

# Introduction to Time Series Analysis

# Introduction to Time Series Analysis\*

\*For neuroscience basics.

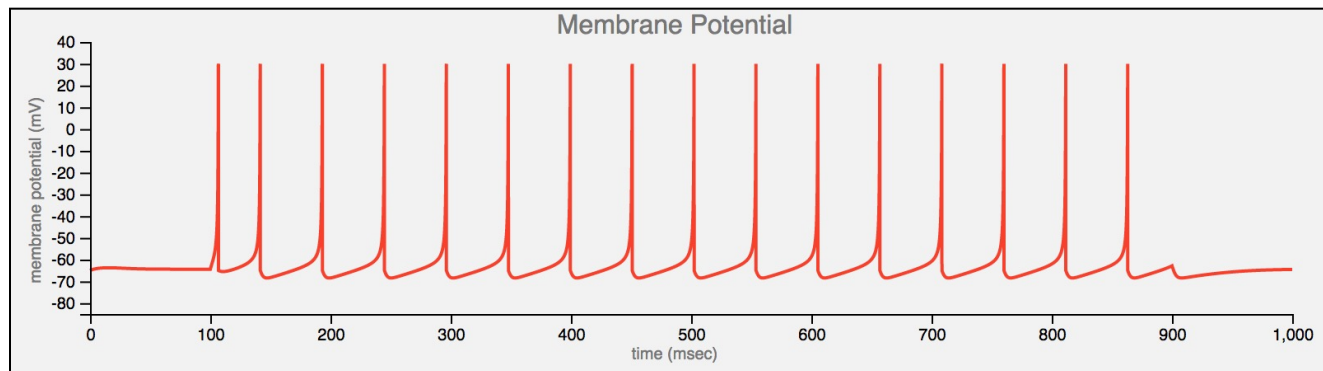
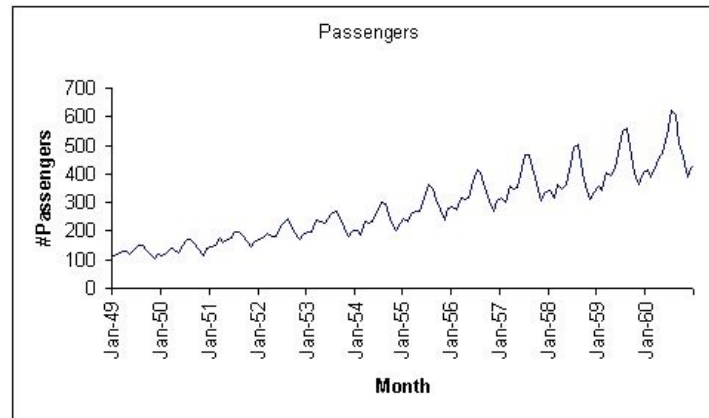
Time series models (e.g. economic, climate forecasts) go beyond our scope



# Introduction to Time Series Analysis

## What are time series?

~~Any variable sampled at regular intervals across time~~

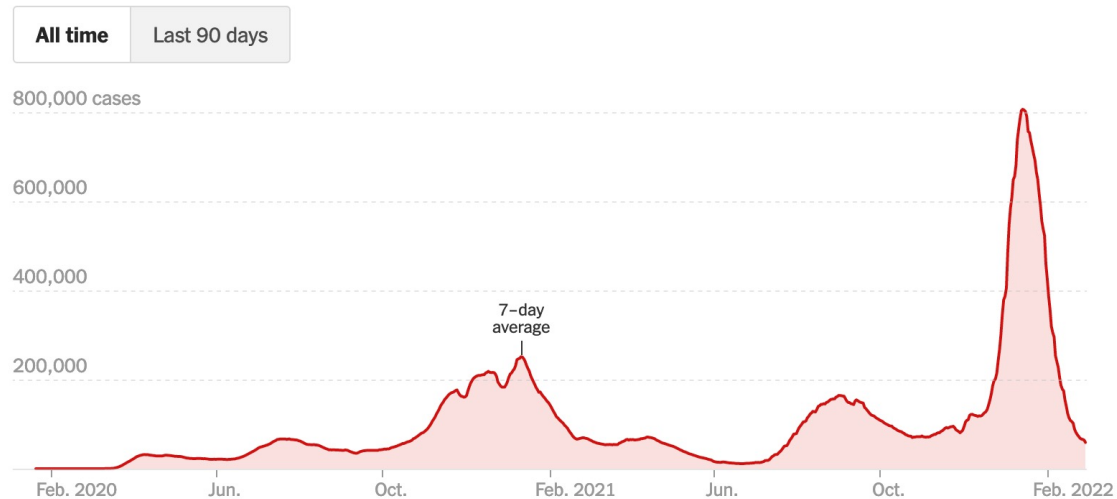


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### New reported cases

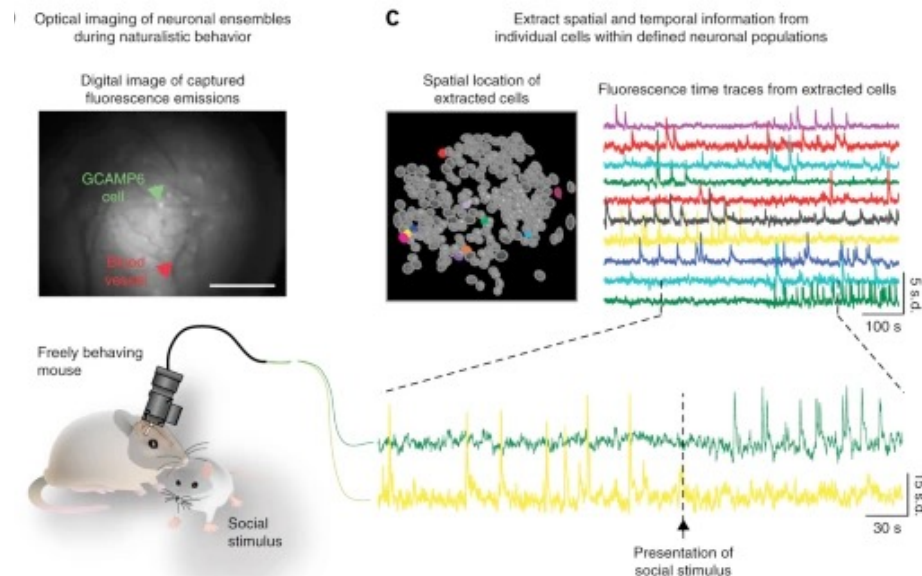


# Introduction to Time Series Analysis

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- Neural data: neuron spikes, LFPs,  $\text{Ca}^{++}$  signals (neurons, fiber photometry), neurochemical measures (eg. voltammetry), EEG, fMRI BOLD



