

18/3/19 ERGODIC RANDOM PROCESS

Let  $X(t)$  be a random process and  
 $x(t)$  be a sample.

Time average of the function of  $x(t)$  is defined  
 by:

$$\bar{x} = \lim_{T \rightarrow \infty} \frac{1}{2T} \int_{-T}^T x(t) dt$$

In real life, it is not possible to know all elements of r.p. We need to use the few that we have available, to analyse behaviour of process.

We can use time average to determine statistical average  $E[x(t)]$

Statistical average

$$E[x(t)] = \begin{cases} \sum_{-\infty}^{\infty} x p(x, t) \\ \int_{-\infty}^{\infty} x f(x, t) dx \end{cases}$$

A stationary process  
 Definition:  $X(t)$  is ergodic if

$$E[x(t)] = \bar{x}$$

$E[x(t)]$  is also called the ensemble average.

Mean Ergodic Theorem:

$\bar{x}_T$  = average in a particular time interval

If  $X(t)$  is a stationary random process

and  $\bar{x}_T = \frac{1}{2T} \int_{-T}^T x(t) dt$ , then  $X(t)$  is said

to be mean ergodic if

$$\lim_{T \rightarrow \infty} V(\bar{x}_T) = 0$$

Example:

$$x(t) = A \cos(\omega t + \phi)$$

$\omega$  is constant.  $A$  is a random variable which has a magnitude of  $+1, -1$  with equal probabilities.

$\phi$  is a random variable uniformly distributed over  $(0, 2\pi)$ .  $A$  and  $\phi$  are independent.

i) Check if it is a mean ergodic process

Stationary process check: ( $E$  independent of  $t$ )

$$a) E[x(t)] = E[A \cos(\omega t + \phi)]$$

$$\begin{aligned} &= E[A] \cdot E[\cos(\omega t + \phi)] \\ &= \left(1 \times \frac{1}{2} + (-1) \frac{1}{2}\right) \cdot E[\cos(\omega t + \phi)] \\ &= 0 \end{aligned}$$

Expectation is thus independent of  $t$ .

Computing the autocorrelation function,

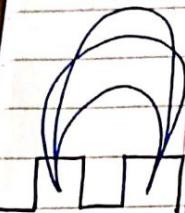
$$R_{xx}(t, t+\tau) = E[x(t)x(t+\tau)]$$

$$= E[A \cos(\omega t + \phi) \cdot A \cos(\omega(t+\tau) + \phi)]$$

$$= E[A^2] \cdot E\left[\frac{1}{2} \left( \cos(\omega t + \phi - \omega t - \omega \tau - \phi) + \cos(2\omega t + \phi + \omega \tau) \right)\right]$$

$$= E[A^2] \cdot E[\cos(-\omega \tau) + \cos(2\omega t + \phi + \omega \tau)]$$

$$\begin{aligned}
 &= \frac{1}{2} \left[ 1 \times \frac{1}{2} + 1 \times \frac{1}{2} \right] \Rightarrow (\cos \omega t + 0) = \frac{1}{2} \cos \omega t \\
 &\text{Second term there is } 0 \text{ because } E[\cos(2\omega t + \phi)] + \\
 &= \int_0^{2\pi} \cos(2(\omega t + \phi) + \omega \tau) \times \frac{1}{2\pi} d\phi \text{ (uniformly distributed)} \\
 &\quad \text{↳ uniform distribution pdf} \\
 &= \frac{1}{2\pi} \sin [2(\omega t + \phi) + \omega \tau]
 \end{aligned}$$



i.e. let  $2\omega t + 2\phi + \omega \tau = u$   
 $du = 2 d\phi$

Elephant

$$\text{Integral} = \frac{1}{2\pi \times 2} \int_{2\omega t + \omega \tau}^{2\omega t + 4\pi + \omega \tau} \cos u du = \frac{1}{2\pi \times 2} [\sin u]_{2\omega t + \omega \tau}^{2\omega t + 4\pi + \omega \tau}$$

Hypoth

$$\begin{aligned}
 &= \frac{1}{4\pi} \left[ \sin(2\omega t + 4\pi + \omega \tau) - \sin(2\omega t + \omega \tau) \right] \\
 &= \frac{1}{4\pi} (0) = 0 \\
 &\Rightarrow R_{xx} \text{ is dependent on } \omega t
 \end{aligned}$$



Now to check if it is a mean ergodic process

$$\bar{x} = \lim_{T \rightarrow \infty} \frac{1}{2T} \int_{-T}^T x(t) dt$$

Zephyr

$$= \lim_{T \rightarrow \infty} \frac{1}{2T} \int_{-T}^T A \cos(\omega t + \phi) dt$$

$$= \lim_{T \rightarrow \infty} \frac{1}{2T} \times A \left[ \frac{\sin(\omega t + \phi)}{\omega} \right]_{-T}^T$$

$$= \lim_{T \rightarrow \infty} \frac{A}{2T} \left( \frac{\sin(\omega T + \phi) - \sin(-\omega T + \phi)}{\omega} \right)$$

(3)

19/3

content

$(\omega t + \phi)$  +  
y distributed  
in pdf

$$\begin{aligned} & \text{since } \left| \sin(\omega T + \phi) - \sin(\omega t + \phi) \right| \\ & \leq 2 \end{aligned}$$

$$\therefore E[x(t)] = \bar{x} = 0 \quad x(t) \text{ is mean ergodic}$$

- Q) A binary transmission process  $x(t)$  has zero mean and autocorrelation function  $R(\tau) = 1 - \frac{|\tau|}{T}$ . Find the mean

and variance of the process  $x(t)$  over  $(0, T)$  and verify whether it is mean ergodic.

$$\text{Note: } V(\bar{x}_T) = \frac{1}{2T} \int_{-T}^T C(\tau) \left(1 - \frac{|\tau|}{T}\right) d\tau$$

↑ autocovariance  
↓ even function

(6r)

$$V(\bar{x}_T) = \frac{1}{T} \int_0^T C(\tau) \left(1 - \frac{|\tau|}{T}\right) d\tau$$

9/3/19 Note: Let  $\bar{x}_T = \frac{1}{2T} \int_{-T}^T x(t) dt$

$$E[\bar{x}_T] = \frac{1}{2T} \int_{-T}^T E[x(t)] dt = E[x(t)] \quad (\text{independent of } t)$$

$$\begin{aligned} E[\bar{x}^2] &= E \left[ \left( \frac{1}{2T} \int_{-T}^T x(t) dt \right)^2 \right] = \frac{1}{(2T)^2} \int_{-T}^T \int_{-T}^T x(t_1) x(t_2) dt_1 dt_2 \\ &= \frac{1}{4T^2} \int_{-T}^T \int_{-T}^T E[x(t_1) x(t_2)] dt_1 dt_2 \end{aligned}$$

①

Now, computing  $(E[x(t)])^2$   
 $\hookrightarrow (E[\bar{x}_T])^2$

$$\begin{aligned}
 &= E[\bar{x}_T]E[\bar{x}_T] \\
 &= \frac{1}{2T} \int_{-T}^T E[x(t_1)] dt_1 \times \\
 &\quad \frac{1}{2T} \int_{-T}^T E[x(t_2)] dt_2 \\
 &= \frac{1}{4T^2} \int_{-T}^T \int_{-T}^T E[x(t_1)] E[x(t_2)] dt_1 dt_2 \quad - (2)
 \end{aligned}$$

