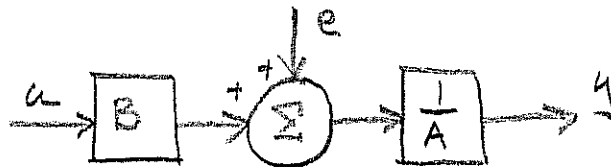


## LESSON 10: ARX MODELS

- OBJECTIVES:
- PROJECTION
  - LEAST-SQUARES

### 1.) ARX MODELS:



$n = \#$  input observations

$m = \#$  output observations

$N = \#$  samples collected

$$A(z)Y(z) = B(z)U(z) + E(z)$$

$$y[k] = \frac{b_0 u[k] + b_1 u[k-1] + \dots + b_m u[k-m]}{a_1 y[k-1] + a_2 y[k-2] + \dots + a_n y[k-n]}$$

→ Z-Transform yields z-domain transfer function:

→ Poles and Zeros

→ Roots of denominator & numerator.

→ Encapsulate frequencies & damping.

→ Derive DFT (DTFT) of transfer function:

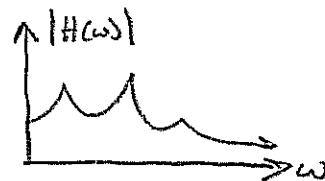
$$z = e^{j\omega T}$$

• Why not build DFT of Transfer Function directly?

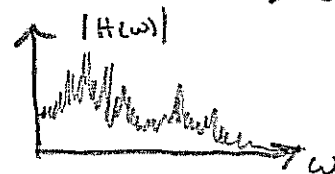
$$\text{DFT}(h[n]) = \frac{\text{DFT}(y[n])}{\text{DFT}(u[n])}$$

Problems: 1.) Data is noisy.

We want:



We get:



2.) Large models:  $n=m=N$

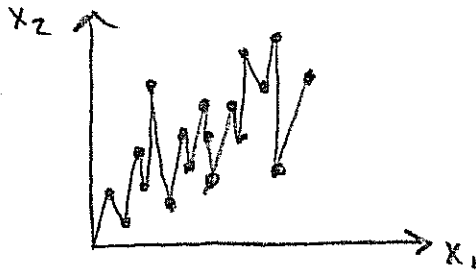
$N$  is often  $O(10^3 - 10^5)$

- Models should be smaller than the data set.

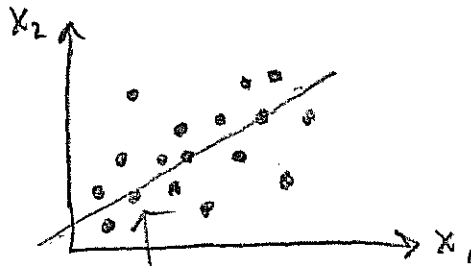
## 2.) Model size Reduction:

- Options:
- 1.) Downsampling
  - 2.) Windowing / Averaging
  - 3.) Projection / Least-squares ← This one

Consider data models:



Model Size = Data Set Size  
(Not very clever)



Linear regression

Model size = 2 < Data Set size

(Actually, Affine)

Projection:

High order → Low order

### EXAMPLE

n	x <sub>1</sub>	x <sub>2</sub>
1	0	1
2	5	8
3	3	4
4	5	6
5	7	10
6	2	4
7	3	7
8	1	5

$$x_2 = f(x_1) = c_0 + c_1 x_1$$

$$\begin{cases} c_0 + c_1 = 1 \\ c_0 + 5c_1 = 8 \\ c_0 + 3c_1 = 4 \\ c_0 + 5c_1 = 6 \\ c_0 + 7c_1 = 10 \\ c_0 + 2c_1 = 4 \\ c_0 + 3c_1 = 7 \\ c_0 + 1c_1 = 3 \end{cases}$$

Least-squares soln:

$$\bar{A} \bar{x} = \bar{b}$$

$\bar{A}$  = Data matrix (8x2)  
 $\bar{x}$  = Vector of least-squares solution (2x1)  
 $\bar{b}$  = Vector of outputs (8x1)

8 eqns, 2 unknowns  
↳ use least-squares!

Square →  $[\bar{A}^T \bar{A}] \bar{x} = \bar{A}^T \bar{b}$

$$\bar{x} = [\bar{A}^T \bar{A}]^{-1} \bar{A}^T \bar{b}$$

$\bar{x}$ : 2x1       $[\bar{A}^T \bar{A}]^{-1}$ : 2x2       $\bar{A}^T \bar{b}$ : 2x1

Size?  
8x8?  
2x2?

