

## JOINT MOMENTS

FOR RV  $E[x]$ ,  $\text{VAR}(x)$  IMPORTANT  
 FOR TWO RVs, ALSO NEED  $\text{Cov}(x, y)$ .  
 FOR R.P.s WE WILL PAY PARTICULAR  
 ATTENTION TO FIRST TWO MOMENTS.

DEFINE MEAN SEQUENCE

$$\mu_x(n) = E[x(n)] \quad -\infty < n < \infty$$

VARIANCE SEQUENCE

$$\sigma_x^2(n) = \text{VAR}(x(n)) \quad -\infty < n < \infty$$

COVARIANCE SEQUENCE

$$\begin{aligned} c_{x[n_1, n_2]} &= \text{cov}(x(n_1), x(n_2)) \\ &= E[(x(n_1) - \mu_x(n_1))(x(n_2) - \mu_x(n_2))] \\ &= E[(x(n_1) - \mu_x(n_1))(x(n_2) - \mu_x(n_2))] \\ &\quad -\infty < n_1 < \infty, \quad -\infty < n_2 < \infty \end{aligned}$$

USUAL DEFINITIONS FOR RVs!

WE NOW DO NOT USE  $E[x_1, x_2]$ , SHOULD  
 OMIT

BE CLEAR, FOR EXAMPLE,

$$E(x(n_1)x(n_2)) = \iint_{-\infty}^{\infty} x_1 x_2 \varphi_{x(n_1), x(n_2)}(x_1, x_2) dx_1 dx_2$$

## SOME OBVIOUS PROPERTIES:

$$C_x(L_{n_2, n_1}) = C_x(n_1, n_2) \quad \text{WHY?}$$

$$C_x(n_1, n_2) = \sigma_x^2(n_2) \quad \text{why?}$$

SEE SIMILAR DEFINITIONS FOR CONT-TIME  
R.F.

EXAMPLE : w/GN  $X[n] \sim N(0, \sigma^2)$  AND IID

$$\Rightarrow \mu_{\{x\}_n} = E[x_n] = 0 \quad -\infty < n < \infty$$

$$\sigma_{x^2}(n) = \text{VAR}[x(n)] = \sigma^2 \quad -\infty < n < \infty$$

$$\begin{aligned}
 C_{X[n_1, n_2]} &= \text{cov}(x[n_1], x[n_2]) \\
 &= E[x[n_1]x[n_2]] \quad \text{MEAN} = 0 \\
 &= \begin{cases} E[x[n_1]]E[x[n_2]] & n_1 \neq n_2 (\text{IND.}) \\ E[x^2[n_1]] & n_1 = n_2 \end{cases}
 \end{aligned}$$

$$= \quad \circ \quad n_1 \neq n_2$$

$$G^+ = n_1 \oplus n_2$$

$$= G \delta(n_2 - n_1) \quad \delta(n) = 1 \quad n=0 \\ 0 \quad n \neq 0$$

## DISCRETE IMPULSE

EXAMPLE : MA R.P.  $x[n] = \frac{1}{2}(v[n] + v[n-1])$

$$\mu_{x\{n\}} = E[x\{n\}] \quad \uparrow_{WGN \ N(0, \sigma_v^2)}$$

$$= \frac{1}{2} (E(v(n)) + E(v(n+1))) = 0$$

$-\infty \notin P \triangleleft$

$$C_x(n_1, n_2) = E[x(n_1)x(n_2)] \quad \text{MEAN} = 0$$

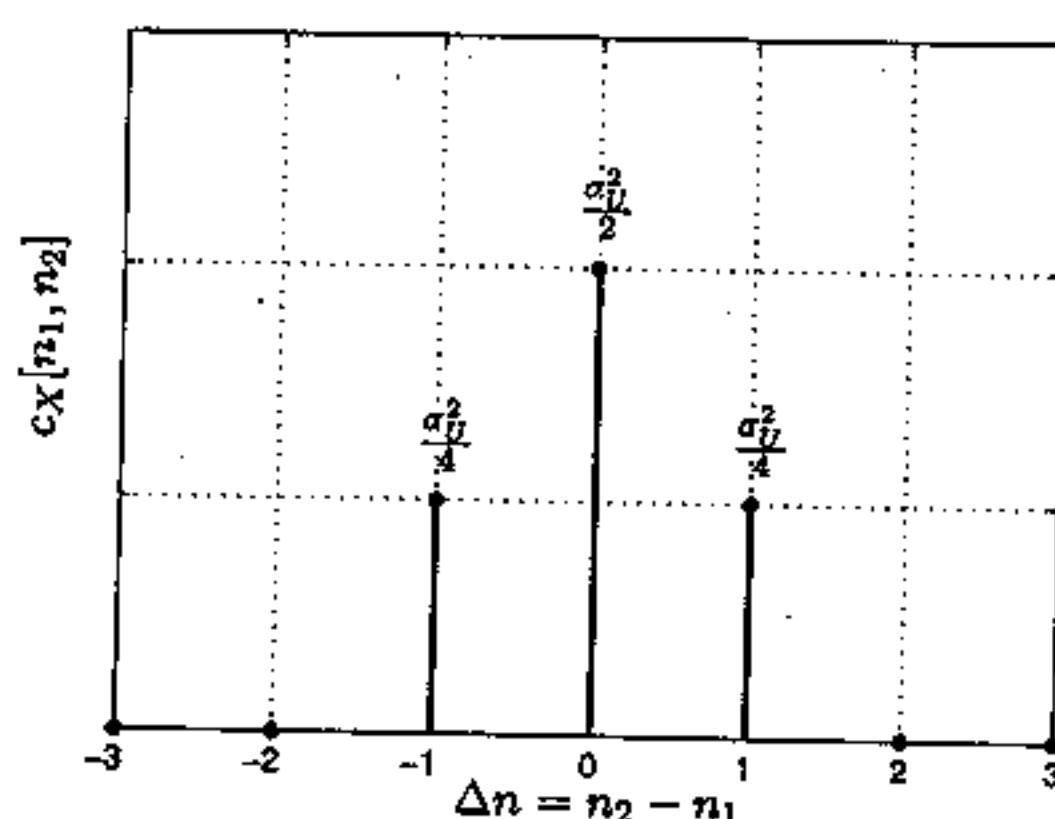
$$\begin{aligned}
 &= \frac{1}{4} E \left\{ (v(n_1) + v(n_1-1)) (v(n_2) + v(n_2-1)) \right\} \\
 &= \frac{1}{4} E [v(n_1)v(n_2)] + \frac{1}{4} E [v(n_1)v(n_2-1)] \\
 &\quad + \frac{1}{4} E [v(n_1-1)v(n_2)] + \frac{1}{4} E [v(n_1-1)v(n_2-1)]
 \end{aligned}$$

$$\text{But } E[v(k)v(\ell)] = \sigma_v^2 \delta[\ell-k]$$

$$\begin{aligned}
 C_x(n_1, n_2) &= \frac{1}{4} (\sigma_v^2 \delta[n_2-n_1] + \sigma_v^2 \delta[n_2-n_1-1] \\
 &\quad + \sigma_v^2 \delta[n_2-n_1+1] + \sigma_v^2 \delta[n_2-n_1]) \\
 &= \frac{\sigma_v^2}{2} \delta[n_2-n_1] + \frac{\sigma_v^2}{4} \delta[n_2-n_1-1] \\
 &\quad + \frac{\sigma_v^2}{4} \delta[n_2-n_1+1]
 \end{aligned}$$

NOTE: DEPENDS ONLY ON  $n_2 - n_1 = \Delta n$

$$\begin{aligned}
 &= \frac{\sigma_v^2}{2} \delta[\Delta n] + \frac{\sigma_v^2}{4} \delta[\overbrace{\Delta n-1}^{=0 \text{ UNLESS}}] \xrightarrow{\Delta n-1=0} \Delta n=1 \\
 &\quad + \frac{\sigma_v^2}{4} \delta[\overbrace{\Delta n+1}^{=0 \text{ UNLESS}}]
 \end{aligned}$$



$\leftarrow$  = COVARIANCE  
 BETWEEN TWO  $x(n)$   
 RP SAMPLES SPACED  
 $\Delta n$ , TIME  
 SAMPLES APART

Figure 16.13: Covariance sequence for moving average random process.

