



EECS 16B

Designing Information Devices and Systems II

Lecture 12

Prof. Yi Ma

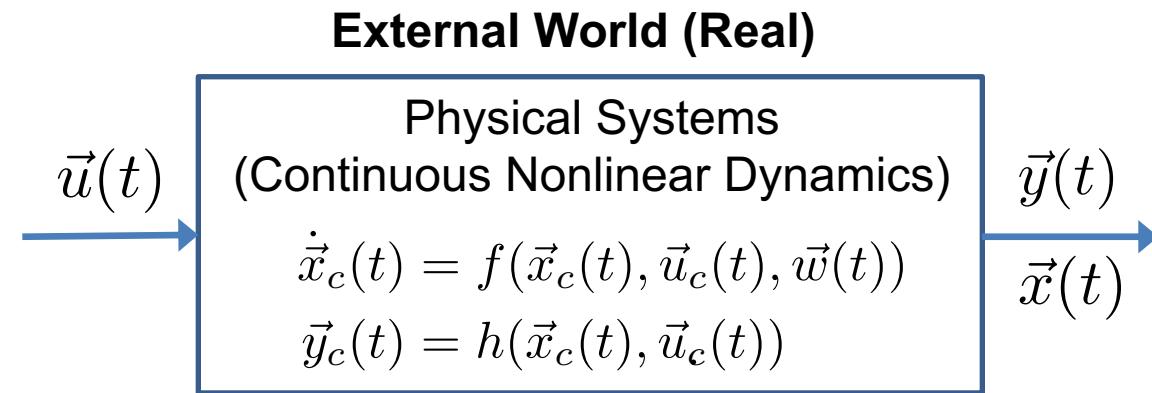
Department of Electrical Engineering and Computer Sciences, UC Berkeley,
yima@eecs.berkeley.edu

Outline

- System Modeling
- Discretization (scalar and vector case)
- System Identification

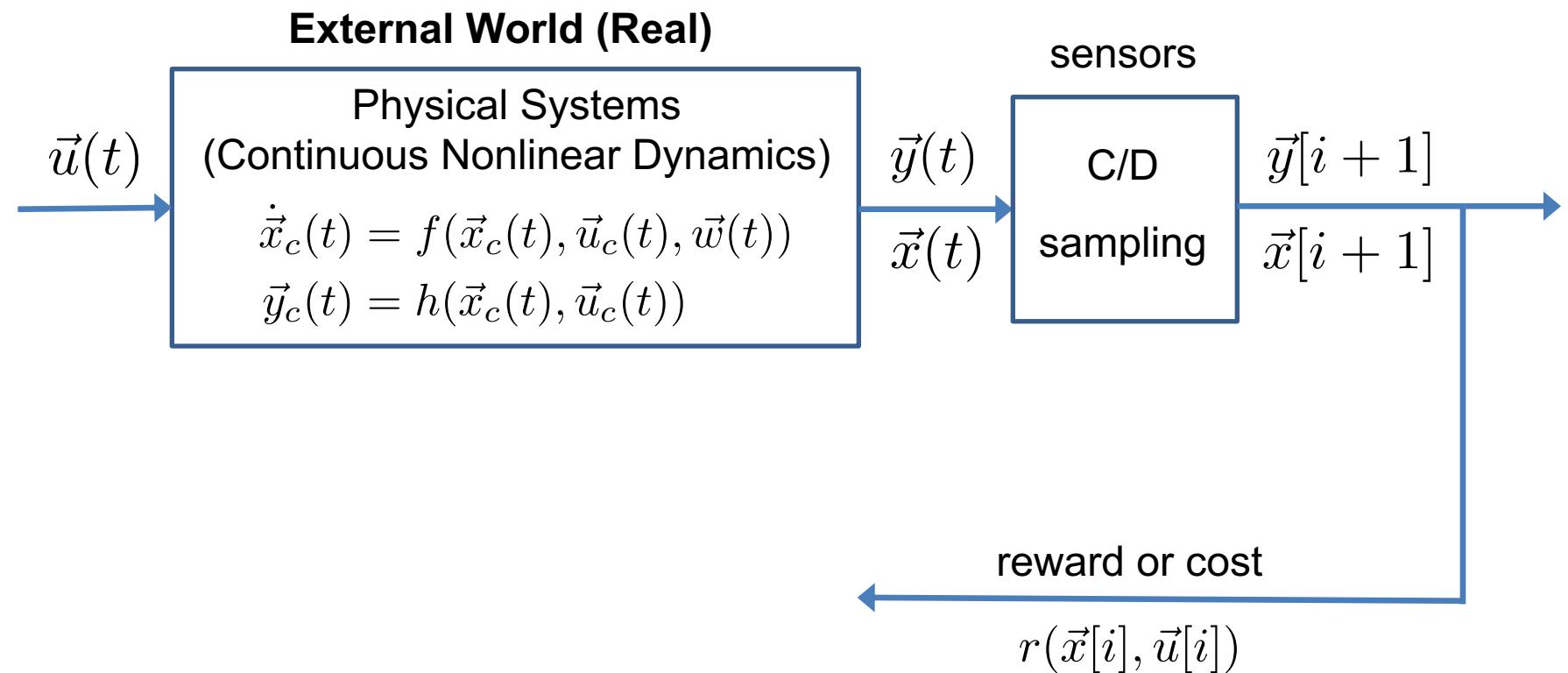
System Modeling & Control

All autonomous intelligent (AI) systems rely on closed-loop learning and control:



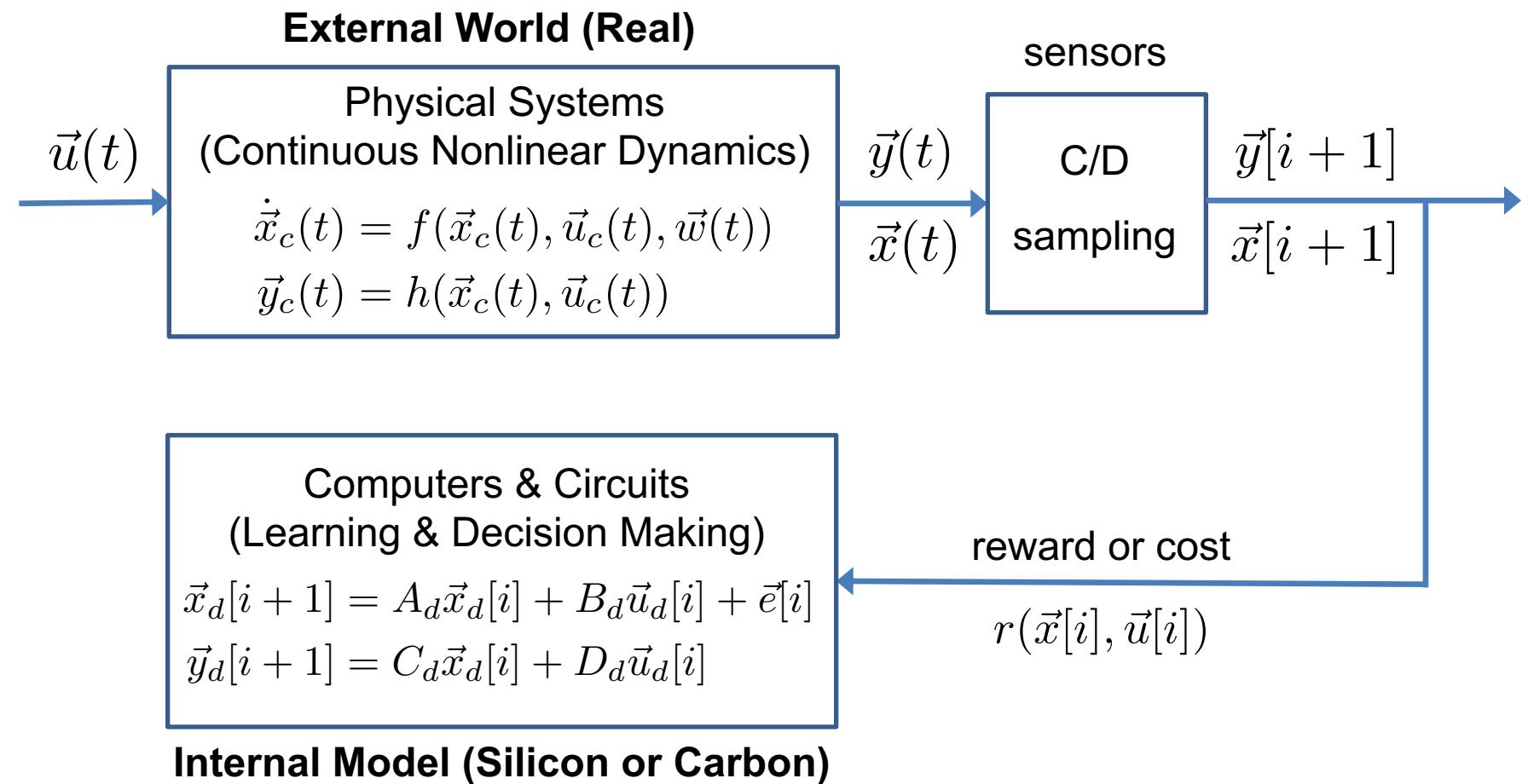
System Modeling & Control

All autonomous intelligent (AI) systems rely on **closed-loop** learning and control:



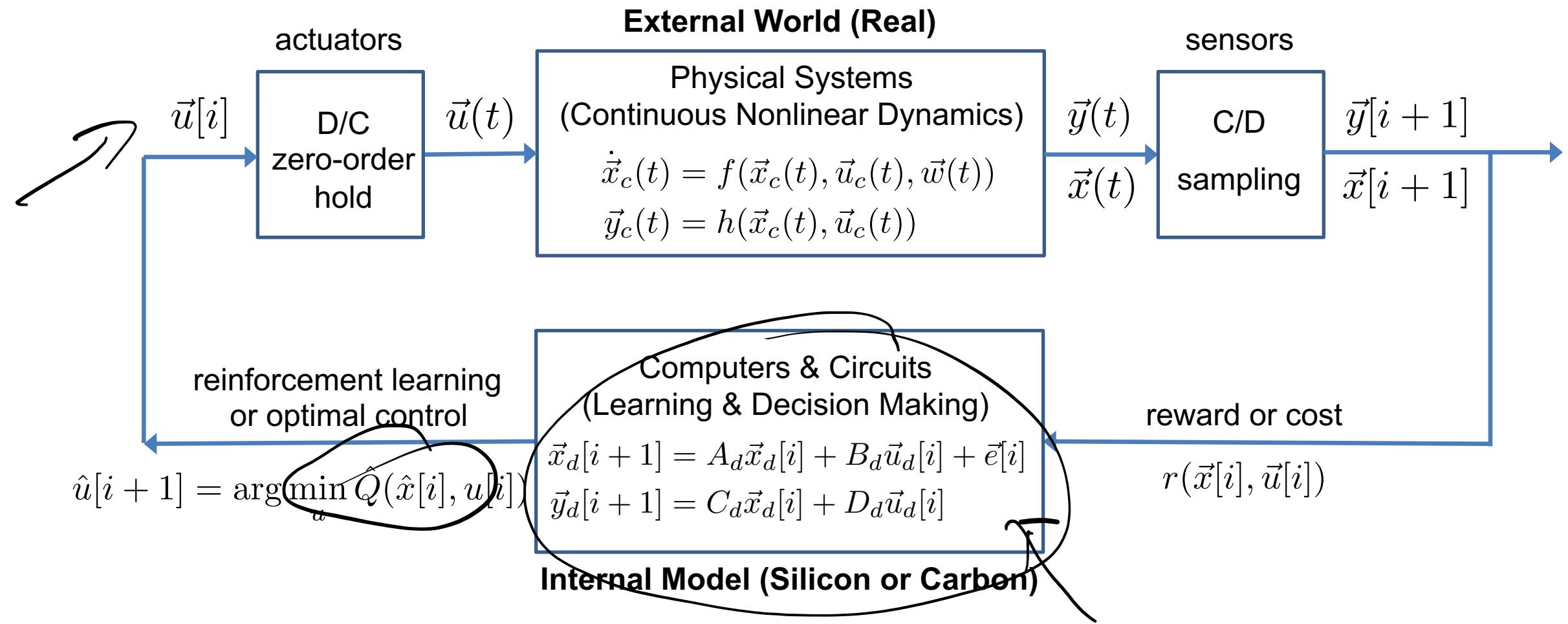
System Modeling & Control

All autonomous intelligent (AI) systems rely on closed-loop learning and control:

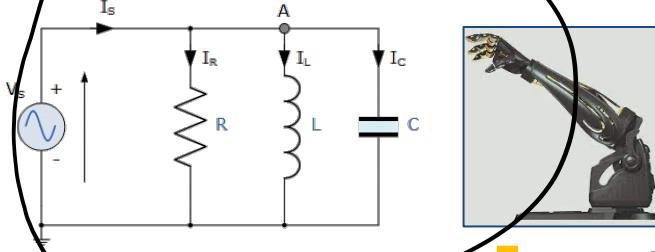


System Modeling & Control

All autonomous intelligent (AI) systems rely on **closed-loop** learning and control:



System Modeling



mathematical modeling
from first principles

$$\dot{\vec{x}}_c(t) = f(\vec{x}_c(t), \vec{u}_c(t), \vec{w}(t))$$

$$\vec{y}_c(t) = h(\vec{x}_c(t), \vec{u}_c(t))$$

approximation
& linearization

$$\dot{\vec{x}}(t) = A\vec{x}(t) + B\vec{u}(t) + \vec{n}(t)$$

$$\vec{y}(t) = C\vec{x}(t) + D\vec{u}(t)$$

discretization
& digitization

$$\vec{x}_d[i+1] = A_d\vec{x}_d[i] + B_d\vec{u}_d[i] + \vec{e}[i]$$

$$\vec{y}_d[i+1] = C_d\vec{x}_d[i] + D_d\vec{u}_d[i]$$

ODE: Newton's law.

PDE: Maxwell's equations.

SDE: Markov processes

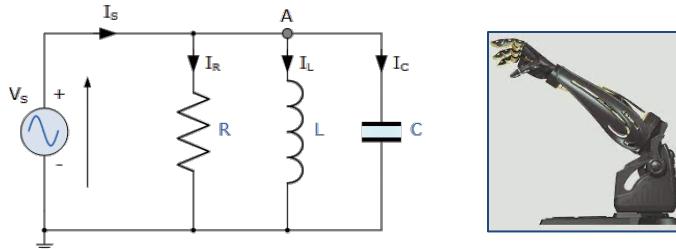
objectives of learning

* learn what is useful to predict.