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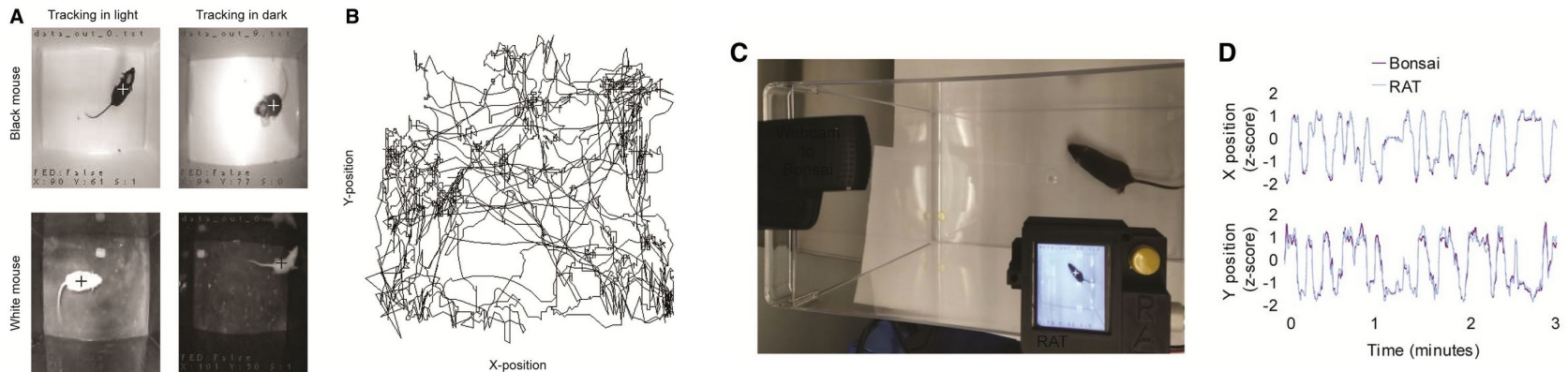
- Neural data: neuron spikes, LFPs,  $\text{Ca}^{++}$  signals (neurons, fiber photometry), neurochemical measures (eg. voltammetry), EEG, fMRI BOLD
- Other physiology: heart/respiratory rate, GSR, pupil dilation

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- Behavior measures: position (x,y coordinates), speed, heading, gaze position, responses (e.g. lever presses)

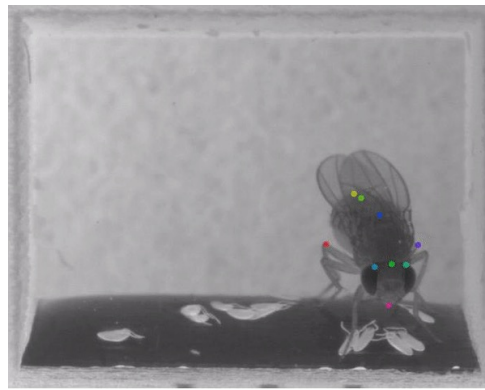
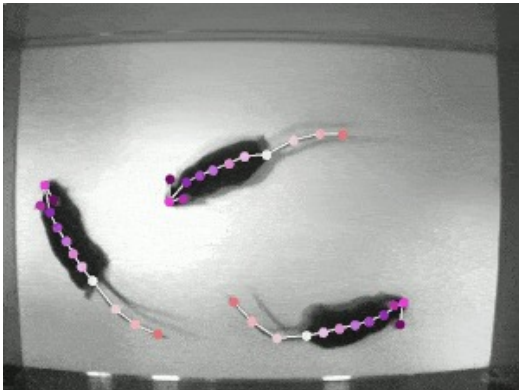


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- Other physiology: heart/respiratory rate, GSR, pupil dilation
- Behavior measures: position (x,y coordinates), speed, heading, gaze position, responses (e.g. lever presses)
- Size or counts of something growing or shrinking
- Temperature
- Image pixels in an animation
- Anything!

# Introduction to Time Series Analysis

What are time series?

~~Any variable sampled at regular intervals across time~~

Regular intervals = equally spaced!!

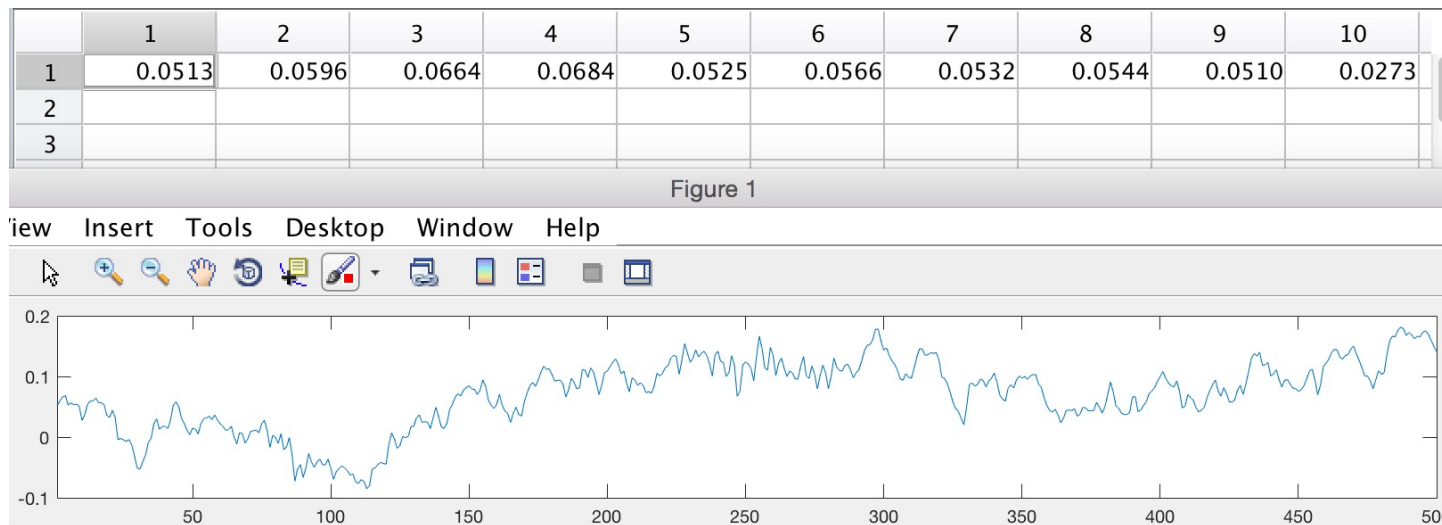
# Introduction to Time Series Analysis

## What are time series?

~~Any variable sampled at regular intervals across time~~

Regular intervals = equally spaced!!

