^2 f_y(y) dy$$

$$= \int_0^1 x^2 dx - \int_0^1 y^2 dy$$

$$\therefore E[zw] = 1/3 - 1/3 = 0 //$$

$$\begin{aligned} \mathbb{E}[z] &\geq \mathbb{E}[z] = \mathbb{E}[x+y] \\ &= \mathbb{E}[x] + \mathbb{E}[y] = 1 \end{aligned}$$

$$\begin{aligned} \mathbb{E}[w] &\rightarrow \mathbb{E}[w] = \mathbb{E}[x-y] \\ &= \mathbb{E}[x] - \mathbb{E}[y] \\ &= 0 // \end{aligned}$$

$$\begin{aligned} \therefore C(z,w) &= \mathbb{E}[zw] - \mathbb{E}[z]\mathbb{E}[w] \\ &= 0 - 1(0) \\ &= 0 // \end{aligned}$$

e.g. x, y and z are R.V's with mean '0' and

$$\text{Var}(x) = \text{Var}(y) = \text{Var}(z) = 20$$

$$\text{Cov}(x,y) = \text{Cov}(x,z) = 10$$

$$\text{Cov}(y,z) = 5$$

$$(i) \text{ find } \text{Cov}(3x+y, 3x+z)$$

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

$$\underline{\mathbb{E}[xy] = 10}$$

$$\text{Cov}(x,z) = 10 \Rightarrow \underline{\mathbb{E}[xz] = 10}$$

$$\text{Cov}(y,z) = 5 \Rightarrow \underline{\mathbb{E}[yz] = 5}$$

$$\begin{aligned} (i) \quad \text{Cov}(3x+y - \mathbb{E}[3x+y])(3x+z - \mathbb{E}[3x+z])) \\ &= \mathbb{E}[(3x+y)(3x+z)] \end{aligned}$$

$$= \mathbb{E}[9x^2 + 3xz + 3xy + yz]$$

$$= 9\mathbb{E}[x^2] + 3\mathbb{E}[xz] + 3\mathbb{E}[xy] + \mathbb{E}[yz]$$

$$= 9 \times 20 + 3 \times 10 + 10 \times 3 + 5 = 245 //$$

• Joint characteristic function:

$$\begin{aligned}\phi_x(w) &= \mathbb{E}[e^{jwX}] \\ &= \int_{-\infty}^{\infty} e^{jwX} f_X(x) dx\end{aligned}$$

= $\mathcal{F}[f_X(x)] \rightarrow$ Fourier transform.

$$\therefore \phi_{x,y}(w_1, w_2) = \mathbb{E}[e^{j(w_1x + w_2y)}]$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{j(w_1x + w_2y)} f_{x,y}(x, y) dx dy$$

$$\left(\mathbb{E}[g(x, y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{x,y}(x, y) dx dy \right)$$

→ Conditional expectations

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

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

$$\mathbb{E}[g(x)|M] = \int_{-\infty}^{\infty} g(x) f_{x|M}(x|m) dx$$

$$\mathbb{E}[x|y=y] = \int_{-\infty}^{\infty} x f_{x|y}(x|y) dx$$

$$\mathbb{E}[y|x=x] = \int_{-\infty}^{\infty} y f_{y|x}(y|x) dy$$

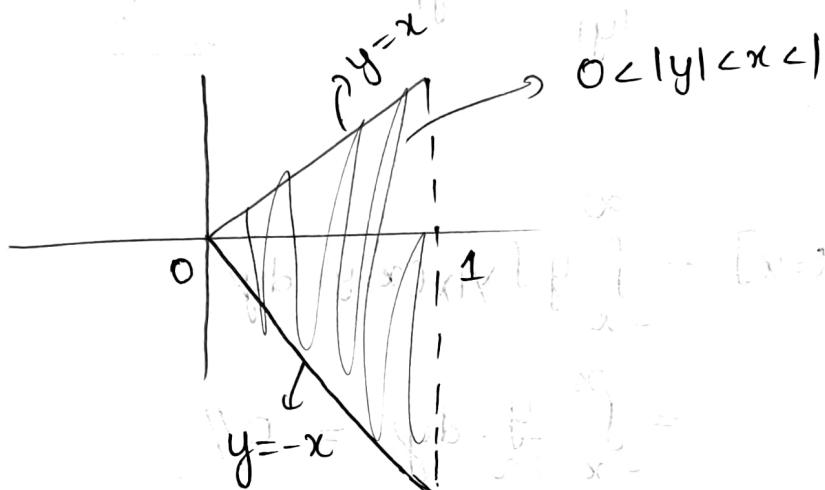
$$\mathbb{E}[X] = (\text{mean}) + (\text{variance})$$

