

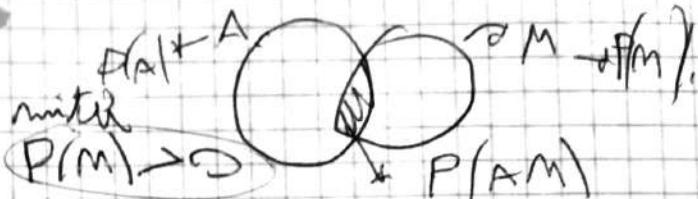
STOCHASTIC PROCESSES

AN QUEUING THEORY

MIDTERM - QUESTIONS 1 - 75.

1) CONDITIONAL PROBABILITY

$$P(A|M) = \frac{P(AM)}{P(M)}$$

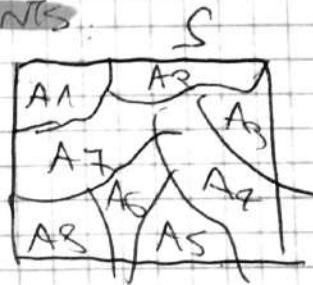


2) TOTAL PROBABILITY THEOREM FOR EVENTS:

Given A_1, \dots, A_n events

(1) $A_i \cdot A_j = \emptyset \quad i \neq j$
 (n mutually exclusive events)

(2) $A_1 + A_2 + \dots + A_n = S$
 (sum of events is S)



$$P(B) = P(B|A_1) \cdot P(A_1) + \dots + P(B|A_n) \cdot P(A_n)$$

3) BAYES' FORMULA - 1st type.

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

with $P(B) \neq 0$

$$\begin{aligned} P(A_1 \cdot A_2) &= P(A_1) \cdot P(A_2) \\ P(A_2 \cdot A_3) &= P(A_2) \cdot P(A_3) \\ P(A_1 \cdot A_3) &= P(A_1) \cdot P(A_3) \\ P(A_1 \cdot A_2 \cdot A_3) &= P(A_1) \cdot P(A_2) \cdot P(A_3) \end{aligned}$$

(for 3 events)

4) INDEPENDENT EVENTS: Events $A_1, A_2, A_3 \dots$ are independent if

A and B are independent if

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

$\Rightarrow P(A|B) = P(A)$ $P(B|A) = P(B)$
 (B has no effect on A) (A has no effect on B)

5) GENERAL EXPRESSION OF $P(A+B)$:

$$P(A+B) = P(A) + P(B) - P(AB)$$

PROPERTIES OF DISTRIBUTION FUNCTION $F_X(x)$

- 1) $F_X(-\infty) = 0$ $(X - \text{prob})$
- 2) $F_X(+\infty) = 1$ (non decreasing)
- 3) $F_X(x)$ is a non-decreasing function

$$F_X(x_1) \leq F_X(x_2) \quad \text{if } x_1 \leq x_2$$

- 4) $F_X(x^+) = F_X(x)$ continuous from the left
- 5) $P\{X=x\} = F_X(x) - F_X(x^-)$ (point)

- 6) if $F_X(x_0) = 0$, then $F_X(x) = 0 \quad \forall x \leq x_0$ (discrete)

$$\lim_{x \rightarrow +\infty} F_X(x) = F_X(\infty^-) = F_X(\infty) = 1$$

- 7) CLASSIFICATION OF R.V. Types of R.V.

- CONTINUOUS R.V.

A random variable X is continuous if $F_X(x)$ is continuous. The probability to be in a single point

~~of $F_X(x)$ is 0. Prob. from 0 to 1 prob. in point~~

$$F_X(x^-) = F_X(x) = P\{X=x\} = 0 \quad \forall x$$

- DISCRETE R.V.

A random variable X is discrete if $F_X(x)$ is staircase. In discontinuity points:

$$F_X(x_i) - F_X(x_i^-) = P\{X=x_i\} = p_i$$

(step height)

there are discontinuity points

- MIXED R.V.:

A random variable X is mixed if $F_X(x)$ is discontinuous but not staircase.

8) DEFINITION OF PROBABILITY DENSITY FUNCTION
 PROPERTIES

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

PROBABILITY

PROPERTIES

DEFINITION

1) $f_X(x) \geq 0$ (since $F_X(x)$ is monotonically increasing)

2) Integration of PDF $f_X(x)$ yields $F_X(x)$:

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

3) NORMALIZATION:

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

9) ~~REMOVED~~ FUNCTIONS:
 PDF of a ~~discrete~~ r.v.

$$P\{x_1 < X \leq x_2\} = F_X(x_2) - F_X(x_1) = \int_{x_1}^{x_2} f_X(u) du$$

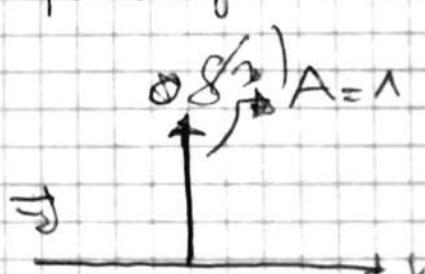
9) DEFINITION OF DELTA FUNCTION ($\delta(x)$) ASU

$$\delta(x) \triangleq \int_{-\infty}^{+\infty} \phi(x) \cdot \delta(x) dx = \phi(0) \quad \forall \phi(x) \text{ continuous}$$

Function to describe the derivative in points of discontinuity.

ASU PROPERTIES:

1) AREA OF DISCRETE EVENT: $\int_{-\infty}^{+\infty} \delta(x) dx = 1$



2) SAMPLING PROPERTY: $\int_{-\infty}^{+\infty} \phi(x) \cdot \delta(x - x_0) dx = \phi(x_0)$

3) DERIVATIVE OF STEP: $f_X(x) = \frac{d}{dx} U(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$

10) PDF of $f_x(x)$ of a Gaussian RANDOM VARIABLE, MEAN, VARIANCE:

For Gaussian R.V. X :

$$f_x(x) = \frac{1}{\theta \sqrt{2\pi}} \cdot e^{-\frac{(x-\eta)^2}{2\theta^2}}$$

* normal distribution

with parameters

$$\eta = \text{mean}$$

$$\theta = \text{s.d.}$$

MEAN: $\mu = E\{X\}$

$$= E\{(X - \mu)^2\}$$

VARIANCE: $\sigma_x^2 = \theta^2$ ($\theta = \text{standard deviation}$)

11) PDF of EXPONENTIAL R.V.:

For exponential R.V. X :

$$f_x(x) = c \cdot e^{-cx} \cdot U(x)$$

where c is a parameter.

$U(x)$ is the unitary step of x .

12) PDF of ERLANG R.V. made of EXPONENTIAL R.V.

for an Erlang R.V. X :

$$f_x(x) = \frac{c^n}{(n-1)!} \cdot x^{n-1} \cdot e^{-cx} U(x)$$

with c, n parameters

If $n=1$, Erlang is exponential PDF.

$$f_x(x) = \frac{c^1}{(1-1)!} \cdot x^{1-1} \cdot e^{-cx} U(x)$$

unitary step.

$$f_x(x) = c \cdot e^{-cx} \cdot U(x)$$

13) Conditional Distribution $F_x(x|M)$

$$F_x(x|M) = P\{X \leq x | M\} = \frac{P\{X \leq x, M\}}{P(M)}$$

17) TOTAL PROBABILITY THEOREM FOR
 $F_x(x)$ with given A_1, \dots, A_n of S :

If A_1, \dots, A_n is a partition of S

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

18) DERIVE $f_x(x|X \leq a)$ in terms of $f_x(x)$

→ By definition of conditional distribution

$$F_x(x|X \leq a), \text{ where } M = \{X \leq a\} \text{ (a set)}$$

$$F_x(x|X \leq a) = \frac{P\{X \leq x, X \leq a\}}{P\{X \leq a\}} \quad \text{value}$$

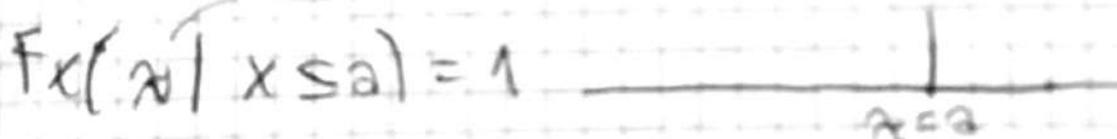
We have 3 cases - (assuming $X \leq a$)

1) ~~$x > a$~~



$$\Rightarrow F_x(x|X \leq a) = 1$$

2) ~~$x = a$~~



3) $x < a$



$$\Rightarrow \frac{F_x(x)}{F_x(a)}$$

$$f_x(x|X \leq a) = \begin{cases} 0 & x \geq a \\ \frac{f_x(x)}{F_x(a)} & x < a \end{cases}$$

16) RELATIONSHIPS BETWEEN $F_x(x)$ and $f_x(x)$

(direct & inverse)

Given $F_x(x) \rightarrow f_x(x)$ Given $f_x(x) \rightarrow F_x(x)$

$f_x(x) = \frac{d}{dx} F_x(x)$ $F_x(x) = \int_{-\infty}^x f_x(u) du$

17) MIXED Bayes FORMULA (2nd type).
Bouger

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

18) EXPECTED VALUE (mean) $E\{X\}$ in continuous and DISCRETE cases.

Continuous: $E\{X\} = \int_{-\infty}^{+\infty} x f_x(x) dx = \eta_x$ (mean)

DISCRETE, DISCRETE, MIXED

DISCRETE ONLY: (weighted sum by probability)
with x_n any possible value of X .

$$E\{X\} = \sum_n x_n \cdot P\{X=x_n\} = \eta_x$$

19) EXPECTED VALUE of $y = g(x)$ in terms of $f_x(x)$ (like 20)

For $y = g(x)$.

$$E\{y\} = E\{g(x)\} = \int_{-\infty}^{+\infty} g(x) f_x(x) dx$$

20) EXPECTED VALUE of $E\{x|M\}$ (CONDITIONAL EXPECTED VALUE)

$$E\{x|M\} = \int_{-\infty}^{+\infty} x \cdot g_x(x|M) dx$$

21) ~~Definition~~ and ~~VARIANCE~~ and Relation with $E\{X\}$ and $E\{X^2\}$

$$\sigma_x^2 \stackrel{\text{def}}{=} E\{(X - \mu_x)^2\} = \int_{-\infty}^{+\infty} (x - \mu_x)^2 f_X(x) dx$$

RELATION with $E\{X\}$ and $E\{X^2\}$:

$$E\{X^2\} = \sigma_x^2 + E\{X\}^2 \geq 0$$

(variance is generally positive)

~~22) Extend to fall in $\mathcal{I}(\phi, T)$.~~
~~Sketch for "time of occurrence".~~

23) PROBABILITY of a "Poisson-distributed" R.V.,
~~X points~~ MEAN AND VARIANCE:

$$P\{X=k\} = e^{-\lambda t} \cdot \frac{(\lambda t)^k}{k!}$$

$$\text{MEAN} \quad E\{X\} = \mu = \eta \quad \text{VARIANCE} \quad \sigma_x^2 = \eta$$

24) PROBABILITY of k successes in n trials in a
 repeated-trials experiment.

$$\binom{n}{k} \cdot P^k \cdot q^{n-k} = \frac{n!}{k!(n-k)!} \cdot P^k \cdot q^{n-k}$$

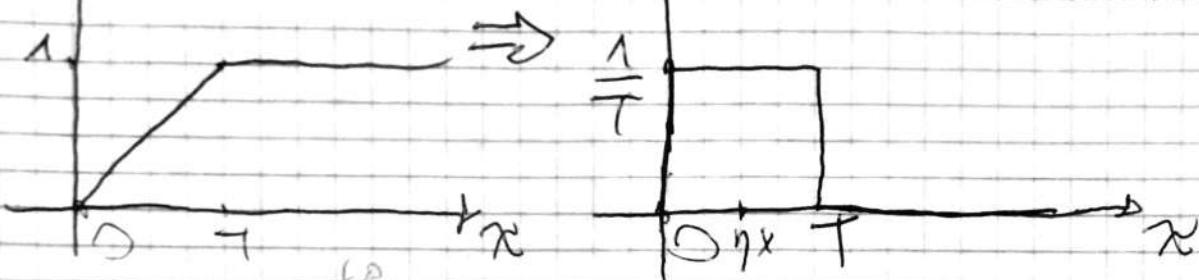
where P = probability of success.

$$q = 1 - P \quad (\text{probability of failure})$$

2) DISTRIBUTION FUNCTION AND PDF OF R.V.

Time occurrence in a random interval $(0, T)$.

