

Ex 10.1

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Given,  $\{x_t, t \in \mathbb{Z}\}$  is a weakly stationary process

$$x_0 = 1$$

$$x_1 = x_{-1} = f$$

$$x_t = 0, |t| > 1$$

$x$	...	0	0	$f$	1	$f$	0	0	...
$t$	...	-3	-2	-1	0	1	2	3	...

Using definition 6.1.13, if  $\{x_t, t \in \mathbb{Z}\}$  is the a.s. of a stationary stochastic process, then

$$x_t = \frac{1}{2\pi} \int_{-\pi}^{\pi} e^{it\omega} f(\omega) d\omega \text{ for } t \in \mathbb{Z}$$

Thus, as per remark 6.1.14,

$$\text{if } \sum_{t=-\infty}^{\infty} |x_t| < \infty$$

$$\text{then spectral density } f(\omega) = \sum_{t=-\infty}^{\infty} x_t e^{-it\omega}$$

$$\text{Now } \sum_{t=-\infty}^{\infty} |x_t| = |0| + |0| + \dots + |0| + |f| + |1| + |f| + |0| + |0| + \dots + |0|$$

$$= 1 + 2|f| < \infty$$

$$\Rightarrow f(\omega) = \sum_{t=-\infty}^{\infty} x_t e^{-it\omega}$$

$$= 0 + 0 + \dots + x_{-1} e^{-i(-1)\omega} + x_0 e^{-i(0)\omega} + x_1 e^{-i(1)\omega} + 0 + \dots + 0$$

$$= f e^{i\omega} + 1 + f e^{-i\omega} = 1 + f(e^{i\omega} + e^{-i\omega})$$

Now according to Euler's formula

$$e^{i\omega} = \cos(\omega) + i \sin(\omega)$$

$$\Rightarrow 1 + f(e^{i\omega} + e^{-i\omega}) = 1 + f(\cos(\omega) + i \sin(\omega) + \cos(-\omega) + i \sin(-\omega))$$

$$= 1 + f(\cos(\omega) + \cos(\omega) + i \cancel{\sin(\omega)} - i \cancel{\sin(\omega)})$$

$$= 1 + 2f \cos \omega$$



also per remark 6.1.14,  $f(\omega) \geq 0 \quad \forall \omega \in [-\pi, \pi]$

$$\Rightarrow 1 + 2f \cos \omega \geq 0$$

$$\Rightarrow |f| \leq \frac{1}{2}$$

since  $\cos(-\pi) = -1$   
since  $\cos(\omega) \in [-1, 1] \quad \forall \omega \in [-\pi, \pi]$

$\Rightarrow \{r_k, k \in \mathbb{Z}\}$  can not be the acf of a weakly stationary process if  $\rho > \frac{1}{2}$

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### Ex 10.3

a) Given process  $\{X_t = \varepsilon_t + b\varepsilon_{t-1}, t \in \mathbb{Z}\}$ ,  $\varepsilon_t$  is white noise  
to prove that this is a generalized linear process  
we need to prove that

i)  $\{X_t, t \in \mathbb{Z}\}$  is a stationary process

ii)  ~~$X_t = \sum_{k=-\infty}^{\infty} b_k \varepsilon_{t-k}$~~   $X_t = \sum_{k=-\infty}^{\infty} b_k \varepsilon_{t-k}, t \in \mathbb{Z}$

i.e. it is an <sup>infinite</sup> linear combination of white noise random variables.

to prove i) we need to show  $\rightarrow E[X_t] = \mu \quad \forall t \in \mathbb{Z}$

$$\rightarrow E[X_t^2] < \infty \quad \forall t \in \mathbb{Z}$$

$$\rightarrow \text{cov}[X_s, X_{s+t}] = \gamma_t \quad \forall s, t \in \mathbb{Z}$$

$$\rightarrow E[X_t] = E[\varepsilon_t + b\varepsilon_{t-1}] = E[\varepsilon_t] + bE[\varepsilon_{t-1}]$$

$$\Rightarrow E[X_t] = 0 + b(0) = 0$$

as it is given that  $\varepsilon_t$  is white noise and we know  $E[\varepsilon_t] = 0$

$$\rightarrow E[X_t^2] = \text{var}[X_t] + E[X_t]^2$$

$$= \text{var}(\varepsilon_t) + b^2 \text{var}(\varepsilon_{t-1})$$

$$(\text{and } \text{var}(\varepsilon_t) = \text{var}(\varepsilon_{t-1}) = \sigma_\varepsilon^2)$$

$$= (1+b^2)\sigma_\varepsilon^2$$

$$\text{and } (1+b^2) < \infty \text{ and } \sigma_\varepsilon^2 < \infty$$

$$\Rightarrow E[X_t^2] = (1+b^2)\sigma_\varepsilon^2 < \infty$$

$$\rightarrow \text{cov}(X_s, X_{s+t}) = E[(X_s - E[X_s])(X_{s+t} - E[X_{s+t}])]$$
$$= E[X_s \cdot X_{s+t}]$$

$$\text{for } t = -1, \text{cov}(X_s, X_{s-1}) = E[X_s \cdot X_{s-1}] = E[(\varepsilon_s + b\varepsilon_{s-1})(\varepsilon_{s-1} + b\varepsilon_{s-2})]$$
$$= E[\varepsilon_s \varepsilon_{s-1}] + bE[\varepsilon_s \varepsilon_{s-2}] + bE[\varepsilon_{s-1}^2]$$
$$+ bE[\varepsilon_{s-1} \varepsilon_{s-2}]$$

