

MVE 136 L13

$$\text{ACF: } r_x(n) \triangleq E \{ \underline{X(n_0) X(n_0 - n)} \} : r_x(n) = r_x(-n)$$

$$\text{PSD: } P_x(e^{j\omega}) \triangleq \text{DTFT} \{ r_x(n) \}$$

Wiener - Khintchine Thm. alt. def.

$$P_x(e^{j\omega}) = \lim_{N \rightarrow \infty} \frac{1}{N} E \{ | \bar{X}_N(e^{j\omega}) |^2 \}$$

$$\text{when } \bar{X}_N(e^{j\omega}) = \sum_{n=0}^{N-1} x(n) e^{-j\omega n} = \text{DTFT} \{ x_N(n) \}$$

$$x_N(n) = \begin{cases} x(n) & , n=0, \dots, N-1 \\ 0 & , \text{otherwise} \end{cases}$$

$$\hat{P}_{\text{per}}(e^{j\omega}) \triangleq \frac{1}{N} | X_N(e^{j\omega}) |^2$$

Strengths: 1) Efficient to compute FFT

$$2) \lim_{N \rightarrow \infty} E \{ \hat{P}_{\text{per}}(e^{j\omega}) \} = P_x(e^{j\omega})$$

$\therefore$ Periodogram is asymptotically unbiased.

An alternative route:

$$\text{Since } P_x(e^{j\omega}) = \text{DTFT} \{ \underline{r_x(n)} \}$$

1) Estimate $r_x(n)$

$$\hat{r}_x(n) = \frac{1}{N} \sum_{n_0=n}^{N-1} x(n_0) x(n_0 - n)$$

$$n=0, \pm 1, \pm 2, \dots, \pm(N)$$

$$2) \hat{P}_{\text{per}}(e^{j\omega}) = \text{DTFT} \{ \hat{r}_x(n) \}$$

$$\text{DTFT} \{ \hat{r}_x(n) \} = \frac{1}{N} | X_N(e^{j\omega}) |^2$$

(2) ... N ...
 same result as before!

1) Finite sequence impact!
 (finite freq resolution)

2) Expected value is correct.
 the floor (large) is the var. of
 of $\hat{P}_{per}(e^{j\omega})$

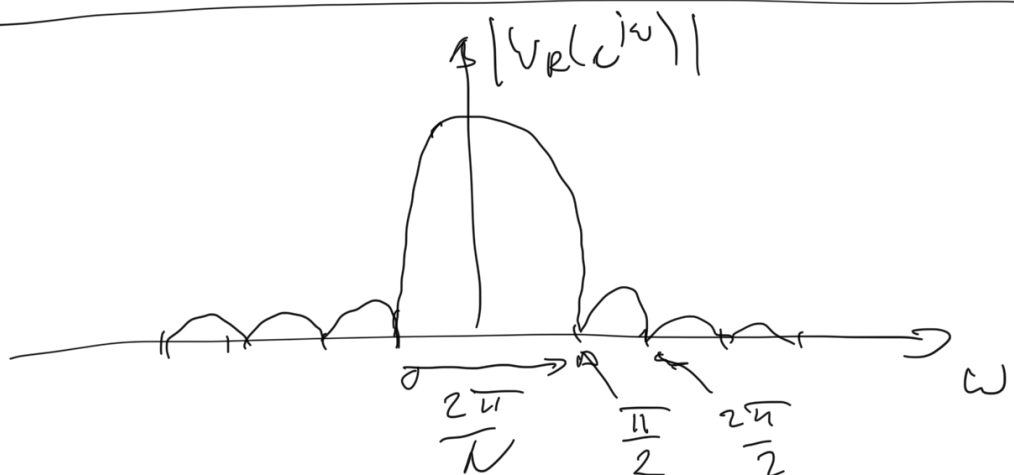
Bias for finite N ?

$$w_R(n) = \begin{cases} 1 & n=0, \dots, N-1 \\ 0 & \text{otherwise} \end{cases}$$

$$\hat{X}_N(e^{j\omega}) = \sum_{n=0}^{N-1} x(n) e^{-j\omega n} = \sum_{n=-\infty}^{\infty} w_R(n) x(n) e^{-j\omega n}$$

$$\Rightarrow \hat{X}_N(e^{j\omega}) = W_R(e^{j\omega}) * \underline{X}(e^{j\omega}) =$$

$$= \frac{1}{2\pi} \int_{-\pi}^{\pi} W_R(e^{jz}) \underline{X}(e^{j(\omega-z)}) dz$$



Variance of $\hat{P}_{per}(e^{j\omega})$

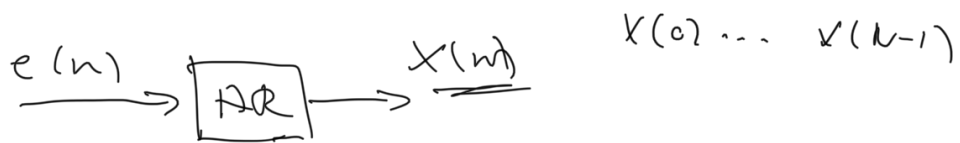
As $N \rightarrow \infty$... N ... $E \{ \hat{P}_{per}(e^{j\omega}) \} \rightarrow 0$...

assuming $x(n)$ is a white noise process with variance σ^2

$$\Rightarrow \text{var} \{ \hat{P}_{xx}(e^{j\omega}) \} = E \left\{ \left(\hat{P}_{xx}(e^{j\omega}) - P_x(e^{j\omega}) \right)^2 \right\} \\ \approx P_x(e^{j\omega})$$

Note that $\text{var} \{ \hat{P}_{xx} \} \not\rightarrow 0$ as $N \rightarrow \infty$

$\Rightarrow$ The estimate is not consistent



What is PSD

$$1) \text{ From the AR-model } \hat{x}(n) = \frac{1}{A(e^{j\omega})} e(n)$$

$$2) \hat{P}_x(e^{j\omega}) = P_{AR}(e^{j\omega}) = \left| \frac{1}{A(e^{j\omega})} \right|^2 \sigma_e^2$$

Parameter technique!

AR-estimated as LR.

$$\hat{x}(n) = e(n) - a_1 \hat{x}(n-1) - \dots - a_p \hat{x}(n-p)$$

$$\hat{x}(n) = -a_1 \hat{x}(n-1) - \dots - a_p \hat{x}(n-p)$$

$$\min_{\{a_1, \dots, a_p\}} \sum_{n=p}^{N-1} (\hat{x}(n) - \hat{x}(n))^2 = \min_{\{a_i\}} L(a_1, \dots, a_p)$$

$$L(a_1, \dots, a_p) = \sum_{n=p}^{N-1} \left(\hat{x}(n) + \sum_{i=1}^p a_i \hat{x}(n-i) \right)^2$$

$$\frac{\partial}{\partial a_i} L(a_1, \dots, a_p) = 0 \quad i = 1, \dots, p$$

$$\frac{\partial}{\partial a_i} L = \sum_{n=p}^{N-1} 2 \left(\hat{x}(n) + \sum_{i=1}^p a_i \hat{x}(n-i) \right) \hat{x}(n-i)$$

$$\Rightarrow \sum_{n=p}^{n-1} x(n) x(n-r) = - \sum_{n=p}^{n-1} \sum_{i=1}^p a_i x(n-i) x(n-r)$$

$$r = 1 \dots p$$

$$\begin{bmatrix} \vdots \\ a_1 \\ \vdots \\ a_p \end{bmatrix} = 0$$

p eqn
and p
unknowns!

YW-equal with
sample correlation