$\Rightarrow$  IF TWO R.P. SAMPLES SPACED MORE  
THAN 1 SAMPLE APART  $\Rightarrow$  UNCORRELATED

SINCE  $x(0) = \frac{1}{2}(v(0) + v(-1))$   
 $x(1) = \frac{1}{2}(v(2) + v(1))$  WHY?

EXAMPLE : RANDOMLY PHASE SAWTOOTH

$$\mu_{x(n)} = E[x(n)] = E[\cos(2\pi(\omega_0)n + \Theta)] \\ = \int_0^{2\pi} \underbrace{\cos(2\pi(\omega_0)n + \Theta)}_{g(\theta)} \underbrace{\frac{1}{2\pi} d\theta}_{p(\theta)} = 0$$

$$\begin{aligned} \langle x[n_1, n_2] \rangle &= E[x[n_1]x[n_2]] \\ &= \int_0^{2\pi} \underbrace{\cos(2\pi(\omega_0)n_1 + \Theta) \cos(2\pi(\omega_0)n_2 + \Theta)}_{g(\theta)} \cdot \underbrace{\frac{1}{2\pi} d\theta}_{p(\theta)} \\ &= \int_0^{2\pi} \left[ \frac{1}{2} \cos(2\pi(\omega_0)(n_2 - n_1)) + \frac{1}{2} \cos(2\pi(\omega_0)(n_1 + n_2) + 2\Theta) \right] \\ &\quad \uparrow \text{NOT DEPENDENT} \quad \cdot \frac{d\theta}{2\pi} \\ &= \frac{1}{2} \cos(2\pi(\omega_0)(n_2 - n_1)) + \frac{1}{2} \left. \frac{1}{2\pi} \sin(2\pi(\omega_0)(n_1 + n_2) + 2\Theta) \right|_0^{2\pi} \\ &= \frac{1}{2} \cos(2\pi(\omega_0)(n_2 - n_1)) \end{aligned}$$

AGAIN COVARIANCE ONLY DEPENDS ON SPACING BETWEEN SAMPLES,  $\Delta n$ .

NOTE :  $\langle x[n_1, n_2] \rangle = f(\Delta n)$  AND IS SYMMETRIC (EVEN SEQUENCE)

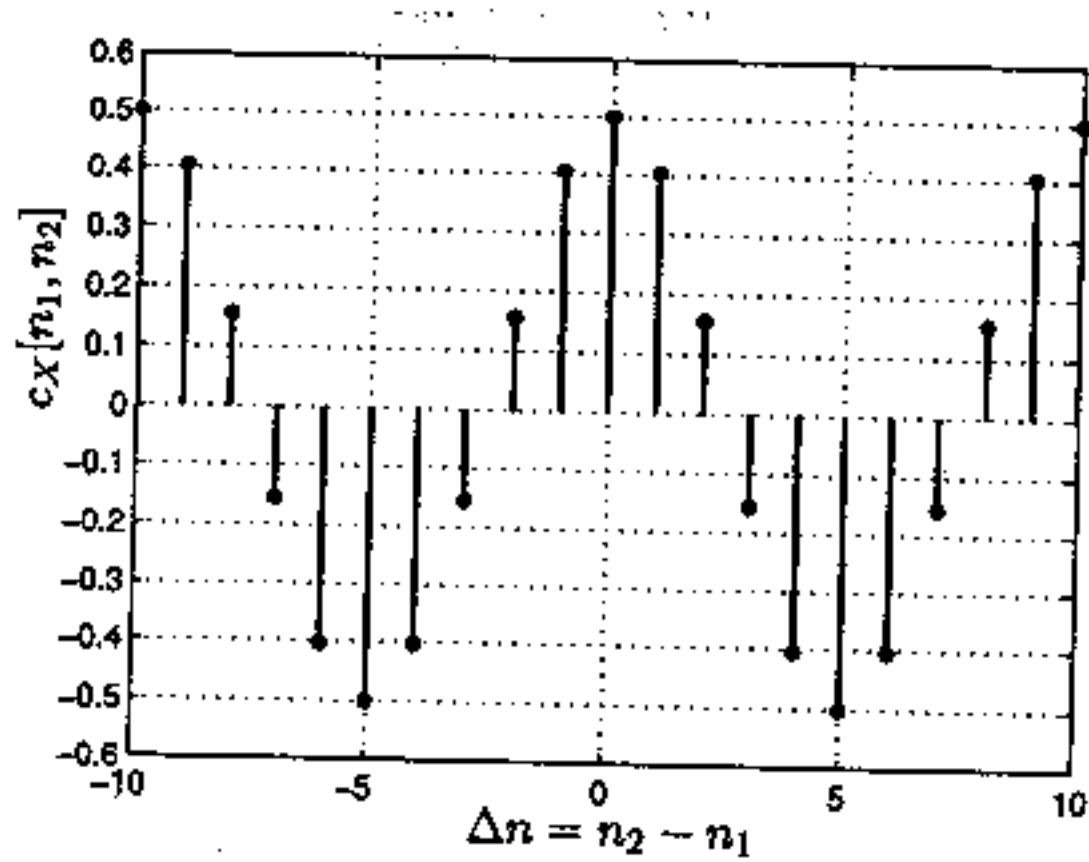
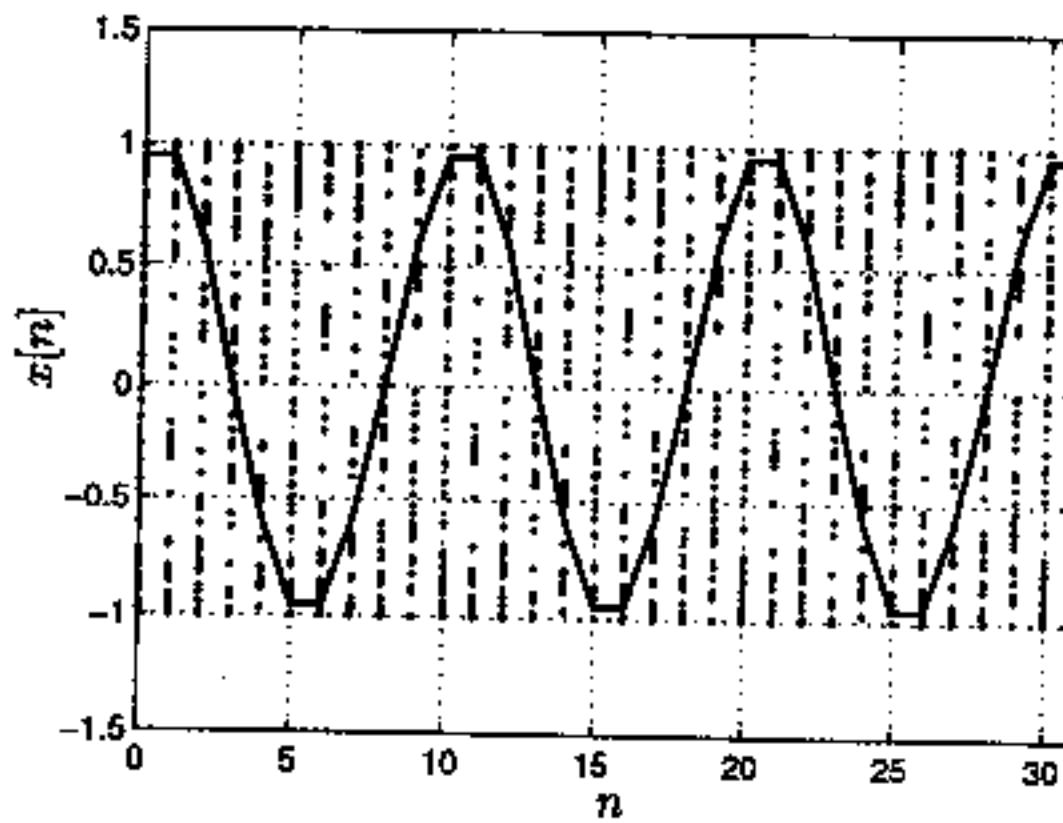


Figure 16.14: Covariance sequence for randomly phased sinusoid.

$$f(-\Delta n) = f(\Delta n)$$

HOW FAR APART  
DO SAMPLES HAVE  
TO BE SO THAT  
THEY ARE UNCORRE-  
LATED?

