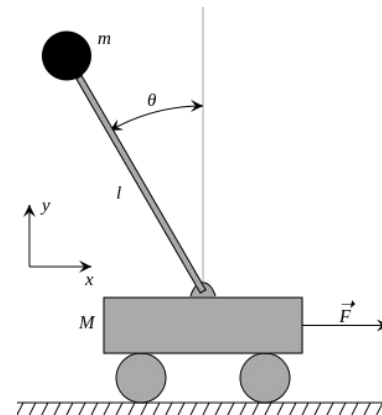
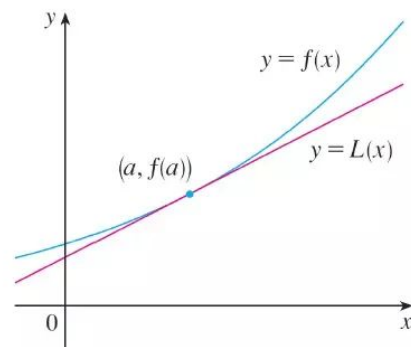




Logo credits go to Moses Won

# Discussion 7B

## Linearization & Stability



# Discussion Feedback

Any feedback is welcome!

- <https://forms.gle/HQtVmncbCj2aj69z9>

# Recap

We've learned how to model state-space equations

- CT Systems were modeled by differential equations.
- DT Systems were modeled by difference equations.

A state-space system is **linear** if it can be written as:

**Continuous-Time**

$$\frac{d}{dt} \vec{x}(t) = \mathbf{A} \vec{x}(t) + \mathbf{B} \vec{u}(t)$$

*↑ eigenvalues  $\lambda_1, \dots, \lambda_n$*

**Discrete-Time**

$$\vec{x}[t + 1] = \mathbf{A} \vec{x}[t] + \mathbf{B} \vec{u}[t]$$

Linear systems are “**nice**” since they are predictable and easy to analyze.

# Linearization

$$\frac{d}{dt} \vec{x} = f(\vec{x}, \vec{u})$$

if  $f$  is nonlinear

If a system is **nonlinear**, not all hope is lost! **Linearization** is a way to create a linear approximation of the function  $f(\mathbf{x}, \mathbf{u})$  around an **operating point**  $(\mathbf{x}^*, \mathbf{u}^*)$ .

- Note that we are approximating  $f(\mathbf{x}, \mathbf{u})$  and NOT the function  $\mathbf{x}$ .

**Taylor's Theorem** says we can approximate  $f(\mathbf{x}, \mathbf{u})$  at the point  $(\mathbf{x}^*, \mathbf{u}^*)$  as:

$$f(x, u) = f(x^*, u^*) + \frac{\partial f(x^*, u^*)}{\partial x} \cdot (x - x^*) + \frac{\partial f(x^*, u^*)}{\partial u} \cdot (u - u^*)$$

Scalar func.  $\nearrow$  constant  $\nearrow$  constants  $\nearrow$

We can use the **Jacobians** of the function  $f$  to create a **linear** approximation.

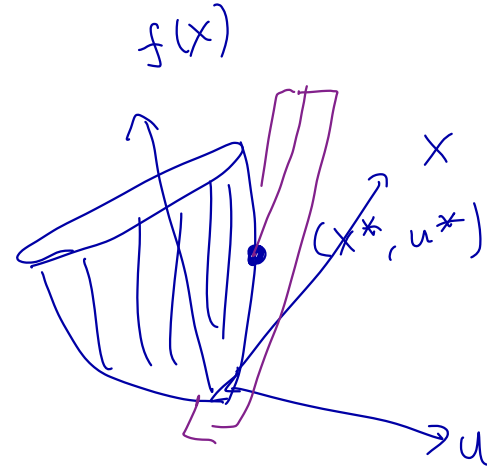
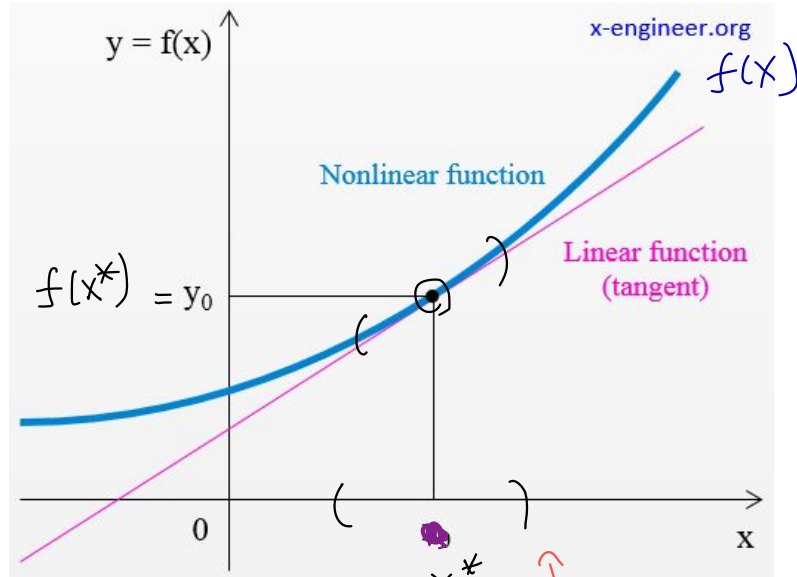
$$f(\vec{x}, \vec{u}) = f(\vec{x}^*, \vec{u}^*) + J_{\vec{x}}(\vec{x}^*, \vec{u}^*) \cdot (\vec{x} - \vec{x}^*) + J_{\vec{u}}(\vec{x}^*, \vec{u}^*) \cdot (\vec{u} - \vec{u}^*)$$

