RESEARCH ON TAP

# Neuroscience to Data Science and Back

Tuesday, May 2, 2023

bu.edu/research/events

BOSTON UNIVERSITY

**Boston University** Office of Research

# Agenda

- Welcome Remarks
- Presentations
  - Chantal E. Stern
  - David C. Somers
  - Emily P. Stephen
  - Chandramouli Chandrasekaran
  - Brian DePasquale
  - Marc W. Howard
  - Sucheta Chakravarty
  - Michael Hasselmo
  - Michael Economo
  - Jeffrey Gavornik
- Closing Remarks

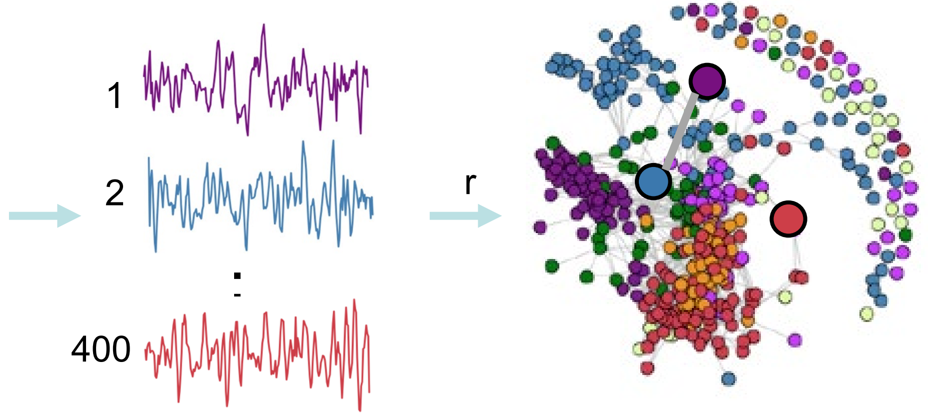
# How Does the Functional Reconfiguration of Human Brain Networks Support Cognition?


## Chantal E. Stern

Director, Cognitive Neuroimaging Center
Rajen Kilachand Center for Integrated Life Sciences and Engineering
Professor, Department of Psychological and Brain Sciences, CAS
Professor, Graduate Program in Neuroscience

# The Human Brain as a Network

(Schaefer et al. 2018)




- **Node:** A brain region of interest
- **Edge:** Functional connectivity (correlation) between two nodes
- **Community:** A group of nodes (defined *a priori* or in a data-driven manner)

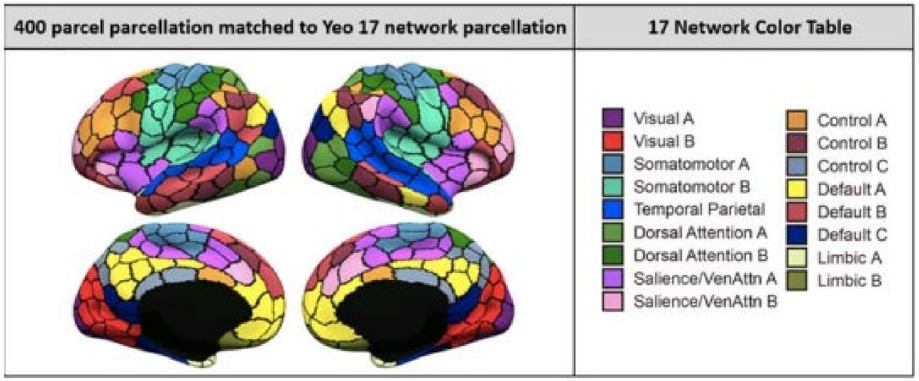
Morin, Chang, Ma, McGuire, Stern (2021)

Morin, Moore, Isenburg, Ma, Stern (2022)

Isenburg, Morin, Rosen, Somers, Stern (2023)

