

**SYDE 556/750**

## **Simulating Neurobiological Systems**

### **Lecture 4: Temporal Representations**

Chris Eliasmith

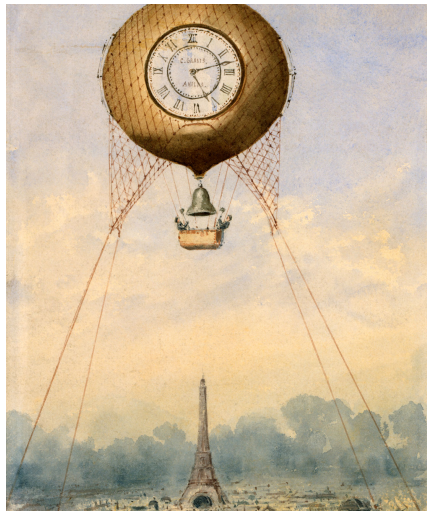
Sept 18 & 23, 2024

- ▶ Slide design: Andreas Stöckel
- ▶ Content: Terry Stewart, Andreas Stöckel, Chris Eliasmith

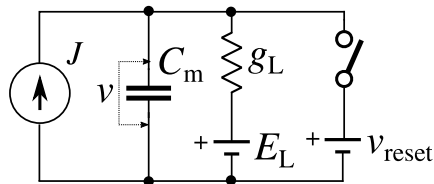
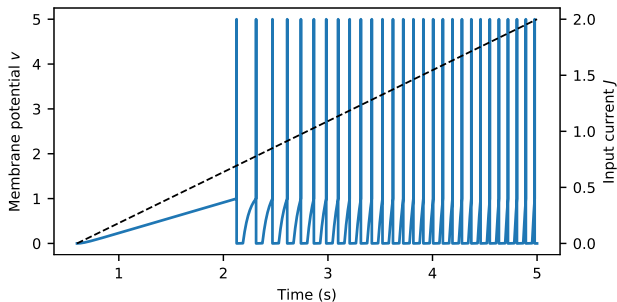


UNIVERSITY OF  
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ENGINEERING



## Reminder: The LIF Neuron



$$\frac{d}{dt}v(t) = -\frac{1}{\tau_{RC}}(v(t) - J),$$

$$v(t) \leftarrow \delta(t - t_{th}),$$

$$v(t) \leftarrow 0,$$

$$\text{if } v(t) < 1,$$

$$\text{if } t = t_{th},$$

$$\text{if } t > t_{th} \text{ and } t \geq t_{th} + \tau_{ref},$$

# Temporal Decoding

- For population decoders, we needed to integrate their responses,  $\mathbf{a}(\mathbf{x})$ , over the represented variable,  $\mathbf{x}$ .

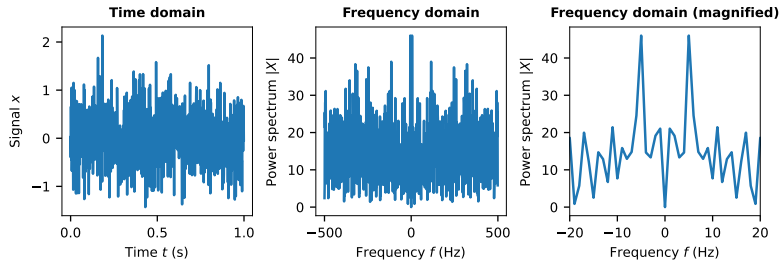
# Temporal Decoding

- ▶ For population decoders, we needed to integrate their responses,  $\mathbf{a}(\mathbf{x})$ , over the represented variable,  $\mathbf{x}$ .
- ▶ For temporal decoders, we will likely want to integrate their responses,  $\mathbf{a}(t)$ , over the represented variable,  $\mathbf{x}(t)$ .

# Temporal Decoding

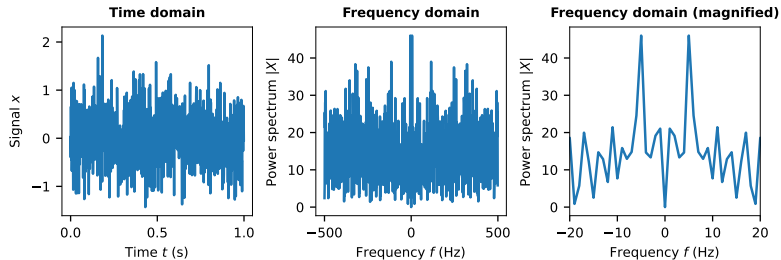
- ▶ For population decoders, we needed to integrate their responses,  $\mathbf{a}(\mathbf{x})$ , over the represented variable,  $\mathbf{x}$ .
- ▶ For temporal decoders, we will likely want to integrate their responses,  $\mathbf{a}(t)$ , over the represented variable,  $\mathbf{x}(t)$ .
- ▶ What space do we want to sample to estimate the integrals?