* represent & organize

System Modeling

ReLU



mathematical modeling
from first principles

$$\dot{\vec{x}}_c(t) = f(\vec{x}_c(t), \vec{u}_c(t), \vec{w}(t))$$

$$\vec{y}_c(t) = h(\vec{x}_c(t), \vec{u}_c(t))$$

approximation
& linearization

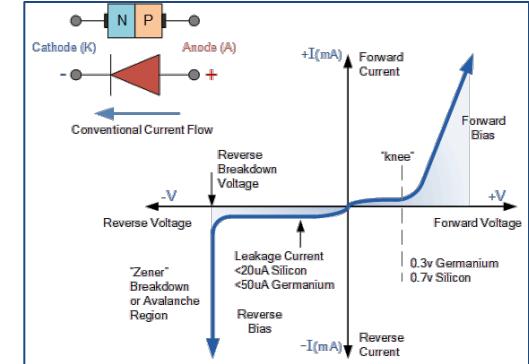
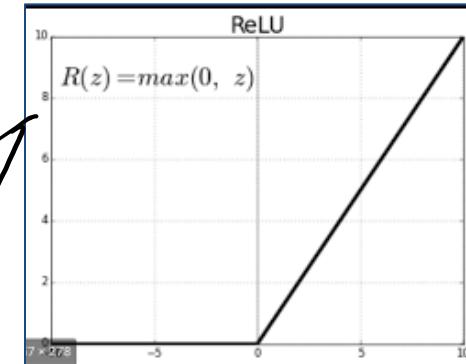
$$\dot{\vec{x}}(t) = A\vec{x}(t) + B\vec{u}(t) + \vec{n}(t)$$

$$\vec{y}(t) = C\vec{x}(t) + D\vec{u}(t)$$

discretization
& digitization

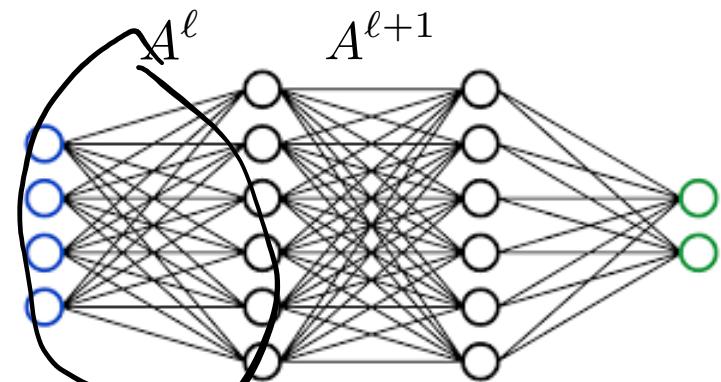
$$\left\{ \begin{array}{l} \vec{x}_d[i+1] = A_d \vec{x}_d[i] + B_d \vec{u}_d[i] + \vec{e}[i] \\ \vec{y}_d[i+1] = C_d \vec{x}_d[i] + D_d \vec{u}_d[i] \end{array} \right.$$

t too simple?