# Network Reconfiguration Supporting Memory-Guided Attention

1

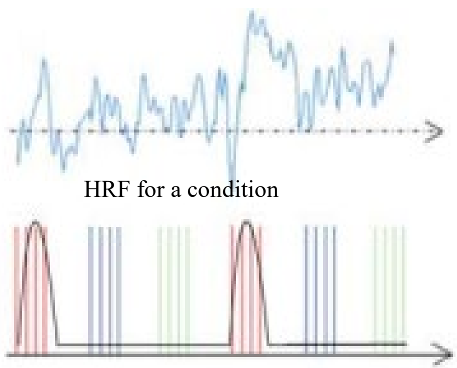



2

Time-series from a node

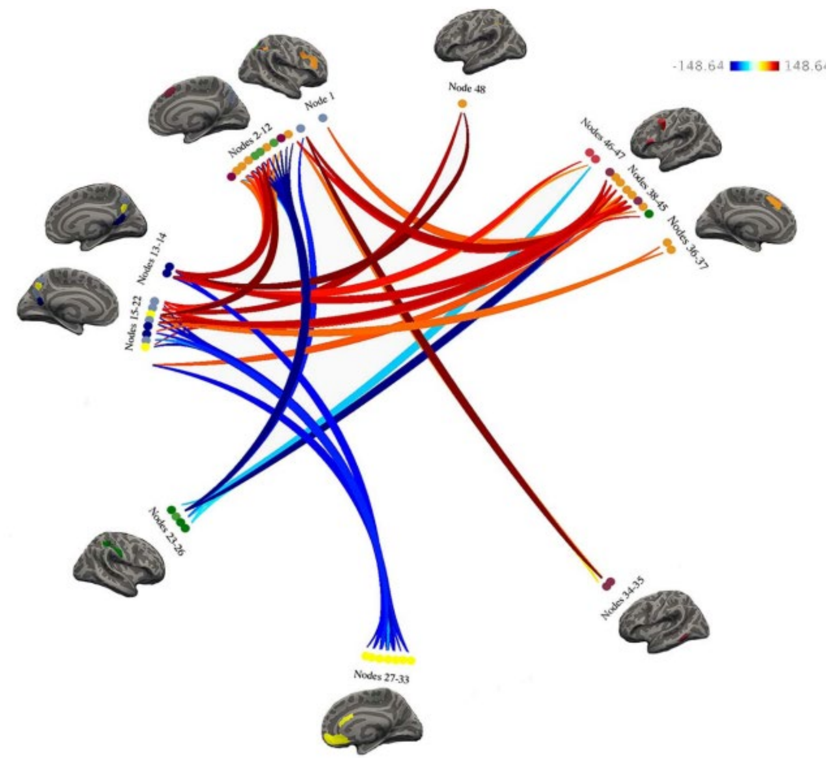
X

HRF for a condition



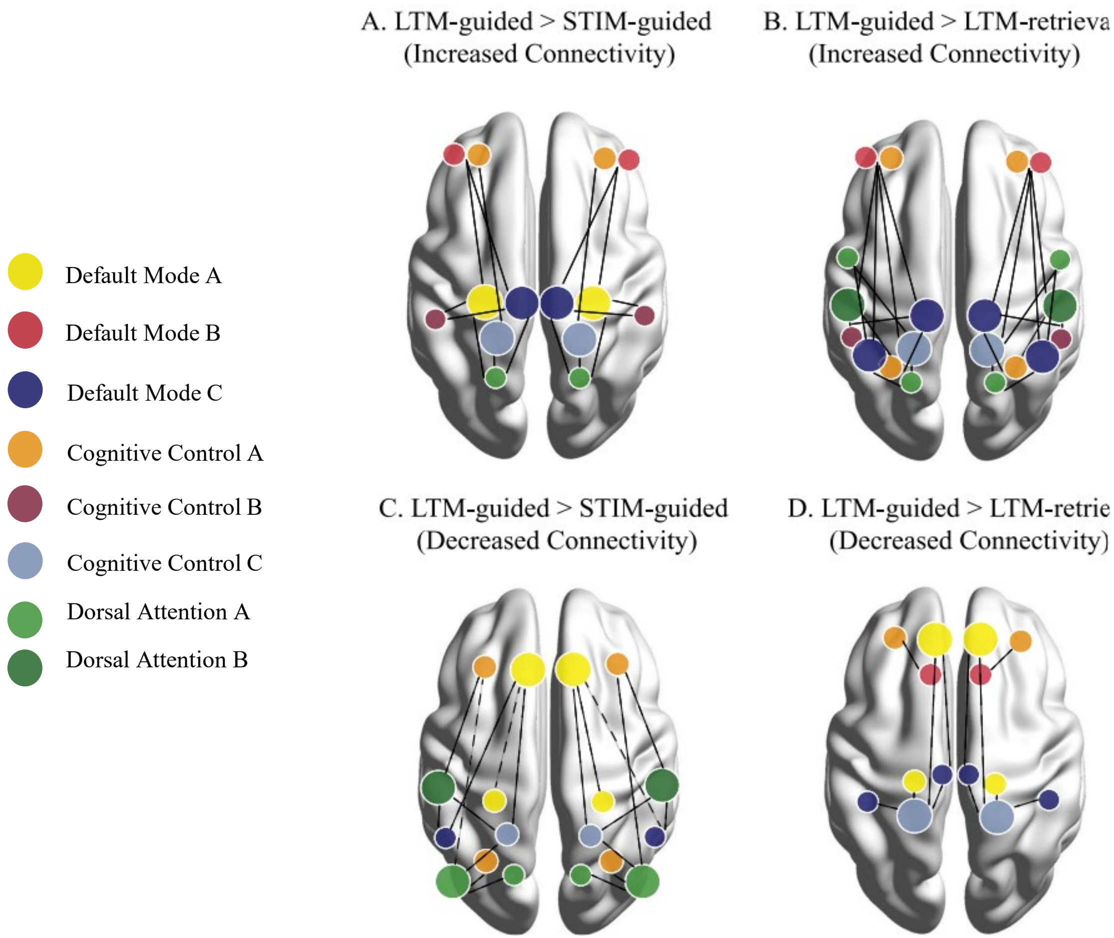
3

Node-to-node regression for all pairwise comparisons




Isenburg, Morin, Rosen, Somers, Stern (2023)

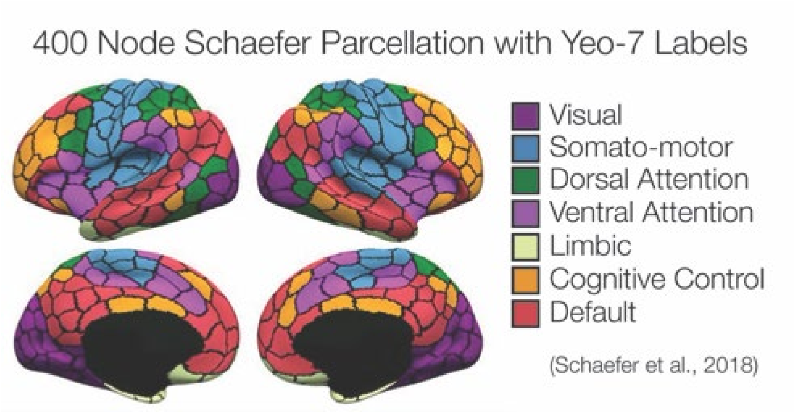
# Network Reconfiguration Supporting Memory-Guided Attention