If we perform ① - ②, we get

$$\begin{aligned}
 \text{Var}(\bar{x}_T) &= \frac{1}{4T^2} \int_{-T}^T \int_{-T}^T (E[x(t_1)x(t_2)] - \\
 &\quad E[x(t_1)]E[x(t_2)]) dt_1 dt_2 \\
 \Rightarrow \text{Var}(\bar{x}_T) &= \frac{1}{4T^2} \int_{-T}^T \int_{-T}^T C(t_1, t_2) dt_1 dt_2 \quad \begin{matrix} \nearrow \text{autocovariance} \\ \searrow \text{autocorrelation} \end{matrix} \\
 &= \frac{1}{4T^2} \int_{-2T}^{2T} C(\tau) (2T - |\tau|) d\tau \quad \hookrightarrow \text{this is done by Jacobian transformation.}
 \end{aligned}$$

$$\boxed{\text{X}} \left\{ \text{Var}(\bar{x}_T) = \frac{1}{T} \int_0^{2T} C(\tau) (1 - |\tau|) d\tau \right.$$

Solution for P

Given,  $R(\tau) = 1 - \frac{|\tau|}{T}$   $E[x(t)] = 0$

Cross covariance  $C(\tau) = R(\tau) - E[x(t)] \underbrace{E[x(t+\tau)]}$

$$\begin{aligned} \text{Var}(x_T^-) &= \frac{1}{T} \int_0^{2T} \left(1 - \frac{|\tau|}{T}\right) \left(1 - \frac{|\tau|}{T}\right)^2 d\tau \\ &= \frac{1}{T} \int_0^{2T} \left(1 - \frac{\tau}{T}\right)^2 d\tau \\ &= \frac{1}{T} \left[ \frac{\left(1 - \frac{\tau}{T}\right)^3}{3} \right]_0^{2T} \end{aligned}$$

Since  $T > 0$ ,  $|\tau| = \tau$

~~Canceling  $\frac{1}{T}$ ,~~

$$= \left(1 - \frac{2\tau}{T}\right)^3 - (1) = \frac{(1-2)^3 - 1}{-3}$$

$$= -\frac{8-1}{6} - 1 = \frac{-7}{6} = \frac{2}{3}$$

$$\int (ax+b)^m dx = \frac{(ax+b)^{m+1}}{a(m+1)}$$

Since  $\text{Var}(x_T^-)$  does not approach 0 at  $T \rightarrow \infty$

Given,  $x(t)$  is not mean ergodic.

①

when mean=0, autocorrelation =  
autocovariance.

discrete

time

sigma

3. If  $X(t)$  is a zero mean WSS with  $R_{XX}(T) = e^{-2|T|}$ , show that  $\bar{X}(t)$  is mean ergodic.

$$\text{Soln: } \text{Var}(\bar{X}_T) = \frac{1}{2T} \left( 1 + \frac{e^{-4T}}{4T} - \frac{1}{4T} \right)$$

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

|||

More problems: (on mean ergodicity)

①  $X(t) = a \sin(\omega t + \theta)$

$a$  is constant

$\theta$  is uniformly distributed on  $(0, 2\pi)$

Check if  $X(t)$  is mean ergodic.

PROBLEMS ON MEAN ERGODICITY

②  $X(t)$  has mean 0.

$$R(T) = e^{-2\lambda T}$$

20/3/19 Power Spectral Density: (PSD)

↳ characterization based on frequency domain

If you have a function of time  $f(t)$ , then  
Laplace transform

$$\mathcal{L}\{f(t)\} = \int_0^\infty e^{-st} f(t) dt$$

Not in syllabus

But, in this case, we have the Fourier transform.

Intuition: If we know Laplace transform,  $\int \mathcal{L}\{f(t)\} e^{st} ds$   
gives us  $f(t)$ .

PSD uses the Fourier transform, which is:

For a function  $f(t)$ , which could be a signal,

$$\text{then } F\{f(t)\}(w) = \int_{-\infty}^{\infty} f(t) \cdot e^{-i\omega t} dt = \hat{f}(w)$$

Here, the inversion process is:

If we have a Fourier transform  $\hat{f}(w)$ , then

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \hat{f}(w) e^{i\omega t} dw$$

→ autocorrelation function,

Some specific to be specific

PSD is a Fourier transform of a function.

When  $\int_{-\infty}^{\infty} |s(t)|^2 dt < \infty$ , is integrable,

then we can get a Fourier transform.

Now,

Let  $x(t)$  be a random process.

Let  $R_{xx}(\tau)$  be an autocorrelation function of  $x(t)$ .

Then PSD of  $x(t)$  is defined by

$$F(R_{xx}(\tau))(w)$$

$$= S_{xx}(w) = \int_{-\infty}^{\infty} R_{xx}(\tau) e^{-i\omega \tau} d\tau$$

(a)

$$\text{eg. } R_{xx}(\tau) = e^{-a|\tau|} \quad a > 0$$

Let us check if PSD exists.

$$\text{PSD is: } S_{xx}(\omega) = \int_{-\infty}^{\infty} e^{-a|\tau|} e^{-i\omega\tau} d\tau$$

\*  $|\tau|$  is  $\tau$  for  $\tau > 0$   
 \*  $-\tau$  for  $\tau < 0$

Splitting over intervals,

$$S_{xx}(\omega) = \int_{-\infty}^{0} e^{-a-\tau} e^{-i\omega\tau} d\tau + \int_{0}^{\infty} e^{-a\tau} e^{-i\omega\tau} d\tau$$

$$= \int_{-\infty}^{0} e^{a\tau - i\omega\tau} d\tau + \int_{0}^{\infty} e^{-a\tau - i\omega\tau} d\tau$$

$$= \left[ \frac{e^{(a-i\omega)\tau}}{a-i\omega} \right]_{-\infty}^{0} + \left[ \frac{e^{-\tau(a+i\omega)}}{-(a+i\omega)} \right]_{0}^{\infty}$$

$$= \frac{1}{a-i\omega} - 0 + 0 - \left( - \frac{1}{a+i\omega} \right)$$

$$= \frac{1}{a-i\omega} + \frac{1}{a+i\omega} = \frac{a+i\omega + a-i\omega}{a^2 - i^2\omega^2}$$

$$= \frac{i2a}{a^2 + \omega^2}$$

10. 00  
9. 71  
0. 29

SRKHTI

$x(\tau)$ 

$$\textcircled{1} \quad e^{-a|\tau|} \quad a > 0$$

$$\textcircled{2} \quad e^{-a\tau} \quad a > 0, \tau > 0$$

$$\textcircled{3} \quad e^{b\tau} \quad b > 0, \tau < 0$$

$$\textcircled{4} \quad \tau e^{-a\tau} \quad a > 0, \tau \leq 0$$

$$\textcircled{5} \quad 1$$

$$F \{ x(\tau) \}$$

$$\frac{2a}{a^2 + \omega^2}$$

$$1/a + i\omega \quad \text{not PSD}$$

$$1/b - i\omega \quad \text{not PSD}$$

$$1/(a + i\omega)^2 \quad \text{not PSD}$$

$$2\pi \delta(\omega - \omega_0)$$

$\hookrightarrow$  Dirac-Delta  
function

$$\text{Note: } \delta(x) = \begin{cases} \infty & x = 0 \\ 0 & x \neq 0 \end{cases}$$