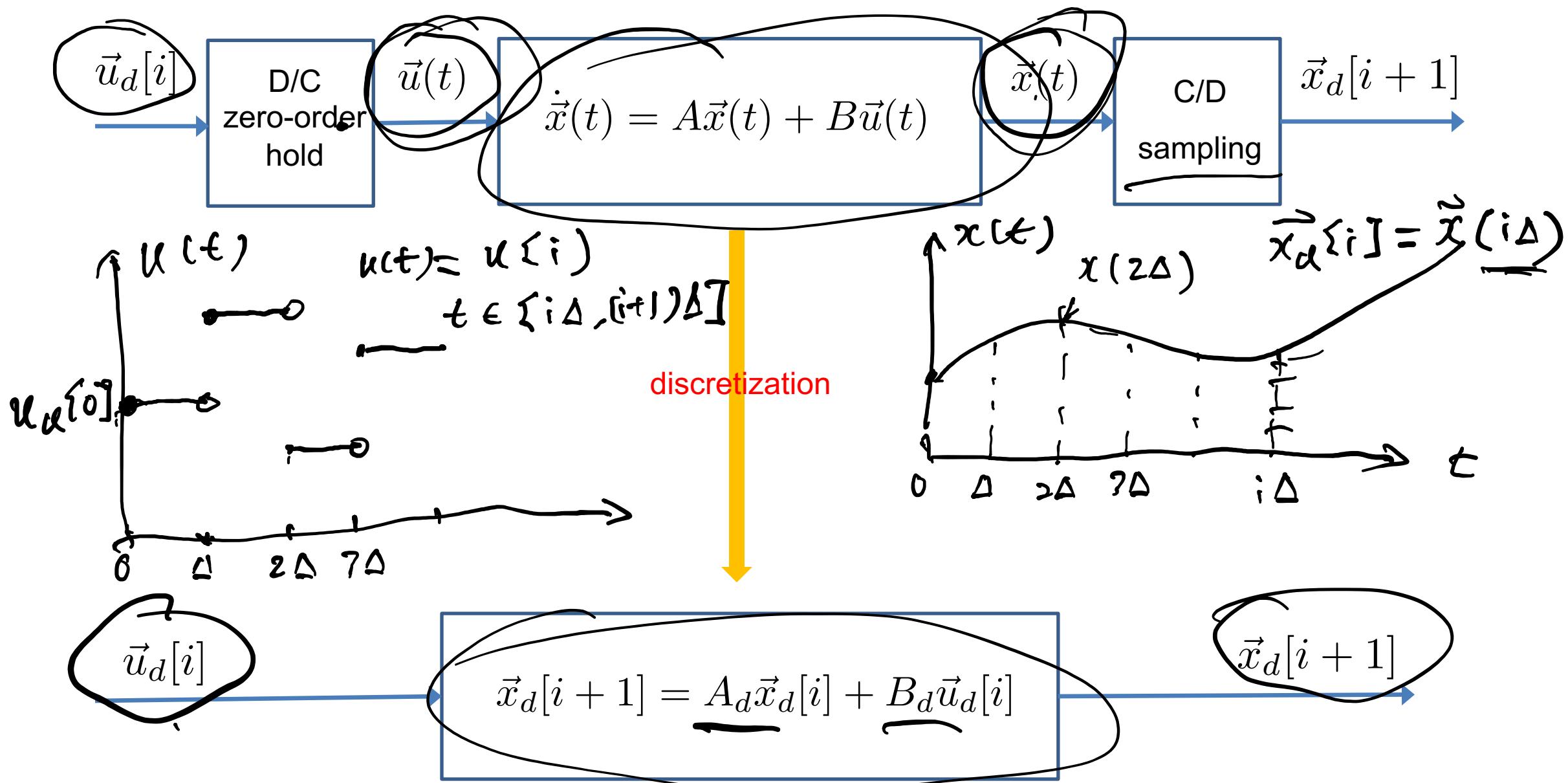


$$\vec{x}_d[i+1] = \sigma_x(A_d \vec{x}_d[i] + B_d \vec{u}_d[i]) + \vec{e}[i]$$

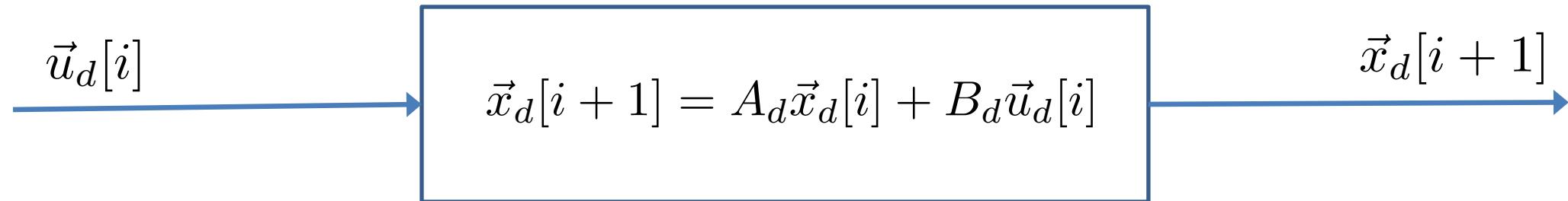
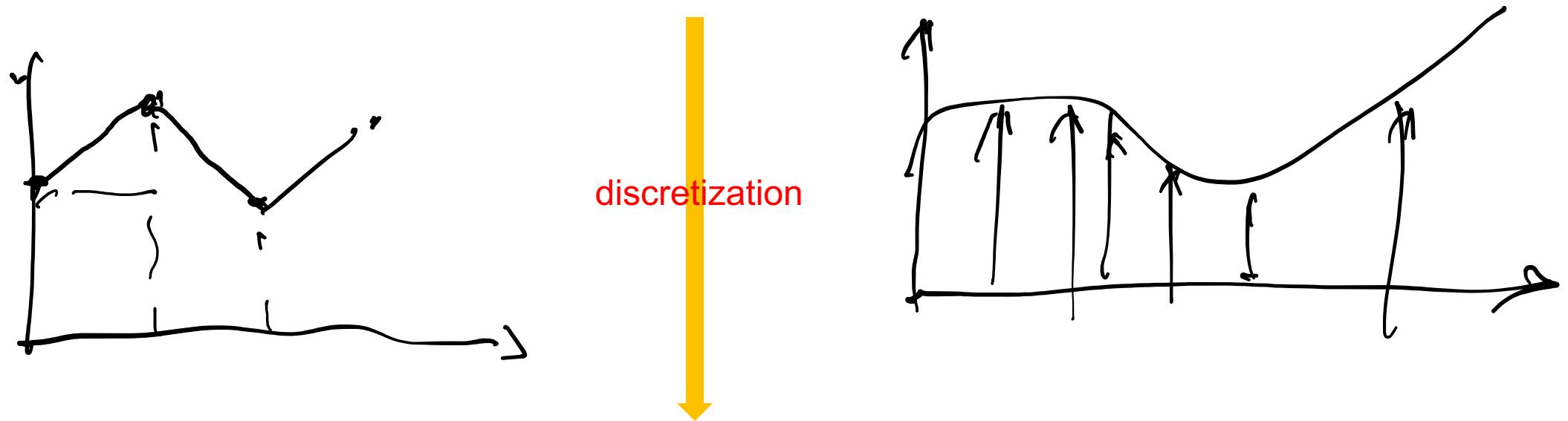
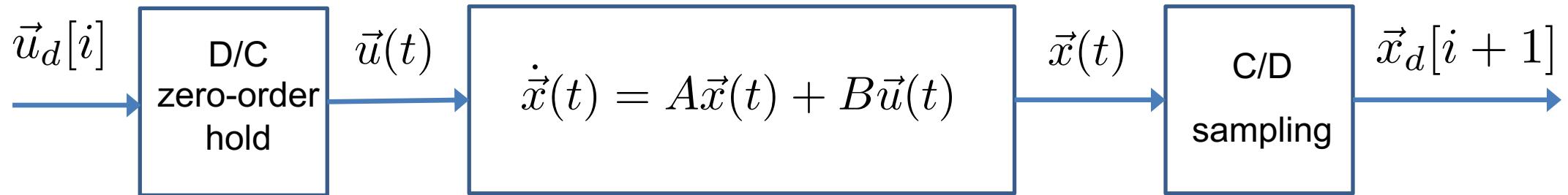
$$\vec{y}_d[i+1] = \sigma_y(C_d \vec{x}_d[i] + D_d \vec{u}_d[i])$$