$F_X(x)$ & telephone call $\Rightarrow g_X(x)$ & MEAN
VARIANCE



$$g_X(x) = \begin{cases} \frac{1}{T} & \text{if } 0 \leq x \leq T \\ 0 & \text{otherwise.} \end{cases}$$

MEAN:

$$\begin{aligned} E[X] &= \int_{-\infty}^{+\infty} x \cdot g_X(x) dx = \int_0^T \frac{1}{T} x dx = \frac{x^2}{2T} \Big|_0^T \\ &= \frac{T^2}{2T} - 0 = \frac{T}{2} \end{aligned}$$

VARIANCE:

~~$$\sigma_X^2 = E[X^2] - \bar{x}^2$$~~

$$\begin{aligned} \sigma_X^2 &= E[(X - \bar{x})^2] = \int_{-\infty}^{+\infty} (x - \bar{x})^2 \cdot g_X(x) dx \\ &= \int_0^T \left(x - \frac{T}{2}\right)^2 \cdot \frac{1}{T} dx = \int_0^T \left(x^2 - 2x\frac{T}{2} + \frac{T^2}{4}\right) \cdot \frac{1}{T} dx \\ &= \int_0^T \frac{x^2}{T} - \frac{2xT}{2} + \frac{T^2}{4} dx = \int_0^T \frac{x^2}{T} - x + \frac{T^2}{4} dx \\ &= \int_0^T \frac{x^3}{3T} - \frac{x^2}{2} + \frac{xT}{T} dx = \frac{1}{3T} x^3 - \frac{1}{2} x^2 + T \cdot \frac{x}{T} \Big|_0^T \\ &= \frac{1}{3T} \left(\frac{T^3}{3} - \frac{T^2}{2} + T^2\right) = \frac{4T^2 - 6T^2 + 3T^2}{12} = \frac{1}{12} T^2 \end{aligned}$$

Q1) Obtain the mixed Bayes Formula
(Bayes 2nd type)

1ST-TYPE BAYES.

$$P(A|M) = \frac{P(M|A) \cdot P(A)}{P(M)} \quad P(M) > 0$$

If $P(A) > 0$ and $M = \{x_1 \leq X \leq x_2\}$

$$P(A|x_1 \leq X \leq x_2) = \frac{[F_x(x_2|A) - F_x(x_1|A)] \cdot P(A)}{F_x(x_2) - F_x(x_1)}$$

If we set:

$$x_2 = x_1 + \Delta x$$

$$\text{for } M = \{X = x\}$$

$$P(A|x_1 < X \leq x_1 + \Delta x)$$

$$\frac{\Delta x}{\Delta x} \frac{F_x(x_1 + \Delta x|A) - F_x(x_1|A)}{F_x(x_1 + \Delta x) - F_x(x_1)} \cdot P(A)$$

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

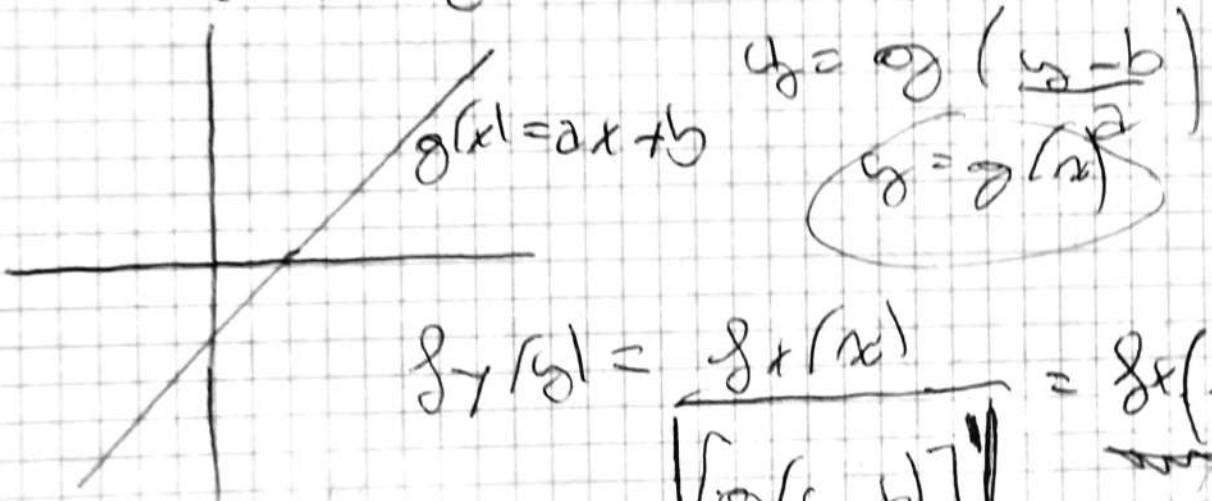
23) Given $y = g(f(x))$

Apply fundamental theorem to $\int_a^b g(f(x)) dx$

Need to solve equation $y_0 = g(f(x))$ to find
 $x_1, x_2, x_3, \dots, x_n$

$$y_0 = ax + b \Rightarrow x = \frac{y_0 - b}{a}$$

$$\Rightarrow y_0 = g(f(x_1)) = \dots = g(f(x_n))$$



$$g'(y_0) = \frac{g'(x)}{\left[g'\left(\frac{y_0 - b}{a}\right)\right]'} = \frac{g'\left(\frac{y_0 - b}{a}\right)}{1}$$

25) n points in interval $(0, T)$.

Probability K points fall in subinterval (t_1, t_2)

REPEATED TRIALS problem with elementary event:
"Place a single point in $(0, T)$ ".

$A = \{ \text{single point falls in } (t_1, t_2) \}$

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

$$\text{where } t_2 \triangleq t_2 - t_1$$

If we repeat the experiment n times:
with $q = 1 - p$

$$P\{K \text{ points falling in } (t_1, t_2)\} = \binom{n}{k} \cdot p^k \cdot q^{n-k}$$

26) For experiment (in 25), we have:

$$n \rightarrow +\infty, T \rightarrow +\infty \quad \lambda = \frac{n}{T} \quad (\text{infinite points in infinite time}).$$

Probability that K points fall in interval of length t_2 .

$$P\{K \text{ points fall in } t_2\} = e^{-\lambda t_2} \cdot \frac{(\lambda t_2)^K}{K!}$$

27) Given $y_g = g(x)$, FUNDAMENTAL THEOREM to obtain $\delta y/g$ from $\delta x/w$

We need to solve the equation $y_g = g(x)$ to find its real roots:

① For a given y_g , find: x_1, x_2, \dots, x_n

$$\Rightarrow y_g = g(x_1) = g(x_2) = \dots = g(x_n)$$

$$\text{Then: } \frac{\delta y/g}{1} = \frac{\delta x(x_1)}{f'(x_1)} + \frac{\delta x(x_2)}{f'(x_2)} + \dots + \frac{\delta x(x_n)}{f'(x_n)}$$

where $g'(x) = \frac{d}{dx} g(x)$

18) for a certainty the equation $g = g(x)$ has no real roots, then:

$$g'(x) = 0 \text{ so that } g$$

29) MEAN $E\{Y\}$ for $y = g(x)$ in terms of $g_x(x)$

$$E\{Y\} = E\{g(x)\} = \int_{-\infty}^{+\infty} g(x) \cdot g_x(x) dx$$

30) CHARACTERISTIC FUNCTION OF R.V. X.

$e^{j\omega x} = \cos(\omega x) + j \sin(\omega x)$
For a R.V. X , the characteristic function Φ_X is the Fourier Transform of the PDF:

$$\Phi_X(\omega) = \int_{-\infty}^{+\infty} e^{j\omega x} \cdot g_x(x) dx \sim \{g_x(x)\}$$

Fourier transform

+ TIKHIEV-GUPTA INEQUALITY

$$P\{|X - \mu| \geq K\sigma_K\} \leq \frac{1}{K^2}$$

The probability that a R.V. is displaced from its average μ more than K times the standard deviation σ_K is smaller than $\frac{1}{K^2}$.

31) JOINT DISTRIBUTION of two R.V. X and Y :

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

32) RELATIONSHIP (direct and inverse) between

$$F_{XY}(x, y) \text{ and } f_{XY}(x, y).$$

$$F_{XY}(x, y) \rightarrow f_{XY}(x, y) \quad (\text{assuming derivative exists up to 2nd order})$$

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

2) Direct method. Get $F_Y(y)$ from $f_X(x)$.
→ Apply it to $y = 2x + b$

(1) Given $y \in \mathbb{R}$, determine set of values of x where
if $y \leq y$ $\Rightarrow x \in I_{y \leq y}$

→ $x \in I_{y \leq y}$ iff $y \leq y$

Events $\{y \leq y\} = \{x \in I_{y \leq y}\}$ (same)

Are equal, as they have the same outcomes.

$$F_Y(y) = P\{Y \leq y\} = P\{X \in I_{y \leq y}\} \leq F_X(x)$$

$$\therefore f_Y(y) = \frac{d}{dy} F_Y(y) = \frac{d}{dx} F_X(x)$$

APPLICATION:

For $y(x) = 2x + b$, we need to find ~~Y~~:
~~set $I_{y \leq y}$~~ Solve ~~for x~~ for x .

$$y(x) \leq y$$

$$\Rightarrow 2x + b \leq y \Rightarrow x \leq \frac{y-b}{2} \text{ for } x > 0$$

$$F_Y(y) = P\left\{X \leq \frac{y-b}{2}\right\} = F_X\left(\frac{y-b}{2}\right)$$

$$\therefore f_Y(y) = \left[F_X\left(\frac{y-b}{2}\right) \right]' = f_X\left(\frac{y-b}{2}\right) \cdot \frac{1}{2}$$

Application of fundamental theorem to $f_X(x) = 2x + b$
 $y = 2x + b$

3.2.3 UNCORRELATED RVs

Two random variables X and Y are said to be UNCORRELATED if covariance

$$C_{XY} = 0$$

$$\Rightarrow E\{XY\} = \eta_X \eta_Y$$

where

$$C_{XY} \triangleq E\{(X - \eta_X) \cdot (Y - \eta_Y)\}$$

3g) ~~Write~~ Write $f_{XY}(x, y)$ when X and Y are jointly normal (Gaussian).

$$f_{XY}(x, y) = A \cdot e^{-\frac{1}{2}(\frac{x^2}{a^2} + bxy + \frac{y^2}{c^2} + dx + ey)}$$

with a, b, c, d, e parameters s.t:

$$ax^2 + bxy + cy^2 + dx + ey \geq 0 \quad \forall x, y$$

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

Sufficient condition \Rightarrow SCHWARTZ THEOREM.

Continuity of $\frac{\partial^2}{\partial x \partial y} f_{xy}(x, y)$ and $\frac{\partial^2}{\partial y \partial x} f_x(x, y)$

$$\frac{\partial}{\partial y} f_{xy}(x, y)$$

$$f_{xy}(x, y) \rightarrow f_{xy}(x, y)$$

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

33) Relationship between MARGINAL and joint DENSITY of two R.V. X and Y:

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

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

34) Probability, $P\{(X, Y) \in D\}$ in terms of $f_{xy}(x, y)$:

$$P\{(X, Y) \in D\} = \iint_D f_{xy}(x, y) dxdy$$

35) Expression $f_y(y | X=x)$ in terms of $f_{xy}(x, y)$

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

because:

$$f_{xy}(x, y) = f_y(y | X=x) \cdot f_x(x)$$

36) Relationship between $f_{x,y}(x|y=y)$ and $f_{x,y}(y|x=x)$

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

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

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

From this, the 3rd - triple Bayes formula can be derived:

37) (TO THE PROBABILITY THEOREM TO OBTAIN $f_{y|y}$)

When another R.V. is defined over S: R.V. X defined over S:

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

38) (INDEPENDENT R.V. X AND Y)

Two R.V.s X and Y are said to be independent if

$$P\{X \leq x, Y \leq y\} = P\{X \leq x\} \cdot P\{Y \leq y\}, \forall x, y$$

or, equivalently:

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

or, equivalently:

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

4) ~~Joint distribution / F~~ of n random variables.

For example, take $n = 3$ random variables (X_1, Y_1, Z)

~~$F_{XYZ}(x_1, y_1, z)$ expresses~~

$F_{XYZ}(a, b, c) \triangleq P\{X \leq a, Y \leq b, Z \leq c\}$

+1) Fundamental theorem to get $f_{Y_1, \dots, Y_n}(y_1, \dots, y_n)$ from $f_{X_1, \dots, X_n}(x_1, \dots, x_n)$ when $y_1 = g_1(x_1, \dots, x_n)$

① Find real roots ~~of $\frac{\partial f_{X_1, \dots, X_n}}{\partial x_1, \dots, \partial x_n} = 0$ when $f_{Y_1, \dots, Y_n} = g_n(x_1, x_n)$~~

$$\left\{ \begin{array}{l} y_1 = g_1(x_1, \dots, x_n) \\ y_2 = g_2(x_1, \dots, x_n) \end{array} \right.$$

$$y_n = g_n(x_1, \dots, x_n)$$

Assuming $[y_1, \dots, y_n]$ is a given fixed vector.

IF there are ~~no real roots~~

$$\Rightarrow f_{Y_1, \dots, Y_n} = 0$$

REAL ROOTS

* IF there are real roots $[x_1, \dots, x_n]$
there are

$[x_1, \dots, x_n]$ for

the given vector $[y_1, \dots, y_n]$:

$$f_{Y_1, \dots, Y_n} = \frac{f_{X_1, \dots, X_n}}{|\Delta([x_1, \dots, x_n])|} \cdot f_{X_1, \dots, X_n}$$

where $\Delta =$

$$J(x_1, \dots, x_n) \triangleq \begin{vmatrix} \frac{\partial g_1(x_1, \dots, x_n)}{\partial x_1} & \frac{\partial g_1(x_1, \dots, x_n)}{\partial x_n} \\ \frac{\partial g_2(x_1, \dots, x_n)}{\partial x_1} & \frac{\partial g_2(x_1, \dots, x_n)}{\partial x_n} \\ \vdots & \vdots \\ \frac{\partial g_n(x_1, \dots, x_n)}{\partial x_1} & \frac{\partial g_n(x_1, \dots, x_n)}{\partial x_n} \end{vmatrix}$$

42) CHAIN RULE for a sequence of R.V.

$$g(x_1, \dots, x_n) = g(x_n | x_{n-1}, \dots, x_1) g(x_{n-1} | x_{n-2}, \dots, x_1) \cdots g(x_2 | x_1) \cdot g(x_1)$$

43) RULES TO REMOVE "LEFT" AND "RIGHT" R.V.s.
FROM A ~~CONDITIONAL~~ DENSITY OF TYPE:

$$g(x_1, x_2, x_3 | x_4, x_5, x_6)$$

LEFT: Integrate with respect to ~~x₂, x₃~~ to remove

Remove x_2, x_3 :

~~$$g(x_1 | x_4, x_5, x_6)$$~~

$$g(x_1 | x_4, x_5, x_6) = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} g(x_1, x_2, x_3 | x_4, x_5, x_6) dx_2 dx_3$$

RIGHT: ~~Multiply by conditional density of~~
R.V. you want to remove and integrate with respect to it.
Given remaining R.V.s.