WHY IS MEAN ZERO HERE?



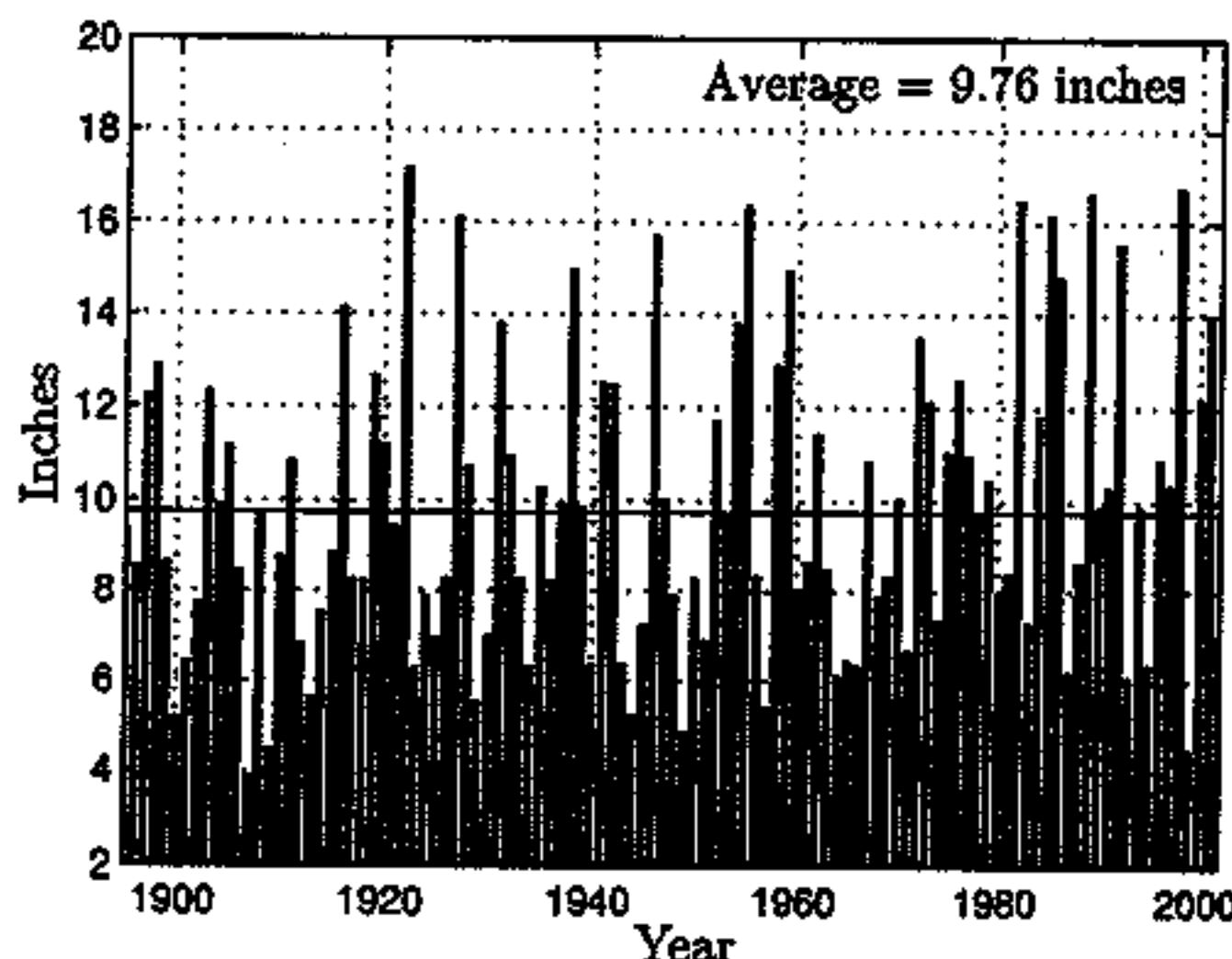
SCATTER  
DIAGRAM

16.15: Fifty realizations of randomly phased sinusoid plotted in an overlaid scatter diagram with one realization shown with its points connected by straight lines.

### REAL WORLD EXAMPLE - RAINFALL IN RI

QUESTION: IS RAINFALL IN RI INCREASING?  
 ⇒ POTENTIAL INDICATOR OF GLOBAL  
 WARMING

ANALYZE LAST 100 YEARS OF ANNUAL  
 SUMMER RAINFALL FOR A TREND



AVERAGE OBTAINED

USING

$$\bar{x} = \frac{1}{N} \sum_{n=0}^{N-1} x[n]$$

$$n=0 \Rightarrow 1895$$

$$n=107 \Rightarrow 2002$$

Figure 16.1: Annual summer rainfall in Rhode Island from 1895 to 2002.

IS  $\mu_x(n) = \mu \approx 9.76$  CORRECT?

MAY BE  $\mu_x(n) = an + b$  FOR SOME  $a, b$   
(NONSTATIONARY R.P.)?

APPROACH: ASSUME  $\mu_x(n) = an + b$  AND  
ESTIMATE  $a, b$ . IS  $a = 0$ ? IF  $a > 0$ ,  
RAINFALL INCREASING, AND IF  $a < 0$ ,  
RAINFALL DECREASING.

TO ESTIMATE  $a, b$  USE LEAST SQUARES  
(TAKE ELE 661 - ESTIMATION THEORY  
TO LEARN MORE!)

MINIMIZE LEAST SQUARES ERROR

$$J(a, b) = \sum_{n=0}^{N-1} (x[n] - (an + b))^2$$

OVER  $a, b \Rightarrow \hat{a}, \hat{b}$

NOTE: IF WE ASSUMED  $\mu_X(n) = \mu = b$

(NO CHANGE IN MEAN),

$$J(b) = \sum_{n=0}^{N-1} (x(n) - b)^2$$

$$\frac{\partial J}{\partial b} = 0 \Rightarrow \hat{b} = \frac{1}{N} \sum_{n=0}^{N-1} x(n) = 9.76$$

$$\text{NOW, } \frac{\partial J}{\partial b} = -2 \sum_n (x(n) - a_n - b) = 0$$

$$\frac{\partial J}{\partial a} = -2 \sum_n (x(n) - a_n - b)n = 0$$

$$\sum_n a_n + \sum_n b = \sum_n x(n)$$

$$\sum_n a_n^2 + \sum_n b_n = \sum_n n x(n)$$

$$\begin{bmatrix} N & \sum_n n \\ \sum_n n & \sum_n n^2 \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} \sum_n x(n) \\ \sum_n n x(n) \end{bmatrix}$$

