

ASEN 5044, Fall 2024

# Statistical Estimation for Dynamical Systems

## Lecture 06: Discrete Time Linear State Space Systems

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Thursday 9/12/2024



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# Announcements

- **Prof. Ahmed out of country next week (SPIE Defense & Security Conference in UK)**
  - No live classes next Tues 09/17 or Thurs 09/19, BUT pre-recorded Lecture Videos to be posted – WATCH THEM!! (will need them for HW 2)
  - TF Aidan to cover Prof. Ahmed's hours next Wed 09/18 4:30-6 pm, AERO N353
  - Regular in-person lectures to resume Tues 09/24
- **HW 1 due tomorrow Fri 9/13 at 11:59 pm**
- **Submit to Gradescope (linked via Canvas) –**
  - All submissions must be legible!!! – zero credit otherwise
- Advanced Questions: these are optional/extra credit (follow instructions)
- HW 2 will be posted today, due Fri 09/20; HW 3 to be posted next Thurs 09/19
- Quiz 3: this Friday-<sup>Tues</sup>~~Sat~~day via Canvas; NO QUIZ NEXT WEEK
- **MIDTERM 1 – TO BE RELEASED Thurs 10/03, DUE Thurs 10/10**
  - Take home exam, to focus on material covered in HWs1-4 + quizzes up to that point

# Overview

## Last time: Linearization of nonlinear to linear SS models

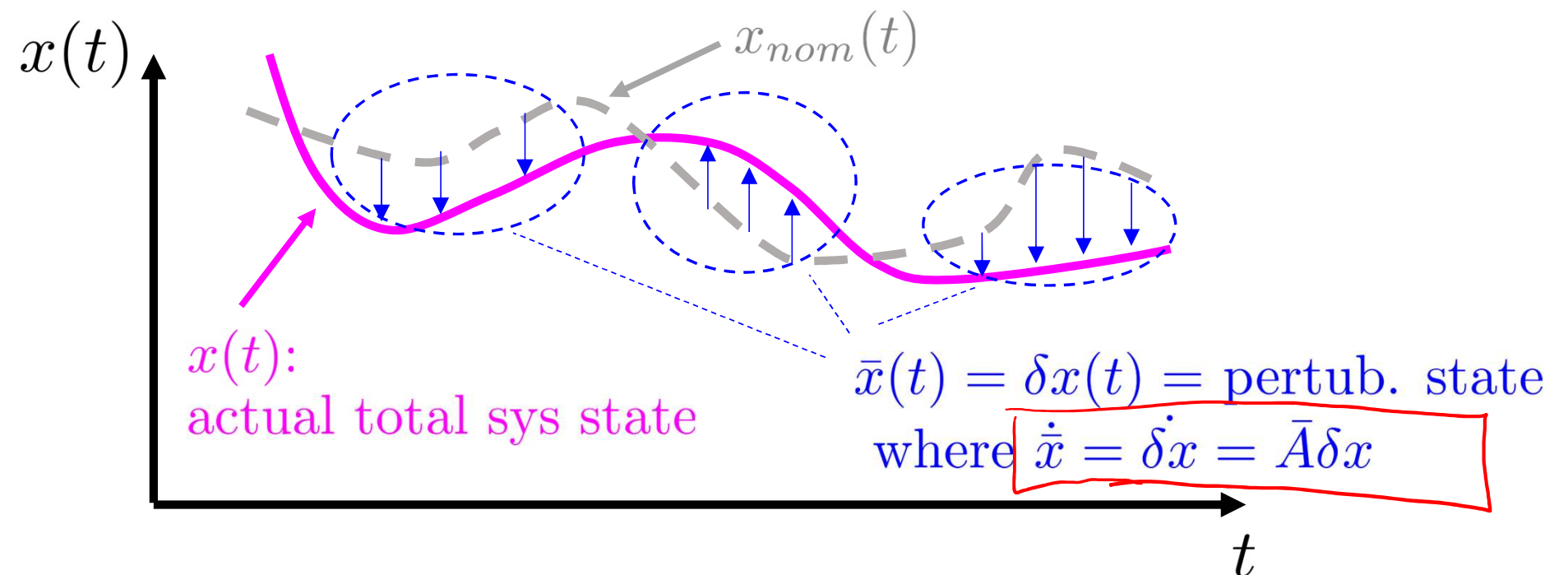
- Please read slides 13-16 of Lec 05 on your own!! (and work out the example on your own!)

$$\bar{x} = \delta x = \begin{bmatrix} \delta x_1 \\ \delta x_2 \end{bmatrix} = \text{perturbation state vector } (\neq \text{total state vector } x(t)!!)$$

$$\delta x(t) \triangleq x(t) - x_{nom}(t)$$

→ What is actual total state of NL system at any time (w.r.t. op. pt.)?

$$\begin{aligned} x(t) &= x_{nom}(t) + \delta x(t) \\ &= \begin{bmatrix} x_{nom,1}(t) \\ x_{nom,2}(t) \end{bmatrix} + \begin{bmatrix} \delta x_1 \\ \delta x_2 \end{bmatrix} \end{aligned}$$



# Overview

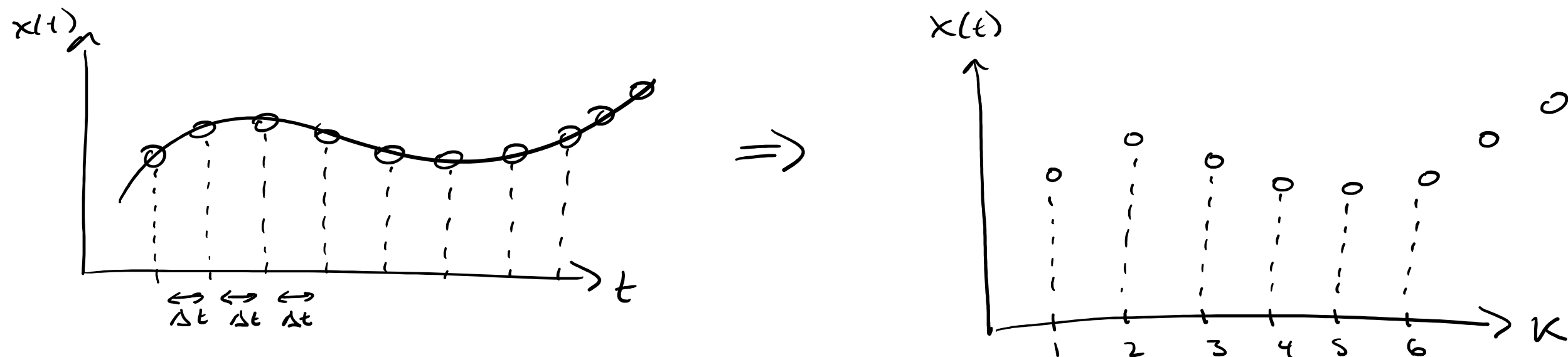
## Today:

- Discrete time (DT) linear systems,
- Converting continuous time (CT) systems to DT systems

**READ: Chapter 2.1 in Simon book (intro to probability)**

# Discrete Time Dynamic System Models

- State vector = “internal memory” of what system is doing at any given time
- In applications: only care to know what system is doing at fixed time instants, **esp. sampled intervals for digital systems**



- Some systems are naturally “**episodic**”, i.e. agnostic to physical time
  - Baseball innings; rounds of poker, pool, squash, boxing, negotiation...
  - Finite state automata for computing, event-based systems
  - **Often naturally described by finite difference equations (FDEs)**