→ Conditional variance:

$$\sigma_{x|y}^2 = \mathbb{E}_{x|y}[(x - \mu_{x|y})^2]$$

e.g.: $f_{x,y}(x,y) = \begin{cases} 1 & , 0 < |y| < x < 1 \\ 0 & , \text{else} \end{cases}$

find $\mathbb{E}(x|y=y)$ and $\mathbb{E}(y|x=x)$



$$f_x(x) = \int_{-\infty}^{\infty} f_{x,y}(x,y) dy = \int_{-x}^x 1 dy = 2x, \quad 0 < x < 1$$

$$f_y(y) = \int_{-\infty}^{\infty} 1 dx \quad x, y > 0 = \int_0^{\infty} 1 dx = \infty$$

$$= \int_{-\infty}^0 1 dx, \quad y < 0$$

$$= 1 - |y|, \quad |y| < 1$$

$$f_{x|y}(x|y) = \frac{f_{x,y}(x,y)}{f_y(y)} = \frac{1}{1-|y|}, \quad 0 < |y| < x < 1$$

$$f_{Y|X}(x, y) = \frac{f_{XY}(x, y)}{f_X(x)} = \frac{1}{2x}, \quad 0 < y < x < 1$$

$$\mathbb{E}[X|Y=y] = \int_{-\infty}^{\infty} x f_{X|Y}(x, y) dx$$

$$= \int_{\frac{|y|}{2}}^{\infty} \frac{x}{1-y} dx = \frac{1+|y|}{2}, \quad |y| < 1$$

~~$$\mathbb{E}[Y|X=x] = \int_{-\infty}^{\infty} y f_{Y|X}(x, y) dy$$~~
~~$$= \int_{-x}^{x} \frac{y}{2x} dy = 0$$~~

(*) $\mathbb{E}[\mathbb{E}[Y|X]] = \mathbb{E}[Y]$ $\mathbb{E}[\mathbb{E}[g(x, y)|X]] = \mathbb{E}[g(x, y)]$

Proof: $g(x) = \mathbb{E}[Y|X]$

$$\begin{aligned} \mathbb{E}[g(x)] &= \int_{-\infty}^{\infty} g(x) f_X(x) dx \\ &= \int_{-\infty}^{\infty} f_X(x) \left(\int_{-\infty}^{\infty} y \cdot f_{Y|X}(x|y) dy \right) dx \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y \cdot f_{XY}(x, y) dx dy \\ &= \underline{\underline{\mathbb{E}[Y]}}$$

$$(\mathbb{E}[g(x, y)]) = \int \int g(x, y) f_{XY}(x, y) dx dy$$

$\rightarrow x$ and y are R.V's with joint pdf $f_{xy}(x,y)$

$$Z = ax + by \implies \mu_Z = a\mu_x + b\mu_y$$

$$\text{Var}(z) = \mathbb{E}[(z - \mu_z)^2]$$

$$= \mathbb{E}[(a(x - \mu_x) + b(y - \mu_y))^2]$$

$$= \mathbb{E}[a^2(x - \mu_x)^2 + b^2(y - \mu_y)^2]$$

$$+ 2ab(x - \mu_x)(y - \mu_y)]$$

$$\therefore \text{Var}(z) = \underline{a^2 \text{Var}(x) + b^2 \text{Var}(y) + 2ab \text{Cov}(x,y)}$$

Central limit theorem (CLT):

Let x_1, x_2, x_3, \dots be iid R.V's with mean μ and variance σ^2

$$\lim_{n \rightarrow \infty} \frac{1}{\sqrt{n}} \sum_{i=1}^n \frac{x_i - \mu}{\sigma} = N(0, 1)$$

Covariance matrix:

$$V = \begin{bmatrix} x \\ y \end{bmatrix}, \quad \mu = \begin{bmatrix} \mu_x \\ \mu_y \end{bmatrix}$$

$$\text{Covariance matrix} = \mathbb{E}[(V - \mu)(V - \mu)^T]$$

$$= \mathbb{E}\left[\begin{bmatrix} x - \mu_x \\ y - \mu_y \end{bmatrix} \begin{bmatrix} x - \mu_x & y - \mu_y \end{bmatrix}^T\right]$$

$$\lesssim = \begin{bmatrix} \sigma_x^2 & \text{C}_{xy} \\ \text{C}_{xy} & \sigma_y^2 \end{bmatrix}$$

