

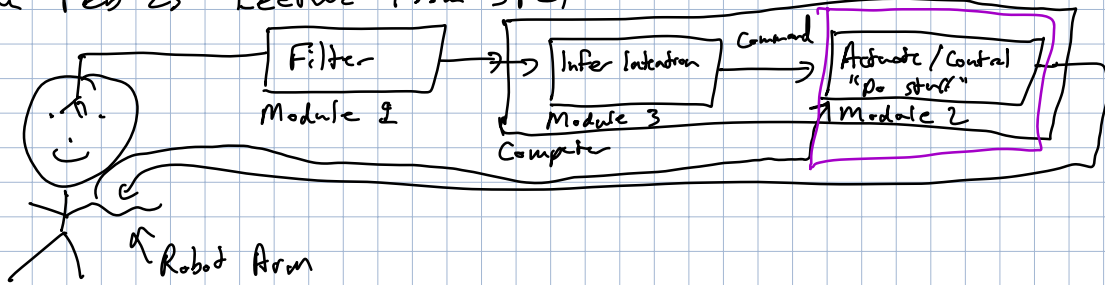
16B 9/30/21

Prof ANANT SAHAI

Today: Intro to control
 Continuous time \rightarrow discrete-time
 System Identification from data.

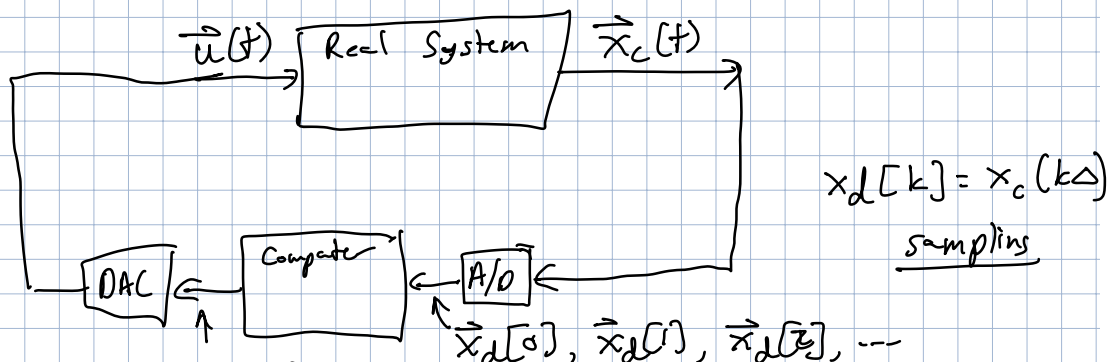
Midterm: Oct 18th

Wed Feb 25th Lecture from SPL

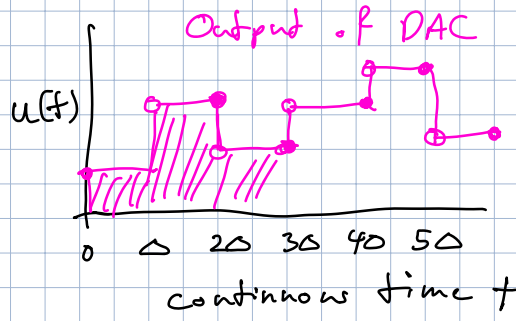
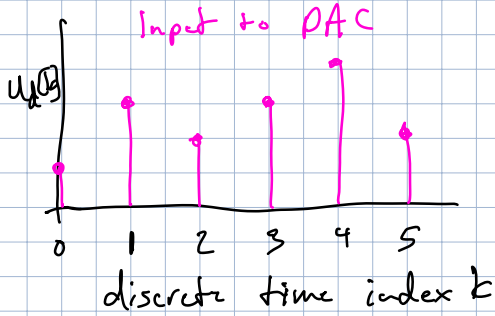


Foundations of Machine learning to interact with a dynamic world.
 Modules 1,2,3 1 2 3 1 2 3 1 2 3

Real World	Computational World "Software"
Continuous time	Discrete time
time flows	time "ticks"
time infinitely divisible	a clock tick
Differential Equations.	Recurrence Relations
$\frac{d}{dt} \vec{x}(t) = f(\vec{x}(t), \dots)$	$\vec{x}_d[k+1] = g(\vec{x}_d[k], \dots)$



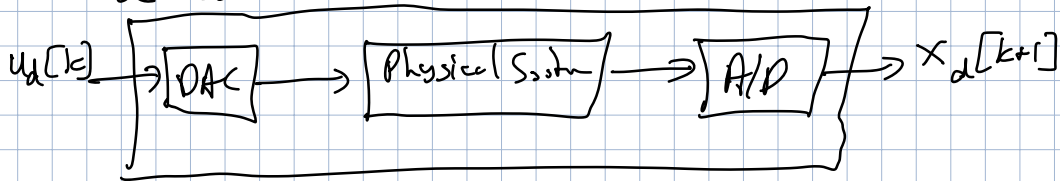
$\vec{u}_d[0], \vec{u}_d[1], \dots$



Diff Eqz for Real System

$$\frac{d}{dt} \vec{x}_c(t) = \underbrace{A}_{\text{Nature of the physical system}} \vec{x}_c(t) + \underbrace{B}_{\text{Engineer's choice of input}} \vec{u}(t) + \underbrace{\vec{w}(t)}_{\text{Nature's input}}$$

Want a discrete-time model for



Want / Goal: Discrete-time model:

$$\vec{x}_d[k+1] = A_d \vec{x}_d[k] + B_d \vec{u}_d[k] + \vec{w}_d[k]$$

Remember Discussion ZB

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

If you applied controls $u(t) = u_d[i]$ if $t \in (i\Delta, (i+1)\Delta]$

Then $x_d[i+1] = e^{\lambda\Delta} x_d[i] + b \left(\frac{e^{\lambda\Delta} - 1}{\lambda} \right) u_d[i]$ if $\lambda \neq 0$

