

EE269

Signal Processing for Machine Learning

Lecture 5

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Systems

$$x[n] \rightarrow \boxed{\text{system}} \rightarrow y[n]$$

- ▶ Processing operation performed on the signal
e.g., a natural system, designed filter, predictor

Systems

$$x[n] \rightarrow \boxed{\text{system}} \rightarrow y[n]$$

► Linear Systems

$$x_1[n] \rightarrow \boxed{\mathcal{T}} \rightarrow y_1[n] \quad x_2[n] \rightarrow \boxed{\mathcal{T}} \rightarrow y_2[n]$$

$$c_1 x_1[n] + c_2 x_2[n] \rightarrow \boxed{\mathcal{T}} \rightarrow c_1 y_1[n] + c_2 y_2[n] .$$

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► **Example.** *Moving average:* average of the last M values of the signal

$$y[n] = \frac{1}{M} \sum_{k=0}^{M-1} x[n - k] =: \mathcal{T}_{ma}\{x[n]\} .$$

Linear? Suppose that

$$y_1[n] = \mathcal{T}_{ma}\{x_1[n]\} \quad \text{and} \quad y_2[n] = \mathcal{T}_{ma}\{x_2[n]\}$$

Systems

- ▶ **Example.** *Moving average:* average of the last M values of the signal

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Systems

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► Time invariant Systems

$$x[n] \rightarrow \boxed{\mathcal{T}} \rightarrow y[n] ,$$

implies that for all n_0 ,

$$x[n - n_0] \rightarrow \boxed{\mathcal{T}} \rightarrow y[n - n_0] .$$

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► Example. *An accumulator*

$$y[n] = \mathcal{T}_{acc}\{x[n]\} = \sum_{k=-\infty}^n x[k] .$$

Is \mathcal{T}_{acc} is time-invariant? $y[n - n_0] =? \mathcal{T}_{acc}\{x[n - n_0]\}$

Linear Time Invariant (LTI) Systems

- ▶ Impulse response

$$\delta[n] \rightarrow \boxed{\mathcal{T}} \rightarrow h[n]$$

- ▶ Time invariant \implies

$$\delta[n - k] \rightarrow \boxed{\mathcal{T}} \rightarrow h[n - k]$$

Linear Time Invariant (LTI) Systems

- ▶ Impulse response

$$\delta[n] \rightarrow \boxed{\mathcal{T}} \rightarrow h[n]$$

- ▶ Time invariant systems:

$$\delta[n - k] \rightarrow \boxed{\mathcal{T}} \rightarrow h[n - k]$$

using the Delta basis:

$$x[n] = \sum_{k=-\infty}^{\infty} x[k] \delta[n - k] \rightarrow \boxed{\mathcal{T}} \rightarrow y[n]$$

$$y[n] = \mathcal{T} \left\{ \sum_{k=-\infty}^{\infty} x[k] \delta[n - k] \right\} .$$

Linear Time Invariant (LTI) Systems

- ▶ Impulse response

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- ▶ Linearity

$$y[n] = \sum_{k=-\infty}^{\infty} x[k] \mathcal{T}\{\delta[n - k]\} = \sum_{k=-\infty}^{\infty} x[k] h[n - k]$$

- ▶ LTI systems are entirely described by their impulse response

Convolution

$$y[n] = \sum_{k=-\infty}^{\infty} x_1[k]x_2[n-k] = x_1[n] * x_2[n] .$$

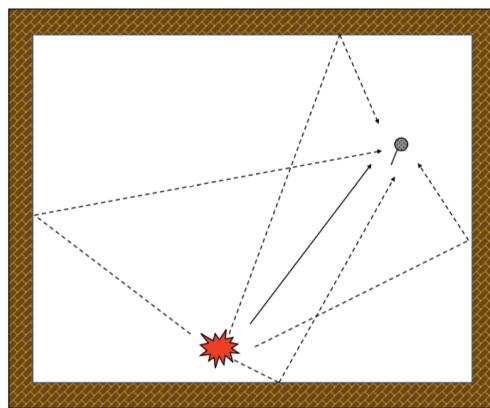
- ▶ LTI systems convolve with $h[n]$

$$x[n] \rightarrow \boxed{\mathcal{T}} \rightarrow y[n] \quad \implies y[n] = x[n] * h[n]$$

