

Bradley Voytek, Ph.D.  
UC San Diego

Department of Cognitive Science  
Halıcıoğlu Data Science Institute  
Neurosciences Graduate Program

bvoytek@ucsd.edu  
@bradleyvoytek

UC San Diego

**Who is this guy?**



# VOYTEKlab

Natalie Schaworonkow, PhD  
Post-doctoral Fellow



Thomas Donoghue, PhD  
Just-defended (!) PhD



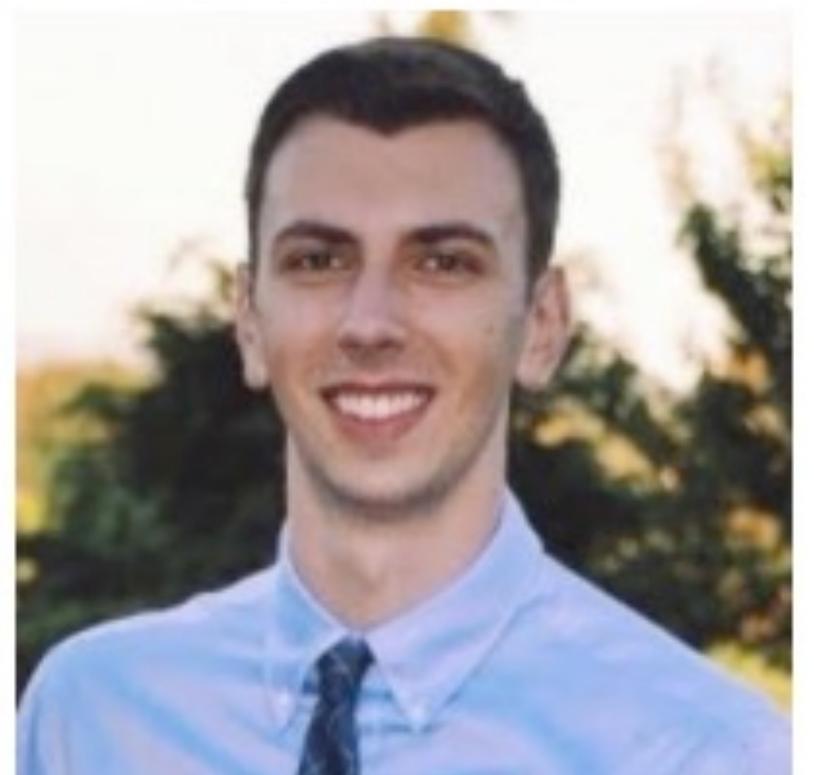
Richard Gao  
Just-defended (!) PhD



Ryan Hammonds  
Software Developer



Andrew Bender  
Neuroscience PhD student



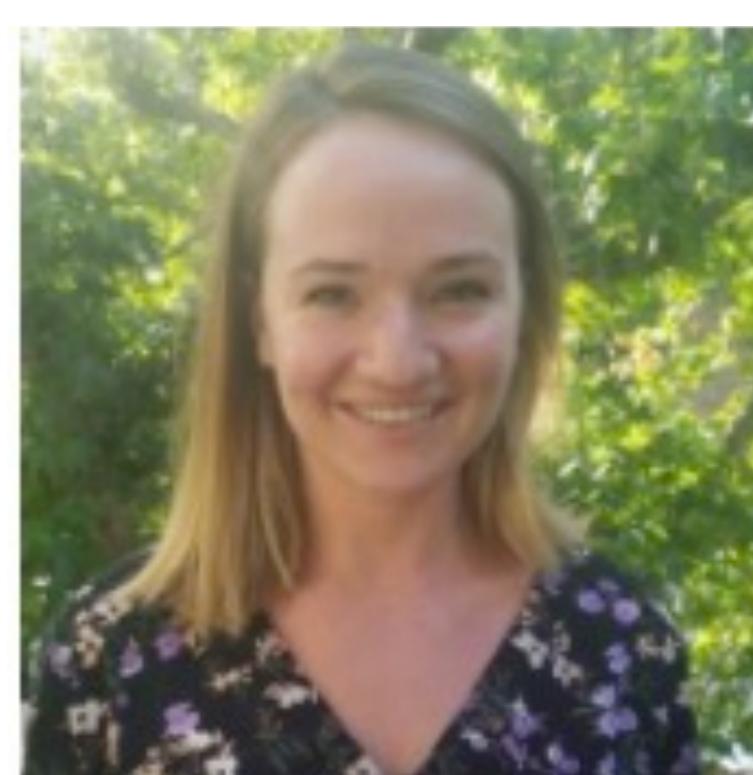
Eena Kosik  
Cogsci PhD student



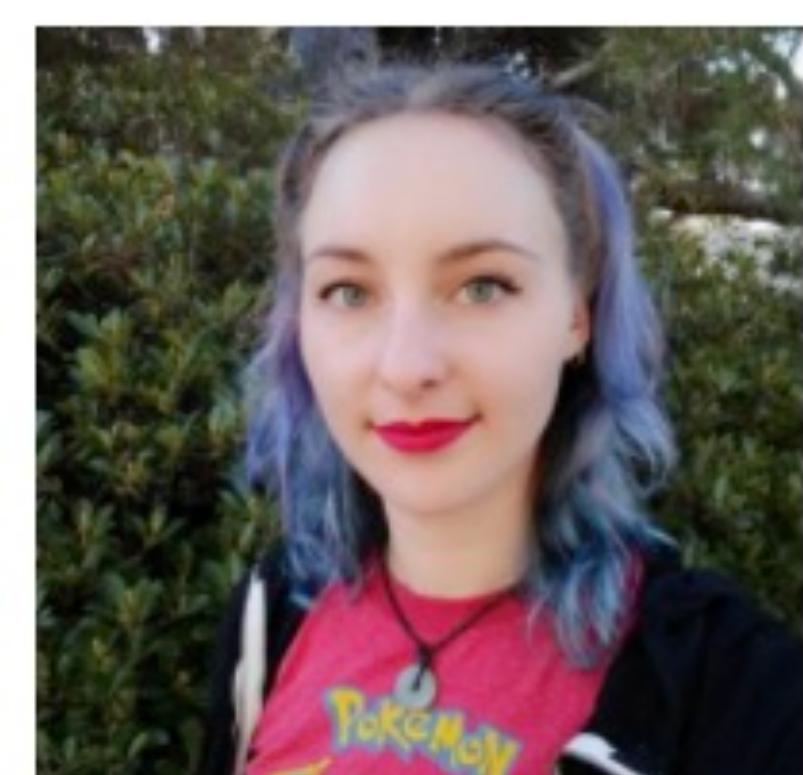
Michael (MJ) Preston  
Neuroscience PhD student



Sydney Smith  
Neuroscience PhD student



Quirine van Engan  
Cogsci PhD student



# Support

- Alfred P. Sloan Research Fellowship in Neuroscience
- Whitehall Foundation
- NSF BCS COGNEURO 1736028 (Neuroscience)
- NSF DGE NRT 1735234 (Data Science)
- NIH NIGMS R01 GM134363 (Software Engineering)
- Kavli Innovative Research Grant

# WIRED



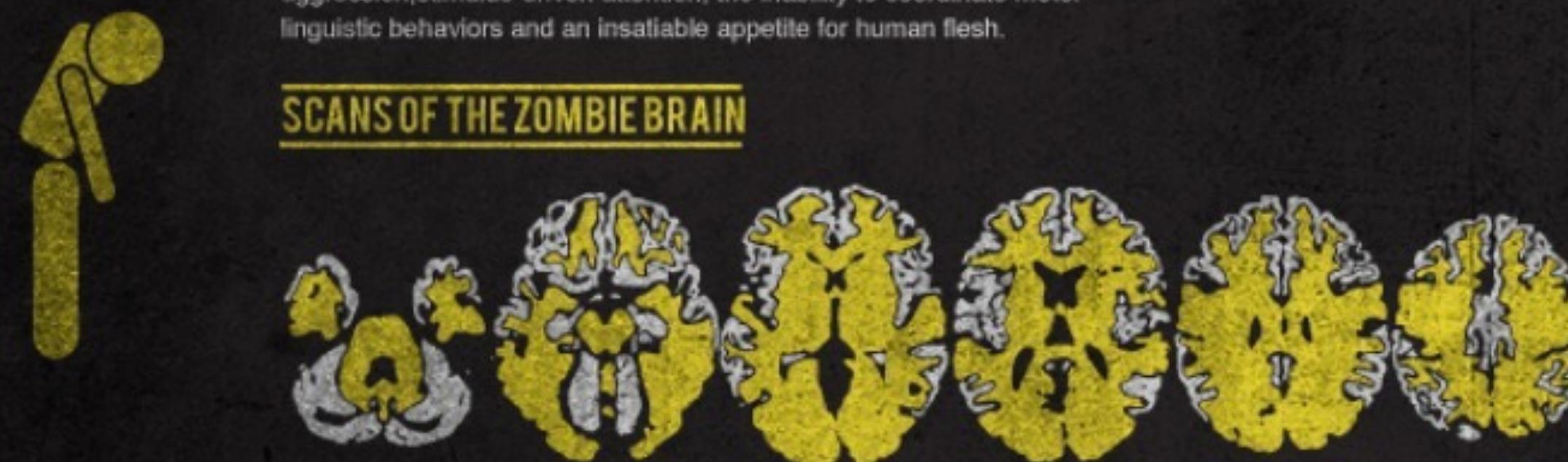
## THE SCIENCE OF SURVIVING THE ZOMBIE APOCALYPSE

### THE ZOMBIEDISORDER

#### CONSCIOUSNESS DEFICIT HYPOACTIVITY DISORDER

Consciousness Deficit Hypoactivity Disorder (CDHD): The loss of rational, voluntary and conscious behavior replaced by delusional/impulsive aggression, stimulus-driven attention, the inability to coordinate motor linguistic behaviors and an insatiable appetite for human flesh.

#### SCANS OF THE ZOMBIE BRAIN



■ ZOMBIE

■ HUMAN

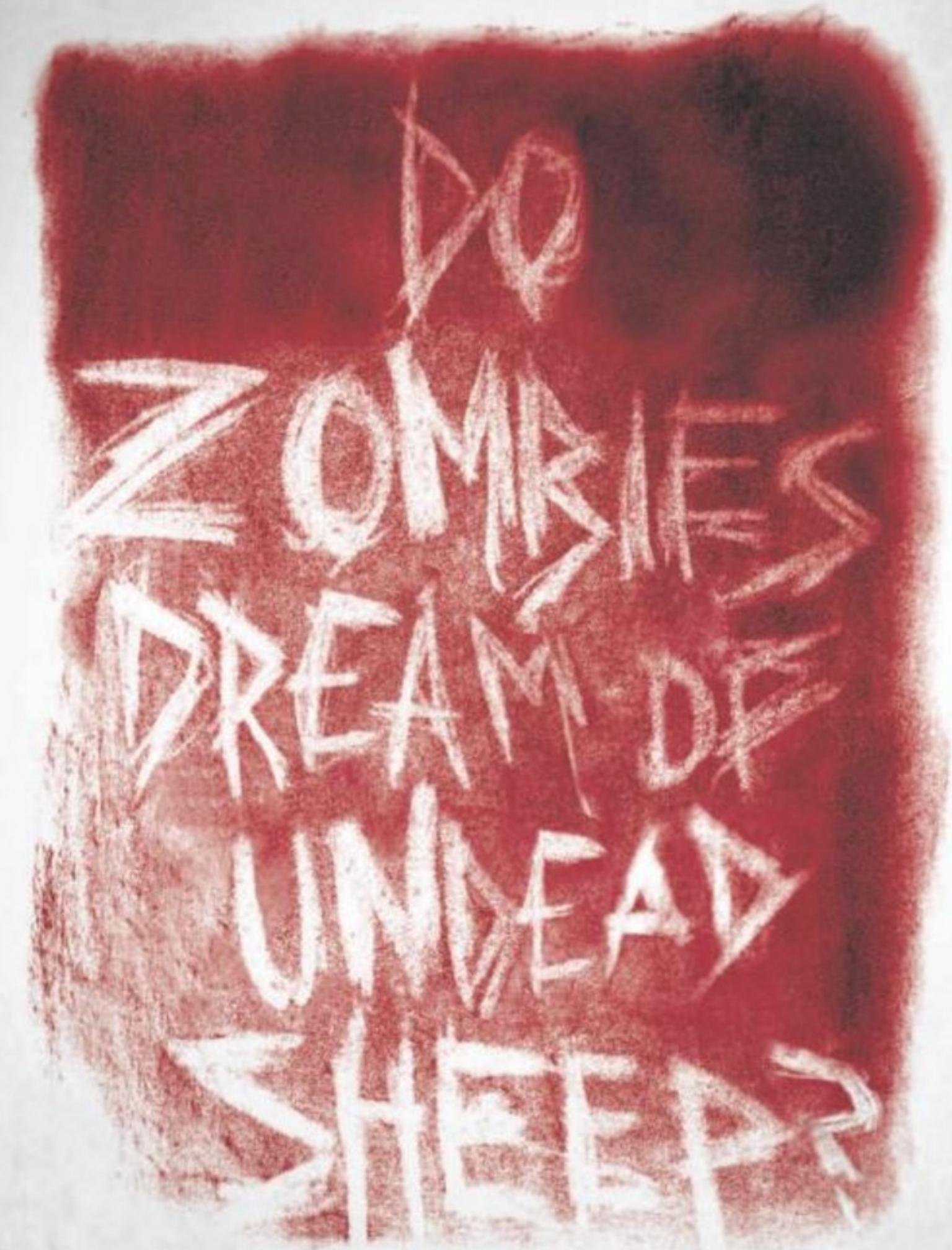
Through detailed scans, the exact brain areas that have been destroyed in the zombie can be reconstructed.

The scans show significant brain tissue loss in the zombie. The gray area shows what a human brain would look like. The profile of damage corroborates the behavioral observations of zombies.

WIRED

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BRADLEY VOYTEK



A NEUROSCIENTIFIC VIEW  
OF THE ZOMBIE BRAIN

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LYPSE

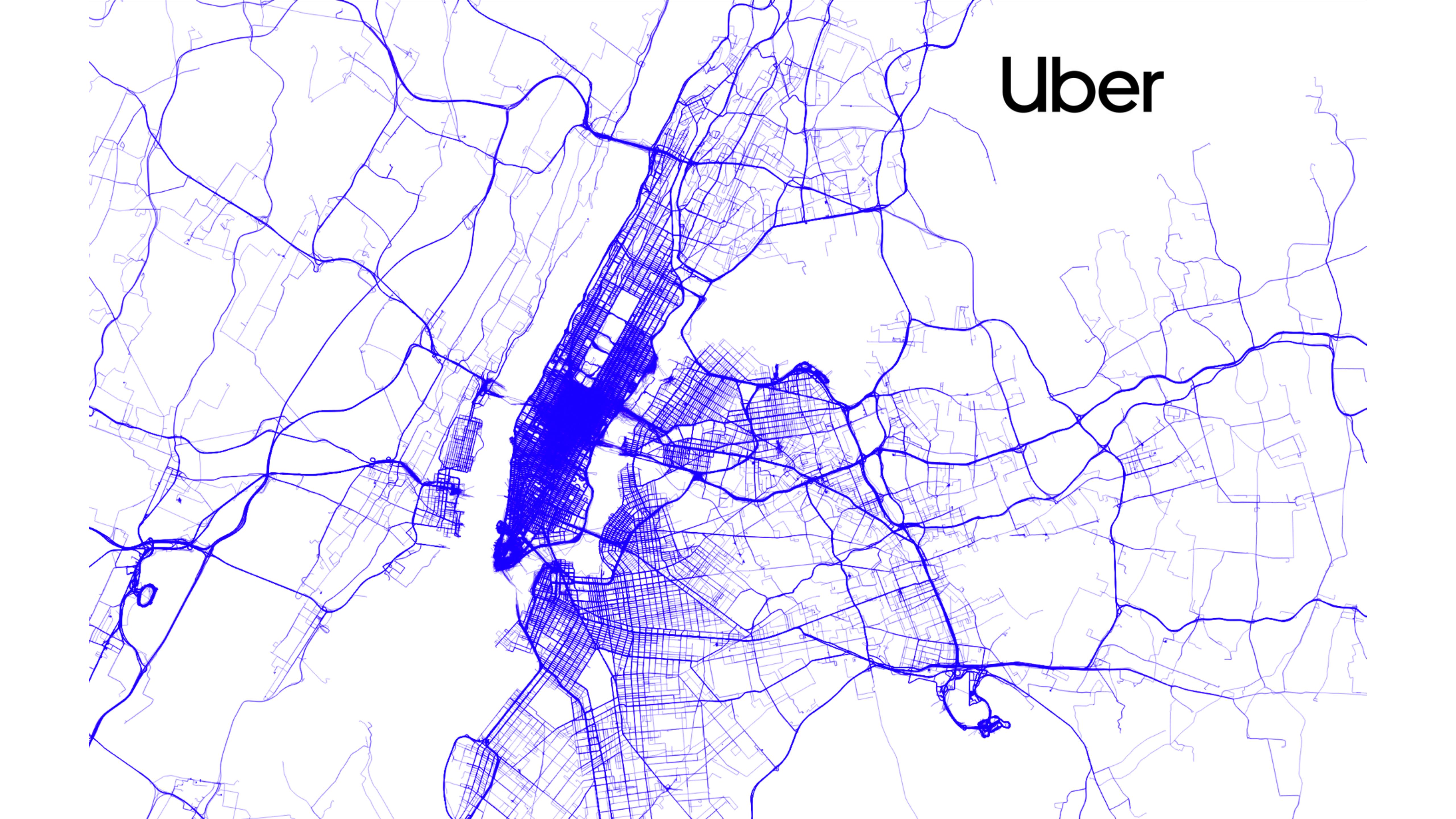


infant brain tissue.  
The gray area shows  
what it would look like  
if it corroborates  
the mutations of zombies.