# Discrete Time (DT) Dynamic System Models

- Convenient to specify dynamics as updates to internal system memory (i.e. state vector) from one discrete time step to another
- Linear DT models: matrices **summarize changes between integer time steps  $k$**

$$k = 0, 1, 2, 3, \dots$$

$$x(k+1) = x_{k+1} = \begin{bmatrix} x_1(k+1) \\ x_2(k+1) \\ \vdots \\ x_n(k+1) \end{bmatrix} = \underbrace{F(k)x(k) + G(k)u(k)}_{\text{Linear Time-Varying DT SS Model}}, \quad u(k) = \begin{bmatrix} u_1(k) \\ u_2(k) \\ \vdots \\ u_m(k) \end{bmatrix}$$

$$y(k+1) = y_{k+1} = \begin{bmatrix} y_1(k+1) \\ \vdots \\ y_p(k+1) \end{bmatrix} = H(k+1)x(k+1) + M(k+1)u(k+1)$$

$F(k)$ : State Transition Matrix (STM)  $\in \mathbb{R}^{n \times n}$

$G(k)$ : Control effect matrix  $\in \mathbb{R}^{n \times m}$

$H(k+1)$ : Sensing matrix  $\in \mathbb{R}^{p \times n}$

$M(k+1)$ : Direct transmission matrix  $\in \mathbb{R}^{p \times m}$

→ If no dependence on  $k$  (time step), then we get LTI DT SS:  $F, G, H, M$ , i.e.  $x_{k+1} = Fx_k + Gu_k$  etc.



# Example: Linear Car Dealer Model (episodic LTI DT system)

- You are haggling with car dealer Gary Slick for a used Ferrari
- At negotiation round  $k$ , **Slick's offer** =  $x_1(k)$  and **your offer** =  $x_2(k)$
- Offering algorithm (finite difference equation, FDE):
  - At each round  $k$ , you both lay down offers simultaneously
  - For round  $k+1$ , you update by adding fraction  $\mu$  of difference to  $x_2(k)$
  - For round  $k+1$ , Slick updates by subtracting fraction  $\lambda$  of difference from  $x_1(k)$



FDE: let  $\Delta_k = x_1(k) - x_2(k)$  (offer difference)

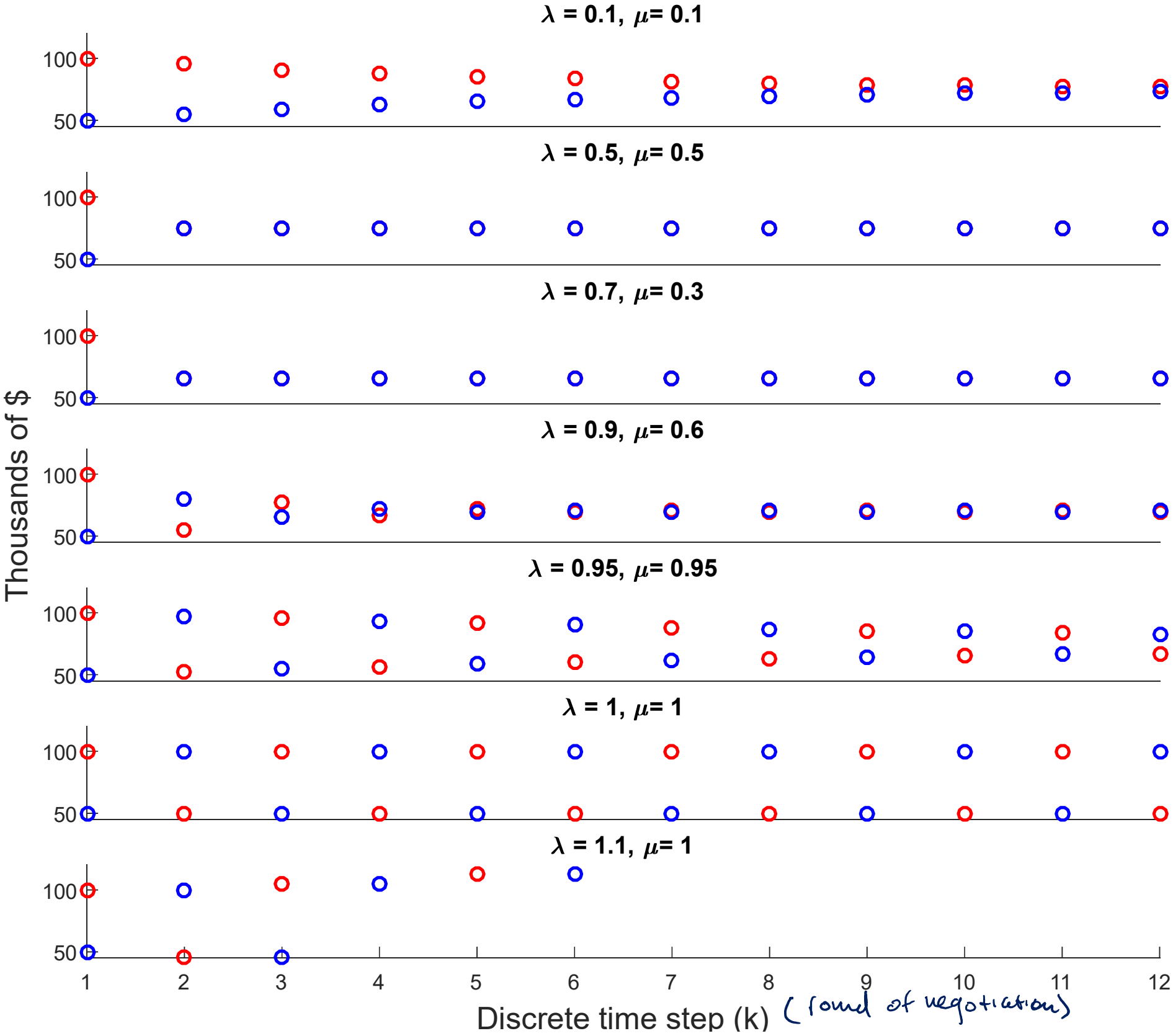
Slick's offer at time  $k + 1$ :  $x_1(k + 1) = x_1(k) - \lambda \cdot \Delta_k = x_1(k) - \lambda[x_1(k) - x_2(k)]$

Your offer at time  $k + 1$ :  $x_2(k + 1) = x_2(k) + \mu \cdot \Delta_k = x_2(k) + \mu[x_1(k) - x_2(k)]$

→ Simplify into LTI DT SS Model: Define  $x(k + 1) = \begin{bmatrix} x_1(k + 1) \\ x_2(k + 1) \end{bmatrix} = \begin{bmatrix} (1 - \lambda)x_1(k) + \lambda x_2(k) \\ \mu x_1(k) + (1 - \mu)x_2(k) \end{bmatrix}$

→ Rewrite in  $F$  matrix times  $x(k)$  form:  $x(k + 1) = \begin{bmatrix} (1 - \lambda) & \lambda \\ \mu & (1 - \mu) \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \end{bmatrix} = Fx(k), \quad x(k) \in \mathbb{R}^{2 \times 1}$

Negotiations Between You (blue) and Slick (red) for Different  $\lambda$  and  $\mu$ ,  $x_0 = [100, 50]$





# Converting CT Linear Models to Sampled DT Linear Models

- How to translate from CT model (linear system of ODEs) for a given system?