This means you are discretizing time



# Events (e.g. neuron spiking, lever pressing) can be turned into a time series

“samples” are short time windows

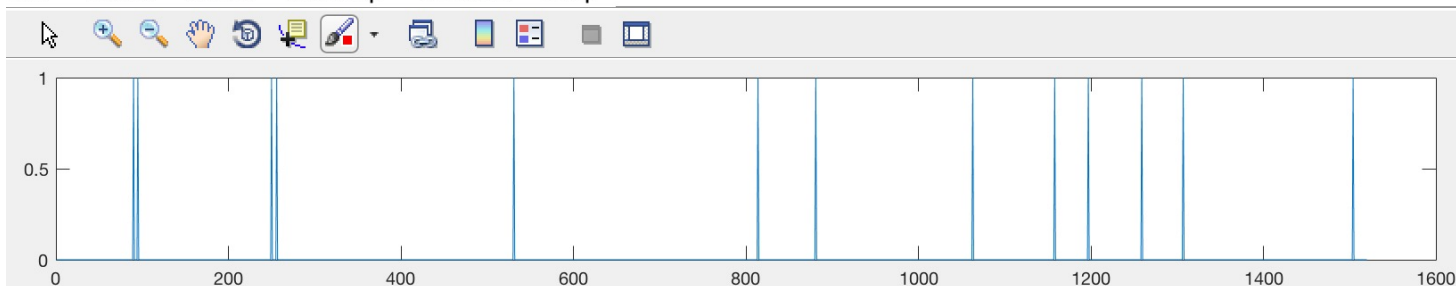
0 = no event in the time window

1 = event occurred

	1	2	3	4	5	6	7	8	9	10	
1	0	0	0	0	0	0	0	0	0	0	
2											
3											

Figure 1

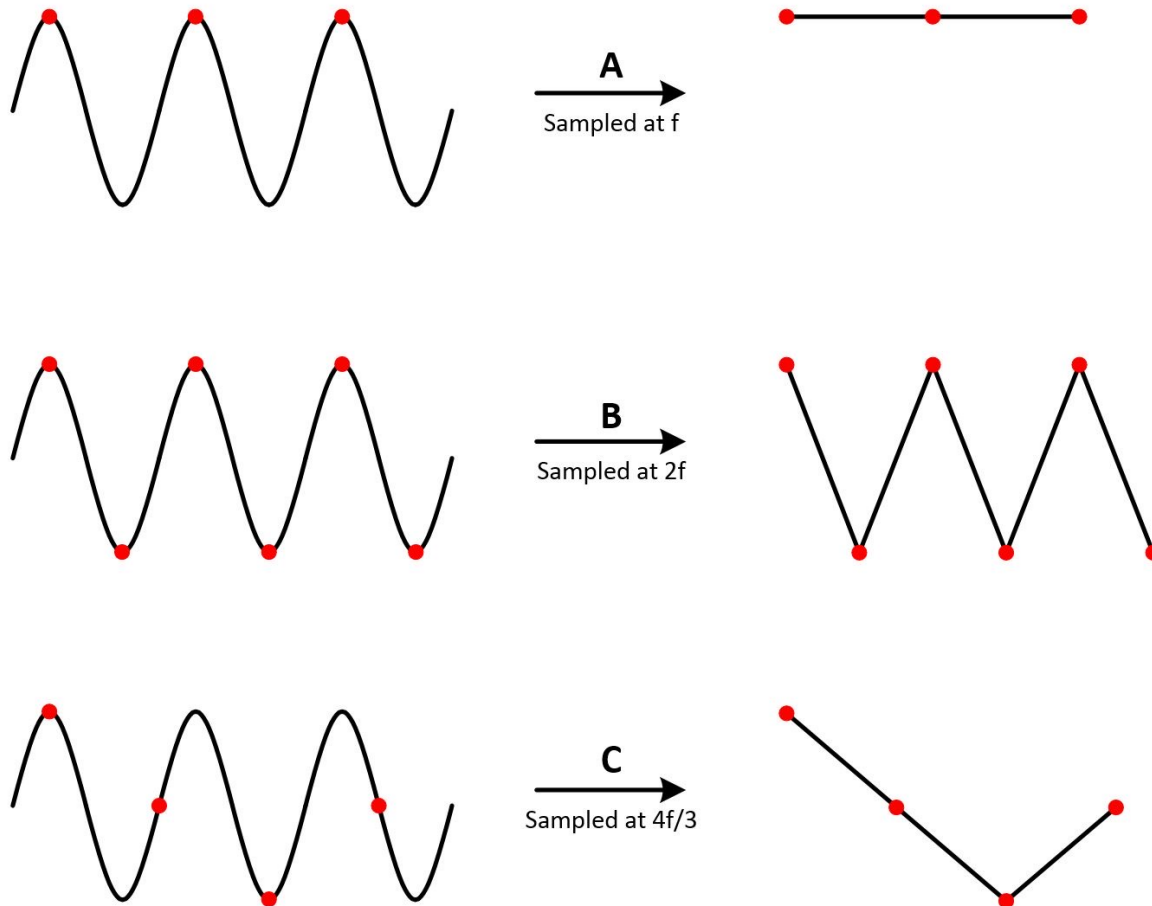
View Insert Tools Desktop Window Help



# Considerations in time series sampling:

\*You must have a concept of relevant timescales for your measure

- sampling rate too low -> you will not optimally capture trends in the data

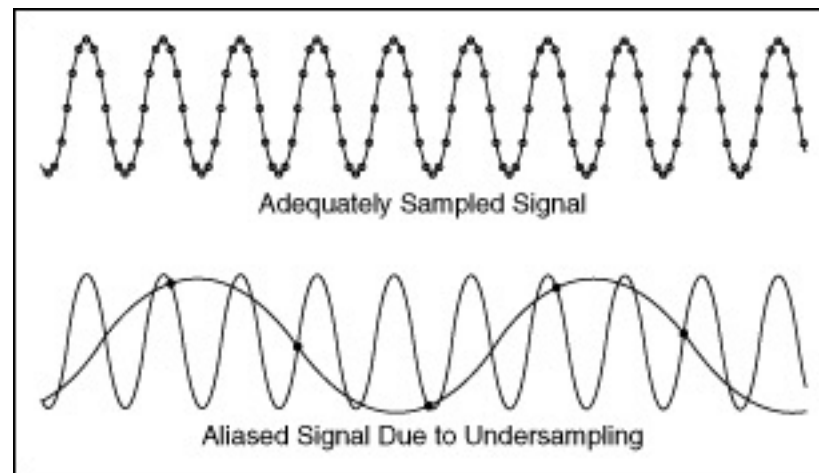


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## Aliasing



Nyquist theorem for periodic signals: the sampling rate for a periodic signal must be  $\geq 2 \times$  the highest frequency of interest

## Considerations in time series sampling:

\*You must have a concept of relevant timescales for your measure

- sampling rate too low -> you will not optimally capture trends in the data
- sampling rate too high -> file sizes explode

# Considerations in time series sampling:

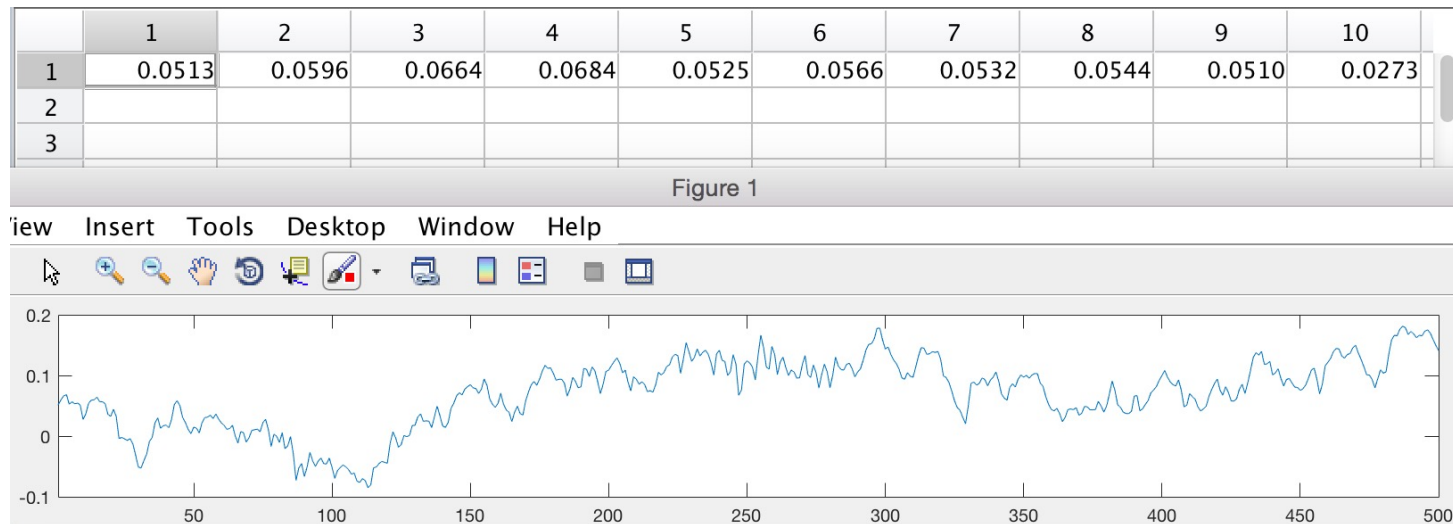
\*You must have a concept of relevant timescales for your measure