# **My path as a data scientist**

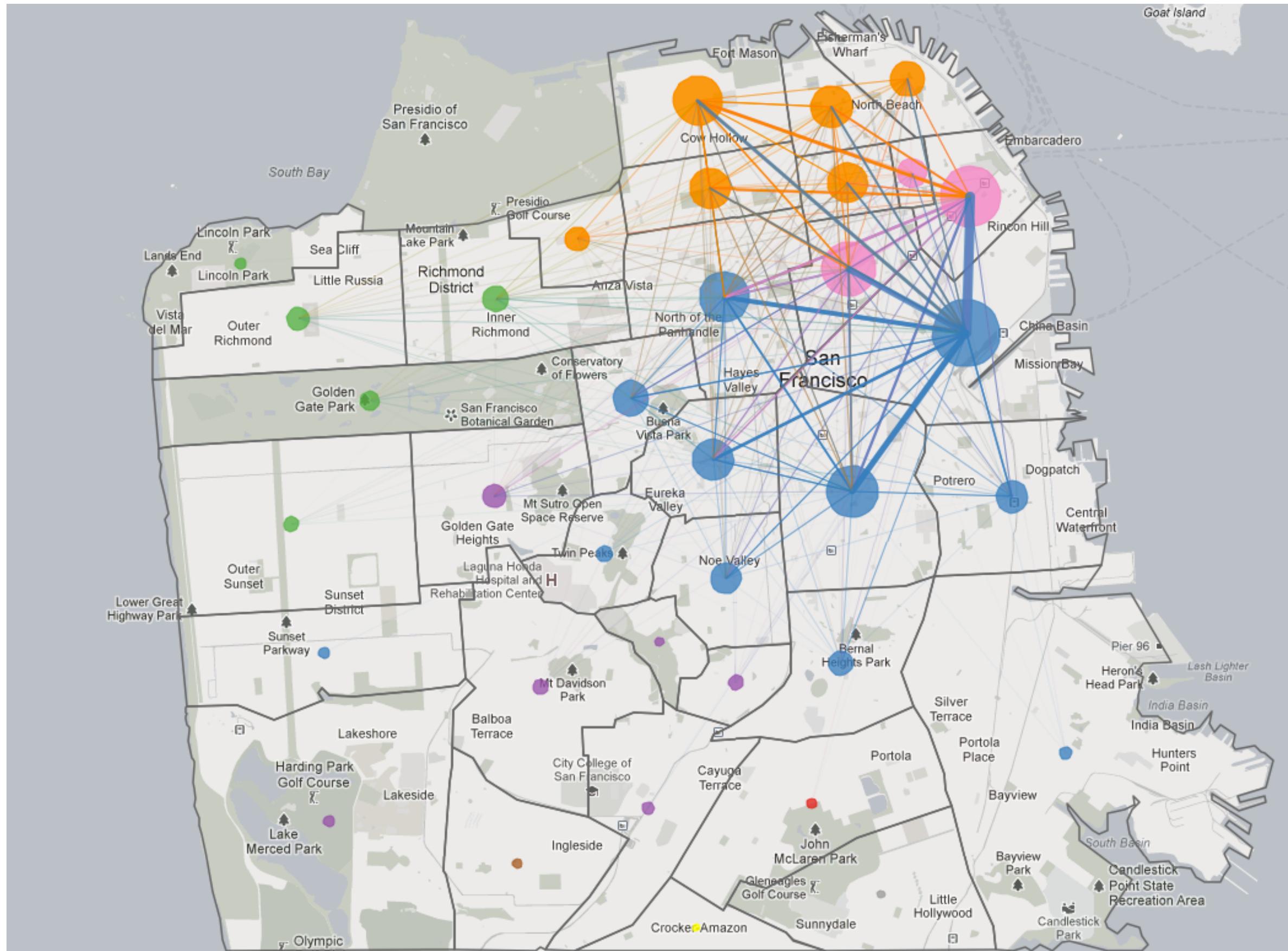
# uber





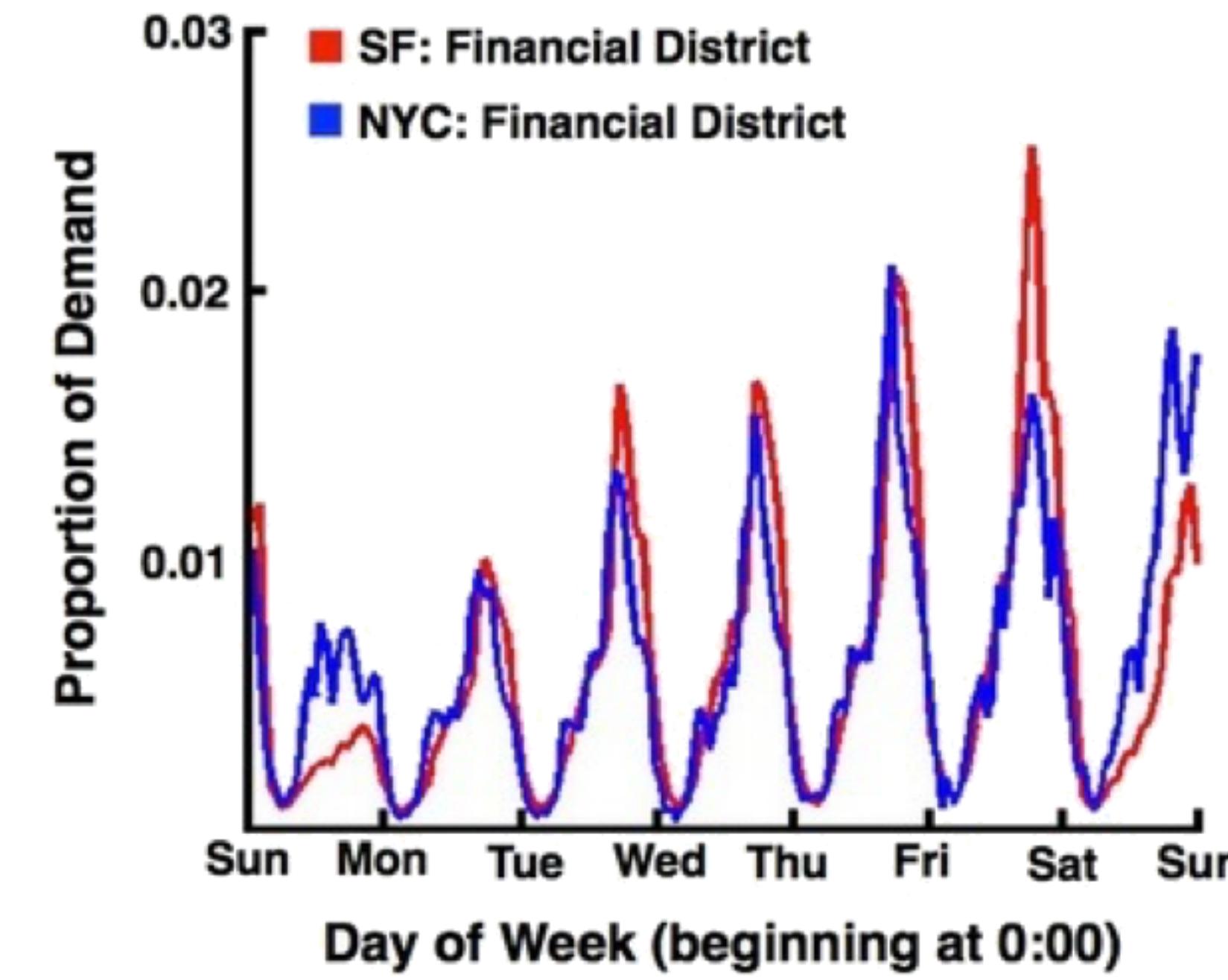
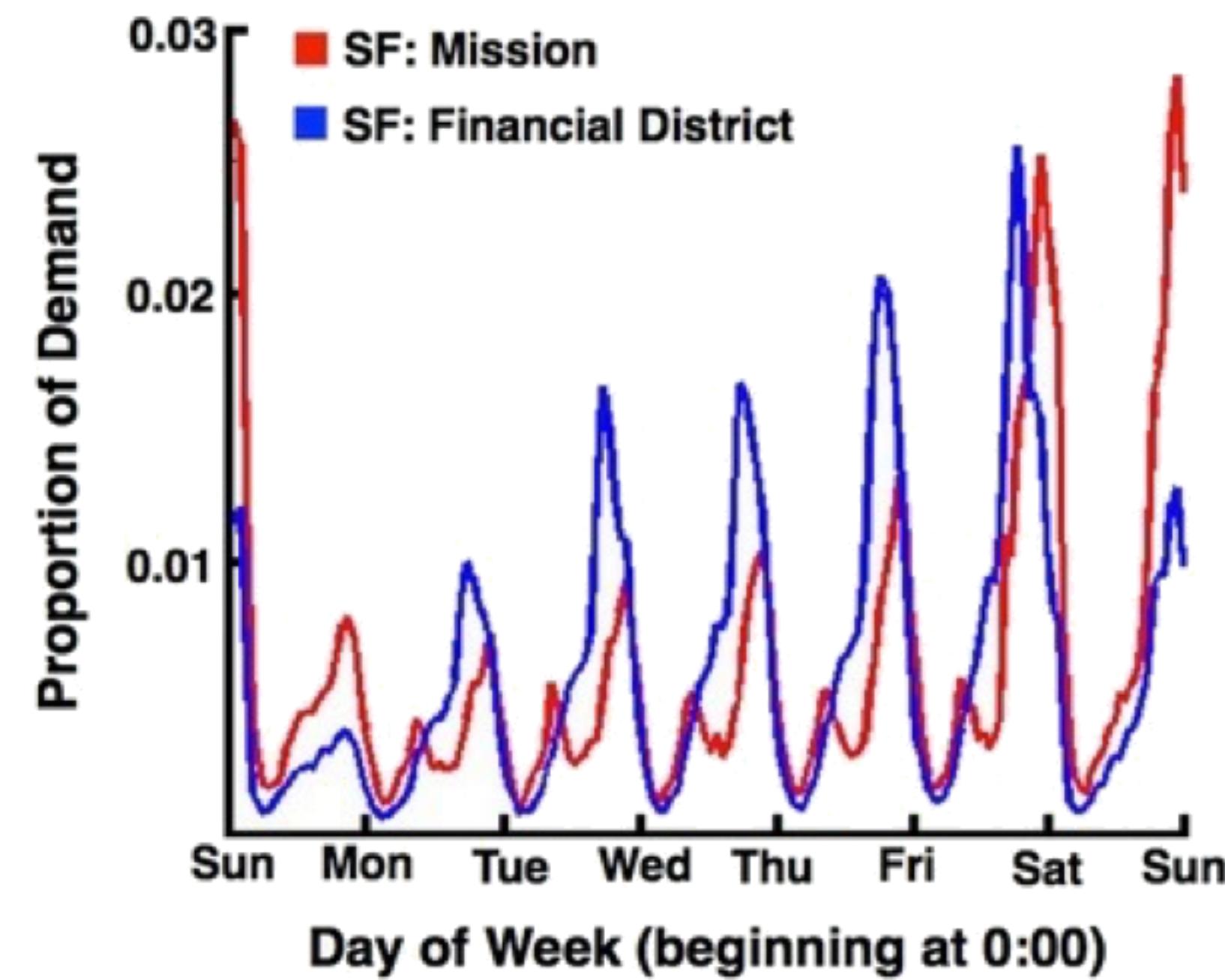
# Uber

# City dynamics



- Aggregating data into arbitrary geographical units: here neighborhoods, but under the hood you'd use e.g., hexagonal tiling.
- Turns lat/lng pairs and time into temporal profiles of demand between parts of a city.

# Spatiotemporal dynamics

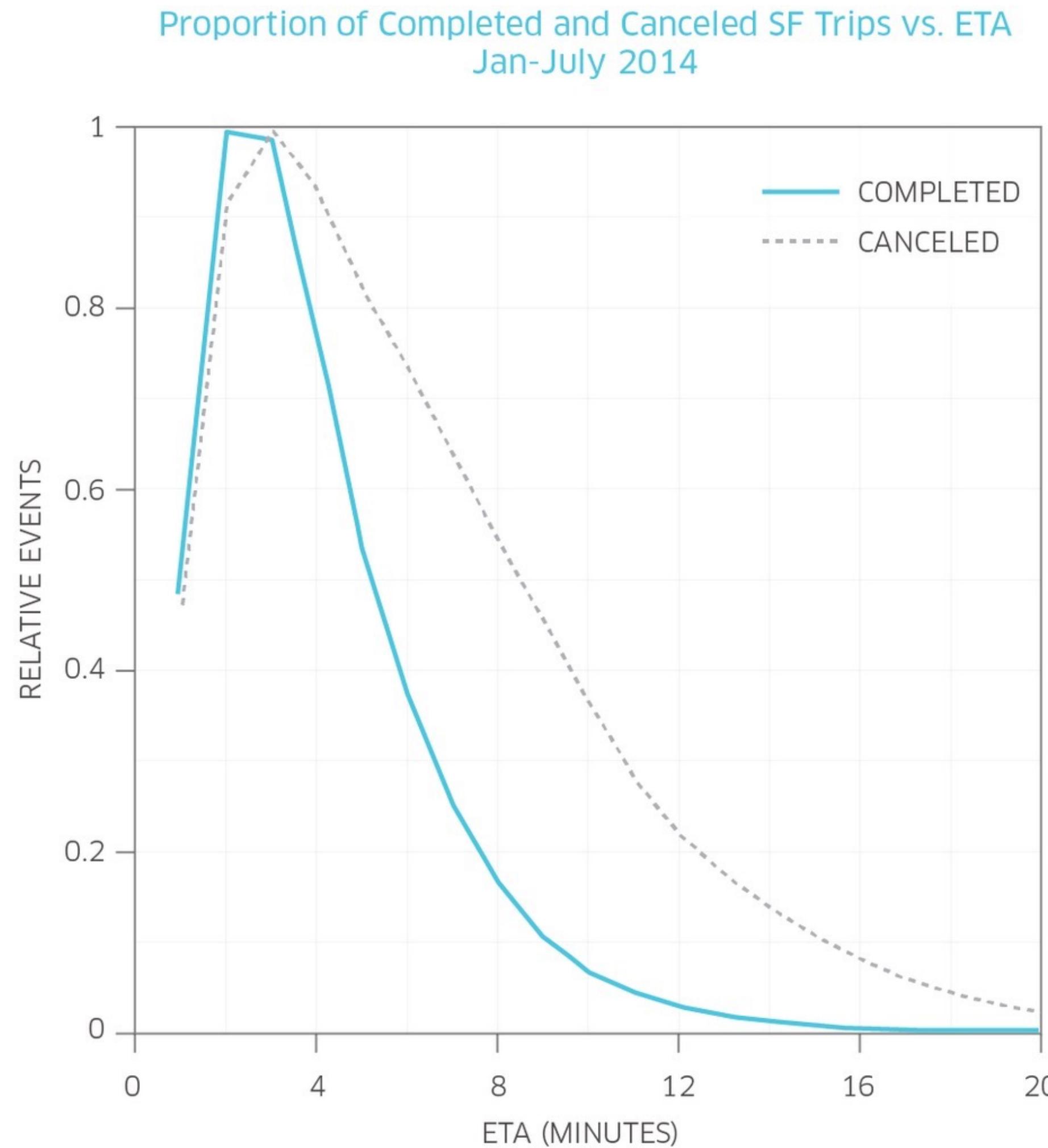


# Spatiotemporal dynamics

- Looking at dynamics over time allows you to correlate neighborhoods within and between cities.
- Can identify “types” of neighborhoods: those with peak weekend and late night demands are more “party”-like whereas M-F peaks are more “business” regions.



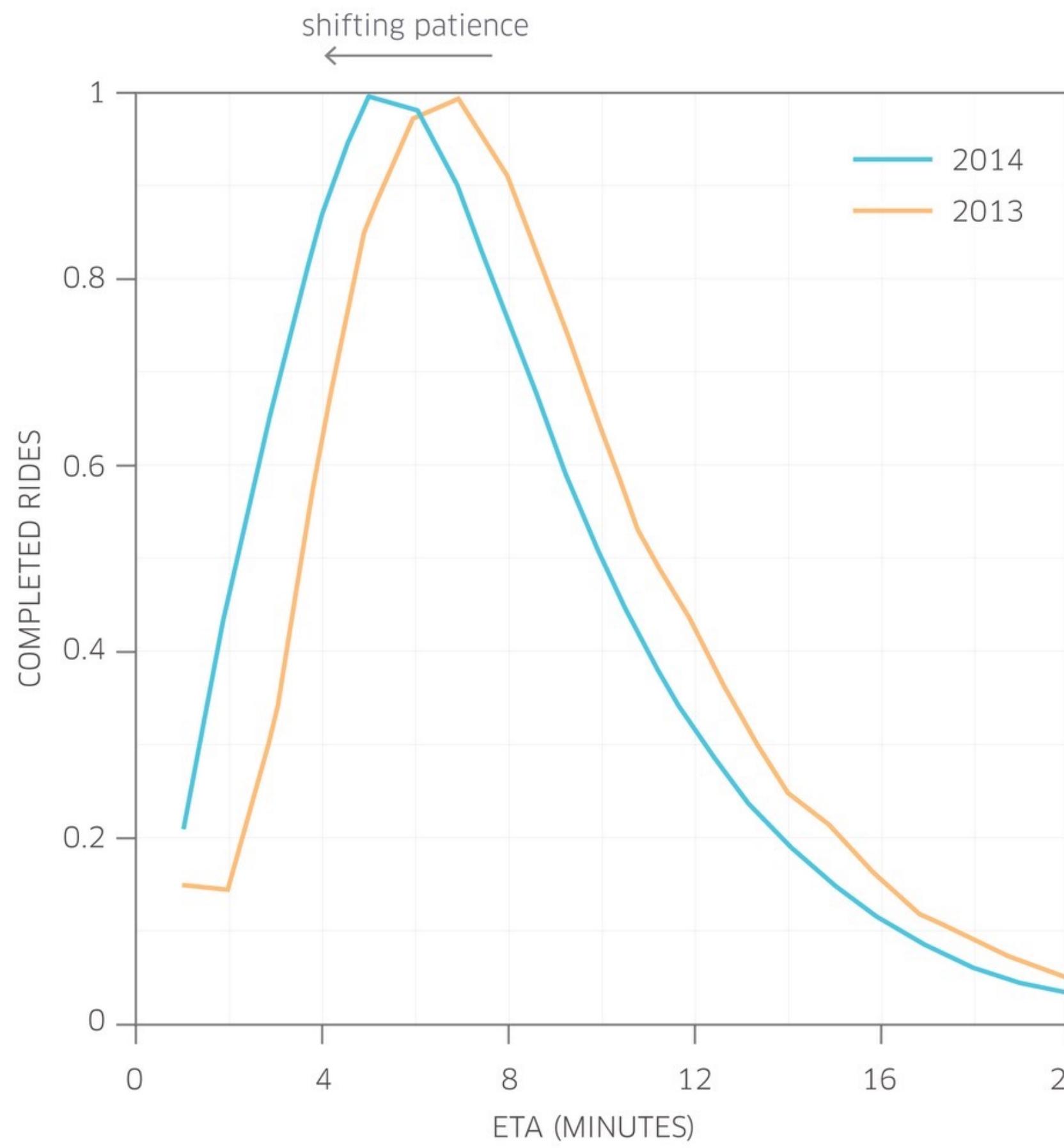
# Rider patience



- Plot histograms of ride completion rates as a function of the ETA of the nearest available car.
- Clear peaks and decays.
- Decay rate reveals how “patient” riders are in each country, city, or neighborhood: how long they’re willing to wait for a car.