System Modeling: Discretization



System Modeling: Discretization



Discretization: Scalar Case

Scalar Case: $\dot{x}(t) = ax(t) + bu(t)$ $\rightarrow x_d[i+1] = A_d x_d[i] + B_d u_d[i]$

$$\Rightarrow u(t) = u_d[i] + \epsilon \{ \frac{i\Delta}{t_0}, [i+1]\Delta \}$$

$$x(t) = e^{a(t-t_0)} x(t_0) + \int_{t_0}^t e^{a(t-\tau)} \underbrace{b u_d[\tau]}_{d\tau} d\tau$$

$$t_0 = i\Delta, t = (i+1)\Delta$$

$$x_d[i+1] = x((i+1)\Delta) = e^{a\Delta} x_d[i] + \int_{i\Delta}^{(i+1)\Delta} e^{a(t-\tau)} \underbrace{b u_d[\tau]}_{d\tau} d\tau$$

$$x_d[i+1] = \left(e^{a\Delta} x_d[i] + \frac{e^{a\Delta} - 1}{a} b u_d[i] \right)$$

A_d B_d

$\frac{e^{a\Delta} - 1}{a}$ ($= \Delta$ if $a=0$)

$a = 0?$

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

Discretization: Vector Case

Vector Case: $\dot{\vec{x}}(t) = A\vec{x}(t) + B\vec{u}(t)$ $\rightarrow \vec{x}_d[i+1] = A_d\vec{x}_d[i] + B_d\vec{u}_d[i]$

Diagonalizable: $\underbrace{\Lambda = V^{-1}AV}_{z = V^{-1}\vec{x}}$

$$V\Lambda = AV \quad \{v_1, v_2, \dots, v_n\} \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix} = A\{v_1, v_2, \dots, v_n\}$$

$$\lambda_i v_i = A v_i$$

$$\vec{z} = \underbrace{V^{-1}\vec{x}}_{\vec{z}} \quad \vec{x} = \underbrace{V\vec{z}}_{\vec{x}} \quad \frac{d\vec{z}(t)}{dt} = V^{-1} \frac{d\vec{x}}{dt}$$

$$\frac{d\vec{z}(t)}{dt} = \underbrace{V^{-1}AV}_{\Lambda} \vec{z}(t) + \underbrace{V^{-1}B\vec{u}(t)}_{\tilde{u}(t)}$$
$$\Lambda = \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix}$$

Discretization: Vector Case

Vector Case: $\dot{\vec{x}}(t) = A\vec{x}(t) + B\vec{u}(t)$

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

Diagonalizable: $A = V^{-1}\Lambda V$

$$\frac{d\vec{z}(t)}{dt} = \Lambda \vec{z}(t) + (V^{-1}B\vec{u}(t))$$

$$\vec{z}(t) = \begin{bmatrix} z_1(t) \\ z_2(t) \\ \vdots \\ z_n(t) \end{bmatrix}$$

$$\frac{d\vec{z}_k(t)}{dt} = \lambda_k \vec{z}_k(t) + (V^{-1}B\vec{u}(t))_k$$

$$\hat{u}_{ik}[i] = \hat{u}_{ik}(iA).$$

$$\vec{z}_{k,d}[i+1] = e^{\lambda_k \Delta} \vec{z}_{k,d}[i] + \frac{e^{\lambda_k \Delta} - 1}{\lambda_k} \hat{u}_{ik}[i]$$

$$\vec{x}_d[i+1] = \sum \vec{z}_d[i+1] \quad \vec{z}_d[i] = V^{-1} \vec{x}_d[i]$$

