

Lecture 12

Markov Sequences

Note: We will always assume a discrete or continuous density function

Defn: The sequence Y_n is Markov if

$$p(y_n | y_i, i < n) = p(y_n | y_{n-1})$$

Transition density

- y_n only depends on the last sample.

Example 1)

X_n are i.i.d. $N(0, \sigma^2)$

$$Y_n = \sum_{i=1}^n X_i \quad n \geq 1$$

$$Y_n = Y_{n-1} + X_n$$

$$p(y_n | y_i, i < n) = p(y_n | x_i, i < n)$$

$$\sim N\left(\sum_{i=1}^{n-1} x_i, \sigma^2\right)$$

$$\sim N(y_{n-1}, \sigma^2)$$

$$= p(y_n | y_{n-1})$$

Distribution for Markov Chain

$$\begin{aligned} p(y) &= p_n(y_n | y_{i \leq n}) p(y_{i \leq n}) \\ &= p_n(y_n | y_{n-1}) p(y_{i \leq n}) \\ &= p_n(y_n | y_{n-1}) p_{n-1}(y_{n-1} | y_{n-2}) \dots \\ &\quad p_2(y_2 | y_1) p_1(y_1) \end{aligned}$$

$$p(y) = \left(\prod_{i=2}^n p_i(y_i | y_{i-1}) \right) p_1(y_1)$$

Example) binary y_i from before

$$p(y) = \left(\prod_{i=2}^{N+1} p_i(y_i | y_{i-1}) \right) p_1(y_1)$$

$$p(y_i | y_{i-1}) = \begin{cases} 1-p & y_i = y_{i-1} \\ p & y_i = 1 - y_{i-1} \end{cases}$$

$$p(y_1) = 1/2$$

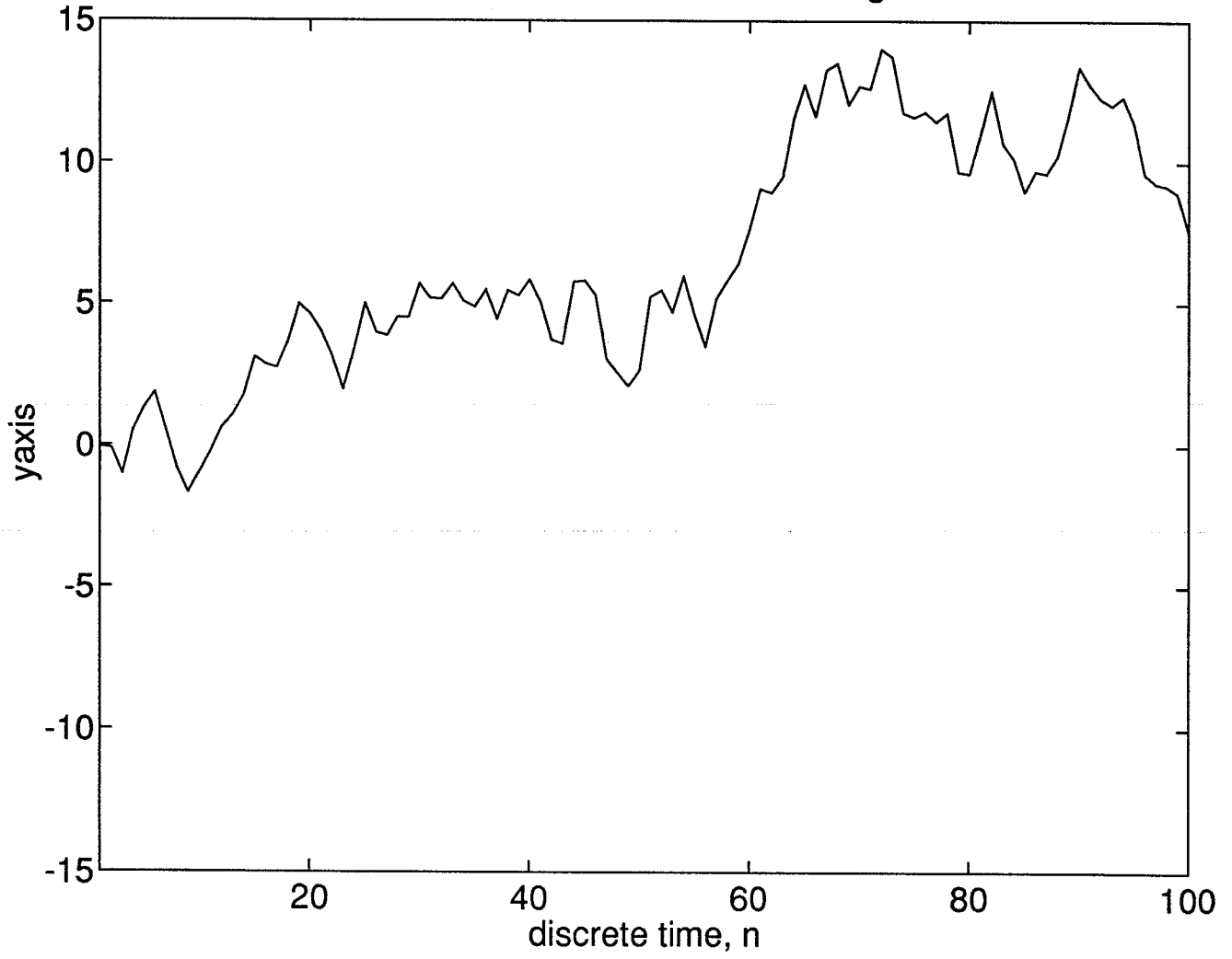
Define: $K \triangleq N - \sum_{i=2}^{N+1} \delta_{y_i - y_{i-1}}$

