

Discussion 6A

System Identification

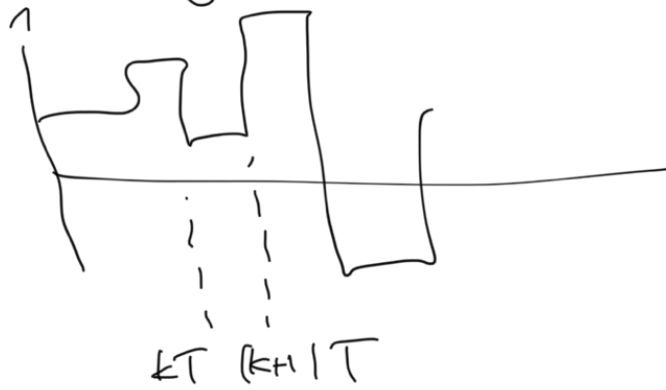
* Least Squares

* System ID



Discretization

↳ solving diff eqs w/ constant inputs



Solve diff eq just in this interval

$$\frac{dx(t)}{dt} = \lambda x(t) + u(t)$$

↳ From Week 1, know how to solve!

From kT to $kT+T$

$$u(t) = u[k] = \text{const.}$$

"Trick": in this specific time interval, have a diff eq like from week 1 w/

constant inputs

Solution?

$$x(t) = x(kT) e^{\lambda(t-kT)} + \mu u[k] \int_{kT}^t e^{\lambda(t-\tau)} d\tau$$

CT $\rightarrow x(kT) = x[k] \leftarrow$ DT

$$x[k+1] = e^{\lambda T} x[k] + (1 - e^{\lambda T}) u[k]$$

(For $\frac{dx}{dt} = \lambda(x) + u(t)$) \leftarrow special case

How to solve in vector case?

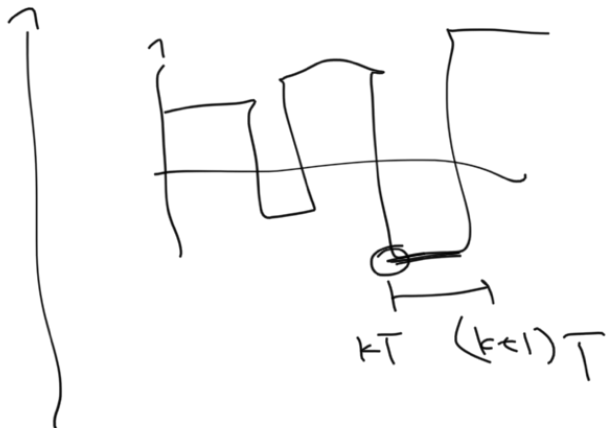
a) diagonalization

\rightarrow change basis so you have a system of scalar constant-input diff eqs like we already saw

b) non-diagonalizable

\rightarrow can do by direct integration (ITC)
 \rightarrow or have to use matrix exponential (out of scope)

$$\frac{dx}{dt} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 1/\mu \end{bmatrix} u(t)$$



$$\frac{dx}{dt} = v(t)$$

$$\frac{dv}{dt} = \frac{u(t)}{M} \quad \text{Solve for } t \in (kT, (k+1)T)$$

$$\int_{v(kT)}^{v((k+1)T)} dv = \int_{kT}^{(k+1)T} \frac{u(t)}{M} dt = \int_{kT}^{(k+1)T} \frac{u[k]}{M} dt$$

$$v((k+1)T) - v(kT) = \frac{u[k]}{M} ((k+1)T - kT) = \frac{u[k]}{M} T$$

$$v[k+1] - v[k] = \frac{u[k]}{M} T$$

$$v[k+1] = v[k] + \frac{u[k]}{M} T$$

(Discretize $x(t)$ similarly — see D.3.5c)