and γ are jointly gaussian if

$$f_{XY}(x, y) = f_V(v)$$

$$= \frac{1}{2\pi|\Sigma|} \exp\left\{-\frac{(v-\mu)^T \Sigma^{-1} (v-\mu)}{2}\right\}$$

$$\bar{X} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \quad f_{\bar{X}}(x_1, x_2, \dots, x_n)$$

$$= P(x_1 \leq x, \dots, x_n \leq x_n)$$

$$\therefore f_{\bar{X}}(x_1, \dots, x_n) = \underbrace{\frac{\partial^n f}{\partial x_n \cdots \partial x_1}}_{\text{1st derivative}}$$

$$\therefore f_{x_1}(x_1) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{\bar{X}}(x_1, \dots, x_n) dx_2 \cdots dx_n$$

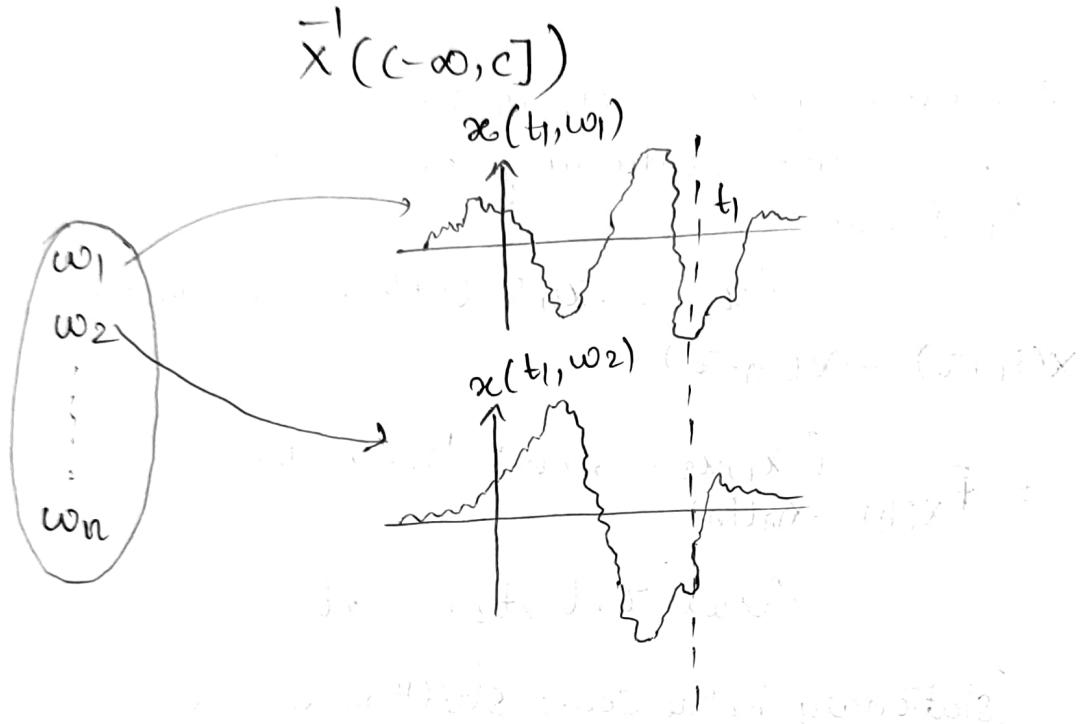
$$\cancel{f_{\bar{X}}(x_1, \dots, x_n) = \frac{1}{2\pi|\Sigma|} \exp\left\{-\frac{(v-\mu)^T \Sigma^{-1} (v-\mu)}{2}\right\}}$$

Random Processes :

30/03/22

A random variable 'X' is a mapping ($X : \Omega \rightarrow \mathbb{R}$) such that

$$\{w \in \Omega, X(w) \leq c\} \in \mathcal{F} \quad \text{where } c \in \mathbb{R}$$



→ We define a random process $X(t; w)$ or $X(t)$ as an ensemble of time functions, such that together with a probability rule that assigns probability to any meaningful event associated with an observation of one of the sample functions of the random process.

e.g.: $X(t) = A \cos(2\pi f_c t + \Theta)$

A, f_c are constants

$$\Theta \sim U[-\pi, \pi]$$

$$X(t, w) = A \cos(2\pi f_c t + \Theta(w))$$

for $n \geq 1$ (nth order distribution function)

$$f_{X(t_1) X(t_2) \dots X(t_n)}(x_1, x_2, \dots, x_n; t_1, t_2, \dots, t_n)$$

$$= P(X(t_1) \leq x_1, \dots, X(t_n) \leq x_n)$$

→ A random process $X(t)$ is said to be strict-sense stationary or strictly stationary if for each n ,

$$f_{X(t_1+\tau) \dots X(t_n+\tau)}(x_1, \dots, x_n; t_1+\tau, t_2+\tau, \dots, t_n+\tau)$$

$$= f_{X(t_1) \dots X(t_n)}(x_1, x_2, \dots, x_n; t_1, t_2, \dots, t_n)$$

forall $\tau, t_1, t_2, \dots, t_n$

(stationary in the sense shifting constant ' τ ')