# Random Signals

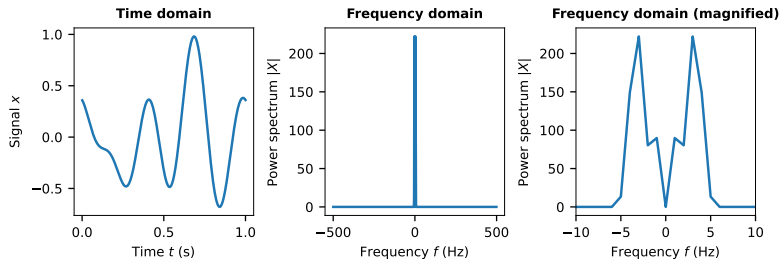


**White Noise**  
(zero mean)

# Random Signals

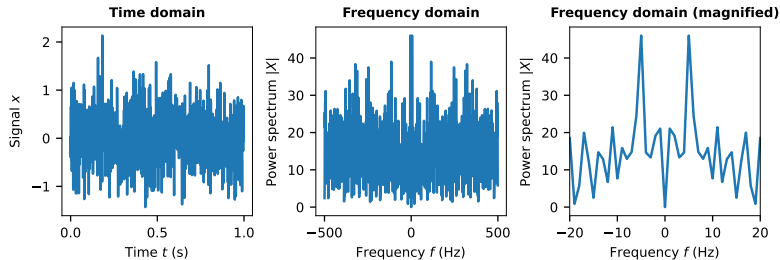


**White Noise**  
(zero mean)

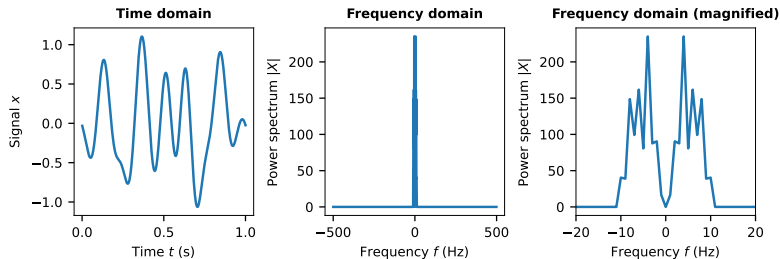


**Bandlimited**  
White Noise  
(zero mean,  
5 Hz bandwidth)

# Random Signals



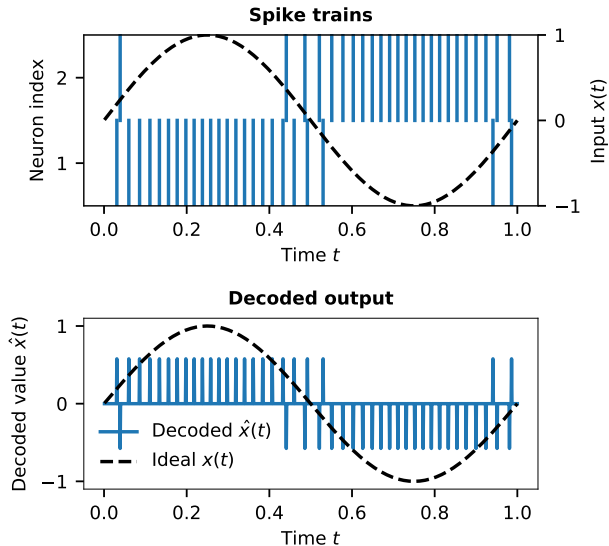
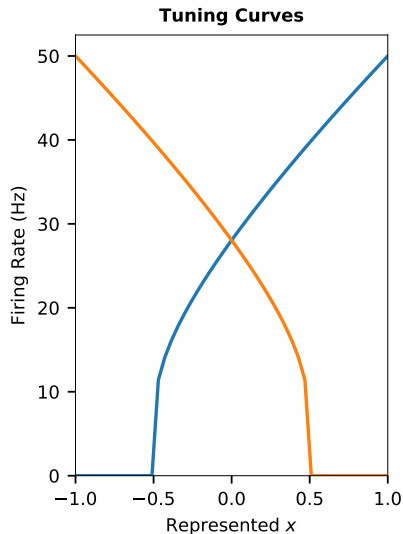
**White Noise**  
(zero mean)



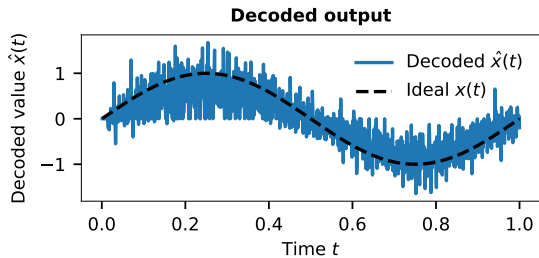
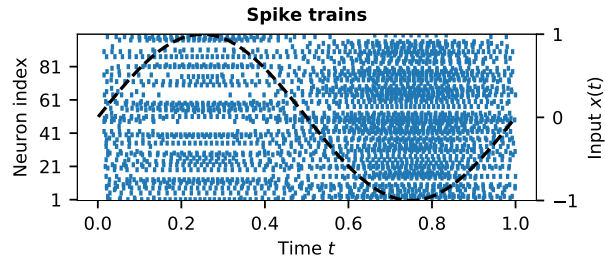
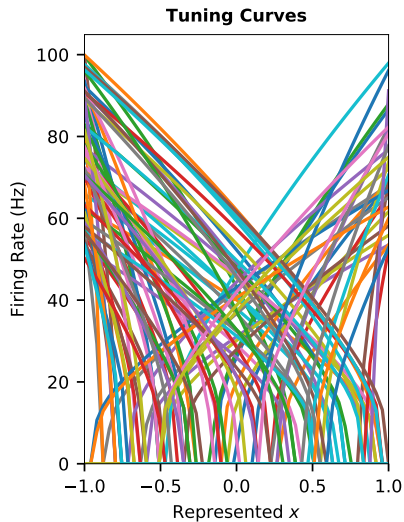
**Bandlimited**  
White Noise  
(zero mean,  
10 Hz bandwidth)



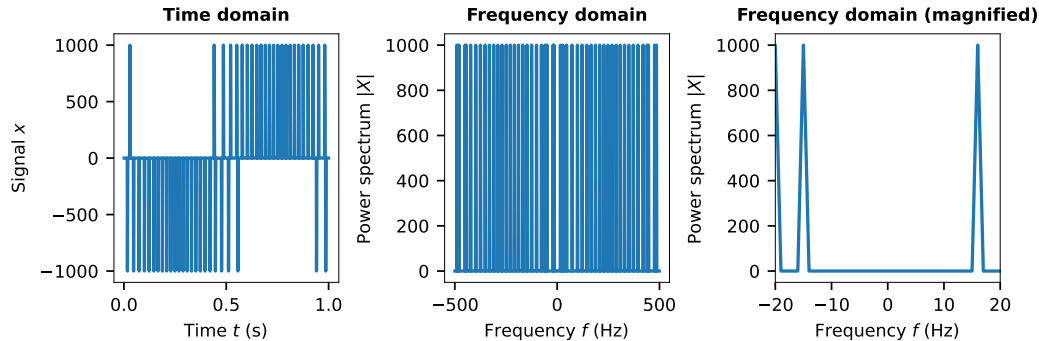
# Temporal Decoding of Two Neurons - Weighted Spikes