(I) Least Squares and SVD Recap

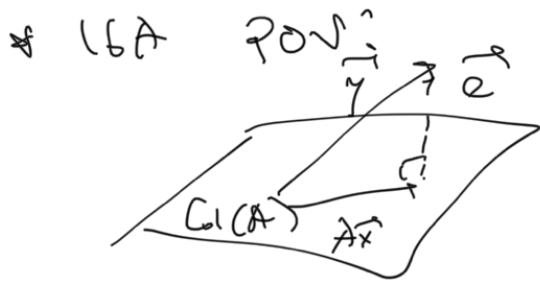
Problem Statement:

$$\vec{y} = A\vec{x} + \vec{e}$$

$$A \in \mathbb{R}^{m \times n}, \quad m > n, \quad \text{rank } n$$

(tall matrix, lin. ind. columns)

$$\text{Goal: Find } \vec{x}^* = \min_{\vec{x}} \|\vec{e}\|^2 = \min_{\vec{x}} \|A\vec{x} - \vec{y}\|^2$$



$$\underline{\vec{x} = (A^T A)^{-1} A^T \vec{y}}$$

★ 16B POV SVD!

$$\vec{x}^* = \min_{\vec{x}} \|A\vec{x} - \vec{y}\|^2 = \|U\Sigma V^T \vec{x} - \vec{y}\|^2$$

Note $\|U\vec{x}\| = \|\vec{x}\|$

↑ unitary transformation is length-preserving

$$= \|U^T U \Sigma V^T \vec{x} - U^T \vec{y}\|^2$$

$$= \|\Sigma V^T \vec{x} - U^T \vec{y}\|^2$$

$$= \left\| \begin{bmatrix} \Sigma_c \\ 0 \end{bmatrix} V^T \vec{x} - \begin{bmatrix} U_c^T \\ U_2^T \end{bmatrix} \vec{y} \right\|^2$$

$$= \left\| \begin{bmatrix} \Sigma_c V^T \vec{x} - U_c^T \vec{y} \\ -U_2^T \vec{y} \end{bmatrix} \right\|^2$$

↑ can't change (fixed)
w/ choice of \vec{x}

We can choose \vec{x}^* s.t. this top term is 0

$$\underline{\vec{x}^* = \sqrt{\Sigma_c^{-1}} U_c^T \vec{y}}$$

- * 16A and 16B eqns are equal (they should be)
- * SVD POV can help elucidate geometric nature of problem / relation to matrix fundamental subspaces

$$\left. \begin{array}{l} U_c \\ \vec{u}_1 \dots \vec{u}_r \\ \text{span Col}(A) \end{array} \right\} \left. \begin{array}{l} U_2 \\ \vec{u}_{r+1} \dots \vec{u}_m \\ \text{span Null}(A^T) \end{array} \right\} \text{span } \mathbb{R}^m$$

(From $A\vec{u}_i = \sigma_i \vec{u}_i$)

Consider $\vec{y}^* = A\vec{x}^* = U\Sigma U^T (\sqrt{\Sigma_c^{-1}} U_c^T \vec{y})$

$$\begin{aligned}
 &= U\Sigma \Sigma_c^{-1} U_c^T \vec{y} \\
 &= U \begin{bmatrix} \Sigma_c \\ 0 \end{bmatrix} \Sigma_c^{-1} U_c^T \vec{y} \\
 &= U \begin{bmatrix} I \\ 0 \end{bmatrix} U_c^T \vec{y} \\
 &= [U_c \ U_2] \begin{bmatrix} I \\ 0 \end{bmatrix} U_c^T \vec{y} \\
 &= (U_c I + U_2 0) U_c^T \vec{y} \\
 &= U_c U_c^T \vec{y}
 \end{aligned}$$

What is this?