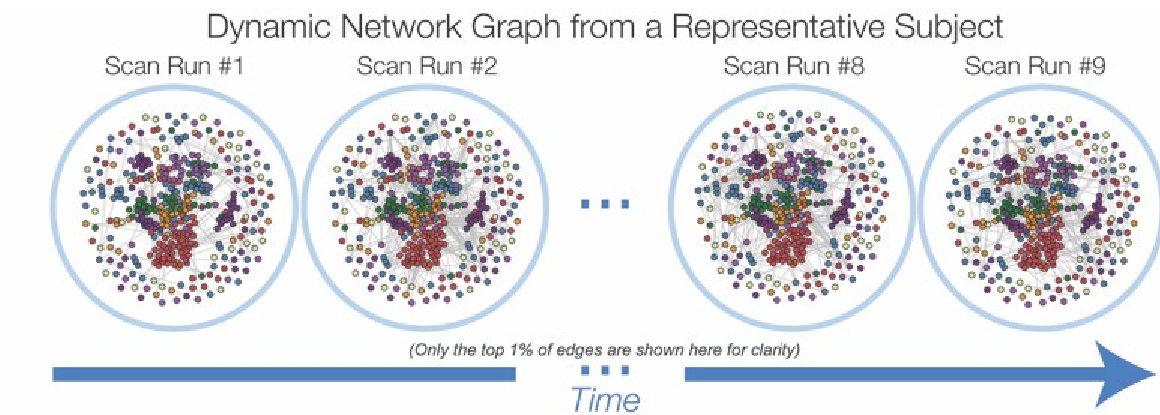


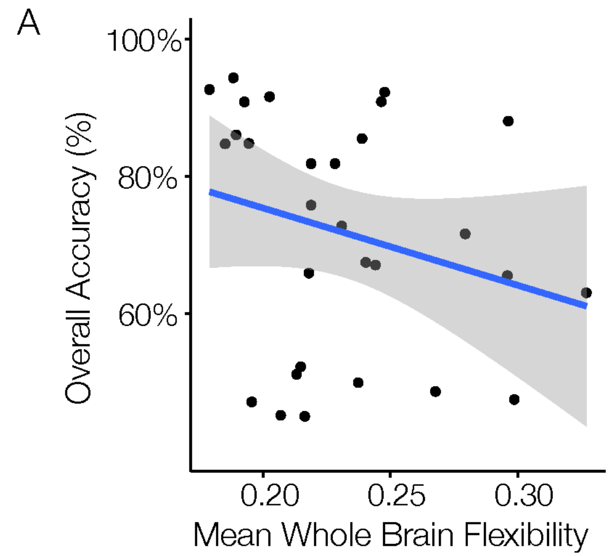

Results identified both network-based and node-specific interactions that facilitate different components of long-term memory - guided attention

Isenburg, Morin, Rosen, Somers, Stern (2023)

# Dynamic network analysis demonstrates the formation of stable functional networks during rule learning




Fast and accurate learning is associated with the formation of a stable brain network architecture

Morin, Chang, Ma, McGuire, Stern 2021

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# Connectome Fingerprinting:

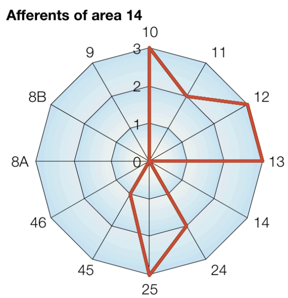
## Individualized Predictions of Human Brain Functional Organization

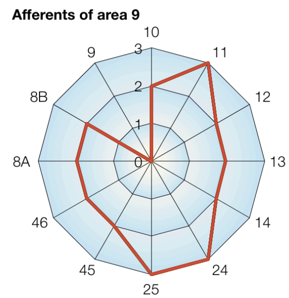
David C. Somers

Professor and Chair
Psychological & Brain Sciences

# Brain Structure Predicts Brain Function

**<u>Passingham's Conjecture (2002):</u>** Each cortical brain region has a unique pattern of connectivity.

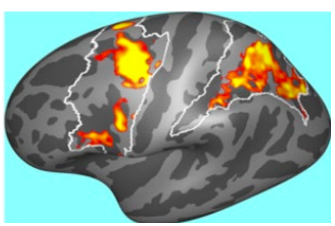


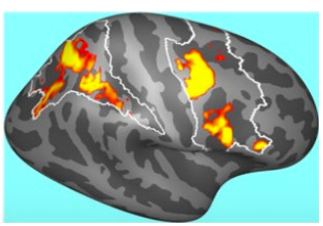




If we can establish these patterns AND
measure the connectivity of a particular bit of brain tissue,

we can predict the functional brain region identity of the tissue.

**<u>Connectome Fingerprinting:</u>** A computational modeling approach for non-invasively predicting individualized Functional brain organization from the individual's connectome



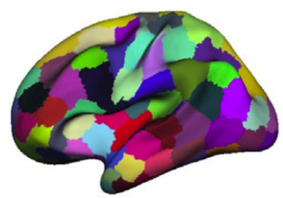


Saygin et al., 2011; Tavor et al., 2016; Osher et al. 2016; Tobyne et al., 2018; Osher et al., 2019

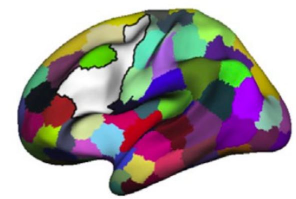
# Connectome Fingerprinting – Building a Model

## 1. Define Model Space:

Parcellation (P)



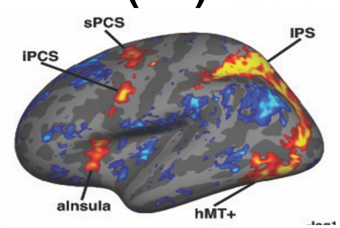
Search Space (V)