(i) for $n=1$

$$f_{X(t_1+\tau)}(x; t_1+\tau) = f_{X(t_1)}(x; t_1)$$

= $f_X(x)$ if independent of time.

(ii) for $n=2$

$$f_{X(t_1+\tau) X(t_2+\tau)}(x_1, x_2; t_1+\tau, t_2+\tau)$$

$$= f_{X(t_1) X(t_2)}(x_1, x_2; t_1, t_2)$$

$$= f_{X(t_1) X(t_2)}(x_1, x_2; t_2-t_1)$$

→ Mean

$$\mu_{X(t)} = \int_{-\infty}^{\infty} x f_x(x, t) dx$$

if $X(t)$ is strictly stationary then,

$$\mu_{X(t)} = \int_{-\infty}^{\infty} x f_x(x) dx \text{ independent of time.}$$

→ Auto-correlation

$$R_{XX}(t_1, t_2) = \mathbb{E}[X(t_1) X(t_2)]$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1 x_2 f_x(x_1, x_2; t_1, t_2) dx_1 dx_2$$

$$R_{XX}(t_1, t_2) = R_X(t_2 - t_1)$$

→ A random process $X(t)$ is a wide-sense stationary or widely stationary if

(i) $\mu_{X(t)}$ is independent of time.

(ii) $R_{XX}(t_1, t_2)$ depends only on the $t_2 - t_1$.

$$\rightarrow R_X(\tau) = \mathbb{E}[X(t+\tau) X(t)]$$

(i) Mean square value of $X(t) \Rightarrow \mathbb{E}[X^2(t)] = R_X(0)$

(ii) $R_X(\tau) = R_X(-\tau)$

$$R_X(\tau) = \mathbb{E}[X(t+\tau) X(t)]$$

$$R_X(-\tau) = \mathbb{E}[X(t-\tau) X(t)]$$

$$= \mathbb{E}[X(t) X(t-\tau)]$$

$$= R_X(\tau)$$

$$(iii) R_x(\tau) \leq R_x(0)$$

$$\mathbb{E}[(x(t+\tau) + x(t))^2] \geq 0$$

$$\mathbb{E}[x^2(t+\tau) + 2x(t+\tau)x(t) + x^2(t)] \geq 0$$

$$2R_x(0) + 2R_x(\tau) \geq 0$$

$$R_x(0) \geq -R_x(\tau)$$

e.g.: $U[a, b]$

$$f_x(x) = \frac{1}{b-a}, \quad a \leq x \leq b$$

$$\text{e.g.: } X(t) = A \cos(2\pi f_c t + \theta)$$

A, f_c are constants

$$\theta \sim U[-\pi, \pi]$$

$$f_\theta(\theta) = \frac{1}{2\pi}, \quad -\pi \leq \theta \leq \pi$$

$$(i) \mu_x = \mathbb{E}[x(t)]$$

$$= \int_{-\pi}^{\pi} A \cos(2\pi f_c t + \theta) \cdot \frac{1}{2\pi} d\theta$$

$$\therefore \mu_x = 0 //$$

$$(ii) \mathbb{E}[x(t+\tau) x(t)]$$

$$= \mathbb{E}[A^2 \cos(2\pi f_c t + 2\pi f_c \tau + \theta) \cos(2\pi f_c t + \theta)]$$

$$= \frac{A^2}{2\pi} \int_{-\pi}^{\pi} \cos(2\pi f_c t + 2\pi f_c \tau + \theta) \cos(2\pi f_c t + \theta) d\theta$$

$$= \frac{A^2}{2\pi} \times \frac{1}{2} \int_{-\pi}^{\pi} [\cos(4\pi f_c t + 2\pi f_c \tau + 2\theta) + \cos(2\pi f_c \tau)] d\theta$$

$$\begin{aligned} \mathbb{E}[X(t+\tau)X(t)] &= \frac{A^2}{2\pi} \times \frac{1}{2} \left[\int_{-\pi}^{\pi} \cos(4\pi f_c t + 2\pi f_c \tau + \varphi_0) d\theta \right. \\ &\quad \left. + \int_{-\pi}^{\pi} \cos(2\pi f_c \tau) d\theta \right] \\ &= \frac{A^2}{2\pi} \times \frac{1}{2} \times \cos(2\pi f_c \tau) (\cancel{\frac{1}{2}}) \\ &= \underline{\underline{\frac{A^2}{2} \cos(2\pi f_c \tau)}} \end{aligned}$$