$A_{n \times n}$ $B_{n \times m}$

Discretization: Vector Case

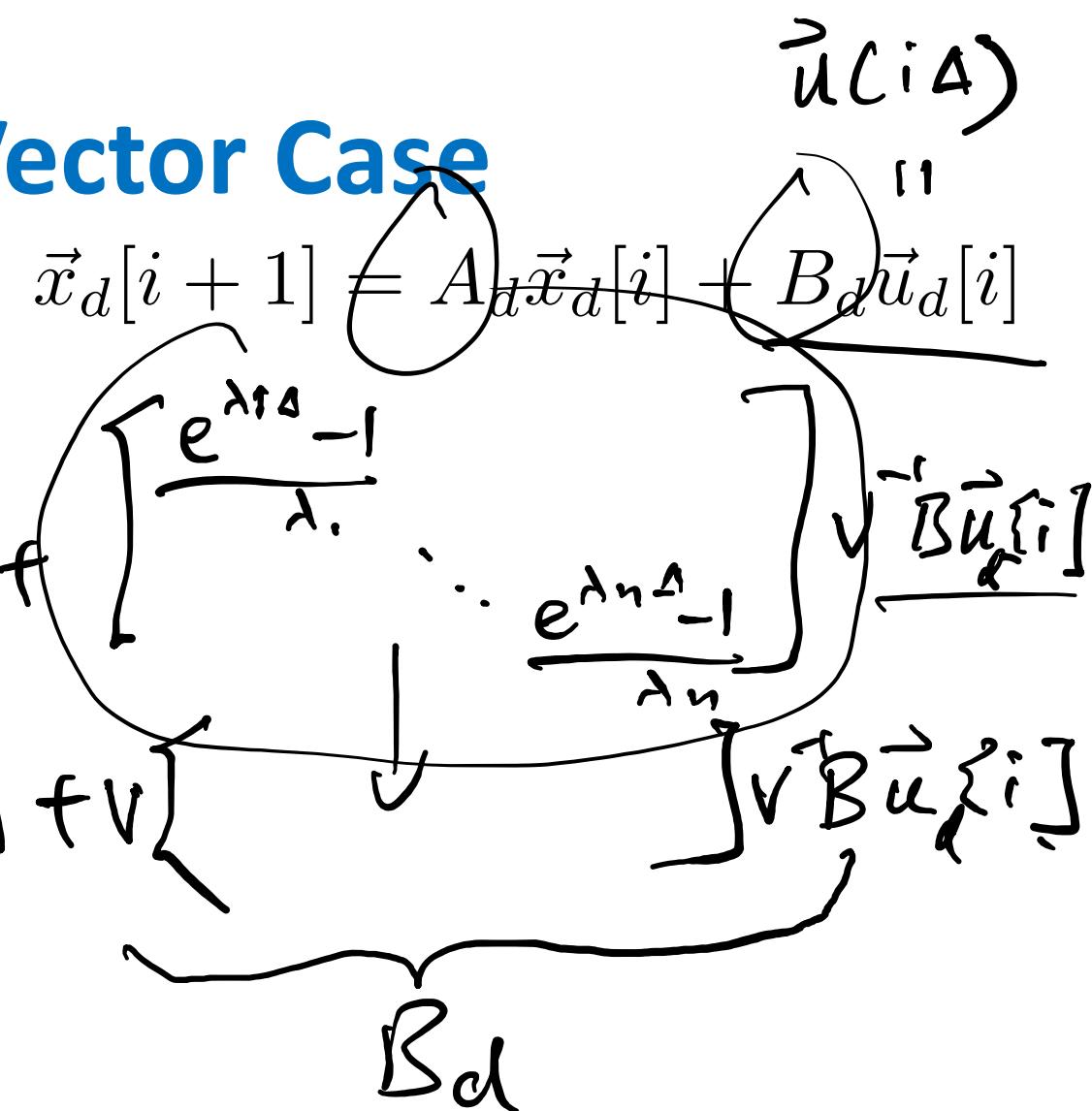
Vector Case: $\dot{\vec{x}}(t) = A\vec{x}(t) + B\vec{u}(t)$

Diagonalizable: $A = V^{-1}\Lambda V$

$$\vec{x}_d[i+1] = \begin{bmatrix} e^{\lambda_1 \Delta t} & & \\ & \ddots & \\ & & e^{\lambda_n \Delta t} \end{bmatrix} \vec{x}_d[i]$$

$$\vec{x}_d[i+1] = V \underbrace{\left[V^{-1} \vec{x}_d[i] + V \right]}_{A_d} + \underbrace{V \vec{B} \vec{u}[i]}_{B_d}$$

A_d



Discretization: General Case

General Case: $\dot{\vec{x}}(t) = \underbrace{A\vec{x}(t)} + \underbrace{B\vec{u}(t)}$

$$\vec{x}_d[i+1] = \underbrace{A_d\vec{x}_d[i]} + \underbrace{B_d\vec{u}_d[i]}$$

$$\vec{x}(t) = e^{A(t-t_0)}\vec{x}(t_0) + \int_{t_0}^t e^{A(t-\tau)}B\vec{u}(\tau)d\tau$$

$$e^{\lambda t} = 1 + \lambda t + \frac{(\lambda t)^2}{2} + \frac{(\lambda t)^3}{6} + \dots = \sum_{i=0}^{\infty} \frac{(\lambda t)^i}{i!}$$

$$e^{At} = 1 + At + \frac{(At)^2}{2} + \frac{(At)^3}{6} + \dots = \sum_{i=0}^{\infty} \frac{(At)^i}{i!}$$

$$\vec{x}_d[i+1] = \underbrace{e^{A\Delta}\vec{x}_d[i]} + \int_{i\Delta}^{(i+1)\Delta} e^{A(t-\tau)}Bd\tau \vec{u}_d[i]$$

$$A_d = e^{A\Delta}$$

$$B_d = (e^{A\Delta} - I)A^{-1}B$$

$$e^{A\Delta}$$

$$\frac{e^{A\Delta} - 1}{\alpha}$$

System Identification

Problem: consider the discrete linear time invariant system:

$$\underline{\vec{x}[i+1]} = \underline{(\hat{A}\vec{x}[i])} + \underline{(\hat{B}\vec{u}[i])} + \vec{e}[i]$$