$$\textcircled{6} \quad s(\tau)$$

$$\textcircled{7} \quad e^{i\omega_0 \tau}$$

$$2\pi \delta(\omega - \omega_0)$$

$$\textcircled{8} \quad \cos(\omega_0 \tau)$$

$$\pi \delta(\omega - \omega_0) + \pi \delta(\omega + \omega_0)$$

$$\textcircled{9} \quad \sin(\omega_0 \tau)$$

$$-i\pi[\delta(\omega - \omega_0) - \delta(\omega + \omega_0)]$$

$\hookrightarrow$  not PSD

Properties: (PSD)



$$\textcircled{1} \quad S_{xx}(\omega) \geq 0 \quad (\text{Wiener-Khintchine theorem})$$

$$\textcircled{2} \quad S_{xx}(-\omega) = S_{xx}(\omega)$$

$$\textcircled{3} \quad S_{xx}(\omega) \text{ is always real.}$$

$\textcircled{4}$  Average power (or) mean square value

$$E[X^2(t)] = R_{xx}(0) = \frac{1}{2\pi} \int_{-\infty}^{\infty} S_{xx}(\omega) d\omega$$

$$\therefore S_{xx}(\omega) = \int_{-\infty}^{\infty} R_{xx}(\tau) e^{-i\omega\tau} d\tau$$

(Cor),

(11)

By inversion theorem,

$$R_{xx} = \frac{1}{2\pi} \int_{-\infty}^{\infty} S_{xx}(\omega) e^{+i\omega\tau} d\omega$$

$$\text{So, } R_{xx}(0) = E[x^2(t)] = \frac{1}{2\pi} \int_{-\infty}^{\infty} S_{xx}(\omega) d\omega$$

$$\textcircled{5} \quad S_{xx}(\omega) = S_{xx}^*(\omega) \text{ (or) } S_{xx}(\omega)$$

(i.e. if  $z = x+iy$ , then  $\bar{z} = x-iy$ )

$$\textcircled{6} \quad \text{If } \int_{-\infty}^{\infty} |R_{xx}(\tau)| d\tau < \infty \quad \begin{cases} \text{e.g. } \int_{-\infty}^{\infty} |x| dx = \infty \\ \text{(b) not integrable since not finite} \end{cases}$$

then  $S_{xx}(\omega)$  is continuous.

Problem:

Determine the autocorrelation function of the random process with PSD given by

$$S_{xx}(\omega) = \begin{cases} S_0 & |\omega| < \omega_0 \\ 0 & \text{otherwise} \end{cases}$$

Applying the formula,

$$R_{xx}(\tau) = \frac{1}{2\pi} \int_{-\infty}^{\infty} S_{xx}(\omega) e^{+i\omega\tau} d\omega$$

$$= \frac{1}{2\pi} \int_{-\omega_0}^{\omega_0} S_0 e^{i\omega\tau} d\omega = \frac{1}{2\pi} \times S_0 \left[ \frac{e^{i\omega\tau}}{i\omega} \right]_{-\omega_0}^{\omega_0}$$

$$= \frac{S_0}{2\pi i \tau} \times e^{i\tau(\omega_0 + \omega_0)} = \frac{S_0}{2\pi i \tau} e^{2\omega_0 i \tau}$$

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

$$(\text{cor}), \frac{S_0}{2\pi i \tau} [e^{-i\omega_0 \tau} - e^{-i\omega_0 \tau}]$$

$$= \frac{S_0}{2\pi i \tau} \sin(\omega_0 \tau)$$

(,) By Euler's formula,

Refer Oliver Hebe's Book for more problems.

Find  $E[X^2(t)]$  for  $S_{XX}(\omega) = \frac{24}{\omega^2 + 16}$  Ans. 3

22/3/19 Exercise Problems : 8.31 of Oliver Hebe

$$\textcircled{1} S_{YY}(\omega) = \frac{9}{\omega^2 + 64}$$

Find a) average power,  
b) autocorrelation

a) Average power  $E[X^2(t)] = R_{XX}(0)$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} S_{YY}(\omega) (e^{i\omega t})^T d\omega = \frac{1}{2\pi} \int_{-\infty}^{\infty} \frac{9}{\omega^2 + 64} d\omega$$

$\downarrow \omega = 1$   
 $\text{at } t=0$

$$= \frac{9}{2\pi} \times \frac{1}{8} \left( \tan^{-1} \frac{\omega}{8} \right) \Big|_{-\infty}^{\infty} = \frac{9}{2\pi} \times \frac{1}{8} \times \pi$$

$$\int \frac{1}{\omega^2 + a^2} d\omega = \frac{1}{a} \tan^{-1} \frac{\omega}{a}$$

(b) If you consult the table,  $\frac{9}{16}$

and apply Fourier inverse transform

we see that:

$$e^{-a|\tau|} \rightarrow \frac{2a}{\omega^2 + a^2}$$

$$S(\omega) = \frac{9}{\omega^2 + 8^2} \times \frac{2 \times 8}{2 \times 8} \Rightarrow$$

$$\frac{9}{2 \times 8} \times \frac{2 \times 8}{\omega^2 + 8^2}$$

(,) constant

$$= \frac{9}{16} e^{-8|\tau|}$$

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(or) use this method:

$$R_{xx}(T) = \frac{1}{2\pi} \int_{-\infty}^{\infty} S_{xx}(\omega) e^{i\omega T} d\omega$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \frac{9}{\omega^2 + 8^2} e^{i\omega T} d\omega$$

should evaluate to the result given.

8.3D

$$S_{xx}(\omega) = \begin{cases} 4 - \frac{\omega^2}{9} & |\omega| \leq 6 \\ 0 & \text{otherwise} \end{cases}$$

We have to use direct method here.