$$\begin{array}{l} \dot{x} = Ax(t) + Bu(t) \\ y(t) = Cx(t) + Du(t) \end{array} \quad \xrightarrow{??} \quad \begin{array}{l} x_{k+1} = \underline{F}x_k + \underline{G}u_k \\ y_k = Hx_k + Mu_k \end{array}$$

- Suppose  $u(k)$  follows a **zero-order hold (ZOH) discretization of  $u(t)$** :

$$u(t) = \text{some const.}, t \in [t_k, t_{k+1})$$

- Recall: general state solution  $x(t)$  is (for given  $x(t_0)$ ):

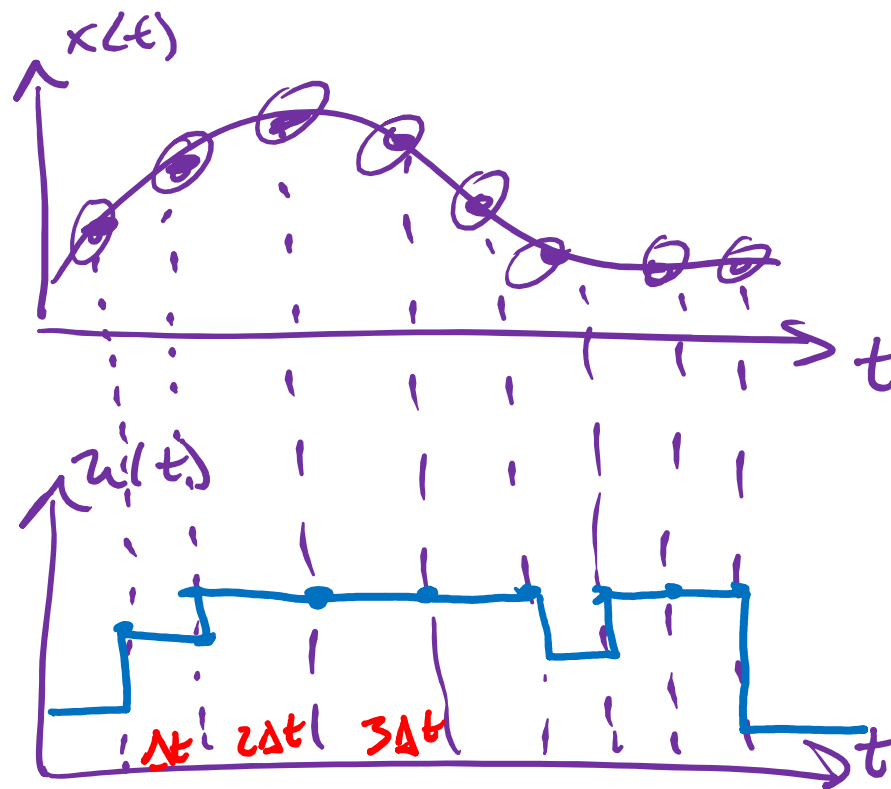
$$x(t) = \underbrace{e^{A(t-t_0)}}_{n \times n} x(\underline{t_0}) + \int_{t_0}^t \underbrace{e^{A(t-\tau)}}_{n \times n} \underbrace{B}_{n \times m} \underbrace{u(\tau)}_{m \times 1} d\tau$$

→ If we use ZOH input  $u(t)$  with fixed  $\Delta t$  sample time, then:

$$x(t) = x(t_0 + \Delta t) = e^{A\Delta t} x(t_0) + \left[ \int_{t_0}^t e^{A(t-\tau)} d\tau \right] B u(t_0)$$

$$x(k+1) = Fx(k) + Gu(k)$$

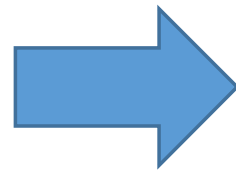
Zero order  
hold  
(ZOH)



# Converting CT Linear Models to Sampled DT Linear Models

- **FACT:** if CT LTI SS model has ZOH input  $u(t)$  applied for fixed sample periods  $\Delta t = t - t_0$ , then can explicitly find DT LTI matrices  $(F, G, H, M)$  such that:

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



$$\begin{aligned}x_{k+1} &= Fx_k + Gu_k \\ y_k &= Hx_k + Mu_k\end{aligned}$$

$$F = e^{A\Delta t}$$

$$G = \left[ \int_{t_0}^t e^{A(t-\tau)} d\tau \right] B$$

$$H = C$$

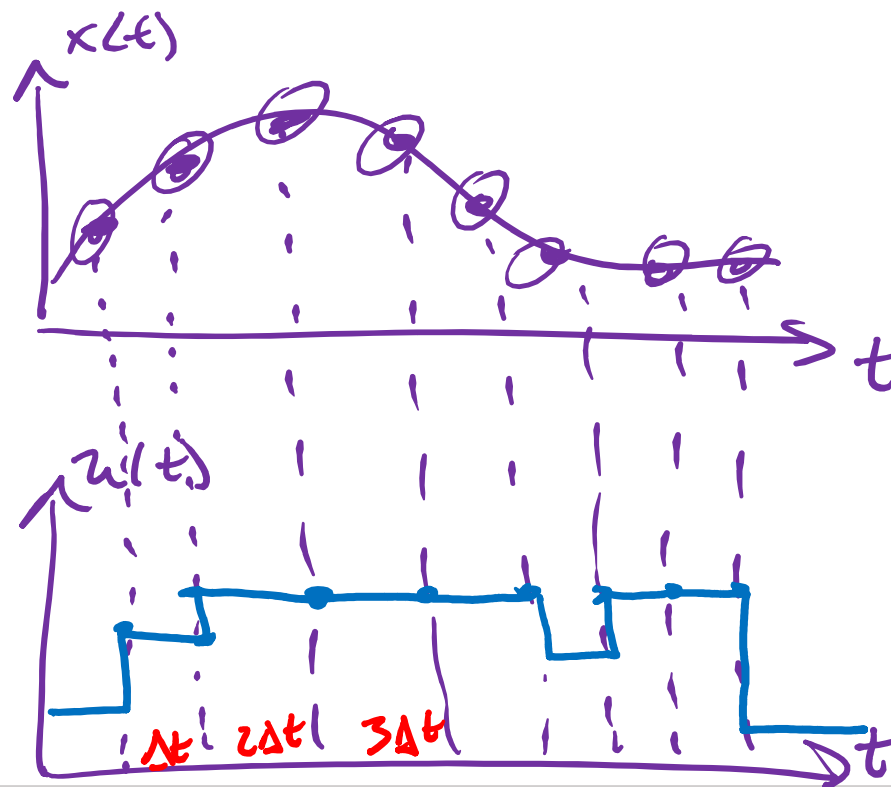
$$M = D$$

How to get this??

*Chapter 1 of Simon book  
gives formula for  $G$   
if  $A$  is invertible...*

*...but what if  $A$  is singular generally?*

e.g.  $A = \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix}$  → Inverse doesn't exist!  
(note: this is  $A$  matrix  
for the simple block  
mass problem in Lec 3!)