## 2. Training Data Set (N):

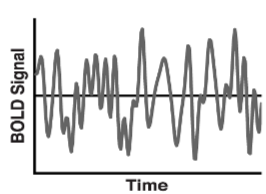
Identify functional brain regions

V vertices

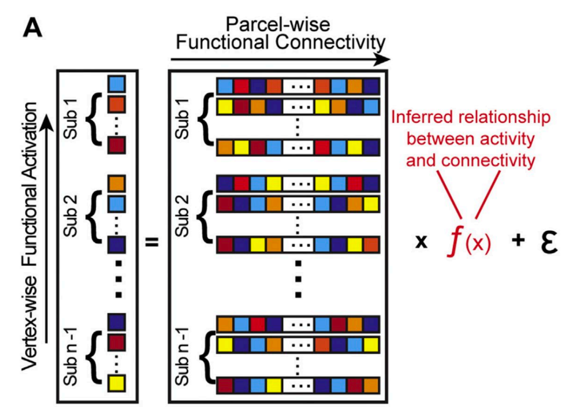



Measure brain connectivity

V x P matrix

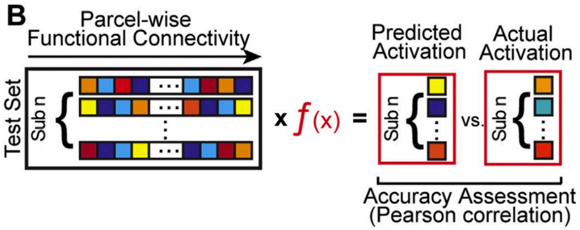


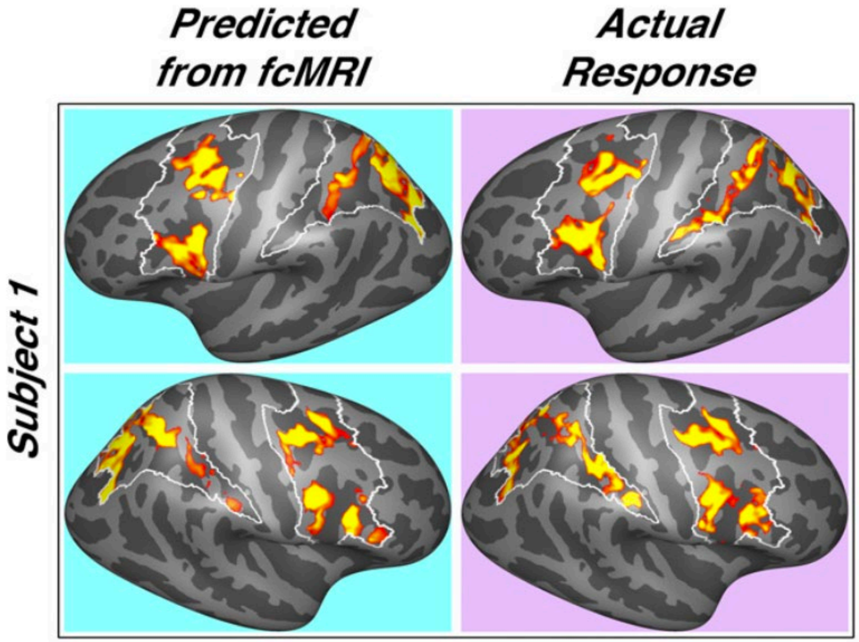

## 3. Model Specification (f):



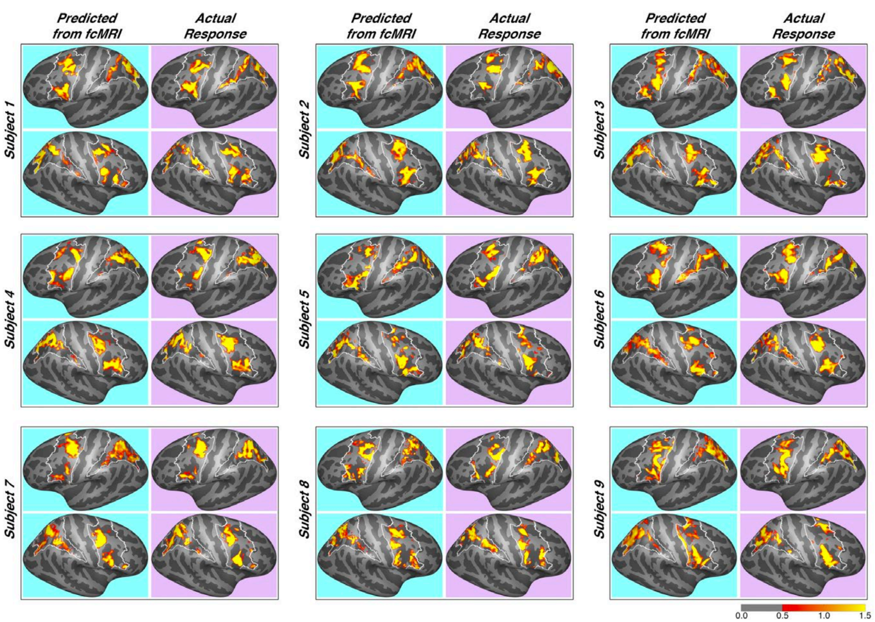

Tobyne, Somers, Brissenden, Michalka, Noyce, Osher, NeuroImage 2018

# Model Predictions & Validation

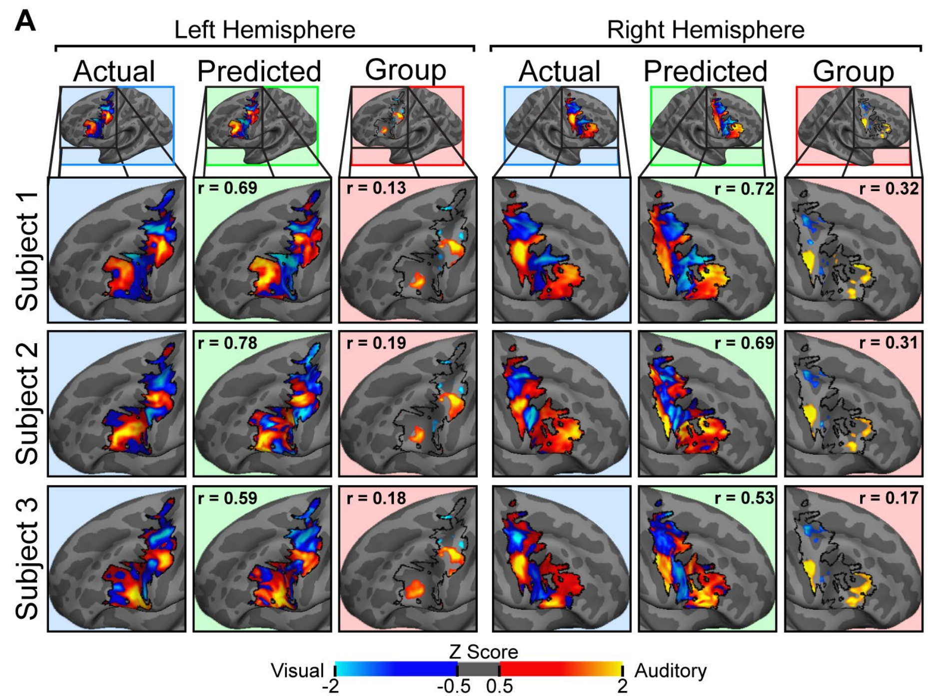


# Model Predictions & Validation




Osher, Brissenden & Somers, J. Neurophysiol. 2019




Tobyne, Somers, et al. NeuroImage 2018

# CF Application to Neurosurgical Planning

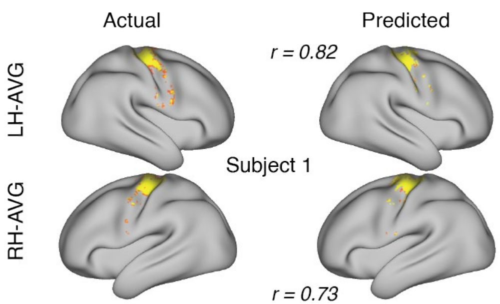
## Motor Function & Language Function

Healthy Controls → Glioma Patients & Healthy Controls → Interoperative Visualization Integration

