

Lecture 13

Wednesday, February 23, 2022 8:57 AM

Admin

① off → tomorrow 3-4pm

↳ email me if you need a different time.

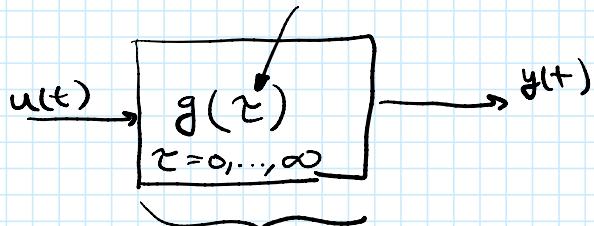
② graded hwsl back tomorrow.

Objectives

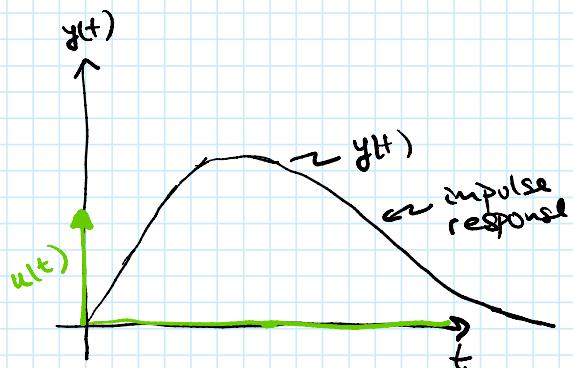
- ① Define "transfer func." modeling for linear dynamical systems
- ② Define "black-box" modeling structures for dynamic systems

Relevant Reading: Ljung chaps. 2-4.

- Consider a linear time invariant system.



Impulse Response completely characterizes the system.



Continuous time convolution

$$y(t) = \int_0^{\infty} g(\tau) u(t-\tau) d\tau$$

Impulse

$$u(t) = \begin{cases} \delta(t=0) & \\ 0 & \text{otherwise.} \end{cases}$$

- Given Impulse response $\{g(t) | t = 0, \dots, \infty\}$ and input $\{u(s) | s \leq t\}$
⇒ can define output $\{y(s) | s \leq t\}$

- In discrete time

$$y(t) = \sum_{k=1}^{\infty} g(k) u(t-k)$$

- We frequently describe the shift using an algebraic time shift operator: \mathbf{z}

$$\mathbf{z} u(t) = u(t+1)$$

→ Backward shift operator: \mathbf{z}^{-1}

$$g(u(t)) = u(t+1)$$

\rightarrow Backward shift operator: g^{-1}

$$g^{-1}(u(t)) = u(t-1)$$

$$\begin{aligned} \Rightarrow y(t) &= \sum_{k=1}^{\infty} g(k) [g^{-k} u(t)] \\ &= \left\{ \sum_{k=1}^{\infty} [g(k) g^{-k}] \right\} u(t) \\ &\quad \underbrace{\qquad\qquad\qquad}_{\text{"Transfer funcn."}} : G(g). \end{aligned}$$

$$\Rightarrow y(t) = G(g) u(t)$$

Example: Finding a transfer funcn:

$$y(t) = u(t) + c u(t-1)$$

$$= u(t) + c g^{-1} u(t)$$

$$= [1 + c g^{-1}] u(t)$$

$$\Rightarrow G(g) = G(g^{-1}) = 1 + c g^{-1}$$

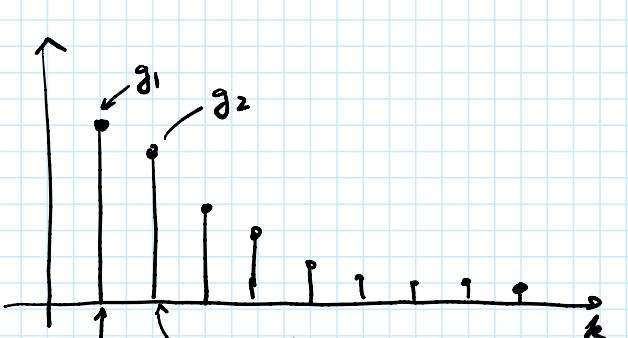
Note: Related to z transform: $G(z) = 1 + cz^{-1} = \frac{z+c}{z}$.