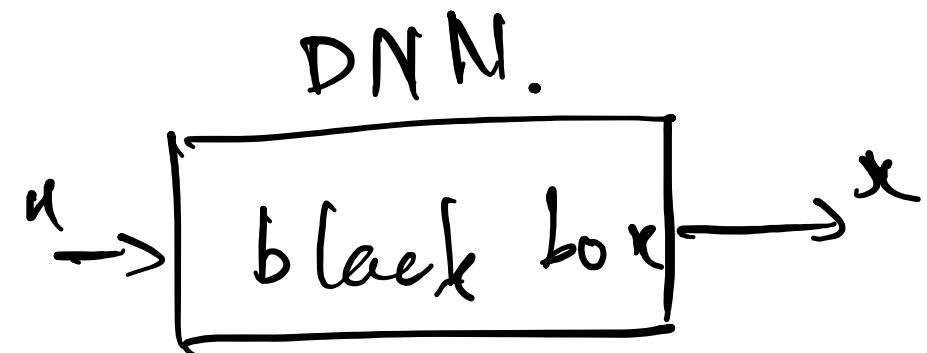
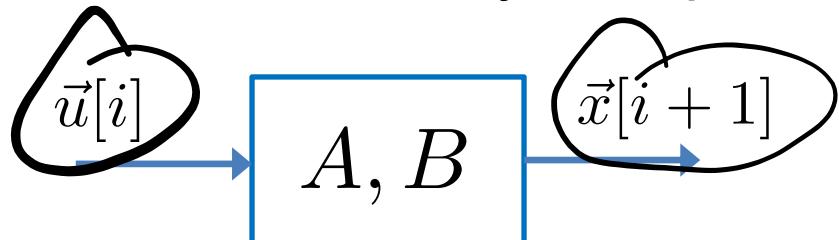
unknown

Given: observed inputs and outputs:

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

$$\vec{x}[0], \vec{x}[1], \dots, \vec{x}[l], \dots$$

Objective: learn the system parameters:



$$\vec{x}^T[i] = \left[\vec{x}[i]^T \vec{u}[i]^T \right] \begin{bmatrix} A^T \\ B^T \end{bmatrix} + \vec{e}^T[i]$$

$$\underline{y} = \underline{Ax} + \underline{b}$$

Least Squares (Gauss 1809)

$$\vec{s} \in \mathbb{R}^a, \quad D \in \mathbb{R}^{a \times b}, \quad \vec{p} \in \mathbb{R}^b, \quad \vec{e} \in \mathbb{R}^a$$

$$\vec{s} = D \begin{matrix} \vec{p} \\ \text{unknown} \end{matrix} + \vec{e}, \quad \text{rank}[D] = b \qquad D = [\vec{d}_1, \vec{d}_2, \dots, \vec{d}_b]$$

$$\vec{p}_\star = \arg \min_{\vec{p}} \|\vec{s} - D\vec{p}\|_2^2$$

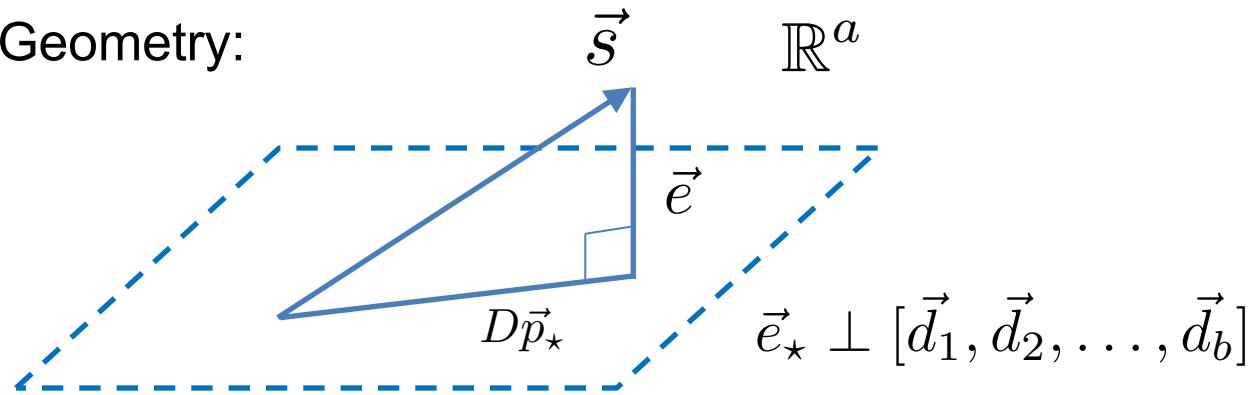
Least Squares (Gauss 1809)

$$\vec{s} \in \mathbb{R}^a, \quad D \in \mathbb{R}^{a \times b}, \quad \vec{p} \in \mathbb{R}^b, \quad \vec{e} \in \mathbb{R}^a$$

$$\vec{s} = D \underset{\text{unknown}}{\vec{p}} + \vec{e}, \quad \text{rank}[D] = b \quad D = [\vec{d}_1, \vec{d}_2, \dots, \vec{d}_b]$$

$$\vec{p}_\star = \arg \min_{\vec{p}} \|\vec{s} - D\vec{p}\|_2^2$$

Geometry:



$$D^\top \vec{e} = D^\top (\vec{s} - D\vec{p}_\star) = \vec{0}$$