$$\text{SOLVE } \Rightarrow \hat{a} = 0.0173, \hat{b} = 8.8336$$

$$\mu_X(n) = 0.0173n + 8.8336$$

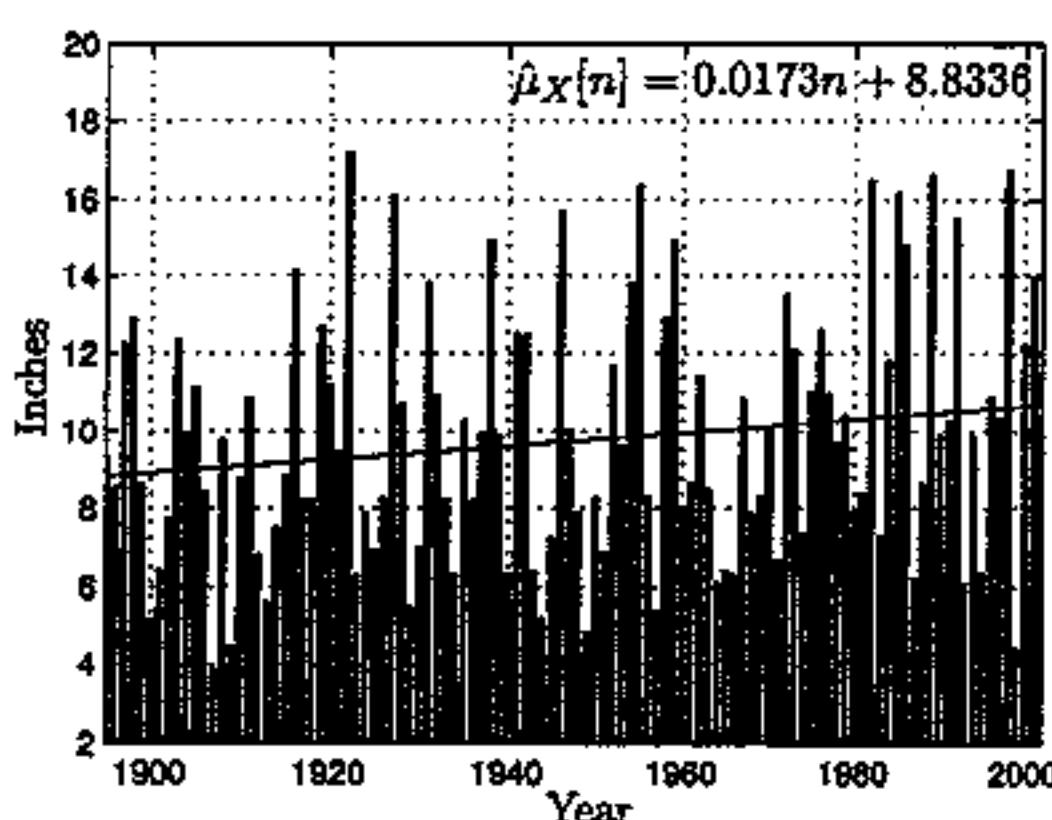


Figure 16.16: Annual summer rainfall in Rhode Island and the estimated mean sequence,  $\hat{\mu}_X[n] = 0.0173n + 8.8336$ , where  $n = 0$  corresponds to the year 1895.

IS  $a > 0$ ?

MAYBE WAIT

ANOTHER 100

YEARS TO SEE

IF  $\hat{a} > 0$  WITH

MORE DATA?

TO SEE IF  $\hat{a} > 0$  DUE TO "STATISTICAL ERROR", LET  $x[n] = \underbrace{a_n + b}_{Mx[n]} + e(n)$

$Mx[n] \uparrow$  ZERO

MEAN  
ERROR

ASSUME  $e[n] \sim N(0, \sigma^2)$

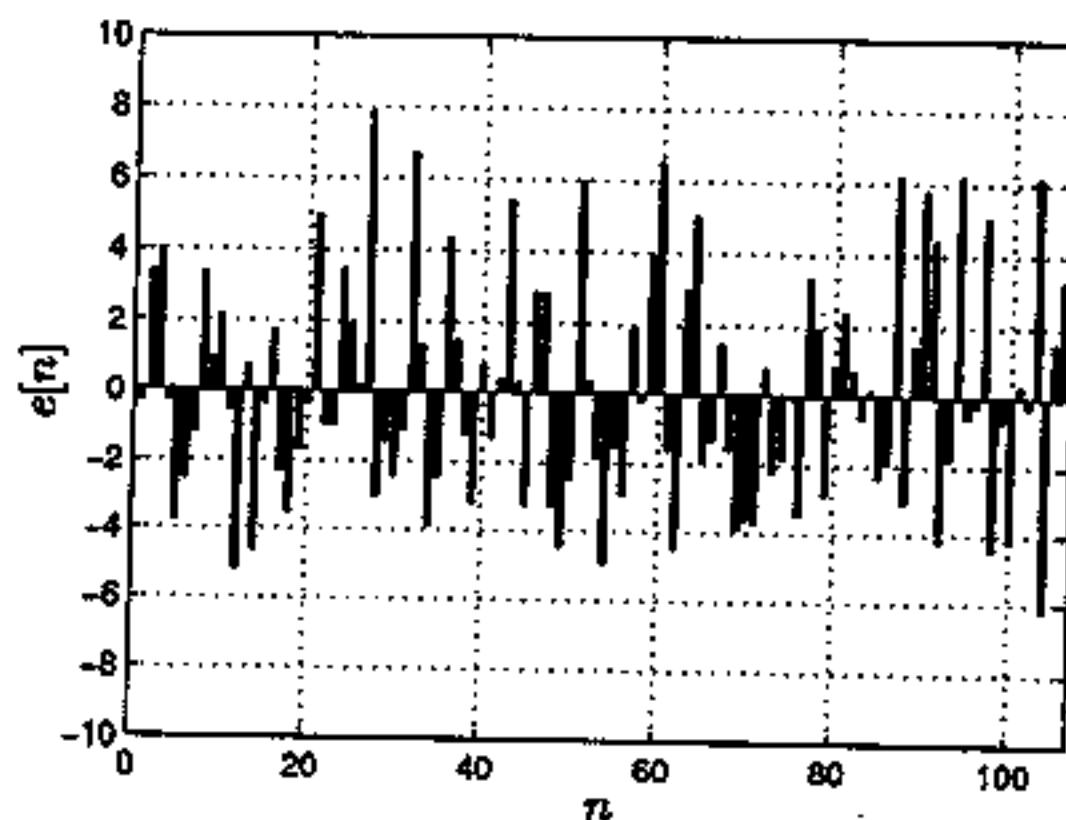
WHAT SHOULD WE USE FOR  $\sigma^2$ ?

$$\sigma^2(\hat{a}, \hat{b}) = \sum_n (x[n] - (\hat{a}n + \hat{b}))^2 \\ = \sum_n (a_n + b + e[n] - (\hat{a}n + \hat{b}))^2$$

$$\approx \sum_n e[n]^2 \quad \text{IF } \hat{a} \approx a$$

$$\hat{b} \approx b$$

USE  $\sigma^2 = \frac{1}{N} \sum_{n=0}^{N-1} \underbrace{(x[n] - (\hat{a}n + \hat{b}))^2}_{\approx e[n]}$



$$\sigma^2 = 10.05$$

$\Rightarrow$  WE ASSUME NOW

THAT

$$x[n] = b + u[n]$$

$$u[n] \sim N(0, 10.05)$$

OR CONSTRAIN

$$a = 0$$

COULD WE STILL OBSERVE INCREASE  
IN MEAN RAINFALL BASED ON ESTIMATED  
 $\hat{a}, \hat{b}$  EVEN THOUGH  $a = 0$ ?

