



# Linear Systems I

CMPT 882

Jan. 11





#### Linear Systems

- Differential equations generally do not have closed-form solutions
  - Numerical methods can be used to obtain approximate solutions
  - Other analysis techniques offer insight into the solutions

### Linear Systems

- Differential equations generally do not have closed-form solutions
  - Numerical methods can be used to obtain approximate solutions
  - Other analysis techniques offer insight into the solutions
- Linear time-invariant (LTI) systems:  $\dot{x} = Ax + Bu$ 
  - Damped mass spring systems
  - Circuits involving resistors, capacitors, inductors
  - Approximations of nonlinear systems





## Linear Systems





(If flying near hover, and slowly) Bouffard, 2012

#### Road Map

- Basic properties and closed form solution
- Stability
- Linearization
- Controllability and observability

#### Road Map

- Linear Systems (This and next lecture)
  - Basic properties and closed form solution
  - Stability
  - Linearization
  - Controllability and observability
- Nonlinear systems (Two lectures)
- Optimization and optimal control (New unit, ~8 lectures)

# LTI Systems

• Linear time-invariant (LTI) systems:  $\dot{x} = Ax + Bu$ 



#### Linear System

- Existence and Uniqueness of Solutions of  $\dot{x} = f(x, u)$ 
  - $\exists L > 0, \forall u, x_1, x_2, ||f(x_1, u) f(x_2, u)|| \le L ||x_1 x_2||$
- Existence and Uniqueness of Solutions of  $\dot{x} = Ax + Bu$ 
  - $\exists L > 0, \forall u, x_1, x_2, ||Ax_1 + Bu Ax_2 Bu|| \le L ||x_1 x_2||$

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- Existence and Uniqueness of Solutions of  $\dot{x} = Ax + Bu$ 
  - $\exists L > 0, \forall u, x_1, x_2, ||Ax_1 + Bu Ax_2 Bu|| \le L ||x_1 x_2||$
  - $\Leftrightarrow \exists L > 0, \forall u, x_1, x_2, ||Ax_1 Ax_2|| \le L ||x_1 x_2||$

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- Existence and Uniqueness of Solutions of  $\dot{x} = Ax + Bu$ 
  - $\exists L > 0, \forall u, x_1, x_2, ||Ax_1 + Bu Ax_2 Bu|| \le L||x_1 x_2||$
  - $\Leftrightarrow \exists L > 0, \forall u, x_1, x_2, ||Ax_1 Ax_2|| \le L ||x_1 x_2||$
  - But  $||Ax_1 Ax_2|| = ||A(x_1 x_2)|| \le ||A||_i ||x_1 x_2||$
- Recall:

• 
$$||A||_{p,i} = \sup_{x \neq 0} \frac{||Ax||_p}{||x||_p}$$

•  $||A||_{\infty,i} = \max_{i}^{x \neq 0} \sum_{j=1}^{n} |a_{ij}|$  (maximum row sum)

• 
$$\dot{x} = Ax + Bu$$
,  $x(0) = x_0$   
•  $x(t) = e^{At}x_0 + \int_0^t e^{A(t-\tau)}Bu(\tau)d\tau$   
 $e^{At} = I + \frac{At}{1!} + \frac{A^2t^2}{2!} + \cdots$ 

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- Zero input solution:  $x(t) = e^{At}x_0$ 
  - $z = Tx \Rightarrow \dot{z} = TAT^{-1}z$ ,  $z_0 = Tx_0$

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-----



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• Define  $\tilde{A} = TAT^{-1} \Rightarrow \dot{z} = Jz$ 

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- Solution in terms of  $z: z(t) = e^{Jt} z_0$

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- Define  $\tilde{A} = TAT^{-1} \Rightarrow \dot{z} = Jz$
- Solution in terms of  $z: z(t) = e^{Jt}z_0$

• Diagonal 
$$J: z(t) = \begin{bmatrix} e^{\lambda_1 t} & 0\\ 0 & e^{\lambda_2 t} \end{bmatrix} \begin{bmatrix} z_{10}\\ z_{20} \end{bmatrix}$$





$$f(J) = e^{Jt}$$
  

$$f(\cdot) = e^{\cdot t}$$
  

$$f'(\cdot) = te^{\cdot t}$$
  

$$f''(\cdot) = t^2 e^{\cdot t}$$



• If  $\dot{x} = Ax$ ,  $x(0) = x_0$ , then  $x(t) = e^{At}x_0$ 

 $e^{At}$  "propagates" a state forward by a duration of t, according to the system dynamics A



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• State transition matrix





- If  $\dot{x} = Ax$ ,  $x(0) = x_0$ , then  $x(t) = e^{At}x_0$
- $e^0 = I$  (follows from the above)