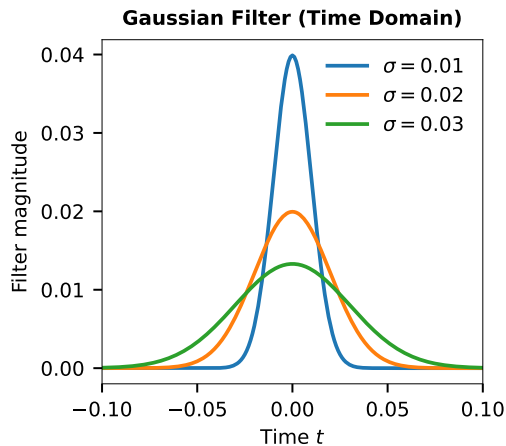
# Temporal Decoding of One Hundred Neurons - Weighted Spikes



# Frequency Response of Two Neurons



# Filtering by Convolution



## Gaussian Filter

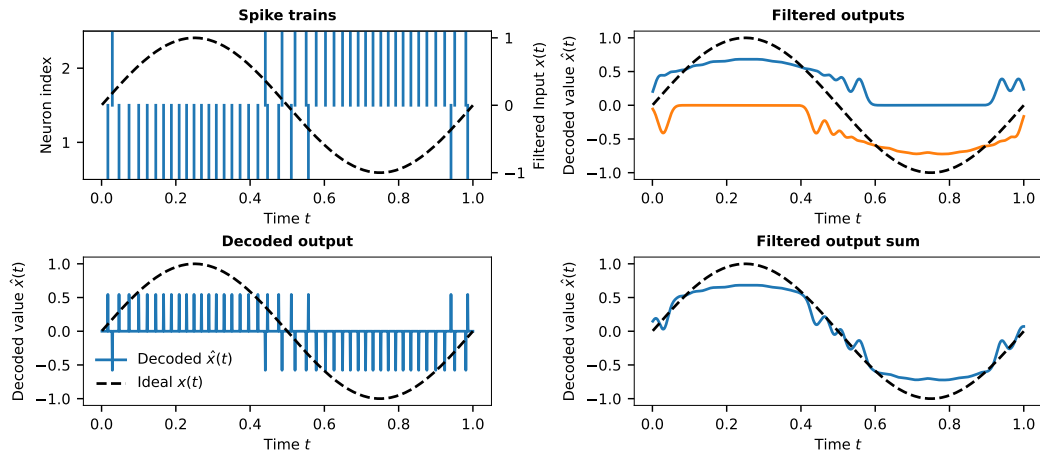
$$h(t) = c \exp\left(\frac{-t^2}{\sigma^2}\right)$$

