

# Question of the Day

**Fill in the blank:**

“All models are \_\_\_\_\_, but some are \_\_\_\_\_.”

“If you have a hammer, then everything looks like \_\_\_\_\_”

Your alien friend sees that people use umbrellas in the rain, and infer that umbrellas are a rain-blessing artifact. He is committing the fallacy of \_\_\_\_\_

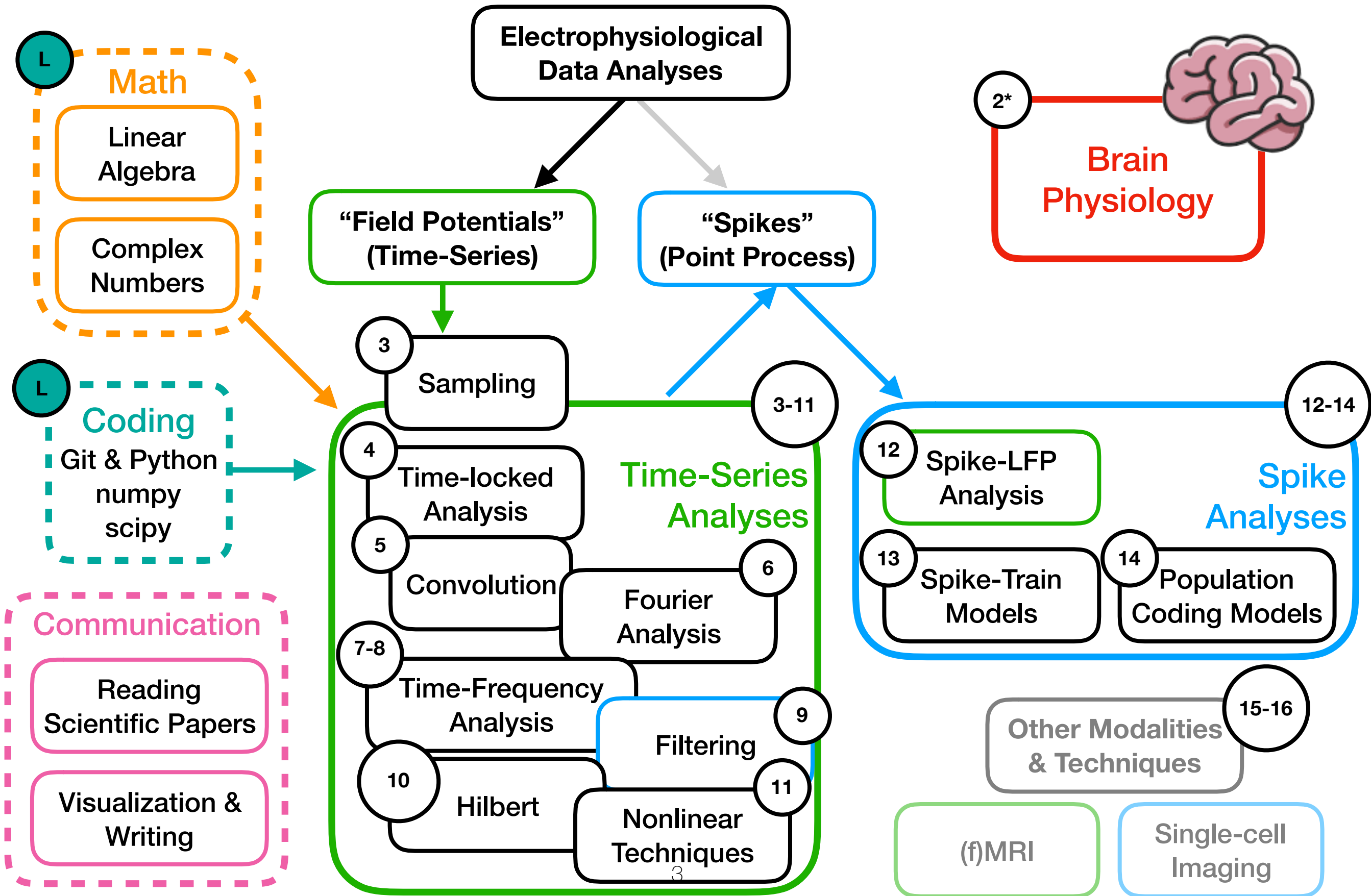


## Spikes: Rate Models & Rate-LFP Analyses

Lecture 13  
July 24, 2019



# Course Outline: Road Map

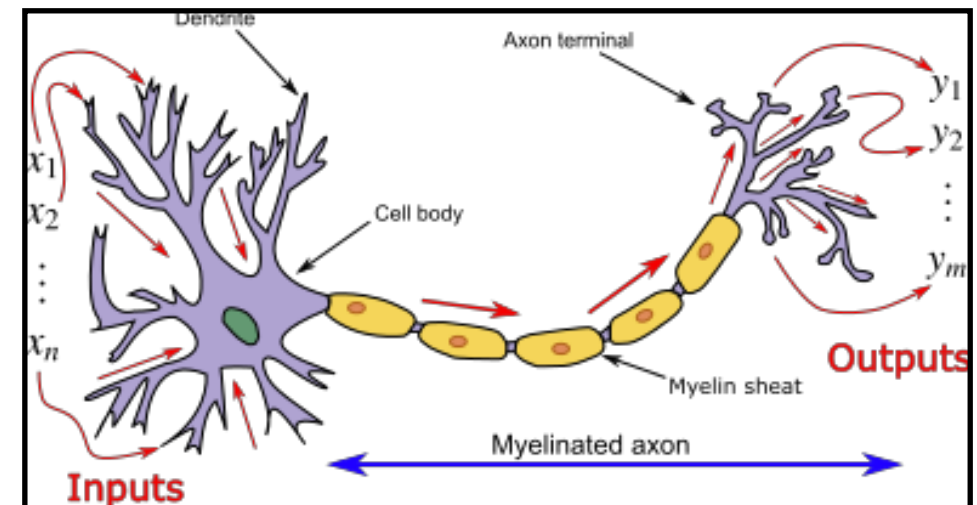
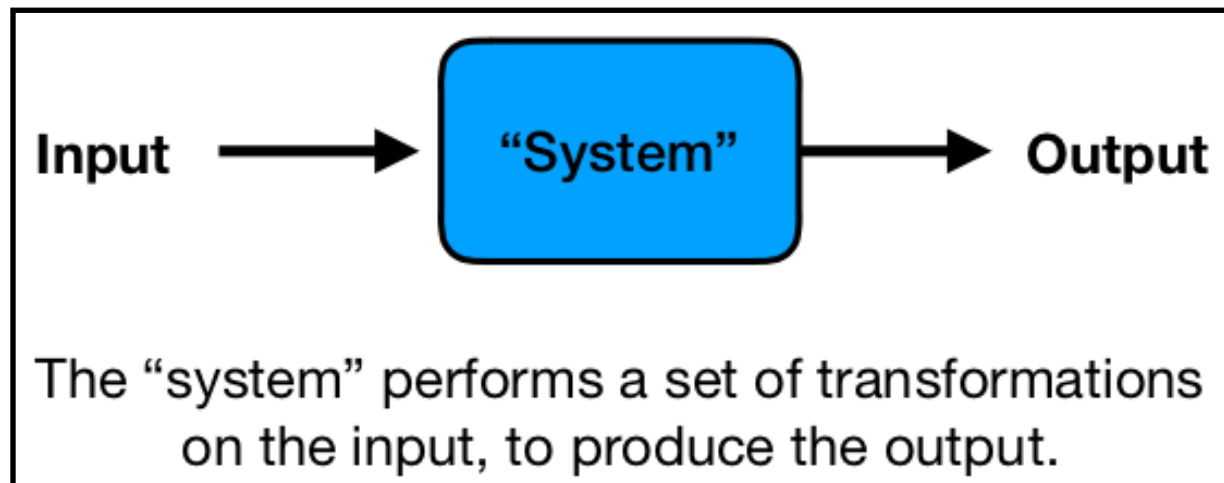
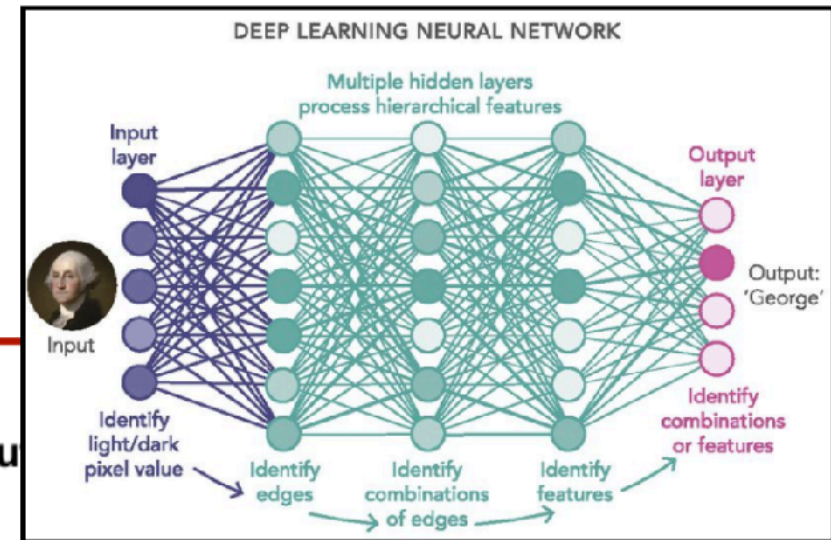
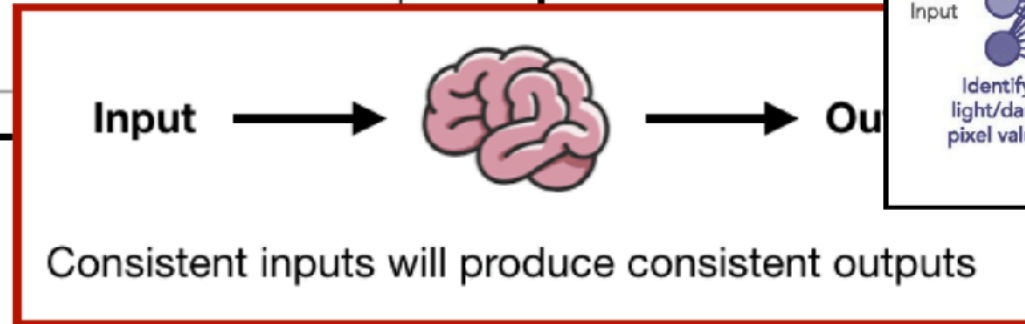
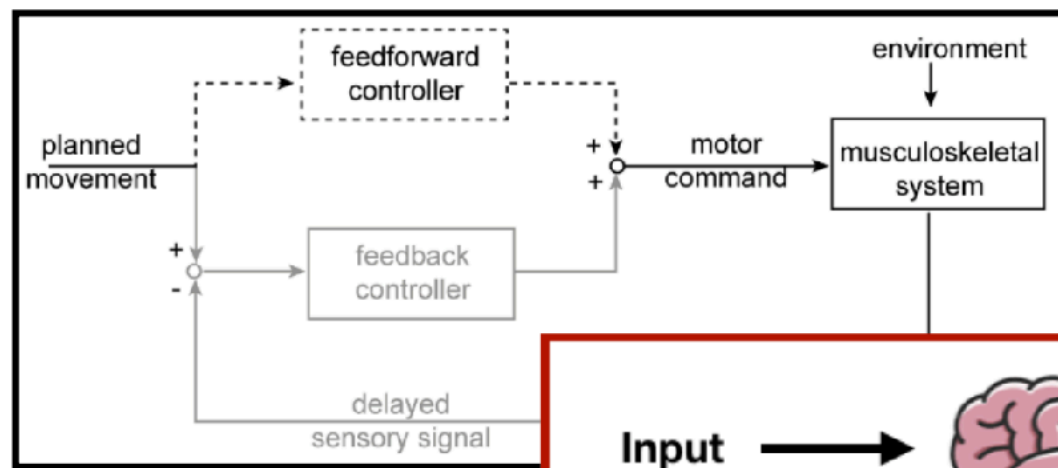