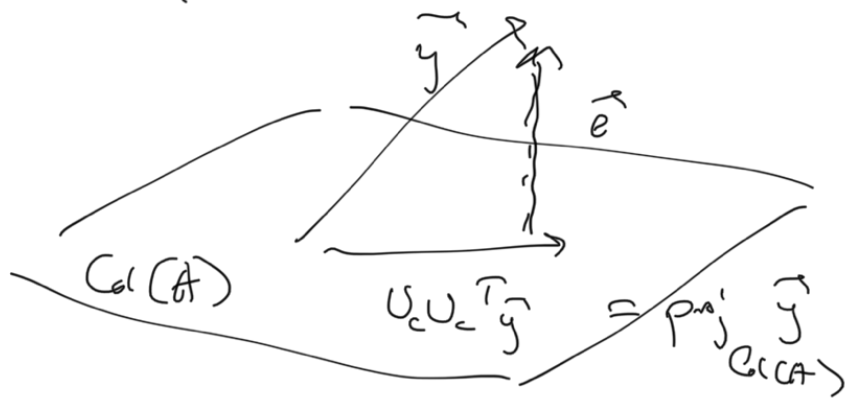
$$= \begin{bmatrix} \uparrow & & \uparrow \\ \vec{u}_1 & \dots & \vec{u}_r \\ \perp & & \perp \end{bmatrix} \begin{bmatrix} \leftarrow \vec{u}_1^T \rightarrow \\ \vdots \\ \leftarrow \vec{u}_r^T \rightarrow \end{bmatrix} \vec{y}$$

$$\begin{aligned}
 &= \begin{bmatrix} \uparrow & & \uparrow \\ u_1 & \dots & u_r \\ \downarrow & & \downarrow \end{bmatrix} \begin{bmatrix} u_1^T y \\ \vdots \\ u_r^T y \end{bmatrix} \\
 &= \begin{bmatrix} \uparrow & & \uparrow \\ u_1 & \dots & u_r \\ \downarrow & & \downarrow \end{bmatrix} \begin{bmatrix} \langle u_1, y \rangle \\ \vdots \\ \langle u_r, y \rangle \end{bmatrix}
 \end{aligned}$$

$$= \langle \vec{u}_1, \vec{y} \rangle \vec{u}_1 + \langle \vec{u}_2, \vec{y} \rangle \vec{u}_2 + \dots + \langle \vec{u}_r, \vec{y} \rangle \vec{u}_r$$

Projection of \vec{y} onto the columns of U_c

\Rightarrow projection onto the $\text{Col}(A)$!

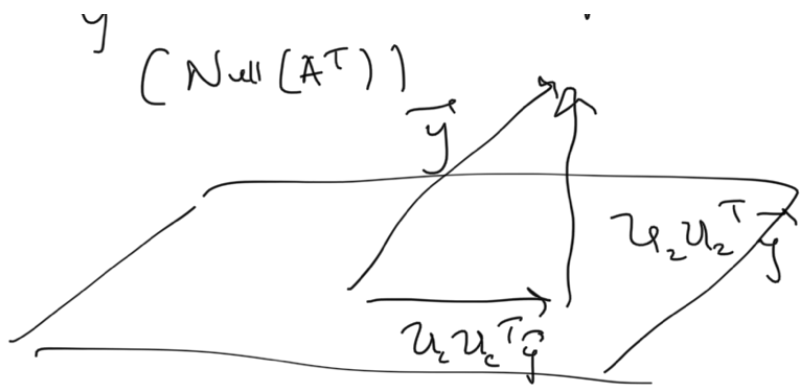


In fact,

$$\vec{z} = I\vec{y} = UU^T\vec{y} = \begin{bmatrix} u_1 & u_2 \end{bmatrix} \begin{bmatrix} u_1^T \\ u_2^T \end{bmatrix} \vec{y}$$

$$= u_1 u_1^T \vec{y} + u_2 u_2^T \vec{y}$$

projection of \vec{y} onto the \perp complement of $\text{Col}(A)$



When we choose \vec{x}^* s.t.