- sampling rate too low -> you will not optimally capture trends in the data
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\* Each observation has a *time stamp*

- these time stamps are necessary to align different streams of data

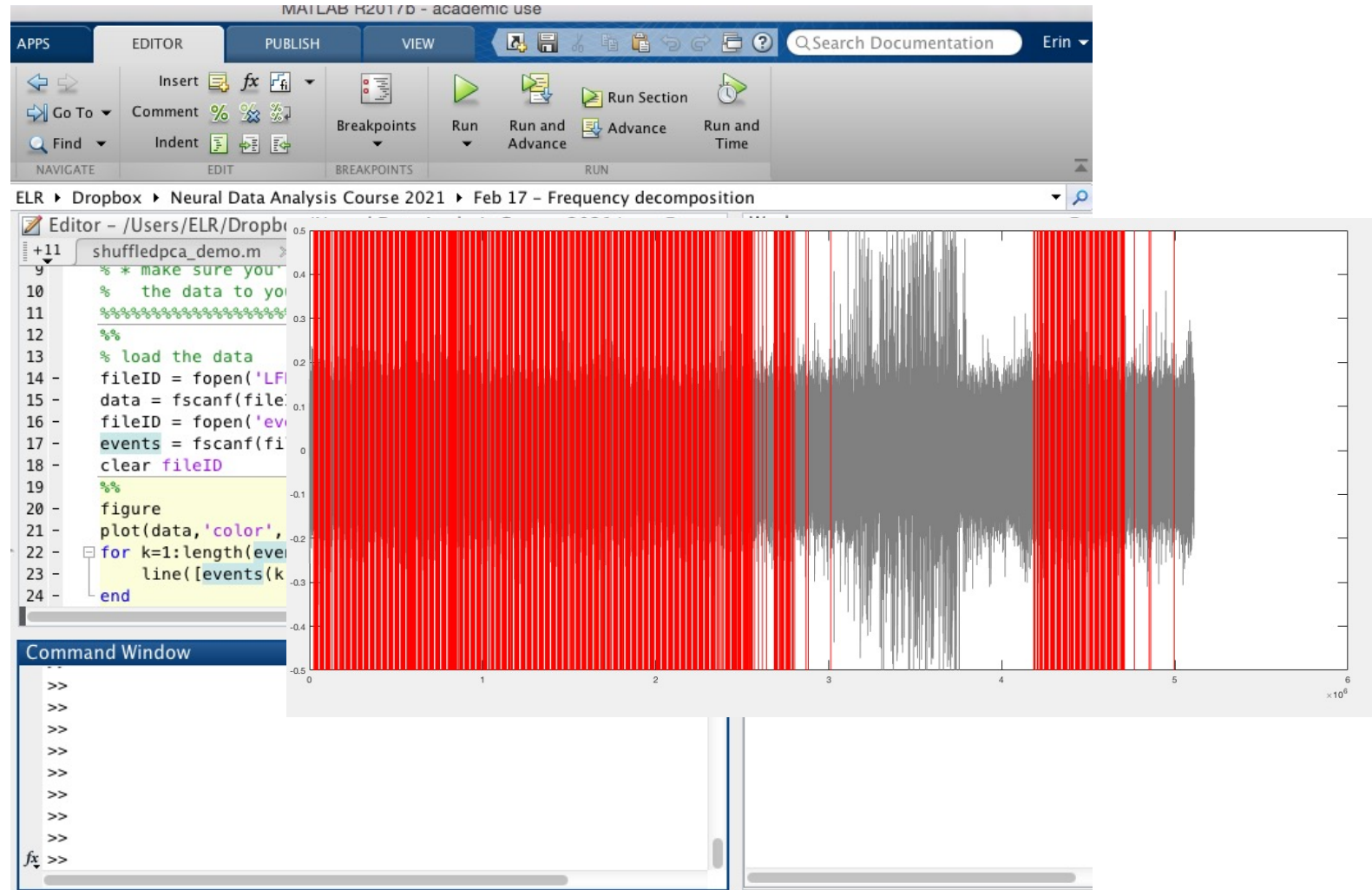
This means you are discretizing time



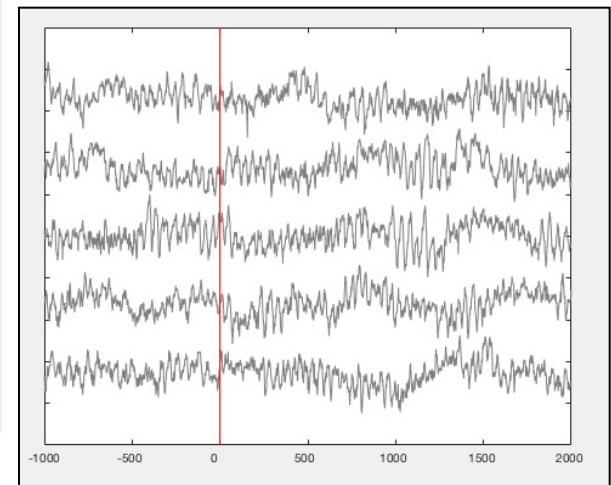
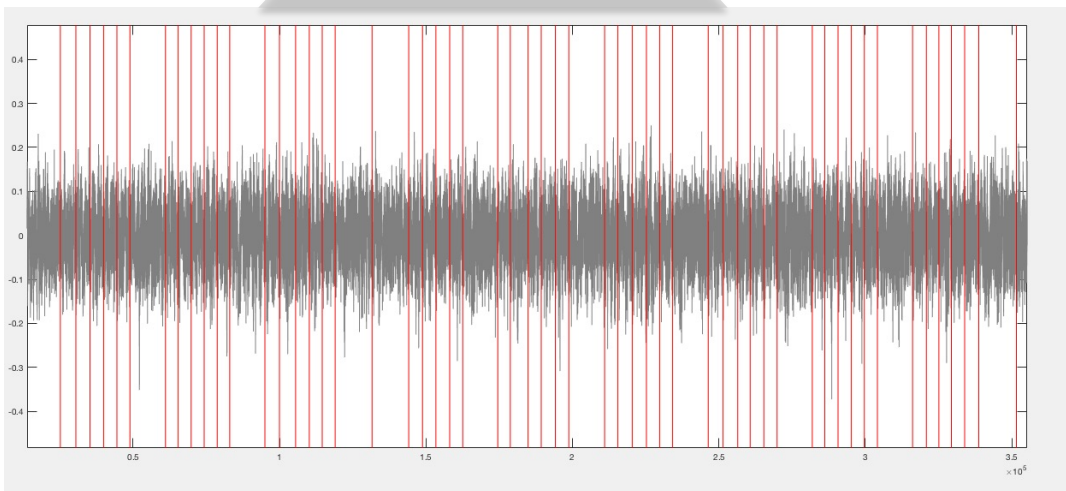
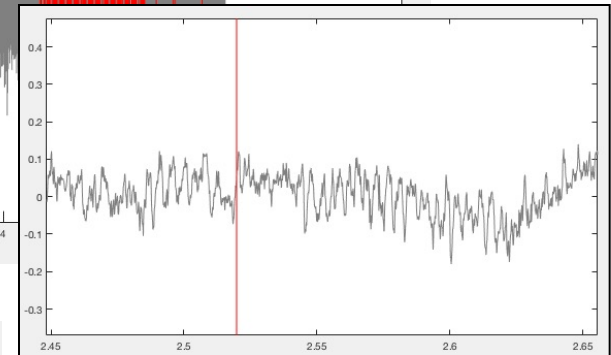
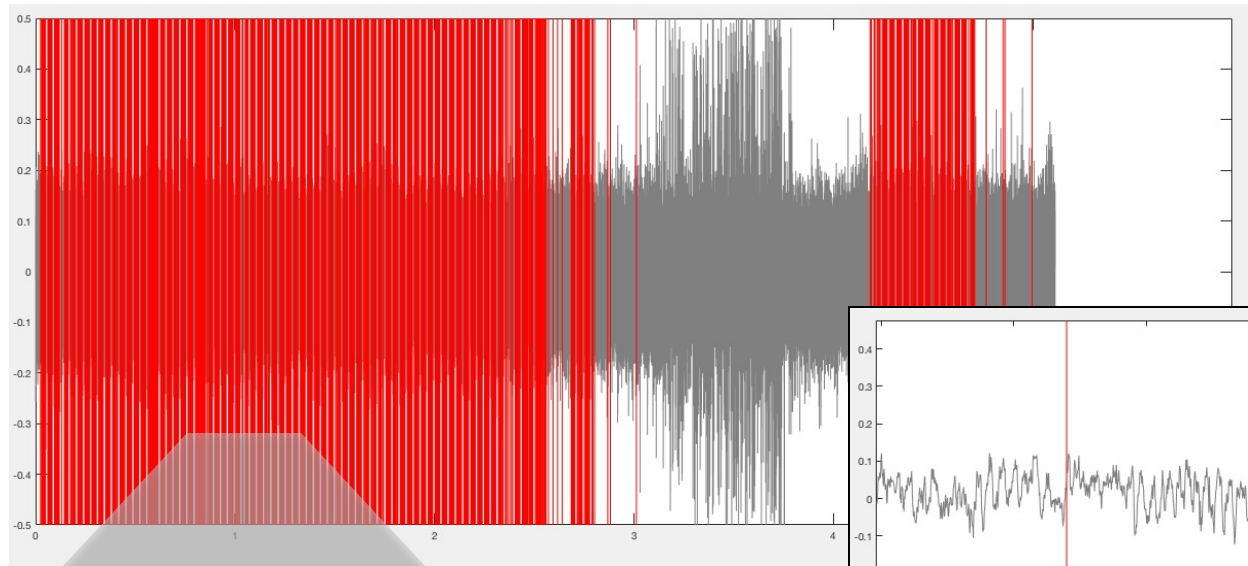