Auto Covariance:

$$C_{xx}(t_1, t_2) = \mathbb{E}[(X(t_1) - \mu_{x(t_1)})(X(t_2) - \mu_{x(t_2)})]$$

Joint Random processes:

$\rightarrow X(t), Y(t)$

$$n \geq 0, m \geq 0 \quad n+m \geq 1$$

$$f_{x(t_1) \dots x(t_n), y(t_1) \dots y(t_m)}(x_1, \dots, x_n, y_1, \dots, y_m | t_1, \dots, t_n, u_1, \dots, u_m) = P(X(t_1) \leq x_1, \dots, X(t_n) \leq x_n, Y(u_1) \leq y_1, \dots, Y(u_m) \leq y_m)$$

$$= P(X(t_1) \leq x_1, \dots, X(t_n) \leq x_n, Y(u_1) \leq y_1, \dots, Y(u_m) \leq y_m)$$

Cross-correlation

$$R_{xy}(t, u) = \mathbb{E}[X(t)Y(u)]$$

$$R_{yx}(t, u) = \mathbb{E}[Y(t)X(u)] \neq R_{xy}(t, u)$$

\rightarrow if $X(t)$ & $Y(u)$ jointly stationary then,

$$R_{xy}(\tau) = \mathbb{E}[X(t+\tau)Y(t)]$$

Correlation matrix

$$R(t, u) = \begin{bmatrix} R_{xx}(t, u) & R_{xy}(t, u) \\ R_{yx}(t, u) & R_{yy}(t, u) \end{bmatrix}$$

→ If $x(t)$ and $y(t)$ are jointly stationary then,

$$R(\tau) = \begin{bmatrix} R_{xx}(\tau) & R_{xy}(\tau) \\ R_{yx}(\tau) & R_{yy}(\tau) \end{bmatrix}$$

$$\rightarrow R_{xy}(-\tau) = E[x(t-\tau)y(t)] \\ = E[y(t)x(t-\tau)] = R_{yx}(\tau)$$

e.g.: $X_1(t) = x(t)\cos(2\pi f_c t + \theta)$ $x(t)$ is a stationary

$X_2(t) = x(t)\sin(2\pi f_c t + \theta)$ Random process.

$\theta \sim U[0, 2\pi]$ is independent of $x(t)$

find $R_{12}(\tau, t) = E[X_1(t+\tau)x_2(t)]$

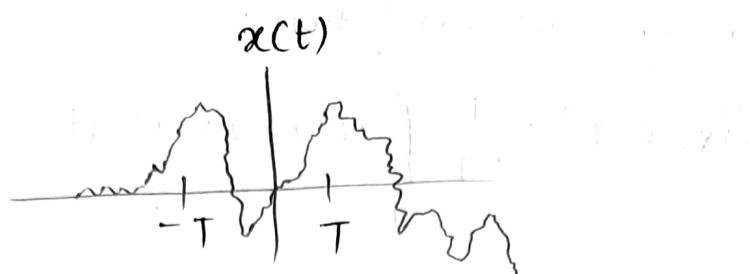
$$\begin{aligned} \underline{\text{Sol:}} \quad &= E[X_1(t+\tau)x_2(t)] \\ &= E[x(t+\tau)\cos(2\pi f_c t + \theta + 2\pi f_c \tau) \\ &\quad x(t)\sin(2\pi f_c t + \theta)] \\ &= E\left[\frac{x(t+\tau)x(t)}{2}\right] \times \sin(2\pi f_c t + \theta + 2\pi f_c \tau) \cos(2\pi f_c t + \theta + 2\pi f_c \tau) \\ &= E\left[\frac{x(t+\tau)x(t)}{2}\right] \times (\sin(4\pi f_c t + 2\theta + 4\pi f_c \tau) \\ &\quad - \sin(2\pi f_c \tau)) \\ &= \frac{1}{2} E[x(t+\tau)x(t)\sin(4\pi f_c t + 2\theta + 4\pi f_c \tau)] \\ &\quad - \frac{1}{2} E[x(t+\tau)x(t)\sin(2\pi f_c \tau)] \end{aligned}$$

