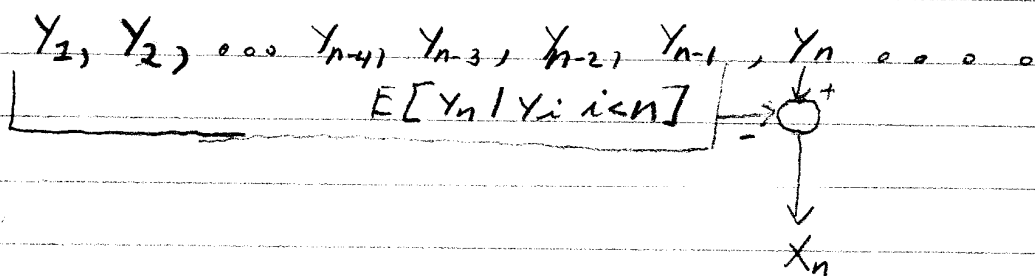


## Lecture 3

### Whitening

Let  $Y$  be a zero mean Gaussian discrete time random Process.



- Use all previous values of  $Y_i, i < n$  to predict  $Y_n$

$$\hat{Y}_n = E[Y_n | Y_{n-1}, Y_{n-2}, \dots, Y_1]$$

- Define the prediction errors  $X_n$

$$X_n = Y_n - \hat{Y}_n$$

$$= Y_n - E[Y_n | Y_i, i < n]$$

↑  
predictor

prop 1)  $E[Y_n | Y_i, i < n] = \sum_{i=1}^{n-1} a_{ni} Y_i$

Gaussian  $\Rightarrow$  Linear for some  $a_{ni}$   
 $\Rightarrow X_i$ 's Gaussian

property 2)  $X_n \perp\!\!\!\perp Y_i$  for  $i < n$   
if independent

For Gaussian, enough to be uncorrelated

$$(i < n) \quad E[X_n Y_i] = E[(Y_n - E[Y_n | Y_j, j < n]) Y_i]$$

$$= E[Y_n Y_i - E[Y_n Y_i | Y_j, j < n]]$$

includes  $Y_i$

$$= E[Y_n Y_i] - E[E[Y_n Y_i | Y_j, j < n]]$$

$$= 0$$

prop 3)  $X_n \perp\!\!\!\perp (Y_{n-1}, Y_{n-2}, \dots, Y_1)$

Because its pairwise independent  
and Gaussian

prop 4)  $X_n \perp\!\!\!\perp X_j$  for  $n \neq j$

assume that  $j < n$  ( $n < j$  the same)

$$E[X_n X_j] = E\left[X_n \left(Y_j - \sum_{i=1}^{j-1} a_{ji} Y_i\right)\right]$$

$$= E[X_n Y_j] - \sum_{i=1}^{j-1} a_{ji} E[X_n Y_i]$$

$\parallel$   $\parallel$   
 $0$   $0$

$$= 0$$

prop 5) Since the  $X_i$ 's are independent, we can write the distribution

$$\text{Let } \sigma_i^2 = E[X_i^2]$$

$$p_x(x) = \prod_{i=1}^N \frac{1}{\sqrt{2\pi} \sigma_i} \exp\left\{-\frac{1}{2\sigma_i^2} x_i^2\right\}$$