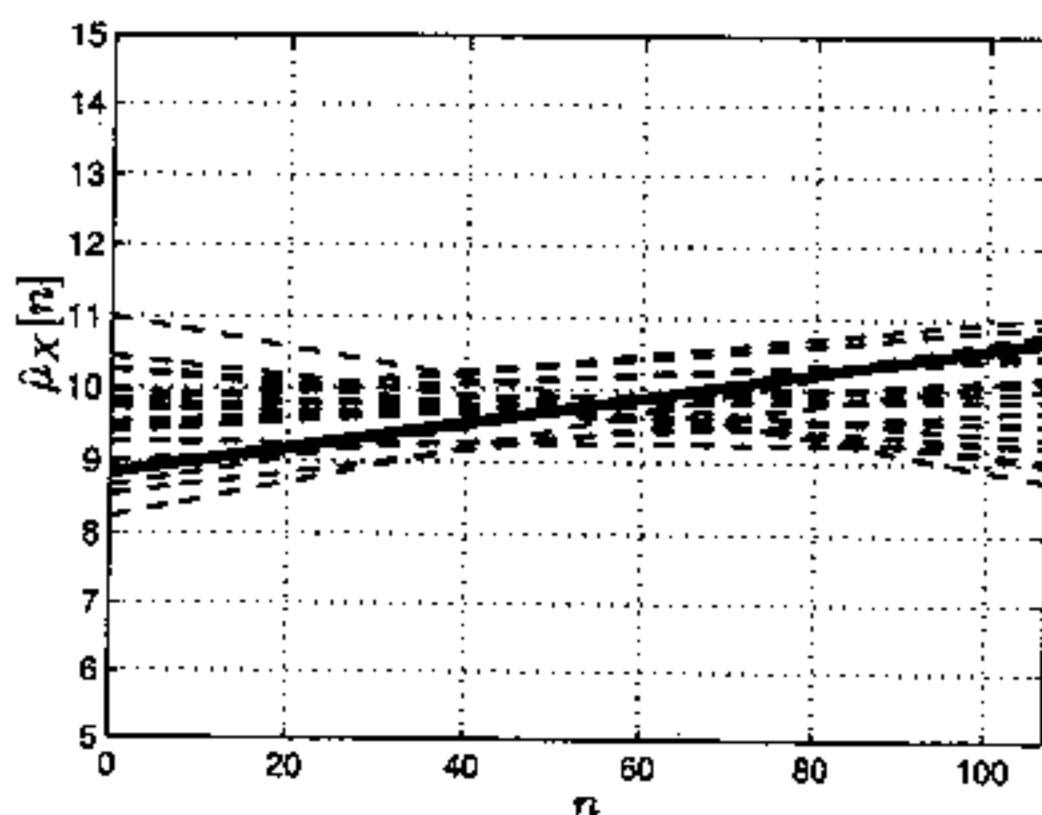
Figure 16.17: Least squares error sequence for annual summer rainfall in Rhode Island fitted with a straight line.

OR IS  $\hat{a} = 0.0173$  DUE TO ERROR IN  
ESTIMATING  $a$  BECAUSE OF  $u[n]$ ?

$$\begin{bmatrix} N & \sum_n \\ \sum_n & \sum_n^2 \end{bmatrix} \begin{bmatrix} \hat{b} \\ \hat{a} \end{bmatrix} = \begin{bmatrix} \sum_n (b + u[n]) \\ \sum_n n(b + u[n]) \end{bmatrix}$$

↑ IF  $u[n] = 0$   
 $\Rightarrow \hat{b} = b$   
 $\hat{a} = 0$

IF  $u[n] \neq 0$ ,  $\hat{a} \neq 0$ .



TRUE  $a$   
IS ZERO!

NOT EVIDENT  
FROM DATA,  
THOUGH.

Figure 16.18: Twenty realizations of the estimated mean sequence  $\hat{\mu}_X[n] = \hat{a}n + \hat{b}$  based on the random process  $X[n] = 9.76 + U[n]$  with  $U[n]$  being WGN with  $\sigma^2 = 10.05$ . The realizations are shown as dashed lines. The estimated mean sequence from Figure 16.16 is shown as the solid line.

---

(WSS)  
CHAPTER 17 - WIDE SENSE STAT. R.P.

WILL ALLOW US TO ANALYZE FREQUENCY  
CONTENT OF R.P. - SIMILAR TO FOURIER  
TRANSFORM OF DETERMINISTIC SIGNAL

HAVE ALREADY ENCOUNTERED WSS R.P.,  
WGN, MA PROCESS, RANDOMLY PHASED SINEWAVES

A WSS R.P. IS DEFINED AS ONE WHOSE

$$\mu_x[n] = \mu \quad (\text{CONSTANT}) \quad -\infty < n < \infty$$

$$c_x(n_1, n_2) = g(|n_2 - n_1|) \quad -\infty < n_1, n_2 < \infty$$

- $\Rightarrow$
- 1) MEAN CONSTANT
  - 2) COVARIANCE ONLY DEPENDS ON SPACING BETWEEN R.P. SAMPLES

### EXAMPLE : MA PROCESS

$$\mu_x[n] = 0 \quad (\mu = 0)$$

$$c_x(n_1, n_2) = \begin{cases} \frac{1}{2} \sigma_v^2 & |n_2 - n_1| = 0 \\ \frac{1}{4} \sigma_v^2 & |n_2 - n_1| = 1 \\ 0 & |n_2 - n_1| > 1 \end{cases}$$

$$\text{NOTE THAT } \text{VAR}(x[n]) = \sigma_x^2[n]$$

$$= c_x(n, n) = \frac{1}{2} \sigma_v^2 \text{ OR}$$

VARIANCE IS ALSO CONSTANT

---

A WSS R.P. IS A SPECIAL CASE OF STATIONARY R.P. OR

STAT. R.P.  $\Rightarrow$  WSS

WSS  $\not\Rightarrow$  STAT R.P. (IN GENERAL)

WSS MUCH MORE USEFUL - ONLY INVOLVES CONSTRAINTS ON FIRST TWO MOMENTS.

PROOF : ASSUME  $x[n]$  IS STATIONARY OR

$$P_{x[n_1, n_2, \dots, n_w]} = P_{x[n_1, \dots, n_N]}$$

FOR ALL  $n_1, n_2, \dots, n_N$ , ALL  $N$ , AND ALL  $n_0$ .

NOW LET  $N=1$  AND  $n_1=n$

$$\Rightarrow P_{x(n+n_0)} = P_{x(n)}$$

$$\text{LET } n=0 \Rightarrow P_{x(n_0)} = P_{x(0)} \quad \text{ALL } n$$

PDF CAN'T DEPEND ON TIME  $\Rightarrow \mu_{x(n)} = \mu$

FOR  $-\infty < n < \infty$ .

NEXT LET  $N=2$

$$P_{x(n_1+n_0), x(n_2+n_0)} = P_{x(n_0), x(n_2)}$$

$$\text{LET } n_0 = -n_1$$

$$\Rightarrow P_{x(0), x(n_2-n_1)} = P_{x(n_0), x(n_2)}$$

$$\Rightarrow E[x(n_1)x(n_2)] = E[x(0)x(n_2-n_1)]$$

$$\text{LET } n_0 = -n_2$$

$$\Rightarrow P_{x(n_1-n_2), x(0)} = P_{x(n_1), x(n_2)}$$

$$\Rightarrow E[x(n_1)x(n_2)] = E[x(0)x(n_1-n_2)]$$

OR COMBINING RESULTS

$$E[x(n_1)x(n_2)] = E[x(0)x(1_{n_2-n_1})]$$

$$\begin{aligned} \text{so } C_x(n_1, n_2) &= E[x(n_1)x(n_2)] - E\{x(n_1)\}E\{x(n_2)\} \\ &= E[x(0)x(n_2-n_1)] - \mu^2 \\ &= g(n_2-n_1) \end{aligned}$$

### AUTOCORRELATION SEQUENCE

ASSUME HENCEFORTH THAT  $x(n)$  IS WSS.

