

#### **EECS 16B**

# Designing Information Devices and Systems II Lecture 28

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#### **Outline**

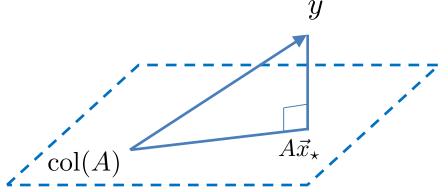
- Final Review (part two)
  - Solutions to Linear Equations
  - System Discretization & Identification
  - System Stability
  - System Controllability
  - Minimum Energy Control
  - Principal Component Analysis (PCA)

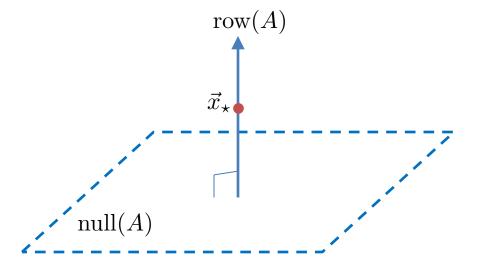
## **Solutions to Systems of Linear Equations**

$$\vec{y} = A\vec{x}: \ \vec{x}_{\star} = A^{\dagger}\vec{y}$$

#### Cases:

- 1. square and full rank (inverse);
- 2. full column rank (least squares, system identification);
- 3. full row rank (least norm, minimum energy control);
- 4. general cases.



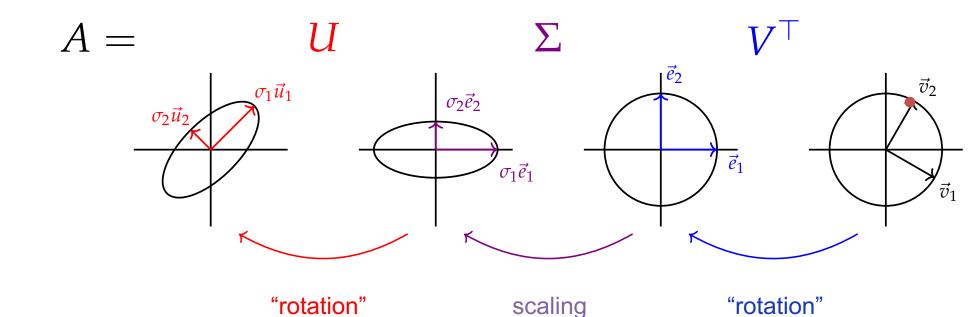


### Solutions to Systems of Linear Equations

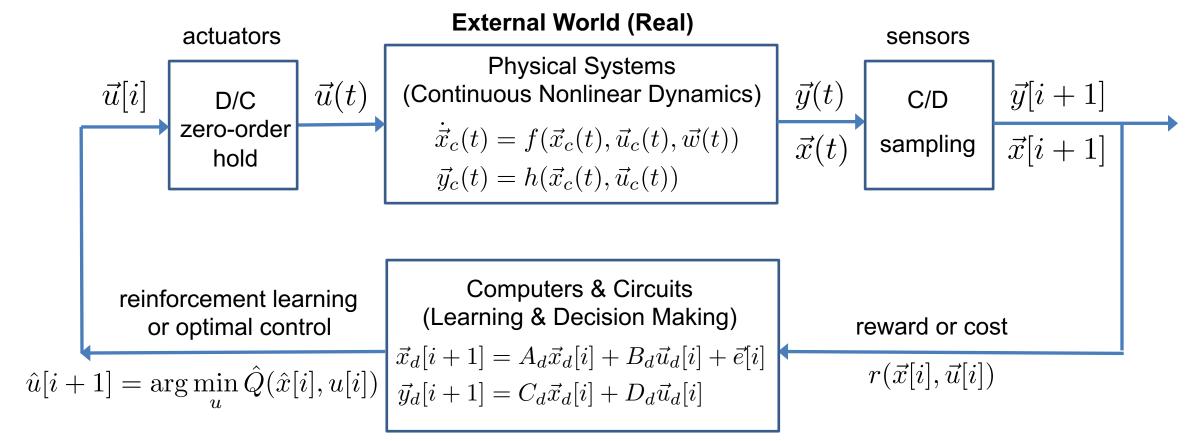
$$\vec{y} = A\vec{x}: \vec{x}_{\star} = A^{\dagger}\vec{y}$$

#### Cases:

- 1. square and full rank (inverse);
- 2. full column rank (least squares, system identification);
- 3. full row rank (least norm, minimum energy control);
- 4. general cases: pseudo inverse, PCA etc.