$$\begin{aligned} \|\vec{e}\| &= \left\| \begin{bmatrix} 0 \\ u_2^T \vec{y} \end{bmatrix} \right\| = \left\| u \begin{bmatrix} 0 \\ u_2^T \vec{y} \end{bmatrix} \right\| \\ &= \left\| \begin{bmatrix} u_1 & u_2 \end{bmatrix} \begin{bmatrix} 0 \\ u_2^T \vec{y} \end{bmatrix} \right\| \\ &= \| u_2 u_2^T \vec{y} \| \end{aligned}$$

↑ only leaving 1 component's contribution in the error

* ASIDE: similar exercise w/ min norm solution

$$\vec{x} = \min_{\vec{x}} \|\vec{x}\| \quad \text{s.t.} \quad A\vec{x} = \vec{y}$$

(wide matrix, lin. ind. rows)

$$\|\vec{x}\| = \|V^T \vec{x}\| = \left\| \begin{bmatrix} v_1^T \vec{x} \\ \vdots \\ v_r^T \vec{x} \\ v_{r+1}^T \vec{x} \\ \vdots \\ v_n^T \vec{x} \end{bmatrix} \right\|$$

$\underbrace{\vec{v}_1 \dots \vec{v}_r}_{\text{span } \mathbb{R}^r}, \underbrace{\vec{v}_{r+1} \dots \vec{v}_n}_{\text{span } \mathbb{R}^{n-r}}$

Col(A^T) Null(A)

To minimize $\|\vec{x}\|^2$ s.t. $V^T \vec{x}^* = 0$

$$\begin{bmatrix} \langle \vec{v}_{r+1}, \vec{x}^* \rangle \\ \vdots \\ \langle \vec{v}_n, \vec{x}^* \rangle \end{bmatrix} = 0$$

\vec{x}^* is \perp to Null(A)

(No component of \vec{x}^* lies in Null(A))

If we did change of basis

$$\vec{x}_V^* = V^T \vec{x}^* = \begin{bmatrix} c_1 \\ \vdots \\ c_r \\ c_{r+1} \\ \vdots \\ c_n \end{bmatrix} \left. \begin{array}{l} \} \rightarrow \perp \text{ basis for Col}(A^T) \\ \} \rightarrow \perp \text{ basis for Null}(A) \end{array} \right\}$$

Coordinates of \vec{x}^* in the V basis

Then minimum norm solution, which has no component lying along the Null(A), looks like:

$$\vec{x}_V^* = \begin{bmatrix} c_1 \\ \vdots \\ c_r \\ 0 \\ \vdots \\ 0 \end{bmatrix} \leftarrow \text{all } 0!$$

★ LS Example: Polynomial Fitting

Known output follows:

$$y = a_0 + a_1 x + a_2 x^2$$

eq. $\Delta x = v_0 t + \frac{1}{2} a t^2$

x	y
0	0
0.5	4
1	10
1.5	18
2	30

$$\vec{A} + \vec{e} = \vec{y} \quad ?$$

Unknown params: a_0, a_1, a_2

Measure: y_1, y_2, y_3, y_4, y_5

"Input": x_1, x_2, x_3, x_4, x_5

$$\begin{cases} y_1 = a_0 + a_1 x_1 + a_2 x_1^2 \\ \vdots \\ y_5 = a_0 + a_1 x_5 + a_2 x_5^2 \end{cases}$$

$$\begin{bmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ 1 & x_3 & x_3^2 \\ 1 & x_4 & x_4^2 \\ 1 & x_5 & x_5^2 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{bmatrix}$$

$$\rightarrow \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0.5 & 0.25 \\ 1 & 1 & 1 \\ 1 & 1.5 & 2.25 \\ 1 & 2 & 4 \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 4 \\ 10 \\ 18 \\ 30 \end{bmatrix}$$

$$\hat{p} \approx \hat{y}$$

$$\hat{\hat{p}} = (D^T D)^{-1} D^T \hat{y}$$

$$a_0 = 0.17$$

$$a_1 = 4.5$$

$$a_2 = 5.14$$

I was roughly using $\Delta x \approx 5t + \frac{1}{2} 10t^2$

④ System ID

Just LS applied to state space models!