$E[x(n_1)x(n_2)]$  DEPENDS ONLY ON  $|n_2-n_1|$ .

LET  $n_1 = n$ ,  $n_2 = n+k$

$E[x(n_1)x(n_2)] = E[x(n)x(n+k)]$  DEPENDS  
ONLY ON  $k$  (AND MORE GENERALLY ON  $|k|$ )

$\Rightarrow$  DEFINE  $r_{xx}(k) = E[x(n)x(n+k)] \quad -\infty \leq k \leq \infty$

CALLED THE AUTOCORRELATION SEQUENCE (ACS)

NOTE: NOT DEPENDENT ON  $n$ , ALTHOUGH  
USED IN DEFINITION

$k$  = TIME DIFFERENCE BETWEEN SAMPLES  
CALLED THE LAG

ACS MEASURES CORRELATION (WILL SEE LATER)  
BETWEEN WSS RP. SAMPLES

EXAMPLE : DIFFERENCE

$$x(n) = v(n) - v(n-1)$$

$$v(n) \sim N(\mu, \sigma_v^2) \quad \text{IID}$$

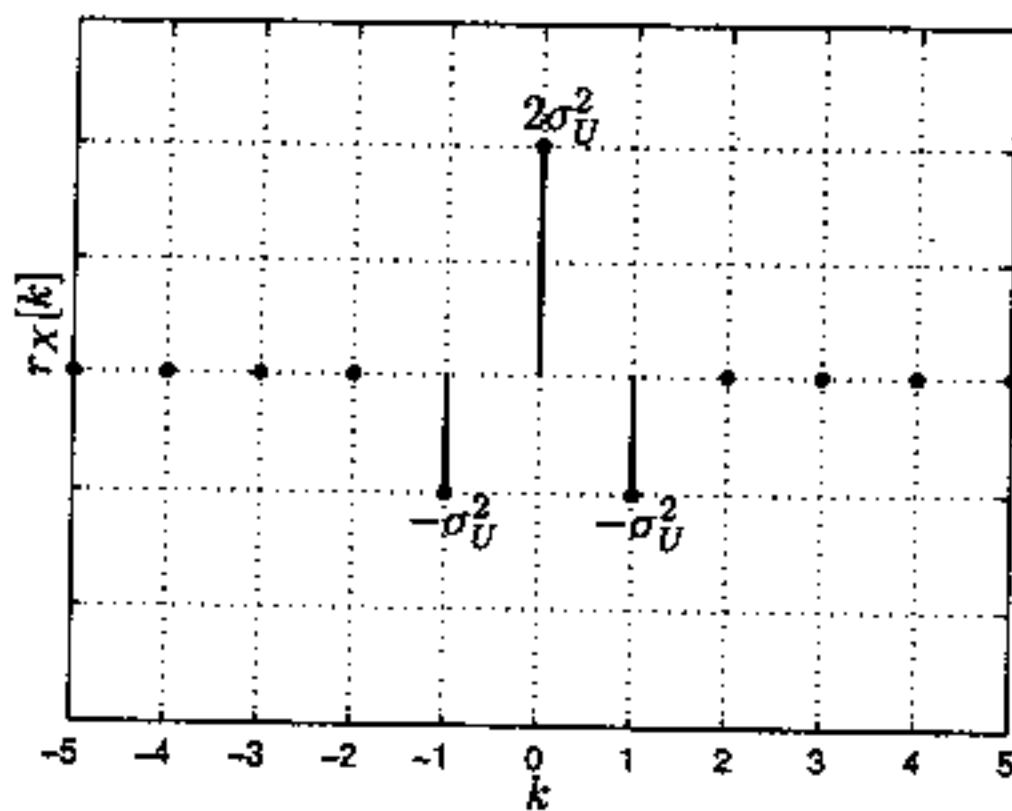
$$\begin{aligned} r_x(k) &= E[x(n)x(n+k)] \\ &= E[(v(n) - v(n-1))(v(n+k) - v(n+k-1))] \\ &= E[v(n)v(n+k)] - E[v(n)v(n+k-1)] \\ &\quad - E[v(n-1)v(n+k)] + E[v(n-1)v(n+k-1)] \end{aligned}$$

$$\begin{aligned} \text{For } n_1 \neq n_2, \quad E[v(n_1)v(n_2)] &= E(v(n_1))E(v(n_2)) \\ &= \mu^2 \quad \text{WHY?} \end{aligned}$$

$$\begin{aligned} \text{For } n_1 = n_2 = n, \quad E[v(n_1)v(n_2)] &= E(v^2(n)) \\ &= E(v^2(0)) = \sigma_v^2 + \mu^2 \\ &\quad \text{WHY?} \end{aligned}$$

$$\Rightarrow E[v(n)v(n+k)] = \mu^2 + \sigma_v^2 \delta(n+k)$$

$$\begin{aligned} r_x(k) &= \mu^2 + \sigma_v^2 \delta(k) - [\mu^2 + \sigma_v^2 \delta(k-1)] \\ &\quad - [\mu^2 + \sigma_v^2 \delta(k+1)] + \mu^2 + \sigma_v^2 \delta(k) \\ &= 2\sigma_v^2 \delta(k) - \sigma_v^2 \delta(k-1) - \sigma_v^2 \delta(k+1) \end{aligned}$$



WHAT IS CORRELATION COEFFICIENT BETWEEN 2 SUCCESSIVE SAMPLES?

Figure 17.4: Autocorrelation sequence for differenced random process.

BY DEFINITION

$$\rho_{x(n), x(n+1)} = \frac{\text{cov}(x(n), x(n+1))}{\sqrt{\text{var}(x(n)) \text{var}(x(n+1))}}$$