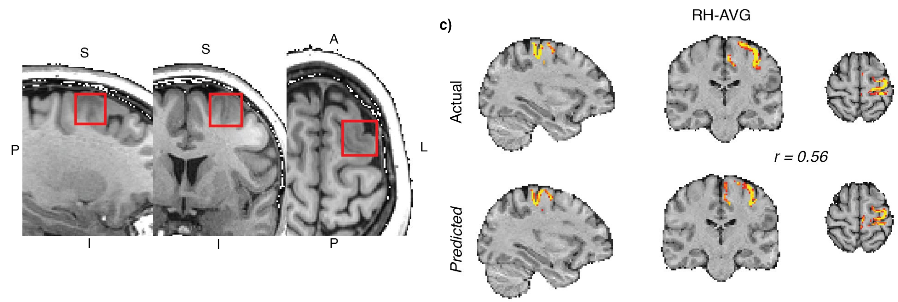
Training Data: HCP-YA

Test Data: Brigham & Women's Hospital

Healthy Controls




Glioma Patient Predictions




Vaibhav Tripathi

NIH: R43-NS117226

Collaboration w/ Brigham & Women's Hospital: A. Golby, Y. Tie, L. Rigolo & Charles River Analytics: B. Bracken, A. Winder

# Application to Neurosurgical Patients

## Potential Advantages of Connectome Fingerprinting:

- Application at neurosurgical centers that lack a dedicated fMRI team
- Application to patients who are unable to perform fMRI tasks
- Reduced scanner time

## Challenges:

- Sufficient Resting-State Data
- Cross-scanner harmonization
- Localized neurovascular decoupling in vicinity of tumors

## Next Steps:

- Breath-holding scans to probe neurovascular decoupling
- Voxel-level estimates of signal reliability
- Bayesian combination of CF, Task, Structural & Breath-holding data