$$a) \quad x[k+1] = ax[k] + bu[k] + e[k] \quad \leftarrow \begin{array}{l} \text{noise,} \\ \text{disturbance,} \\ \text{error} \end{array}$$

Observe initial state $x[0]$:

input $u[0]$, output $x[1]$

input $u[1]$, output $x[2]$

⋮

$$x[1] = ax[0] + bu[0] + e_1$$

$$x[2] = ax[1] + bu[1] + e_2$$

⋮

$$x[n+1] = ax[n] + bu[n] + e_n$$

$$\begin{bmatrix} x[1] \\ \vdots \\ x[n+1] \end{bmatrix} = \begin{bmatrix} x[0] & u[0] \\ \vdots & \vdots \\ x[n] & u[n] \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix}$$

$$\begin{bmatrix} \vdots \\ x[n+1] \end{bmatrix} = \begin{bmatrix} x[n] & u[n] \\ \vdots & \vdots \\ x[n] & u[n] \end{bmatrix} \begin{bmatrix} 1 & 0 \\ \vdots & \vdots \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} \vdots \\ e \end{bmatrix}$$

\vec{y} D \vec{p}

$$\vec{y} \approx D \vec{p}$$

Know how to solve!

$$\boxed{\vec{p}^* = (D^T D)^{-1} D^T \vec{y}}$$

Best fitting parameters for identifying the system

b) Vector Case

Messy symbolically, but essentially, unrolling vector system into a bunch of scalar eqns

$$\begin{bmatrix} x_0[k+1] \\ x_1[k+1] \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_0[k] \\ x_1[k] \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u[k]$$

$$\hookrightarrow x_0[k+1] = 0$$

$$x_1[k+1] = x_1[k] + u[k]$$

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & \dots & \dots & a_{nn} \end{bmatrix}$$

since $\vec{x} \in \mathbb{R}^n$

$n \times n$

$$B = \begin{bmatrix} \dots & \dots & \dots \\ b_{11} & \dots & b_{1m} \\ \vdots & & \vdots \\ b_{n1} & \dots & b_{nm} \end{bmatrix} \quad \text{since } \vec{u} \in \mathbb{R}^m$$

$$\begin{bmatrix} x_1[k+1] \\ \vdots \\ x_n[k+1] \end{bmatrix} = \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} x_1[k] \\ \vdots \\ x_n[k] \end{bmatrix} + \begin{bmatrix} b_{11} & \dots & b_{1m} \\ \vdots & & \vdots \\ b_{n1} & \dots & b_{nm} \end{bmatrix} \begin{bmatrix} u_1[k] \\ \vdots \\ u_m[k] \end{bmatrix}$$

Look at one row:

$$x_j[k+1] = \sum_{j=1}^n a_{ij} x_j[k] + \sum_{j=1}^m b_{ij} u_j[k]$$

$$= \underbrace{\begin{bmatrix} x_1[k] & \dots & x_n[k] & u_1[k] & \dots & u_m[k] \end{bmatrix}}_{n+m \text{ entries } n \text{ total}} \begin{bmatrix} a_{j1} \\ \vdots \\ a_{jn} \\ b_{j1} \\ \vdots \\ b_{jm} \end{bmatrix}$$

Can do this for all $j=1 \dots n$

\Rightarrow create a giant stacked vector of parameters

$$\vec{p} \in \mathbb{R}^{(n+m)n}$$

$$D \in \mathbb{R}^{nK \times n(n+m)}$$

$K = \#$ of time steps you observe

(not including initial state $\vec{x}[0]$)