Remove x_4 :

$$g(x_1, x_2, x_3 | x_5, x_6) = \int_{-\infty}^{+\infty} g(x_1, x_2, x_3 | x_5, x_6) dx_4$$

RIGHT Given $f(x_1, x_2, x_3 | x_4, x_5, x_6)$. To remove a variable from the right, multiply by the conditional density of x_4 . To remove and integral with respect to it.

$$f(x_1, x_2, x_3 | x_4, x_5, x_6) = \int_{-\infty}^{+\infty} f(x_1, x_2, x_3 | x_5, x_6) \cdot f(x_4 | x_5, x_6) dx_4$$

Remove x_4

IF want to remove 2 variables.

$$\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} f(x_1, x_2, x_3 | x_4, x_5, x_6) dx_4 dx_5$$

4) Chapman-Kolmogorov EQUATION in the real case $f(x_r | x_n, x_r, x_k)$.

$$f(x_n | x_3) = \int_{-\infty}^{+\infty} f(x_n | x_2, x_3) \cdot f(x_2 | x_3) dx_2$$

\Rightarrow Some rule for removing x_2 from the right. $x_1 = x_n, x_2 = x_r, x_3 = x_k$.

$$f(x_n | x_k) = \int_{-\infty}^{+\infty} f(x_n | x_r, x_k) \cdot f(x_r | x_k) dx_r$$

4) RELATIONSHIP among CONDITIONAL DENSITIES when x_1 is independent of x_2 , assuming x_3 .

$$f(x_1, x_2 | x_3) = f(x_1 | x_3) \cdot f(x_2 | x_3)$$

(CONDITIONAL INDEPENDENCE).

46) DEFINITION OF MARKOFF SEQUENCE OF R.V.
(ordered random variables).

"An ordered sequence X_1, \dots, X_n is called Markoff sequence if, for any n ,

$$F(x_n | x_{n-1}, x_{n-2}, \dots, x_1) = F(x_n | x_{n-1}) \quad \forall n,$$

→ holds for PDF as well

↑ only depends on $n-1$, future only depends on present

47) CHAIN RULE FOR MARKOFF SEQUENCES

~~$$f(x_1, x_2, \dots, x_n) = f(x_1) f(x_2 | x_1) f(x_3 | x_1, x_2) \dots f(x_n | x_1, \dots, x_{n-1})$$~~

~~$$f(x_1, x_2, \dots, x_n) = f(x_n | x_{n-1}) f(x_{n-1} | x_{n-2}) \dots f(x_2 | x_1) f(x_1)$$~~

future only depends on present

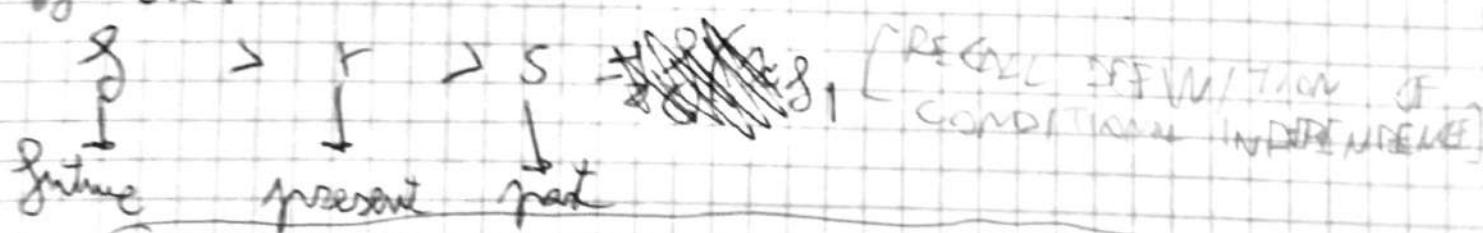
48) FUNDAMENTAL PROPERTIES OF MARKOFF SEQUENCES

- ① A subsequence of a Markoff sequence is Markoff
- ② The reverse of a Markoff sequence is also Markoff

$$f(x_n | x_{n+1}, \dots, x_{n+k}) = f(x_n | x_{n+1})$$

future is independent of past

- ③ Future is independent of past, if present is given.



$$\Rightarrow f(x_3, x_5 | x_1) = f(x_3 | x_1) \cdot f(x_5 | x_1)$$

4) CHAPMAN - KOLMOGOROV EQUATION FOR MARKOFF SEQUENCES.

If $x \rightarrow r \rightarrow s \rightarrow \text{next}$
 (present) $\xrightarrow{\text{future}}$ $\xrightarrow{\text{next}}$ $\xrightarrow{\text{next}}$ $\xrightarrow{\text{next}}$

$$f(x_s | x_g) = \int_{-\infty}^{+\infty} f(x_g | x_r) \cdot f(x_r | x_s) dx_r$$

"Any future given away past just depends on present".

5) CONDITION FOR A MARKOFF SEQUENCE TO BE HOMOGENEOUS

A Markoff sequence is said to be homogeneous if the "one-step" transitional densities do not depend on n .

ONE-STEP TRANSITIONAL DENSITY:

$$f(x_n | x_{n-1})$$

$$\Rightarrow f_{X_n}(x | x_{n-1} = g) = f_{X_{n-1}}(x | x_{n-2} = g) \quad \forall n$$

(all transitions have the same value of

S1) TRANSITION CONDITION FOR A MARKOFF SEQUENCE TO BE STATIONARY

A Markoff sequence is said to be stationary if it is homogeneous and marginal densities do not depend on n . (full row)

$$f_{X_n}(x) = f_{X_{n-1}}(x) \quad \forall n.$$

52) TRANSITION MATRIX for a Markoff Sequence.

All transition probabilities $\Pi_{ij}[n_1, n_2]$ for a Markoff chain can be arranged in a transition matrix from X_{n_1} to X_{n_2} :

$$\Pi[n_1, n_2] \triangleq \begin{bmatrix} \Pi_{11}[n_1, n_2] & \Pi_{12}[n_1, n_2] & \dots & \Pi_{1N}[n_1, n_2] \\ \Pi_{21}[n_1, n_2] & \Pi_{22}[n_1, n_2] & \dots & \Pi_{2N}[n_1, n_2] \\ \vdots & \vdots & \ddots & \vdots \\ \Pi_{N1}[n_1, n_2] & \Pi_{N2}[n_1, n_2] & \dots & \Pi_{NN}[n_1, n_2] \end{bmatrix}$$

↑
Row
↓
Column (square)

~~MARKOFF CHAINS (definition)~~

A Markoff sequence of discrete R.V.s taking values on a finite number N of values $2_1, 2_2, \dots, 2_N$ on the same alphabet is a Markoff chain.

It satisfies:

$$P\{X_n = 2_j | X_{n-1} = 2_i, \dots, X_1 = 2_k\} \quad \forall j$$

$$= P\{X_n = 2_j | X_{n-1} = 2_i\} \quad \forall n$$

STATE PROBABILITY: $p_i[n] \triangleq P\{X_n = 2_i\}$

($n_2 - n_1$) STEP

TRANSITION PROBABILITY: $\Pi_{ij}[n_1, n_2] \triangleq P\{X_{n_2} = 2_j | X_{n_1} = 2_i\}$

~~PROPERTIES~~

- NORMALIZATION: The marginal probability is 1.

$$\sum_i p_i[n] = 1 \quad \forall n$$

- NORMALIZATION - CONDITIONAL PROBABILITY:

$$\sum_j \Pi_{ij}[n_1, n_2] = 1 \quad \forall n_1, n_2$$

S3) Chapman-Kolmogoroff Equation

Markoff chain in matrix form.

$$TP[n_1, n_3] = \begin{bmatrix} \pi_{11}[n_1, n_3] & \pi_{12}[n_1, n_3] & \dots & \pi_{1N}[n_1, n_3] \\ \pi_{21}[n_1, n_3] & \pi_{22}[n_1, n_3] & \dots & \pi_{2N}[n_1, n_3] \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{N1}[n_1, n_3] & \pi_{N2}[n_1, n_3] & \dots & \pi_{NN}[n_1, n_3] \end{bmatrix}$$

where:

$$\boxed{\pi[n_1, n_3] = \boxed{\pi[n_1, n_2]} \cdot \boxed{\pi[n_2, n_3]}}$$

Corresponds to:

$$\delta(x_3 | x_1) = \begin{cases} \delta(x_3 | x_2) \\ \delta(x_2 | x_1) \end{cases}$$

where $\pi^{[n_1, n_2]}$ is the one-step transitional probability from n_1 to n_2 .

SEVEN PROBABILITY THEOREM FOR MARKOFF CHAIN

STATE PROBABILITY VECTOR:

For a Markoff chain, the state probability vector for X_{n_1} is the row vector given by

$$P[n_1] \triangleq [p_1[n_1], \dots, p_N[n_1]]^T$$

TOTAL PROBABILITY THEOREM

$$P[n_2] = P[n_1] \cdot \boxed{\pi[n_1, n_2]}$$

post - mine
transitions prob.
from n_1 to n_2 .

It is the state probability

vector of X_{n_2} starting

from X_{n_1} with
conditional probability given

$$by \boxed{\pi[n_1, n_2]}.$$

$$\pi[n_1, n_2] = \begin{bmatrix} \pi_{11}[n_1, n_2] & \dots & \pi_{1N}[n_1, n_2] \\ \pi_{21}[n_1, n_2] & \dots & \pi_{2N}[n_1, n_2] \\ \vdots & \ddots & \vdots \\ \pi_{N1}[n_1, n_2] & \dots & \pi_{NN}[n_1, n_2] \end{bmatrix}$$

ss) CHAPMAN - KOLMOGOROV EQUATION for HOMOGENEOUS MARKOFF CHAINS IN MATRIX FORM.

$$\Pi[n+k] = \Pi[n] \cdot \Pi[k]$$

A Markoff chain is said to be homogeneous if the transition probabilities depend only on the DIFFERENCE $n_2 - n_1 \triangleq m$, not individually on n_2 and n_1 so that:

$$\Pi_{i,j}[m] \triangleq P_i^j | X_{n+m} = a_j | X_n = a_i \quad \forall n$$

so) RELATIONSHIP BETWEEN STATE VECTOR and TRANSITION MATRIX for a HOMOGENEOUS MARKOFF CHAIN.

Given a one-step transition matrix of a homogeneous Markoff chain:

$$\Pi[1] = \Pi = \begin{bmatrix} \pi_{11} & \pi_{12} & \dots & \pi_{1N} \\ \pi_{21} & \pi_{22} & \dots & \pi_{2N} \\ \vdots & & & \\ \pi_{N1} & \pi_{N2} & \dots & \pi_{NN} \end{bmatrix}$$

One can always select a STATE VECTOR (eigenvector of Π) P such that the resulting chain is STATIONARY (does not change with n).

~~STATE VECTOR THE CONDITIONS FOR A MARKOFF CHAIN TO BE HOMOGENEOUS: THE TRANSITION PROBABILITIES DEPEND ONLY ON THE DIFFERENCE $m \triangleq n_2 - n_1$~~

51.5) Obtain the condition of ~~stationarity~~
in matrix terms for a Markoff chain.

*~~We call it sequence~~

A Markoff Chain is said to be Stationary if it
is homogeneous and:

$$P[1] = P[2] = \dots = P[n] \quad \text{Proof:}$$

Let's call the state vector for X_1 :

$$P[1] = P.$$

If the first two R.V. X_1 and X_2 of a
homogeneous Markoff sequence have the same
PDF, then the sequence is ~~stationary~~.

\Rightarrow If X_2 has same state vector as X_1 :

$$P[1] = P[2] = P. \quad (\text{Condition for } \underset{\text{stationarity}}{\text{stationarity}})$$

Then ~~assuming~~ the homogeneous chain is
stationary, since we have:

$$P = P \cdot \Pi \quad (\text{stationarity})$$

This means that P is the eigenvector
of Π .

$$P[3] = P[2]\Pi = P\Pi = P,$$

and:

$$P[n] = P \quad (\text{no change with } n)$$

$$P[0] = P$$

\Rightarrow the Markoff Chain is stationary, as
~~the states~~ all states have the same
distribution of probabilities at different stage

So S) Give a method to generate a
Markoff sequence and demonstrate it.

Given a sequence x_1, x_2, \dots, x_n (INDEPENDENT)
r.v.s with marginal densities $f_{x_i}(x_i)$, we form:
 $y_1 = x_1$
 $y_2 = x_1 + x_2$
 \vdots
 $y_n = x_1 + x_2 + \dots + x_n$

$$= x_1$$

$$= y_1 + x_2$$

$$\boxed{y_n = x_1 + x_2 + \dots + x_n} \quad = y_{n-1} + x_n$$

The new sequence $\{y_n\}$ is Markoff.