*Zero order  
hold  
(ZOH)*

# Computing the G matrix

- How to actually compute the G matrix integral?  $G = \left[ \int_{t_0}^t e^{A(t-\tau)} d\tau \right] \cdot B$

- First look at expansion of the integral:

$$\begin{aligned}
 \int_{t_0}^t e^{A(t-\tau)} d\tau &= \int_0^{\Delta t} e^{A(\Delta t-\tau)} d\tau \rightarrow \text{Now, plug in series def. of matrix exp.:} \\
 &= \int_0^{\Delta t} \sum_{i=0}^{\infty} \frac{A^i (\Delta t-\tau)^i}{i!} d\tau \\
 &= \sum_{i=0}^{\infty} \int_0^{\Delta t} \frac{A^i (\Delta t-\tau)^i}{i!} d\tau = \sum_{i=0}^{\infty} A^i \int_0^{\Delta t} \frac{(\Delta t-\tau)^i}{i!} d\tau \\
 &\quad \xrightarrow{\text{easy to show!}} = \sum_{i=1}^{\infty} A^{i-1} \frac{\Delta t^i}{i!}
 \end{aligned}$$

$$\rightarrow \text{so } G = \left[ \sum_{i=1}^{\infty} A^{i-1} \frac{\Delta t^i}{i!} \right] \cdot B \rightarrow \text{What does this converge to?} \\
 \text{How to compute ??}$$

# Computing the G matrix

- Turns out there is a sneaky trick to computing this series for ZOH
- Note that ZOH assumption implies that *for any  $t \in [t_0, t_0 + \Delta t)$  that  $\dot{u}(t) = 0$*

Therefore we have  $\dot{x}(t) = A x(t) + B u(t)$  ,  $x(t_0) = x_0$   
 $\dot{u}(t) = 0$  ,  $u(t_0) = u_0$  [const. over  $\Delta t$  interval]

Define! Augmented state vector  $x_a \triangleq \begin{bmatrix} x(t) \\ u(t) \end{bmatrix}$

$$\text{s.t. } \dot{x}_a = \underbrace{\begin{bmatrix} A & B \\ 0 & 0 \end{bmatrix}}_{=\hat{A}} \begin{bmatrix} x(t) \\ u(t) \end{bmatrix}, \quad x_a(t_0) = \begin{bmatrix} x_0 \\ \underline{u_0} \end{bmatrix}$$

$$\rightarrow \dot{x}_a = \hat{A} x_a, \quad \text{where } \hat{A} \in \mathbb{R}^{(n+m) \times (n+m)}$$

$n = \# \text{ } x \text{ states}$   
 $m = \# \text{ } u \text{ inputs}$

$\rightarrow$  Sol'n for  $t_0 \rightarrow t_0 + \Delta t$   $t =$  :

$$\boxed{x_a(t) = e^{\hat{A} \Delta t} x_a(t_0)} \quad (!)$$

# Computing the G matrix

- But if we expand the matrix exponential in this case:

$$e^{\hat{A}\Delta t} = I + \hat{A}\Delta t + \frac{\hat{A}^2 \Delta t^2}{2!} + \dots$$

$$\text{where } \hat{A}^2 = \begin{bmatrix} A & B \\ 0 & 0 \end{bmatrix} \begin{bmatrix} A & B \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} A^2 & AB \\ 0 & 0 \end{bmatrix}$$

$$\hat{A}^3 = \begin{bmatrix} A & B \\ 0 & 0 \end{bmatrix} \begin{bmatrix} A^2 & AB \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} A^3 & A^2 B \\ 0 & 0 \end{bmatrix}$$

$$\vdots$$

$$\hat{A}^i = \begin{bmatrix} A^i & A^{i-1} B \\ 0 & 0 \end{bmatrix}$$

= Series expansion of  $\int_0^{t+\Delta t} e^{A(t-\tau)} d\tau$  from before!!

→ plug into series:

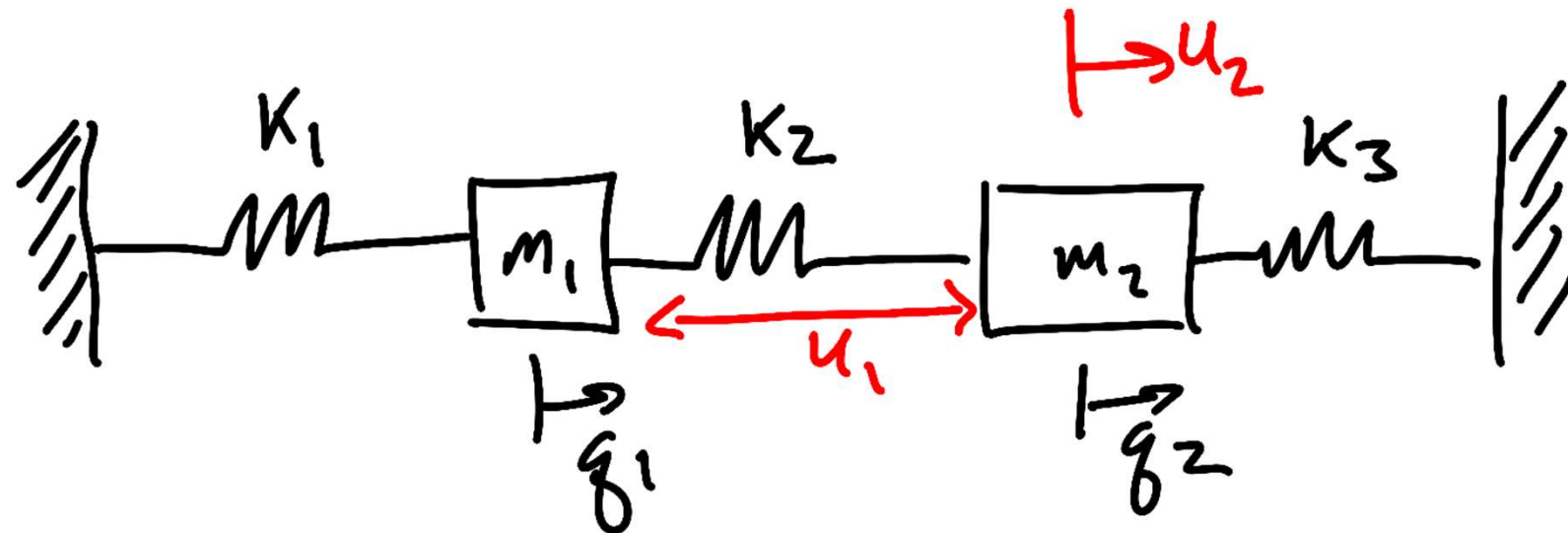
$$e^{\hat{A}\Delta t} = \begin{bmatrix} e^{A\Delta t} & \left[ \sum_{i=1}^{\infty} A^{i-1} \frac{\Delta t^i}{i!} \right] B \\ 0 & I_{m \times m} \end{bmatrix} = \begin{bmatrix} F & G \\ 0 & I_{m \times m} \end{bmatrix}$$

$$= \exp(\hat{A} \cdot \Delta t) \in \mathbb{R}^{[n+m] \times [n+m]}$$

[in Matlab]

# Example: Convert CT SS model to DT SS model

- System of 2 masses and 3 springs: 2 actuator inputs  $u$  and 2 sensor outputs  $y$



$$x = [q_1(t), \dot{q}_1(t), q_2(t), \dot{q}_2(t)]^T$$

$$u = [u_1(t), u_2(t)]^T$$

$$y = [q_1(t), q_2(t)]^T$$

For  $k_1 = k_2 = k_3 = 1$  N/m and  $m_1 = m_2 = 1$  kg, use simple physics to get CT linear SS model

$$\dot{x} = Ax(t) + Bu(t)$$

$$y(t) = Cx(t) + Du(t)$$

Two characteristic oscillatory motion “modes” (eigenvectors) corresponding to eigenvalues of  $A$  with natural frequencies:

$$\text{eig}(A) = \lambda_{1,2} = \pm j1.73, \quad \lambda_{3,4} = \pm j1.00$$

$$\rightarrow \omega_{n,1,2} = 1.73 \text{ rad/s}, \quad \omega_{n,3,4} = 1.00 \text{ rad/s}$$