# Example: Aligning time series to an event

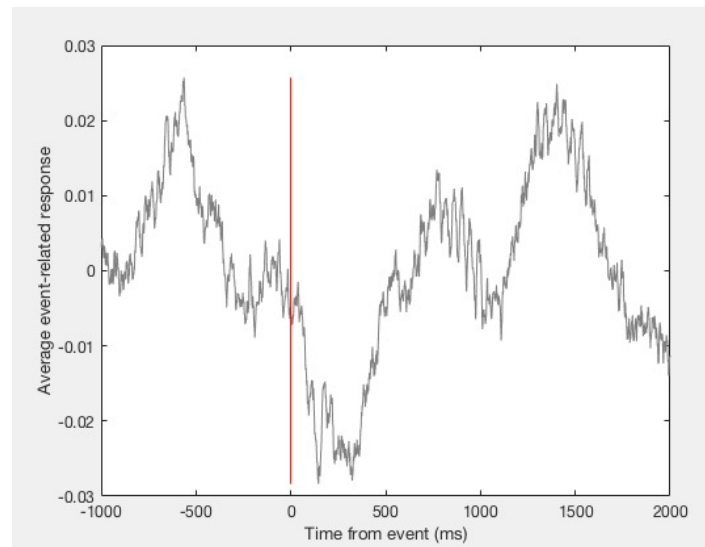
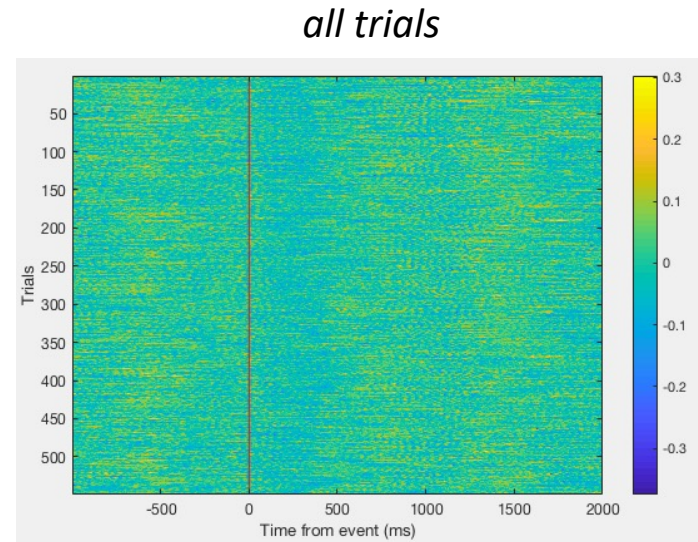
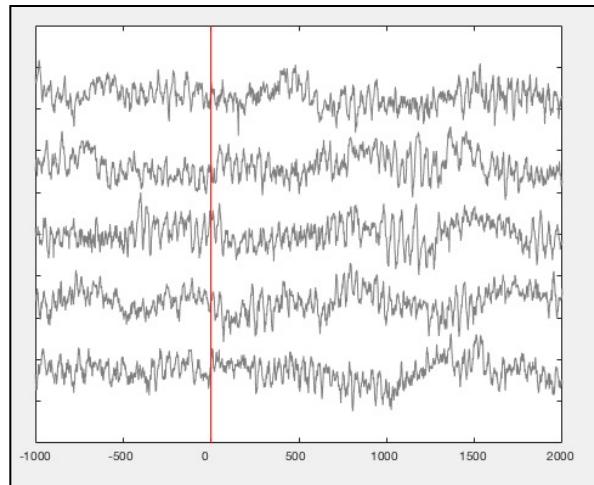
See *TimeSeriesDemoScript.m* or Time Series Demo in R