- ▶ In Hilbert spaces

$$x_1[n] * x_2[n] = \langle x_1^*[n-k], x_2[k] \rangle$$

Convolution with acoustic impulse response



Circular convolution in \mathbb{R}^N

$$y[n] = \sum_{k=0}^{N-1} x[k]h[(n - k) \bmod N] = x[n] \circledast h[n] .$$

- Matrix vector notation

$$y = Hx$$

$$H = \begin{bmatrix} h[0] & h[N-1] & h[N-2] & \dots & h[2] & h[1] \\ h[1] & h[0] & h[N-1] & \dots & h[3] & h[2] \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ h[N-1] & h[N-2] & h[N-3] & \dots & h[1] & h[0] \end{bmatrix}$$

Circular convolution in \mathbb{R}^N

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Fourier basis: $w_k[n] = \frac{1}{\sqrt{N}} e^{j \frac{2\pi}{N} nk}$

$$w_k^H H = H[k] w_k^H$$

$$Fy = FHx = \text{diag}(H[0], \dots, H[N-1])Fx$$

Multiplication in DFT domain

Fourier basis: $w_k[n] = \frac{1}{\sqrt{N}} e^{j \frac{2\pi}{N} nk}$

$$y[n] = h[n] \circledast x[n]$$

$$Y[k] = H[k]X[k] \quad \forall k$$

Diagonalization of Circulant matrices

$$y[n] = \sum_{k=0}^{N-1} x[k]h[(n - k) \bmod N] = x[n] \circledast h[n] .$$

Fourier basis: $w_k[n] = \frac{1}{\sqrt{N}} e^{j \frac{2\pi}{N} nk}$

$$\begin{aligned} FH &= \text{diag}(H[0], \dots, H[N-1])F \\ H &= F^H \text{diag}(H[0], \dots, H[N-1])F \end{aligned}$$

Deconvolution

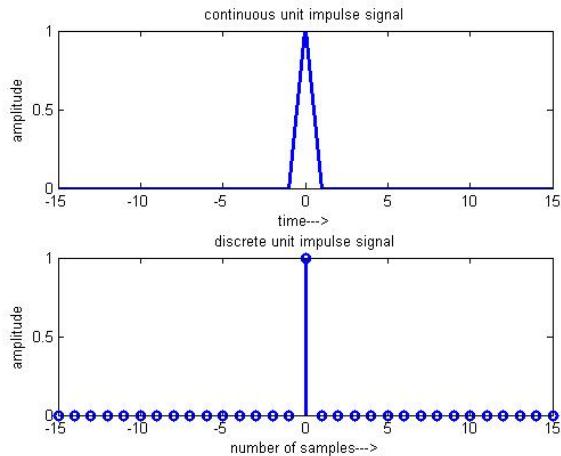
$$x[n] \rightarrow \boxed{h_1[n]} \rightarrow \boxed{h_2[n]} \rightarrow y[n]$$

$$y = H_2 H_1 x$$

$$\begin{aligned} Fy &= FH_2 H_1 x = \text{diag}(H_2[0 : N - 1]) FH_1 x \\ &= \text{diag}(H_2[0 : N - 1]) \text{diag}(H_1[0 : N - 1]) Fx \end{aligned}$$

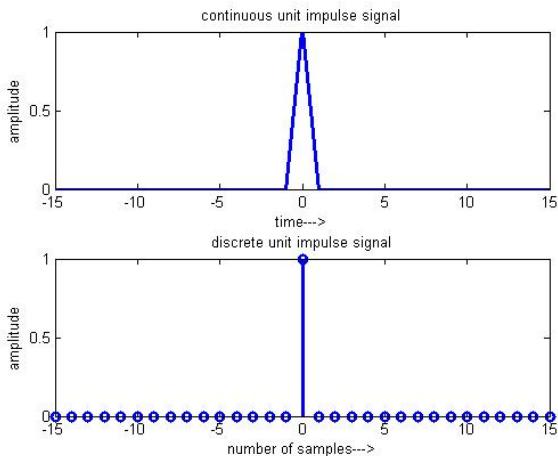
Estimating impulse response

- ▶ generate an approximation to $\delta[n]$



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- ▶ generate an approximation to $\delta[n]$



- ▶ sweeps the frequency from low to high frequency (chirp signal)