PROOF: ~~Show~~ we want to show that:

$\{y_n\}$ is Markoff

→ Find joint PDF of $y_1 = x_1, y_2 = x_1 + x_2, \dots, y_n = x_1 + \dots + x_n$.

$$f_{y_1, y_2, \dots, y_n} = \frac{f_{x_1, x_2, \dots, x_n}(x_1, x_2, \dots, x_n)}{\prod f(x_1, \dots, x_n)}$$

Solving the system given y_1, y_2, \dots, y_n :

$$\left\{ \begin{array}{l} y_1 = x_1 \quad \rightarrow g_1(x_1, \dots, x_n) \\ y_2 = x_1 + x_2 \quad \rightarrow g_2(x_1, \dots, x_n) \\ \vdots \\ y_n = x_1 + x_2 + \dots + x_n \quad \rightarrow g_n(x_1, \dots, x_n) \end{array} \right.$$

We have:

$$\left\{ \begin{array}{l} x_1 = y_1 \\ x_2 = y_2 - y_1 \\ \vdots \\ x_n = y_n - y_{n-1} \end{array} \right. \quad \text{REAL ROOT! (one!)}$$

Since x_1, x_2, \dots, x_n are independent, we have:

$$f_{x_1, x_2, \dots, x_n}(x_1, x_2, \dots, x_n)$$

$$= f_{x_n}(x_n) \cdot f_{x_2}^{(1)}(x_2) \cdots f_{x_1}(x_1)$$

$$J(x_1, \dots, x_n) \triangleq \begin{vmatrix} \frac{\partial f_{x_1}(x_1, \dots, x_n)}{\partial x_1} & \dots & \frac{\partial f_{x_1}(x_1, \dots, x_n)}{\partial x_n} \\ \frac{\partial f_{x_2}(x_1, \dots, x_n)}{\partial x_1} & \dots & \frac{\partial f_{x_2}(x_1, \dots, x_n)}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial f_{x_n}(x_1, \dots, x_n)}{\partial x_1} & \dots & \frac{\partial f_{x_n}(x_1, \dots, x_n)}{\partial x_n} \end{vmatrix}$$

TRIANGULAR

DETERMINANT =

\downarrow

Result = product of
diagonal elements

$$\begin{vmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 \end{vmatrix}$$

$\frac{\partial x_1}{\partial z_1}$

$\frac{\partial x_2}{\partial z_2}$

$\frac{\partial x_n}{\partial z_n}$

$$\Rightarrow f_{y_1, y_2, \dots, y_n} = f_{x_1}(y_1) \cdot f_{x_2}(y_2 - y_1) \cdot$$

$$f_{x_3}(y_3 - y_2) \cdots f_{x_n}(y_n - y_{n-1})$$

For conditional PDF:

$$f_{y_n | y_{n-1}, y_{n-2}, \dots, y_1}(y_n) = \frac{f(y_1, y_2, \dots, y_n)}{f(y_1, y_2, \dots, y_n)}$$

$$= f_{x_n}(y_n - y_{n-1})$$

$$= f_{y_n}(y_n - y_{n-1})$$

\Rightarrow It is Markoff!

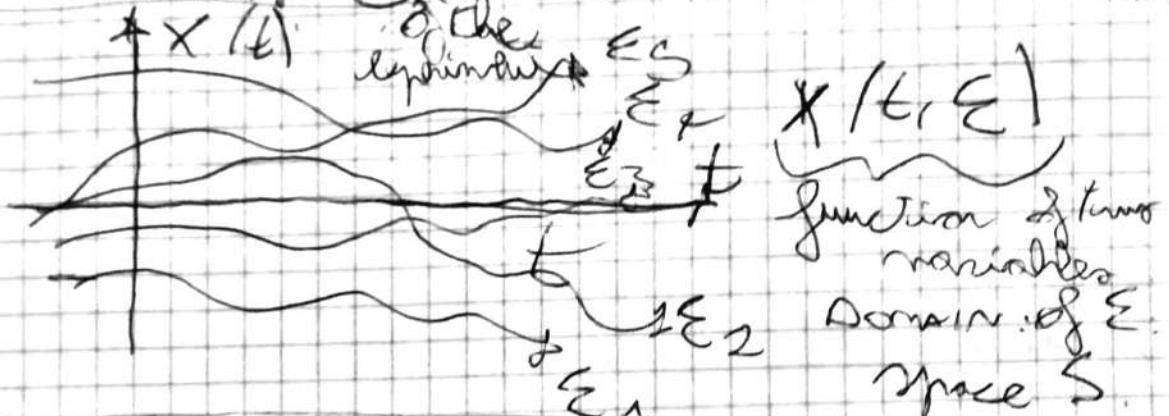
3.3) ~~Markov~~ Conditions For A Markov Chain To Be Homogeneous:

A Markov Chain is said to be homogeneous if the transition probabilities depend only on the DIFFERENCE ($m \in n_2 - n_1$), not individually on n_2 and n_1 , so that:

$$\text{Homogeneous} \quad \pi_{i,j[m]} \triangleq P\{X_{n+m} = a_j | X_n = a_i\} \quad \forall n.$$

6) DEFINITION OF STOCHASTIC PROCESS

- Given an experiment, a family of real or complex time functions $X(t, \varepsilon)$ assigned to all outcomes ε is a STOCHASTIC PROCESS

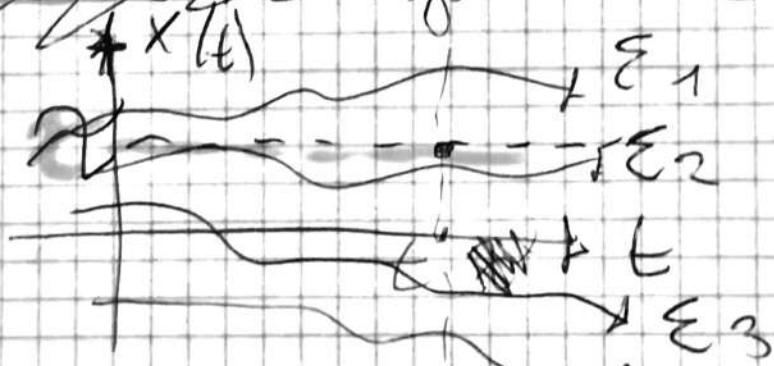


- C) FIRST-ORDER DISTRIBUTION FUNCTION AND FIRST-MODE PDF for a STOCHASTIC PROCESS $X(t)$:

FIRST-ORDER DISTRIBUTION FUNCTION for a stochastic process $X(t)$:

$$F_X(x; t) \triangleq P\{X(t) \leq x\}$$

FIRST-MODE PDF for a stochastic process $X(t)$



FIRST-MODE PDF for a stochastic process $X(t)$:

$$f_X(x; t) \triangleq \frac{d}{dx} F_X(x; t)$$

6a) Definition of mean, auto correlation, auto covariance for a process $X(t)$:

• MEAN of a stochastic process $X(t)$:

The MEAN $\eta(t)$ of a real process $X(t)$ is the expected value of the R.V. $X(t)$:

$$\eta(t) = E\{X(t)\} = \int_{-\infty}^{+\infty} x \cdot g(x, t) dx$$

• AUTOCORRELATION of a stochastic process $X(t)$:

The AUTOCORRELATION $R(t_1, t_2)$ of a real process $X(t)$ is the EXPECTED VALUE of the product of two R.V. $X(t_1)$ and $X(t_2)$ $R(t_1, t_2) = E\{x(t_1) \cdot x(t_2)\}$

~~$$R(t_1, t_2) = E[X(t_1) \cdot X(t_2)]$$~~

$$R(t_1, t_2) \triangleq \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2 \cdot g(x_1, x_2; t_1, t_2) dx_1 dx_2$$

• AUTO COVARIANCE of a stochastic process $X(t)$:

The AUTO COVARIANCE $C(t_1, t_2)$ of a real stochastic process $X(t)$ is:

$$C(t_1, t_2) \triangleq E\{[X(t_1) - \eta(t_1)][X(t_2) - \eta(t_2)]\}$$

If we have: $t_2 > t_1$ (where t_2, t_1 generic time)
 $\Rightarrow X(t_2) - X(t_1)$ is a Poisson R.V. with parameter $\lambda(t_2 - t_1)$

$$\Rightarrow E\{X(t_2) - X(t_1)\} = \lambda(t_2 - t_1)$$

$$\text{If } t_2 > 0$$

$$\Rightarrow E\{X(t)\} = \lambda t$$

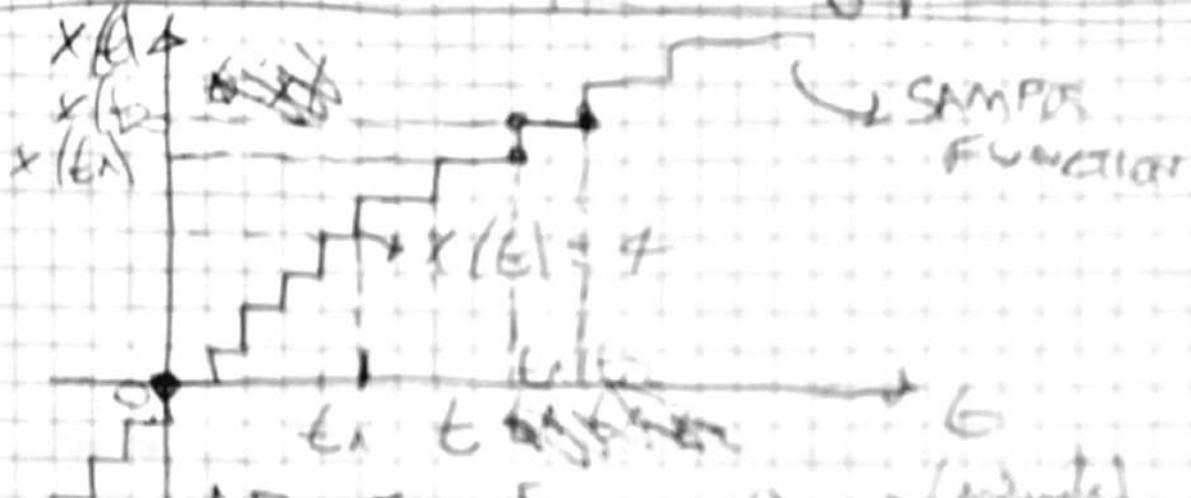
63) DESCRIBE the Poisson (counting) Process

Obtain its MEAN VALUE, with a sample function

A Poisson Process is defined as

$$X(E) = 0 \quad \text{for } E = 0$$

$$X(t_2) - X(t_1) = \text{Number of points in } [t_1, t_2]$$



N.B. Each function of a Poisson process is independent

Time one sample space of random variables in $(-\infty, +\infty)$. Interval size

For a given $t > 0$ consider

$$X(t) = \# \text{ points in } (0, t)$$

For $T \rightarrow \infty$, we have X_T and similarly we have that $X(t)$ is Poisson distributed

$$P\{X(t) = k\} = e^{-\lambda t} \frac{(\lambda t)^k}{k!}$$

If we have $t_2 > t_1$,

$$X(t_2) - X(t_1) \sim \text{Poisson distribution}$$

$$\text{So } X(t_2) - X(t_1) \sim \text{Poisson distribution}$$

$$\text{If } t_2 \rightarrow 0$$

$$(E\{X(t)\})^2 = \lambda \rightarrow \text{normal}$$

54) Obtain the (AUTOCORRELATION) of
Counting Process.

$$R_{XX}(t_1, t_2) = E\{x(t_1) \cdot x(t_2)\} = \{P(x(t_1) = 1, x(t_2) = 1)$$

$$\text{for } (t_1, t_2 > 0)$$

$$R_{XX}(t_1, t_2) = E\{x(t_1) \cdot x(t_2)\} = \{P_{t_1, t_2} t_2 + t_2 - t_1^2\}$$

$$(t_1^2 t_2 + t_1 t_2 - t_1^2)$$

$$\Rightarrow R(t_1, t_2) = \lambda^2 t_1 t_2 + \lambda \min(t_1, t_2)$$

55) Describe the Poisson ~~continuous process~~ process, obtain its mean value and sketch a sample function.

Let $x(t)$ be a Poisson ~~process~~ continuous process and $\varepsilon > 0$ a given constant. Then:

$$y(t) = \frac{x(t+\varepsilon) - x(t)}{\varepsilon}$$

If K is the number of points in $(t, t+\varepsilon)$,

$$\Rightarrow P[y(t) = \frac{K}{\varepsilon}] = \frac{K}{\varepsilon} \text{ So:}$$

$$P\{y(t) = \frac{K}{\varepsilon}\} = e^{-\lambda\varepsilon} \cdot \frac{(\lambda\varepsilon)^K}{K!}$$

MEAN:

$$E\{y(t)\} = \sum E\{x(t+\varepsilon) - x(t)\} = \frac{\lambda\varepsilon}{\varepsilon} = \lambda$$

$$\text{Since } E\{x(t)\} = \lambda t \rightarrow \varepsilon \text{ here}$$

(constant mean)

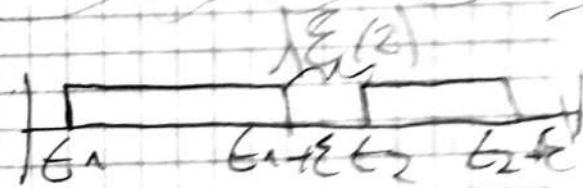
Q) OBTAIN THE AUTOCORRELATION OF A
POISSON INCREMENTS PROCESS

$$R_{YY}(t_1, t_2) = E\{Y(t_1) \cdot Y(t_2)\}$$

$$R_{YY}(t_1, t_2) = E\left[\frac{x(t_1+\epsilon) - x(t_1)}{\epsilon} \cdot \frac{x(t_2+\epsilon) - x(t_2)}{\epsilon}\right]$$

$$= \frac{1}{\epsilon^2} \cdot E\{[x(t_1+\epsilon) - x(t_1)] [x(t_2+\epsilon) - x(t_2)]\}$$