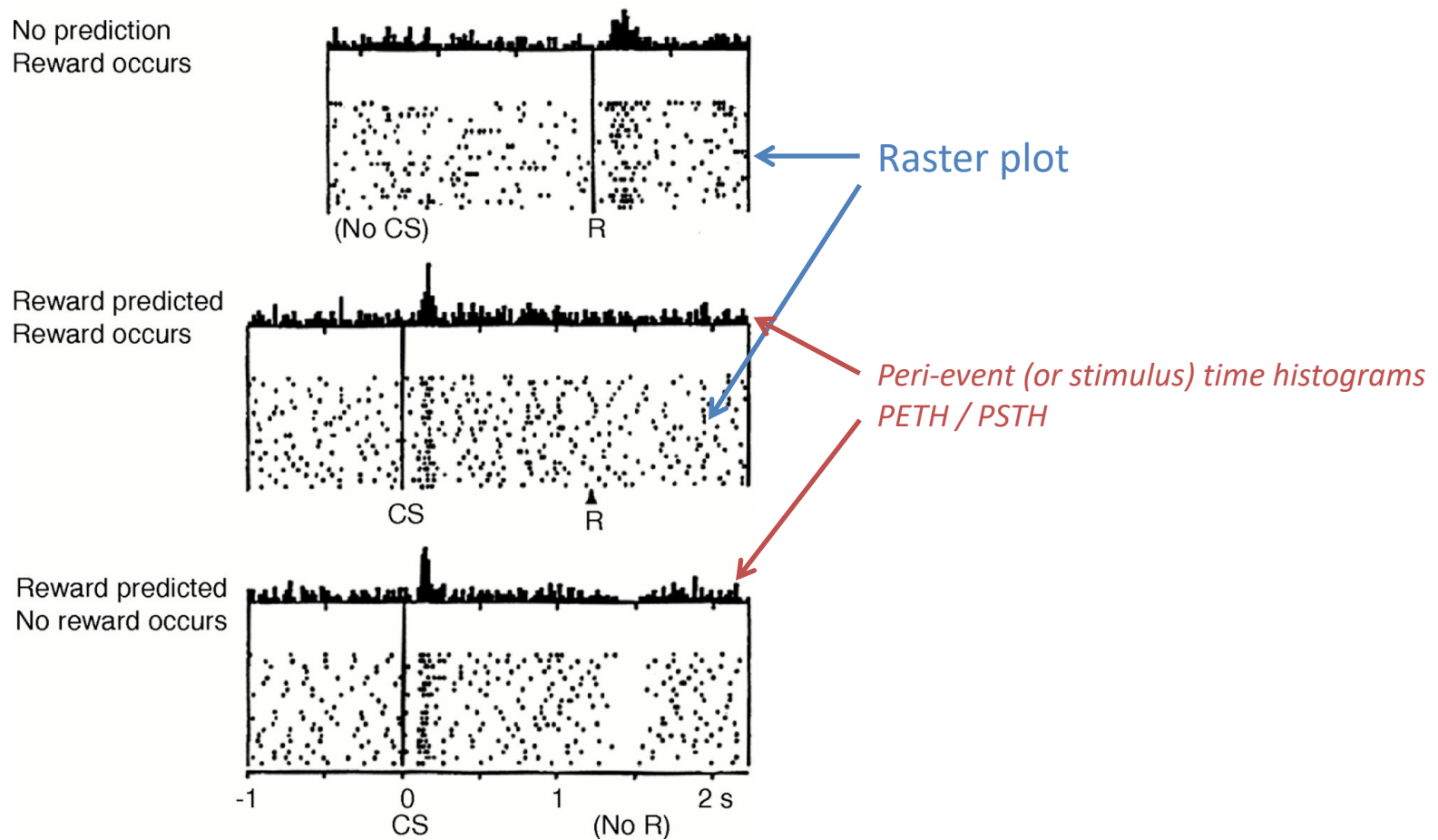
# Example: Aligning time series to an event



# Example: Aligning time series to an event



# This also works for time series of discrete observations

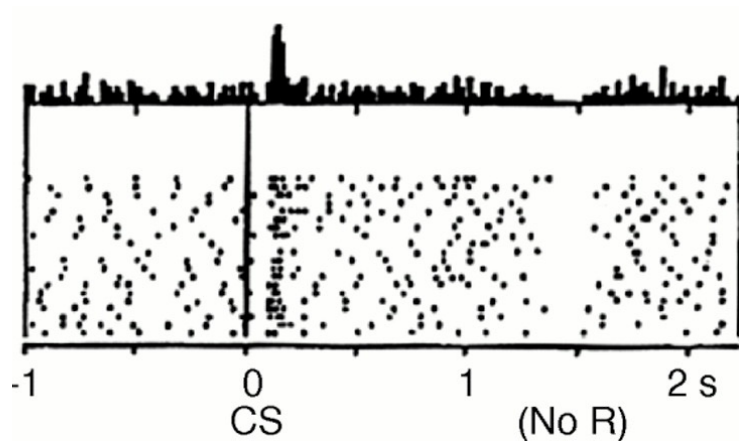


## *Why do this?*

\*Aligning data repeatedly samples changes in your data relative to ongoing events

e.g.

- look for event-related responses



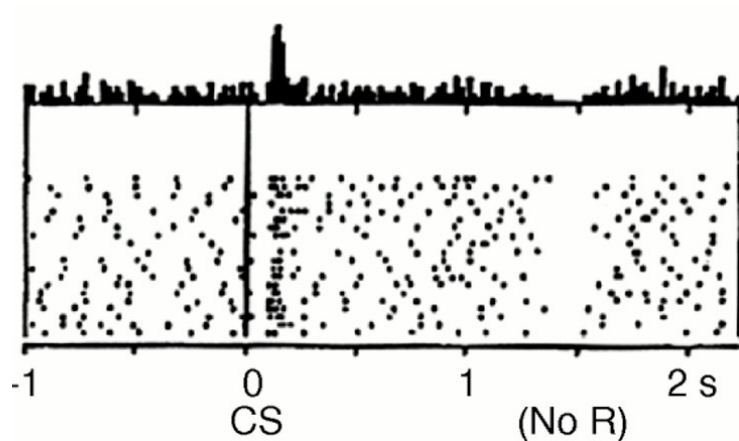
Schultz et al., 1997 Science

## Why do this?

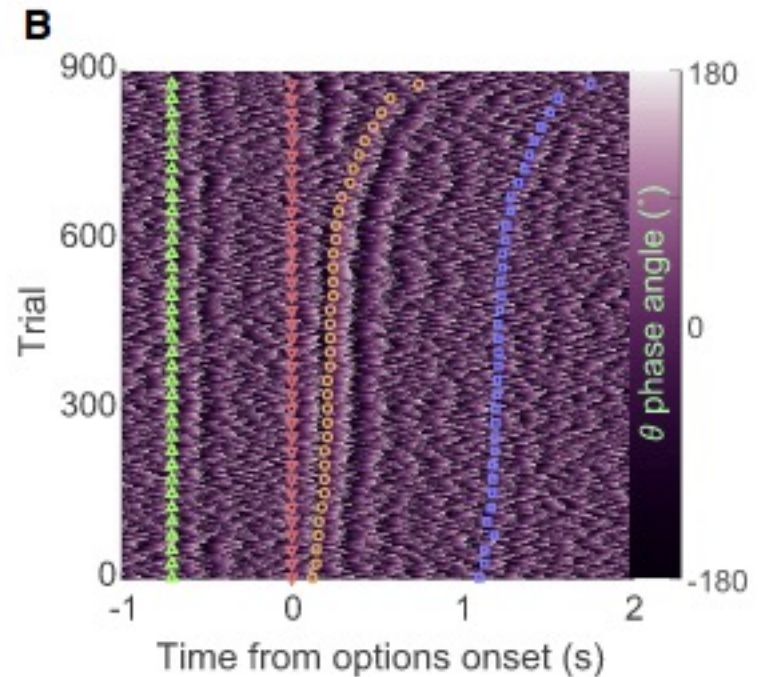
\*Aligning data repeatedly samples changes in your data relative to ongoing events

e.g.

- look for event-related responses
- contrast responses to different events
- consider if data are aligned to the wrong event



Schultz et al., 1997 Science



Knudsen and Wallis, 2020

# Optional steps to consider...

*Preprocessing* = steps taken to “clean up” the data before further analysis

Examples:

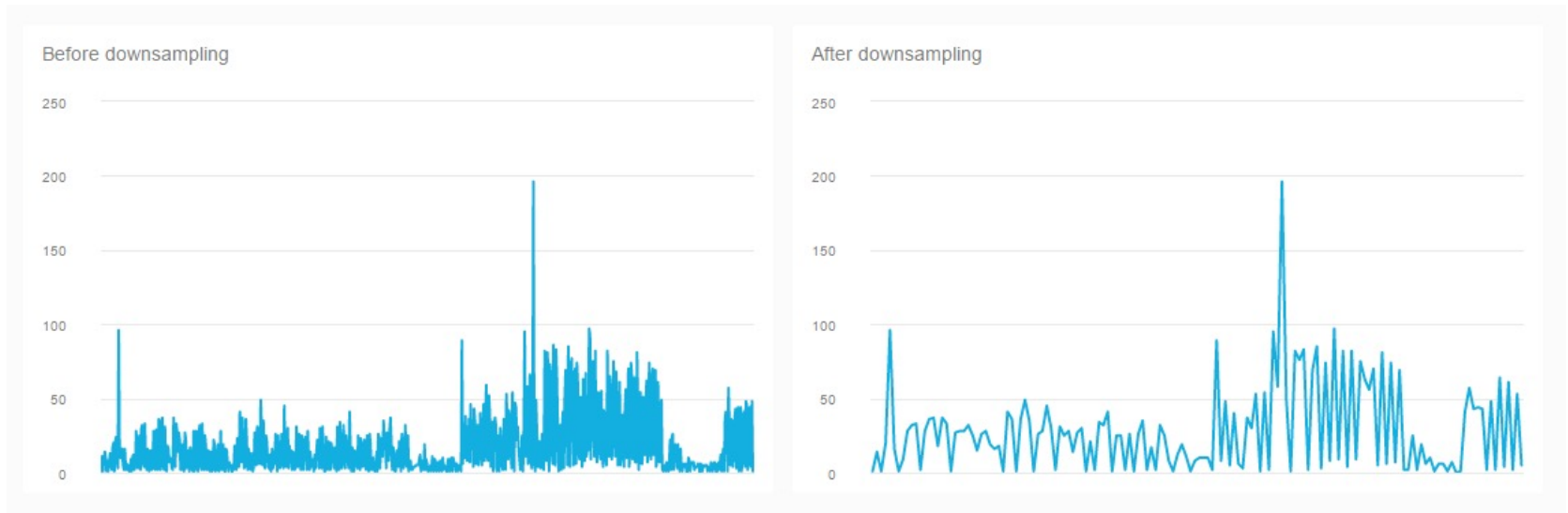
normalizing (mean-subtraction, z-scoring, normalizing to a baseline, etc.)

# Optional steps to consider...

*Preprocessing* = steps taken to “clean up” the data before further analysis

Examples:

normalizing (mean-subtraction, z-scoring, normalizing to a baseline, etc.)  
downsampling





# Optional steps to consider...

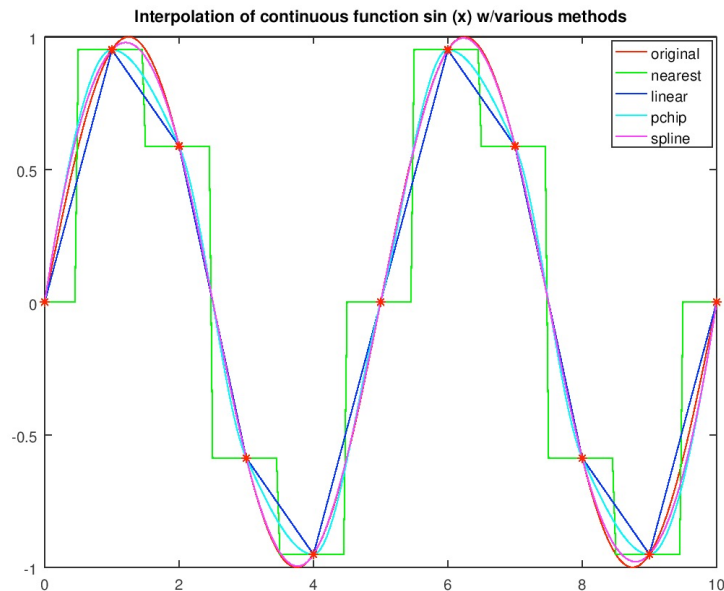
*Preprocessing* = steps taken to “clean up” the data before further analysis

Examples:

normalizing (mean-subtraction, z-scoring, normalizing to a baseline, etc.)

downsampling

interpolating

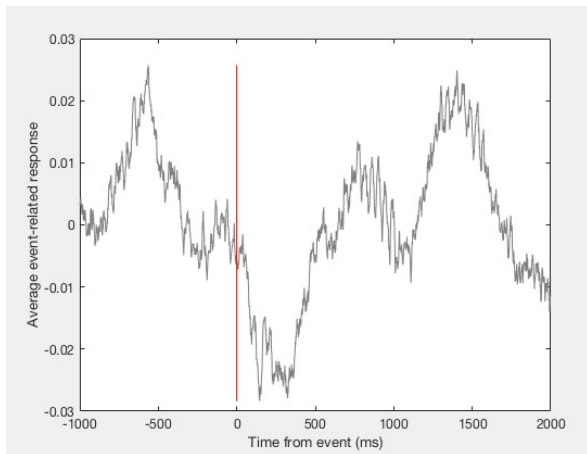


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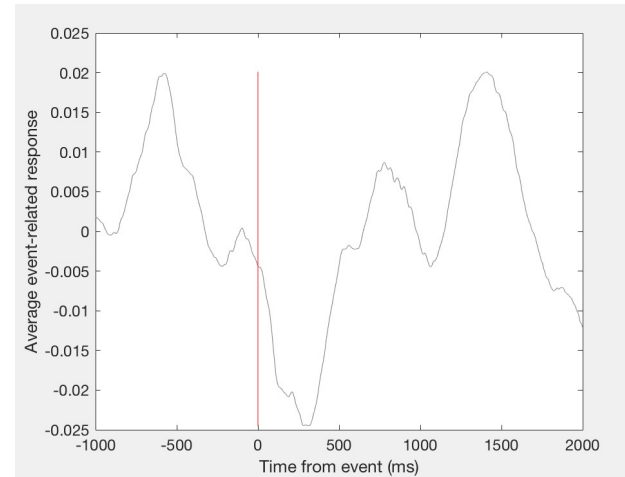
*Preprocessing* = steps taken to “clean up” the data before further analysis

Examples:

- normalizing (mean-subtraction, z-scoring, normalizing to a baseline, etc.)
- downsampling
- interpolating
- smoothing



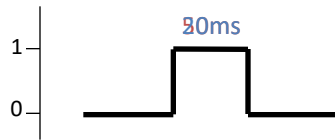
100ms moving average



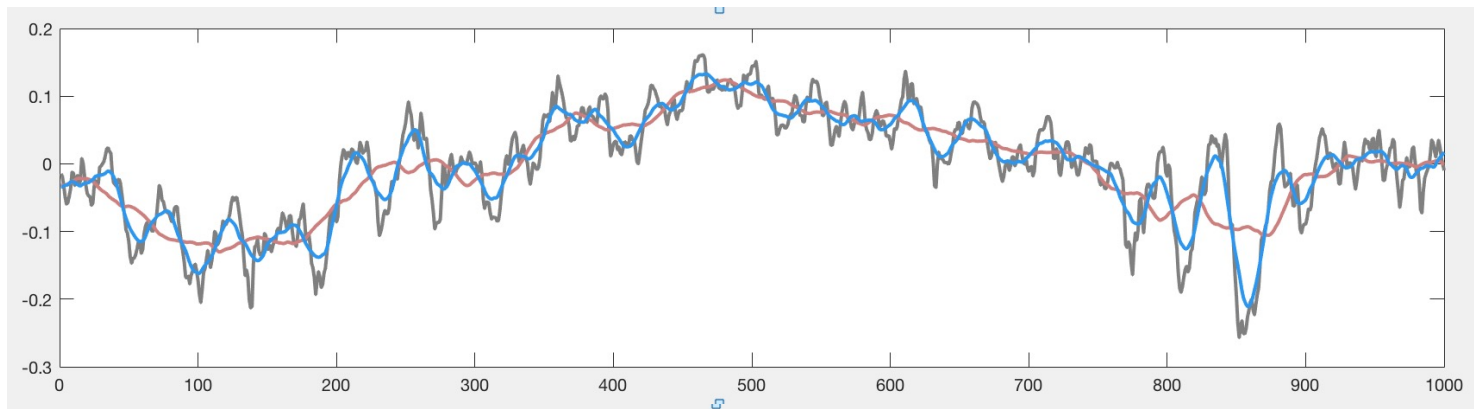
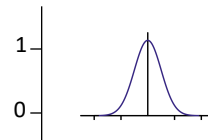
# Data smoothing

