

# ME547: Linear Systems

## Modeling: State-Space Models

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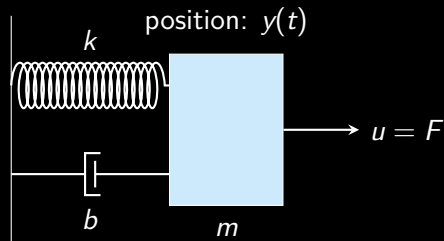
# Why state space?

- ▶ static/memoryless system: *present* output depends **only** on its present input:  $y(k) = f(u(k))$
- ▶ dynamic system: *present* output depends on **past** and its present input,
  - ▶ e.g.,  $y(k) = f(u(k), u(k-1), \dots, u(k-n), \dots)$
  - ▶ described by differential or difference equations, or have time delays
- ▶ how much information from the past is needed?

# The concept of states of a dynamic system

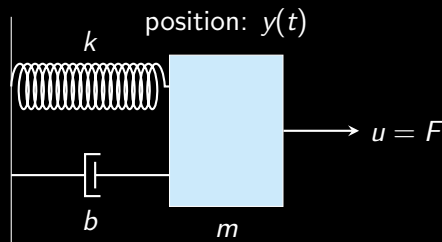
- ▶ the *state*  $x(t)$  is the information you need at time  $t$  that together with future values of the input, will let you compute future values of the output  $y$
- ▶ loosely speaking:
  - ▶ the “aggregated effect of past inputs”
  - ▶ the necessary “memory” that the dynamic system keeps at each time instance

# Example



- ▶ to predict the future motion, we need to know
  - ▶ *current* position and velocity
  - ▶ *future* force
- ▶  $\Rightarrow$  states: position and velocity

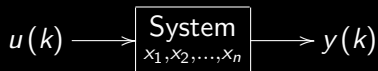
# The order of a dynamic system



- ▶ the number,  $n$  of state variables that is *necessary and sufficient* to uniquely describe the system
- ▶ for a given dynamic system,
  - ▶ the choice of state variables is *not unique*
  - ▶ however, its order  $n$  is fixed
  - ▶ i.e. you need not more than  $n$  but not less than  $n$  state variables

# States of a discrete-time system

consider a discrete-time dynamic system:



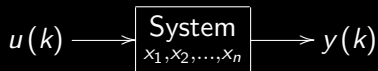
- ▶ the state at any instance  $k_0$  is the **minimum** set of variables,

$$x_1(k_0), x_2(k_0), \dots, x_n(k_0)$$

that fully describe the system and its response for  $k \geq k_0$  to any given set of inputs

- ▶ loosely speaking,  $x_1(k_0), x_2(k_0), \dots, x_n(k_0)$  defines the system's memory

# Discrete-time state-space description



general case

$$\begin{aligned}x(k+1) &= f(x(k), u(k), k) \\ y(k) &= h(x(k), u(k), k)\end{aligned}$$

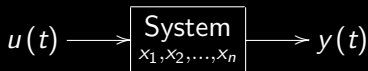
- ▶  $u(k)$ : input
- ▶  $y(k)$ : output
- ▶  $x(k)$ : state
- ▶  $x(k+1) = f(\cdot)$ : state Eq
- ▶  $y(k) = h(\cdot)$ : output Eq

linear time-invariant (LTI) case

$$\begin{aligned}x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) + Du(k)\end{aligned}$$

- ▶  $\Sigma(A, B, C, D)$  denotes a state-space realization
- ▶ also written as  $\Sigma = \left[ \begin{array}{c|c} A & B \\ \hline C & D \end{array} \right]$

# Continuous-time state-space description



general case

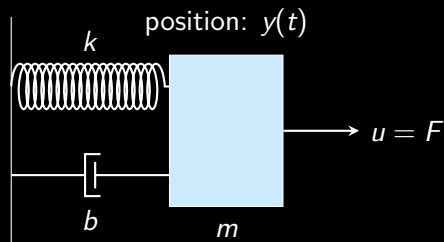
$$\frac{dx(t)}{dt} = f(x(t), u(t), t)$$
$$y(t) = h(x(t), u(t), t)$$

LTI case

$$\frac{dx(t)}{dt} = Ax(t) + Bu(t)$$
$$y(t) = Cx(t) + Du(t)$$

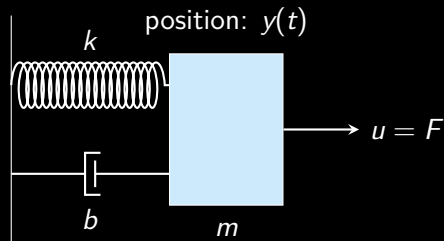


## Example: mass-spring-damper



$$x(t) = \begin{bmatrix} \text{mass position} \\ \underbrace{p(t)} \\ \underbrace{v(t)} \\ \text{mass velocity} \end{bmatrix} \in \mathbb{R}^2$$

## Example: mass-spring-damper



$$\underbrace{\frac{d}{dt} \begin{bmatrix} p(t) \\ v(t) \end{bmatrix}}_{x(t)} = \underbrace{\begin{bmatrix} 0 & 1 \\ -\frac{k}{m} & -\frac{b}{m} \end{bmatrix}}_A \underbrace{\begin{bmatrix} p(t) \\ v(t) \end{bmatrix}}_{x(t)} + \underbrace{\begin{bmatrix} 0 \\ \frac{1}{m} \end{bmatrix}}_B u(t)$$
$$y(t) = \underbrace{\begin{bmatrix} 1 & 0 \end{bmatrix}}_C \underbrace{\begin{bmatrix} p(t) \\ v(t) \end{bmatrix}}_{x(t)}$$

# Coding a state-space system in MATLAB

```
A = [0,1;-3,-2];  
B = [0;1];  
C = [2,1];  
D = 0;  
sys_ss = ss(A,B,C,D)  
  
[yout, T] = step(sys_ss);  
figure, plot(T, yout)
```

# Coding a state-space system in Python

```
import control as co
import matplotlib.pyplot as plt
import numpy as np
A = np.array([[0,1],[-3,-2]])
B = np.array([[0],[1]])
C = np.array([2,1])
D = np.array([0])

sys_ss = co.ss(A,B,C,D)
print(sys_ss)

T,yout = co.step_response(sys_ss)

plt.figure(1,figsize = (6,4))
plt.plot(T,yout)
plt.grid(True)
plt.ylabel("y")
plt.xlabel("Time (sec)")
plt.show()
```