(as  $\varepsilon_t$  are uncorrelated)

$$= bE[\varepsilon_{s-1}^2] = b\sigma_\varepsilon^2$$



$$\begin{aligned}
 \text{for } t=1, E[X_s X_{s+1}] &= E[(\varepsilon_s + b \varepsilon_{s-1})(\varepsilon_{s+1} + b \varepsilon_s)] \\
 &= E[\varepsilon_s \varepsilon_{s+1}] + b E[\varepsilon_s^2] + b E[\varepsilon_{s-1} \varepsilon_{s+1}] \\
 &\quad + b^2 E[\varepsilon_{s-1} \varepsilon_s] \\
 &= b E[\varepsilon_s^2] = b \sigma_\varepsilon^2
 \end{aligned}$$

$$\text{for } t=0, E[X_s X_s] = E[X_s^2] = \text{Var}(X_s) = (1+b^2) \sigma_\varepsilon^2$$

$$\Rightarrow \gamma_t = \text{Cov}(X_s, X_{s+t}) = \begin{cases} (1+b^2) \sigma_\varepsilon^2, & t=0 \\ b \sigma_\varepsilon^2, & t=\pm 1 \\ 0, & \text{otherwise} \end{cases}$$

for  $t > 1$   
 $t < -1$

$$\begin{aligned}
 E[X_s X_{s+t}] &= E[(\varepsilon_s + b \varepsilon_{s-1})(\varepsilon_{s+t} + b \varepsilon_{s+t-1})] \\
 &= E[\varepsilon_s \varepsilon_{s+t} + b \varepsilon_s \varepsilon_{s+t-1} + b \varepsilon_{s-1} \varepsilon_{s+t} \\
 &\quad + b^2 \varepsilon_{s-1} \varepsilon_{s+t-1}] \\
 &= 0 + 0 + 0 + 0 = 0
 \end{aligned}$$

$$\Rightarrow \gamma_t = \text{Cov}(X_s, X_{s+t}) = \begin{cases} (1+b^2) \sigma_\varepsilon^2, & t=0 \\ b \sigma_\varepsilon^2, & t=\pm 1 \\ 0, & \text{otherwise} \end{cases}$$

Hence  $X_t = \varepsilon_t + b \varepsilon_{t-1}$  is a (weakly) stationary process

Now, to prove (i) we can show that  $X_t = \varepsilon_t + b \varepsilon_{t-1}$  is a linear combination of  $\varepsilon_t$ 's

$$\text{as } X_t = \sum_{k=-\infty}^{\infty} b_k \varepsilon_{t-k}, \quad t \in \mathbb{Z}$$

$$\Rightarrow X_t = \dots + b_0 \varepsilon_{t-0} + b_1 \varepsilon_{t-1} + \dots$$

where all other  $b_k = 0$  for  $k \neq 0, 1$

Hence

$$b_0 = 1$$

$$\text{and } b_1 = b \quad \forall b \in \mathbb{R}$$



Hence  $\{X_t, t \in \mathbb{Z}\}$  is a generalized linear process of  $BER$

b)  $f_t = \frac{\lambda_t}{\lambda_0}$

$$f_1 = \frac{\lambda_1}{\lambda_0} = \frac{b \sigma_\varepsilon^2}{(1+b^2) \sigma_\varepsilon^2} = \frac{b}{1+b^2}$$

c) in markdown file

d) given  $\sigma_\varepsilon^2 = 1$

$$\text{for } b = \frac{1}{3}, f_t = \begin{cases} 1 & , t=1 \\ \frac{1/3}{1+1/9} = 0.3 & , t=\pm 1 \\ 0 & , \text{otherwise} \end{cases}$$

$$\text{for } b=3, f_t = \begin{cases} 1 & , t=0 \\ \frac{3}{1+9} = 0.3 & , t=\pm 1 \\ 0 & , \text{otherwise} \end{cases}$$

Hence these 2 distributions have the same autocorrelation for different  $b$  values and can't be distinguished without knowing the laws of the white noise