K = # of transitions

$N - K$ = # of no transition

$$p(y) = (1-p)^{N-K} p^K (1/2)$$

Continuous Valued Markov Chain: Sigma = 1



Example 2)

Let Y_i and B_i be binary sequences of 0's and 1's

$$P\{B_i = 1\} = p$$

$$P\{B_i = 0\} = 1-p$$

$$P\{Y_1 = 0\} = P\{Y_1 = 1\} = 1/2$$

Define

$$Y_{n+1} = \begin{cases} Y_n & B_n = 0 \\ 1 - Y_n & B_n = 1 \end{cases}$$

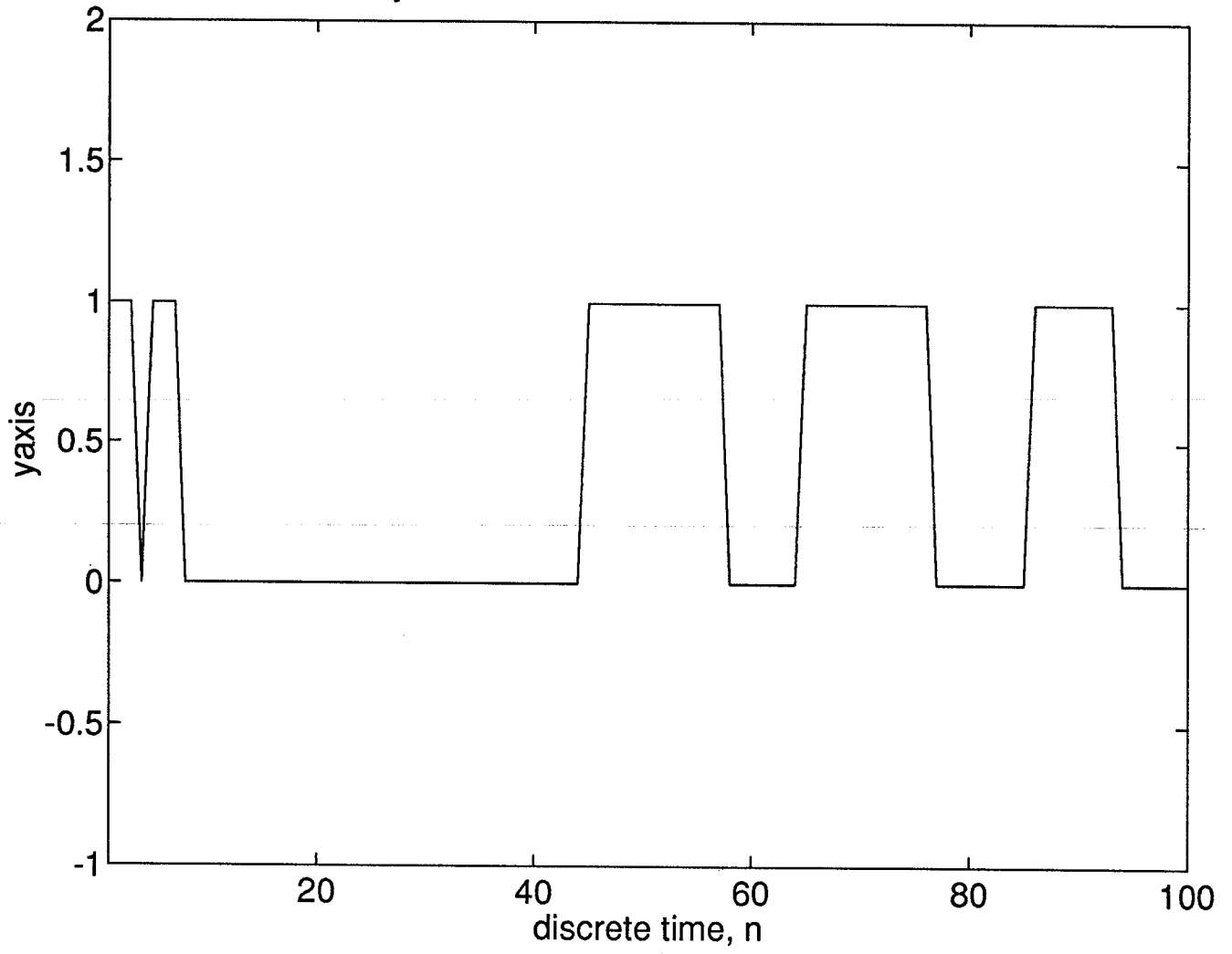
$B_n = 1 \Rightarrow$ transition

$B_n = 0 \Rightarrow$ no transition

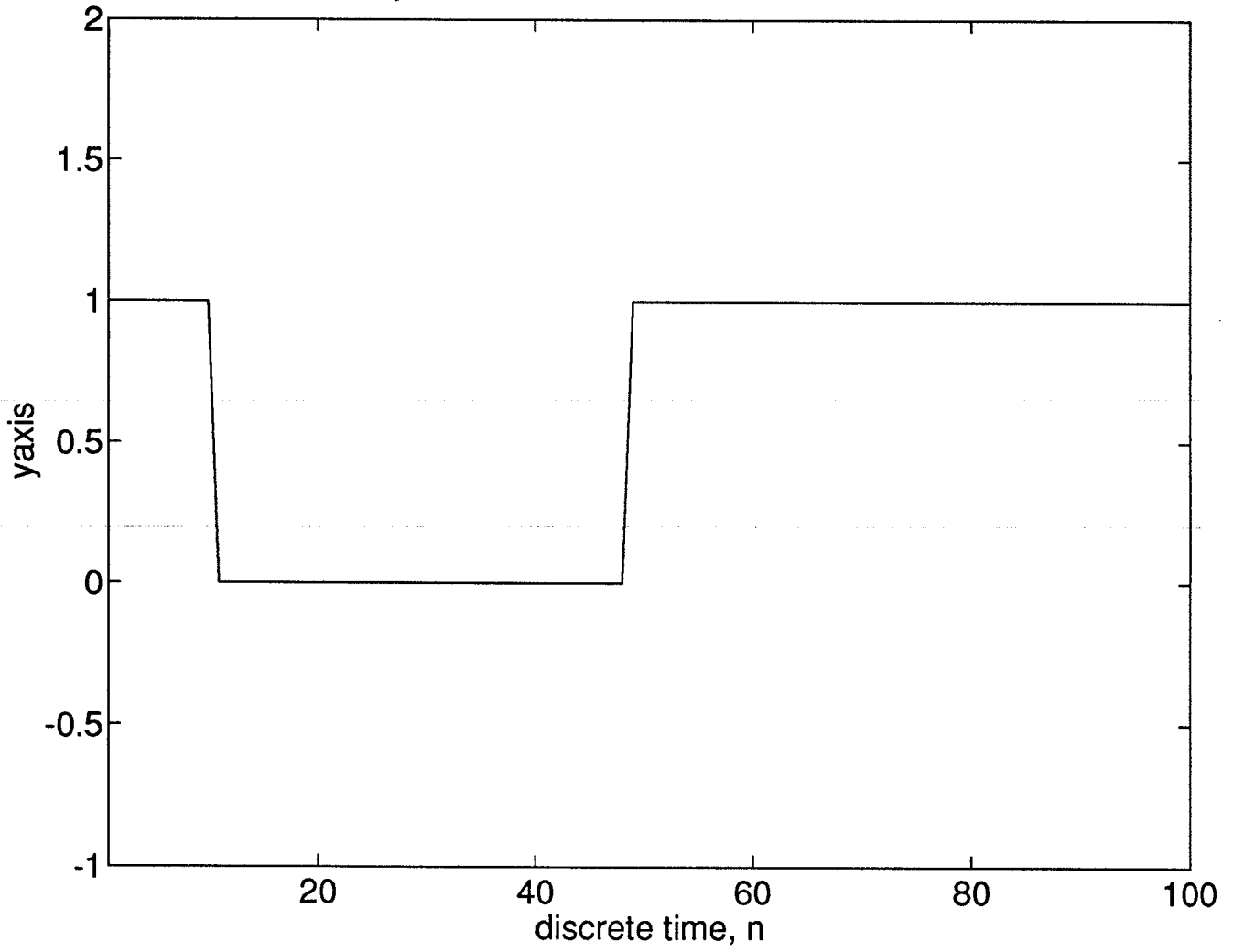
$$P(Y_n | Y_i, i < n) = P(Y_n | Y_{n-1})$$