where  $c$  chosen s.t.  $\int_{-\infty}^{\infty} h(t) dt = 1$

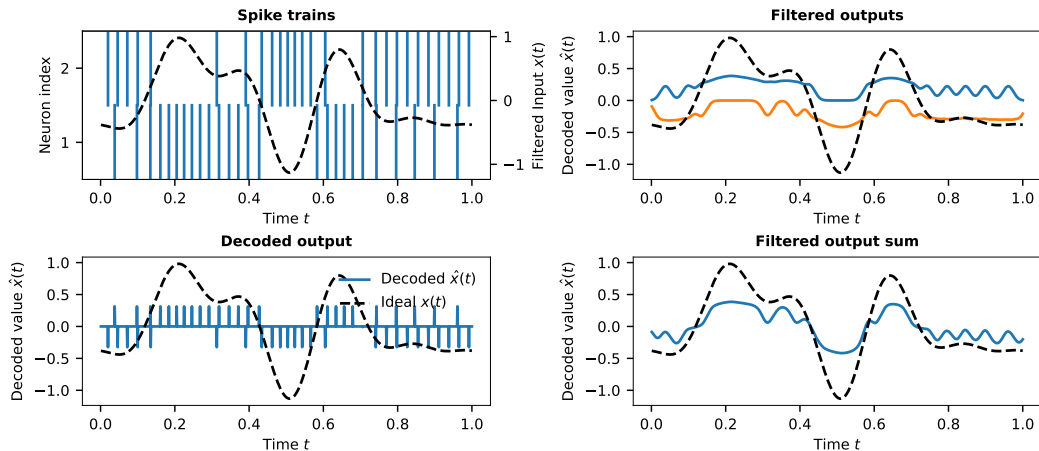
## Convolution

$$(f * h)(t) = \int_{-\infty}^{\infty} f(t - t') h(t') dt'$$

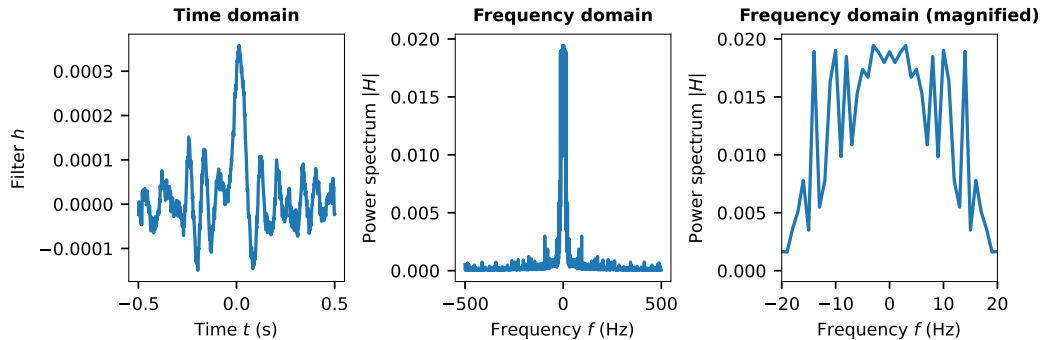
# Filtering a Spike Train



# Filtering a Spike Train for a Random Signal

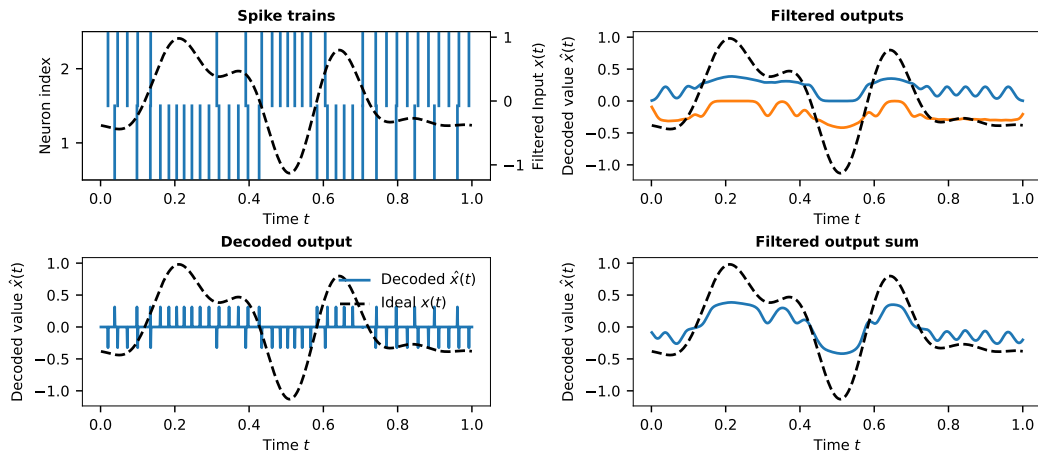


# Optimal Filter



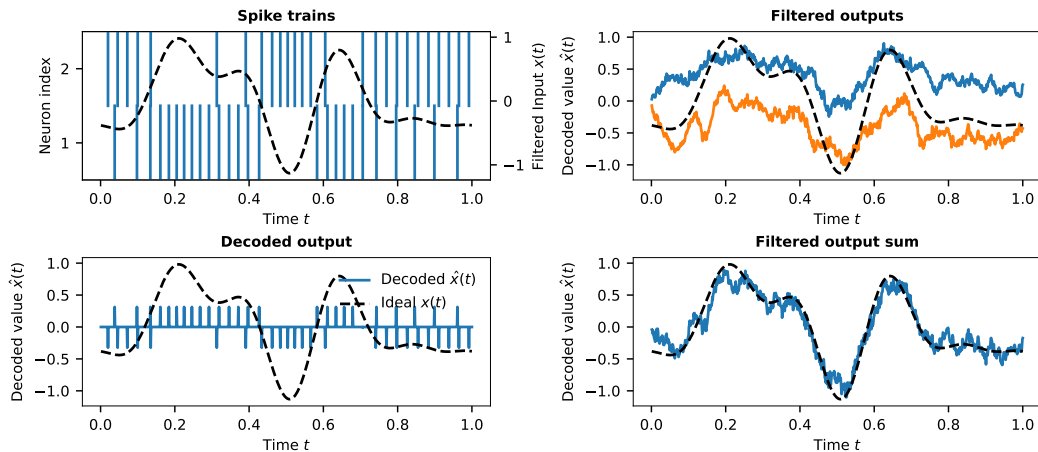
$$H(\omega) = \frac{X(\omega)\bar{R}(\omega)}{|R(\omega)|^2}$$