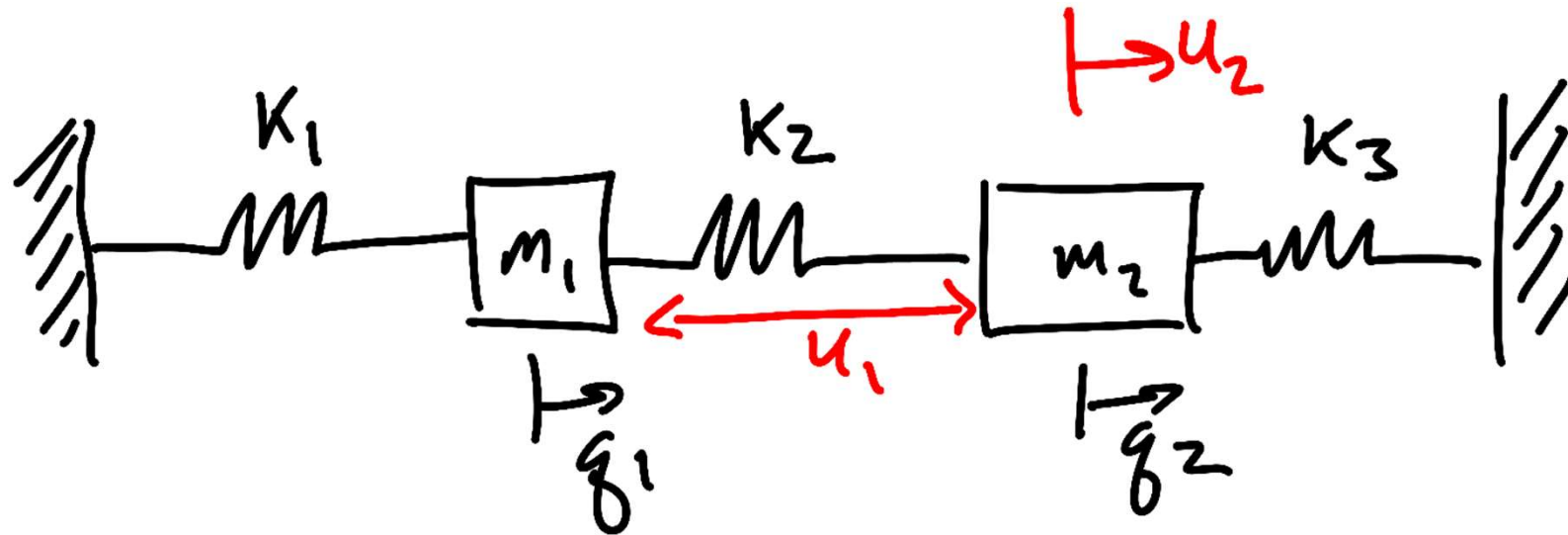
[2.72 Hz and 1.57 Hz, resp.]

$$A = \begin{bmatrix} 0 & 1.0 & 0 & 0 \\ -2.0 & 0 & 1.0 & 0 \\ 0 & 0 & 0 & 1.0 \\ 1.0 & 0 & -2.0 & 0 \end{bmatrix} \quad B = \begin{bmatrix} 0 & 0 \\ -1 & 0 \\ 0 & 0 \\ 1 & 1 \end{bmatrix} \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \quad \rightarrow \hat{A} = \begin{bmatrix} A & B \\ 0 & 0 \end{bmatrix}$$



# Example: Convert CT SS model to DT SS model (cont'd)

- System of 2 masses and 3 springs: 2 actuator inputs  $u$  and 2 sensor outputs  $y$



$$x = [q_1(t), \dot{q}_1(t), q_2(t), \dot{q}_2(t)]^T$$

$$u = [u_1(t), u_2(t)]^T$$

$$y = [q_1(t), q_2(t)]^T$$

Converted to DT SS model using the same state variables with ZOH and sample rate  $\Delta t = 0.2$  sec

$$\begin{aligned}
 x_{k+1} &= Fx_k + Gu_k, & x_k &= [q_1(k), \dot{q}_1(k), q_2(k), \dot{q}_2(k)]^T \\
 y_k &= Hx_k + Mu_k, & u_k &= [u_1(k), u_2(k)]^T \\
 & & y_k &= [q_1(k), q_2(k)]^T
 \end{aligned}$$

$$\hat{A} = \begin{bmatrix} A & B \\ 0 & 0 \end{bmatrix} \rightarrow e^{\hat{A}\Delta t} = \begin{bmatrix} F & G \\ 0 & I \end{bmatrix}$$

$$F = \begin{bmatrix} 9.6033e-01 & 1.9735e-01 & 1.9734e-02 & 1.3227e-03 \\ -3.9337e-01 & 9.6033e-01 & 1.9470e-01 & 1.9734e-02 \\ 1.9734e-02 & 1.3227e-03 & 9.6033e-01 & 1.9735e-01 \\ 1.9470e-01 & 1.9734e-02 & -3.9337e-01 & 9.6033e-01 \end{bmatrix}$$