# Thanks!


- NIH
  - R01-EY022229
  - R43-NS117226
  - F31-NS103306
  - F32-EY026796
- NSF
  - BCS-1829394

# Updating Classical Statistical Models to Gain Multivariate Insight in Speech Perception

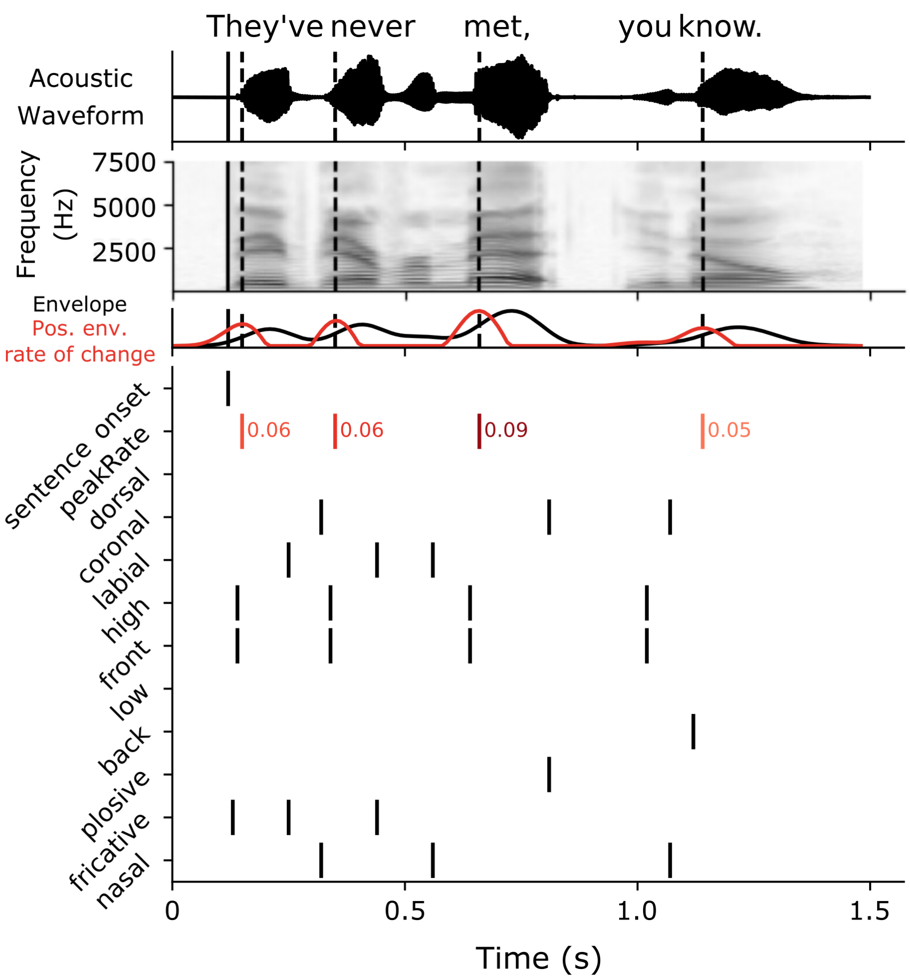

## Emily P. Stephen

Assistant Professor
Mathematics and Statistics, CAS

# During speech perception, how does the brain organize low-level features like phonemes into higher-order objects like words and phrases?

**Stephen**, Li, Metzger, Oganian, Chang (2021). Biorxiv

# Classic Feature-Temporal Receptive Field models represent a signal as a sum of impulse responses to a set of feature events