# Filtering a Spike Train for a Random Signal (Optimal Filter)

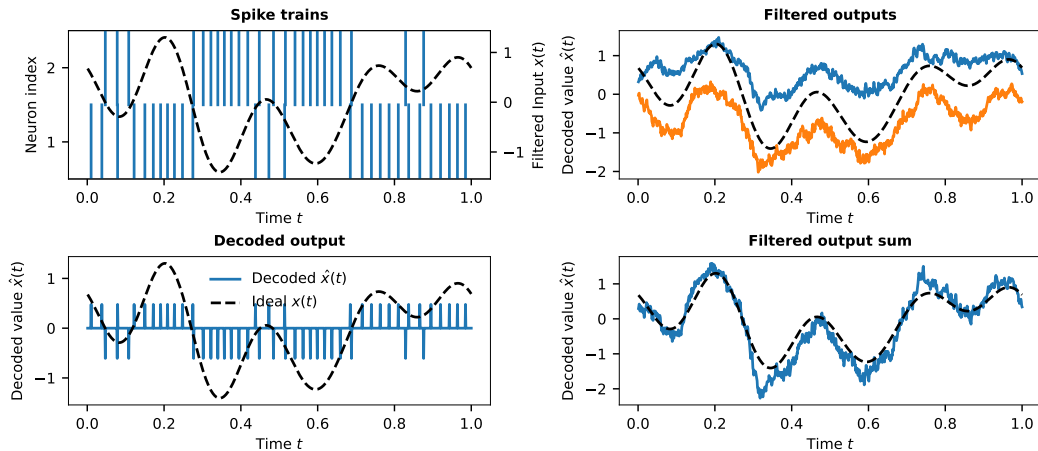




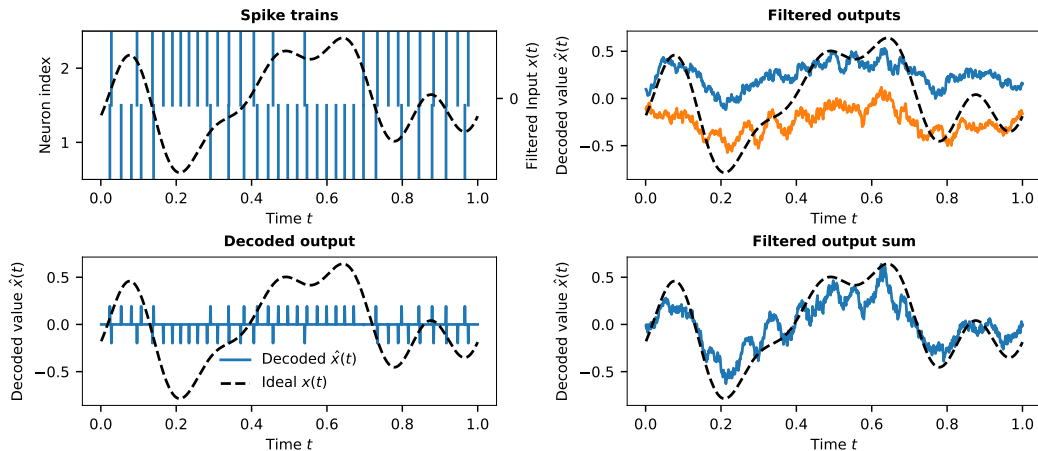
# Filtering a Spike Train for a Random Signal (Optimal Filter)



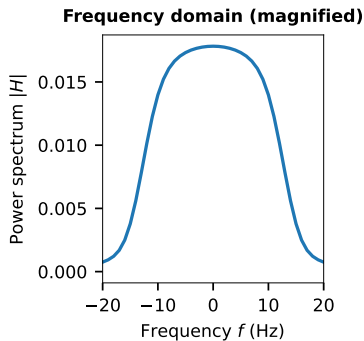
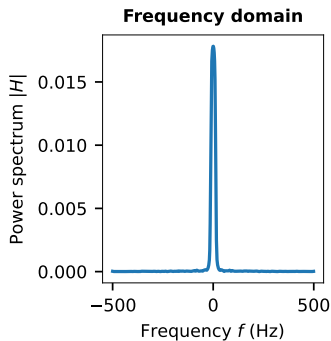
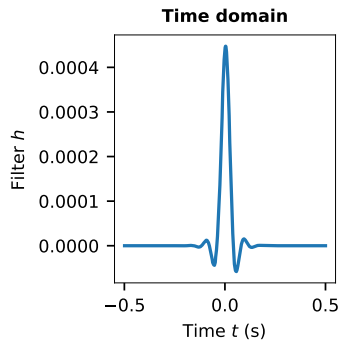
# Filtering a Spike Train for a Random Signal (Optimal Filter)



# Filtering a Spike Train for a Random Signal (Optimal Filter)

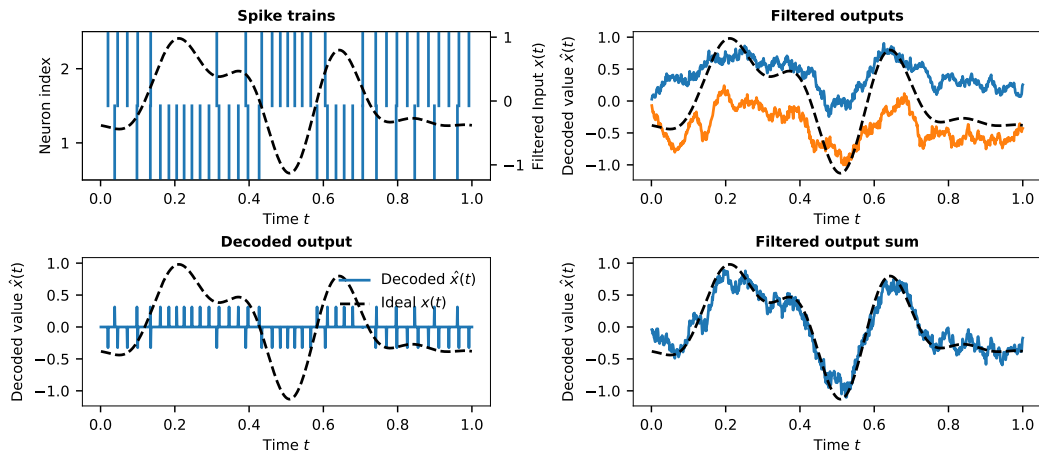


# Optimal Filter (Improved)

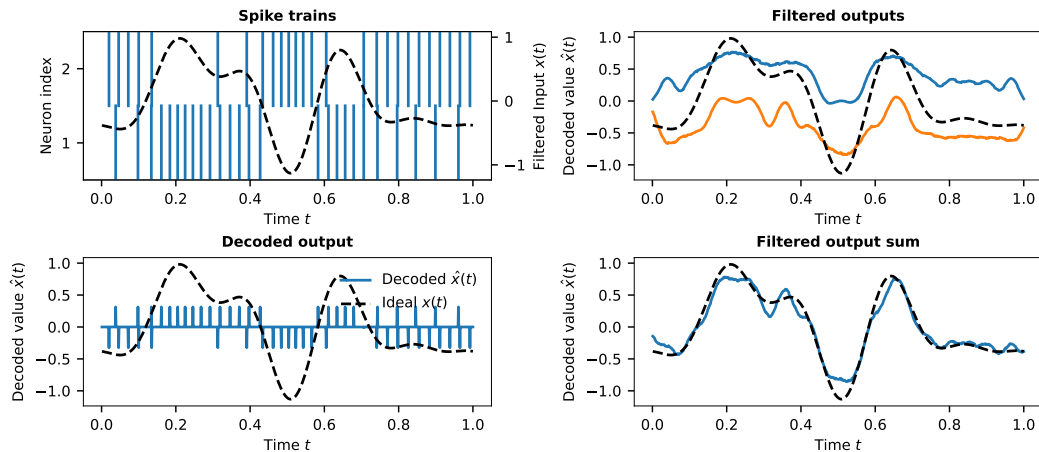


$$H(\omega) = \frac{X(\omega)\bar{R}(\omega) * W(\omega)}{|R(\omega)|^2 * W(\omega)}$$