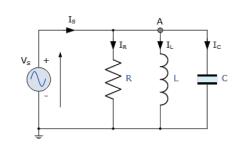


## System Modeling, Analysis, & Control



**Internal Model** 

## **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

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

**Discretization** (Lecture 12)

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

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

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

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

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

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

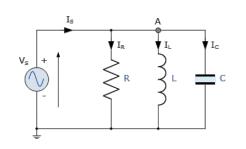
## **System Modeling: Identification**

Identification: (Lecture 13)  $\vec{x}[i+1] = A\vec{x}[i] + B\vec{u}[i] + \vec{e}[i]$ 

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

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

#### **System Analysis**







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

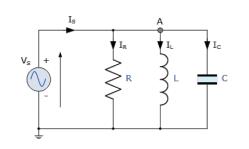
$$\vec{x}_d[i+1] = A_d \vec{x}_d[i] + B_d \vec{u}_d[i] + \vec{e}[i]$$
  
$$\vec{y}_d[i+1] = C_d \vec{x}_d[i] + D_d \vec{u}_d[i]$$

#### **Stability Criteria** (Lecture 14)

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

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

#### **System Control**







# 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

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

#### **Controllability** (Lecture 15)

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

$$\vec{u}[i] = F\vec{x}[i]$$

$$\vec{x}[i]$$

## **System Control**

#### Controllable Canonical Form: (Lecture 16)

$$\vec{x}[i+1] = A\vec{x}[i] + Bu[i] + \vec{e}[i] \in \mathbb{R}^n$$

$$A = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & 0 & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 0 & 1 \\ a_1 & a_2 & \cdots & a_{n-1} & a_n \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ 1 \end{bmatrix}$$

$$\det(\lambda I - A) = \lambda^n - a_n \lambda^{n-1} - a_{n-1} \lambda a^{n-2} - \dots - a_2 \lambda - a_1$$

$$F = \begin{bmatrix} f_1 & f_2 & \cdots & f_{n-1} & f_n \end{bmatrix}$$

### **System Control**

#### Design control input to steer the state of a controllable system:

$$\vec{x}[i+1] = A\vec{x}[i] + Bu[i]$$
  $\mathcal{C} \doteq [A^{n-1}B \mid \cdots \mid AB \mid B] \in \mathbb{R}^{n \times n}$  is invertible.

$$\mathcal{C}_{\ell} \doteq [A^{\ell-1}B \mid \cdots \mid AB \mid B] \in \mathbb{R}^{n \times \ell}$$

#### **System State Estimation**

#### Estimate the state of the system from observable outputs:

$$\vec{x}_d[i+1] = A\vec{x}_d[i] + B\vec{u}_d[i]$$
  
 $\vec{y}_d[i+1] = C\vec{x}_d[i] + D\vec{u}_d[i]$ 

### SVD, Low-Rank Approximation, PCA

$$A = [\vec{a}_1, \vec{a}_2, \dots, \vec{a}_n] \in \mathbb{R}^{m \times n} \qquad A = \sum_{i=1}^r \sigma_i \vec{u}_i \vec{v}_i^\top = U_r \Sigma_r V_r^\top$$

Low-rank Approximation:  $\min_{B\in\mathbb{R}^{m\times n}}\|A-B\|_F^2 \quad \mathrm{subject\ to} \quad \mathrm{rank}(B)=\ell \quad \text{(Lecture 24)}$ 

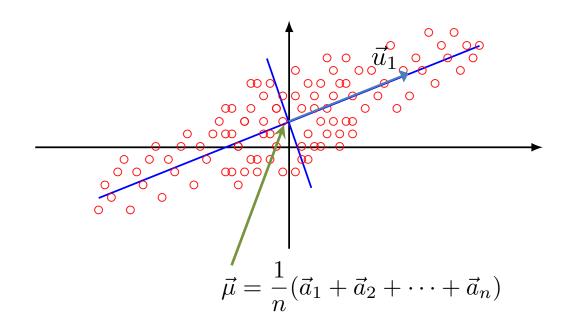
$$A = [\vec{a}_1, \vec{a}_2, \dots, \vec{a}_n] = \sum_{i=1}^r \sigma_i \vec{u}_i \vec{v}_i^{\top} = \sum_{i=1}^\ell \sigma_i \vec{u}_i \vec{v}_i^{\top} + \sum_{i=\ell+1}^r \sigma_i \vec{u}_i \vec{v}_i^{\top}$$

### SVD, Low-Rank Approximation, PCA

$$A = [\vec{a}_1, \vec{a}_2, \dots, \vec{a}_n] \in \mathbb{R}^{m \times n} \qquad \vec{\mu} = \frac{1}{n} (\vec{a}_1 + \vec{a}_2 + \dots + \vec{a}_n) = \mathbf{0}$$

#### Principal Component: (Lecture 24)

find a normal vector  $\|\vec{u}\|_2 = 1$  such that  $\max_{\vec{u}} \|\vec{u}^{\top} A\|_2^2 = \|\vec{u}\vec{u}^{\top} A\|_2^2$ .



### SVD, Low-Rank Approximation, PCA

$$A = [\vec{a}_1, \vec{a}_2, \dots, \vec{a}_n] \in \mathbb{R}^{m \times n} \qquad \vec{\mu} = \frac{1}{n} (\vec{a}_1 + \vec{a}_2 + \dots + \vec{a}_n) = \mathbf{0}$$

**Principal Components: (Lecture 24)** 

$$\text{Find projection:} \quad \max_{U_\ell} \|U_\ell U_\ell^\top A\|_F^2 \quad \Leftrightarrow \min_{U_\ell} \|A - U_\ell U_\ell^\top A\|_F^2 \quad \Leftrightarrow \quad \min_{U_{m-\ell}} \|U_{m-\ell} U_{m-\ell}^\top A\|_F^2$$