# Goals for Today

1. Conceptualize neuron as computational device
2. Compute spike counts, smoothing & firing rate
3. Understand correlation and rate-LFP analyses



# Single Neuron as a Computational Device

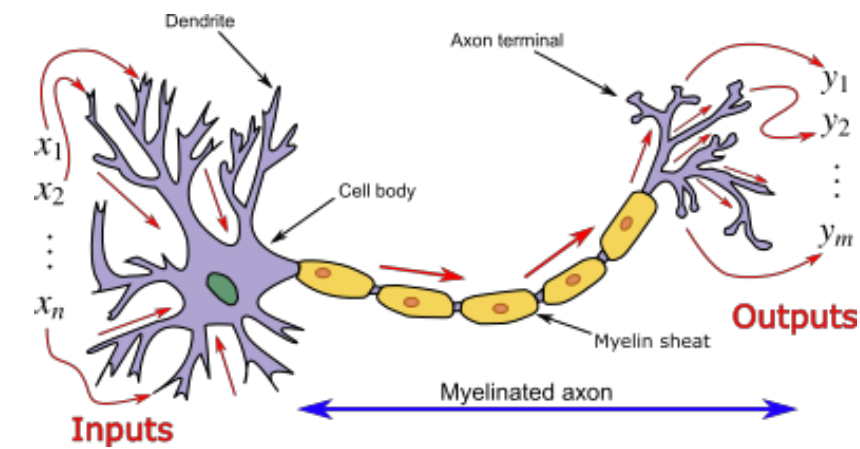


**Systems engineering view:** neuron receives (sensory or synaptic) input, performs a “computation”, and sends the result as an output.

This is a **model**, or abstraction, of the biological cell!



# Single Neuron as a Computational Device



$$f\left(\sum_i w_i x_i + b\right)$$

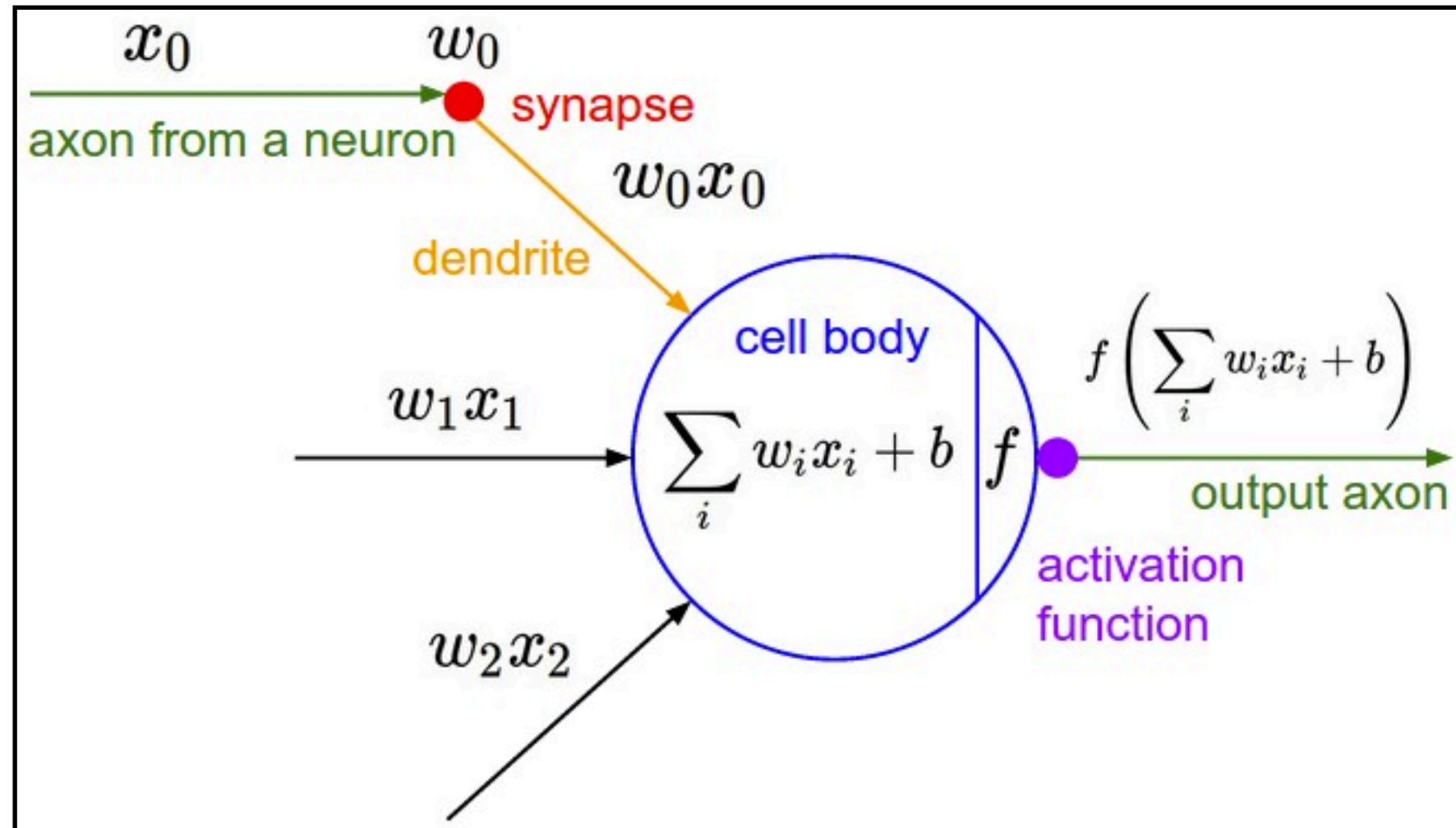
**dot product**

w: “synaptic” weights

x: inputs

b: bias

f( ): nonlinearity



**But what is x, physically?**





# Information Encoding

The biological neuron only receives and emits discrete **action potentials**.

What aspect of the action potential “encodes information”, that we can manipulate computationally?

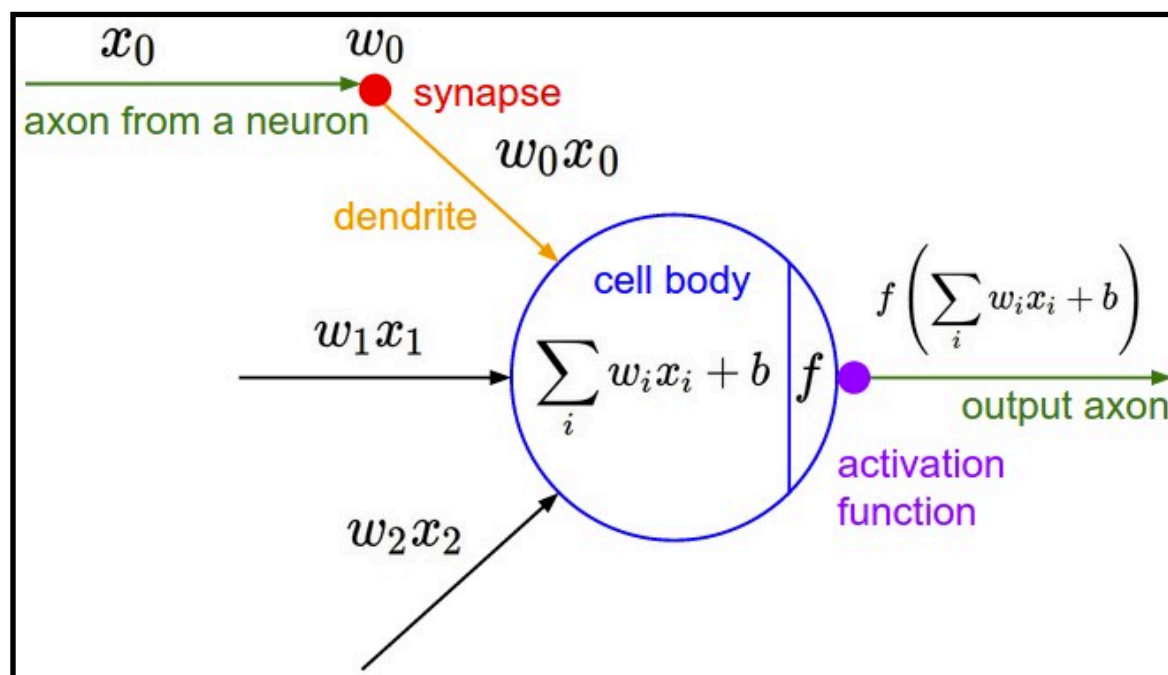
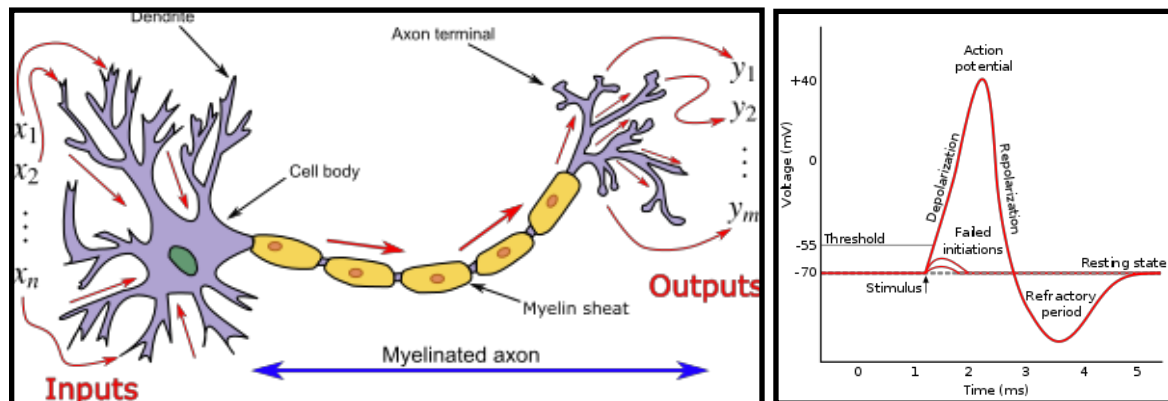
Action potentials (more or less) have constant amplitudes and widths...