# Rider patience

Willingness to Wait in a City, 2013 vs. 2014



- The entire curve moves backward with each year Uber is in a city.
- From this we can infer that people are getting more accustomed to the service and expect more of it over time.

**With parameterization, we can then  
run large scale analyses that were  
not possible without it.**

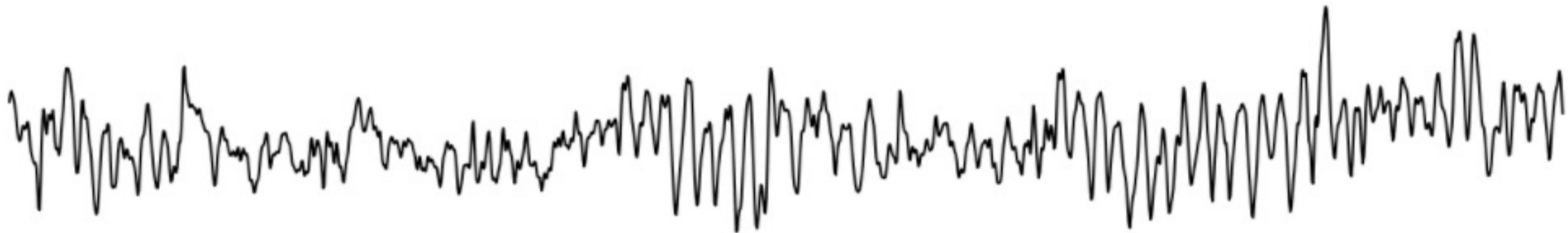
# **Neural oscillations**

**Oscillations are correlated with everything**

**Tens-of-thousands of oscillation papers**

**How do we measure oscillations?**

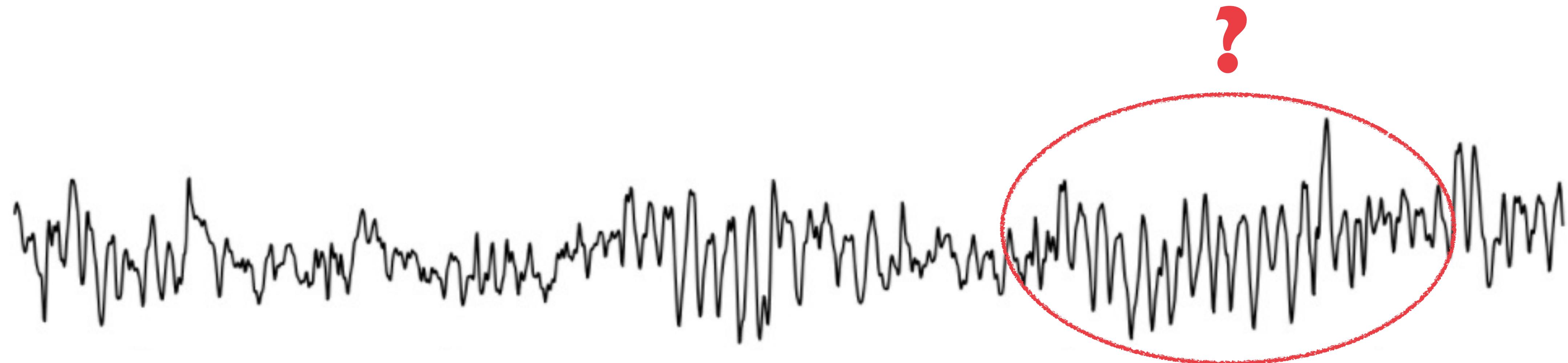
# **what's an oscillation?**



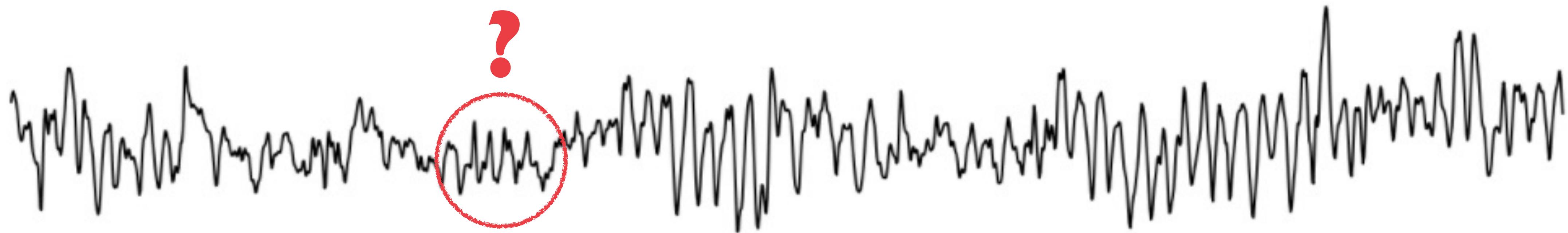
# what's an oscillation?