EXAMPLE CONTINUED:

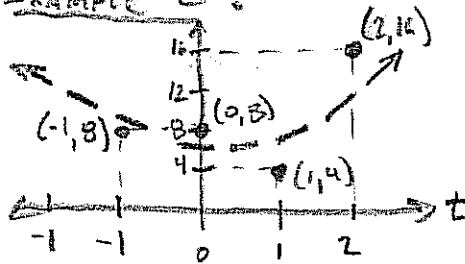
$$\begin{bmatrix} 1 & 0 \\ 1 & 5 \\ 1 & 3 \\ 1 & 5 \\ 1 & 7 \\ 1 & 2 \\ 1 & 3 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \end{bmatrix} = \begin{bmatrix} 8 \\ 4 \\ 6 \\ 10 \\ 4 \\ 7 \\ 3 \end{bmatrix} = \begin{bmatrix} 8 & 26 \\ 26 & 122 \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \end{bmatrix} = \begin{bmatrix} 43 \\ 184 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \end{bmatrix} = \begin{bmatrix} 1.54 \\ 1.18 \end{bmatrix}$$

Linear Model:  $x_2 = 1.54 + 1.18x_1$

→ More Complex Models OK? YES!

EXAMPLE 2:



$$f(t) = c_0 + c_1 t + c_2 t^2$$

parabolic regression

$$\bar{A}\bar{x} = \bar{b}$$

$$\begin{bmatrix} c_0 + t_1 c_1 + t_1^2 c_2 \\ c_0 + t_2 c_1 + t_2^2 c_2 \\ c_0 + t_3 c_1 + t_3^2 c_2 \\ c_0 + t_4 c_1 + t_4^2 c_2 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & -1 & 1 \\ 1 & 0 & 0 \\ 1 & 1 & 1 \\ 1 & 2 & 4 \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \\ c_2 \end{bmatrix} = \begin{bmatrix} 8 \\ 3 \\ 4 \\ 16 \end{bmatrix}$$

$$\begin{bmatrix} 4 & 2 & 6 \\ 2 & 6 & 8 \\ 6 & 8 & 18 \end{bmatrix} \begin{bmatrix} c_0 \\ c_1 \\ c_2 \end{bmatrix} = \begin{bmatrix} 36 \\ 28 \\ 78 \end{bmatrix}$$

$$\begin{bmatrix} c_0 \\ c_1 \\ c_2 \end{bmatrix} = \begin{bmatrix} 5 \\ -1 \\ 3 \end{bmatrix}$$

Parabolic Model:  $f(t) = 5 - t + 3t^2$

→ We can use same process to find ARX coefficients!

$$\begin{bmatrix} a_1, a_2, \dots, a_n \\ b_0, b_1, \dots, b_m \end{bmatrix}$$

## 3.) Least-squares for ARX:

Basic form:  $\bar{\Phi} \hat{\theta} = \bar{b}$   
 $(\bar{A} \bar{x} = \bar{b})$

$$\hat{\theta} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \\ b_0 \\ b_1 \\ \vdots \\ b_m \end{bmatrix} \leftarrow \text{we want this}$$

$s \times 1$

$n = \#$  output observations  
 $m = \#$  input observations  
 $N = \#$  samples collected  
 $S = n + p + 1$   
 define:  $p = \max(m, n)$

$$y[k] = \frac{b_0 u[k] + b_1 u[k-1] + \dots + b_m u[k-m]}{a_1 y[k-1] + a_2 y[k-2] + \dots + b_n u[k-n]}$$

$$\bar{b} = \begin{bmatrix} y[p+1] \\ y[p+2] \\ \vdots \\ y[k] \\ \vdots \\ y[N] \end{bmatrix} \leftarrow \text{Output signal, minus some of the initial points.}$$

$(N-p) \times 1$

What if the system is at rest for  $k < 0$ ?

$$\bar{\Phi} = \begin{bmatrix} -y[p] - y[p-1] \dots - y[p+1-n] & u[p+1] & u[p] & \dots & u[p+1-m] \\ -y[p+1] - y[p] \dots - y[p+2-n] & u[p+2] & u[p+1] & \dots & u[p+2-m] \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -y[k-1] - y[k-2] \dots - y[k-n] & u[k] & u[k-1] & \dots & u[k-m] \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -y[N] - y[N-1] \dots - y[N-n] & u[N] & u[N-1] & \dots & u[N-m] \end{bmatrix} (N-p) \times S$$

$$H(z) = \frac{Y(z)}{U(z)} = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2} + \dots + b_m z^{-m}}{1 + a_1 z^{-1} + a_2 z^{-2} + \dots + a_n z^{-n}}$$

$$H(z) = z^{-(n-n)} \frac{b_0 z^m + b_1 z^{m-1} + b_2 z^{m-2} + \dots + b_m}{z^n + a_1 z^{n-1} + a_2 z^{n-2} + \dots + a_n}$$

Roots Give Poles

\* Uses "batch" of data samples  $\rightarrow$  "Batch" Least-Squares