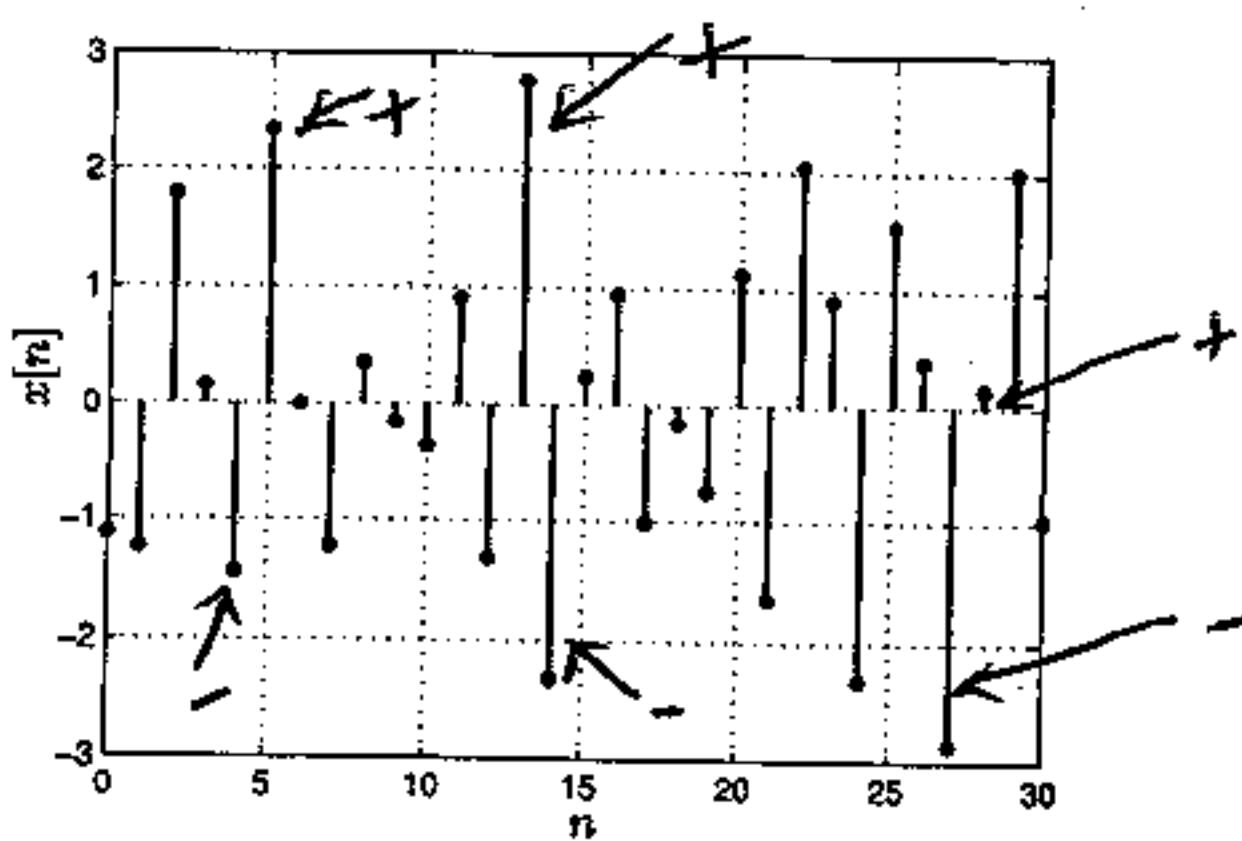
SINCE  $x(n)$  HAS ZERO MEAN (WHY?),

$$\begin{aligned} \rho_{x(n), x(n+1)} &= \frac{E[x(n)x(n+1)]}{\sqrt{E[x^2(n)] E[x^2(n+1)]}} \\ &= \frac{r_{x(1)}}{\sqrt{r_{x(0)} r_{x(0)}}} = \frac{r_{x(1)}}{r_{x(0)}} \end{aligned}$$

(ONLY DEPENDS ON SPACING BETWEEN R.P. SAMPLES!)

$$\text{HERE, } \rho_{x(n), x(n+1)} = \frac{-\sigma_v^2}{2\sigma_v^2} = -\frac{1}{2}$$

⇒ NEGATIVE CORRELATION



HENCE, IF STOCK PRICE GOES DOWN ON MON., THEN CALL BROKER ON TUES. AND —?

Figure 17.3: Typical realization of a differenced IID Gaussian random process with  $U[n] \sim \mathcal{N}(1, 1)$ .

SOME OBSERVATIONS ABOUT ACS:

$$1) r_x[0] > 0$$

$$2) r_x[-k] = r_x[k] \text{ EVEN SEQUENCE}$$

$$3) |r_x[k]| \leq r_x[0]$$

$$1) r_x[0] > 0$$

PROOF:  $r_x[k] = E[x(n)x(n+k)]$

$$r_x[0] = E[x^2(n)] > 0$$

= AVERAGE POWER

ACROSS NR RESISTOR

IF  $x[n]$  = VOLTAGE

DOESN'T CHANGE WITH TIME

$$2) r_x[-k] = r_x[k] \text{ EVEN SEQUENCE}$$

PROOF:  $r_x[k] = E[x(n)x(n+k)]$

$$r_x[-k] = E[x(n)x(n-k)]$$

LET  $n = m+k$ ,  $n$  IS ARBITRARY

$$\Rightarrow r_x[-k] = E[x(m+k)x(m)]$$

$$= E[x(m)x(m+k)] \quad \begin{matrix} \text{NOT} \\ \text{DEPENDENT} \\ \text{ON } m \end{matrix}$$

$$= E[x(n)x(n+k)]$$

$$= r_x[k]$$

ABSOLUTE

$$3) \text{ MAXIMUM VALUE AT } k=0, |r_x[k]| \leq r_x[0]$$

CAUCHY-SCHWARZ INEQUALITY SAYS:

$$|E_{V,W}[VW]| \leq \sqrt{E_V[V^2]E_W[W^2]}$$

EQUALITY HOLDS IF AND ONLY IF

$W = CV$  ( $C$  A CONSTANT)

(like  $|V \cdot W| \leq \|V\| \|W\|$  EUCLIDEAN VECTORS)

PROOF : LET  $V = x[n]$ ,  $W = x[n+k]$

$$\begin{aligned} |E(x[n]x[n+k])| &\leq \sqrt{E(x^2[n])E(x^2[n+k])} \\ |r_{x(2k)}| &\leq \sqrt{r_{x(0)}r_{x(0)}} = |r_{x(0)}| \\ &= r_{x(0)} \end{aligned}$$

ALREADY SHOWED THAT FOR ZERO MEAN WSS RP.

$$r_{x(n),x(n+k)} = \frac{r_{x(k)}}{r_{x(0)}}$$

NOW KNOW THAT AS EXPECTED

$$|r_{x(n),x(n+k)}| \leq 1 \text{ WHY?}$$

### ACS EXAMPLES

- 1) WHITE NOISE - DEFINED AS WSS RP. WITH ZERO MEAN, IDENTICAL VARIANCE  $\sigma^2$ , AND UNCORRELATED SAMPLES

NO MENTION OF PDF'S HERE  $\Rightarrow$  NOT NEL

ESSARILY WGN.  $x(n)$ 's DO NOT HAVE TO BE INDEPENDENT, ONLY UNCORRELATED.

$$\begin{aligned} r_{x(k)} &= E[x(n)x(n+k)] \\ &= E[x(n)]E[x(n+k)] \quad \text{FOR } k \neq 0 \end{aligned}$$

DUE TO UNCORRELATED ASSUMPTION

$$(\text{cor}(x, y) = 0 \Rightarrow E[xy] - E[x]E[y] = 0)$$

$$r_{x(k)} = 0 \quad k \neq 0 \quad \text{SINCE } E[x(n)] = 0 \text{ ALL } n$$

FOR  $k = 0$

$$r_{x(k)} = E(x^2(n)) = \text{Var}(x(n)) = \sigma^2$$

$$\therefore r_{x(k)} = \sigma^2 \delta[k]$$

ASIDE :  $(x(n_1, n_2))$  FOUND FROM  $r_{x(k)}$  AND  $\mu$  AS

$$\begin{aligned} c_x(n_1, n_2) &= E[x(n_1)x(n_2)] - E[x(n_1)]E[x(n_2)] \\ &= r_{x(k)} - \mu^2 \end{aligned}$$

ALSO, THEN IF  $n_1 = n, n_2 = n+k$

$$c_x(n, n+k) = r_{x(k)} - \mu^2$$

THUS, IF TWO SAMPLES ARE UNCORRELATED AS  $k \rightarrow \infty$ , THEN  $c_x(n, n+k) \rightarrow 0$  AS  $k \rightarrow \infty$ , AND  $r_{x(k)} \rightarrow \mu^2$  AS  $k \rightarrow \infty$ .

MOST PHYSICAL PROCESSES HAVE THIS PROPERTY.

2) MA R.P.

$$\text{RECALL } C_x(n_1, n_2) = \begin{cases} \frac{\sigma_v^2}{2} & n_1 = n_2 \\ \frac{\sigma_v^2}{4} & |n_2 - n_1| = 1 \\ 0 & |n_2 - n_1| > 1 \end{cases}$$

$$\text{FROM ASIDE: } r_x(k) = C_x(n, n+k) + \mu^2$$

BUT HERE  $\mu = 0$

$$\begin{aligned} r_x(k) &= \frac{\sigma_v^2}{2} & k = 0 \\ &\frac{\sigma_v^2}{4} & k = \pm 1 \\ &0 & |k| > 1 \end{aligned}$$

NOTE:  $r_x(k)$  HAS  $r_x(0) > 0$ ,  $|r_x(k)| \leq r_x(0)$   
 $r_x(-k) = r_x(k)$ .