Average power:  $\frac{1}{2\pi} \int_{-\infty}^{\infty} S_{xx}(\omega) d\omega$

$$= \frac{1}{2\pi} \int_{-6}^{6} 4 - \frac{\omega^2}{9} d\omega$$

$$= \frac{1}{2\pi} \left( 4 [\omega]_{-6}^6 - \left( \frac{\omega^3}{3 \times 9} \right)_{-6}^6 \right)$$

$$= \frac{1}{2\pi} \left( 4 \times 12 - \left( \frac{216 - 216}{27} \right) \right)$$

$$= \frac{1}{2\pi} \left( 48 - \frac{432}{27} \right)$$

$$= \frac{1}{2\pi} \times \frac{1296 - 432}{27} = \frac{864}{27} \times \frac{1}{2\pi}$$

$$= \frac{1}{\pi} \times \frac{432}{243} = \frac{144}{9\pi}$$

108  
1296

$$\int u dv = uv - \int v du + \text{Leibnitz rule}$$

classmate  
Date \_\_\_\_\_  
Page \_\_\_\_\_

$$b) R_{xx}(\tau) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \left(4 - \frac{\omega^2}{9}\right) e^{i\omega\tau} d\tau$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} \left[ \left(4 - \frac{\omega^2}{9}\right) \left(\frac{e^{i\omega\tau}}{i\tau}\right) - \int e^{i\omega\tau} \cdot \frac{-2\omega}{9} d\tau \right]$$

$$= \frac{1}{2\pi} \left[ \left(4 - \frac{\omega^2}{9}\right) \left(\frac{e^{i\omega\tau}}{i\tau}\right) - \left(-\frac{2\omega}{9}\right) \left(\frac{e^{i\omega\tau}}{i\tau^2}\right) \right. \\ \left. + \left(-\frac{2}{9}\right) \left(\frac{e^{i\omega\tau}}{-i\tau^3}\right) \right]_{-\infty}^{\infty}$$

$$\stackrel{i}{\cancel{i}} = \frac{1}{2\pi} \left[ \frac{e^{i\omega\tau}}{\tau} \left( -i\left(4 - \frac{\omega^2}{9}\right) - \frac{2\omega}{9\tau} - i\frac{2}{9\tau^2} \right) \right]_{-\infty}^{\infty}$$

$$= \frac{1}{2\pi} \left[ \frac{e^{6i\tau}}{\tau} \left( -i\left(4 - \frac{36}{9}\right) - \frac{12}{9\tau} - i\frac{2}{9\tau^2} \right) \right.$$

$$\left. - \left( \frac{e^{-6i\tau}}{\tau} \left( -i\left(4 - \frac{36}{9}\right) + \frac{12}{9\tau} - i\frac{2}{9\tau^2} \right) \right) \right]$$

$$= \frac{1}{2\pi} \left[ \cancel{\frac{e^{6i\tau}}{\tau}} - \frac{12}{9\tau} - \frac{12}{9\tau} - \frac{2i}{9\tau^2} + \frac{2i}{9\tau^2} \right]$$

$$= -\frac{24}{9\tau} \times \frac{1}{2\pi} = -\frac{12^4}{9^3\pi} = -\frac{4}{3\pi\tau}$$

$\ln 0 = -\infty$ 

Lauder Bonde

8.33: Which of these can be power spectral density of a W.S.S process?

$$a) S_{XX}(\omega) = \frac{\sin \omega}{\omega}$$

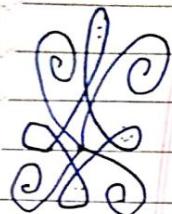
$$b) S_{XX}(\omega) = \frac{\cos \omega}{\omega}$$

$$e) S_{XX}(\omega) = \frac{5\omega}{1+5\omega^2+4\omega^4}$$

$$c) S_{XX}(\omega) = \frac{8}{\omega^2+16}$$

$$d) S_{XX}(\omega) = \frac{5\omega^2}{1+3\omega^2+4\omega^4}$$

$f(\omega)$  is a PSD if  $\int_{-\infty}^{\infty} |f(\omega)| d\omega$  is finite



$$\text{For (i), } \int_{-\infty}^{\infty} \frac{|\sin \omega|}{|\omega|} d\omega < \int_{0}^{\infty} \frac{1}{\omega} d\omega$$

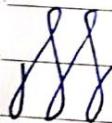
$$= \ln \omega \Big|_0^{\infty} = \infty$$



So (i) cannot be a PSD

Note:

$$F(\alpha f + \beta g) = \alpha F(f) + \beta F(g)$$



8.29 Find PSD of  $R_{XX}(\tau) = 2e^{-|\tau|} + 4e^{-4|\tau|}$

PSD: *Backyardigans*

$$S_{XX}(\omega)$$

$$= 2 F(e^{-|\tau|}) + 4 F(e^{-4|\tau|})$$

$$= 2 \times \frac{1}{1+\omega^2} + 4 \times \frac{2}{4^2+\omega^2}$$

$$= \frac{2}{\omega^2+1} + \frac{8}{\omega^2+16}$$

Definition

$R_{xy}(\tau)$  be cross correlation ( $\tau$ ) function

$$\text{then } S_{xy}(w) = \int_{-\infty}^{\infty} R_{xy}(\tau) e^{-w\tau} d\tau \text{ is}$$

The cross power spectral density.

Note:

Let  $x(n)$  be a discrete time process

Then, PSD of  $x(n)$  is defined by

$$S_{xx}(w) = \sum_{m=-\infty}^{\infty} R_{xx}(m) e^{-imw} \quad w \in (-\pi, \pi)$$

summation should become a function of  $w$  since the function is periodic.

Given  $S_{xx}(w)$ ,

$$R_{xx}(m) = \frac{1}{2\pi} \int_{-\pi}^{\pi} S_{xx}(w) e^{imw} dw$$

Properties (discrete)

$$① S_{xx}(w) \geq 0$$

$$② S_{xx}(-w) = S_{xx}(w)$$

$$③ S_{xx}(-w + 2\pi) = S_{xx}(w) \rightarrow \text{periodic with period } \pi$$

Problems:

$$① \text{Find PSD of } R(\tau) = e^{-a|\tau|}$$

$$\text{Ans: } S_{xx}(w) = \sqrt{\pi/a} e^{-w^2/4a}$$

$$② S_{xx}(w) = 1 \text{ when } |w| < a \quad \text{Find } R_{xx}(\tau)$$

$$③ S_{xx}(w) = \begin{cases} 0 & \text{otherwise} \\ \frac{ab}{\pi} (a - |w|) & |w| \leq a \\ 0 & |w| > a \end{cases} \quad \text{Ans: } \frac{\sin a\tau}{\pi\tau}$$

$$\text{Show that } R_{xx}(\tau) = \frac{ab}{\pi} \left( \frac{\sin a\tau/2}{a\tau/2} \right)^2$$

(17) 23/3/19 Markov Process

Example & Definition:

Let  $(X_n)$  be a discrete process

A process in which the future values do not depend on the past, but do depend on the current value, can be termed as Markov Process.

Let  $X$  represent tossing a coin. We can do a mapping as follows:

$$x(\text{head}) = 1$$

$$x(\text{tail}) = 0$$

So, let  $(X_n)$  be a process which follows the above  $X$ .

$X_n$  can be represented as a binary sequence. You can have multiple observations.

At any  $n^{\text{th}}$  state, the outcome <sup>of trial</sup> are not affected by previous events <sup>( $n-1^{\text{th}}$  trial, for example)</sup> and such. (Independent)

So you will not consider this experiment a Markov process.

Using this process, we can consider  $n^{\text{th}}$  partial sums:

$$\text{let } S_n = X_1 + X_2 + \dots + X_n$$

$$\text{where } S_1 = X_1$$

$$S_2 = X_1 + X_2 \text{ & so on}$$

$S_n$  is thus a collection of random variables & is hence a random process.

We should show that  $(S_n)$  is a Markov process.

$S_1$  can be either 0 or 1  
 $S_2$  can be 1

$S_2$  can have a value of max 2 (0, 1, 2).