One view (rate coding):

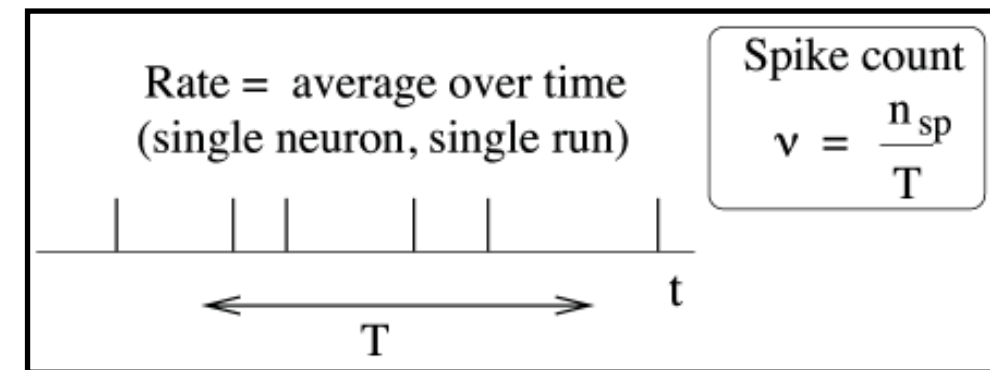
**Number of spikes** within a time window.

**Spike Count:** over a longer window

**Firing Rate:** “instantaneous” quantity



# Spikes, Spike Counts, & Firing Rate



Stimulus

Response

Trial 1



10 spikes -> 100Hz

Trial 2



2 spikes -> 20Hz

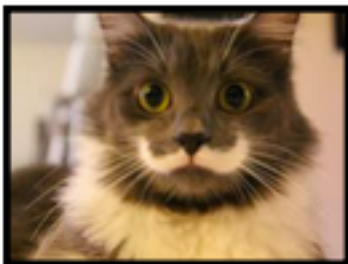
Trial 3



4 spikes -> 40Hz


...

Trial N



12 spikes -> 120Hz

100 ms



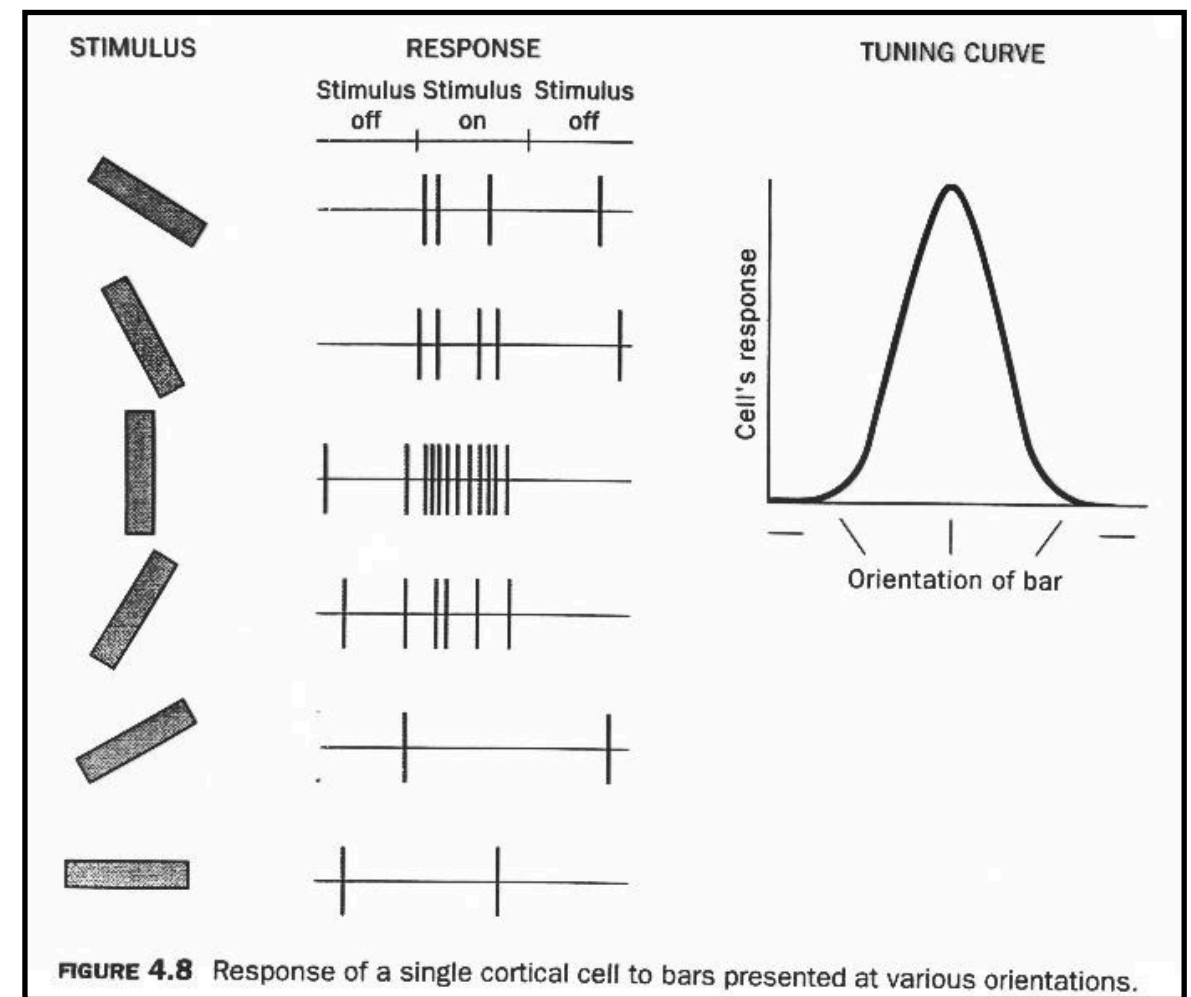
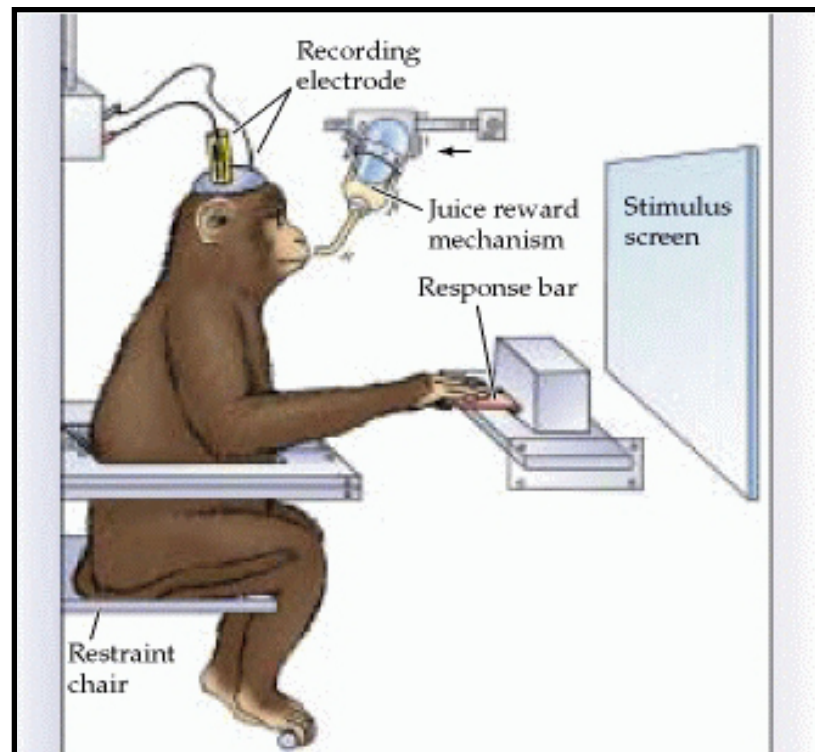
A horizontal line with vertical end caps representing a time scale.

This neuron is a  
“cat” neuron.





# Receptive Fields & Stimulus-Tuned Neurons



Stimulus with **varying aspects** are presented, e.g.:

- location
- orientation (angle)
- color
- sound frequency
- etc...

“This neuron has an orientation preference.”