# what's an oscillation?

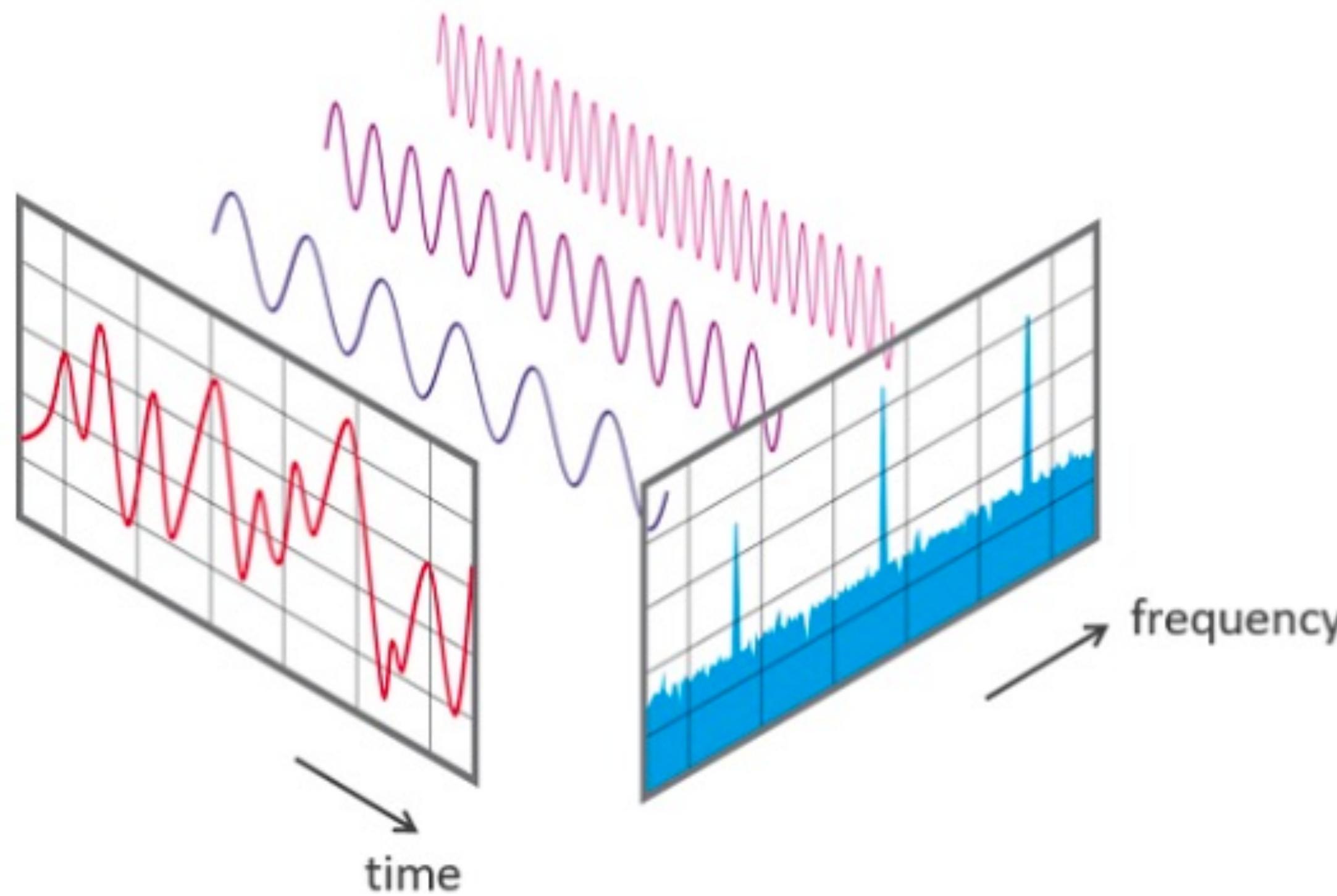


# what's an oscillation?



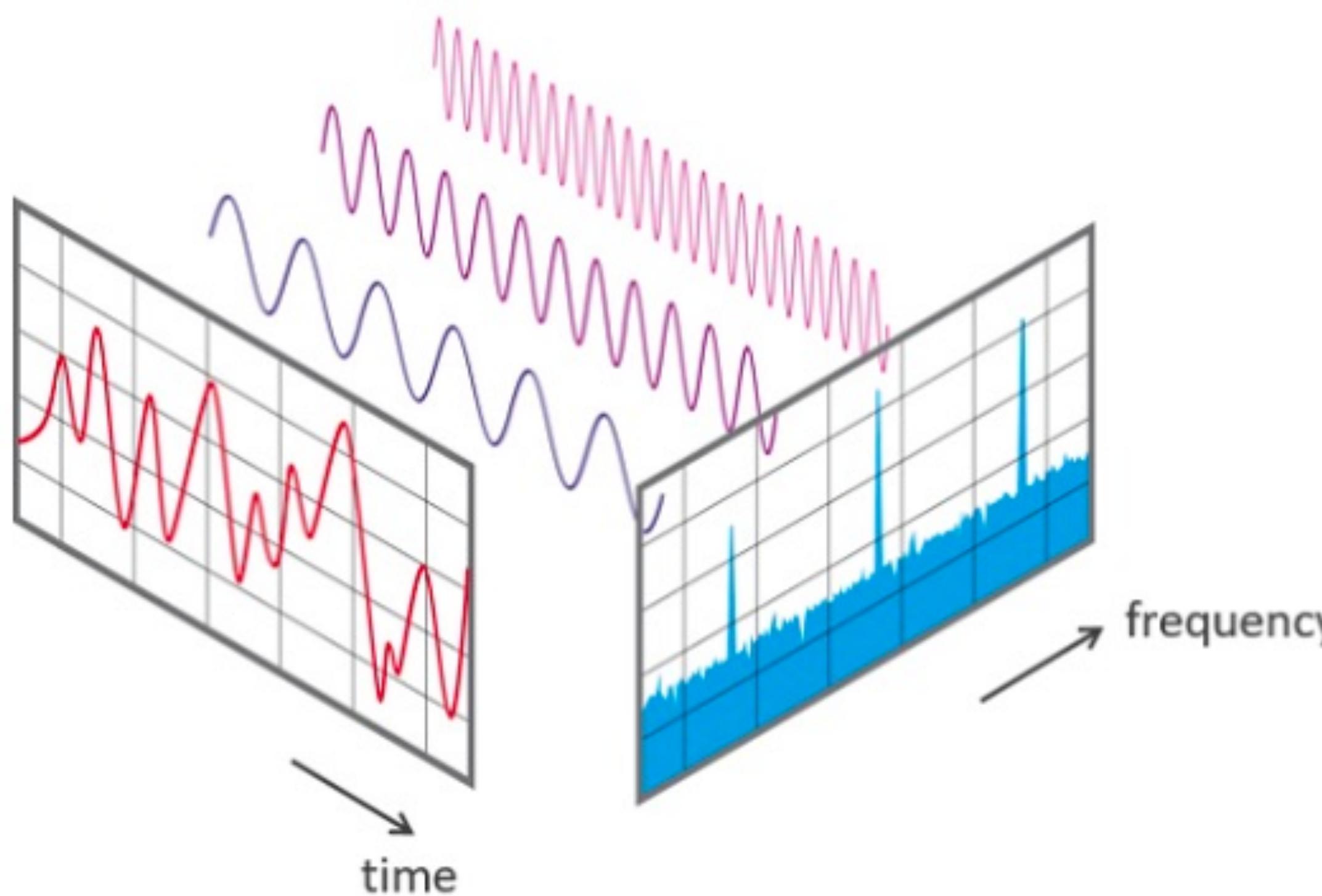
# Detecting oscillations

FFT

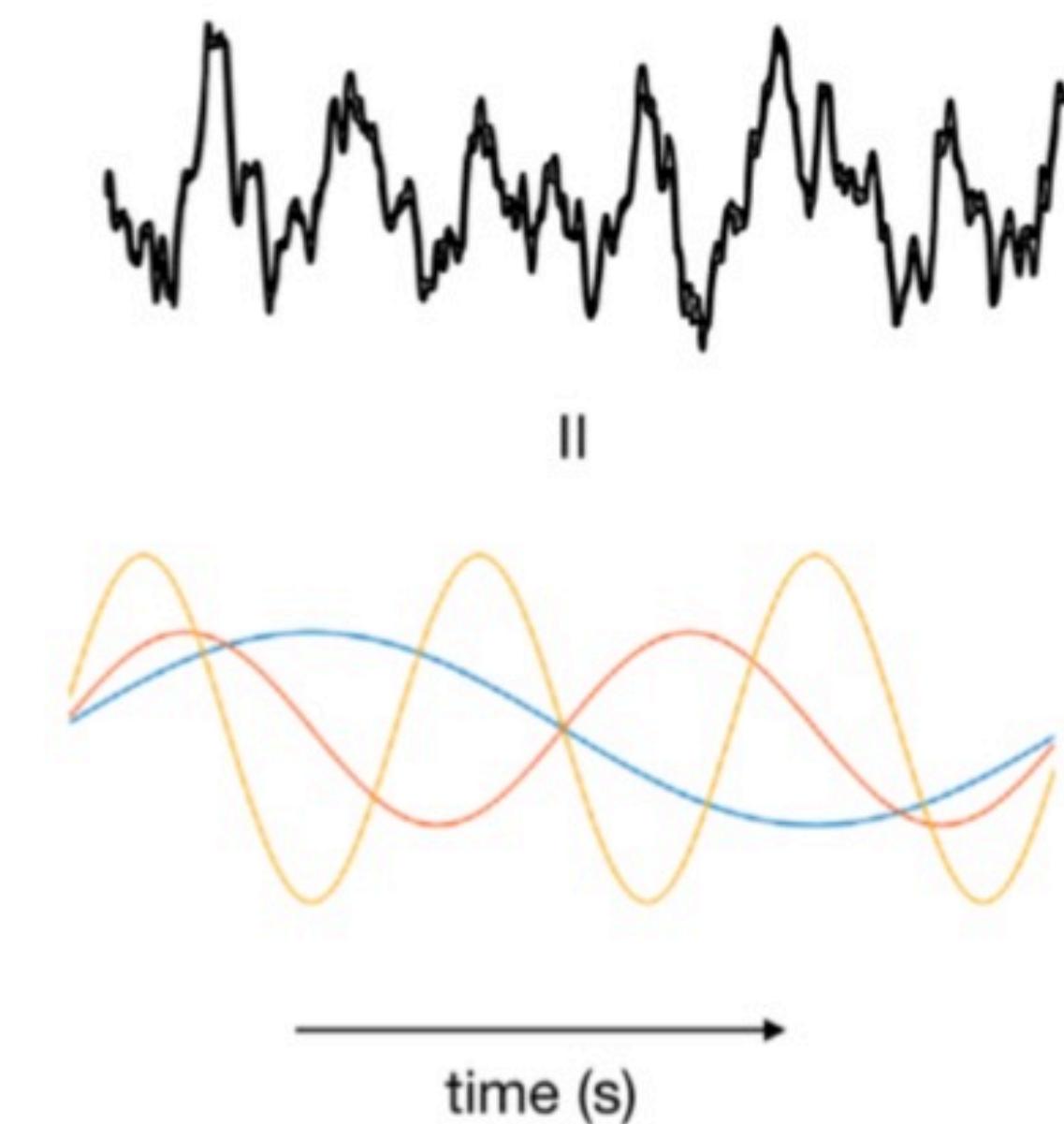


# Detecting oscillations

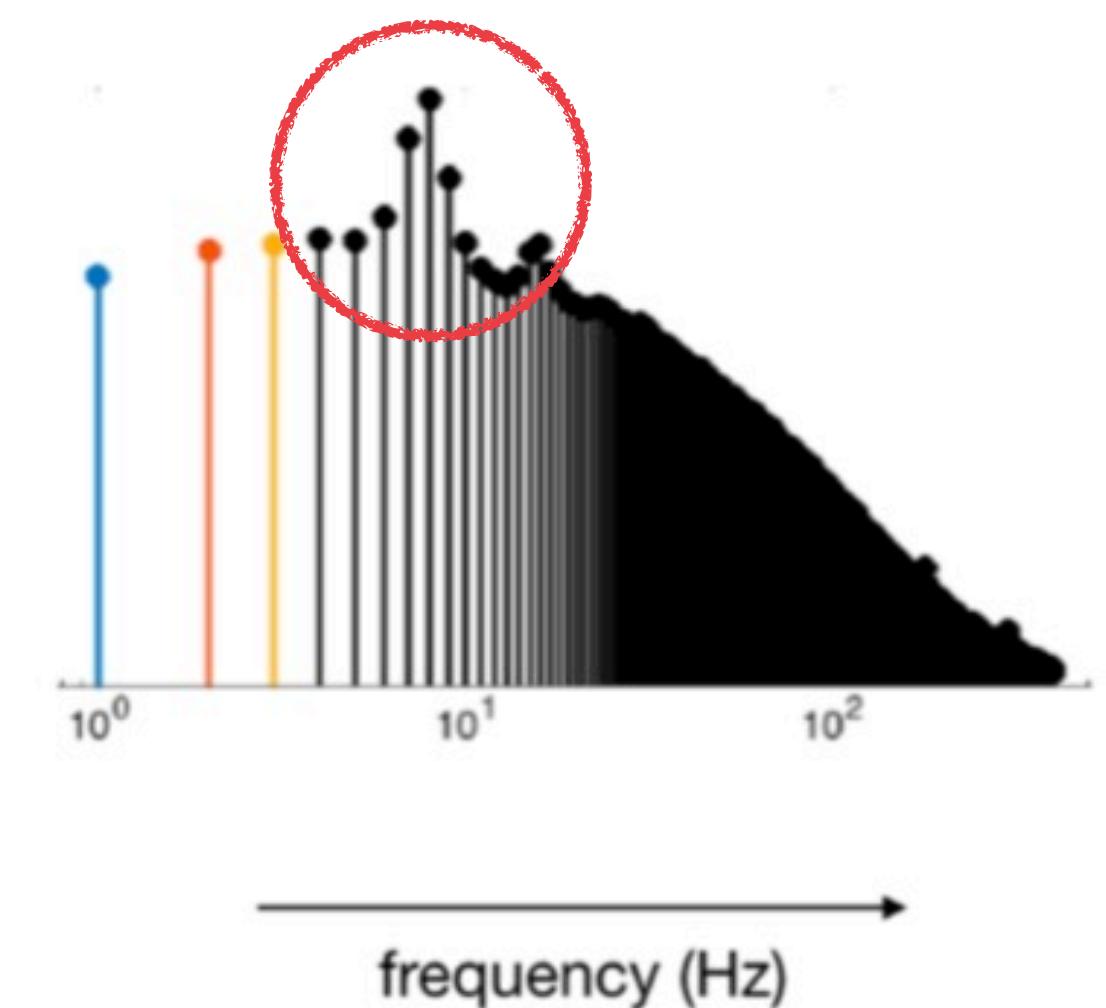
FFT



Time Domain



Frequency Domain



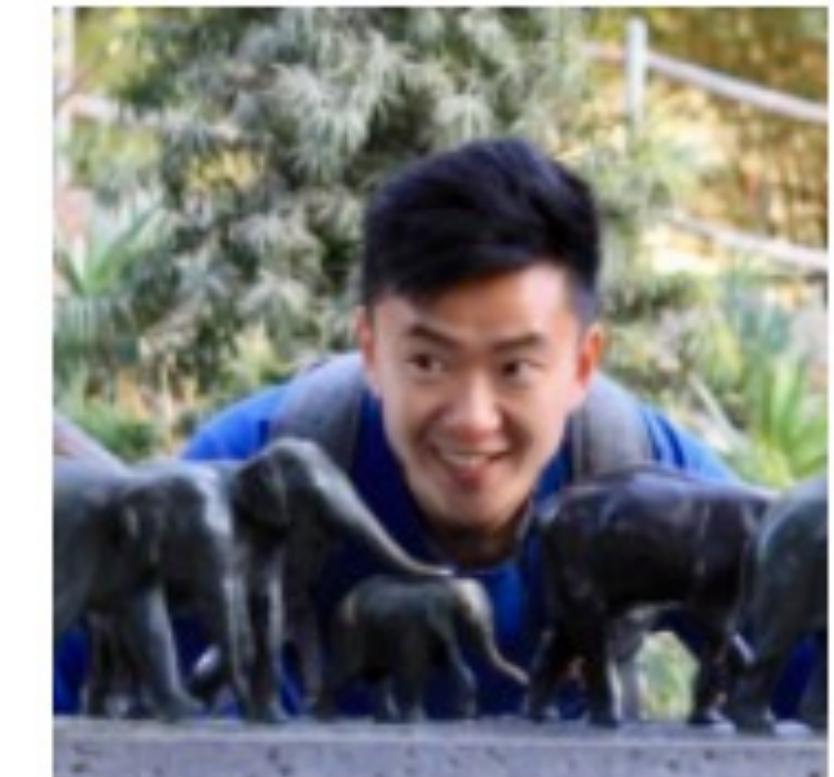
**Where do oscillations come from?**

# Cortical organoids

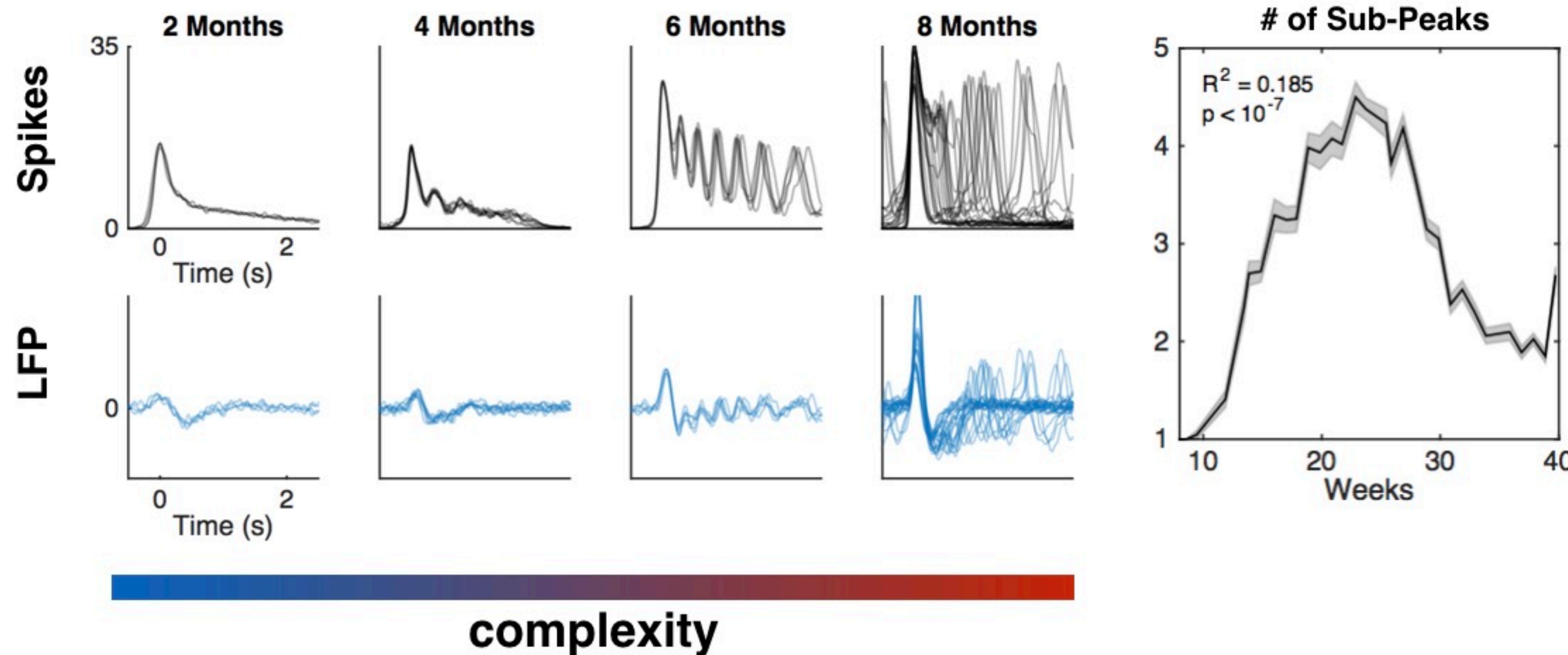


~ 4mm diameter  
~ 100,000 neurons

Richard Gao



# Origin of oscillations



# **Parameterization in my lab**

# Python packages

pip install:

- neurodsp (Cole et al., *J Open Source Softw* 2019)
- fooof (Haller et al., *bioRxiv* 2018)
- bycycle (Cole & Voytek, *J Neurophysiol* 2019)