2 CASES:



① NON-OVERLAPPING:
(INDEPENDENT INTERVALS)

$$t_2 > t_1 + \epsilon \text{ or } t_1 > t_2 + \epsilon$$

$$|t_1 - t_2| > \epsilon \quad (\text{non-overlapping intervals})$$

$$R_{YY}(t_1, t_2) = \frac{1}{\epsilon^2} \cdot \lambda \epsilon \cdot \lambda \epsilon = \lambda^2$$

② OVERLAPPING INTERVALS:

$$\Rightarrow |t_1 - t_2| < \epsilon. \quad \begin{array}{c} \text{overlapped} \\ \text{space in-between} \end{array}$$

$$\text{if } t_1 < t_2:$$

$$R_{YY}(t_1, t_2) = \frac{1}{\epsilon^2} \lambda^2 \cdot (t_2 + \epsilon - t_2) \cdot (t_1 + \epsilon - t_1) + \frac{1}{\epsilon^2} [\lambda(t_1 + \epsilon - t_2)] = \frac{1}{\epsilon^2} |t_1 - t_2|$$

$$\text{if } t_1 > t_2:$$

$$R_{YY}(t_1, t_2) = \frac{1}{\epsilon^2} \left[\lambda^2 \cdot (t_2 + \epsilon - t_2) \cdot (t_1 + \epsilon - t_1) + \lambda \cdot (t_2 + \epsilon - t_2) \right] = \frac{1}{\epsilon^2}$$

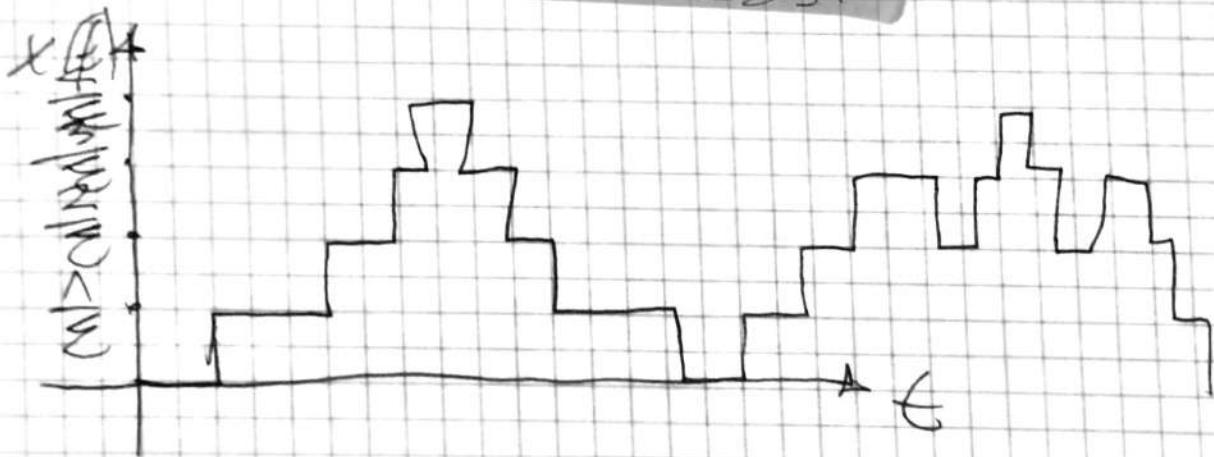
IN GENERAL,

$$R_{YY}(t_1, t_2) = \lambda^2 + \frac{\lambda}{\varepsilon} - \frac{\lambda |t_1 - t_2|}{\varepsilon^2}$$

$$R_{YY}(t_1, t_2) = \begin{cases} \lambda^2 & |t_1 - t_2| > \varepsilon \\ \lambda^2 + \frac{\lambda}{\varepsilon} - \frac{\lambda |t_1 - t_2|}{\varepsilon^2} & |t_1 - t_2| \leq \varepsilon \end{cases}$$

(S)

SKETCH OF A POISSON INCREMENTS PROCESS.



6.3 Describe the Poisson Impulses process
 • obtain its mean value, its autocorrelation
 $R_{ZZ}(t_1, t_2)$ and sketch a sample function.

Consider Poisson Counting Process $X(t)$

\hookrightarrow form stochastic process $Z(t)$:

$$Z(t) = \lim_{\epsilon \rightarrow 0} \sum_{\tau \in [t, t+\epsilon]} [X(t+\epsilon) - X(t)] = \frac{dX(t)}{dt}$$

\hookrightarrow With $\epsilon \rightarrow 0$ in $E\{Y(t)\}$

MEAN:

$$E\{Z(t)\} = \lambda$$

AUTO CORRELATION:

$$R_{ZZ}(t_1, t_2) = \lambda^2 + \lambda \cdot 8(t_1 - t_2)$$

$$\gamma \triangleq t_1 - t_2$$

$$R_{ZZ}(\gamma) = \lambda^2 + \lambda \cdot 8(\gamma)$$

$t_i \rightarrow$ time separation or time axis.

$Z(t) \rightarrow$ derivative of random process $X(t)$

$$Z(t) = \sum_i 8(t - t_i)$$

$$\uparrow R_{ZZ}(\gamma)$$



$$\gamma = t_1 - t_2$$

58) Give 2 properties specifying a Poisson Point Process

1) # POINTS IN AN INTERVAL (t_1, t_2)

The amount of points ~~in~~ in an interval (t_1, t_2) is a POISSON R.V. with parameter λ

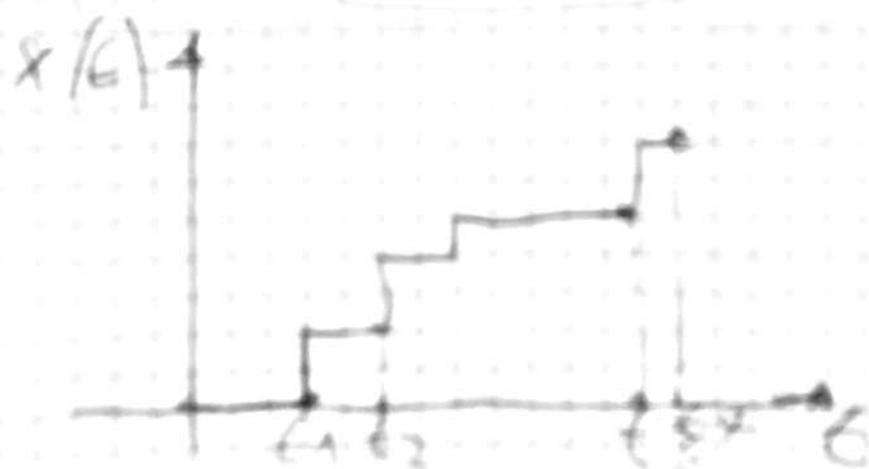
$$\lambda = \int_{t_1}^{t_2} \lambda(t) dt$$

$$P\{N=t\} = e^{-\lambda} \frac{\lambda^t}{t!} \text{ in } (t_1, t_2)$$

2) INDEPENDENCE OF COUNTS IN NON-OVERLAPPING INTERVALS:

$t_1 < t_2 < t_3 < t_4$ then

R.V.s $N(t_1, t_2)$ and $N(t_3, t_4)$ are independent



Q) Find the mean of # points in a random interval

Suppose ζ is a R.V. forming from it

$$n_c = n(t, t + \epsilon)$$

(expected value)

1) Determine statistics of n_c using:

$$(E\{Y\} = E_x\{E\{Y|X\}\})$$

If $\zeta = \zeta$ constant, n_c is a Poisson R.V.
with parameter λ_c .

\Rightarrow The mean amount (value) of points in
an interval of length $n/\epsilon(t, t + \epsilon)$ is:

$$E\{n_c | \zeta\} = \zeta^3 = \lambda_c$$

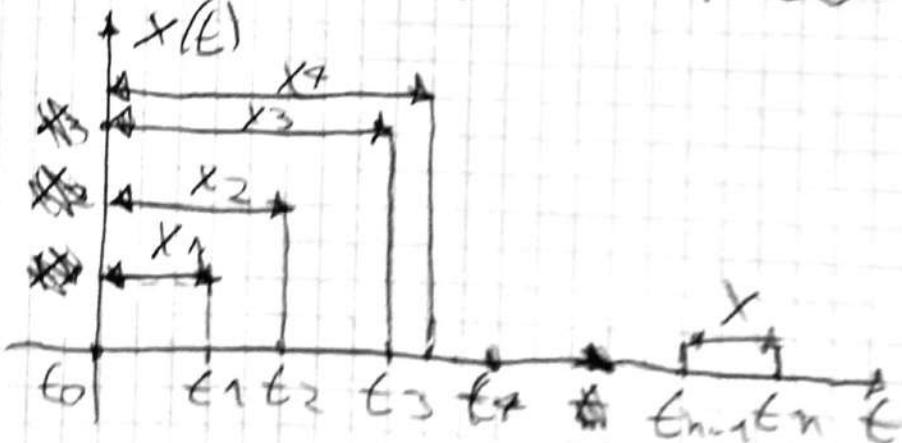
$$E\{n_c | \zeta\} = \lambda_c$$

$$\Rightarrow E\{n_c\} = E\{E\{n_c | \zeta\}\} = E\{1_{n_c}\}$$

\Rightarrow Avg. # points in a random interval is the
Avg. number of points per time unit
multiplied by Avg. time duration.

70) DETERMINE PDF of DISTANCE b/w consecutive points from a FIXED time instant

Consider R.V. $X = \epsilon_n - \epsilon_0$



We want to prove that,

$X_n = t_n - t_0$ is an Erlang-distributed continuous RV with PDF:

$$f_{X_n}(x) = \frac{\lambda^n x^{n-1}}{(n-1)!} e^{-\lambda x} \cdot U(x)$$

Proof By induction:

As $n=1$:

$$f_{X_1}(x) = P\{X_1 \leq x\} = P\{\text{at least one point is in } [t_0, t_0+x]\}$$
$$= 1 - P\{\text{0 points in } [t_0, t_0+x]\} = 1 - e^{-\lambda x}$$

$$f_{X_1}(x) = (1 - e^{-\lambda x})' = -\lambda \cdot (-e^{-\lambda x}) \cdot U(x)$$
$$= \lambda e^{-\lambda x} \cdot U(x)$$

As $n=2$:

$$f_{X_2}(x) = P\{\lambda X_2 \leq x\} = P\{\text{at least two points in } [t_0, t_0+x]\}$$

$$= 1 - P\{\text{0 points in } [t_0, t_0+x]\} - P\{\text{1 point in } [t_0, t_0+x]\}$$
$$= 1 - \frac{e^{-\lambda x}}{1} - e^{-\lambda x} \cdot \frac{(\lambda x)^1}{1!} = (\lambda x)^1 e^{-\lambda x}$$

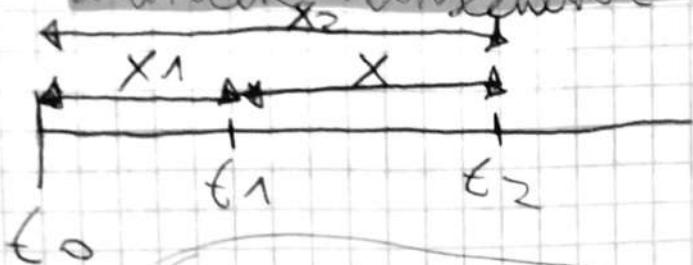
$$= 1 - e^{-\lambda x} - e^{-\lambda x} \cdot (\lambda x)^1$$

$$f_{X_2}(x) = (1 - e^{-\lambda x} - e^{-\lambda x} \cdot (\lambda x)^1)'$$
$$= -(-\lambda \cdot e^{-\lambda x}) - [-\lambda] \cdot e^{-\lambda x} \cdot \lambda x + e^{-\lambda x} \cdot \lambda$$
$$= -(-\lambda e^{-\lambda x}) - [-\lambda^2 x \cdot e^{-\lambda x} + e^{-\lambda x} \cdot \lambda]$$
$$= \lambda \cdot e^{-\lambda x} + \lambda^2 x \cdot e^{-\lambda x} - e^{-\lambda x} \cdot \lambda$$

⇒ By induction for a generic n :

$$f_{X_n}(x) = \frac{\lambda^n x^{n-1}}{(n-1)!} e^{-\lambda x} \cdot U(x)$$

7) Determine the PDF of the distance between consecutive Poisson points.



$$x = x_2 - x_1$$

We know that x_2 is Erlang-2.

x_1 is exponential.

$\Rightarrow x$ must be exponential and independent of x_1 to be Erlang.

$$F_x(x) = P\{x \leq x\} = P\{x_2 - x_1 \leq x\}$$

~~F(x) = ...~~ By THE TOT. PROB. THEOREM

$$P(B) = P(B|A_1) \cdot P(A_1) + \dots + P(B|A_n) \cdot P(A_n)$$

$$\begin{aligned} F_x(x) &= \int_{-\infty}^{\infty} P\{x_2 - x_1 \leq x | x_1 = x_1\} \cdot f_{x_1}(x_1) dx_1 \\ &= \int_{-\infty}^{\infty} P\{x_2 \leq x + x_1 | x_1 = x_1\} \cdot f_{x_1}(x_1) dx_1 \end{aligned}$$

$P\{ \text{at least one point in } (x_1, x_1 + x_1) \}$

$$1 - e^{-\lambda x} \quad (\text{exponential})$$

$$\begin{aligned} F_x(x) &= \int_{-\infty}^{\infty} [1 - e^{-\lambda x}] \cdot f_{x_1}(x_1) dx_1 \\ &\equiv (1 - e^{-\lambda x}) \cdot \underbrace{\int_{-\infty}^{\infty} f_{x_1}(x_1) dx_1}_{= 1 - e^{-\lambda x}} = 1 - e^{-\lambda x} \end{aligned}$$

$$\Rightarrow f_x(x) = \lambda \cdot e^{-\lambda x} \psi(x)$$

7.2) Demonstrate that the distances of Poisson points from a given time instant are a Markoff sequence

Theorem: Distances x_n of Poisson points t_n from a fixed time to are Markoff sequences.