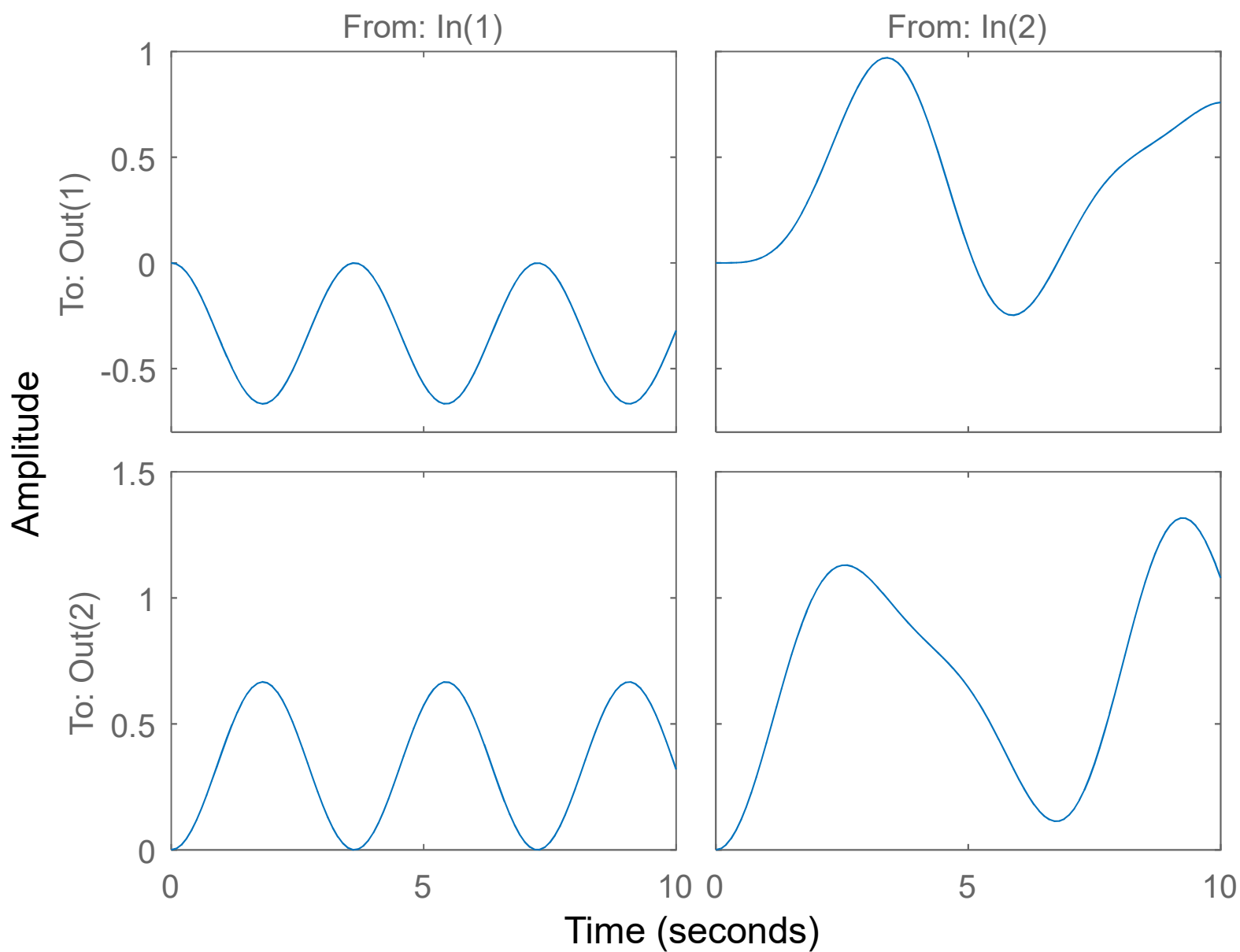
$$G = \begin{bmatrix} -1.9801e-02 & 6.6312e-05 \\ -1.9602e-01 & 1.3227e-03 \\ 1.9801e-02 & 1.9867e-02 \\ 1.9602e-01 & 1.9735e-01 \end{bmatrix}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

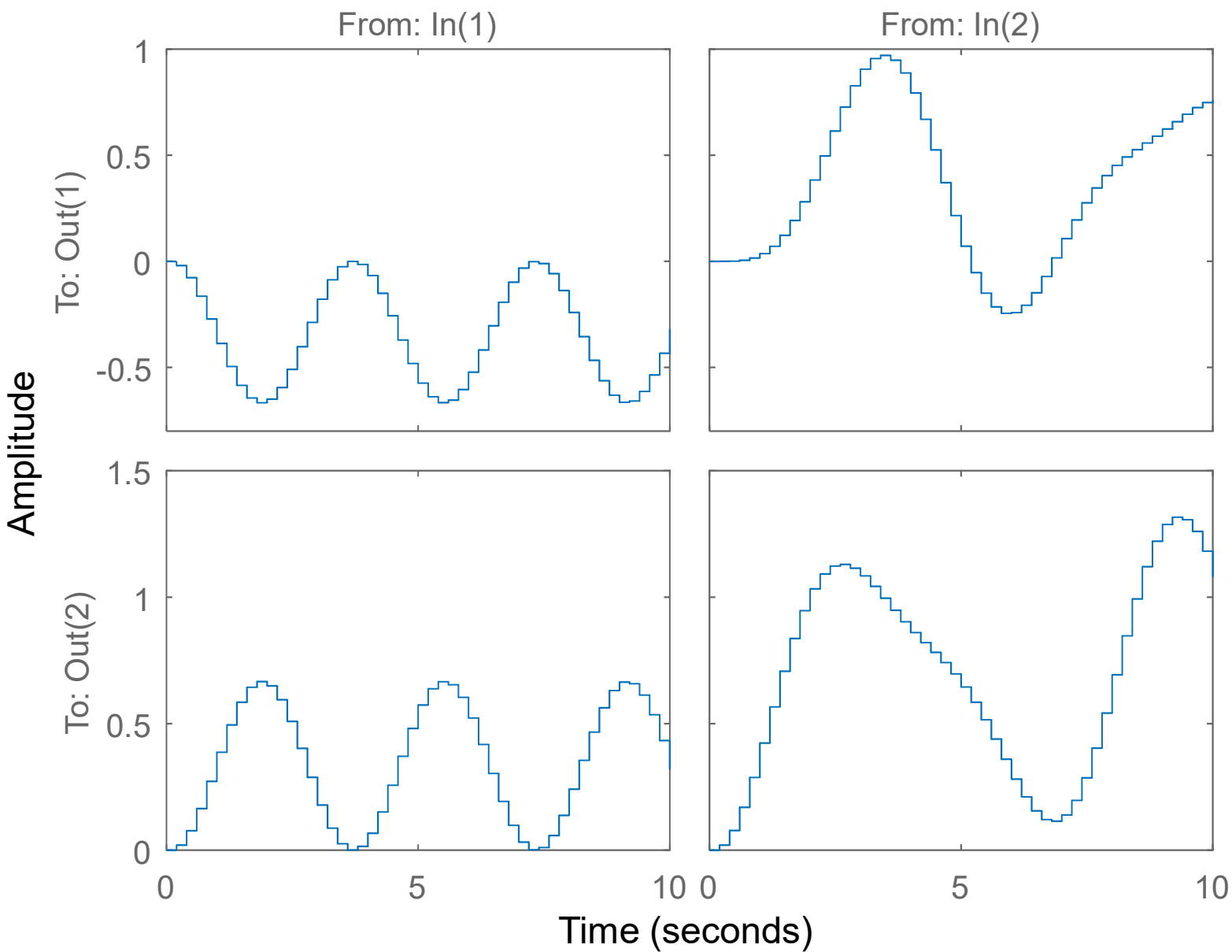
$$M = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