Thomas Donoghue, PhD



Ryan Hammonds



Scott Cole, PhD



Natalie Schawronkow, PhD



# Parameterize our spectra!

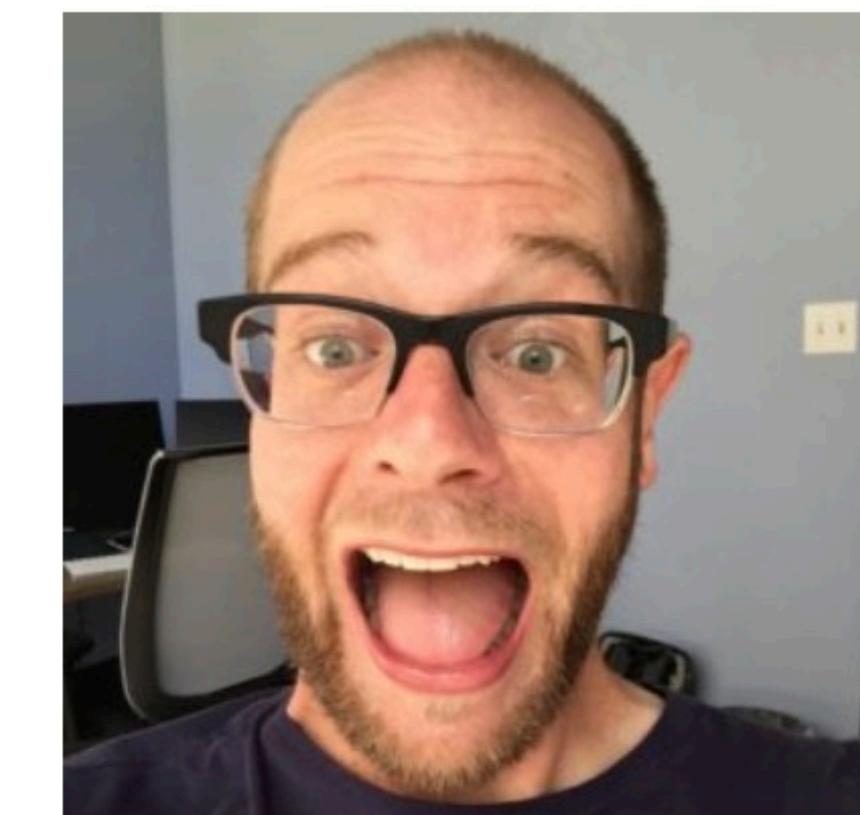
Tom Donoghue, PhD



Matar Haller, PhD & Avgusta Shestyuk, PhD



Erik Peterson, PhD



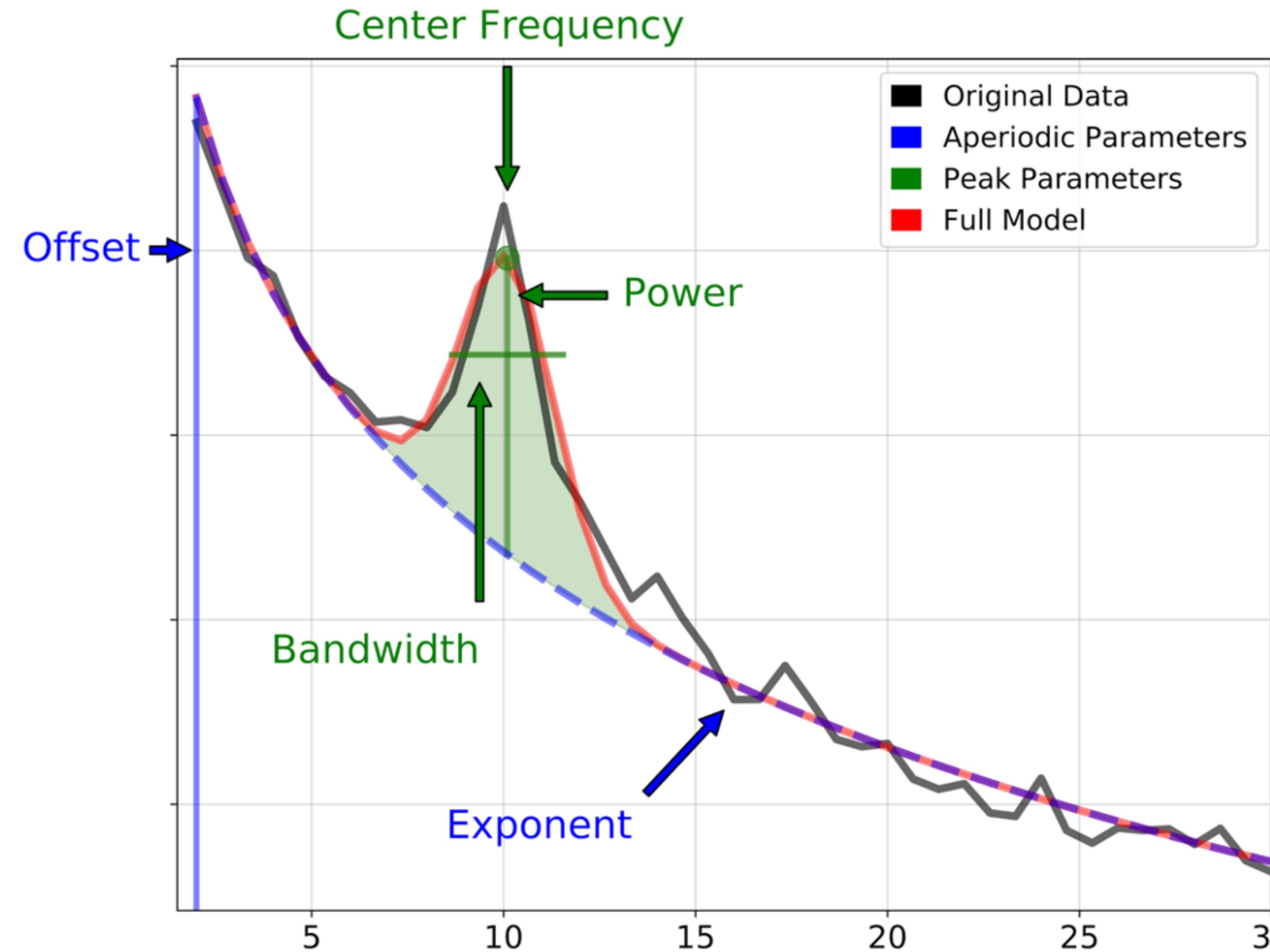
Luyanda Mdanda



Julio Dominguez

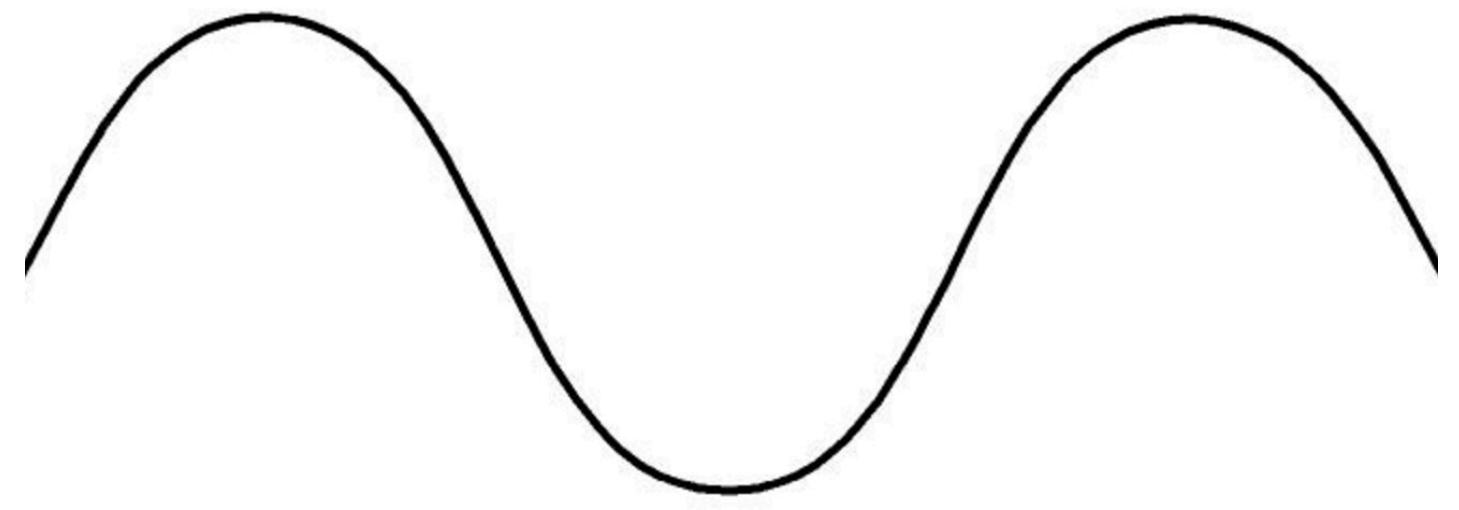


# Parameterizing neural power spectra



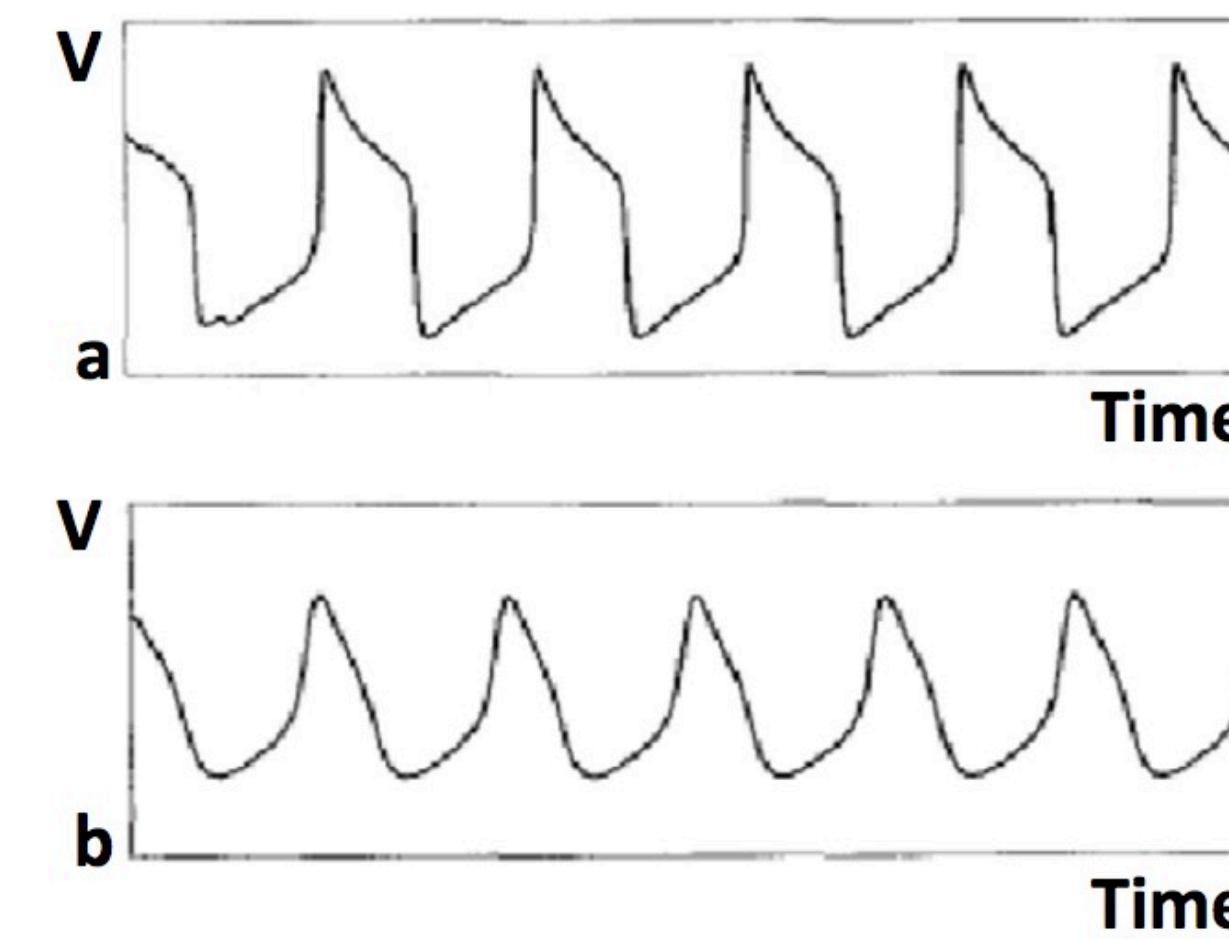
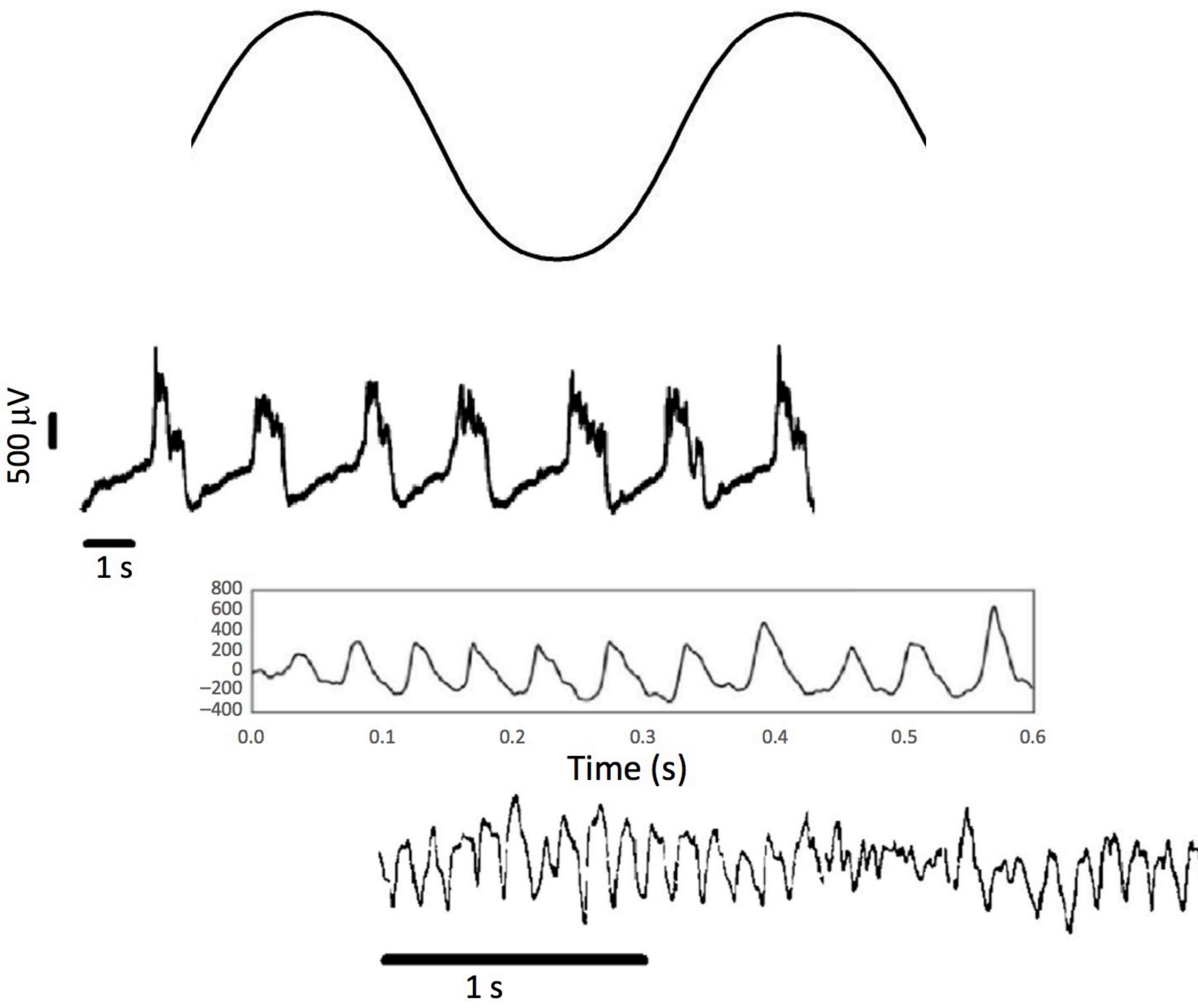
# Parameterization matters

# Meet $\sin$

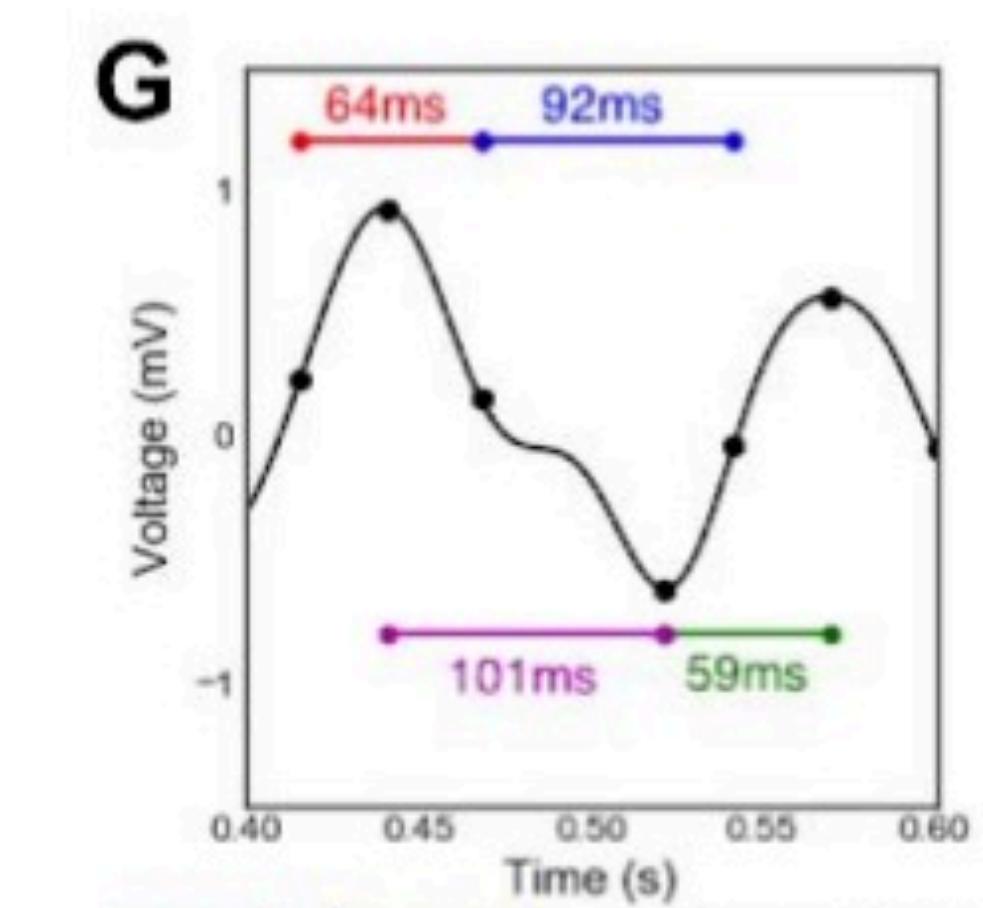
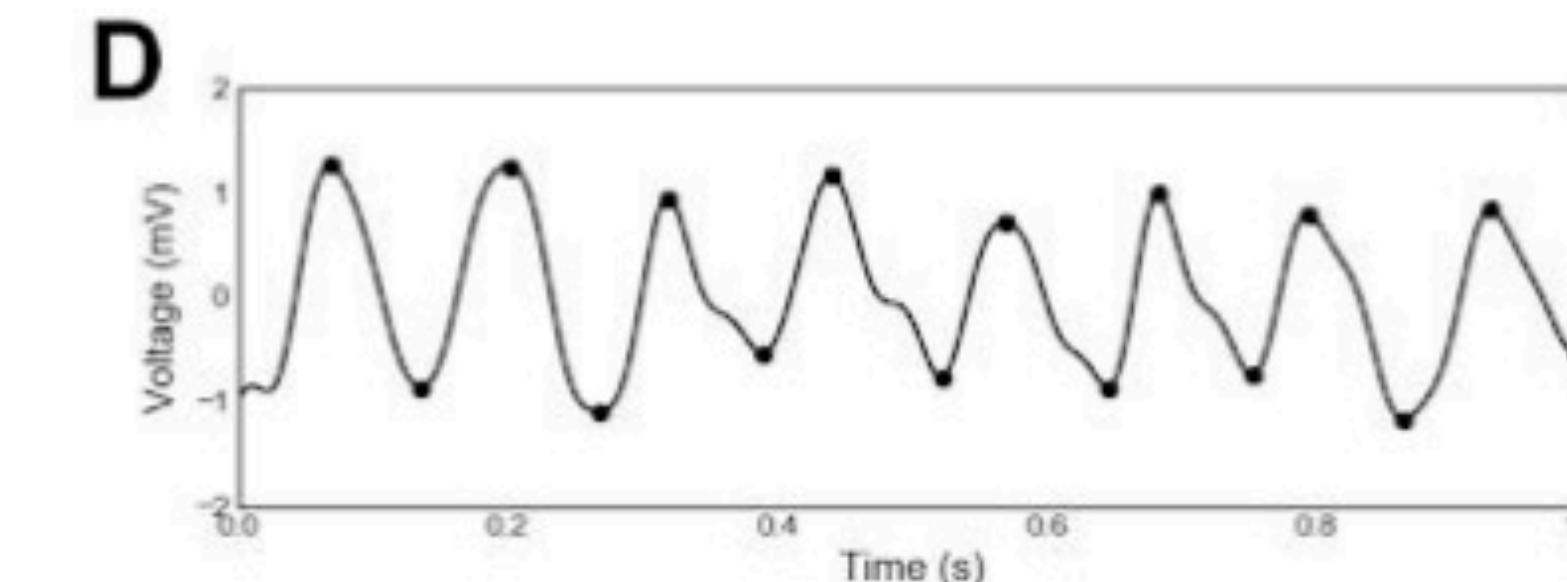
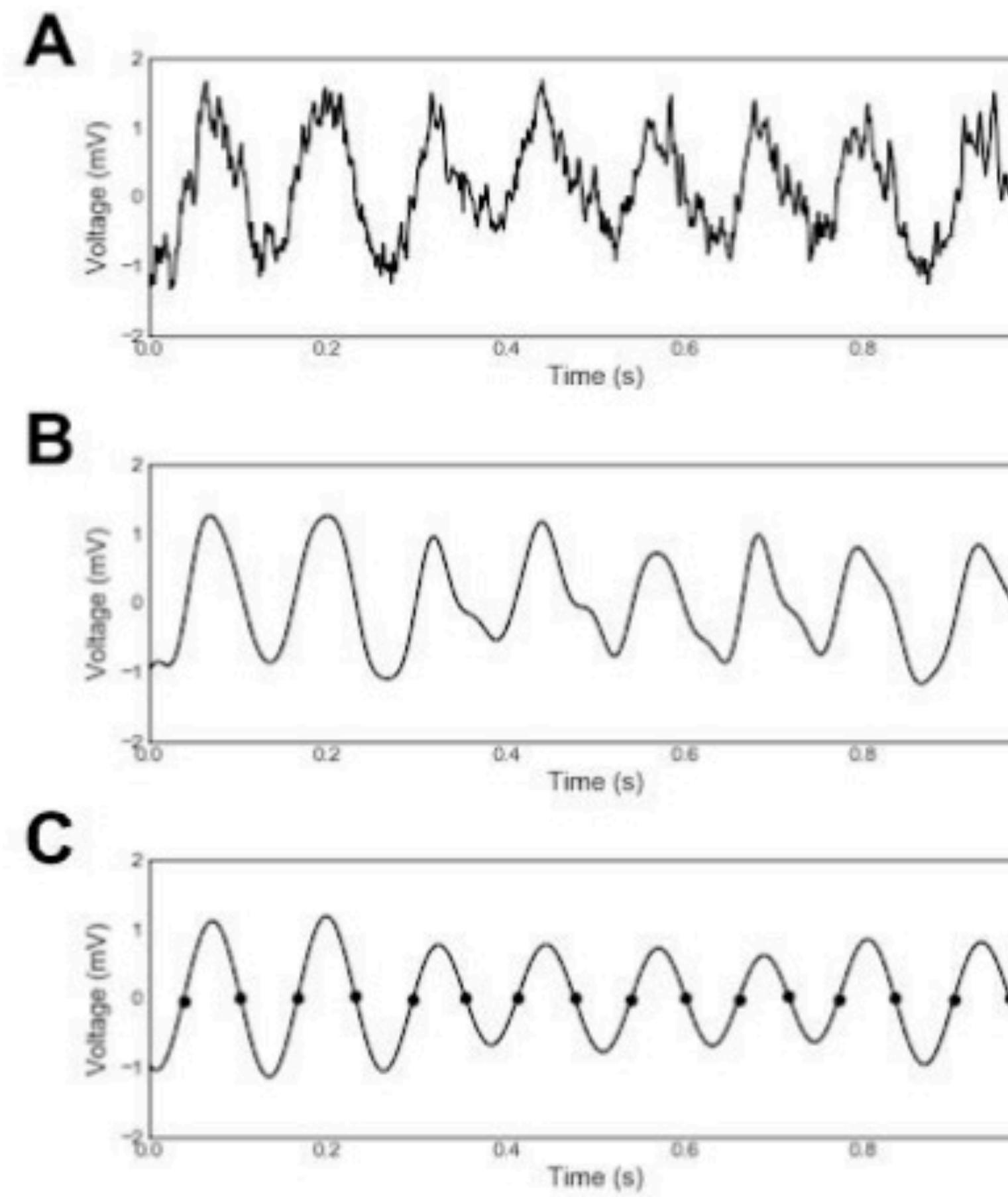


sinusoid

# Neural oscillations are *not* sinusoidal

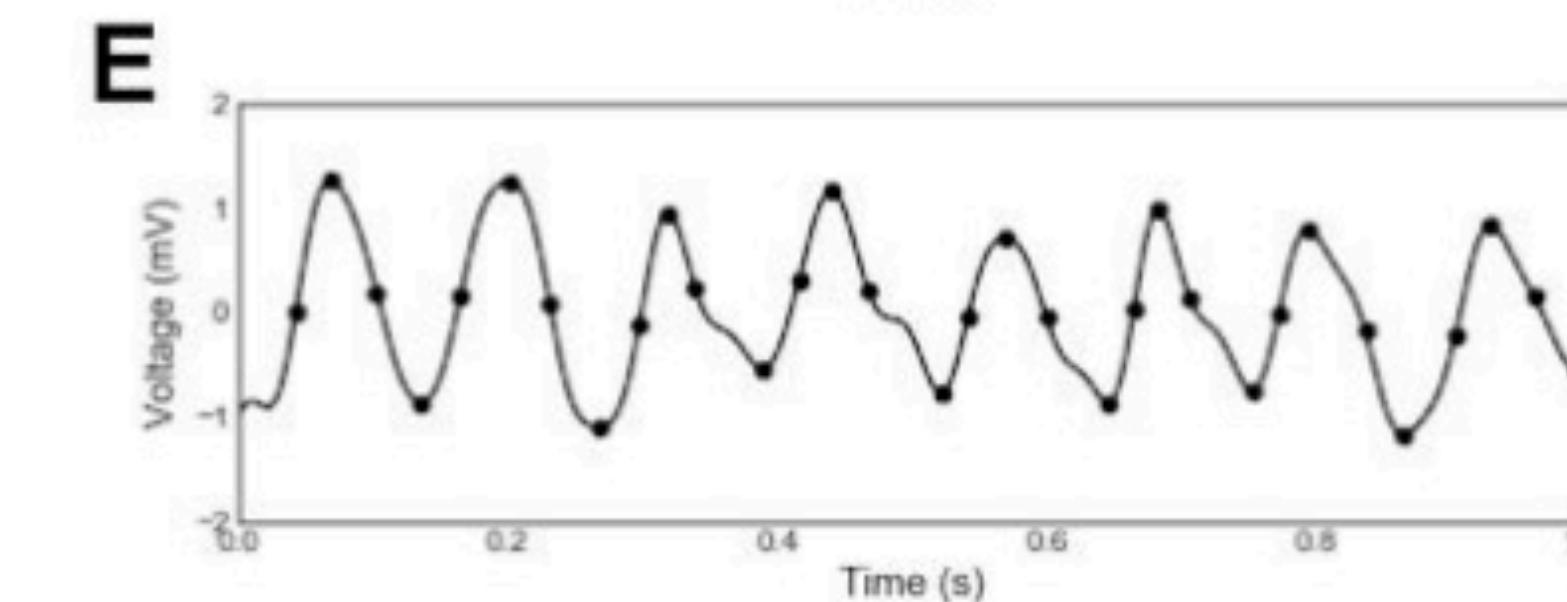
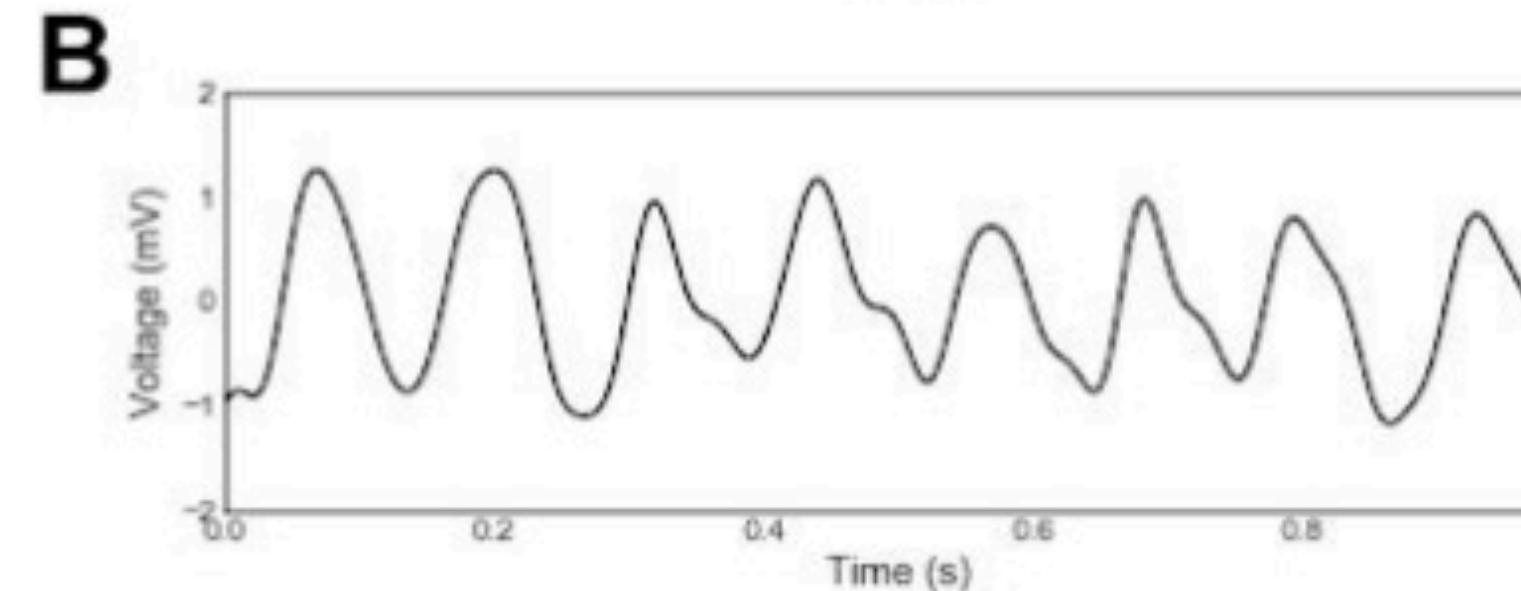