## exercise 2

all moments of the normal distribution are calculated by the use of moment generating functions

$$X_t = \begin{cases} \varepsilon_t & \text{if } t \text{ is even} \\ \frac{\varepsilon_t^2 - 1}{\sqrt{2}} & \text{if } t \text{ is odd} \end{cases}$$

$$\mathbb{E}(X_t) = \begin{cases} \mathbb{E}(\varepsilon_t) = 0 & \text{if } t \text{ even} \\ \mathbb{E}\left(\frac{\varepsilon_t^2 - 1}{\sqrt{2}}\right) = \frac{1}{\sqrt{2}} \cdot \underbrace{(\mathbb{E}(\varepsilon_t^2) - 1)}_{=1 \text{ as } \varepsilon_{t-1} \sim \mathcal{N}(0,1)} = 0 & \text{if } t \text{ odd} \end{cases}$$

$$\text{var}(X_t) = \begin{cases} \text{var}(\varepsilon_t) = 1 < \infty & , t \text{ even} \\ \text{var}\left(\frac{\varepsilon_t^2 - 1}{\sqrt{2}}\right) = \frac{1}{2} \underbrace{\text{var}(\varepsilon_t^2)}_{= \mathbb{E}(\varepsilon_t^4) - \mathbb{E}(\varepsilon_t^2)^2} = \frac{1}{2} \cdot 2 = 1 < \infty & , t \text{ odd} \end{cases}$$

it remains to be shown that the  $X_t$  are uncorrelated but not independent

let  $s \neq t$  show:  $\text{cov}(X_s, X_t) = 0$

s.t. both even: claim follows from ind. of  $\varepsilon_t, \varepsilon_s$   
 s.t. both odd: " " " " " " and measurability of the function  $x \mapsto \frac{x^2 - 1}{\sqrt{2}}$   
 one even, one odd:

$$\text{cov}(X_s, X_t) = \mathbb{E}(X_s \cdot X_t) = \mathbb{E}\left(\frac{\varepsilon_s^2 - 1}{\sqrt{2}} \cdot \varepsilon_t\right) = \frac{1}{\sqrt{2}} (\mathbb{E}(\varepsilon_s^2 \cdot \varepsilon_t) - \mathbb{E}(\varepsilon_s^2) \cdot \mathbb{E}(\varepsilon_t))$$

$$\text{two cases: } 1. t = s-1 \Rightarrow \mathbb{E}(\varepsilon_{s-1}^2 \cdot \varepsilon_s) = \mathbb{E}(\varepsilon_s^2) \cdot \underbrace{\mathbb{E}(\varepsilon_{s-1}^2)}_{=1} \cdot \underbrace{\mathbb{E}(\varepsilon_s)}_{=0} = 0$$

$$2. t = s+1 \Rightarrow \mathbb{E}(\varepsilon_s^2 \cdot \varepsilon_{s+1}) = \mathbb{E}(\varepsilon_s^2) \cdot \underbrace{\mathbb{E}(\varepsilon_{s+1})}_{=0} = 0$$

$\Rightarrow$  The  $X_t$  are uncorrelated

$\Rightarrow X_t$  are white noise

suppose the  $X_t$  are independent:

$$X_2 = \varepsilon_2, \quad X_3 = \frac{\varepsilon_3^2 - 1}{\sqrt{2}}$$

$\{X_2 \in [0, 1]\}$  and  $\{X_3 \in [-\frac{1}{\sqrt{2}}, 0]\}$  both obviously have prob  $< 1$

$$\Rightarrow \mathbb{P}(\{X_2 \in [0, 1]\} \cap \{X_3 \in [-\frac{1}{\sqrt{2}}, 0]\}) > \mathbb{P}(\{X_2 \in [0, 1]\}) \cdot \mathbb{P}(\{X_3 \in [-\frac{1}{\sqrt{2}}, 0]\})$$

$$\stackrel{\text{ind.}}{=} \mathbb{P}(\{X_2 \in [0, 1]\} \cap \{X_3 \in [-\frac{1}{\sqrt{2}}, 0]\}) \stackrel{\text{monotone}}{\neq} \mathbb{P}(\{X_2 \in [0, 1]\}) \quad \Leftarrow$$

$x \mapsto \frac{x^2 - 1}{\sqrt{2}}$  is monotone  
calculate both interval  
limits

$\Rightarrow X_t$  are not independent and therefore no strict white noise

# exercise 4

suppose there exists a stationary solution:

$$\begin{aligned} \text{var}(X_t - \alpha^{u+1} X_{t-u-1}) &= \text{var}(\alpha X_{t-1} + \varepsilon_t - \alpha^{u+1} X_{t-u-1}) \\ &= \dots = \text{var}(\alpha^{u+1} X_{t-u-1} + \varepsilon_t + \dots + \varepsilon_{t-u} - \alpha^{u+1} X_{t-u-1}) \\ &= \text{var}(\varepsilon_t + \dots + \varepsilon_{t-u}) \stackrel{\substack{\uparrow \\ \varepsilon_t \text{ white} \\ \text{noise}}}{=} \text{var}(\varepsilon_t) + \dots + \text{var}(\varepsilon_{t-u}) = u \cdot \sigma_\varepsilon^2 \xrightarrow{u \rightarrow \infty} \infty \end{aligned}$$

by assumpt. of stationarity:  $\mathbb{E}(X_t^2) < \infty$ ,  $\mathbb{E}(X_t) = \mathbb{E}(X_{t-u-1}) \stackrel{\substack{\text{why by shifting} \\ \text{the process by a constant}}}{=} 0$

if we show  $\mathbb{E}(X_t^2) \geq \text{var}(X_t - \alpha^{u+1} X_{t-u-1})$  for all  $u$  we get a contradiction to  $\mathbb{E}(X_t^2) < \infty$  and therefore our claim