Parameterizing System Dynamics

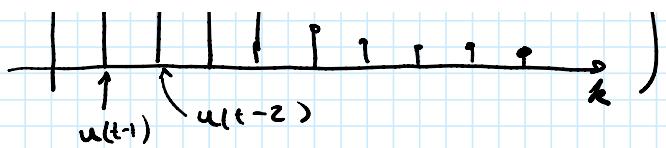
- A linear time invariant system is characterized by its impulse response.

$$u(t) \xrightarrow{G(g)} y(t)$$

$$G(g) = \sum_{k=1}^{\infty} g(k) g^{-k}$$



$\left. \begin{array}{c} g_1 \\ g_2 \\ \vdots \\ \dots \end{array} \right\} g_1, g_2, \dots, g_{30}, \dots \text{ too many params.}$



=> Can we represent the system using fewer parameters?

consider $g(k) = \alpha^{k-1}$, $k=1, 2, 3$; $\alpha < 1$

$$G(\xi) = \sum_{k=1}^{\infty} \alpha^{k-1} \xi^{-k}$$

Multiply by $\frac{a}{\xi}$:

$$\frac{a}{\xi} G(\xi) = \sum_{k=1}^{\infty} a^k \xi^{-k-1} = \sum_{k=2}^{\infty} a^{k-1} \xi^{-k} \Rightarrow \left[\frac{1}{\xi} + \sum_{k=2}^{\infty} a^{k-1} \xi^{-k} \right] - \frac{1}{\xi}$$

$$= \sum_{k=1}^{\infty} a^{k-1} \xi^{-k} - \frac{1}{\xi}$$

$$G(\xi)$$

$$\Rightarrow \frac{a}{\xi} G(\xi) = G(\xi) - \frac{1}{\xi}$$

$$\Rightarrow \left[1 - \frac{a}{\xi} \right] G(\xi) = \frac{1}{\xi}$$

$$\Rightarrow G(\xi) = \frac{\frac{1}{\xi}}{1 - \frac{a}{\xi}} = \frac{1}{\xi - a}$$

=> $G(\xi)$ is represented by a single parameter (1 pole) by using a proper representation.

Model

- Maybe determined based on a priori knowledge.
→ System physics.

- Maybe unknown, need to be estimated:

$$\theta = (\theta_1, \dots, \theta_L) \in \mathbb{R}^d$$

(Adjustable)