∴ If x and y are independent, then

$$E[g(x)h(y)] = E[g(x)]E[h(y)]$$

$$= -\frac{R_x(\tau)}{2} \sin(2\pi f_c \tau)$$

• Ergodicity:



Time-average of sample $x(t)$ is:

$$\bar{X}_x(T) = \frac{1}{2T} \int_{-T}^T x(t) dt$$

$$\mathbb{E}[\bar{X}_x(T)] = \mathbb{E}\left[\frac{1}{2T} \int_{-T}^T x(t) dt\right]$$

$$= \frac{1}{2T} \int_{-T}^T \mathbb{E}[x(t)] dt$$

if sample set of bus is stationary

statistical average

If $x(t)$ is stationary,

$$\mathbb{E}[\bar{X}_x(T)] = \bar{X}_x$$

$$\text{Var}(x) = \mathbb{E}[(x - \bar{X}_x)^2] \geq 0$$

$\text{Var}(x) = 0 \rightarrow x = \bar{X}_x$ with probability 1.

At this instant, random variable becomes const.

→ A random process $x(t)$ is said to be ergodic in mean (or) mean-ergodic if

$$(i) \lim_{T \rightarrow \infty} \bar{X}_x(T) = \bar{X}_x$$

$$(ii) \lim_{T \rightarrow \infty} \text{Var}(\bar{X}_x(T)) = 0$$

• Time-average autocorrelation:

$$R_x(\tau, T) = \frac{1}{2T} \int_{-T}^T x(t+\tau) x(t) dt$$

$$\begin{aligned} E[R_x(\tau, T)] &= E\left[\frac{1}{2T} \int_{t-\tau}^T x(t+\tau) x(t) dt\right] \\ &= \frac{1}{2T} \int_{-T}^T R_x(\tau, t) dt \end{aligned}$$

If $x(t)$ is stationary,

$$E[R_x(\tau, T)] = R_x(\tau)$$

→ A Random process is said to be ergodic in autocorrelation if,

$$(i) \lim_{T \rightarrow \infty} R_x(\tau, T) = R_x(\tau)$$

$$(ii) \lim_{T \rightarrow \infty} \text{Var}(R_x(\tau, T)) = 0$$



$$y(t) = \int_{-\infty}^{\infty} h(\tau) x(t-\tau) d\tau$$

$$\mathbb{E}[y(t)] = \mathbb{E}\left[\int_{-\infty}^{\infty} h(\tau) x(t-\tau) d\tau\right]$$

$$\mathbb{E}[y(t)] = \mathbb{E}\left[\int_{-\infty}^{\infty} h(\tau) x(t-\tau) d\tau\right]$$

$$\mu_y(t) = \int_{-\infty}^{\infty} h(\tau) \mathbb{E}[x(t-\tau)] d\tau$$

$$\mu_y(t) = \int_{-\infty}^{\infty} h(\tau) \mu_x(t-\tau) d\tau$$

If $x(t)$ is stationary,

$$\mu_y(t) = \mu_x \int_{-\infty}^{\infty} h(\tau) d\tau$$

$$\therefore \mu_y(t) = \mu_x H(0)$$

$$H(f) = \int \{h(t)\} e^{-j2\pi ft} dt$$

$$= \int_{-\infty}^{\infty} h(t) e^{-j2\pi ft} dt$$

$$x(t) \xrightarrow{h(t)} y(t)$$

$$R_y(t_1, t_2) = E[y(t_1) \cdot y(t_2)]$$

$$y(t_1) = \int_{-\infty}^{\infty} h(\tau) \cdot x(t_1 - \tau) d\tau$$

$$y(t_2) = \int_{-\infty}^{\infty} h(\tau) \cdot x(t_2 - \tau) d\tau$$

$$R_y(t_1, t_2) = E \left[\int_{-\infty}^{\infty} h(\tau) \cdot x(t_1 - \tau) d\tau \int_{-\infty}^{\infty} h(\tau) \cdot x(t_2 - \tau) d\tau \right]$$

$$= E \left[\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(\tau_1) h(\tau_2) x(t_1 - \tau_1) x(t_2 - \tau_2) d\tau_1 d\tau_2 \right]$$

→ For stable LTI system,

$$R_y(t_1, t_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(\tau_1) h(\tau_2) R_x(t_1 - \tau_1, t_2 - \tau_2) d\tau_1 d\tau_2$$

→ If $x(t)$ is stationary,

WSS

(i) $E[x(t)]$ is independent of time.

(ii) $R_x(t_1, t_2)$ depends only on $t_2 - t_1$.