For D to be a "full" matrix,
 $nK \geq n(m+n)$

$$\Rightarrow K \geq m+n$$

(Need more than $m+n$ timesteps observed)
to do LS / System ID

① System ID and Linear Control

Worksheet

$$x[t+1] = \lambda x[t] + g(u[t])$$

a) Approx $g(u)$ to $O(2)$ about $u^* = 0$

\Rightarrow Taylor expand to order 2 about $u^* = 0$

(before, plain linearization \rightarrow order 1)

Recall: $f(x) \approx f(x^*) + f'(x^*)(x-x^*)$
 $+ \frac{f''(x^*)(x-x^*)^2}{2!}$

$$f(x) \approx \sum_{n=0}^{\infty} \frac{f^{(n)}(x^*)(x-x^*)^n}{n!} + \frac{f'''(x^*)(x-x^*)^3}{3!}$$

+ ...

In this case, $x^* \Rightarrow u^* = 0$

$$f(x) \Rightarrow g(u)$$

Truncate
here to
get $O(2)$

$$g(u) \approx g(0) + g'(0)(u-0) + \frac{g''(0)}{2}(u-0)^2$$

$$= \beta_0 + \beta_1 u + \beta_2 u^2$$

We see:

$$\begin{cases} \beta_0 = g(0) \\ \beta_1 = g'(0) \\ \beta_2 = \frac{g''(0)}{2} \end{cases}$$

Plug into $x[t+1] \approx \lambda x[t] + \beta_0 + \beta_1 u[t] + \beta_2 u[t]^2$

b) $x[0] = 0$

Input $u[0], \dots, u[N-1]$



Observe $x[1] \dots x[N]$

LS estimates of $\lambda, \beta_0, \beta_1, \beta_2$?

$$\Rightarrow \vec{p} = \begin{bmatrix} \lambda \\ \beta_0 \\ \beta_1 \\ \beta_2 \end{bmatrix}$$

$$x[1] = \lambda x[0] + \beta_0 + \beta_1 u[0] + \beta_2 u[0]^2$$

⋮

$x[N]$

$$\vec{y} \approx D \vec{p}$$

$$\begin{bmatrix} x[0] \\ \vdots \\ x[N] \end{bmatrix} \approx \begin{bmatrix} x[0] & | & u[0] & | & u[0] \\ \vdots & & \vdots & & \vdots \\ x[N-1] & | & u[N-1] & | & u[N-1] \end{bmatrix} \begin{bmatrix} 1 \\ B_0 \\ B_1 \\ \vdots \\ B_L \end{bmatrix}$$

$$\hat{\vec{p}} = (D^T D)^{-1} D^T \vec{y}$$

where D, \vec{y}
defined above

② System IO

$$\vec{x}(t+1) = A \vec{x}(t) + B u(t) + \vec{w}(t)$$

$$A = \begin{bmatrix} a_0 & a_1 \\ a_2 & a_3 \end{bmatrix} \quad B = \begin{bmatrix} b_0 \\ b_1 \end{bmatrix} \quad x(t) = \begin{bmatrix} x_0(t) \\ x_1(t) \end{bmatrix}$$

a) Assume $w(t) = 0$
(perfect model)

$$x_0[t+1] = ?$$

$$x_1[t+1] = ?$$

Scalar eqns \Rightarrow unravel $Ax + Bu$

$$\begin{aligned} x_0[t+1] &= a_0 x_0[t] + a_1 x_1[t] + b_0 u[t] \\ x_1[t+1] &= a_2 x_0[t] + a_3 x_1[t] + b_1 u[t] \end{aligned}$$

b) How many inputs / time steps do we need to observe?

$$\begin{array}{c}
 u[0], u[1] \dots u[m] \\
 \text{observe } \downarrow \\
 \vec{x}[1] \dots \vec{x}[m+1]
 \end{array}
 \quad m=?$$

$$m = 4$$

6 unknowns \rightarrow need minimum 6 eqns

- Each time step gives us 2 eqns

$$\boxed{m = \frac{6 \text{ eqn}}{2 \text{ eqns / timestep}} = 3 \text{ timestep,}}$$