# Cycle-by-cycle waveform analyses



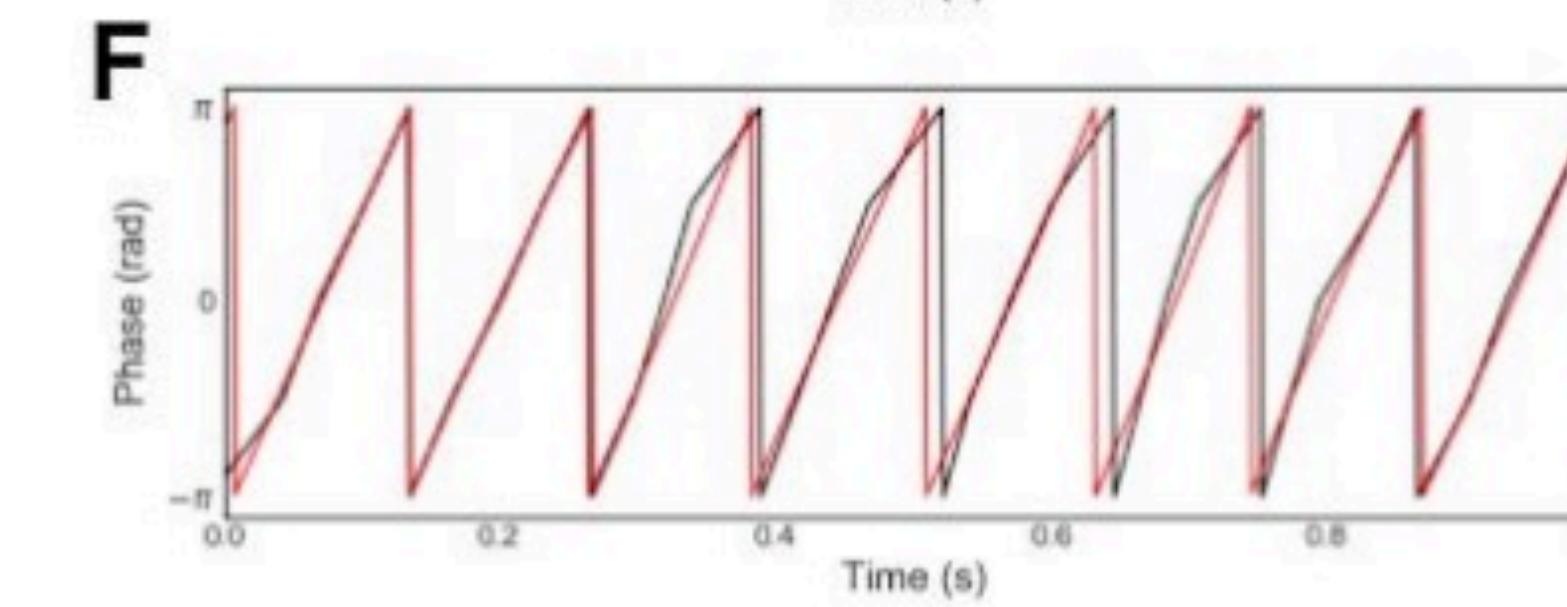
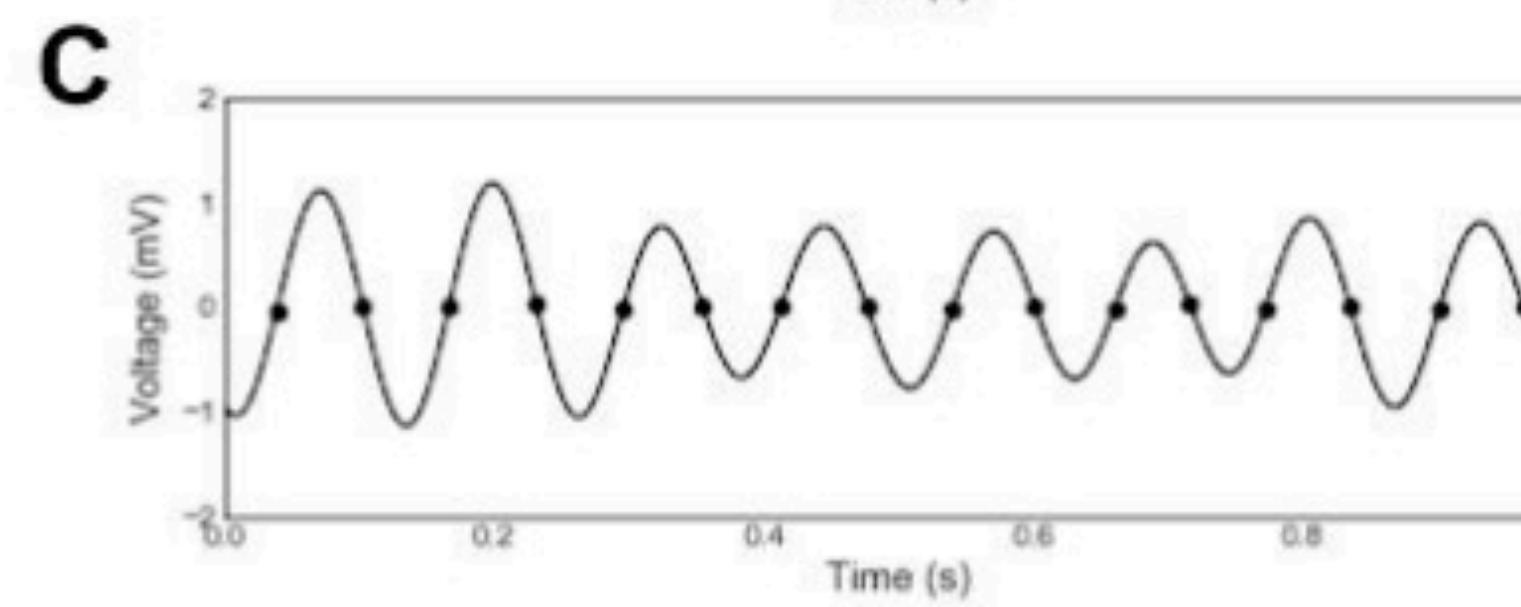
peak-trough symmetry

$$\frac{64\text{ms}}{64\text{ms} + 92\text{ms}} = 0.39$$



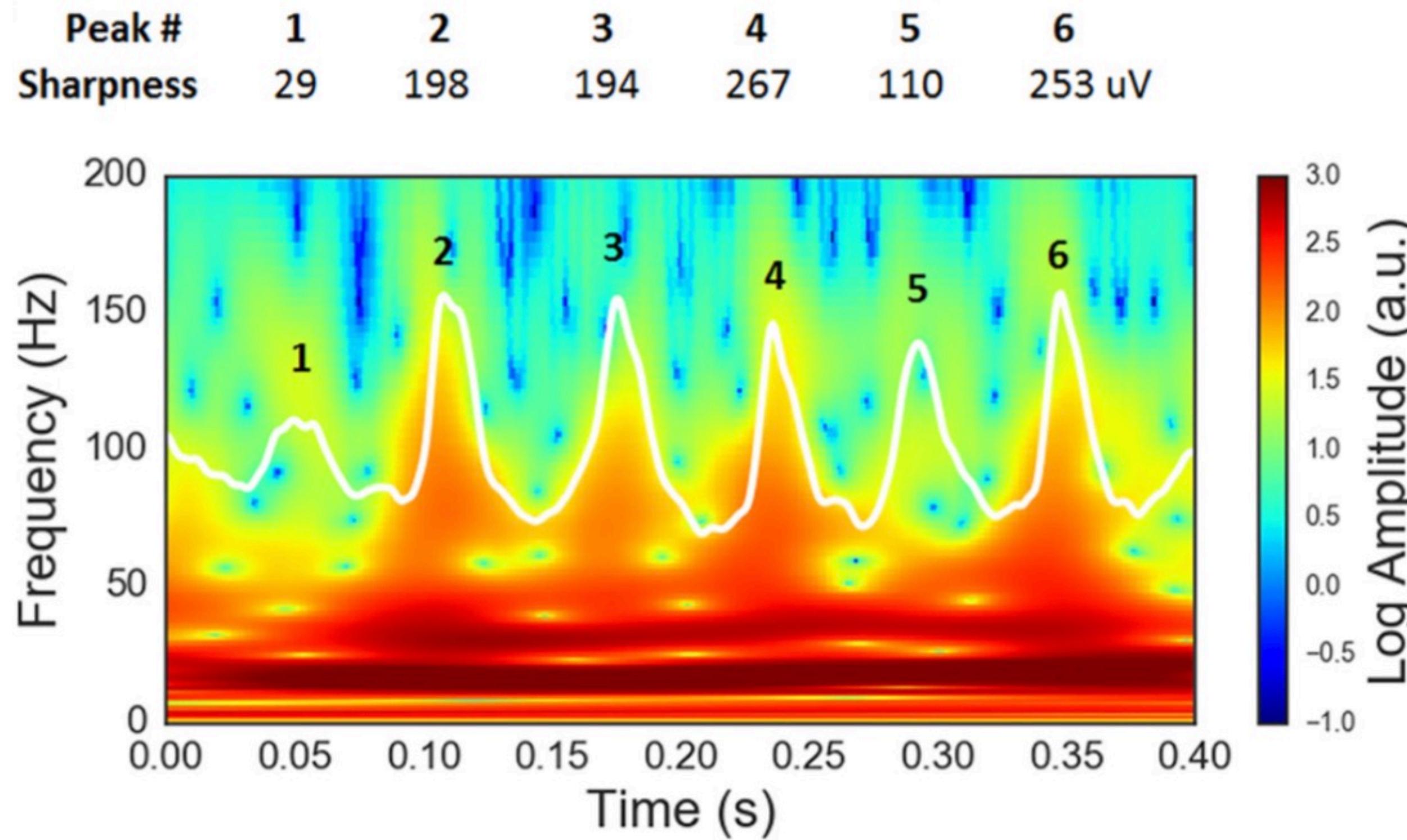
rise-decay symmetry

$$\frac{59\text{ms}}{59\text{ms} + 101\text{ms}} = 0.37$$

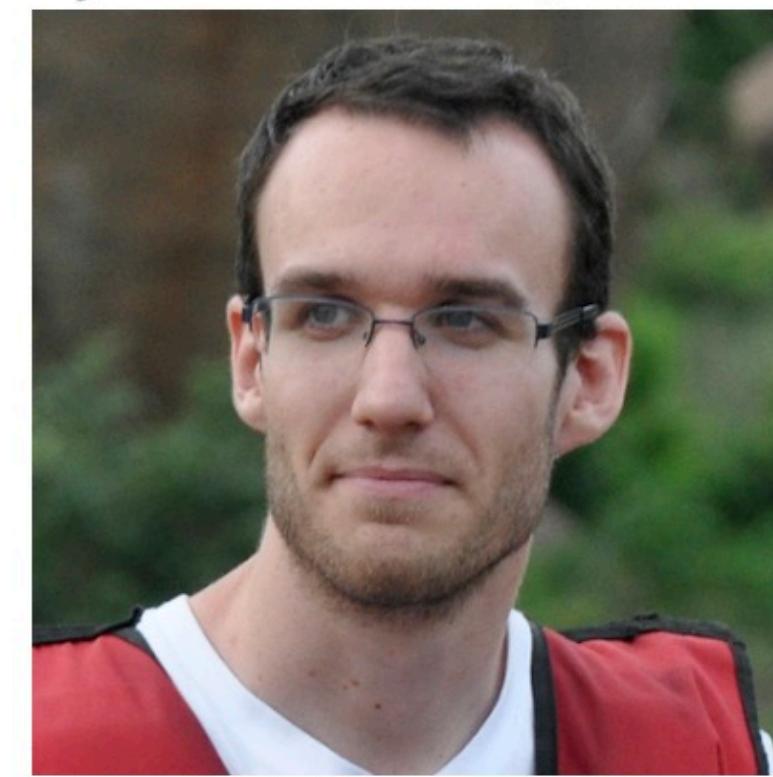


**This matters**

# Oscillations in Parkinson's disease



Scott Cole ([twitter](#), [web](#), [CV](#))  
Formerly: PhD Student  
Currently: Data Scientist, San Francisco



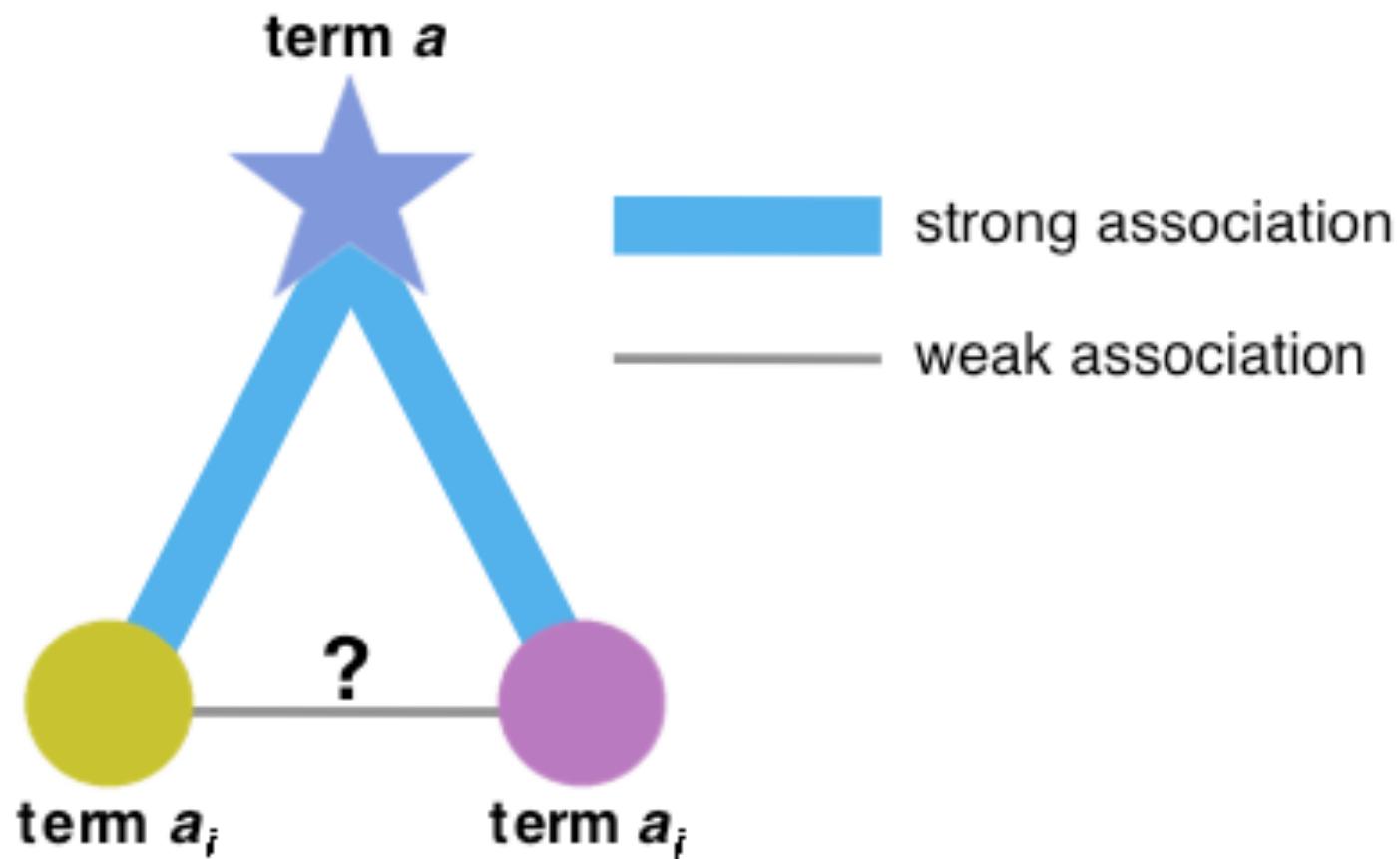
Postdoctoral  
Researcher  
Natalie Schawronkow



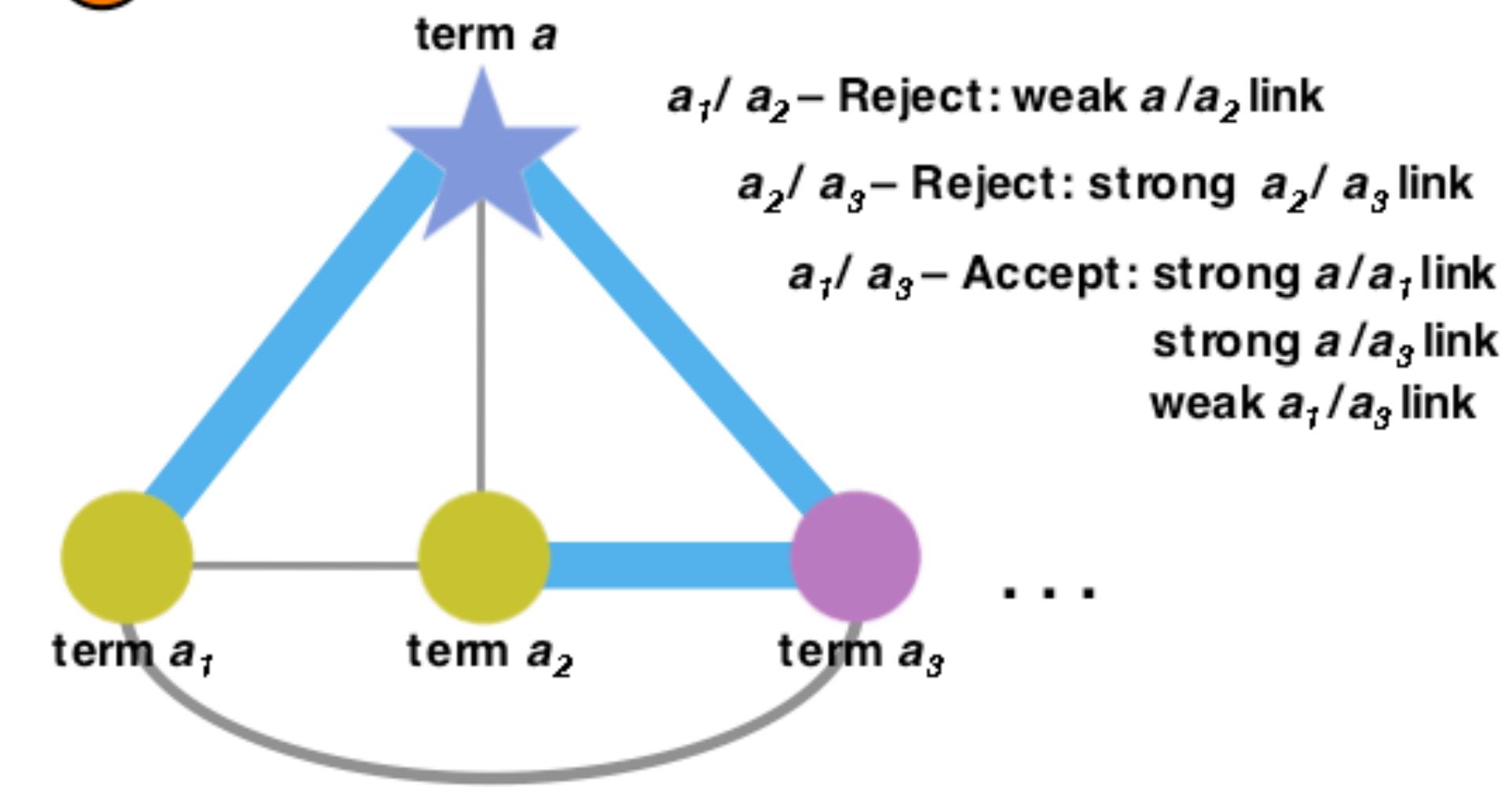
Let's step back for a second and talk about data-driven approaches to **knowledge discovery**: using data to guide us to new hypotheses and ideas.