$$= \begin{cases} 1-p & Y_n = Y_{n-1} \\ p & Y_n = 1 - Y_{n-1} \end{cases}$$

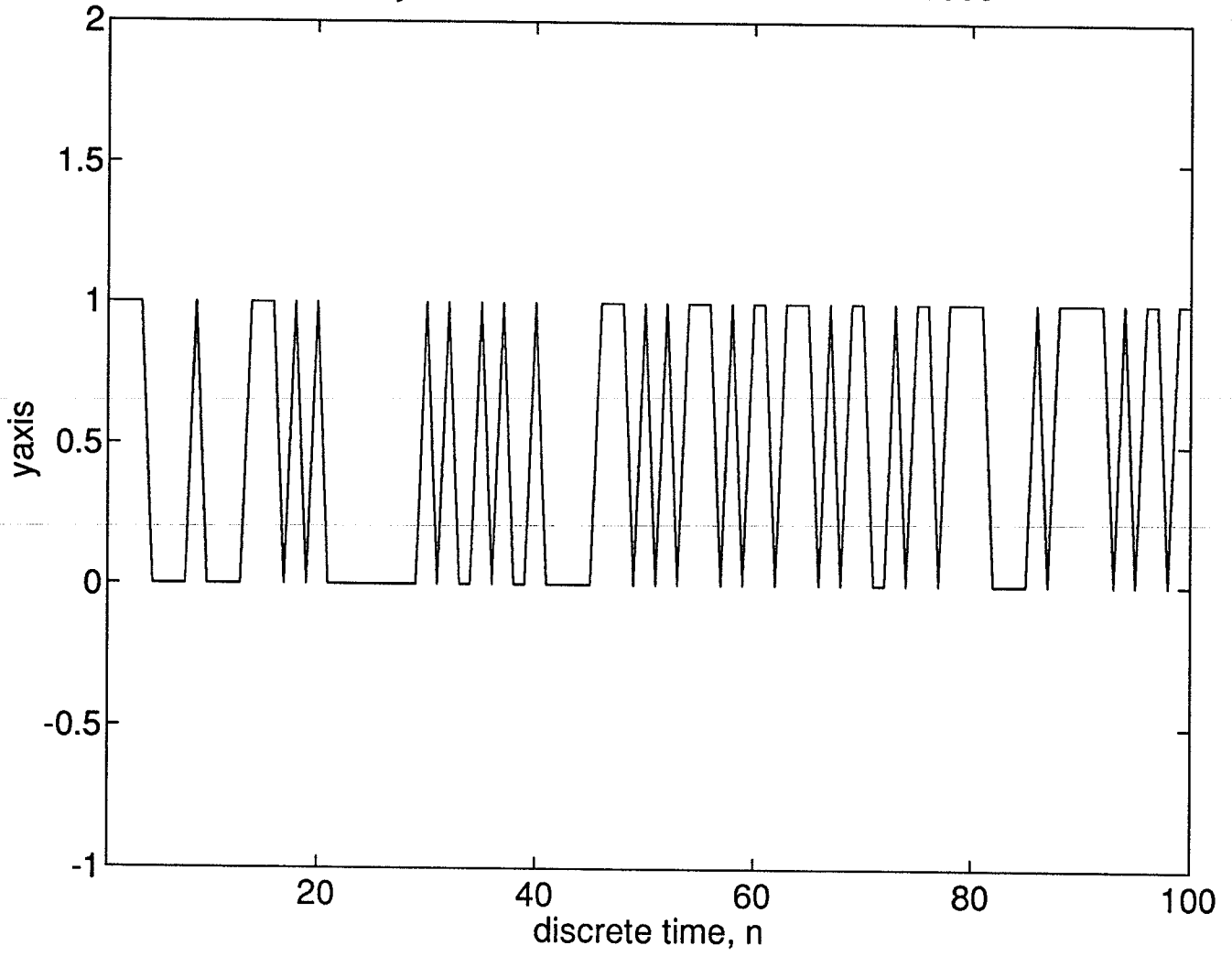
Binary Valued Markov Chain: rho = 0.100000