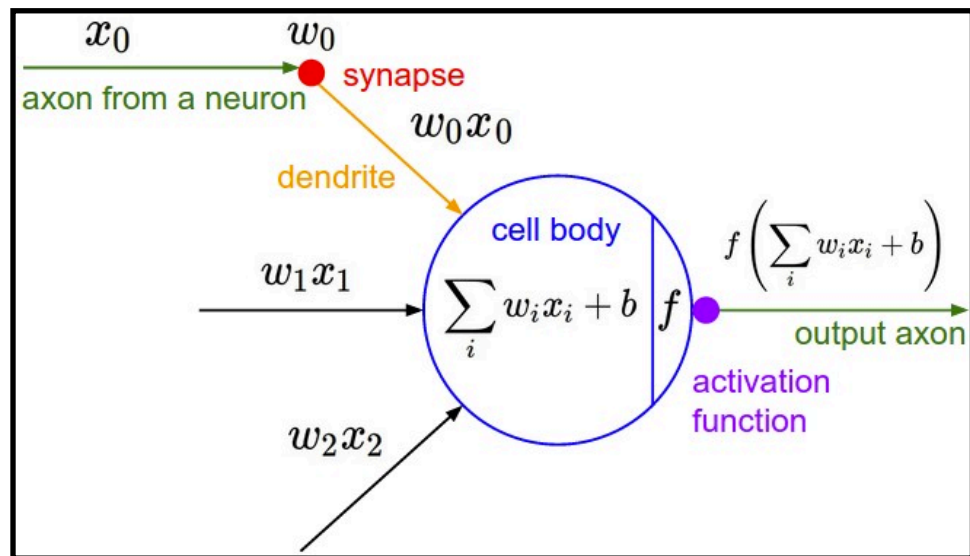
# Receptive Fields & Stimulus-Tuned Neurons

Tuning	Location in the Brain	Special Name?
place	hippocampus	place cells & grid cells
motion	retina, or V5/MT	direction cells/motion cells
grandmother	IT/hippocampus	gnostic/grandmother/Jennifer aniston cells
numerosity	PFC	numerosns
biological motions	premotor/SMA	mirror neuron
phallic images		

Google: “\_\_ tuned neuron” or “neuron responsive to \_\_\_\_” or “\_\_ cell neuroscience”



# Single Neuron as a Computational Device



$$f\left(\sum_i w_i x_i + b\right)$$

## dot product

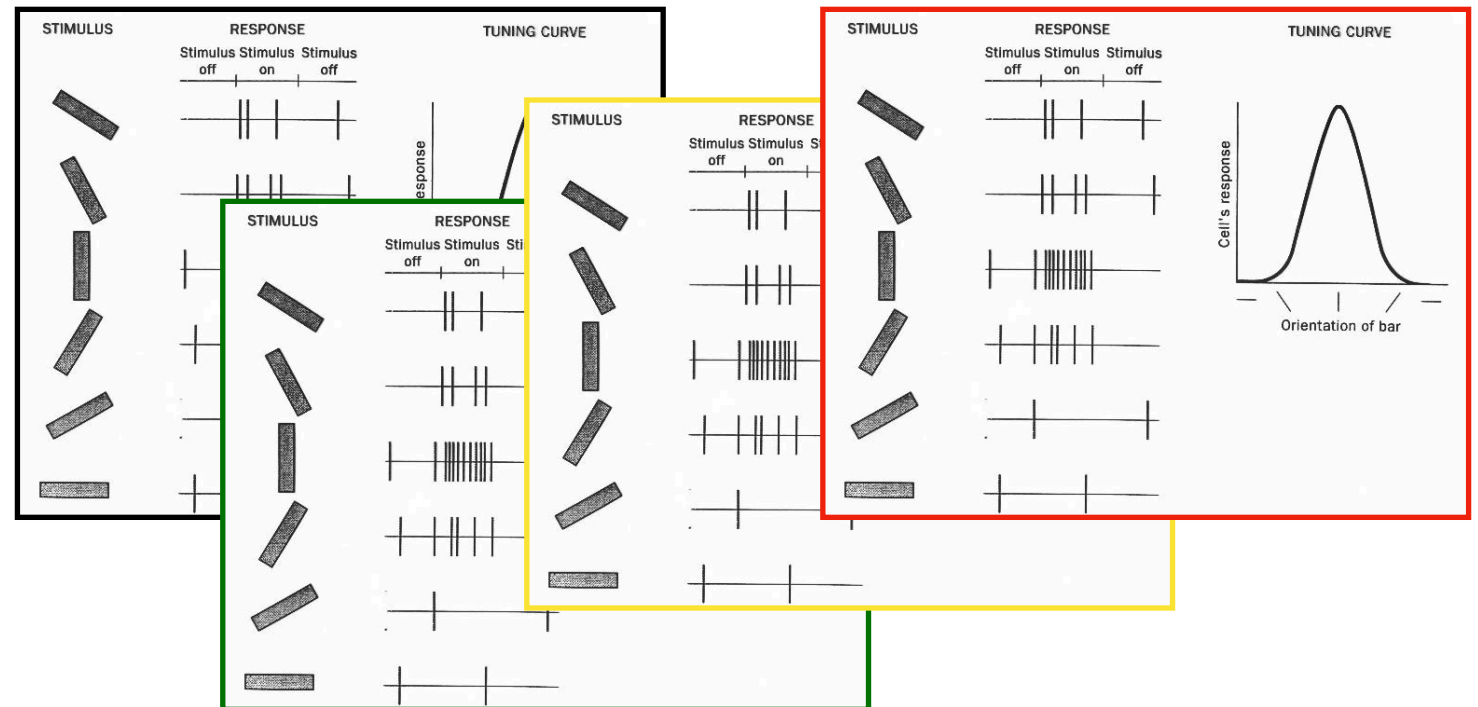
w: “synaptic” weights

x: inputs

b: bias

$f(\cdot)$ : nonlinearity

Different neurons have different “tuning curves”, i.e., sensitive to different values of the variable.

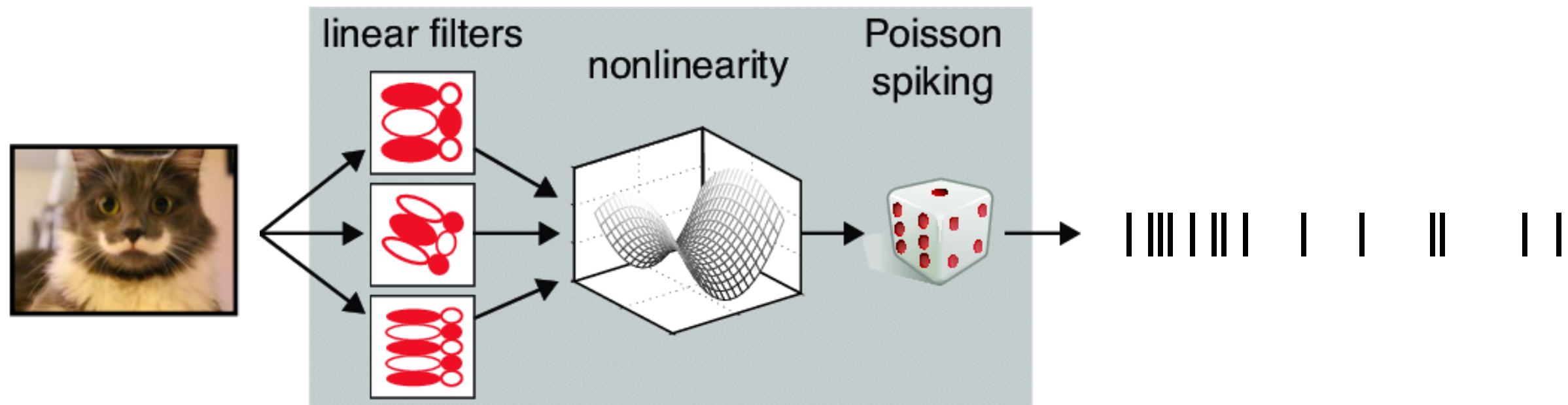


downstream neuron combines them linearly via dot product (linear filter)

**Naive model of a neuron's function!**

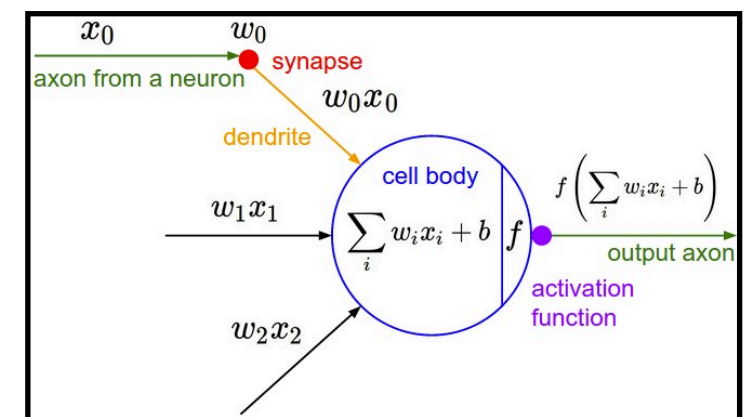


# Linear-Nonlinear Poisson Model



**linear:** dot product / filter of stimulus tuning

**nonlinear:** activation function, e.g., sigmoid, ReLu



**Poisson:** spikes are randomly emitted as a Poisson process, given the **average rate parameter**

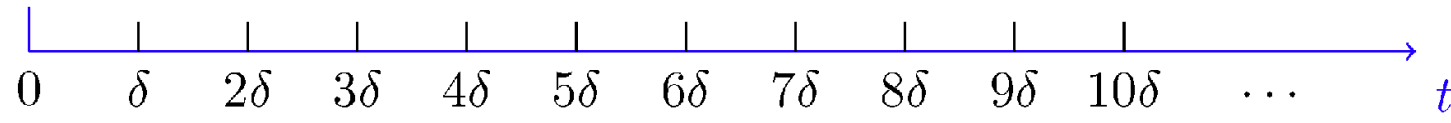
$$P\{N(t) = n\} = \frac{(\lambda t)^n}{n!} e^{-\lambda t}.$$



# Brief Intro to Poisson Spikes

**Poisson:** spikes are randomly emitted as a Poisson process, given the **average rate parameter**

$$P\{N(t) = n\} = \frac{(\lambda t)^n}{n!} e^{-\lambda t}.$$



Generate a random number between 0-1 at every time step.