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• State transition matrix





- $e^0 = I$  (follows from the above)
- $e^{A(t+s)} = e^{At}e^{As}$ •  $x(t+s) = e^{A(t+s)}x_0 = e^{At}e^{As}x_0$

•  $e^{(A+B)t} = e^{At}e^{Bt}$  if and only if AB = BA

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• 
$$(e^{At})^{-1} = e^{-At}$$
  
• So  $e^{At}e^{-A} = I$ 

 $e^{A5}$  t = 5 t = 0

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 by a duration of t, according to
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State transition matrix

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- $e^{0} = I$  (follows from the above) •  $e^{A(t+s)} = e^{At}e^{As}$ •  $x(t+s) = e^{A(t+s)}x_{0} = e^{At}e^{As}x_{0}$ •  $e^{(A+B)t} = e^{At}e^{Bt}$  if and only if AB = BA
- $(e^{At})^{-1} = e^{-At}$ • So  $e^{At}e^{-At} = I$

• 
$$\frac{d}{dt}e^{At} = Ae^{At} = e^{At}A$$

• From definition: 
$$e^{At} = I + \frac{At}{1!} + \frac{A^2t^2}{2!} + \cdots$$

 $e^{At}$  "propagates" a state forward by a duration of t, according to the system dynamics A

State transition matrix



• If  $\dot{x} = Ax + Bu$ ,  $x(0) = x_0$ , then  $x(t) = e^{At}x_0 + \int_0^t e^{A(t-\tau)}Bu(\tau)d\tau$ 

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- Initial conditions:

• Differentiate:

- If  $\dot{x} = Ax + Bu$ ,  $x(0) = x_0$ , then  $x(t) = e^{At}x_0 + \int_0^t e^{A(t-\tau)}Bu(\tau)d\tau$
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 $\frac{d}{dt}\left(\int_{0}^{t} e^{A(t-\tau)}Bu(\tau)d\tau\right) = \frac{d}{dt}\left(\int_{0}^{t} e^{At}e^{-A\tau}Bu(\tau)d\tau\right)$ 

• Initial conditions:

• 
$$x(0) = e^{A(0)}x_0 + \int_0^0 e^{A(t-\tau)}Bu(\tau)d\tau = x_0$$

- Differentiate:
  - $\dot{x} = \frac{d}{dt} (e^{At} x_0) + \frac{d}{dt} \left( \int_0^t e^{A(t-\tau)} Bu(\tau) d\tau \right)$
  - $\dot{x} = Ae^{At}x_0 +$

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- Differentiate: •  $\dot{x} = \frac{d}{dt} \left( e^{At} x_0 \right) + \frac{d}{dt} \left( \int_0^t e^{A(t-\tau)} Bu(\tau) d\tau \right)$   $\frac{d}{dt} \left( \int_0^t e^{A(t-\tau)} Bu(\tau) d\tau \right)$   $\frac{d}{dt} \left( \int_0^t e^{At} x_0 d\tau \right)$   $\frac{d}{dt} \left( e^{At} \int_0^t e^{-A\tau} Bu(\tau) d\tau \right)$ 
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• Initial conditions:  
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$$x(0) = e^{A(0)}x_0 + \int_0^0 e^{A(t-\tau)}Bu(\tau)d\tau = x_0$$
  
• Differentiate:  
•  $\dot{x} = \frac{d}{dt}(e^{At}x_0) + \frac{d}{dt}(\int_0^t e^{A(t-\tau)}Bu(\tau)d\tau)$   
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 $\frac{d}{dt}\int_a^t e^{A(t-\tau)}Bu(\tau)d\tau = x_0$   
 $= \frac{d}{dt}\int_a^t e^{At}e^{-A\tau}Bu(\tau)d\tau$   
 $= Ae^{At}\int_0^t e^{-A\tau}Bu(\tau)d\tau + e^{At}e^{-At}Bu(\tau)d\tau$
#### Solution to LTI System: Proof

• If  $\dot{x} = Ax + Bu$ ,  $x(0) = x_0$ , then  $x(t) = e^{At}x_0 + \int_0^t e^{A(t-\tau)}Bu(\tau)d\tau$ 

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$$= Ae^{At}\int_0^t e^{-A\tau}Bu(\tau)d\tau + e^{At}e^{-A\tau}Bu(\tau)d\tau$$

$$= A\int_0^t e^{A(t-\tau)}Bu(\tau)d\tau + Bu(t)$$

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•  $\dot{x} = Ae^{At}x_0 + A\int_0^t e^{A(t-\tau)}Bu(\tau)d\tau + Bu(t)$   
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LTI System: Stability of  $\dot{x} = Ax$ 

- Equilibrium point of  $\dot{x} = f(x)$  is where f(x) = 0
  - For  $\dot{x} = Ax$ , in general  $\mathbf{0}_n$  is an equilibrium point:  $x_e = \mathbf{0}_n$
  - Also,  $x_e \in N(A)$