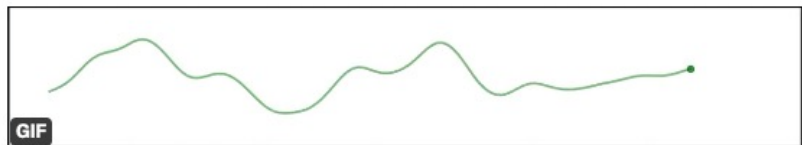
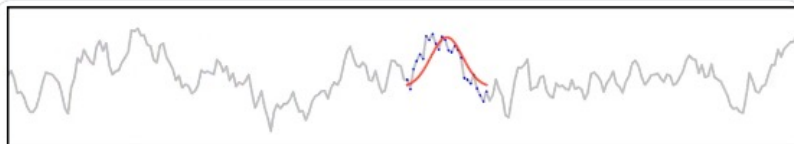
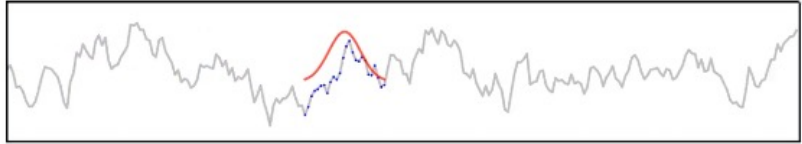
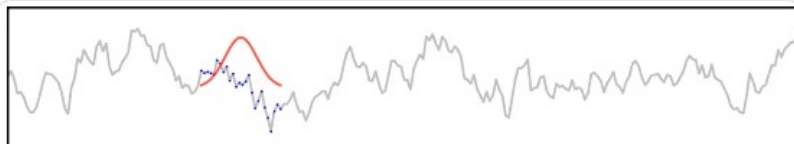
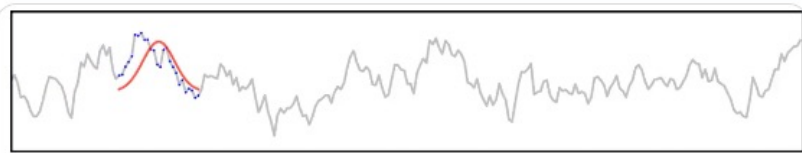
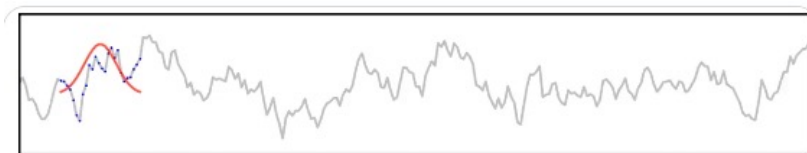
- These techniques *convolve* the time series with another function

e.g. moving average aka “boxcar”



Gaussian kernel

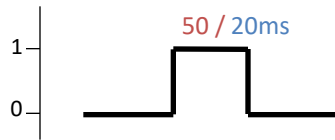




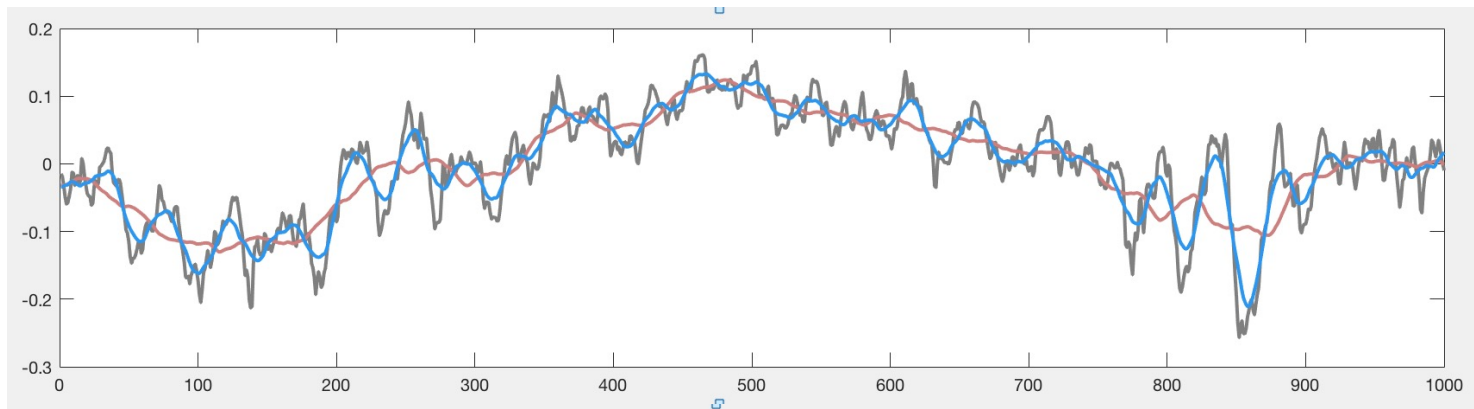
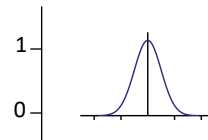
# Data smoothing

- These techniques *convolve* the time series with another function

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Gaussian kernel



- Do this as a preprocessing step, i.e. *before* selecting epochs or trials, to avoid edge effects

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Examples:

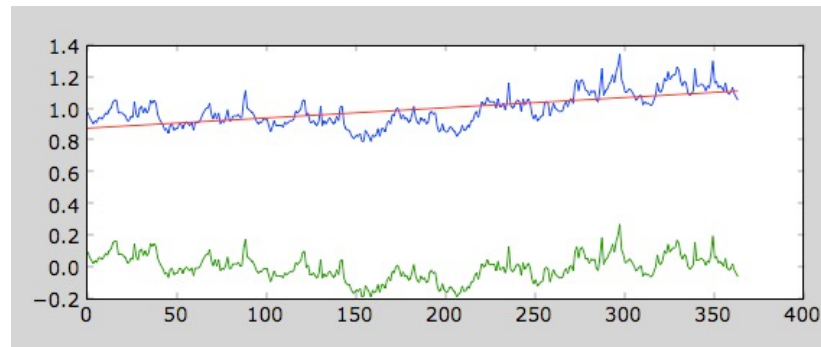
- normalizing (mean-subtraction, z-scoring, normalizing to a baseline, etc.)
- downsampling
- interpolating
- smoothing
- var. de-noising steps

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- detrending



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Best practices: Know your data and which preprocessing steps are appropriate

Apply these steps consistently to *all* data

Best carried out in a “pipeline”



# HW # 6

## HW6: Introduction to Time Series Analysis

You have recorded two neurons with the following parameters:

Sampling frequency 1kHz

Recording duration 7127.914 sec (or 118.7986 min)

Each vector in the attached data set includes the timestamp *in ms* when the neuron fired an action potential, as well as a timestamp, also in *ms*, for a recurring event.

1. Make raster plots of the first 100 events for each neuron's response time-locked to the event. Include times from 500ms before the event to 1s after
2. Plot each neuron's average response over all 699 events as a *lineplot* or PETH in the same time epoch (make sure your x-axis indicates time relative to the event)
3. Smooth each neuron's time series using a 200ms moving average, and replot the *lineplot* from 2