If that number is greater than **(rate \* interval length)** -> no spike.

Otherwise -> spike

**Exercise:** rate = 5Hz, interval length = 0.1s, total time = 2 seconds

**nice property:**

for some duration  $T$ , average count = rate \*  $T$ ; variance = rate

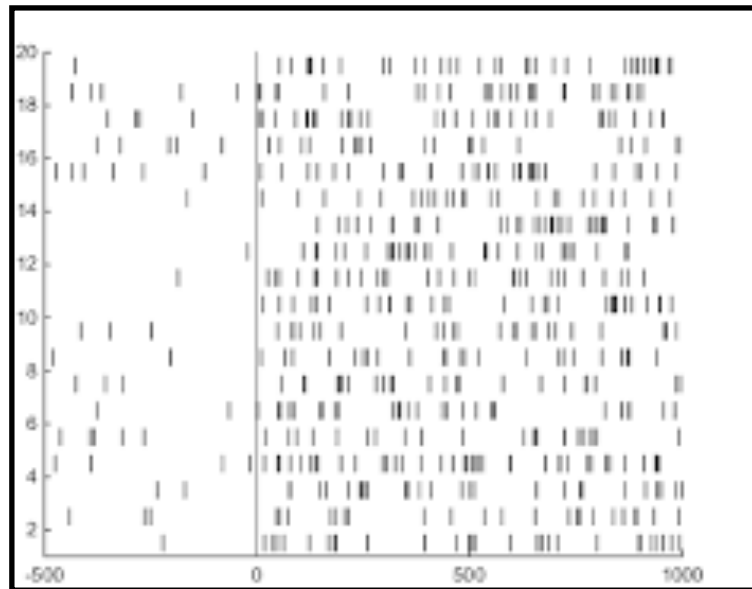


# Rate Encoding Model

Model of how a neuron encodes information via spike trains.

**Assumption:** information (e.g., stimulus intensity) is encoded via a neuron's firing rate.

Assumes precise spike timing on the millisecond scale does not matter (in contrast to **spike timing encoding models**).



Given some spike timestamps, we want to estimate firing rate.

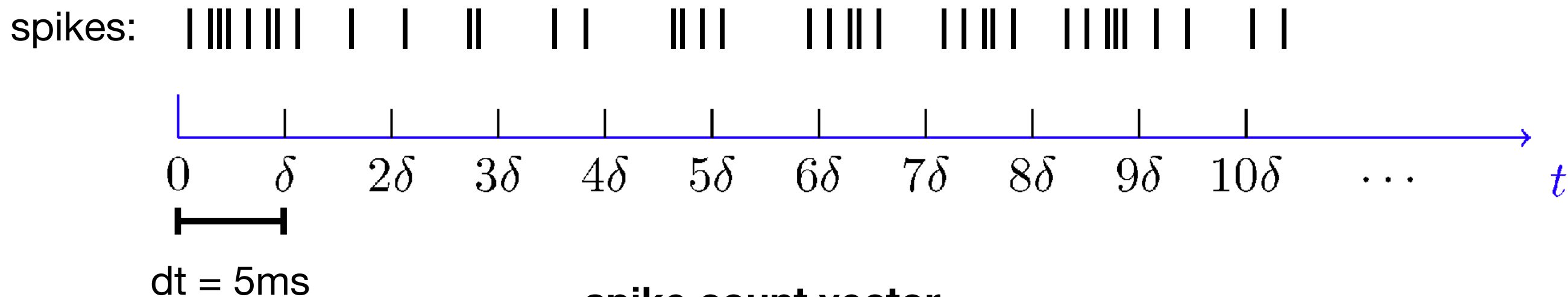




1. Conceptualize neuron as computational device
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# Spike Times to Spike Counts



## spike count vector

6	2	3	2	3	2	4	5	5	2	...
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or

8	5	5	9	7	...
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or

34

## Time bin width is a parameter choice!

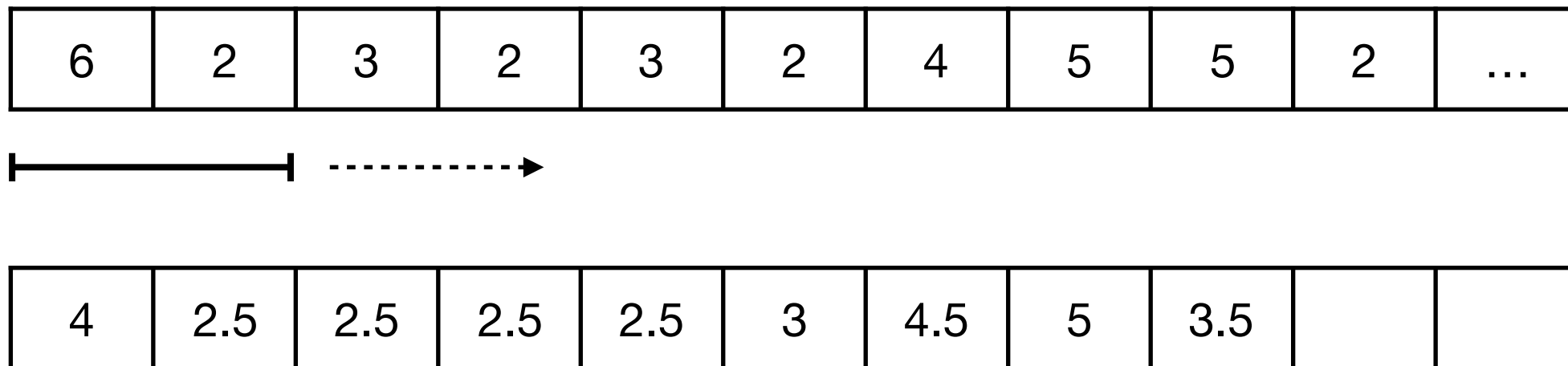
Smaller bins = better temporal resolution, but noisier estimate  
Bigger bins = worse temporal resolution, more accurate estimate



# Spike Counts to Firing Rate

Spike count vector is usually very noisy, we want a more continuous & smooth firing rate estimate.

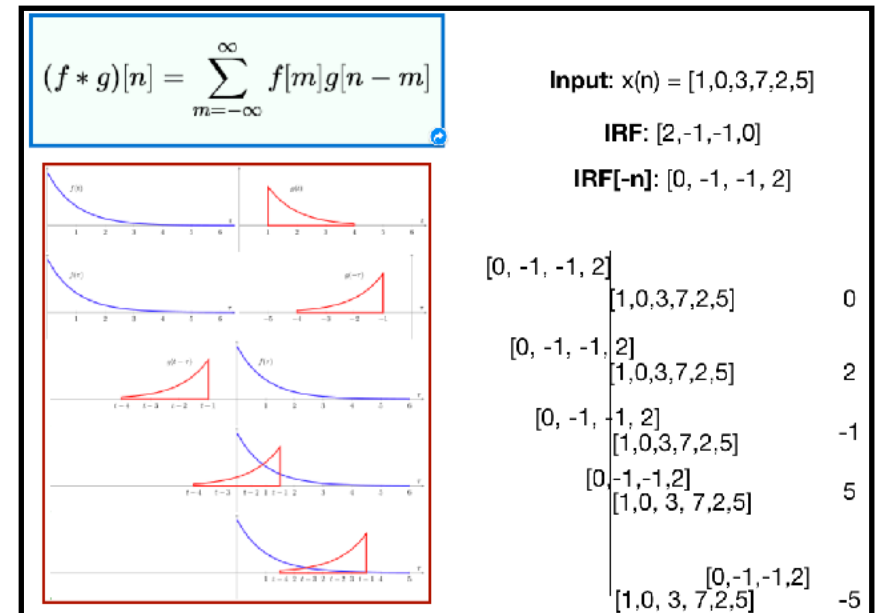
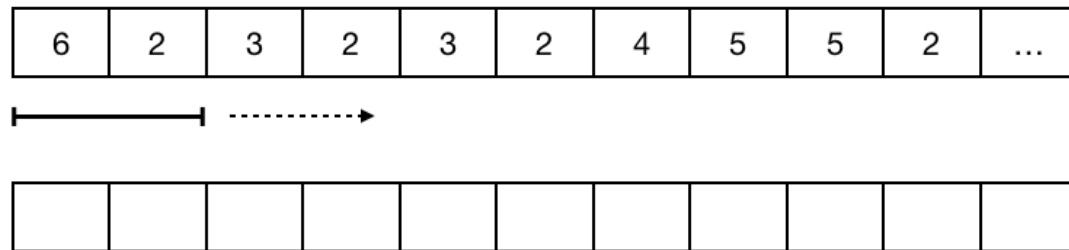
**Solution:** take “moving average”.



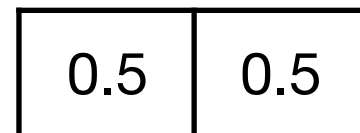
# Moving Average Smoothing as Filter

Spike count vector is usually very noisy, we want a more continuous & smooth firing rate estimate.