→ $x(t)$ is nth-order strict-sense stationary

if

$$f_{x(t_1) x(t_2) \dots x(t_N)}(x_1, \dots, x_N; t_1, t_2, \dots, t_N)$$

$$= f_{x(t_1 + \tau) \dots x(t_N + \tau)}(x_1, \dots, x_N; t_1, \dots, t_N)$$

$$R_y(t_1, t_2) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(\tau_1) h(\tau_2) R_x(t_2 - \tau_1) d\tau_1 d\tau_2$$

↓ where ~~where~~ $\tau = t_1 - t_2$

$$R_y(0)$$

Mean square,

$$\mathbb{E}[y(t)] = R_y(0)$$

$$H(f) = \int_{-\infty}^{\infty} h(\tau) e^{-j2\pi f \tau} d\tau$$

~~for $\tau < 0$ to consider~~

$$h(\tau_1) = \int_{-\infty}^{\infty} H(f) e^{j2\pi f \tau_1} df$$

$$\mathbb{E}[y^2(t)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} H(f) e^{j2\pi f \tau_1} df \right) h(\tau_2) R_x(\tau_2 - \tau_1) d\tau_1 d\tau_2$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} H(f) df h(\tau_2) R_x(\tau_2 - \tau_1) e^{-j2\pi f \tau_1} d\tau_2 d\tau_1$$

~~$H(f)$ is $\frac{1}{2}$ of $R_x(\tau)$ $\alpha = \tau_2 - \tau_1$~~

$$= \int_{-\infty}^{\infty} H(f) \int_{-\infty}^{\infty} h(\tau_2) e^{j2\pi f \tau_2} \left(\int_{-\infty}^{\infty} R_x(\alpha) e^{-j2\pi f \alpha} d\alpha \right) d\tau_2 df$$

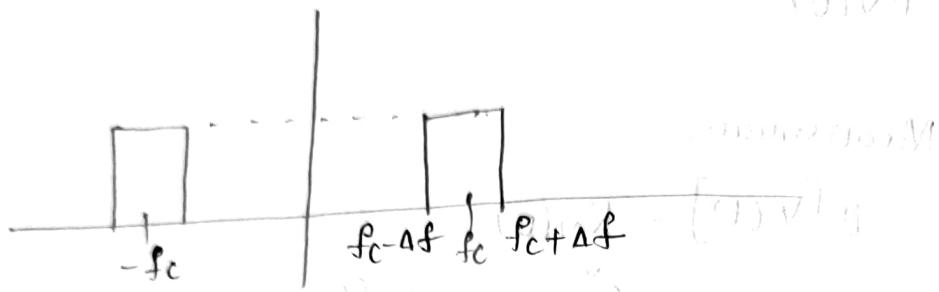
Fourier Transform of
auto-correlation $R_x(\tau)$

$$= \int_{-\infty}^{\infty} |H(f)|^2 S_x(f) df$$

↑
Power spectral density (PSD)

(01)
Power density spectrum.

$$\mathbb{E}[y^2(t)] = \int_{-\infty}^{\infty} |H(f)|^2 S_x(f) df \simeq 2 \Delta f S_x(f)$$



\therefore dimension of $S_x(f)$ is Watt/Hz.

$$S_x(f) = \int_{-\infty}^{\infty} R_x(\tau) e^{j2\pi f\tau} d\tau$$

$$R_x(\tau) = \int_{-\infty}^{\infty} S_x(f) e^{-j2\pi f\tau} df = [S_x(f)]$$

$$(i) S_x(0) = \int R_x(\tau) d\tau$$

$$\mathbb{E}[x^2(t)] = R_x(0) = \int_{-\infty}^{\infty} S_x(f) df$$

$$(ii) S_x(f) \geq 0$$

$$(iii) S_x(f) = \int R_x(\tau) e^{j2\pi f\tau} d\tau$$

$$S_x(f) = \int_{-\infty}^{\infty} R_x(\tau) e^{j2\pi f\tau} d\tau$$

$$= \int R_x(-\tau) e^{j2\pi f\tau} d\tau$$

$$\text{using } u = -\tau$$

$$= \int_{-\infty}^{\infty} R_x(u) e^{j2\pi fu} du$$

$$= S_x(f)$$

$$(iv) P_x(f) = \frac{S_x(f)}{\int_{-\infty}^{\infty} S_x(f) df} \quad \text{satisfies properties of a pdf.}$$

$$\text{eg: } X(t) = A \cos(2\pi f_c t + \theta) \quad \theta \sim U[-\pi, \pi]$$