Note that data-driven approaches to **knowledge discovery** are analogous to the *human process of hypothesis generation*, but automated.

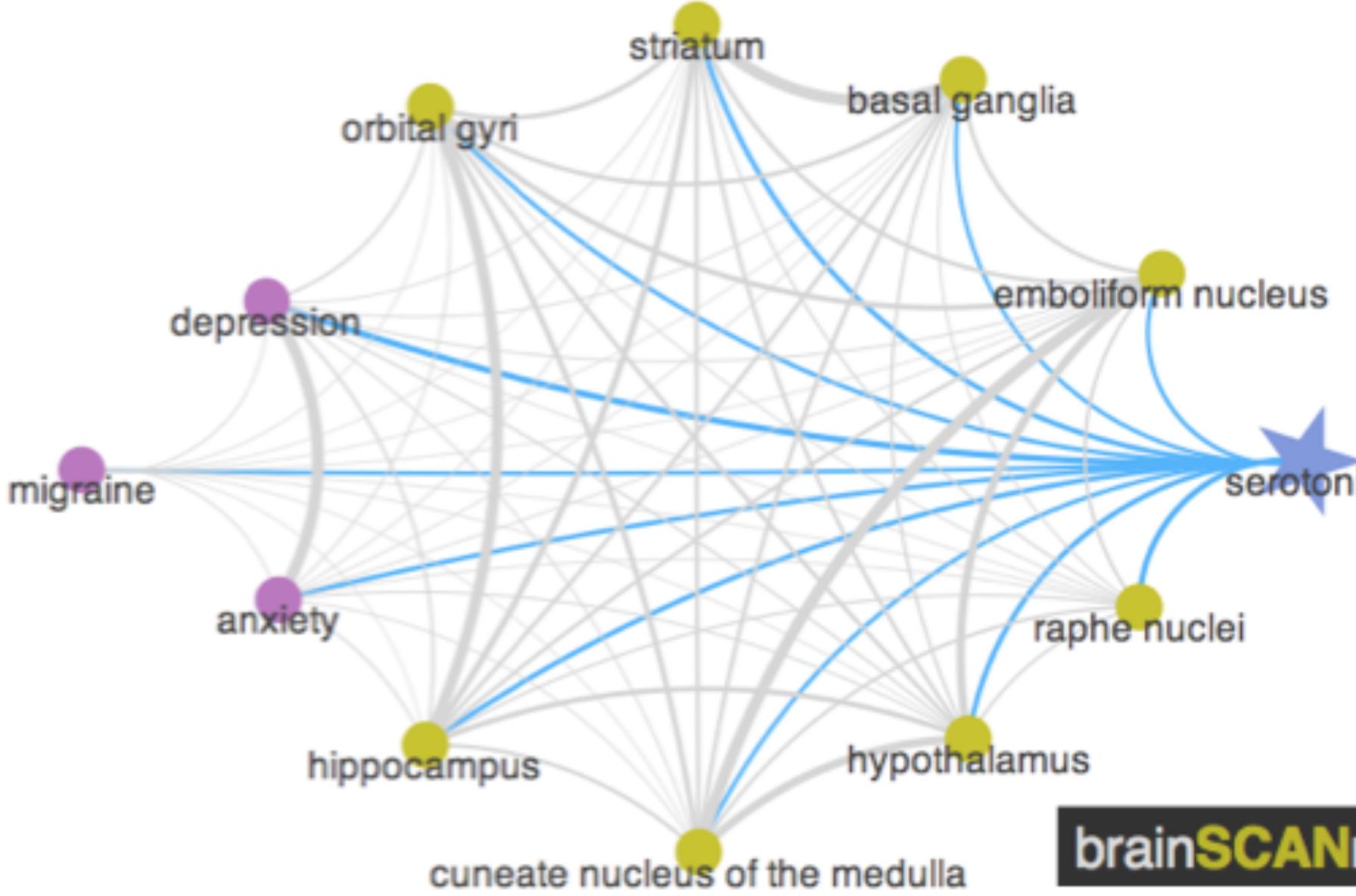
### A Hypothesis-generation model



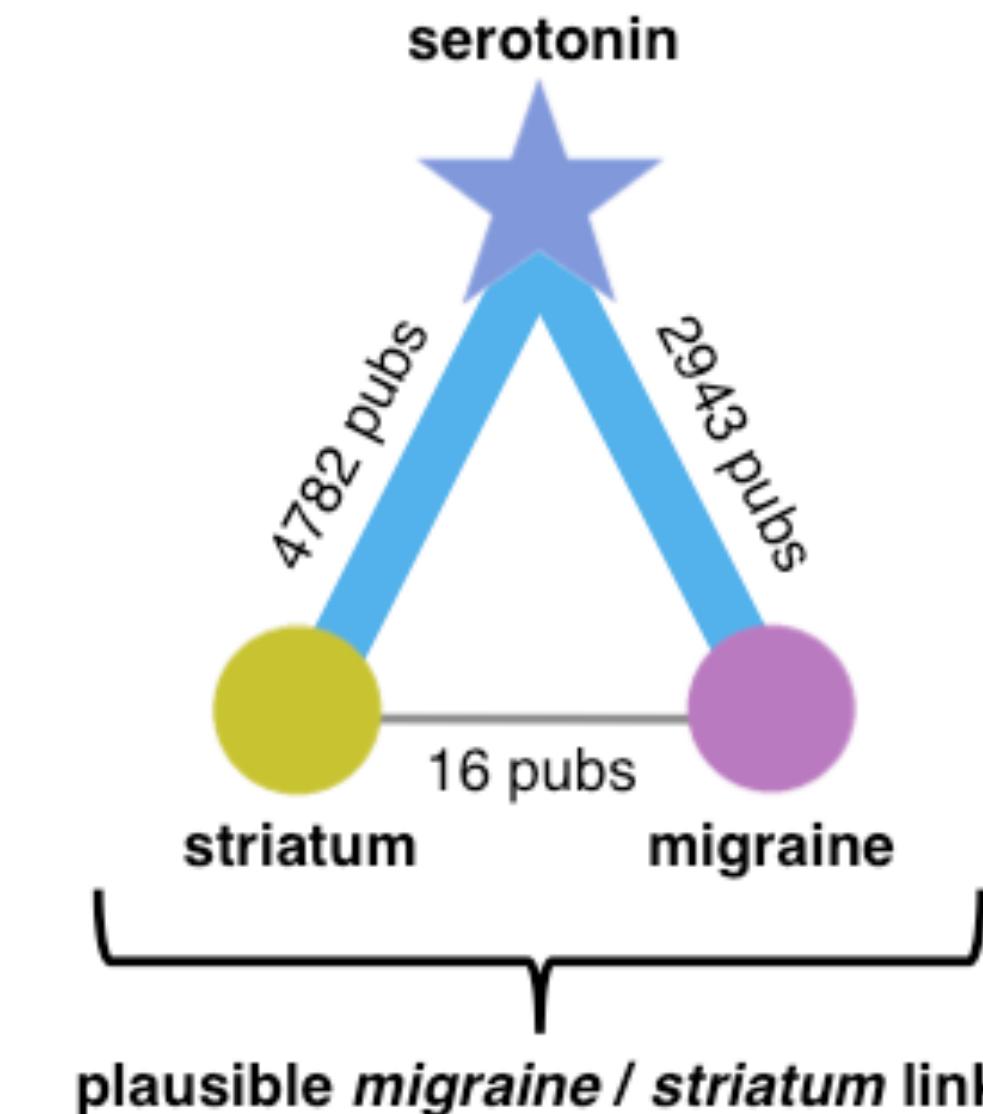
### B Algorithmically generate hypotheses



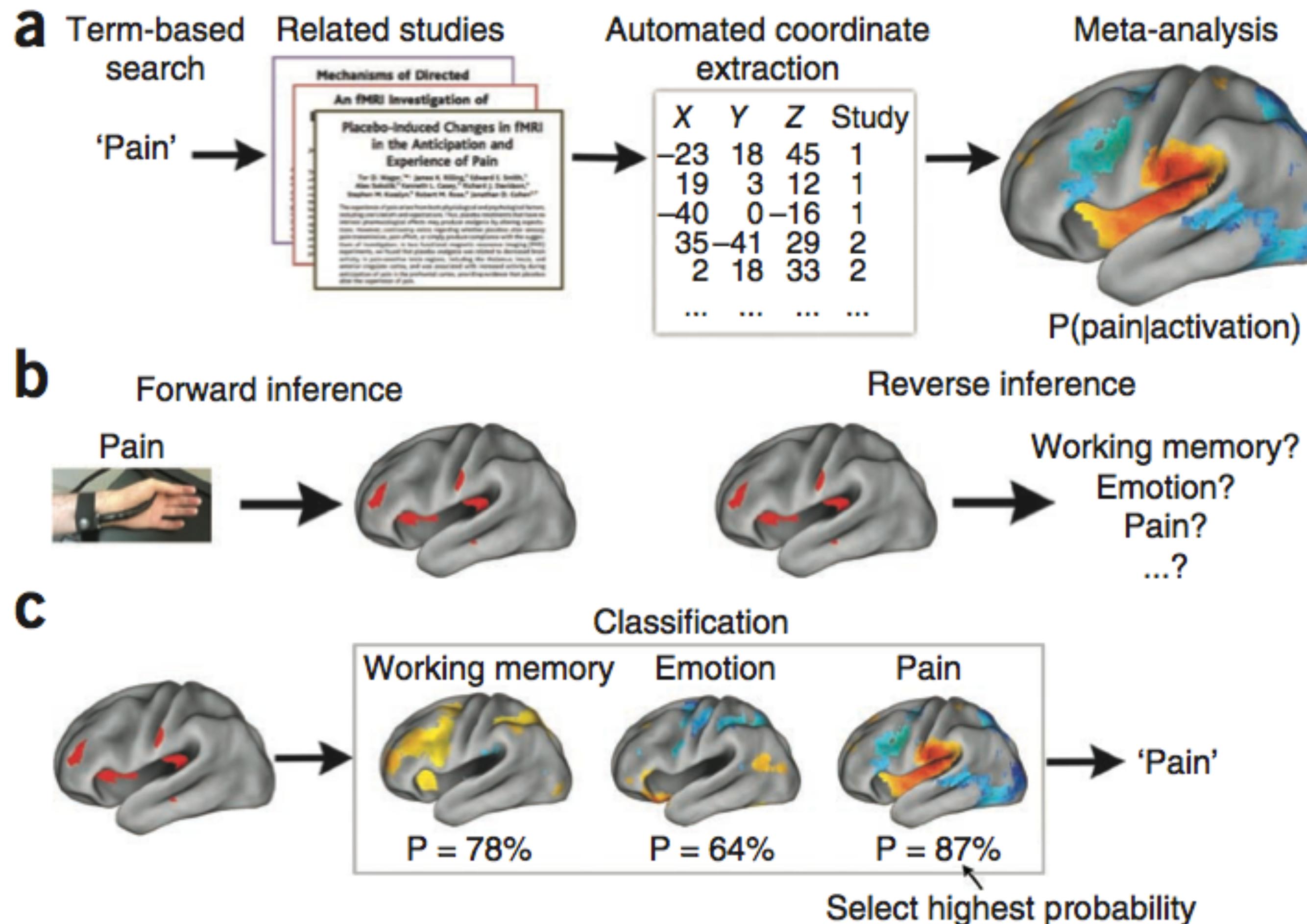
### C Visualize topic network



### D Assess relative topic weights



# NeuroSynth

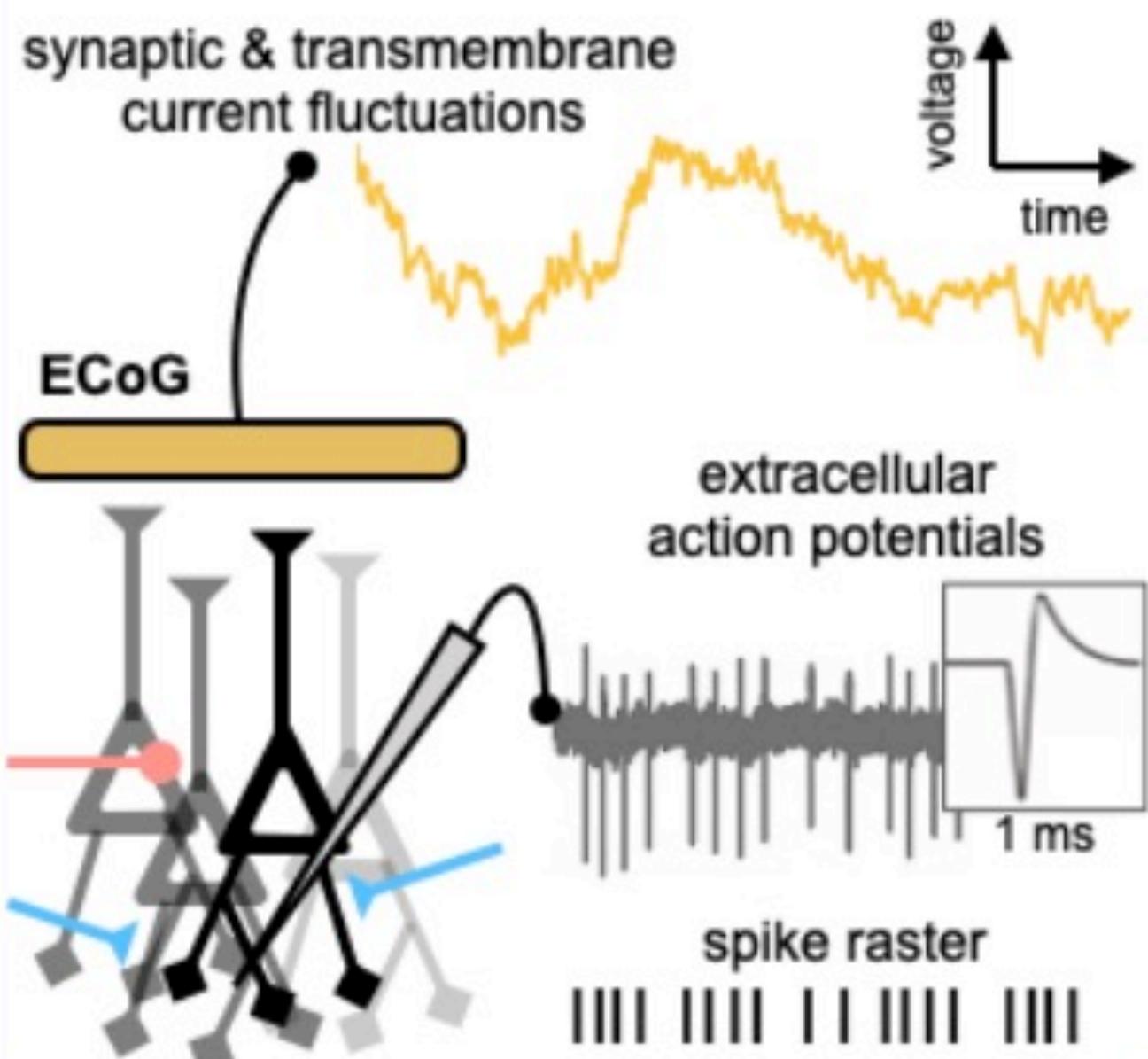


# Integrating tons of neural data

a

neural dynamics bridge structure and function

**cellular & synaptic physiology**  
macaque ECoG & spiking



article roadmap  
Fig. 2  
Fig. 3  
Fig. 4

estimating timescales  
 $\tau$

anatomical hierarchy  
HCP T1w/T2w

neural dynamic timescale  
human iEEG/ECoG

modulation of timescale  
aging & working memory

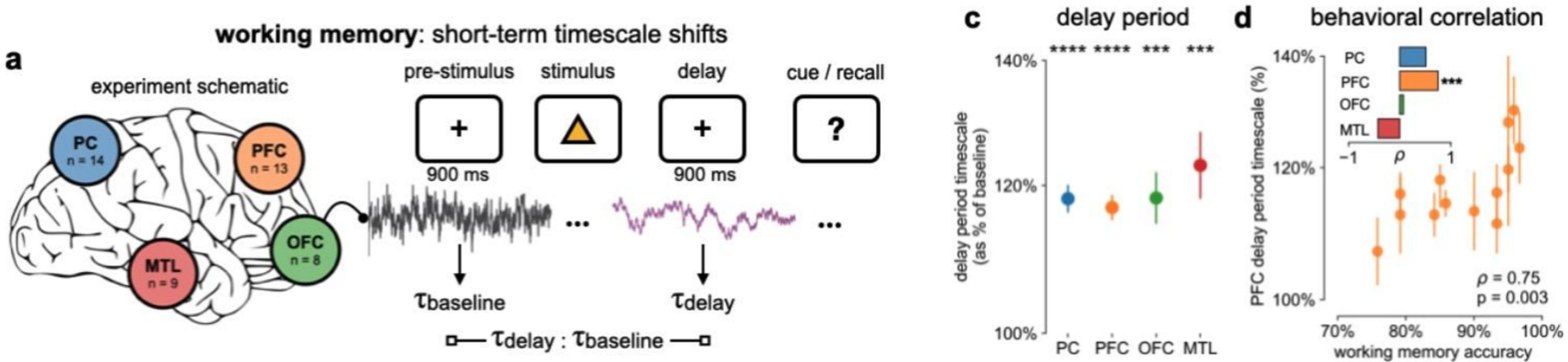
transcriptomic basis  
Allen Brain Atlas

function  
dynamics  
structure

Richard Gao



# Aperiodic timescales in memory and aging



**Data sources:** Frauscher et al., Brain 2018 & Johnson et al., PLOS Biology 2018

Source: Gao, van den Brink, Pfeffer, & Voytek, eLife 2020

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**We can look for connections  
between all of these—cell types,  
gene expression, function,  
oscillations, connectivity—to see  
how they all interrelate.**