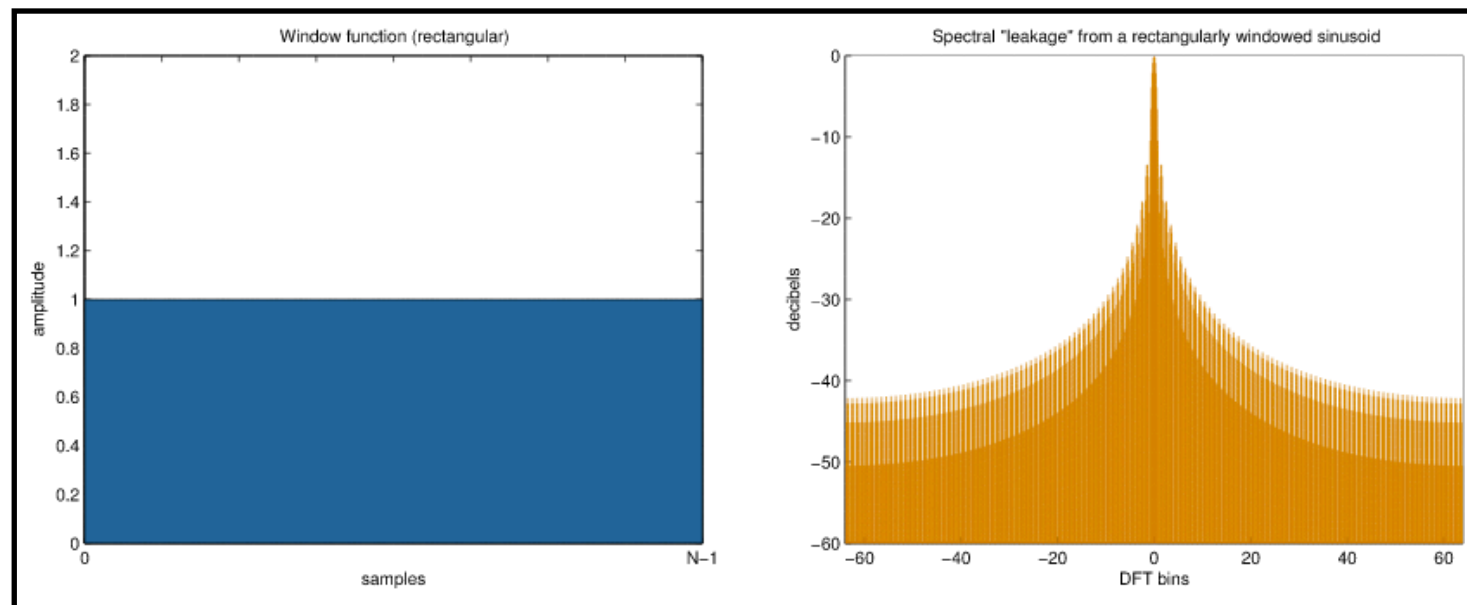
**Solution:** take “moving average”.



Equivalent to  
**convolution** with:

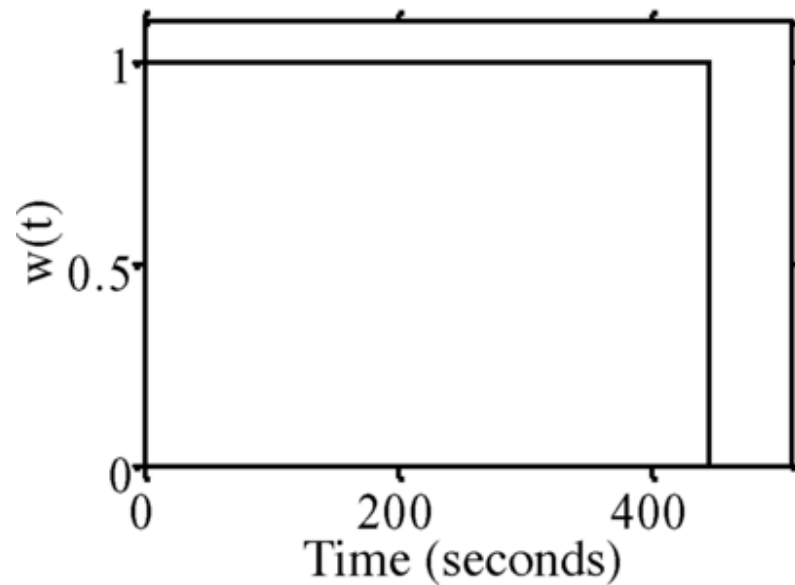


2-point boxcar or rectangular window



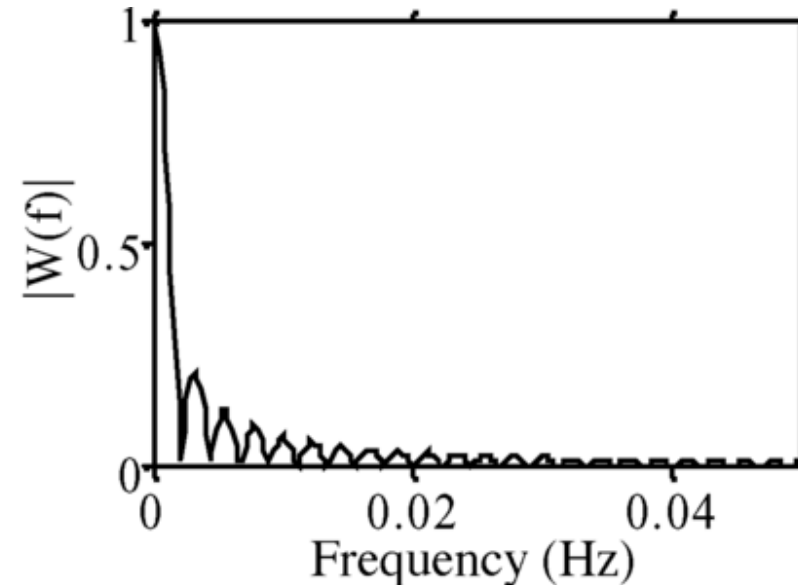
Firing Rate: Smoothed Spike Count

# Time Domain



(a)

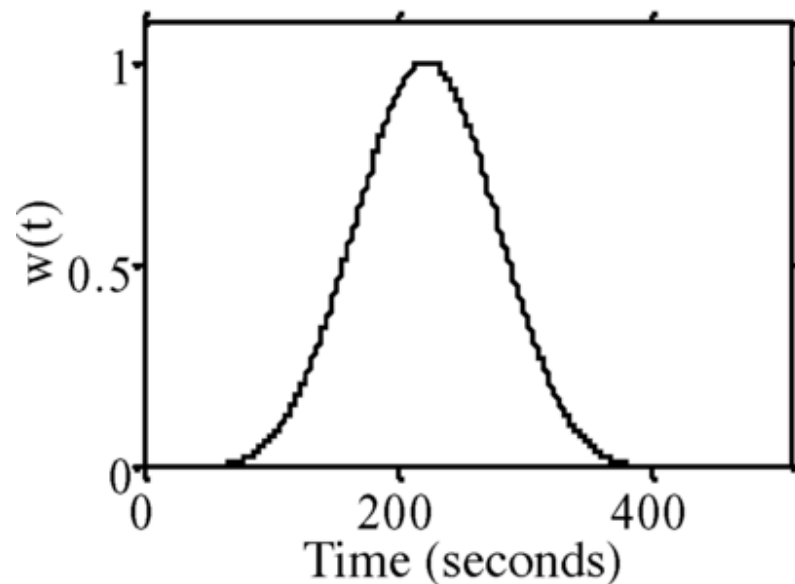
# Frequency Domain



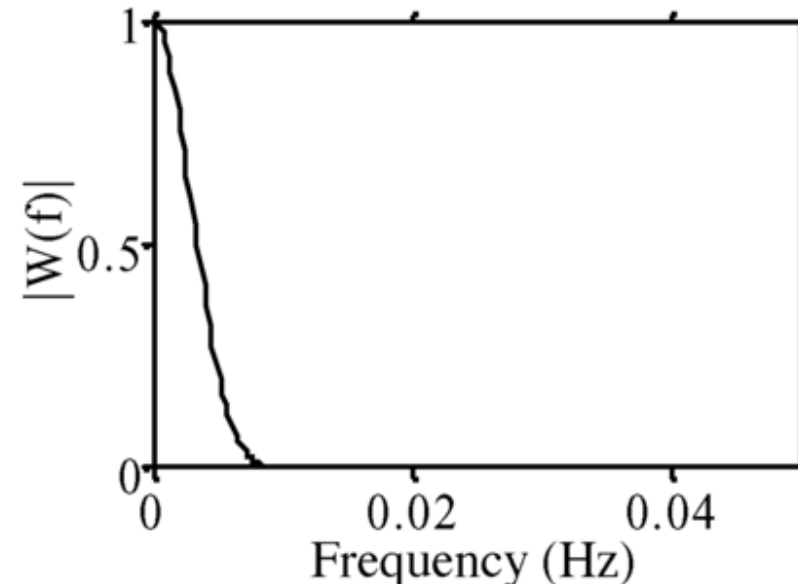
(b)

# Rectangular Window

# Gaussian Window



(c)



(d)