# Sample Input Step Response Output from DT vs CT

Continuous Time Step Response



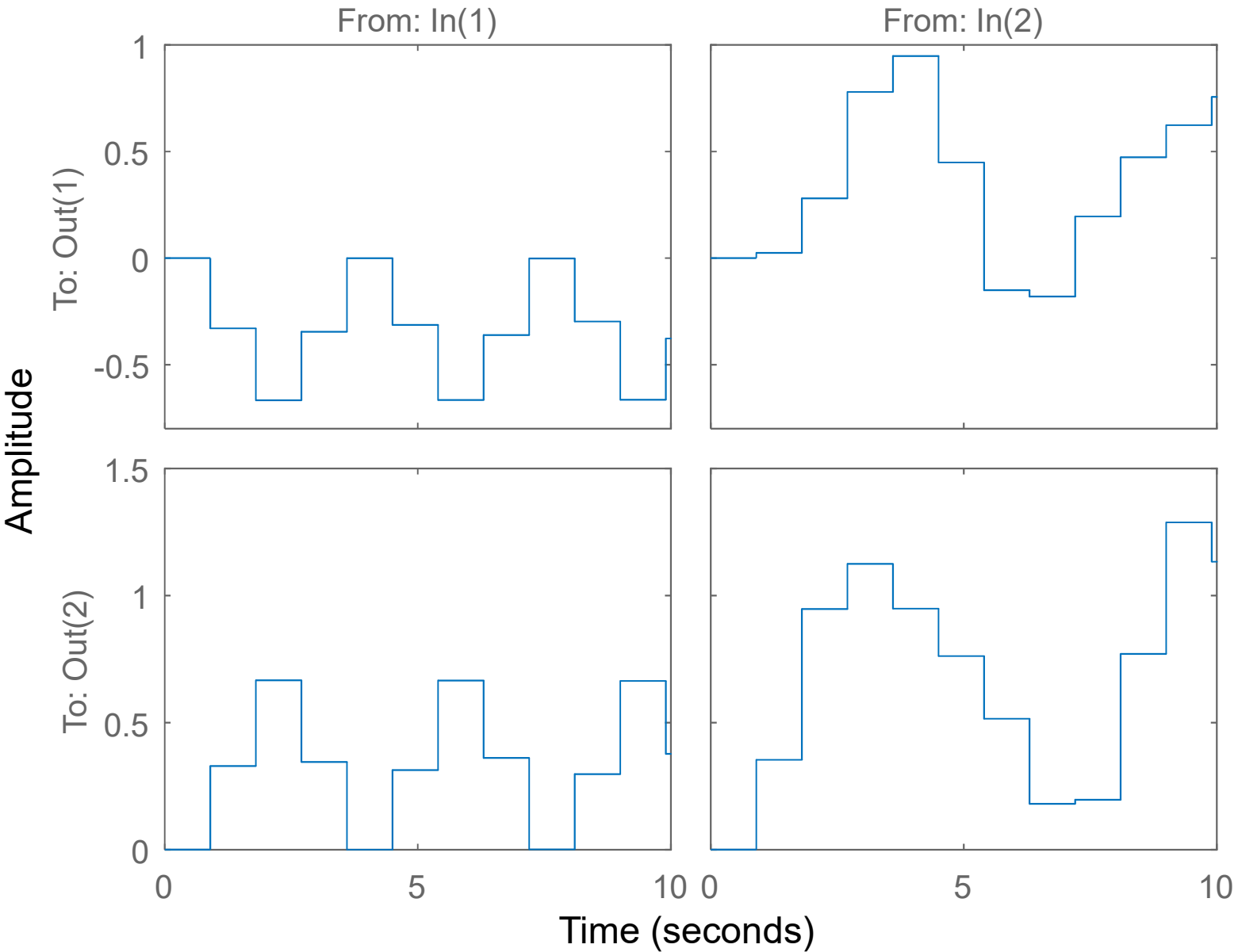
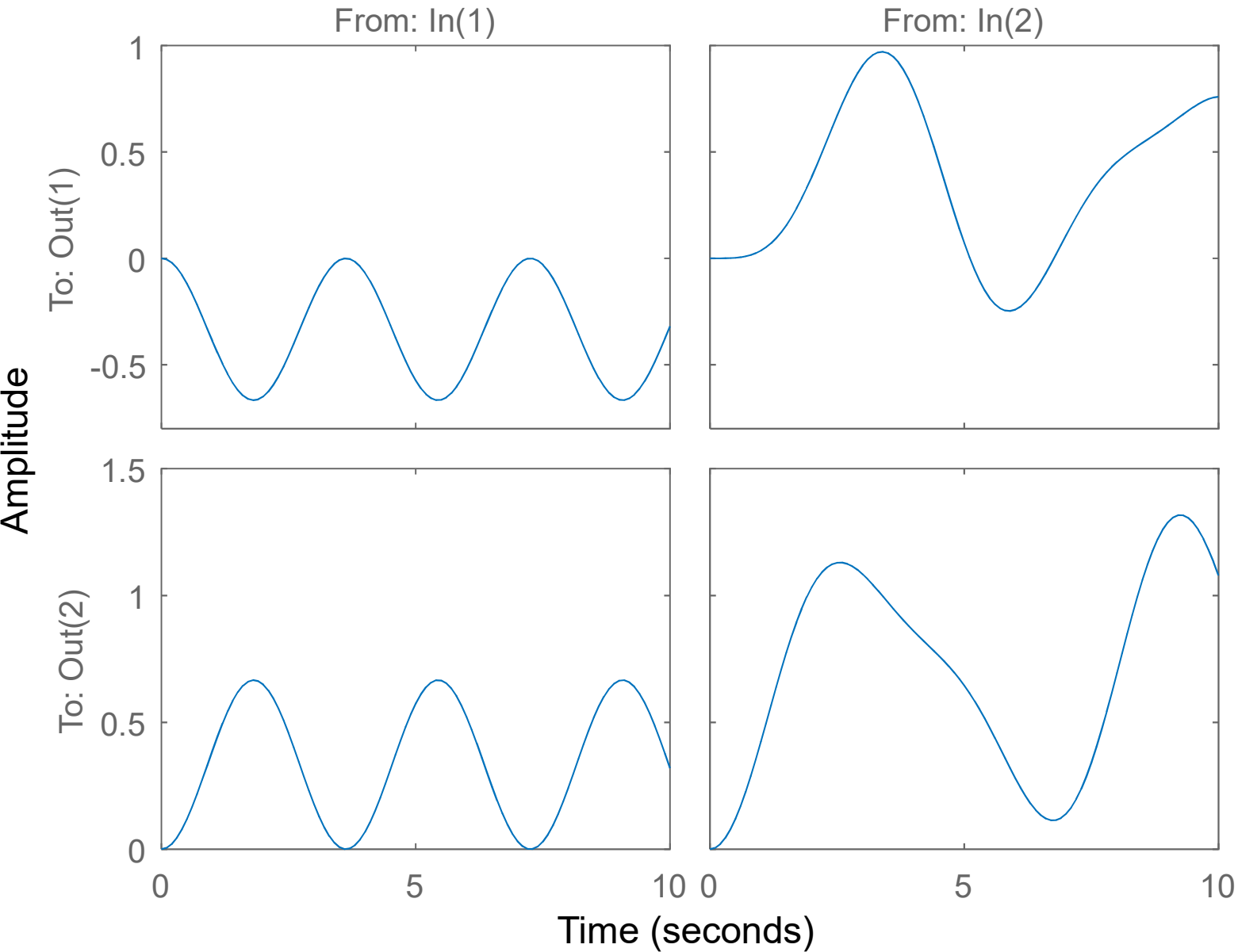
Discretized step response at  $\Delta t = 0.2$