vector func.  $\nearrow$   $\downarrow$  0  $\nwarrow$  matrices  $\nearrow$  Affine but non-linear

$$A \cdot \vec{x}_e + B \cdot \vec{u}_e + C$$

# Visualization

$$f(x) = f(x^*) + \frac{\partial f}{\partial x}(x^*) \cdot (x - x^*)$$



region: linear approx is accurate

# Equilibrium Points

An **equilibrium point** is a point  $(\mathbf{x}^*, \mathbf{u}^*)$  where the system does not change.

Equilibrium points for linear systems can be solved as:

**Continuous-Time**

$$\frac{d}{dt}\vec{x}(t) = \mathbf{A}\vec{x}(t) + \mathbf{B}\vec{u}(t) = \vec{0}$$

**Discrete-Time**

$$\vec{x}[t+1] = \mathbf{A}\vec{x}[t] + \mathbf{B}\vec{u}[t] = \vec{x}[t]$$

Equilibrium points of nonlinear systems can be found by solving

$$\frac{d}{dt}\vec{x} = f(\vec{x}, \vec{u}) = \vec{0}$$

$$\vec{x}[t+1] = f(\vec{x}, \vec{u}) = \vec{x}[t] \quad \text{for all } t$$

$$\text{CT: } \underline{f(\vec{x}^*, \vec{u}^*)} = \vec{0}$$

$$\text{DT: } f(\vec{x}, \vec{u}) = \vec{x}$$

# Putting Everything Together

To linearize a system, we take the following steps:

1. Find all equilibrium points  $(\mathbf{x}^*, \mathbf{u}^*)$  of the function  $\mathbf{f}(\mathbf{x}, \mathbf{u})$ .
2. Pick one of the equilibrium points to linearize around.
3. Compute the Jacobian matrices  $J_{\mathbf{x}}$  and  $J_{\mathbf{u}}$  and evaluate them at  $(\mathbf{x}^*, \mathbf{u}^*)$ .
4. Then linearized system will be of the form:

**Continuous-Time**

$$\frac{d}{dt} \vec{x}_\ell(t) = J_{\vec{x}} \vec{x}_\ell(t) + J_{\vec{u}} \vec{u}_\ell(t) + f(\vec{x}^*, \vec{u}^*)$$

$\Downarrow$  at non-equilibrium pts  
 $\text{'' } (\vec{x} - \vec{x}^*) \quad \text{'' } (\vec{u} - \mathbf{u}^*)$

**Discrete-Time**

$$\vec{x}[t+1] = J_{\vec{x}} \vec{x}_\ell[t] + J_{\vec{u}} \vec{u}_\ell[t]$$

**Note: The equilibrium conditions are different for CT / DT Systems but Steps 2 & 3 are identical for CT and DT Systems.**

# Stability

$$\frac{d}{dt} \vec{x} = A\vec{x} + \cancel{B\vec{u}}$$

A state-space model is **asymptotically stable** if :

- Given zero input ( $u = 0$ ), the state  $x(t)$  converges to 0.

We say a system is **BIBO (Bounded Input Bounded Output)** stable if:

- **For every** bounded input  $u(t)$ , the output  $x(t)$  is also bounded.
  - A function  $f(t)$  is bounded if  $|f(t)| < B$  where  $B$  is a finite value.



Whenever we say **stable** in this class, we are referring to asymptotically stable despite doing all our proofs for BIBO stability.



# What you need to know:

A **linear** continuous-time system is **stable** if:

$$\Re[\lambda_i] < 0 \quad \text{for all } i = 1, \dots, n$$

$$x_i(t) = a_1 e^{\lambda_1 t} + \dots + a_n e^{\lambda_n t}$$

↓  
want them to go to zero

A **linear** discrete-time system is **stable** if:

$$|\lambda_i| < 1 \quad \text{for all } i = 1, \dots, n$$

$$x_i(t) = a_1 \lambda_1^t + \dots + a_n \lambda_n^t$$

↓  
want these to go to zero

$$\frac{d}{dt} \vec{x} = A \vec{x}$$

↓  
 $\lambda_1, \dots, \lambda_n$  eigvals of  $A$

if  $\Re(\lambda_i) = 0 \rightarrow$  unstable

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

$$\left(\frac{1}{2}\right)^t \rightarrow 0 \quad \text{as } t \rightarrow \infty$$

$$(2)^t \rightarrow \infty \quad \text{as } t \rightarrow \infty$$

$|\lambda_i| = 1 \rightarrow$  unstable