# Smoothing is applying a low-pass filter!



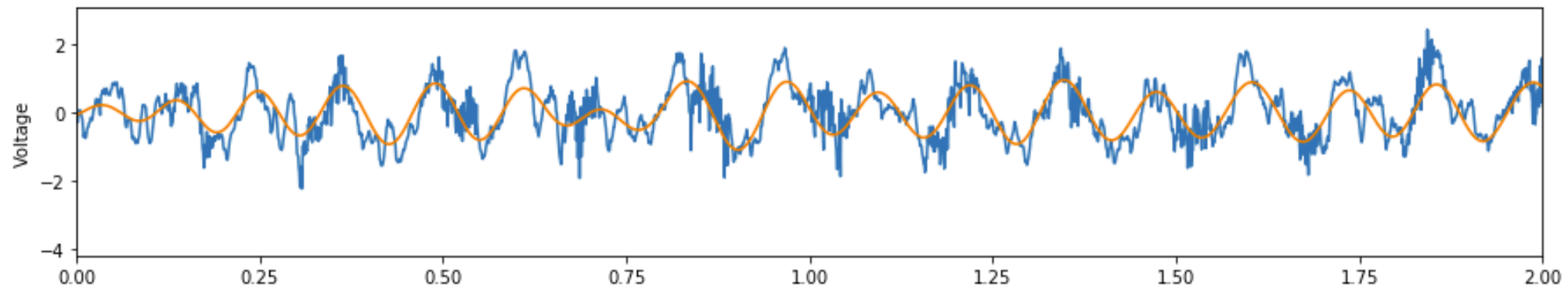
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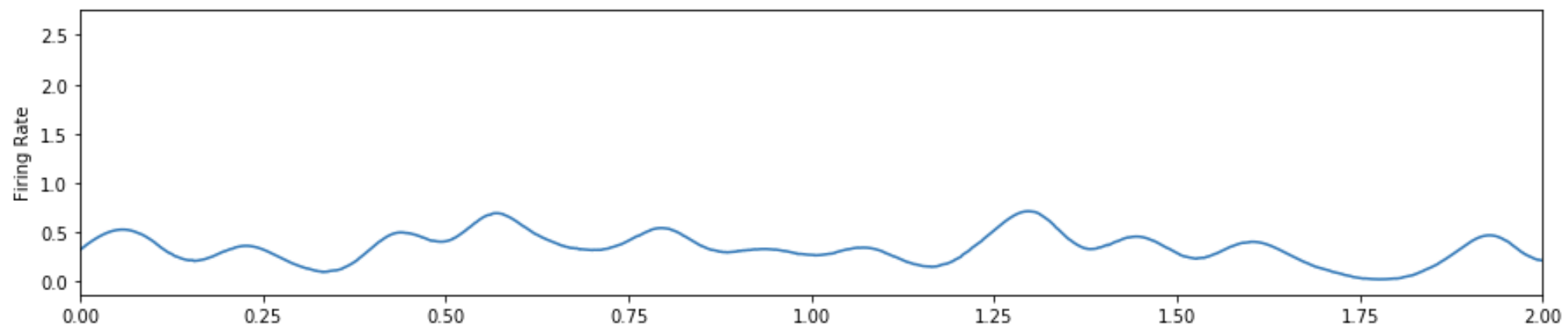
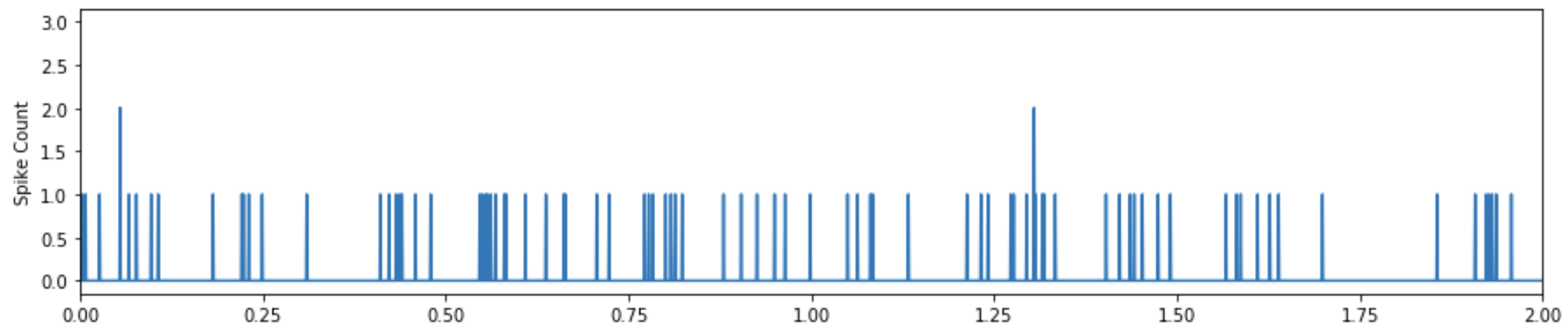
# Firing Rate & LFP Analysis

LFP



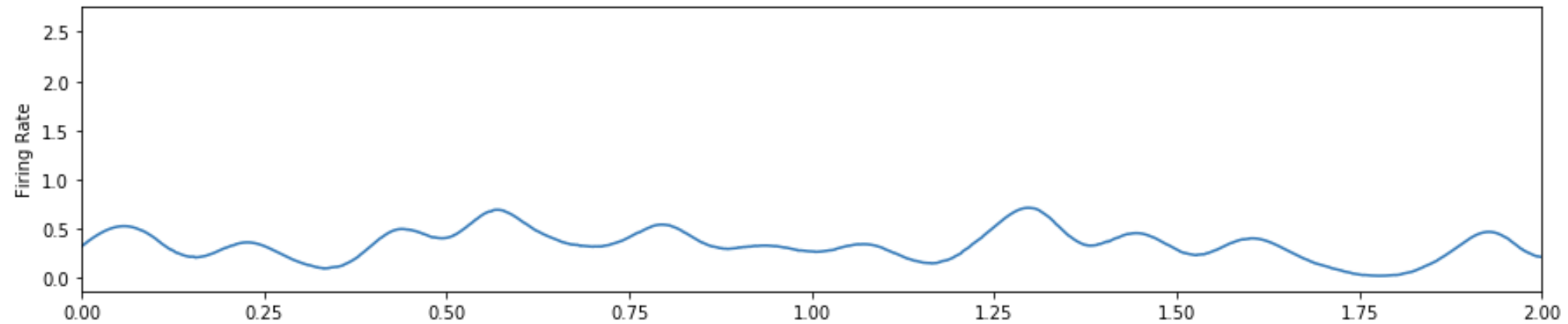
spikes: | ||| | ||| | | | || | | ||| | ||| | ||| | ||| | | | | |

Use same time bin width (dt) to bin spike counts

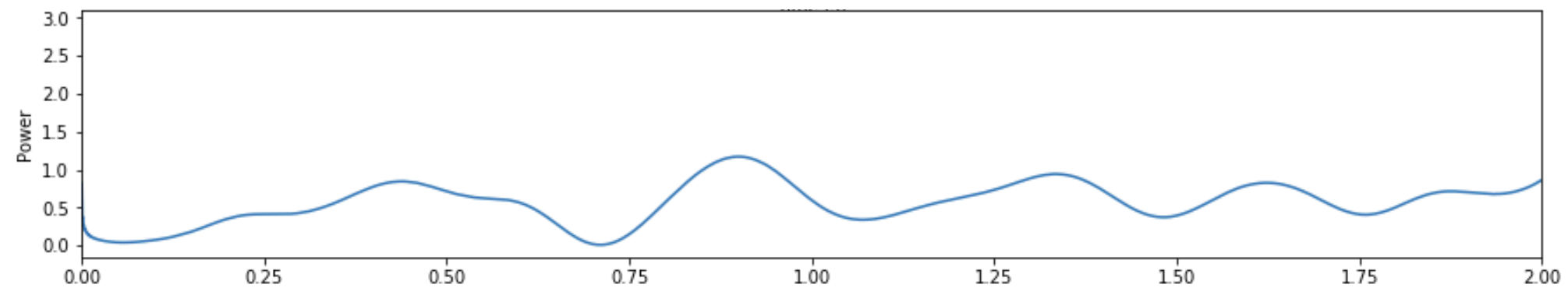


# Firing Rate & LFP Analysis

Firing Rate



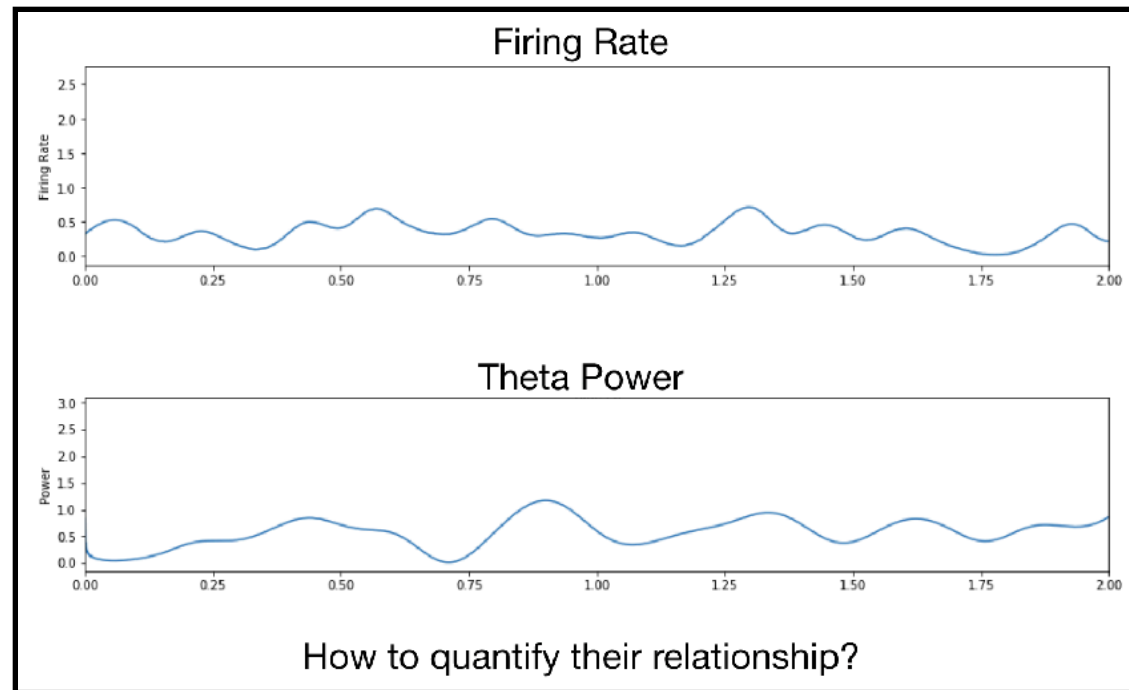
Theta Power



How to quantify their relationship?