From lecture:

$$\vec{x} \in \mathbb{R}^n, \vec{u} \in \mathbb{R}^m$$

$$\Rightarrow n=2, m=1$$

$$\text{Then } \vec{p} \in \mathbb{R}^{(m+1)n} = \mathbb{R}^6$$

$$D \in \mathbb{R}^{nK \times n(m+1)} = \mathbb{R}^{2K \times 6}$$

So to be "tall",

$$2K \geq 6 \Rightarrow \underline{K \geq 3} \Rightarrow m=3 \quad \text{time steps minimum}$$

c) Set up a LS problem $D\vec{p} = \vec{y}$

$$D = \begin{bmatrix}
 x_0[0] & x_1[0] & u[0] & 0 & 0 & 0 \\
 x_0[1] & x_1[1] & u[1] & 0 & 0 & 0 \\
 x_0[2] & x_1[2] & u[2] & 0 & 0 & 0
 \end{bmatrix}$$

$$\begin{pmatrix} x_0[3] & x_1[3] & x_2[3] & 0 & 0 & 0 \\ 0 & 0 & 0 & & & \\ 0 & 0 & 0 & & & \\ 0 & 0 & 0 & & & \\ 0 & 0 & 0 & & & \end{pmatrix}$$

What should \vec{y} , \vec{p} be?

$$\vec{p} = \begin{bmatrix} a_0 \\ a_1 \\ b_0 \\ a_2 \\ a_3 \\ b_1 \end{bmatrix} \quad \vec{y} = \begin{bmatrix} x_0[1] \\ x_0[2] \\ x_0[3] \\ x_0[4] \\ x_1[1] \\ x_1[2] \\ x_1[3] \\ x_1[4] \end{bmatrix}$$

$$x_0[1] = a_0 x_0[0] + a_1 x_1[1] + b_0 u[0]$$

Because symmetry of D , you could flip the order for both \vec{y} and \vec{p}

$$\vec{y} = \begin{bmatrix} x_1[1] \\ \vdots \\ x_1[4] \\ x_0[1] \\ \vdots \\ x_0[4] \end{bmatrix} \quad \vec{p} = \begin{bmatrix} a_2 \\ a_3 \\ b_1 \\ a_0 \\ a_1 \\ b_0 \end{bmatrix}$$

also a valid solution

$$d) \quad \vec{p} = (D^T D)^{-1} D^T \vec{y}$$

Impt: Assumed columns of D are lin. independent
 \rightarrow thus we can invert $D^T D$

e) What could go wrong? WCGW?

Could be that D is not invertible!

$$D = \begin{bmatrix} x_0[0] & x_1[0] & u[0] \\ x_0[1] & x_1[1] & u[1] \\ x_0[2] & x_1[2] & u[2] \\ x_0[3] & x_1[3] & u[3] \\ & & & & 0 \\ & & & & & & \ddots \end{bmatrix}$$

$$\begin{aligned} x_0[0] &= x_1[0] \\ x_0[1] &= x_1[1] \end{aligned} \Rightarrow \vec{x}_0 = \vec{x}_1 \quad \ddots$$

"Control Law" : $u[t] = x_0[t]$

(Plug observed output back into the input)

$$D = \begin{bmatrix} x_0[0] & x_1[0] & u[0] = x_0[0] \\ x_0[1] & x_1[1] & u[1] = x_0[1] \\ x_0[2] & x_1[2] & u[2] = x_0[2] \\ x_0[3] & x_1[3] & u[3] = x_0[3] \\ & & & & 0 \\ & & & & & & \ddots \end{bmatrix}$$

the same column!

By poor choice of inputs, we messed up the system ID (have to be careful!)

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