$$Y = \underbrace{\sum_{f=1}^{F} X_f B_f}_{} + E$$

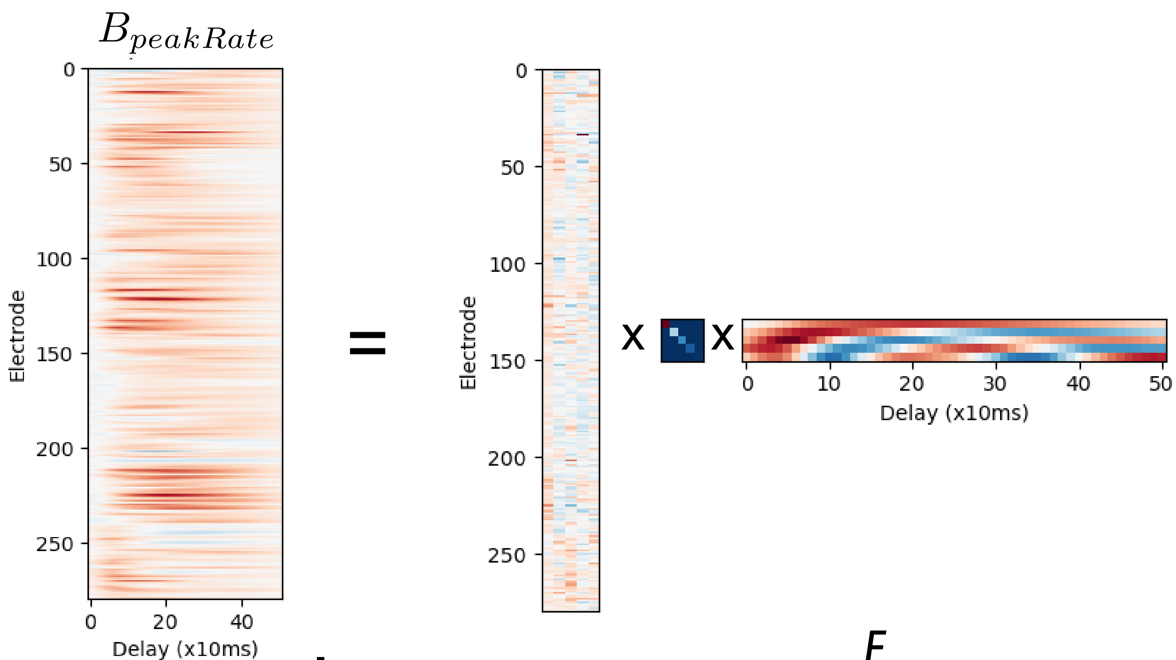
High gamma timeseries T x N

Stimulus feature f timeseries across delays T x D

Response to feature f across electrodes and delays D x N

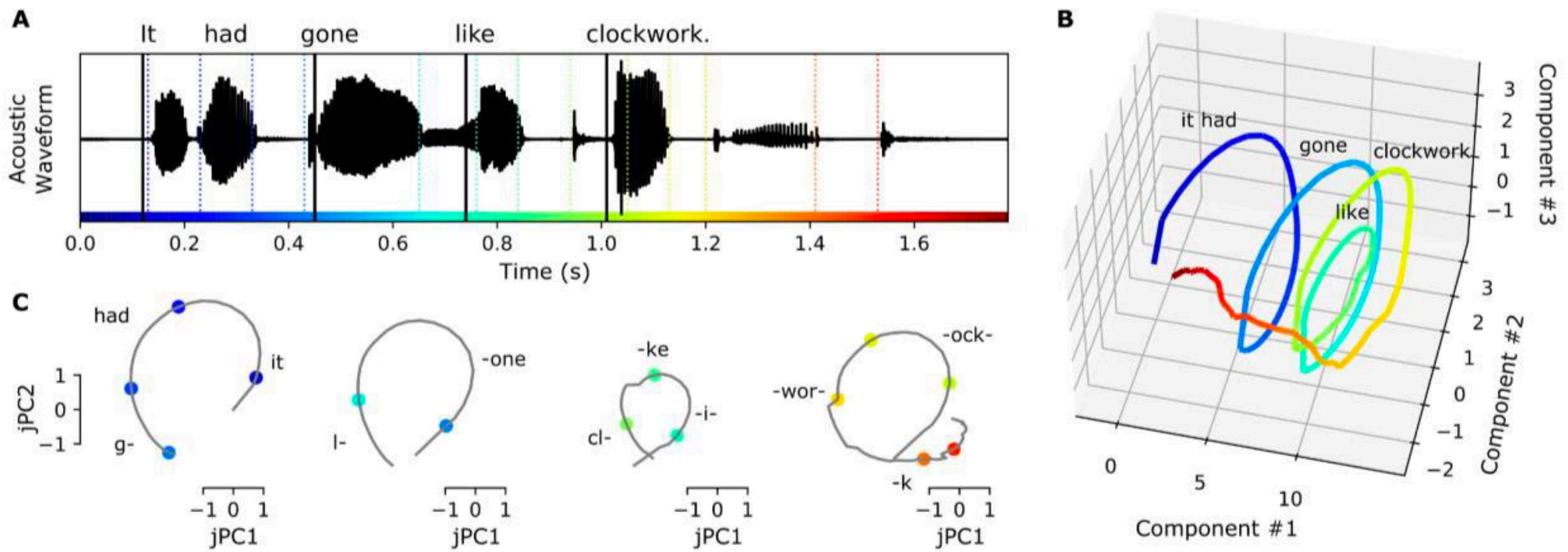
T: # timepoints
N: # electrodes
D: # delays

# Integrative Reduced Rank Regression (iRRR) imposes a group low rank penalty on the multivariate feature response matrices




$$\hat{B} = \underset{B \in \mathbb{R}^{DF \times N}}{\operatorname{argmin}} \frac{1}{2T} ||Y - XB||_F^2 + \lambda \sum_{f=1}^{F} w_f \underbrace{||B_f||_*}_{\text{Nuclear Norm (sum of singular values)}}$$

# The feature-specific subspace related to “peak rate events” could play a role in temporal binding of features into words/phrases



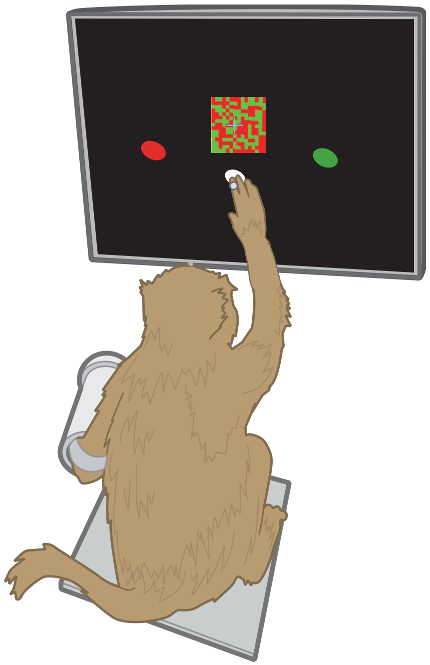

Stephen, Li, Metzger, Oganian, Chang (2021). Biorxiv

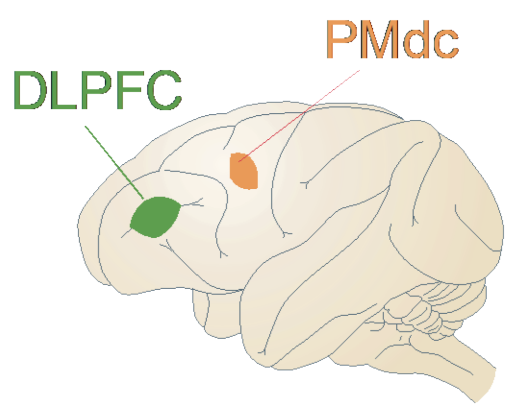
# Dynamical Systems and Machine Learning Approaches to understand Neural Circuit Dynamics