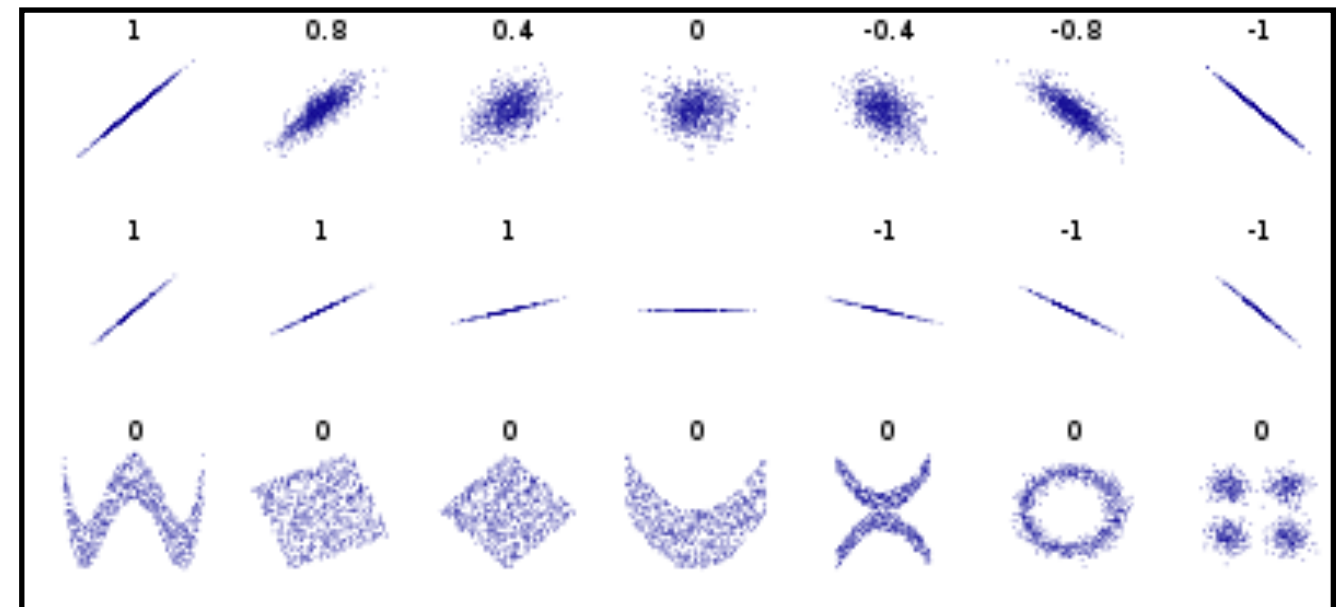


# Correlation



## Pearson Correlation Coefficient

$$\rho_{X,Y} = \text{corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y}$$



For two discrete signals x and y:

$$r_{xy} \stackrel{\text{def}}{=} \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{(n-1)s_x s_y} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}}$$



For two discrete signals  $x$  and  $y$ :

$$r_{xy} \stackrel{\text{def}}{=} \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{(n-1)s_x s_y} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}},$$

**standard deviation**  
of  $x$  and  $y$

covariance

$$\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})$$

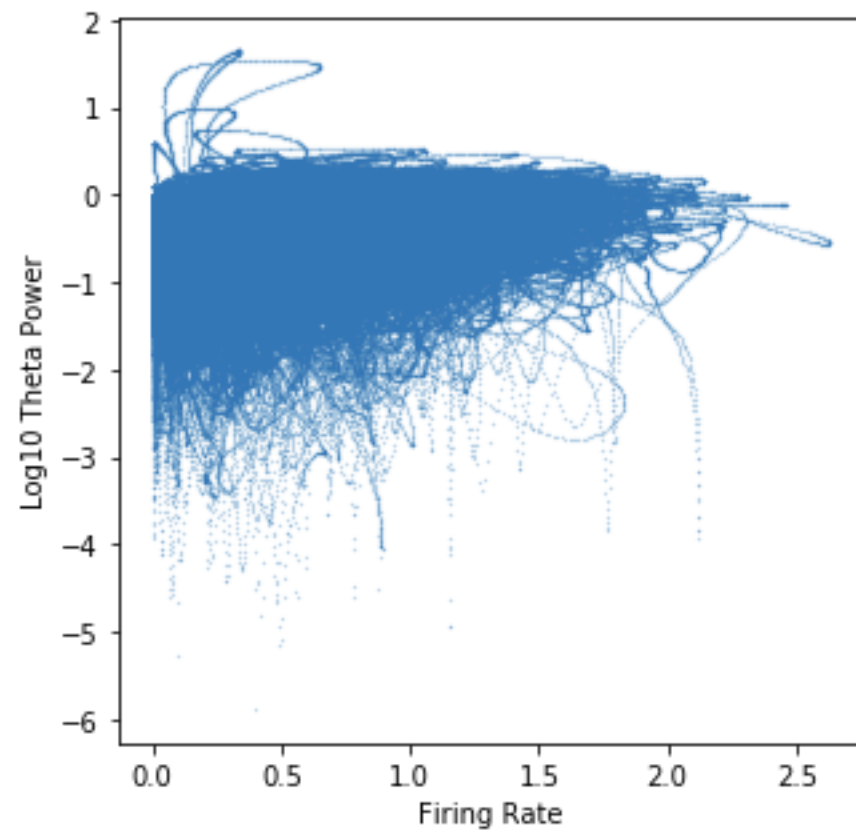
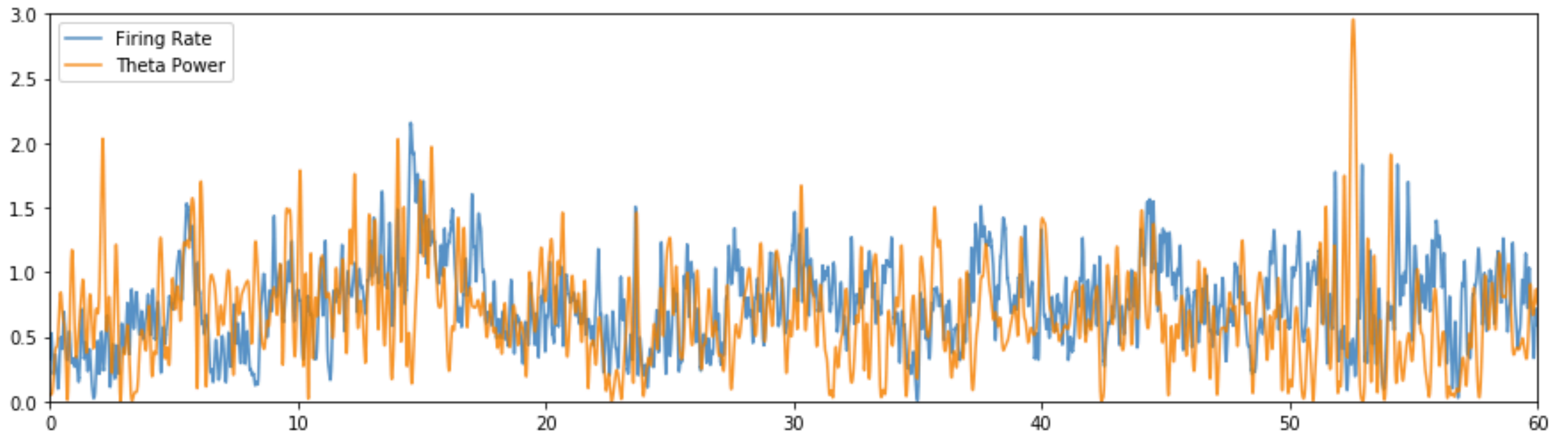
what is this operation if  $\bar{x} = 0, \bar{y} = 0$

**dot product!**

Pearson correlation coefficient is the dot product between 2 mean-subtracted signals, normalized by their standard deviations



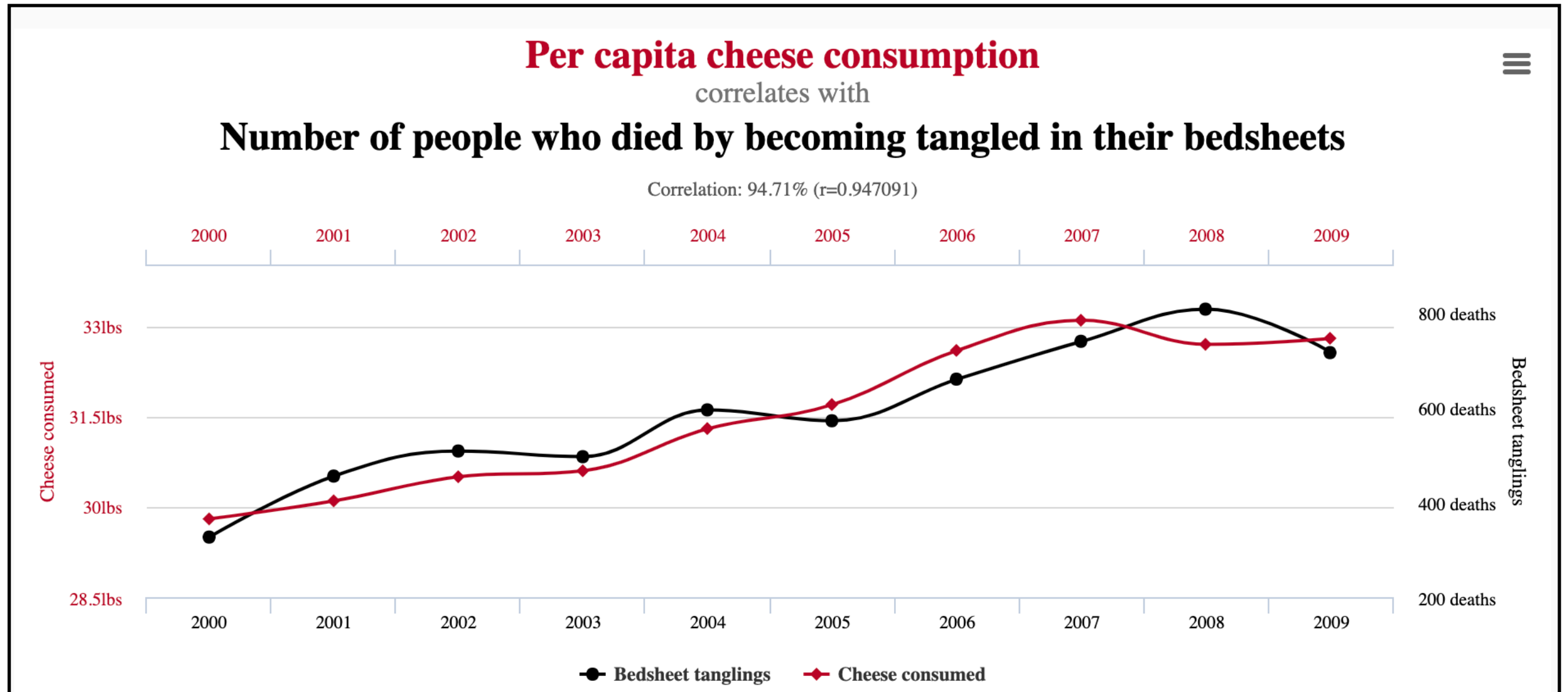
# Rate-Power Correlation



## np.corrcoef()



# Correlation Does Not Imply Causation





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<https://tinyurl.com/cogs118c-att>