Let's do $\lambda=0$ ourselves.

$$\frac{d}{dt} x(t) = 0 \cdot x(t) + b u(t) = b u(t)$$

$$x(t) = x(0) + \int_0^t b u(\tau) d\tau$$

$$x^{(i+1)\Delta} = x(0) + b \sum_{k=0}^i \Delta u_d[k]$$

$$\parallel \\ x_d[i+1] = x_d[i] + b \Delta u_d[i]$$

In Discussion on Monday, extend to the vector case.

$$A \rightarrow A_d \quad \text{given } \Delta$$

$$B \rightarrow B_d$$

How do we get A_d & B_d if we don't have a diff Eq.?

Learn it from experiments & collected data

System Identification: Given a "trace" of the input/output behavior of a system, figure out the system model.

$$x[k+1] = \underbrace{(A)}_{\text{Don't know}} x[k] + \underbrace{(B)}_{\text{Don't know}} u[k] + \underbrace{w[k]}_{\text{disturbance}}$$

Don't know

disturbance
I hope it is small
Treat like "noise".

I know $u[k]$ because I chose these

I know $x[k]$ because I measured them.

2 unknowns. How many equations?

Suppose I collect from $k=0, \dots, k=T$

I know $x[0], \dots, x[T]$

I know $u[0], \dots, u[T-1]$

I have T "equations"

$$x[1] \approx \lambda x[0] + b u[0]$$

$$x[2] \approx \lambda x[1] + b u[1]$$

$$\vdots$$

$$x[T] \approx \lambda x[T-1] + b u[T-1]$$

} T "equations"

Write as:

$$\begin{bmatrix} x[0] & u[0] \\ x[1] & u[1] \\ \vdots & \vdots \\ x[T-1] & u[T-1] \end{bmatrix} \begin{bmatrix} \lambda \\ b \end{bmatrix} \approx \begin{bmatrix} x[0] \\ \vdots \\ x[T] \end{bmatrix}$$

Tall Matrix

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

\leftarrow data \leftarrow parameters \leftarrow solution

Least squares solution: $\hat{\vec{p}} = (D^T D)^{-1} D^T \vec{s}$

estimated parameters \leftarrow Need $D^T D$ to be invertible.

Reasonable if we believe disturbances w are "small"

Because $\hat{\vec{p}}$ minimizes $\|\vec{s} - D \hat{\vec{p}}\|^2$

Vector Case

$\vec{x} \in n$ -dim

$\vec{u} \in m$ -dim

Presumed Model: $\vec{x}[t+1] = A \vec{x}[t] + B \vec{u}[t] + \vec{w}[t]$

$$n \times n \quad A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & & & \\ \vdots & & & \\ a_{n1} & & & a_{nn} \end{bmatrix}$$

$$n \times m \quad B = \begin{bmatrix} b_{11} & \dots & b_{1m} \\ \vdots & & \vdots \\ b_{n1} & & b_{nm} \end{bmatrix}$$

\leftarrow unknown

How many unknowns? $n \cdot n + n \cdot m = n^2 + nm$

Remember: All matrix vector equations are just systems of equations.

$$A = \begin{bmatrix} \vec{a}_1^T \\ \vec{a}_2^T \\ \vdots \\ \vec{a}_n^T \end{bmatrix} \quad B = \begin{bmatrix} \vec{b}_1^T \\ \vec{b}_2^T \\ \vdots \\ \vec{b}_n^T \end{bmatrix} \leftarrow \begin{matrix} r+1 \text{ row} \\ \text{Focus} \\ \text{not row} \end{matrix}$$

$$\vec{a}_r^T = [a_{r1} \ a_{r2} \ \dots \ a_{rn}] \quad \vec{b}_r^T = [b_{r1} \ \dots \ b_{rm}]$$

$$x_r[t+1] \approx \underbrace{\vec{a}_r^T}_{\text{unknowns}} \vec{x}[t] + \underbrace{\vec{b}_r^T}_{\text{known}} u[t]$$

Stack unknowns vertically

$$T \left\{ \begin{bmatrix} \vec{x}[0]^T & \vec{u}[0]^T \\ \vdots \\ \vec{x}[T-1]^T & \vec{u}[T-1]^T \end{bmatrix} \begin{bmatrix} \vec{a}_r \\ \vec{b}_r \end{bmatrix} \approx \begin{bmatrix} x_r[1] \\ x_r[2] \\ \vdots \\ x_r[T] \end{bmatrix} \right.$$

full matrix D \vec{p}_r \vec{s}_r

$$D \vec{p}_r \approx \vec{s}_r$$

Least Squares $\hat{\vec{p}}_r = (D^T D)^{-1} D^T \vec{s}_r$

No r's here!

$$\hat{P} = (D^T D)^{-1} D^T S$$

$$\begin{bmatrix} \hat{p}_1 & \hat{p}_2 & \dots & \hat{p}_n \end{bmatrix} = \begin{pmatrix} \phantom{\hat{p}_1} & \phantom{\hat{p}_2} & \dots & \phantom{\hat{p}_n} \end{pmatrix} \begin{bmatrix} \vec{s}_1 & \vec{s}_2 & \dots & \vec{s}_n \end{bmatrix}$$

$$\begin{bmatrix} \vec{x}^{(1)T} \\ \vdots \\ \vec{x}^{(T)T} \end{bmatrix}$$

We can solve for all the parameters $\{ \cdot \}$