Proof: We know that:

$$x_1 \rightarrow \text{Exponential - 1}$$

$$\vdots$$

$$x_n \rightarrow \text{Exponential - } n$$

and that:

same density $\{ x_2 - x_1 \text{ is exponential } \lambda e^{-\lambda x} U(x)$

$x_n - x_{n-1}$ is exponential $\lambda e^{-\lambda x} U(x)$

$\Rightarrow x_1, \dots, x_n$ must be INDEPENDENT for the sum to generate Exponential distributed x_n .

\Rightarrow Sequence x_n is Markoff since it is generated by summing up exponential

$$R.V SF(x_n | x_{n-1}, \dots, x_1) = SF(x_n | x_{n-1})$$

\Rightarrow Sequence x_n cannot be STATIONARY.

\Rightarrow ~~Markoff~~ x_n is MARKOFF since transition probabilities do not change with n .

Transitional PDF for a Markoff Sequence $\{x_n\}$.

For $x \rightarrow \infty$:

$$F_x(\infty | x_{n-1} = y_n) = P\{x_n \geq x | x_{n-1} = y_n\} <$$

$P\{ \text{at least 1 point in }$

7.2) Demonstrate that the distances of Poisson points from a given time instant are a Markoff sequence.

Theorem: Distances x_n of Poisson Points $\{x_n\}$ from a fixed time t_0 are Markoff sequences.

Proof: We know that:

x_1 is exponential (Erlang - 1)

x_2 is exponential (Erlang - 2)

\vdots

x_n is Erlang - n.

and that:

$x_2 - x_1$ is exponential $\rightarrow \lambda \cdot e^{-\lambda x_1}$

$x_n - x_{n-1}$ is exponential $\rightarrow \lambda e^{-\lambda x_{n-1}}$

All of them have the same density!

Therefore x_1, \dots, x_n must be INDEPENDENT since they generate Erlang-distributed x_n .

$\Rightarrow \{x_n\}_{n \in \mathbb{N}}$ is Markoff since it is generated by summing n i.i.d exponential R.V.s. (controlling marked)

$$F(x_n | x_{n-1}, \dots, x_1) = F(x_n | x_{n-1})$$

$$P\{x_n \leq h | x_{n-1} = x_{n-1}\}$$

(depends only on last point x_{n-1} with

$$x_{n-1} = x_{n-1})$$

\Rightarrow The sequence x_n is STATIONARY, or its marginal PDFs are Erlang, dependent on n.

However, X_n is homogeneous, as transition probabilities do not change with n .

\Rightarrow TRANSITIONAL PDF for Markoff sequence $\{X_n\}$:

$\mathbb{P} X \rightarrow y$:

$$\begin{aligned} F_x(x | X_{n-1}=y) &= P\{X_n \leq x | X_{n-1}=y\} = P\{\text{at least} \\ &\text{one point is in } (t_0+y, t_0+x]\} \\ &= P\{\text{at least one point in } (0, x-y)\} = 1 - e^{-\lambda/(x-y)} \end{aligned}$$

ONE-STEP TRANSITIONAL PDF.

$$f_{X_n}(x | X_{n-1}=y) = \lambda \cdot e^{-\lambda(x-y)} \quad \text{for } x \geq y.$$

(does not depend on n)

$\Rightarrow X_n$ is homogeneous.

13) CONSTRUCTIVE DEFINITION OF A Poisson Point Process:

Given a sequence (X_1, X_2, \dots, X_n) i.i.d. R.V.s with PDF:

$$f(w) = \lambda \cdot e^{-\lambda w} (1/w)$$

\Rightarrow Form set of points $\{x_i\}$ with $E=0$ arbitrary origin.

$$E_n = X_1 + X_2 + \dots + X_n$$

$E_n \rightarrow$ Erlang-distribution.

\Rightarrow We have constructed Poisson random process (Poisson point process).

7) DESCRIBE THE SEMI-RANDOM TELEGRAPH SIGNALS, OBtain ITS MEAN VALUE.

A telegraph signal is a poison-related process $X(t)$ defined as:

$$X(t) = \begin{cases} 1 & \text{if } \# \text{Poisson Points in } (0, t] \text{ EVEN} \\ -1 & \text{if } \# \text{Poisson Points in } (0, t] \text{ ODD} \end{cases}$$

~~Since # points in (0, t] is zero - count of Poisson points is treated as even.~~

We call ~~the~~ SEMI-RANDOM TELEGRAPH SIGNALS.

In other cases, it is count \neq even or odd

Points in $(0, t]$

points =

0 \Rightarrow EVEN \Rightarrow SEMI-RANDOM VALUE TELEGRAPH SIGNAL

otherwise ($\# \text{points} \neq 0$) \Rightarrow EVEN OR ODD \Rightarrow RANDOM VALUE TELEGRAPH SIGNAL

$$E\{X(t)\} = +1 \cdot P\{X(t) = +1\} - 1 \cdot P\{X(t) = -1\}$$

We know:

$$P\{\text{k points in } (0, t]\} = e^{-\lambda t} \cdot \frac{\lambda^k}{k!} \text{ Poisson points}$$

The events $\{k \text{ points in } (0, t]\}$ are mutually exclusive for different values of k , for $t \geq 0$.

$$\begin{aligned} P\{X(t) = +1\} &= P\{\text{even number of points in } (0, t]\} \\ &= P\{\text{0 points in } (0, t]\} + P\{\text{2 points in } (0, t]\} + \\ &\quad P\{\text{4 points in } (0, t]\} + \dots \end{aligned}$$

$$= e^{-\lambda t} + e^{-\lambda t} \cdot (\lambda t)^0 + e^{-\lambda t} \cdot (\lambda t)^2 + \dots$$

$$= e^{-\lambda t} \left[1 + \frac{(\lambda t)^2}{2!} + \frac{(\lambda t)^4}{4!} + \dots \right] = e^{-\lambda t} \cdot \cosh(\lambda t)$$

Since

$$\cosh x = \frac{e^x + e^{-x}}{2}$$

$$\sinh x = \frac{e^x - e^{-x}}{2}$$

ODD:

$$P\{x(t) = -1\} = P\{\text{odd number in } (0, t)\} = e^{-\lambda t} \cdot \sinh(\lambda t)$$

$t < 0$

~~$P\{x(t) = +1\} + P\{x(t) = -1\}$~~

$$P\{x(t) = +1\} + P\{x(t) = -1\} = 1$$

$$\Rightarrow E\{x(t)\} = +1 \cdot e^{-\lambda t} \cdot \cosh(\lambda t) - 1 \cdot e^{-\lambda t} \cdot \sinh(\lambda t) \\ = e^{-\lambda t} \cdot (\cosh(\lambda t) - \sinh(\lambda t))$$

$$= e^{-\lambda t} \cdot \left[\frac{e^{\lambda t} + e^{-\lambda t}}{2} - \frac{e^{\lambda t} - e^{-\lambda t}}{2} \right] = e^{-2\lambda t}$$

$$E\{x(t)\} = e^{-2\lambda |t|}$$

75) AUTOCORRELATION FUNCTION OF A TELEGRAPH SIGNAL

$$R(\epsilon_1, \epsilon_2) = P\{x(\epsilon_1) \cdot x(\epsilon_2)\}$$

We need the probabilities of possible values of $x(\epsilon_1) \cdot x(\epsilon_2)$

$$x(\epsilon_1) \cdot x(\epsilon_2) = +1 \quad \textcircled{1}$$

$$x(\epsilon_1) \cdot x(\epsilon_2) = -1 \quad \textcircled{2}$$

The different combinations yielding such values are, by the product sign rules.

$$\textcircled{1} P\{x(\epsilon_1) \cdot x(\epsilon_2) = +1\} = P\{x(\epsilon_1) = +1, x(\epsilon_2) = +1\} + P\{x(\epsilon_1) = -1, x(\epsilon_2) = -1\}$$

$$\textcircled{2} P\{x(\epsilon_1) \cdot x(\epsilon_2) = -1\} = P\{x(\epsilon_1) = +1, x(\epsilon_2) = -1\} + P\{x(\epsilon_1) = -1, x(\epsilon_2) = +1\}$$

\Rightarrow Compute the conditional probabilities for each case:

$$\textcircled{1} P\{x(\epsilon_1) = +1, x(\epsilon_2) = +1\} = P\{x(\epsilon_2) = +1 | x(\epsilon_1) = +1\}$$

EVENT → for $\square\square\rightarrow\square\square$

$$P\{x(\epsilon_1) = +1\}$$

even number in (ϵ_1, ϵ_2)

$$= e^{-\lambda\epsilon_1} \cdot \cosh[\lambda(\epsilon_1) \cdot e^{-\lambda(\epsilon_2 - \epsilon_1)}] \cdot \cosh[\lambda(\epsilon_2 - \epsilon_1)]$$

$$\textcircled{2} P\{x(\epsilon_1) = -1, x(\epsilon_2) = -1\} = P\{x(\epsilon_1) = -1 | x(\epsilon_2) = -1\}$$

$$P\{x(\epsilon_1) = -1\}$$

$$\textcircled{1} P\{x(t_1) = +1, x(t_2) = -1\}$$

$$= e^{-\lambda t_1} \cdot \cosh(\lambda t_1 \cdot e^{-\lambda(t_2-t_1)}) \sinh(\lambda(t_2-t_1))$$

$$\textcircled{2} P\{x(t_1) = -1, x(t_2) = +1\}$$

$$= e^{-\lambda t_1} \cdot \sinh(\lambda t_1 \cdot e^{-\lambda(t_2-t_1)}) \cosh(\lambda(t_2-t_1))$$

$$\textcircled{3} P\{x(t_1) = -1, x(t_2) = -1\}$$

$$= e^{-\lambda t_1} \cdot \sinh(\lambda t_1 \cdot e^{-\lambda(t_2-t_1)}) \sinh(\lambda(t_2-t_1))$$

$$\Rightarrow R_{xx}(t_1, t_2) = \cancel{e^{-2\lambda(t_2-t_1)}} = \cancel{\text{something}} \quad (\text{for } t_2-t_1=\gamma)$$

$$R_{xx}(t_1, t_2) = e^{-2\lambda|\gamma|}$$

76) DEFINITION OF STRICT-SENSE STATIONARY (SSS) PROCESS AND GENERATE PROPERTY OF ITS MEAN VALUE.

The process $X(t)$ is STATIONARY in STRICT-SENSE (SSS) if its statistics are not affected by a shift in the time origin.

~~Two processes have the same statistics for any ϵ .~~

$$E\{X(t)\} = \eta = \text{constant}$$

77) DEFINITION OF WIDE-SENSE STATIONARY (WSS) PROCESS

A process $X(t)$ is STATIONARY in WIDE SENSE if its updated value is constant. ~~(it is STATIONARY)~~

$$E\{X(t)\} = \eta = \text{constant}$$

And the autocorrelation of $X(t)$ depends only on $\gamma = t_1 - t_2$

$$E\{X(t+\gamma) \cdot X(t)\} = R(\gamma) = R(-\gamma)$$

78) DEFINITION AND PROPERTIES OF THE AUTOCORRELATION FUNCTION OF A STATIONARY PROCESS.

$$1) E\{X(t)\} = \eta \Rightarrow R_{XX}(\gamma) = E\{X(t+\gamma) \cdot X(t)\}$$

2) SYMMETRY: If $X(t)$ is real:

$$R_{XX}(\gamma) = R_{XX}(-\gamma) \Rightarrow \text{real even function.}$$

3) VIP PROPERTY:

$$R(0) = E\{X^2(t)\} \geq 0 \quad (\text{normalized AVG power of } X(t))$$

3) ~~and in R(d)~~. For $x(t)$ real,

~~For $R(\gamma)$ has a maximum in the origin.~~

Complex process $R(0) = E\{ |x(t)|^2 \} = E\{ x(t)x^*(t) \}$

7.9) DEFINITION OF ERGODIC PROCESS.

An SSS process is ERGODIC if its ~~ensemble~~ ~~averages~~ equal appropriate time ~~limits~~ averages of any single sample function $x(t, \varepsilon)$.

EXPLANATION:
 Any statistics of $x(t)$ can be determined with probability 1 from a single sample function $x(t, \varepsilon)$.

8.0) NECESSARY CONDITION FOR A PROCESS TO BE MEAN-ERGODIC (for real or complex $x(t)$):

$$\frac{1}{2T} \int_{-2T}^{2T} C_x(\gamma) / (1 - \frac{1|\gamma|}{2T}) d\gamma \rightarrow 0 \quad \text{for } T \rightarrow \infty.$$

(Can also be written as)

MENDE KINCHIN - THEOREM

NECESSARY &
SUFFICIENT CONDITION

$$\lim_{T \rightarrow +\infty} \frac{1}{2T} \int_{-T}^{+T} C_x(\gamma) d\gamma = 0 \quad \text{for a process to be mean-ergodic.}$$

$x(t)$ can be

If a process $x(t)$ is mean-real or complex ergodic, its statistics can be expressed as real expected value (mean) of appropriate functions.