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  - Also,  $x_e \in N(A)$
- Stable: x(t) is bounded for all  $t \ge 0$ , for all initial conditions  $x_0$
- Asymptotically stable:  $x(t) \rightarrow x_e$  as  $t \rightarrow \infty$
- **Exponentially stable**:  $\exists M, \alpha > 0$  such that  $||x(t)|| \le Me^{-\alpha t} ||x_0||$



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- The system  $\dot{x} = Ax$  is exponentially stable if and only if all eigenvalues of A are in the *open* left half plane, i.e.  $\forall k$ ,  $\operatorname{Re}(\lambda_k) < 0$



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  - z = Tx

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  - $z = Tx \Rightarrow \dot{z} = TAT^{-1}z = \Lambda z$ ,  $z_0 = Tx_0$

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$$z = Tx \Rightarrow \dot{z} = TAT^{-1}z = \Lambda z, \ z_0 = Tx_0$$

• 
$$\begin{bmatrix} z_1(t) \\ z_2(t) \end{bmatrix} = \begin{bmatrix} e^{\lambda_1 t} & 0 \\ 0 & e^{\lambda_2 t} \end{bmatrix} \begin{bmatrix} z_{10} \\ z_{20} \end{bmatrix}$$

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$$z = Tx \Rightarrow \dot{z} = TAT^{-1}z = \Lambda z, \ z_0 = Tx_0$$
  
•  $\begin{bmatrix} z_1(t) \\ z_2(t) \end{bmatrix} = \begin{bmatrix} e^{\lambda_1 t} & 0 \\ 0 & e^{\lambda_2 t} \end{bmatrix} \begin{bmatrix} z_{10} \\ z_{20} \end{bmatrix}$   
• If  $\operatorname{Re}(\lambda_k) < 0, e^{\lambda_k t} \to 0$ , so  $z_k(t) = e^{\lambda_k t} z_{k0} \to 0$ 

K

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• If  $\operatorname{Re}(\lambda_k) < 0$ ,  $e^{\lambda_k t} \to 0$ , so  $z_k(t) = e^{\lambda_k t} z_{k0} \to 0$ 



• If max  $\operatorname{Re}(\lambda_k) = 0$ , z(t) stays bounded only if  $\overline{\lambda}_k$  has Jordan block of size 1

Eigenvalue with largest real part

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- If max  $\operatorname{Re}(\lambda_k) = 0$ , z(t) stays bounded only if  $\overline{\lambda}_k$  has Jordan block of size 1
- $e^{Jt}z_{0} = \begin{bmatrix} e^{\lambda_{1}t} & e^{\lambda_{1}t} & e^{\lambda_{1}t} & & \\ & e^{\lambda_{1}t} & e^{\lambda_{1}t} & & \\ & & e^{\lambda_{2}t} & te^{\lambda_{2}t} & \frac{1}{2}t^{2}e^{\lambda_{2}t} \\ & & & e^{\lambda_{2}t} & te^{\lambda_{2}t} \\ & & & & e^{\lambda_{2}t} & te^{\lambda_{2}t} \end{bmatrix} z_{0}$ • When  $\lambda_i = 0$ ...

• If max  $\operatorname{Re}(\lambda_k) = 0$ , z(t) stays bounded only if  $\overline{\lambda}_k$  has Jordan block of size 1

$$e^{Jt}z_{0} = \begin{bmatrix} 1 & & & & \\ & 1 & t & & \\ & & 1 & & \\ & & & 1 & t & \frac{1}{2}t^{2} \\ & & & & 1 & t \\ & & & & 1 & t \\ & & & & & 1 \end{bmatrix} z_{0}$$

• When  $\lambda_i = 0$ ...

• If max  $\operatorname{Re}(\lambda_k) = 0$ , z(t) stays bounded only if  $\overline{\lambda}_k$  has Jordan block of size 1

$$e^{Jt}z_{0} = \begin{bmatrix} 1 & & & & \\ & 1 & t & & \\ & & 1 & & \\ & & & 1 & t & \frac{1}{2}t^{2} \\ & & & & 1 & t \\ & & & & 1 & t \\ & & & & & 1 \end{bmatrix} z_{0}$$

- When  $\lambda_i = 0$ ...
- Not stable!