$S_n$  can take values from  $0, 1, 2 \dots n$

We know the range of  $\delta n$ , but we don't know what its state is.

$$\text{So, } S_{n+1} = x_{n+1} + S_n$$

$\Rightarrow$  If  $S_n = j$ , then  $0 \leq j \leq n$

then  $S_{n+1} = j$  or  $j+1$

$(S_n)$  is a Markov process.

$\therefore$  The definition of a Markov Process is:

A random process  $\{x(t) / t \in T\}$  is called a first-order Markov process if

$$P \left[ X(t_n) \leq x_n \mid \begin{array}{l} X(t_{n-1}) = x_{n-1}, \\ X(t_{n-2}) = x_{n-2}, \\ \dots, X(t_0) = t_0 \end{array} \right]$$

$$= P[X(t_n) \leq x_n \mid X(t_{n-1}) = x_{n-1}]$$

where  $t_0 < t_1 < t_2 \dots < t_n$   $\hookrightarrow$  conditional cumulative distribution function of future state

i.e. probability value given all past states & equals probability value of future state given early the present state.

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If time is discrete,  $\Rightarrow$  Discrete-time Markov process  
Same for continuous.



### Markov Chain:

If the states are discrete variables (i.e.  $X(t)$  values) then this discrete state Markov process is called Markov chain.

State Space		Discrete Time Markov Chains	
Discrete	Continuous	Discrete	Continuous
Discrete Markov chain	Continuous markov chain	Discrete Markov Process	Cont. time Markov process
		A discrete process $\{X_k \mid k=0, 1, 2, 3, \dots\}$	$\hookrightarrow k$ represents time is called a Markov chain if

$$P[X_{k-j} = j \mid X_{k-i} = i, X_{k-2} = n, \dots, X_0 = m]$$

$$= P[X_{k-j} = j \mid X_{k-i} = i]$$

$$= P_{ijk}$$

$\underbrace{\hspace{1cm}}$   
state  
values

If probability is independent of time variable, the process is called homogeneous Markov chain.

### Homogeneous Markov Chain:

$$P_{ijk} = P_{ij}$$

$P_{ij}$  = Homogeneous State transition probability

The co

(1)  
(2)

The conditions it satisfies are:

$$\textcircled{1} \quad 0 \leq P_{ij} \leq 1$$

$$\textcircled{2} \quad \sum_j P_{ij} = 1 \quad i = 1, 2, \dots, n$$

$\downarrow$  elements in  
(Adding up, row)

transition matrix  $\rightarrow$

(or)

State transition probability matrix

$$\begin{bmatrix} P_{11} & P_{12} & \dots \\ P_{21} & P_{22} & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

matrix form

Problem:

Determine the missing elements denoted by  $x$  in the following transition probability matrix.

$$\begin{bmatrix} x & \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{10} & x & \frac{2}{5} & \frac{3}{5} \\ \frac{1}{5} & \frac{1}{5} & x & \frac{2}{5} \\ x & x & x & 1 \\ \frac{3}{5} & \frac{2}{5} & x & x \end{bmatrix}$$

$$x = 0 \rightarrow \text{closed}$$

$1 - \frac{1}{10} = \frac{9}{10}$  Every ~~on~~ Markov process chain is completely specified by the transition matrix.  
 $3 \times 4$   
 $4 \times 3$   
 $4 \times 10$

The transition matrix can be specified by a state <sup>transition</sup> diagram (graph)  
 No. of states = no. of nodes

1)



classmate

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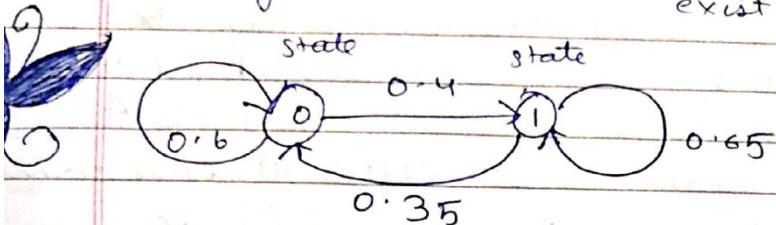
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Pij

$$\text{Let } p = \begin{bmatrix} 0.6 & 0.4 \\ 0.35 & 0.65 \end{bmatrix}$$

No. of nodes = 2 (2 states)

exist i.e. in an  $n \times n$  matrix  
there are  $n$  states.



Note: f

Consider  
prob  
let

3/19 The  $n$ -step state transition probability

let  $X_{n=0,1,2,\dots}^{(n)}$  be a discrete Markov chain

$P_{ij}(n)$  (or)  $p_{ij}^{(n)}$  is called the  $n$ -step state transition probability

Note

the probability where the current state of process,  $i$ , transforms into state  $j$  after  $n$  transitions.

(or)

probability that the system will be in state  $j$  after exactly  $n$  transitions, given that it is presently in state  $i$ .

nd

$$\Rightarrow P_{ij}(n) = \Pr \left\{ X_{m+n} = j \mid X_m = i \right\}$$

Note:

$$P_{ij}(0) = \begin{cases} P_{ij} & i \neq j \\ 1 & i = j \end{cases}$$

(sure event)

(state also)

doesn't change

$$P_{ij}(1) = \frac{P_{ij}}{\sum_k P_{ik}}$$

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Note:  $P_{ij} = \Pr \{ X_k = j \mid X_{k-1} = i \} = P_{ij}$

Consider  $P_{ij}(2)$  (or) the 2-step transition probability.

Let  $m=0$

$$P_{ij}(2) = \Pr \{ X_2 = j \mid X_0 = i \}$$

$$= \sum_k \Pr \{ X_2 = j, X_1 = k \mid X_0 = i \}$$

$$= \sum_k \Pr \{ X_2 = j \mid X_1 = k, X_0 = i \} *$$

$$\Pr \{ X_1 = k \mid X_0 = i \} - \textcircled{1}$$

$$\therefore \underbrace{\Pr \{ X_2 = j, X_1 = k, X_0 = i \}}_{\Pr \{ X_1 = k, X_0 = i \}} * \underbrace{\Pr \{ X_2 = j \mid X_1 = k, X_0 = i \}}_{\Pr \{ X_0 = i \}}$$

$$\therefore \Pr \{ X_1 = k, X_0 = i \} \quad \Pr \{ X_2 = j \mid X_1 = k, X_0 = i \}$$

$$= \frac{\Pr \{ X_2 = j \mid X_1 = k, X_0 = i \}}{\Pr \{ X_0 = i \}}$$

$$= \Pr \{ X_2 = j \mid X_1 = k, X_0 = i \}$$

By Markov property,  $X_2$  future state depends only on present state  $X_1$ .

$$\textcircled{1} = \sum_k \Pr \{ X_2 = j \mid X_1 = k \} \Pr \{ X_1 = k \mid X_0 = i \}$$

$$= \sum_k P_{kj} P_{ik}$$

$$= \sum_k P_{ik} P_{kj}$$

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Graph

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$\therefore$  The equation known as Chapman-Kolmogorov equation:

Carousel  
Ferris-wheel

$$\text{for all } 0 \leq r < n, \quad P_{ij}(n) = \sum_k P_{ik}(r) P_{kj}(n-r)$$

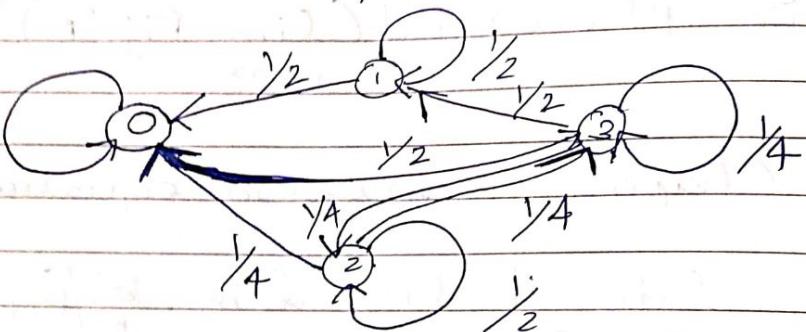
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matrix product rule



Problems:

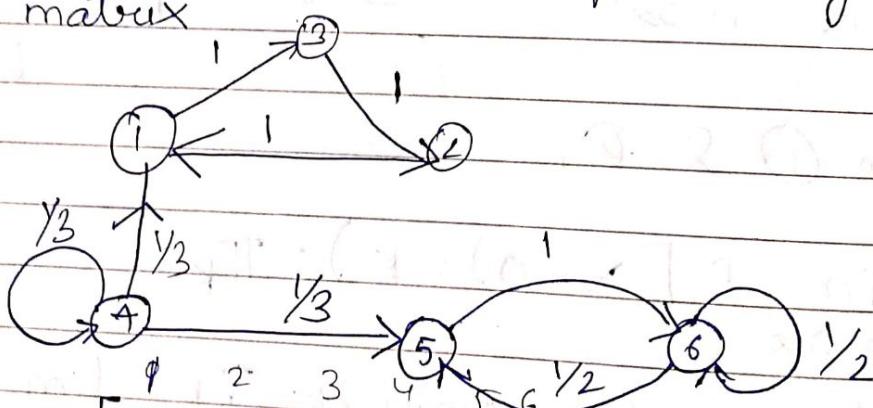
- ① Draw the state transition diagram:

$$\begin{bmatrix} 1/2 & 0 & 0 & 1/2 \\ 1/2 & 1/2 & 0 & 0 \\ 1/4 & 0 & 1/2 & 1/4 \\ 0 & 1/2 & 1/4 & 1/4 \end{bmatrix}$$



②

- Compute the transition probability matrix



$$\begin{array}{c|cccccc} & 0 & 1 & 2 & 3 & 4 & 5 & 6 \\ \hline 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 3 & 1/3 & 0 & 0 & 1/3 & 1/3 & 0 & 0 \\ 4 & 0 & 0 & 0 & 0 & 1/3 & 1/3 & 0 \\ 5 & 0 & 0 & 0 & 0 & 0 & 1/2 & 1/2 \\ 6 & 0 & 0 & 0 & 0 & 1/2 & 1/2 & 0 \end{array}$$

Consider tosses of a biased coin. Note the outcome of next toss depends on the outcome of current toss.

Given that current toss comes up heads, the next toss will come up head with probability 0.6 & tails with 0.4.

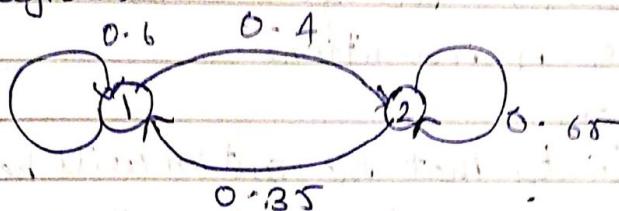
Similarly, given that current toss comes up tails, the next toss will be heads w/ probability 0.35 & tails with 0.65.

i) Compute transition probability matrix.

$$P = [p_{ij}]$$

$$= \begin{bmatrix} H & T \\ T & H \end{bmatrix} = \begin{bmatrix} 0.6 & 0.4 \\ 0.35 & 0.65 \end{bmatrix}$$

ii) Diagram



iii) Compute n-step transition probability

$$P_{12}(3)$$

$$P[1 \rightarrow 1 \rightarrow 1 \rightarrow 2] + P[1 \rightarrow 1 \rightarrow 2 \rightarrow 2]$$

$$+ P[1 \rightarrow 2 \rightarrow 1 \rightarrow 2] + P[1 \rightarrow 2 \rightarrow 2 \rightarrow 2]$$

$$= 0.6 \times 0.4 \times 0.65 + 0.6 \times 0.4 \times 0.65 + 0.4 \times 0.35 \times 0.4$$

$$+ 0.4 \times 0.65 \times 0.65$$

$$= 0.525$$

(Or) multiply matrix n times & find entry

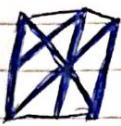
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$$\begin{bmatrix} 0.6 & 0.4 \\ 0.35 & 0.65 \end{bmatrix} \begin{bmatrix} 0.6 & 0.4 \\ 0.35 & 0.65 \end{bmatrix} = \begin{bmatrix} 0.5 & 0.5 \\ 0.4375 & 0.5625 \end{bmatrix} \begin{bmatrix} 0.6 & 0.4 \\ 0.35 & 0.65 \end{bmatrix}$$

$$P_{12} = 0.525$$

$$\boxed{\begin{bmatrix} 0.475 & 0.525 \\ 0.459375 & 0.540625 \end{bmatrix}}$$

26/3/19 Limiting state probabilities (or)  
steady state probabilities



Let  $X_0, X_1, \dots, X_n$  be  $N$ -state random processes with transition matrix

$$P = (P_{ij})_{N \times N}$$

$$\text{Now, } P^n = (P_{ij}(n))_{N \times N}$$

If  $n \rightarrow \infty$ , limit of this matrix (at every entry, find limit) becomes constant.

- Proof: Let  $P[X(0) = i]$  denote probability that process is in state  $i$  before it makes first transition.

initial  
condition

$$\therefore \sum_i P[X(0) = i] = 1$$



For a single random variable itself, all the states/results sum up to 1.

Let  $P[X(n) = j]$  denote state probability i.e. At the end of <sup>me first</sup>  $n$  transitions, probability that process is in state  $j$ .

$$\text{Then } P[X(n) = j] = \sum_{i=1}^N P[X(0) = i] x$$

(1)

$\underbrace{\quad}_{\text{P}_{ij}(n)}$

By

Fr

To find

$$\lim_{n \rightarrow \infty} P[x(n) = j] = \pi_j \quad \text{where } j \text{ varies from 1 to } N$$

(assumed value from 1 to N)  
possible states

$$\pi_j = \lim_{n \rightarrow \infty} P[x(n) = j] \quad \text{L (2)}$$

$$\Rightarrow = \lim_{n \rightarrow \infty} \sum_{i=1}^N P[x(n) = i] p_{ij}(n)$$

Summation is independent of  $n$ , so we can interchange  $\sum$  & limit.

$$\begin{aligned} & \sum_{i=1}^N \lim_{n \rightarrow \infty} P[x(n) = i] p_{ij}(n) \\ &= \sum_{i=1}^N P[x(n) = i] (\lim_{n \rightarrow \infty} p_{ij}(n)) \end{aligned}$$