Families of Transfer Func. Models

- $\Delta \times$ (Auto Regressive with exogenous inputs) model structure

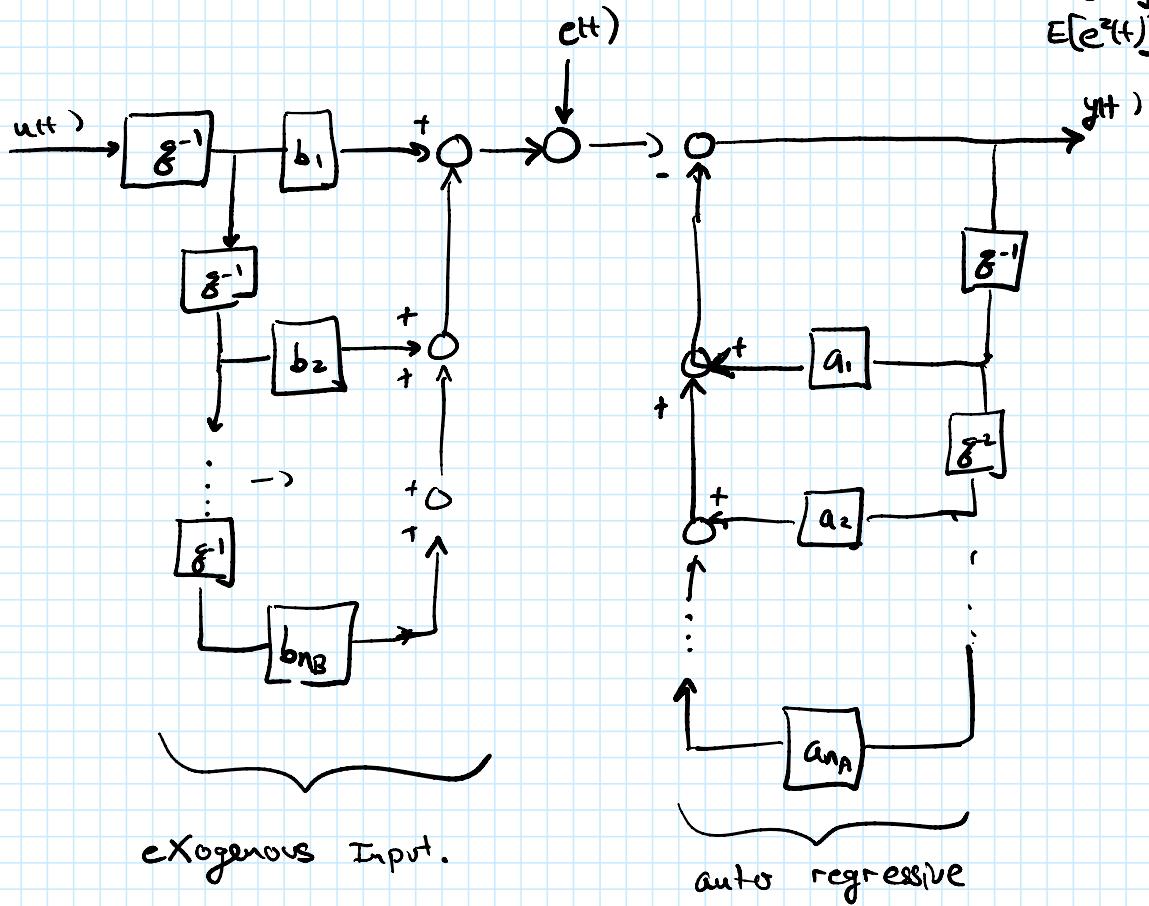
Families of Transfer Function Models

- ARX (Auto Regressive with exogenous inputs) Model structure

$$y(t) + a_1 y(t-1) + \dots + a_{n_A} y(t-n_A) = b_1 u(t-1) + \dots + b_{n_B} u(t-n_B) + e(t)$$

• why not $u(t)$?
→ causal Model.

Gaussian (Uncorrelated)
 $E[e(t)] = 0$
 $E[e^2(t)] = \lambda$



- Adjustable parameters: $\Theta = [a_1, \dots, a_{n_A}, b_1, \dots, b_{n_B}]^T$

$$\text{Define } A(\zeta) = 1 + a_1 \zeta^{-1} + \dots + a_{n_A} \zeta^{-n_A}$$

$$B(\zeta) = b_1 \zeta^{-1} + \dots + b_{n_B} \zeta^{-n_B}$$

Then the ARX structure becomes:

$$A(\zeta) y(t) = B(\zeta) u(t) + e(t)$$

- If $n_A = 0$, then $y(t) = B(\zeta) u(t) + e(t)$
= Finite Impulse Response (FIR) model.

- If $A(\theta) = 0$, then $y(t) = \sum_{j=1}^n y(t-j) + e(t)$

\Rightarrow Finite Impulse Response (FIR) model.

ARMAX (Auto Regressive Moving Average w/ exogenous Inputs) Model

$$\Rightarrow y(t) + a_1 y(t-1) + \dots + a_n y(t-n) = b_1 u(t-1) + \dots + b_m u(t-m) + e(t) + c_1 e(t-1) + \dots + c_n e(t-n)$$

use $C(\theta) = 1 + c_1 \theta^{-1} + \dots + c_n \theta^{-n}$, then

$$A(\theta) y(t) = B(\theta) u(t) + C(\theta) e(t)$$

Then,

$$G(\theta, \theta) = \frac{B(\theta)}{A(\theta)}; \quad H(\theta, \theta) = \frac{C(\theta)}{A(\theta)}$$

- This structure consists of
 - + The moving average part (MA) : $C(\theta)$
 - The autoregressive part : $A(\theta)$
 - ~ The exogenous inputs (\mathbb{X}) : $B(\theta)$