- Local behaviour of nonlinear system  $\dot{x} = f(x, u)$  at operating point  $(x, u) = (\bar{x}, \bar{u})$ 
  - At the operating point,  $\dot{\bar{x}} = f(\bar{x}, \bar{u})$
  - Define new variables  $\tilde{x} = x \bar{x}$ ,  $\tilde{u} = u \bar{u}$



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  - At the operating point,  $\dot{\bar{x}} = f(\bar{x}, \bar{u})$
  - Define new variables  $\tilde{x} = x \bar{x}$ ,  $\tilde{u} = u \bar{u}$
- Taylor approximation:
  - $f(x,u) = f(\bar{x} + \tilde{x}, \bar{u} + \tilde{u})$

- Local behaviour of nonlinear system  $\dot{x} = f(x, u)$  at operating point  $(x, u) = (\bar{x}, \bar{u})$ 
  - At the operating point,  $\dot{\bar{x}} = f(\bar{x}, \bar{u})$
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• From previous slide: 
$$\dot{\tilde{x}} = \frac{\partial f}{\partial x}\Big|_{(\bar{x},\bar{u})} \tilde{x} + \frac{\partial f}{\partial u}\Big|_{(\bar{x},\bar{u})} \tilde{u}$$
  
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  - Newton's laws:  $\ddot{\theta} = \frac{\tau}{ml^2} + \frac{g}{l}\sin\theta$



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$$\frac{\partial x^{l}(\bar{x},\bar{u})}{\partial x^{l}(\bar{x},\bar{u})} = \begin{bmatrix} \frac{\partial f_{1}}{\partial x_{1}} & \frac{\partial f_{1}}{\partial x_{2}} \\ \frac{\partial f_{2}}{\partial x_{1}} & \frac{\partial f_{2}}{\partial x_{2}} \end{bmatrix}_{(\mathbf{0},0)} = \begin{bmatrix} 0 & 1 \\ \frac{g}{l} \cos x_{1} & 0 \end{bmatrix}_{(\mathbf{0},0)} = \begin{bmatrix} 0 & 1 \\ \frac{g}{l} & 0 \end{bmatrix}$$

$$\cdot \frac{\partial f}{\partial u}\Big|_{(\bar{x},\bar{u})} = \begin{bmatrix} \frac{\partial f_{1}}{\partial u} \\ \frac{\partial f_{2}}{\partial u} \end{bmatrix}_{(\mathbf{0},0)}$$

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$$\begin{aligned} & \cdot \frac{\partial f}{\partial x} \Big|_{(\bar{x},\bar{u})} &= \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{bmatrix}_{(\mathbf{0},0)} &= \begin{bmatrix} 0 & 1 \\ \frac{g}{l} \cos x_1 & 0 \end{bmatrix}_{(\mathbf{0},0)} = \begin{bmatrix} 0 & 1 \\ \frac{g}{l} & 0 \end{bmatrix} \\ & \cdot \frac{\partial f}{\partial u} \Big|_{(\bar{x},\bar{u})} &= \begin{bmatrix} \frac{\partial f_1}{\partial u} \\ \frac{\partial f_2}{\partial u} \end{bmatrix}_{(\mathbf{0},0)} &= \begin{bmatrix} 0 \\ 1 \end{bmatrix} \end{aligned}$$

# $\dot{x}_1 = x_2$ $\dot{x}_2 = \frac{g}{l}\sin x_1 + u$ Linearization • Linearize around $\theta = x_1 = 0$ , $\dot{\theta} = x_2 = 0$ , u = 0• $\dot{\tilde{x}} \approx \frac{\partial f}{\partial x}\Big|_{(\bar{x},\bar{u})} \tilde{x} + \frac{\partial f}{\partial u}\Big|_{(\bar{x},\bar{u})} \tilde{u}$ $\cdot \left. \frac{\partial f}{\partial x} \right|_{(\bar{x},\bar{u})} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{bmatrix}_{(\mathbf{a},\mathbf{a})} = \begin{bmatrix} 0 & 1 \\ \frac{g}{l} \cos x_1 & 0 \end{bmatrix}_{(\mathbf{0},0)} = \begin{bmatrix} 0 & 1 \\ \frac{g}{l} & 0 \end{bmatrix}$ • $\frac{\partial f}{\partial u}\Big|_{(\bar{x},\bar{u})} = \begin{bmatrix} \frac{\partial f_1}{\partial u}\\ \frac{\partial f_2}{\partial u} \end{bmatrix}_{(\mathbf{0},0)} = \begin{bmatrix} 0\\1 \end{bmatrix}$ • So $\dot{x} \approx \begin{bmatrix} 0 & 1 \\ \frac{g}{l} & 0 \end{bmatrix} x + \begin{bmatrix} 0 \\ 1 \end{bmatrix} u \qquad \Rightarrow \qquad \begin{aligned} \dot{x}_1 \approx x_2 \\ \dot{x}_2 \approx \frac{g}{l} x_1 + u \end{aligned}$
• Suppose  $\dot{x} = Ax + Bu$ , can we design u to make  $x = \mathbf{0}_n$  stable?

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- Issues
  - Controller saturation
  - Full state information required