**And we can find gaps—missing  
connections where topics *should* be  
related but aren’t.**

We can mine through these  
connections to find potential  
*missing links.*

**That is, we can use the data  
themselves to generate new  
hypotheses *for us*.**

# Feature mapping

## voxel-level information

### **architecture**

- cortical thickness
- white matter connectivity
- myelination
- neuronal density

### **cellular**

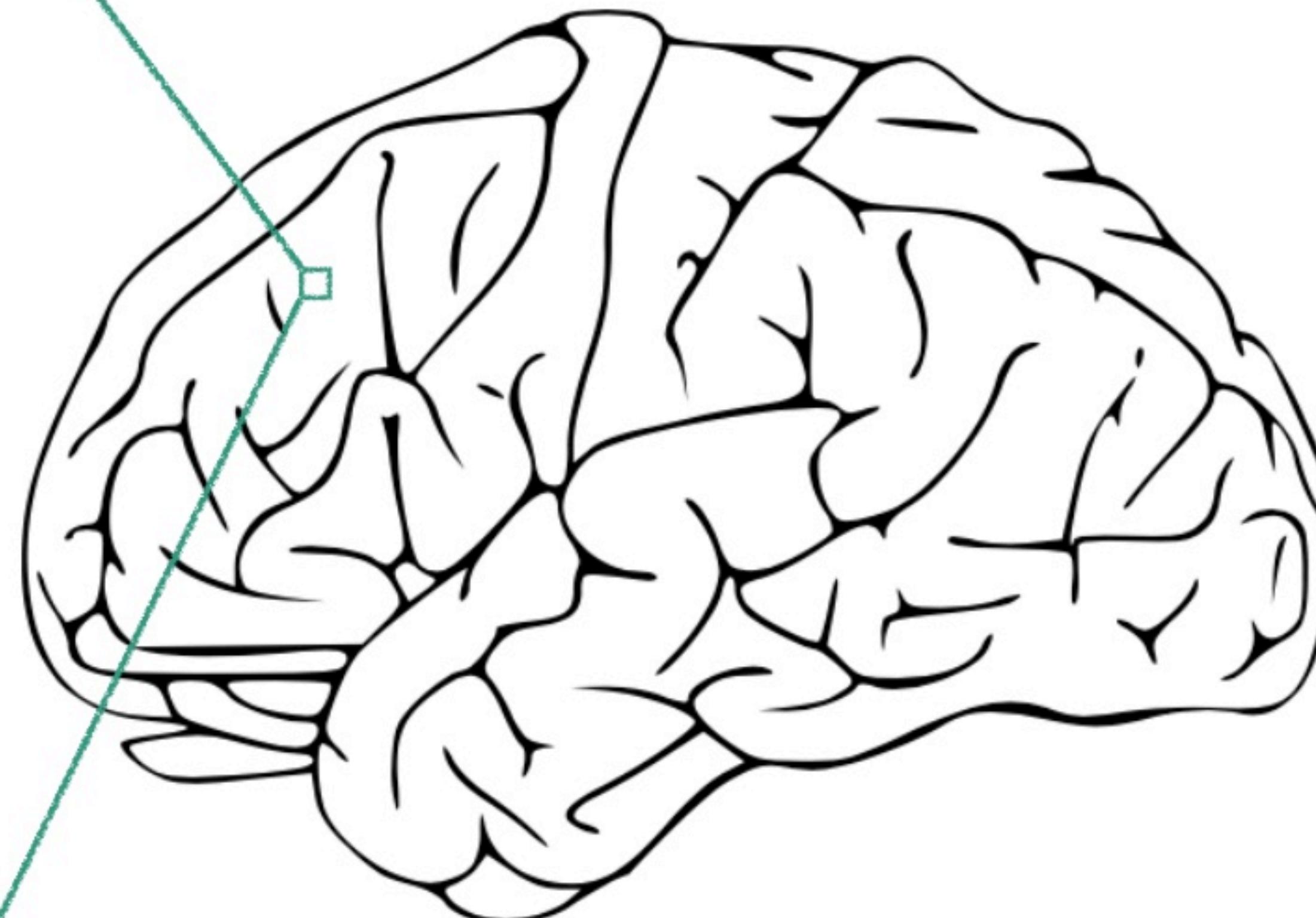
- cell type and morphology
- gene expression
- receptors
- neurotransmitters / modulators

### **dynamics**

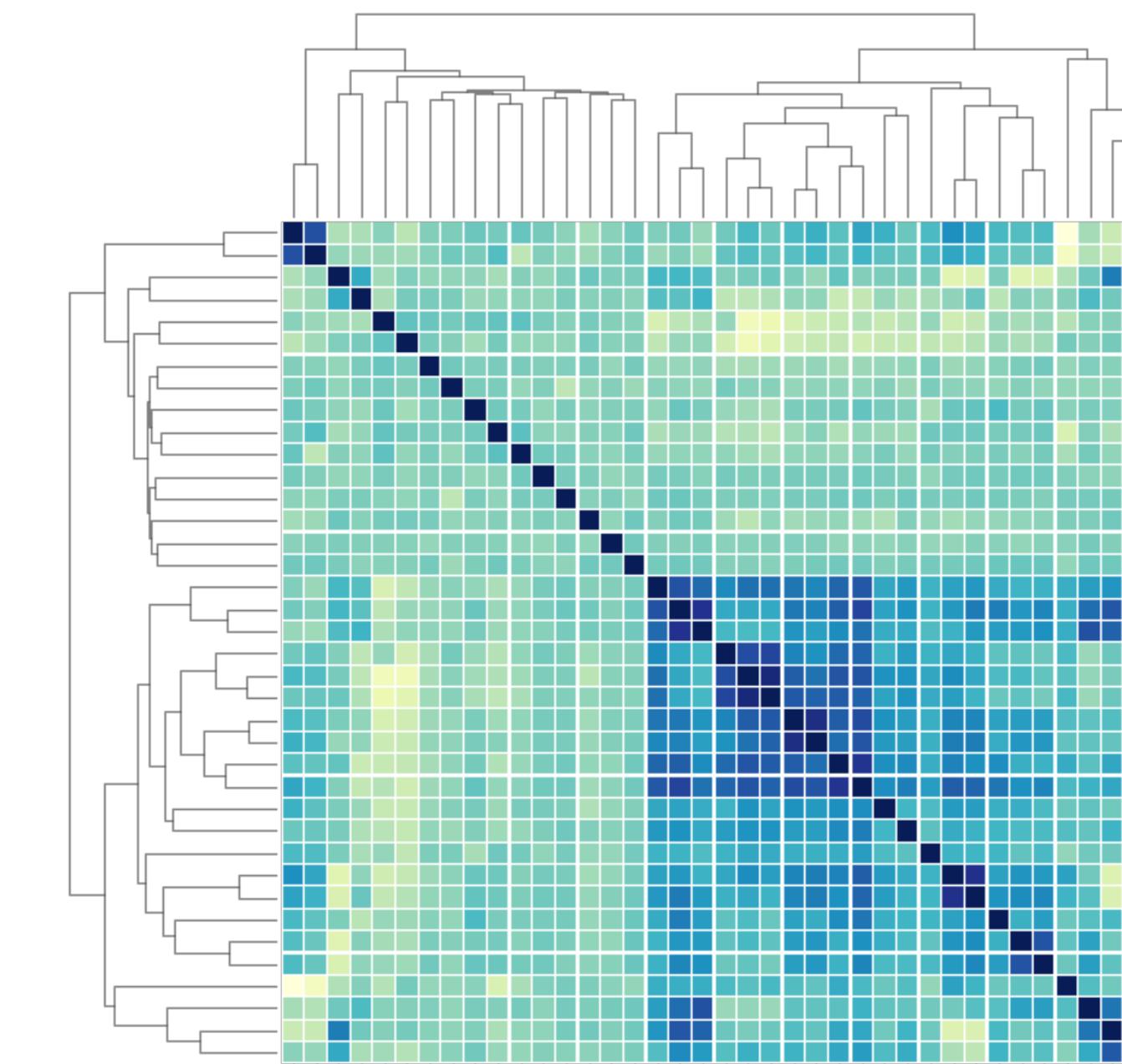
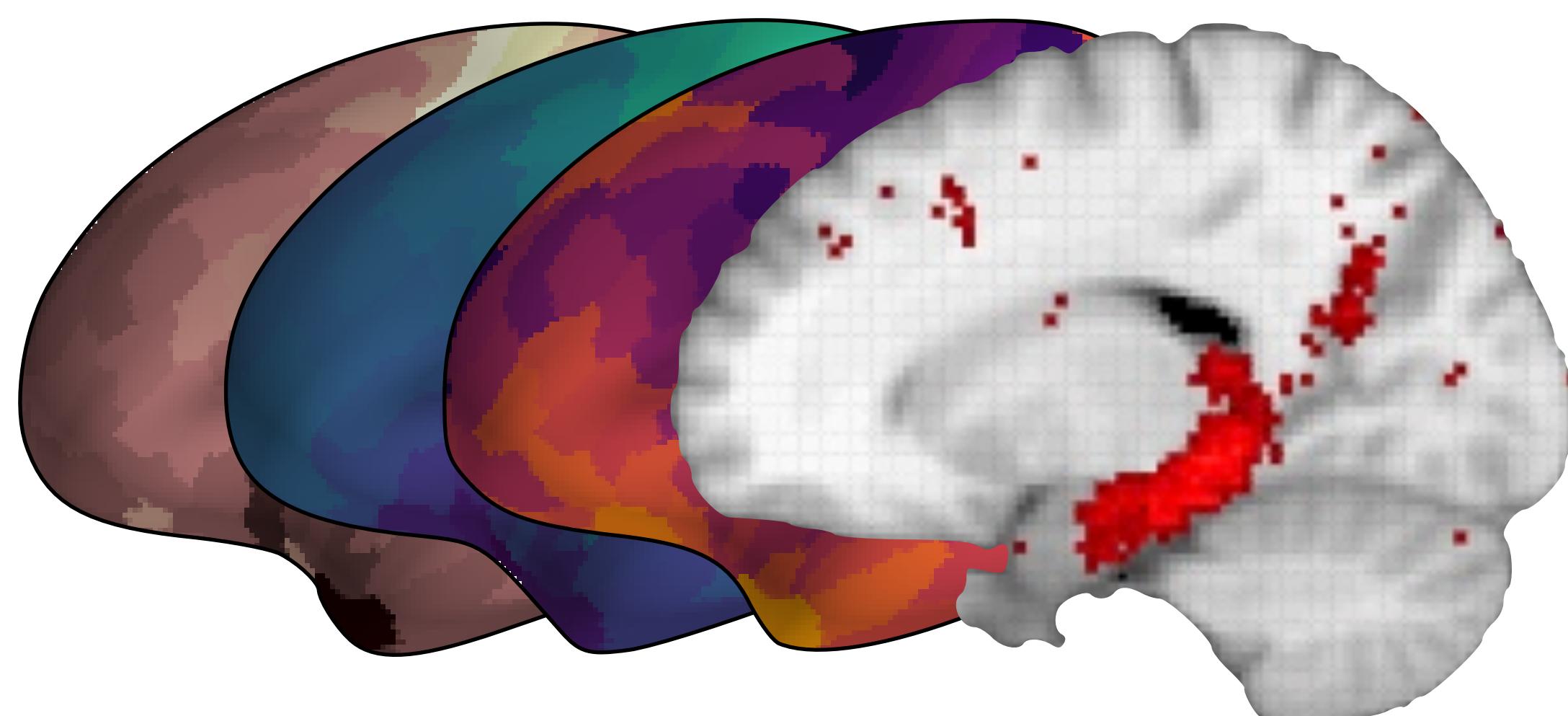
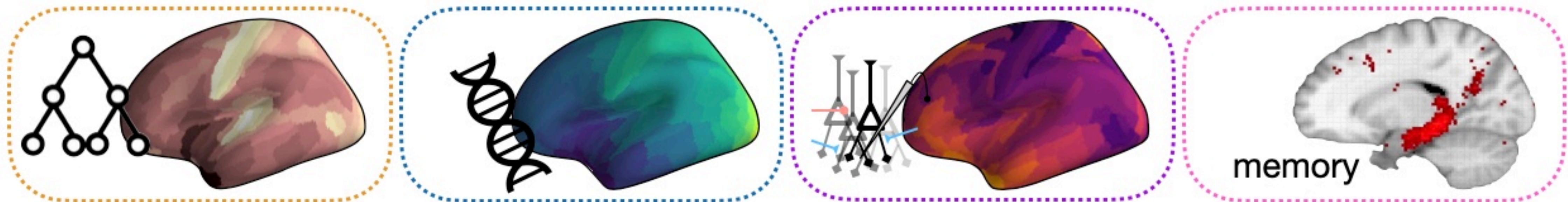
- single-unit
- field potential / oscillations

### **function**

- cognitive correlates
- disease relationships
- development and aging

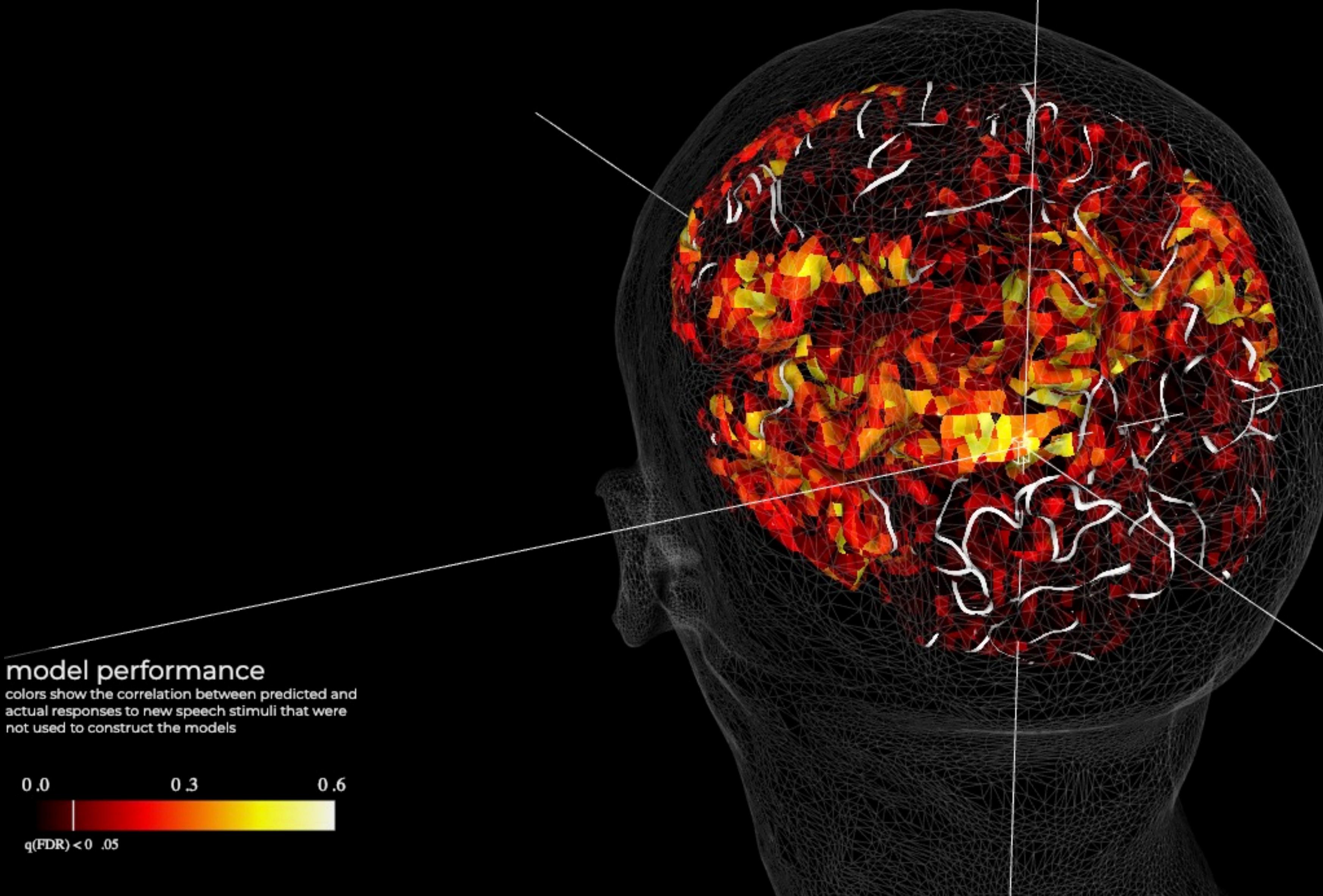


# Integration and mining



• • • • • (show tour)

- ▶ camera
- ▼ data layers
  - selectivity
  - performance
  - performance\_thr
  - PrAGMATIC
- ▶ surface
- Close Controls



voxel [14,89,63] left  
model performance: 0.323 (p=0.000)  
Good, very reliable

country  
village  
countryside  
paradise  
visitors park home  
parade inn hotel  
street tourist  
city town visit  
streets ride  
journey  
procession  
travellers