19) CORRELATED AND INDEPENDENT PROCESSES

~~MEAN~~ $x(t)$ and $y(t)$:

R_{xy}

Real

CROSS-CORRELATION:

The cross-correlation of $x(t), y(t)$ is:

$$R_{xy}(\tau) = \mathbb{E}\{x(t+\tau) \cdot y(t)\}$$

$$t' = t + \tau$$

$$= \mathbb{E}\{y(t') + f(\tau)) \cdot x(t')\} = R_{yx}(-\tau)$$

Autocorrelation

Product of independent $x(t), y(t)$:

Autocorrelation $R_{zz}(t) = x(t) \cdot y(t)$

$$R_{zz}(\tau) = \mathbb{E}\{x(t+\tau) \cdot y(t+\tau) \cdot x(t) \cdot y(t)\}$$

$$= R_{xx}(\tau) R_{yy}(\tau)$$

20) DESCRIBE THE SAMPLE FUNCTIONS OF A RANDOM WALK, obtain its MEAN VALUE and MEAN SQUARE VALUE

Define an experiment:

"Tossing of coin an infinite number of times, with each tossing occurring every T seconds".

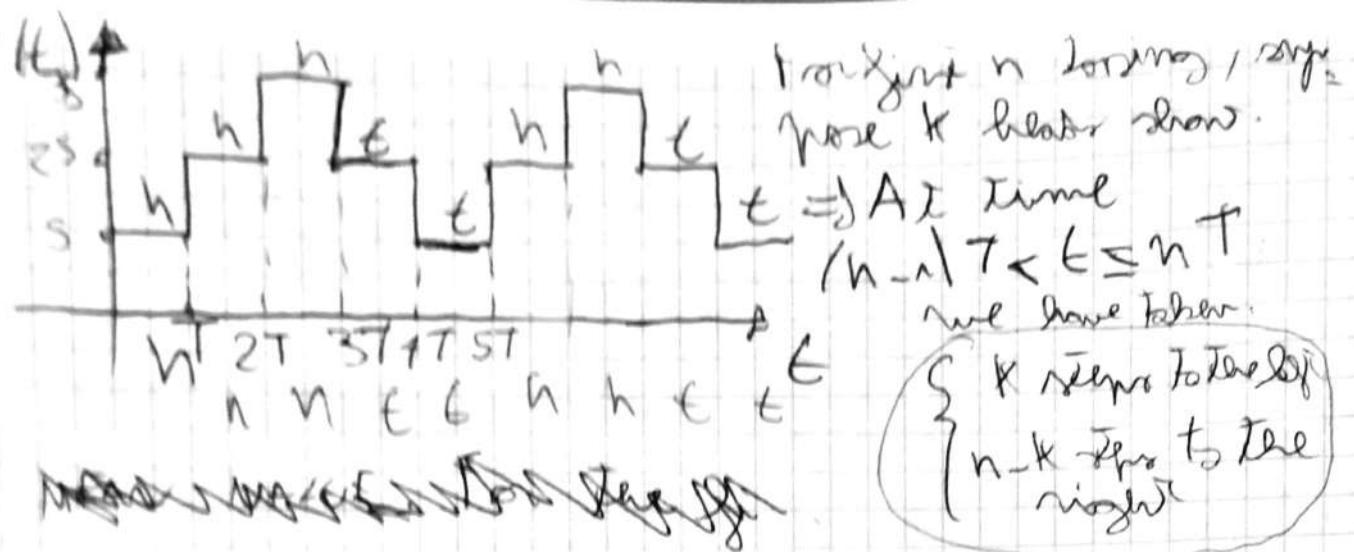
$$\{P\{\text{heads}\} = P\{\text{tails}\} = p = q = \frac{1}{2} \text{ in each trial}\}$$

In each tossing, we take an instantaneous step.

LEFT if head (H)

RIGHT if tail (T)

Our position "t" seconds after the first tossing is $x(t)$ ("RANDOM WALK").



MEAN VALUE

Denote by X_n a sequence of independent R.V.s with equally likely values $\pm s$ depending on the tossing outcome. Then, for:

$$[n-1]T \leq t \leq nT$$

$$X(t) = x_1 + x_2 + \dots + x_m.$$

$$\Rightarrow E\{X(t)\} = 0$$

MEAN SQUARE VALUE:

~~$E\{X(t)^2\} = E\{x_1^2\} + E\{x_2^2\} + \dots + E\{x_n^2\} + \dots + E\{x_{n+1}^2\}$~~

$$E\{X(t)^2\} = E\{x_1^2\} + E\{x_2^2\} + \dots + E\{x_n^2\} + E\{x_{n+1}^2\} + \dots = (ns)^2$$

tosses \rightarrow number of tosses

21) Define a WIENER-LEVY PROCESS, claim

its MEAN VALUE AND ITS MEAN SQUARE VALUE

Answers: Limiting form of Random Walk process $X(t)$. For a Random Walk Process,

$$E\{X(t)\} = 0$$

$$E\{X(t)^2\} = ns^2$$

Now, fixing the time, $t = nT$ and $n = \frac{t}{T}$

$$W = \frac{t}{T}$$

tossing

$$\mathbb{E}\{x^2(t)\} = \left(\frac{t}{T}\right) \cdot s^2$$

keep t constant, but let see step s and interval T tends to zero (continuously take small steps close to one another)

To keep up, we need more and more ~~tosses~~
tossings to reach a certain position (the target much larger)

\Rightarrow Variance $\mathbb{E}\{x^2(t)\} - \mathbb{E}\{x(t)\}^2 = \left(\frac{t}{T}\right) s^2$ will remain finite if $s \rightarrow 0$ as \sqrt{T}

$$\frac{s^2}{T} \rightarrow \alpha$$

$$W(t) = \lim x(t) \text{ for } \begin{cases} T \rightarrow 0 \\ s \rightarrow 0 \\ \frac{s^2}{T} \rightarrow \alpha \end{cases}$$

$$\Rightarrow \text{MEAN: } \mathbb{E}\{w(t)\} = 0$$

MEAN SQUARE VALUE:

~~mean square value~~ keeping $(n-1)T \leq t \leq nT$:
 from $\mathbb{E}\{x^2(t)\} = ns^2$, we get at time $T=t$

$$\mathbb{E}\{x^2(t)\} = \frac{t}{T} s^2 \quad (\text{so } n = \frac{t}{T})$$

$$\lim_{s \rightarrow 0} \frac{s^2}{T} = \alpha = \mathbb{E}\{w^2(t)\} = \alpha t$$

2.2) Write in ANALYTIC TERMS THE REFLECTION PRINCIPLE FOR WIMER-LEVY PROCESSES AND EXPLAIN IT.

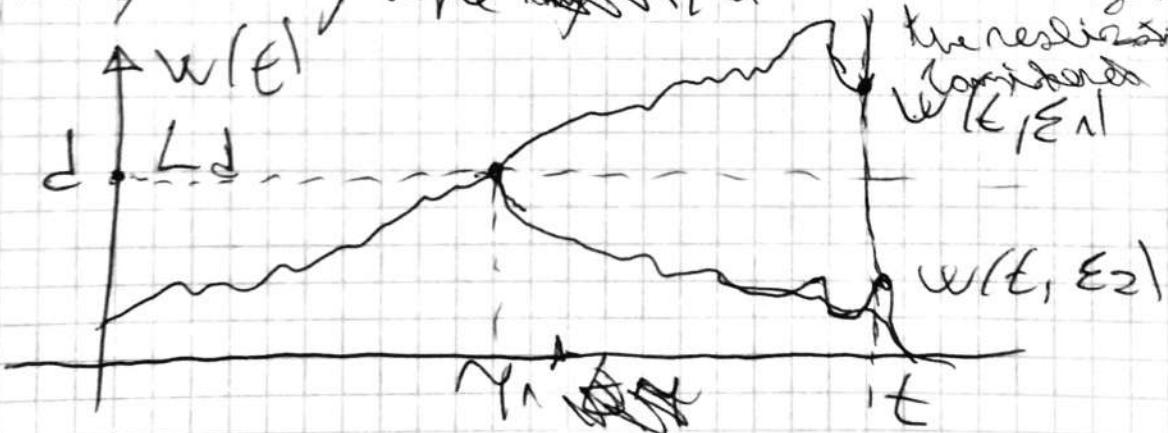
$$P\{X_t \leq w | \gamma_1 \leq t\} = P\{X_t \leq 2d-w | \gamma_1 \leq t\}$$

$$P\{X_t \leq w | \gamma_1 \leq t\} = P\{X_t \leq 2d-w | \gamma_1 \leq t\}$$

"For those realizations that cross L_d before t , the probability that $X_t \leq w$ at that t is lower than w equals the probability of X_t being higher than $2d-w$ ".

REFLECTION PRINCIPLE:

Given a realization of a process describes the shape for the first term (crossing), you can be sure that there is another realization of the process (crossing), proceeding after a symmetric shape (a mirror image) to the realization considered.

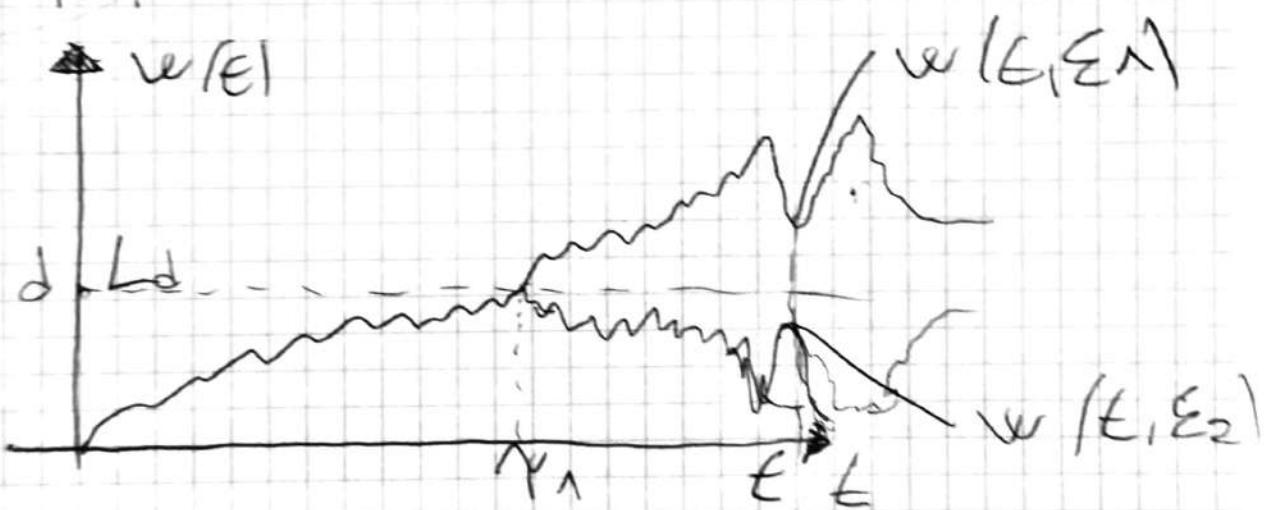


NB: Each process has an infinite number of reflections!

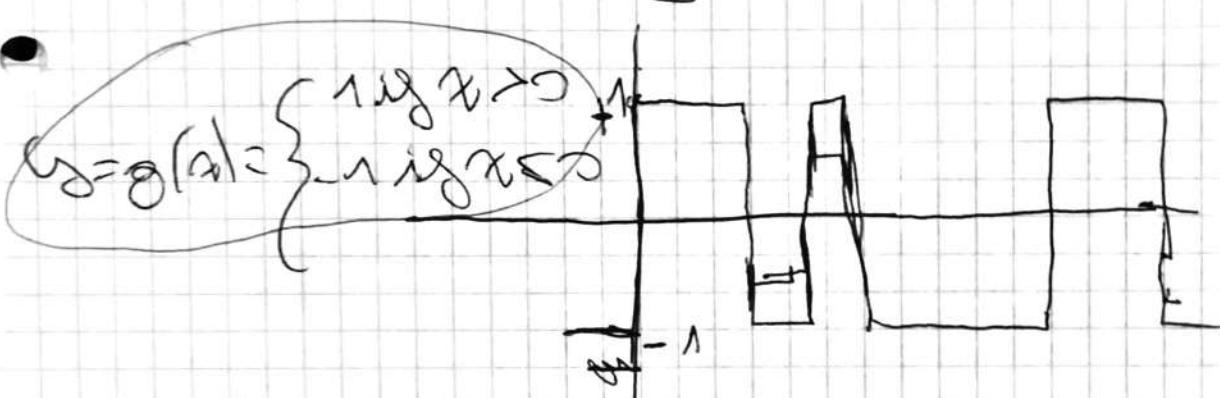
Any sample function of a Wiener-Lévy process that crosses a line $w=d$ (L_d) continues also on symmetric paths.

REFLECTION PRINCIPLE for widths ONLY EXPLAINED.

If, for some experimental outcome ϵ_1 the curve $w(t, \epsilon_1)$ crosses L_d at $t = \gamma_1$ for the first time, then the place contains also another curve $w(t, \epsilon_2)$ that coincides with $w(t, \epsilon_1)$ ~~for $t < \gamma_1$~~ and is the mirror image of $w(t, \epsilon_1)$ with respect to the line L_d for $t > \gamma_1$.



103) OBTAINT MEAN VALUE AND AUTOCORRELATION
OF OUTPUT OF A "HARD LIMITER" IF THE INPUT
IS A SSS process.



$x(t)$ is SSS \Rightarrow MEAN VALUE.