By Chapman-Kolmogorov equations,

$$\begin{aligned} \lim_{n \rightarrow \infty} p_{ij}(n) &= \lim_{n \rightarrow \infty} \sum_k [P_{ik}(n-1)] p_{kj} \\ &= \sum_k \lim_{n \rightarrow \infty} [P_{ik}(n-1)] p_{kj} = \sum_k \pi_k p_{kj} \end{aligned} \quad \text{L (3)}$$

From (1) & (2),

$$\lim_{n \rightarrow \infty} P[x(n) = k] = \pi_k$$

$$\begin{aligned} \Rightarrow \text{The equation implies } \pi_k &= \lim_{n \rightarrow \infty} \sum_{i=1}^n P[x(n) = i] p_{ki}(n) \\ &= \sum_{i=1}^n P[x(n) = i] \times \lim_{n \rightarrow \infty} p_{ki}(n) \end{aligned}$$

Assuming the limit independent of  $k$ ,  
 (  $\rightarrow$  summation )

$$= \lim_{n \rightarrow \infty} \sum_k P_{kj}(n) \times 1 \quad \text{provided, } \lim_n P_{ik}(n)$$

From (3),

$$\pi_j = \sum_k \pi_k P_{kj} \quad j = 1, 2, \dots, N$$

| independent of initial condition  
 $P[X(t_0) = i] = 1]$

$$\text{and } \sum_j \pi_j = 1$$

The  $\pi$ -matrix thus formed can be evaluated as follows:

$$[\pi_1, \pi_2, \dots, \pi_N] = [\pi_1, \pi_2, \dots, \pi_N] *$$



matrix multiplication

$$\begin{bmatrix} \pi_{11} & \dots & \pi_{1N} \\ \vdots & \ddots & \vdots \\ \pi_{N1} & \dots & \pi_{NN} \end{bmatrix}$$

$$\text{and } \pi_1 + \pi_2 + \dots + \pi_N = 1$$

Then  $[\pi_1, \dots, \pi_N]$  is called steady state probability.

Problem example:

Consider the biased coin problem.

$$P = \begin{bmatrix} 0.6 & 0.4 \\ 0.35 & 0.65 \end{bmatrix}$$

Here,

To find limiting probability.

Here, there are 2 states.

$$[\pi_1, \pi_2] = [\pi_1 \ \pi_2] \begin{bmatrix} 0.6 & 0.4 \\ 0.35 & 0.65 \end{bmatrix}$$

$$\text{and } \pi_1 + \pi_2 = 1$$

$$\pi_1 = 0.6\pi_1 + 0.35\pi_2$$

$$\pi_2 = 0.4\pi_1 + 0.65\pi_2$$

Solving, we use this rule (Rule of Thumb),  
take only first  $N-1$  equations

$$\pi_1 = 0.6\pi_1 + 0.35\pi_2 \quad (1) \quad 0.4\pi_1$$

$$\text{and } \underbrace{\pi_1 + \pi_2 = 1}_{\text{one is necessary}}$$

$$0.6\pi_1 + 0.35\pi_2 + \pi_1 = 0.46$$

$$\pi_2 = 0.53$$

$[0.46 \ 0.53]$  is the steady state probability.

Note 1:

From derivation,

when  $P = (P_{ij})$

$$\pi_j = \lim_{n \rightarrow \infty} p_{ij}(n) = \lim_{n \rightarrow \infty} P^n j = 1 \dots N$$

$$(or) \quad \pi_j = \lim_{n \rightarrow \infty} P[x(n)=j]$$

state probability

Note 2:

$$P = \begin{bmatrix} 0.6 & 0.4 \\ 0.35 & 0.65 \end{bmatrix}$$

$P^2$  gives some value  
 $P^3$  and so on.

$$P^2 = \begin{bmatrix} 0.5 & 0.5 \\ 0.485 & 0.514 \end{bmatrix}$$

$$= \begin{bmatrix} \pi_1 & \pi_2 \\ \pi_2 & \pi_1 \end{bmatrix}$$

in limiting behaviour  
when  $n \rightarrow \infty$

Problem:

①  $P = \begin{bmatrix} 0.9 & 0.1 \\ 0.2 & 0.8 \end{bmatrix}$

i) Obtain  $\lim_{n \rightarrow \infty} P^n$

ii) steady state probability distribution

Initial conditions:

$$P[x(0)=1] = \frac{1}{2}$$

$$P[x(0)=2] = \frac{1}{2}$$

Ans:  $[\pi_1, \pi_2] = [2/3, 1/3]$

missed notes

## Stationary Processes

Stationary Processes are of 2 kinds

① SSS - Strict Sense Stationary

② WSS - Wide Sense Stationary

Let  $\{X(t) | t \in (0, T)\}$  be a random process

$$X(t) = X(t+c) \quad \forall c$$

$$F_X(x, t) = F_X(x, t+c) \quad \forall c$$

$$\text{so } F_X(x_1, x_2, t_1, t_2) = F_X(x_1, x_2, t_1+c, t_2+c)$$

For strict sense,

$$f(x_1, x_2, t_1, t_2) = f(x_1, x_2, t_1+c, t_2+c)$$

and for wide sense,

$$f(x_1, x_2, t_1, t_2) = f(x_1, x_2, t_1-t_2, c)$$

$$\hookrightarrow n=2$$

$$\text{where } c = -t_2$$

## Wide Sense Stationary Process

A random process  $X(t)$  is called SSS if its statistical properties are invariant under shift of origin.

$$\text{i.e. } F_x(x_1, x_2, \dots, x_n, t_1, t_2, \dots, t_n)$$

$$= F_x(x_1, x_2, \dots, x_n, t_1+c, t_2+c, \dots, t_n+c) \quad \forall c$$

$$f = \frac{\partial^n F_x}{\partial x_1^n} \Rightarrow f(x_1, x_2, \dots, x_n, t_1+c, t_2+c, \dots, t_n+c)$$

$$= f(x_1, x_2, \dots, x_n, t_1, t_2, \dots, t_n)$$

Refer previous page for  $n=2$  case.  $\forall c$  & for all  $n$ .

Thus,  $\mu_x(t) \equiv \mu_x(0) + ct$ , where  $\mu_x(t)$  is a constant.

$$R_{xx}(t, t+\tau) = R(0, \tau) \quad \tau = t_1 - t_2$$

$$C_{xx}(t, t+\tau) = C_{xx}(0, \tau) \quad \tau = t_1 - t_2$$

## Wide Sense Stationary Process

A random process  $X(t)$  is called WSS if its

i) mean is constant

ii) Autocorrelation depends only on  $t_1 - t_2$  (let's say  $\tau$ )

A random process  $X(t)$  is defined by  
 $X(t) = A\cos t + B\sin t$

$A$  &  $B$  are independent random variables,  
 each of which has a value  $-2$  with  
 probability  $\frac{1}{3}$  and a value  $1$  with  
 probability  $\frac{2}{3}$ . Show that  $X(t)$  is  
 WSS but not SSS.