find PSD of $X(t)$

$$\text{Sol: } E[X^2(t)] = \int_{-\infty}^{\infty} |H(f)|^2 S_x(f) df$$

$$S_x(f) = \int_{-\infty}^{\infty} R_x(\tau) e^{-j2\pi f \tau} d\tau$$

$$R_x(\tau) = E[X(t+\tau)X(t)]$$

$$= E[A^2 \cos(2\pi f_c t + \theta) \cos(2\pi f_c t + \theta + 2\pi f_c \tau)]$$

$$= \frac{A^2}{2\pi f_c} \int_{-\pi}^{\pi} \cos(2\pi f_c t + 2\pi f_c \tau + \theta) \cos(2\pi f_c t + \theta) d\theta$$

$$= \frac{A^2}{2\pi} \times \frac{1}{2} \int_{-\pi}^{\pi} \cos(4\pi f_c t + 2\pi f_c \tau + 2\theta) + \cos(2\pi f_c \tau) d\theta$$

$$= \frac{A^2}{2\pi} \times \frac{1}{2} \times \cos(2\pi f_c \tau) \times 2\pi$$

$$\underline{R_x(\tau) = \frac{A^2}{2} \cos(2\pi f_c \tau)}$$

$$S_x(f) = \int_{-\infty}^{\infty} \frac{A^2}{2} \cos(2\pi f_c \tau) e^{j2\pi f \tau} d\tau$$

$$= \frac{A^2}{2} \int_{-\infty}^{\infty} e^{j2\pi f_c \tau} \frac{e^{j2\pi f \tau} - e^{-j2\pi f \tau}}{2} e^{-j2\pi f \tau} d\tau$$

$$= \frac{A^2}{2} \times \frac{1}{2} \int_{-\infty}^{\infty} (e^{-j2\pi(f-f_c)\tau} + e^{-j2\pi(f+f_c)\tau}) d\tau$$

$$\therefore S_x(f) = \frac{A^2}{4} [S(f-f_c) + S(f+f_c)]$$

$\rightarrow x(t)$ is a random process with

$$R_x(\tau) = \begin{cases} A^2 \left(1 - \frac{|\tau|}{T}\right), & |\tau| < T \\ 0, & \text{otherwise.} \end{cases}$$

find $S_x(f)$

Solt

$$\begin{aligned} S_x(f) &= \int_{-\infty}^{\infty} R_x(\tau) e^{-j2\pi f\tau} d\tau \\ &= \int_{-T}^{T} A^2 \left(1 - \frac{|\tau|}{T}\right) e^{-j2\pi f\tau} d\tau \\ &= \int_{-T}^{0} A^2 (2) e^{-j2\pi f\tau} d\tau + \int_{0}^{T} 0 d\tau \\ &= 2A^2 \int_{-T}^{0} e^{-j2\pi f\tau} d\tau \\ &= \frac{2A^2}{-j2\pi f} \left[e^{-j2\pi f\tau} \right]_{-T}^{0} \\ &= \frac{jA^2}{\pi f} \left[1 + e^{j2\pi fT} \right] \end{aligned}$$

$$\therefore S_x(f) = \frac{A^2}{T} \sin^2(fT)$$

$$\rightarrow S_y(f) = \int_{-\infty}^{\infty} R_y(\tau) e^{-j2\pi f \tau} d\tau$$

$$= \int_{-\infty}^{\infty} \left(\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} h(\tau_1) h(\tau_2) R_x(\tau - \tau_1 + \tau_2) d\tau_1 d\tau_2 \right) e^{-j2\pi f \tau} d\tau$$

$$u = \tau - \tau_1 + \tau_2, \quad \bar{\tau} = u + \tau_1 - \tau_2$$

$$= \left(\int_{-\infty}^{\infty} h(\tau_1) e^{-j2\pi f \tau_1} d\tau_1 \right) \left(\int_{-\infty}^{\infty} R_x(u) e^{-j2\pi f u} du \right)$$

$$\int_{-\infty}^{\infty} h(\tau_2) e^{j2\pi f \tau_2} d\tau_2$$

$\rightarrow x(t), y(t)$ are joint stationary R.P's

$$R_{xy}(\tau) = \mathbb{E}[x(t+\tau)y(t)]$$

cross-spectral density,

$$S_{xy}(f) = \int_{-\infty}^{\infty} R_{xy}(\tau) e^{-j2\pi f \tau} d\tau$$

$$S_{yx}(f) = \int_{-\infty}^{\infty} R_{yx}(\tau) e^{-j2\pi f \tau} d\tau$$

$$S_{xy}(f) = S_{yx}^*(f) = S_{yx}(-f)$$