# Sample Input Step Response Output from DT vs CT

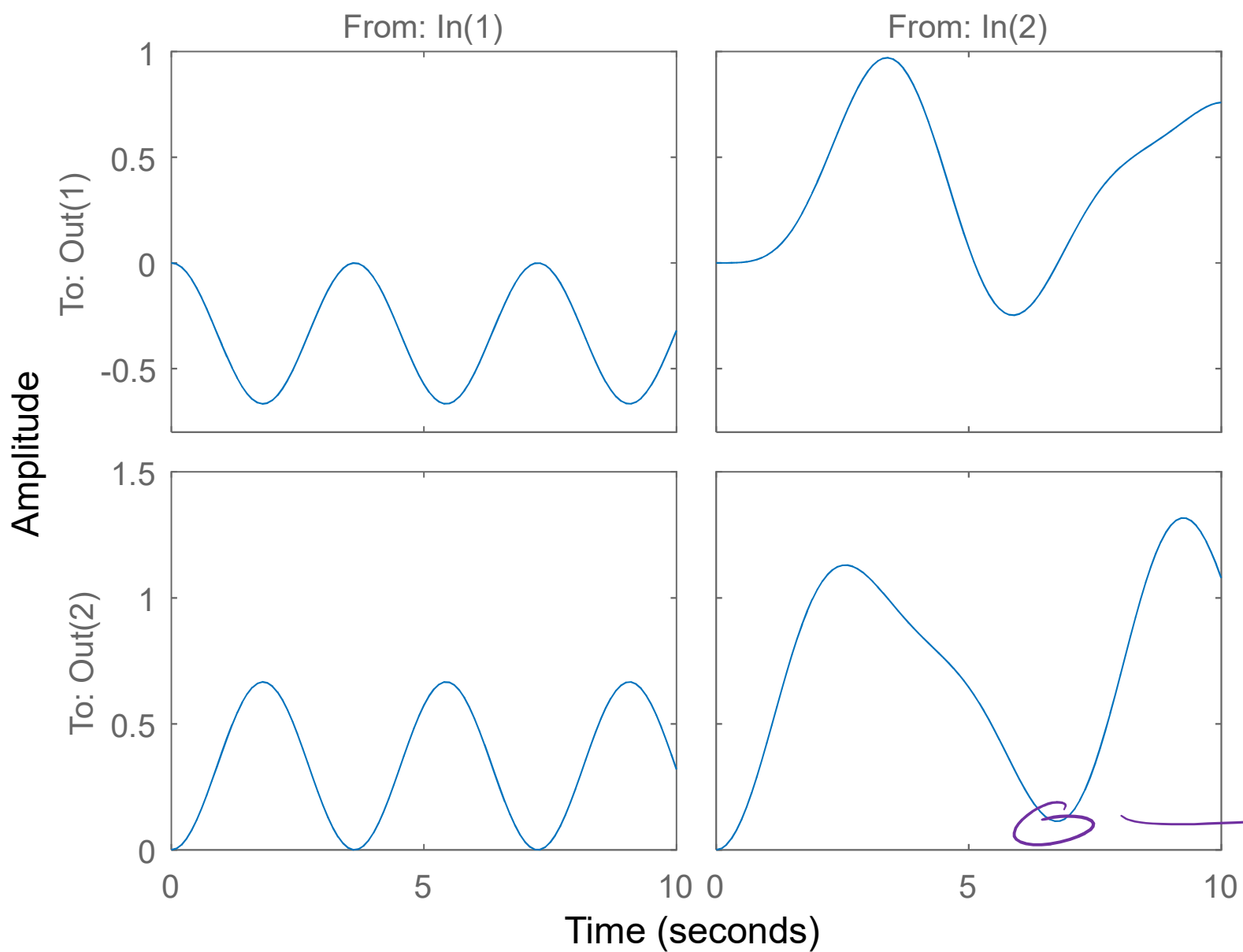
Continuous Time Step Response

Discretized step response at  $\Delta t = 0.9$

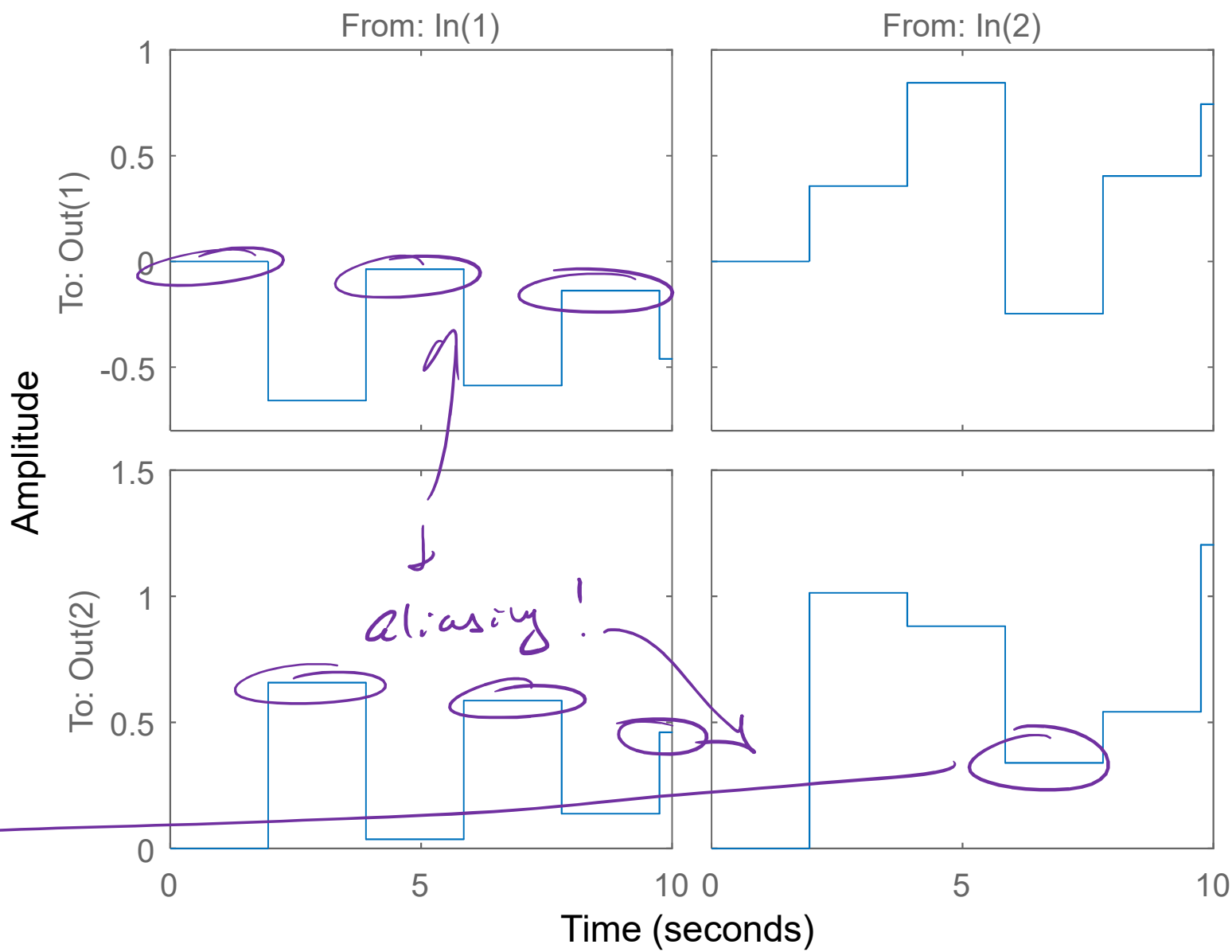


# Sample Input Step Response Output from DT vs CT

Continuous Time Step Response



Discretized step response at  $\Delta t = 1.95$



# Nyquist Rate and CT System Natural Frequencies

- **WARNING FOR CT  $\rightarrow$  DT conversions: cannot just pick any old  $\Delta t$  !!!**
- For LTI systems: fundamental upper bound on how large  $\Delta t$  should be
- Nyquist Sampling Criterion: if sample rate (in rad/s) is  $\omega_{sample} = \frac{2\pi}{\Delta t}$ ,

$$\text{need } \omega_{sample} > 2\omega_{sys,max} \Rightarrow \Delta t < \frac{\pi}{|\lambda_{A,max}|}$$

where  $|\lambda_{A,max}|$  is largest complex magnitude among all eigenvalues of  $A$   
(natural freq./ time constant)

(e.g. max  $\Delta t$  for 2 mass/3 spring example system is  $\sim 1.82$  sec  $\rightarrow \Delta t$  larger than this leads to aliasing...)