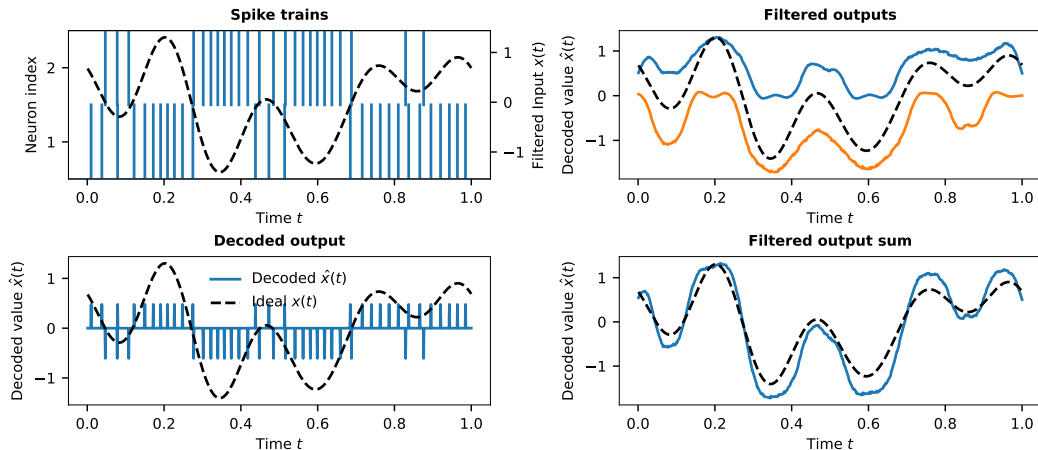
# Filtering a Spike Train for a Random Signal (Improved Optimal Filter)



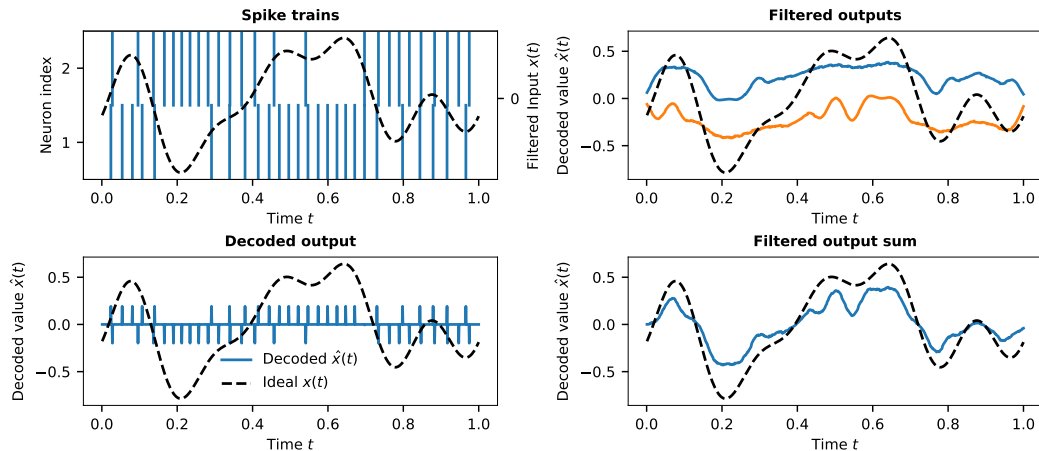
# Filtering a Spike Train for a Random Signal (Improved Optimal Filter)