3) RANDOMLY PHASED SINEWAVE

AGAIN  $\mu = 0$ , AND

$$\begin{aligned} C_x(n_1, n_2) &= \frac{1}{2} \cos(2\pi(\phi_{11})(n_2 - n_1)) \\ \Rightarrow r_x(k) &= \frac{1}{2} \cos[2\pi(\phi_{11})k] \end{aligned}$$

4) AUTOREGRESSIVE R.P.

USED EXTENSIVELY AS MODEL FOR PHYSICAL PROCESSES

A SPECIAL CASE OF AUTOREGRESSIVE (AR)  
RP DEFINED AS

$$x[n] = ax[n-1] + v[n] \quad -\infty < n < \infty$$

WHERE  $|a| < 1$  AND  $v[n]$  IS WGN WITH VARIANCE  $\sigma_v^2$ .

NOTE THAT THE EQUATION IS A FIRST-ORDER RECURSIVE DIFFERENCE EQUATION.

RP EVOLVES AS:

$$\begin{aligned} x[0] &= ax[-1] + v[0] \\ x[1] &= ax[0] + v[1] \\ x[2] &= ax[1] + v[2] \\ &\vdots \end{aligned}$$

AND  $x[n]$  DEPENDS ONLY ON PRESENT AND PAST SAMPLES, FOR EXAMPLE,

$$\begin{aligned} x[2] &= ax[1] + v[2] \\ &= a(ax[0] + v[1]) + v[2] = a^2x[0] + av[1] \\ &\quad + v[2] \\ &= a^2(ax[-1] + v[0]) + av[1] + v[2] \\ &= a^3x[-1] + a^2v[0] + av[1] + v[2] \\ &= \sum_{k=0}^{\infty} a^k v[2-k] \quad \text{LEADING TERM} \\ &\quad a^3x[-1], \text{ ETC } \rightarrow 0 \\ &\quad \text{SINCE } |a| < 1. \end{aligned}$$

CLEARLY, WE MUST HAVE  $|a| < 1$  FOR A STABLE RECURSION.

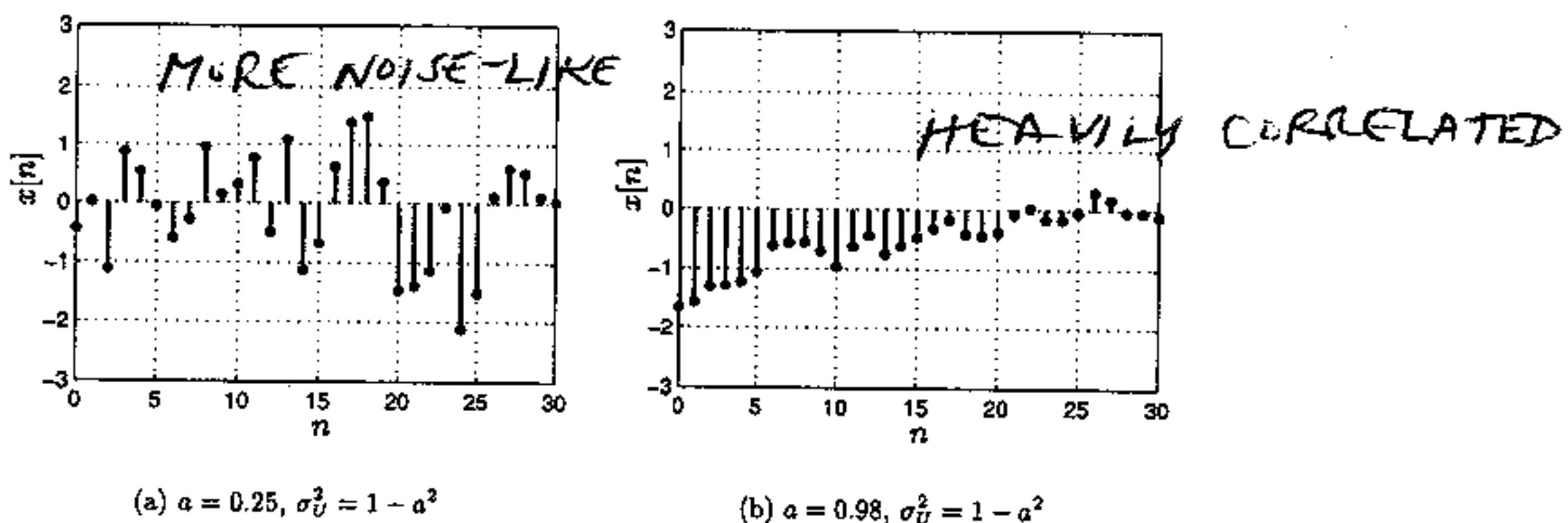
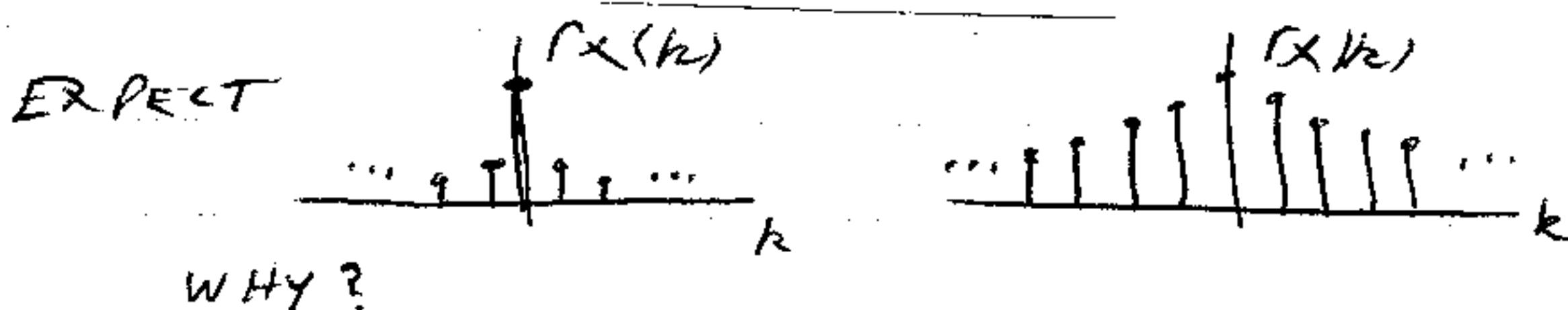


Figure 17.5: Typical realizations of autoregressive random process with different parameters.



```

clear all
randn('state',0)
a1=0.25;a2=0.98;
varu1=1-a1^2;varu2=1-a2^2;
varx1=varu1/(1-a1^2);varx2=varu2/(1-a2^2); % this is r_X[0]
x1(1,1)=sqrt(varx1)*randn(1,1); % set initial condition X[-1]
% see Problems 17.17, 17.18
x2(1,1)=sqrt(varx2)*randn(1,1);
for n=2:31
    x1(n,1)=a1*x1(n-1)+sqrt(varu1)*randn(1,1);
    x2(n,1)=a2*x2(n-1)+sqrt(varu2)*randn(1,1);
end

```

TO DETERMINE ACS :

$$\begin{aligned}
r_x(k) &= E(x(n)x(n+k)) \\
&= E(x(n)(ax(n+k-1) + v(n+k))) \\
&= aE(x(n)x(n+k-1)) + E[x(n)v(n+k)] \\
&= a r_x(k-1) + E[x(n)v(n+k)]
\end{aligned}$$

BUT  $x(n) = \sum_{\ell=0}^{\infty} a^\ell v(n-\ell)$