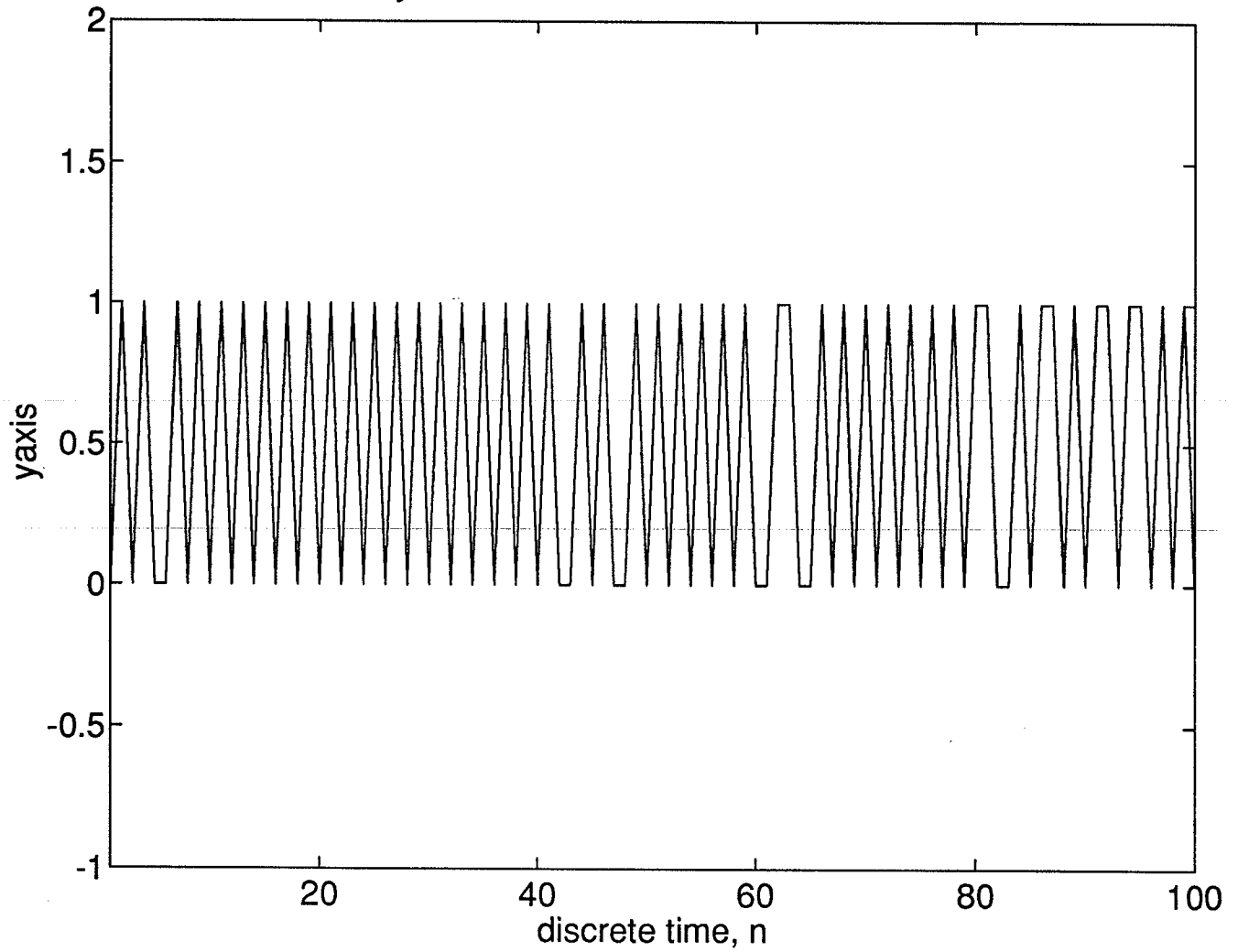
Binary Valued Markov Chain: rho = 0.020000



Binary Valued Markov Chain: rho = 0.500000



Binary Valued Markov Chain: rho = 0.900000



Defn X is a homogeneous Markov sequence if $\forall n$

$$P_n(y_n | y_{n-1}) = p(y_n | y_{n-1})$$

"Transitions do not depend on time"

Example Continuous y_i from before

$$y_n = \sum_{i=0}^n x_i \quad \text{from above}$$

$$P_n(y_n | y_{n-1}) \sim N(y_{n-1}, \sigma^2)$$

not a function of $n \Rightarrow$ homogeneous

Stationary? No!

Lecture 13

Parameter Estimation of Markov Chains

$$p_{\theta}(y) = \left(\prod_{i=2}^{N+1} p_{\theta}(y_i | y_{i-1}) \right) p(y_1)$$

$$\log p_{\theta}(y) = \sum_{i=2}^{N+1} \log p_{\theta}(y_i | y_{i-1}) + c$$

$$\hat{\theta}_{ML} = \underset{\theta}{\operatorname{argmax}} \left\{ \sum_{i=2}^{N+1} \log p_{\theta}(y_i | y_{i-1}) \right\}$$

Example) y discrete as before

$$p_p(y) = (1-p)^{N-K} p^K (y_2)$$

$$\log p_p(y) = (N-K) \log(1-p) + K \log p + c$$

$$\frac{d}{dp} \log p_p(y) = \frac{N-K}{1-p} (-1) + \frac{K}{p} = 0$$

$$(N-K)p = K(1-p)$$

$$Np = K$$

$$p = \frac{K}{N}$$

Generalization

$$p(X_n | X_i \ i < n) = p(X_n | X_{n-1}, X_{n-2}, \dots, X_{n-p})$$

Defn X_n is Markov with order p

Define $Y_n = \begin{bmatrix} X_n \\ X_{n-1} \\ \vdots \\ X_{n-p+1} \end{bmatrix}$

Then Y_n is Markov with order $p=1$.