# Filtering a Spike Train for a Random Signal (Improved Optimal Filter)

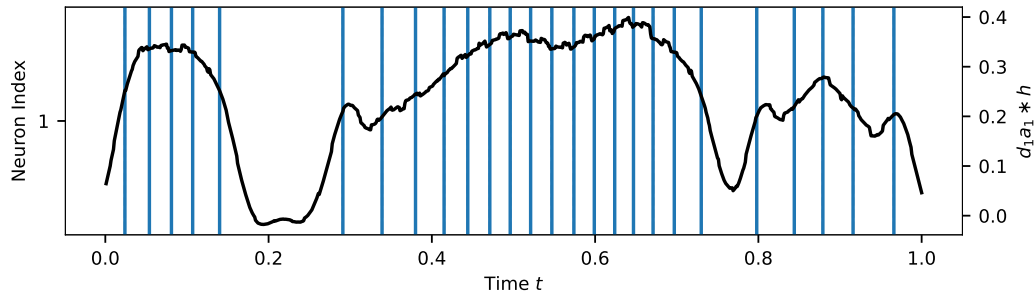


# Filtering a Spike Train for a Random Signal (Improved Optimal Filter)

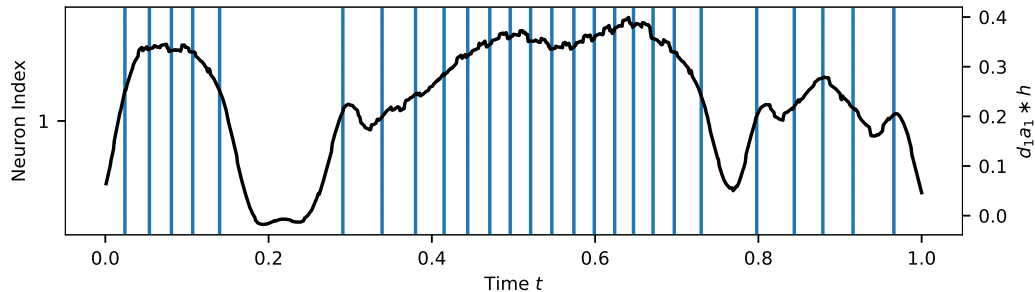




## Pros and Cons of the Optimal Filter



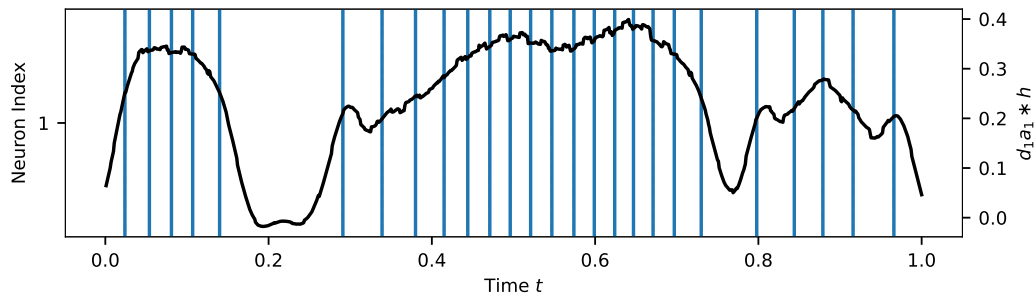
## Pros and Cons of the Optimal Filter



### + Precise

Good for analysing data after the fact

# Pros and Cons of the Optimal Filter



## Precise

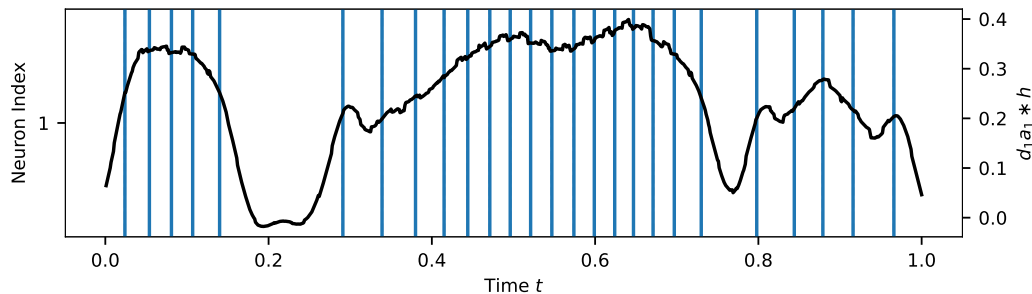
Good for analysing data after the fact



## Non-causal

Does not describe a biological process

# Pros and Cons of the Optimal Filter



## Precise

Good for analysing data after the fact

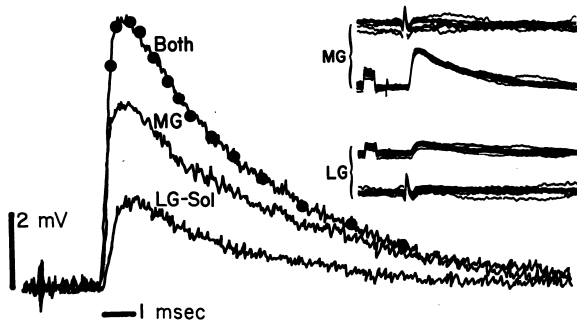
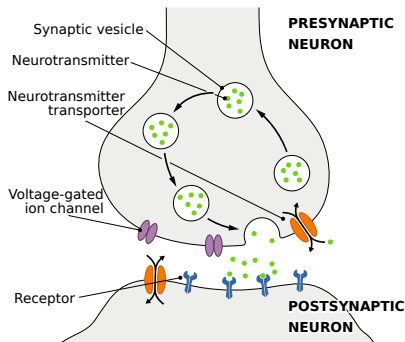


## Non-causal

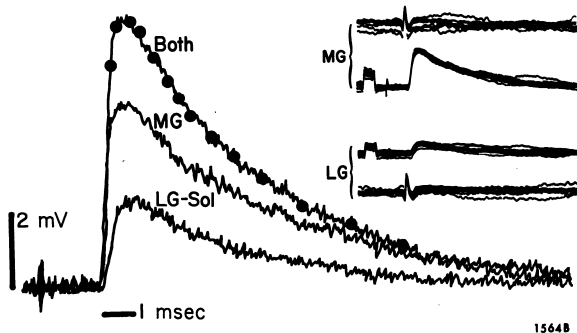
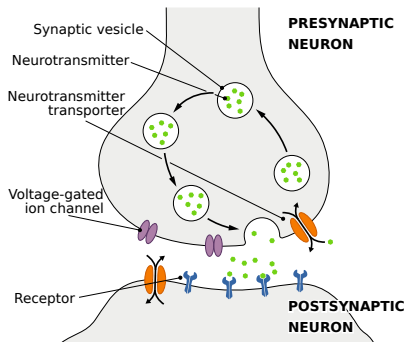
Does not describe a biological process

We need to find a mechanism that low-pass filters spikes over time!

# Synapses as Filters



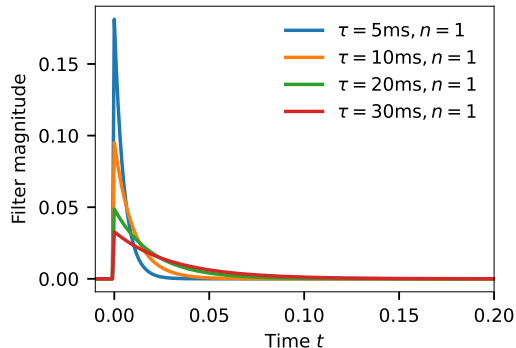
# Synapses as Filters



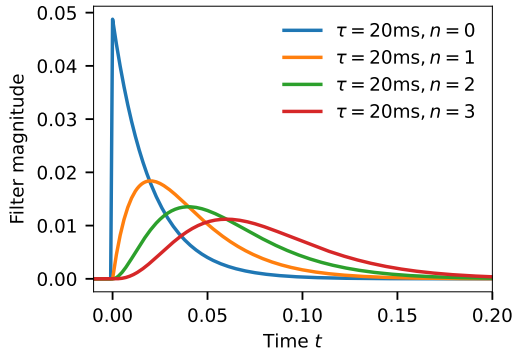
**Post-synaptic currents (EPSCs, IPSCs) are low-pass filtered spike trains!**