~~$$E\{y(t)\} = +1 \cdot P\{x(t) > 0\} - 1 \cdot P\{x(t) \leq 0\}$$~~

~~$$= [1 - F_x(0)] = F_x(0) < 1 - 2F_x(0)$$~~

AUTOCORRELATION:

$$R_{yy}(\tau) = E\{y(t) \cdot y(t+\tau)\}$$

$$= +1 \cdot P\{y(t) \text{ and } y(t+\tau) \text{ same sign}\} +$$

$$- 1 \cdot P\{y(t) \text{ and } y(t+\tau) \text{ different sign}\}$$

$$= +1 \cdot P\{x(t) \cdot x(t+\tau) > 0\} - 1 \cdot P\{x(t) \cdot x(t+\tau) < 0\}$$

Now consider two cases:

(1) POSITIVE

$$\begin{aligned} P\{x(t) \cdot x(t+\tau) > 0\} &= P\{x(t) > 0, x(t+\tau) > 0\} + \\ &\quad P\{x(t) < 0, x(t+\tau) < 0\} \\ &= 1 - F_x(0) - F_x(0) + F_x(0, 0; \tau) + F_x(0, 0; \tau) \\ &= (1 - 2F_x(0) + 2F_x(0, 0; \tau)) \end{aligned}$$

(2) NEGATIVE:

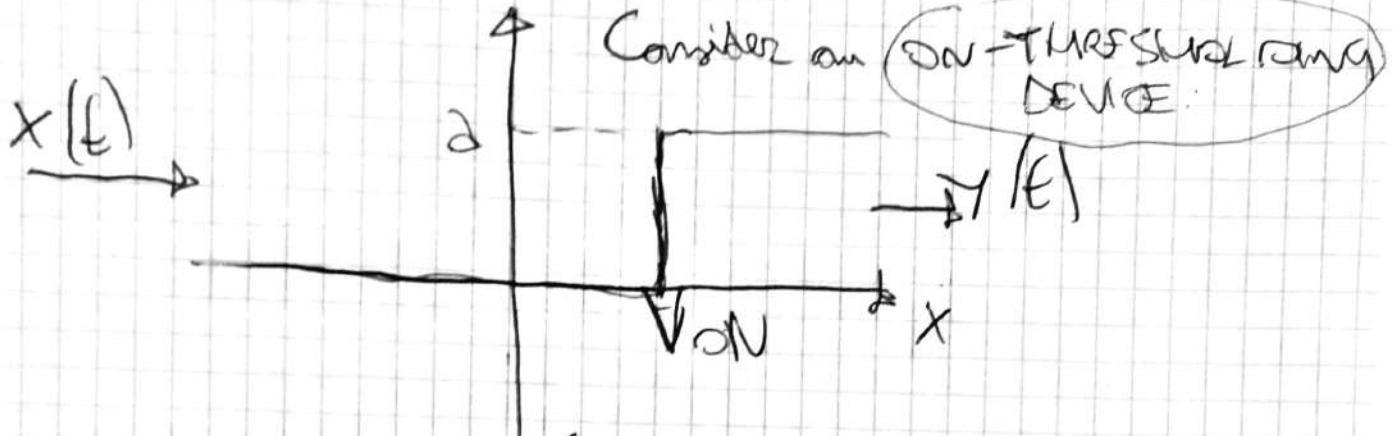
$$\begin{aligned} P\{x(t) \cdot x(t+\tau) < 0\} &= 1 - P\{x(t) \cdot x(t+\tau) > 0\} \\ &= 2F_x(0) - 2F_x(0, 0; \tau) \\ \Rightarrow R_{\tau}(\tau) &= 1 - 4F_x(0) + 4F_x(0, 0; \tau) \end{aligned}$$

(3) NEGATIVE:

$$\begin{aligned} P\{x(t) \cdot x(t+\tau) < 0\} &= 1 - P\{x(t) \cdot x(t+\tau) > 0\} \\ &= 1 - [1 - 2F_x(0) + 2F_x(0, 0, \tau)] \\ &= 1 - 1 + 2F_x(0) - 2F_x(0, 0, \tau) \\ &= (2F_x(0) - 2F_x(0, 0, \tau)) \end{aligned}$$

$$\begin{aligned} \Rightarrow R_{\tau}(\tau) &= +1 \cdot P\{x(t) > 0\} - 1 \cdot P\{x(t) < 0\} \\ &= 1 - 1 - 2F_x(0) + 2F_x(0, 0, \tau) - 2F_x(0) + \\ &\quad 2F_x(0, 0, \tau) = (1 - 4F_x(0) + 4F_x(0, 0, \tau)) \end{aligned}$$

29) OBTAİN MEAN VALUE AND AUTO CORRELATION
 OF THE OUTPUT OF A "THRESHOLD DEVICE"
 If the input is SSS



$$y(t) = \begin{cases} a & \text{if } x(t) \geq V_{ON} \\ 0 & \text{if } x(t) < V_{ON} \end{cases}$$

For input $x(t)$ SSS: MEAN VALUE

$$\mathbb{E}\{y(t)\} = a \cdot P\{x(t) \geq V_{ON}\} = a [1 - F_x(V_{ON})]$$

$$R_y(\gamma) = \mathbb{E}\{y(t+\gamma) \cdot y(t)\} \quad \text{AUTOCORRELATION}$$

$$\begin{aligned} R_y(\gamma) &= a^2 \cdot P\{x(t) \geq V_{ON}, x(t+\gamma) \geq V_{ON}\} \\ &= a^2 \cdot [1 - 2F_x(V_{ON}) + F_{xx}(V_{ON}, V_{ON}; \gamma)] \end{aligned}$$

20) How to obtain (MEAN VALUE) and the (AUTOCORRELATION) of the output of a linear time-invariant system with process SSS input

If input $x(t)$ is SSS \Rightarrow output $y(t)$ is also SSS.

If input $x(t)$ is WSS \Rightarrow output $y(t)$ is WSS

$$E\{y(t)\} = \eta_y = \text{constant} = \eta_x \times \int_{-\infty}^{+\infty} h(\alpha) d\alpha$$

$$R_{yy}(t_1, t_2) = R_{yy}(t_1 - t_2)$$

1. (a) Obtain the (mean value) and the

(AUTOCORRELATION) of a differentiator if input is SSS

A differentiator is a linear system whose output is the derivative of the input.

$$L[x(t)] = x'(t) = \frac{dx(t)}{dt}$$

MEAN:

$$\eta_{x'}(t) = E\{x'(t)\} = L[E\{x(t)\}] = \frac{dE\{x(t)\}}{dt}$$

$$= \frac{d\eta_x(t)}{dt}$$

AUTOCORRELATION:

~~$$R_{x'x'}(t_1, t_2) = \frac{1}{T} \int_{t_1}^{t_2} x'(t) x'(t') dt'$$~~

$$R_{x'x'}(t_1, t_2) \underset{\approx}{=} R_{xx}(t_1, t_2)$$

$$R_{x'x'}(t_1, t_2) = \frac{\partial^2}{\partial t_1 \partial t_2} R_{xx}(t_1, t_2)$$

Q3 Give the definition of Power Spectral Density and its main properties.

$$S(\omega) \triangleq \int_{-\infty}^{+\infty} R(\tau) \cdot e^{-j\omega\tau} d\tau = \{R(\tau)\}$$

The power spectrum density of a WSS process is the Fourier Transform of the autocorrelation function.

Properties:

- INVERSION FORMULAE:

$$R(\tau) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} S(\omega) e^{j\omega\tau} d\omega$$

- If $R(\tau)$ even:

$$R(\tau) = R^*(-\tau) \text{ if } x(\tau) \text{ complex}$$

$$R(\tau) = R^*(-\tau) \text{ if } x(\tau) \text{ real}$$

- If $x(t)$ real:

$R(\tau)$ is real and even.

Spectrum $\Rightarrow S(\omega)$ also real and even.

$$S(\omega) = \int_{-\infty}^{+\infty} R(\tau) \cdot \cos(\omega\tau) d\tau$$

$$R(\tau) = \frac{1}{2\pi} \int_{-\infty}^{+\infty} S(\omega) \cdot \cos(\omega\tau) \frac{d\omega}{2\pi}$$

- If $x(t)$ complex ($S(\omega)$ is real, but not even).

$$S(\omega) \neq S(-\omega)$$

10) Give a procedure to calculate the Power Spectral Density of a process directly from time PSD

$$S_{xx}(w) = \int_{-\infty}^{+\infty} R_{xx}(\tau) e^{-jw\tau} d\tau \quad \left\{ \begin{array}{l} \text{By definition} \\ \text{of PSD} \end{array} \right.$$

~~By the mean-value theorem~~

$$S_{xx}(w) = \int_{-\infty}^{+\infty} e^{-jw\tau} \left(\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2 g_x(x_1, x_2; \tau) dx_1 dx_2 \right) d\tau$$

~~By the mean-value theorem:~~

$$S_{xx}(w) = \int_{-\infty}^{+\infty} e^{-jw\tau} \left\{ \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2 g_x(x_1, x_2; \tau) dx_1 dx_2 \right\} d\tau$$

$$S_{xx}(w) = \int_{-\infty}^{+\infty} e^{-jw\tau} \left\{ \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2 \{ Fg_x(w + \tau) - g_x(w) \} dx_1 dx_2 \right\} d\tau$$

By the mean-value theorem of a R.V.:

$$S_{xx}(w) = \int_{-\infty}^{+\infty} e^{-jw\tau} \left\{ \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2 g_x(x_1, x_2; \tau) dx_1 dx_2 \right\} d\tau$$

Interchange integrals

$$S_{xx}(w) = \int_{-\infty}^{+\infty} \left\{ \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2 \left[\int_{-\infty}^{+\infty} e^{-jw\tau} g_x(x_1, x_2, \tau) d\tau \right] dx_1 dx_2 \right\} d\tau$$

Double-integral ($\int (x_1, x_2, w)$) = $\int \{ g_x(x_1, x_2, w) \}$

Kernel G_x = $\int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} x_1 x_2 G_x(x_1, x_2, w) dx_1 dx_2$

F - Transf. of
2nd-order PSD

112) Obtain Frequency spectrum of the output of a sliding window ~~smoothing~~ slice when the input is a SSS process.



OUTPUT SPECTRUM (\mathcal{F} -transform of $h(t)$).

$$H(\omega) = \frac{1}{2T} \int_{-T}^{+T} e^{-j\omega t} dt = \frac{1}{2T} \frac{e^{-j\omega T} - e^{j\omega T}}{-j\omega}$$

$$\text{Since } \frac{e^x - e^{-x}}{2j} = \sinh(x)$$

$$\Rightarrow H(\omega) = \frac{\sinh(\omega T)}{\omega T}$$

$$\mathbb{E}\left\{\sum_{k=1}^n x_k\right\} = \mathbb{E}\{N(t)\} \cdot \mathbb{E}\{x_k\}$$

$$\mathbb{E}\left\{\left(\sum_{k=1}^n x_k\right)^2\right\} \leq \mathbb{E}\{N(t)^2\} \cdot \mathbb{E}\{x_k^2\} < \infty$$

$$\text{PROOF: } \mathbb{E}\{x^2\} = M$$

$$\mathbb{E}\{S^2\} = \mathbb{E}\left\{\left(\sum_{k=1}^n x_k\right)^2\right\}$$

LINEAR, TIME-INVARIANT -

$$E\{x(t)\} = \int_{-\infty}^{\infty} n_x(\omega) d\omega$$

$$C_{xy}(t_1, t_2) = \int_{-\infty}^{\infty} E\{x(t_1) y(t_2)\} d\omega$$

$$[x(t)] = \frac{d[x(t)]}{dt}$$

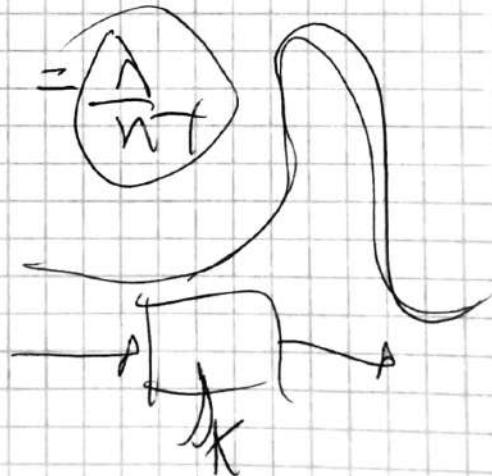
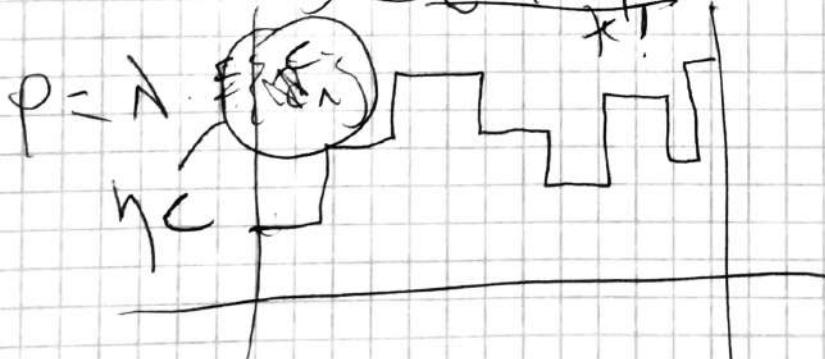


$$R_{yy}(t_1, t_2) = \int_{-\infty}^{\infty} E\{x(t_1)^2\} d\omega = \frac{1}{2\pi} \int_{-\infty}^{\infty} |X(\omega)|^2 d\omega$$

$$\frac{nT}{T} = \frac{E[nT]}{T} = \lambda$$

$$\frac{nT}{T} = \lambda \Rightarrow \frac{\Delta}{T} = \frac{\lambda}{nT}$$

$$P\{N(t)=k\} = e^{-\rho} \cdot \frac{\rho^k}{k!}$$



$$\lim_{T \rightarrow \infty} \frac{1}{T} \int_0^T N(t) dt = \lambda \int_0^\infty N(t) dt$$

$$z_i = c_i$$

$$z_i = \cancel{x_i + c_i} + \begin{array}{l} \text{* service time} \\ \text{waiting time} \end{array}$$

system
time

waiting time