Given  $X(t) = A\cos t + B\sin t$

$x$	-2	1	same for
$P(x)$	$\frac{1}{3}$	$\frac{2}{3}$	$x = B$
$= A$			

$$\begin{aligned} E[X(t)] &= E[A\cos t + B\sin t] \\ &= E[A\cos t] + E[B\sin t] \\ &= -2 \times \frac{1}{3} + 1 \times \frac{2}{3} + -2 \times \frac{1}{3} + 1 \times \frac{2}{3} \\ &= 0 + 0 \neq 0 \end{aligned}$$

$$\begin{aligned} R_{XX}(t, s) &= E[X(t)X(s)] \\ &= E[(A\cos t + B\sin t)(A\cos s + B\sin s)] \\ &= E[A^2 \cos^2 t + AB \cos t \cos s + AB \cos s \cos t + B^2 \sin^2 s] \\ &\quad \text{Sint} \end{aligned}$$

$$\begin{aligned} &= E[A^2 \cos^2 t \cos s] + E[AB \cos t \cos s \sin s] \\ &\quad + E[B^2 \sin^2 s] \quad \text{turns to 0} \end{aligned}$$

$$\begin{aligned} E[A^2] &= \sum x^2 p(x) \quad \text{because } A \text{ & } B \text{ are} \\ &= (-2)^2 \times \frac{1}{3} + 1^2 \times \frac{2}{3} = \frac{4}{3} + \frac{2}{3} = \frac{6}{3} = 2 \\ E[B^2] &= \frac{4}{3} \\ \therefore 2\cos^2 t \cos s + 2\sin^2 s &= 2\cos(t-s) \end{aligned}$$

$$\begin{aligned} E[x^2(t)] &= E[A^2 \cos^2 t + B^2 \sin^2 t + 2AB \cos t \\ &\quad \sin t] \\ &= 2 \cos^2 t + 2 \sin^2 t + 2AB \cos t \sin t \\ &= 2 \end{aligned}$$

$$\begin{aligned} E[x^3(t)] &= E[(A \cos t + B \sin t)^3] \\ &= E[A^3 \cos^3 t + B^3 \sin^3 t \\ &\quad + 3A^2 B \cos^2 t \sin t \\ &\quad + 3A B^2 \cos t \sin^2 t] \end{aligned}$$

$$\begin{aligned} E[A^3] = E[B^3] &= (-2)^3 \times \frac{1}{3} + 1 \times \frac{2}{3} \\ &= -\frac{8}{3} + \frac{2}{3} = -\frac{6}{3} = -2 \end{aligned}$$

$$E[x^3(t)] = -2(\cos 3t + \sin 3t)$$

Not constant

$\Rightarrow X(t)$  is not S&S

### Properties of autocorrelation function:

① Stationary: For a WSS,

$$\begin{aligned} R_{XX}(\tau) &= R_{XX}(0, t-\tau) \quad \tau = t-s \\ &= R_{XX}(t, t+\tau) \end{aligned}$$

②  $R_{XX}(\tau)$  is even always

$$\text{i.e. } R_{XX}(\tau) = R_{XX}(-\tau)$$

$$③ R_{XX}(0) = E[x^2(t)] \quad \text{or average power}$$

or mean square value

$$④ |R_{XX}(\tau)| \leq R_{XX}(0)$$

$$⑤ \mu_x^2(\tau) = \lim_{|T| \rightarrow \infty} R_{XX}(\tau)$$

Proofs:

$$\begin{aligned}
 \textcircled{2} \quad R_{xx}(-\tau) &= R_{xx}(0, -\tau) = R_{xx}(t, t-\tau) \\
 &= E[x(t)x(t-\tau)] \quad \text{where you} \\
 &\quad \text{say } t = t + \tau \\
 &= E[x(t+\tau)x(t+\tau-\tau)] \quad \text{by property} \\
 &= E[R_{xx}(t+\tau, t)] \\
 &= R_{xx}(\tau)
 \end{aligned}$$

$\therefore$  even function

\textcircled{1} By Cauchy-Schwarz inequality,

$$\int fg \leq \int f \int g$$

$$|\langle f, g \rangle| \leq \|f\| \|g\|$$

$$\{E[xy]\}^2 \leq E[x^2] E[y^2]$$

$$\begin{aligned}
 \{E[x(t)x(t+\tau)]\}^2 &\leq E[x^2(t)] \\
 &\quad E[x^2(t+\tau)] \\
 &\leq E[x^2(t)] E[x^2(t)] \\
 &\leq (E[x^2(t)])^2 = [R_{xx}(0)]^2
 \end{aligned}$$

$$\Rightarrow |R_{xx}(\tau)| \leq R_{xx}(0)$$

Compute variance of process  $X(t)$ , whose autocorrelation function is

$$R_{xx}(\tau) = 25 + \frac{4}{1+6\tau^2}$$

$$\begin{aligned}
 \mu_x^2(t) &= \lim_{T \rightarrow \infty} R_{xx}(T) \\
 &= 25
 \end{aligned}$$

$$E[x^2(t)] = R_{xx}(0) = 25 + 4 = 29$$

$$\text{Var}(x(t)) = 29 - 25 = 4$$

Let  $x(t)$  be a random process with

$$R_{xx}(\tau) = \frac{4\tau^2 + 6}{\tau^2 + 1}$$

Find mean square value, mean and variance.

$$\mu_x^2(t) = \lim_{\tau \rightarrow \infty} \frac{4 + 6/\tau^2}{1 + 1/\tau^2} = \frac{4+0}{1+0} = 4$$

$$E[x^2(t)] = R_{xx}(0) = 6 \quad \boxed{\mu_x = 2} \quad = \text{Average power}$$

$$\text{Variance} = 6 - 4 = 2$$

Can the function  $R_{xx}(\tau) = 1 + \tau^4 + \tau^6$  serve as a valid autocorrelation function for a WSS process? Justify.

$$|R_{xx}(\tau)| \leq R_{xx}(0)$$

$$\Leftrightarrow = 1$$

$$\frac{1 + \tau^4}{1 + \tau^6} \leq 1$$

$$1 + \tau^4 \leq 1 + \tau^6$$

$$\tau^4 \leq \tau^6 \quad \tau > 1$$

Now, when  $\tau = 1/2$

$$\frac{1 + (1/2)^4}{1 + (1/2)^6} = \frac{16 + 1}{64 + 1} = \frac{17}{65} = 1.046 > 1$$

which shouldn't happen since  $\tau > 1$  has been found.

$\Rightarrow R_{xx}(\tau)$  is not WSS

Compute mean, variance of  $X(t)$  whose autocorrelation function is

$$R_{XX}(\tau) = \frac{25\tau^2 + 36}{625\tau^2 + 25}$$

$$\mu_x^2 = \lim_{\tau \rightarrow \infty} R_{XX}(\tau)$$

$$= \frac{25 + \frac{36}{\tau^2}}{\frac{625}{\tau^2} + 1} = \frac{25}{625} = \frac{1}{25}$$

$$\mu_x = 1/5$$

$$E[X^2(t)] = R_{XX}(0) = 36 = 9$$

$$\text{Var} = 9 - \frac{1}{25} = \frac{225 - 1}{25} = \frac{224}{25}$$