# Exponential Low-Pass Filter (I)

Synaptic Filter (Time Domain)



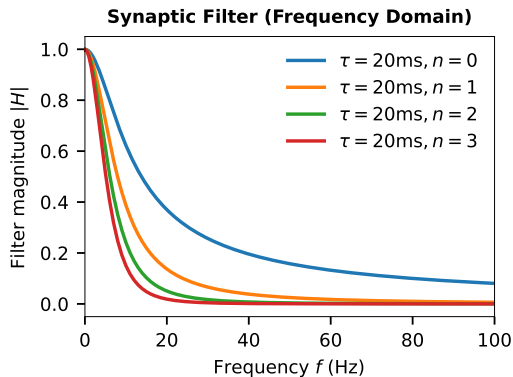
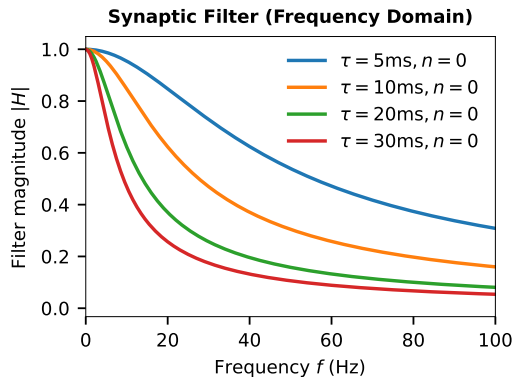
Synaptic Filter (Time Domain)



$$h(t) = \begin{cases} c^{-1} t^n \exp^{-t/\tau} & \text{if } t \geq 0, \\ 0 & \text{otherwise,} \end{cases}$$

$$\text{where } c = \int_0^{\infty} t^n \exp^{-t/\tau} dt.$$

# Exponential Low-Pass Filter (II)

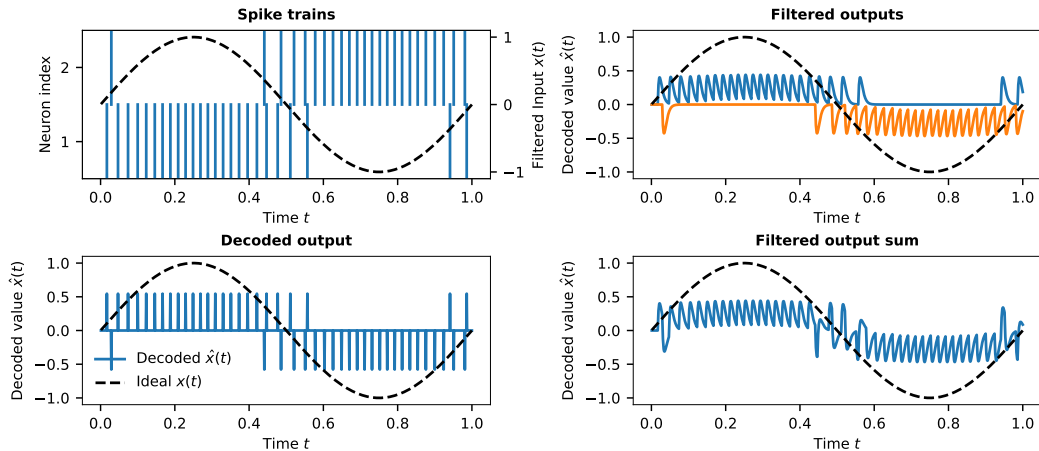


$$h(t) = \begin{cases} c^{-1} t^n \exp^{-t/\tau} & \text{if } t \geq 0, \\ 0 & \text{otherwise,} \end{cases}$$

$$\text{where } c = \int_0^{\infty} t^n \exp^{-t/\tau} dt.$$

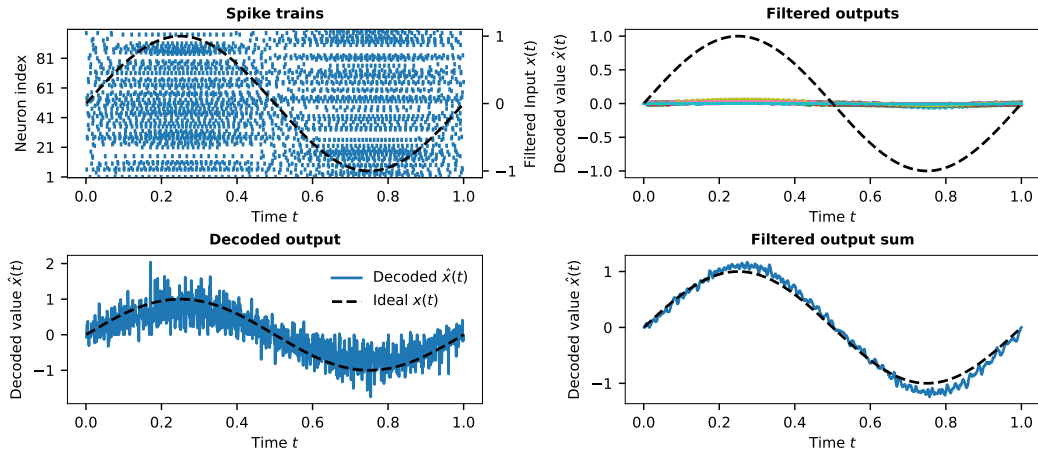


## Example: Synaptic Filter for Two Neurons



$$\tau = 5 \text{ ms}, n = 1$$

## Example: Synaptic Filter for One Hundred Neurons



$$\tau = 5 \text{ ms}, n = 1$$

# Image sources

## **Title slide**

“Captive balloon with clock face and bell, floating above the Eiffel Tower, Paris, France.”

Author: Camille Grávis, between 1889 and 1900.

From Wikimedia.