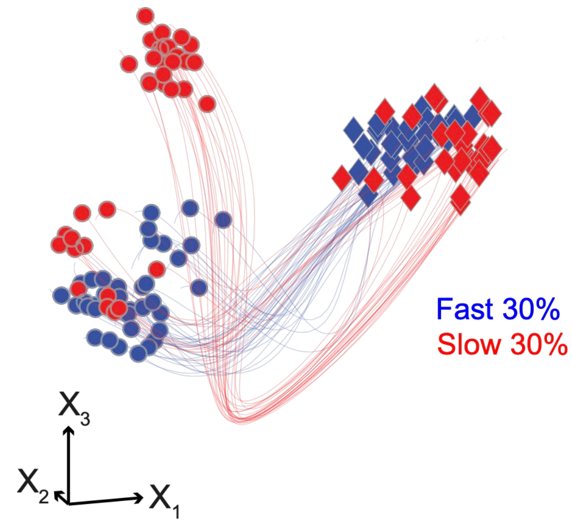

## Chandramouli Chandrasekaran

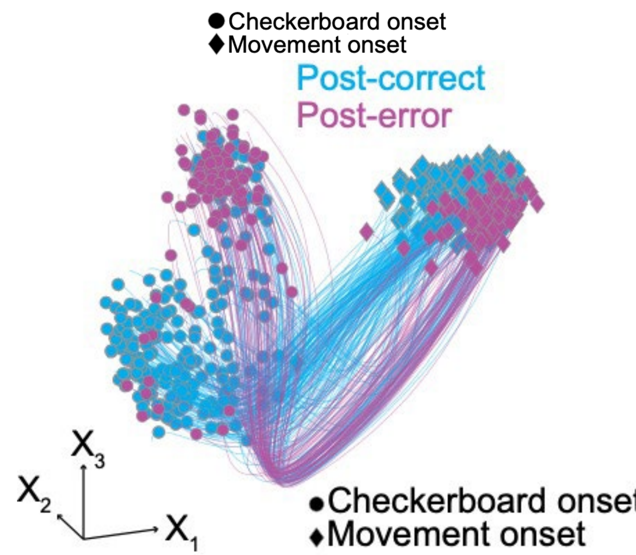
Assistant Professor
Psychological and Brain Sciences, CAS
Anatomy & Neurobiology, BUSM

# Single-trial analysis can help identify computations underlying decision-making

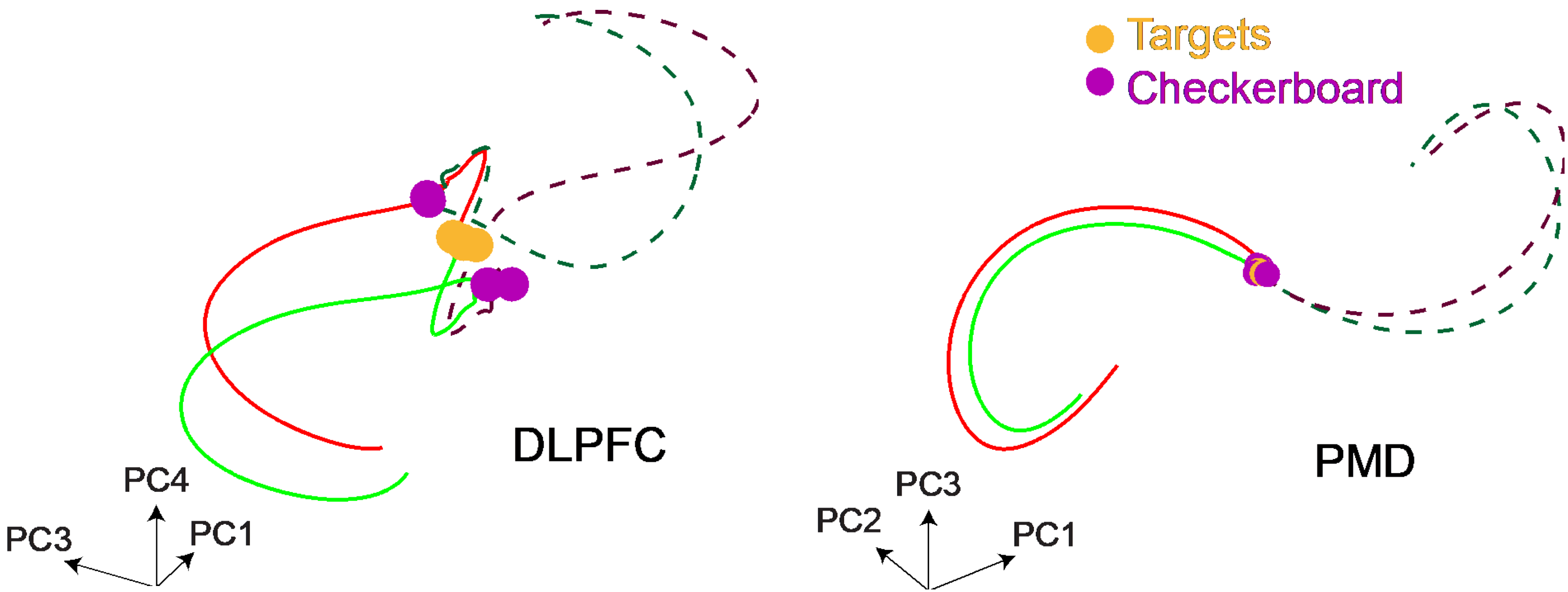




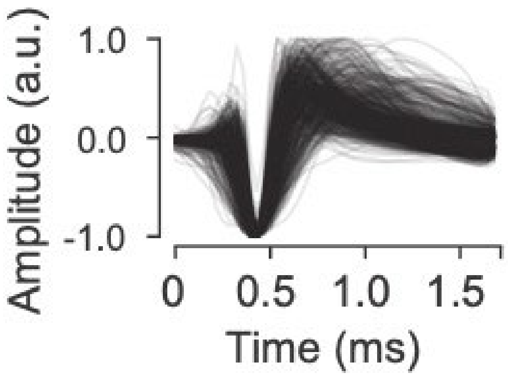



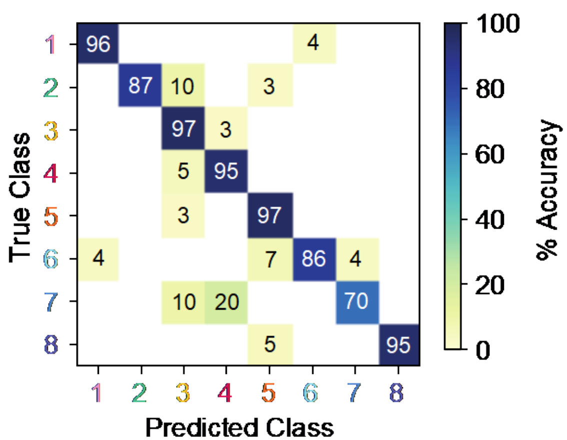



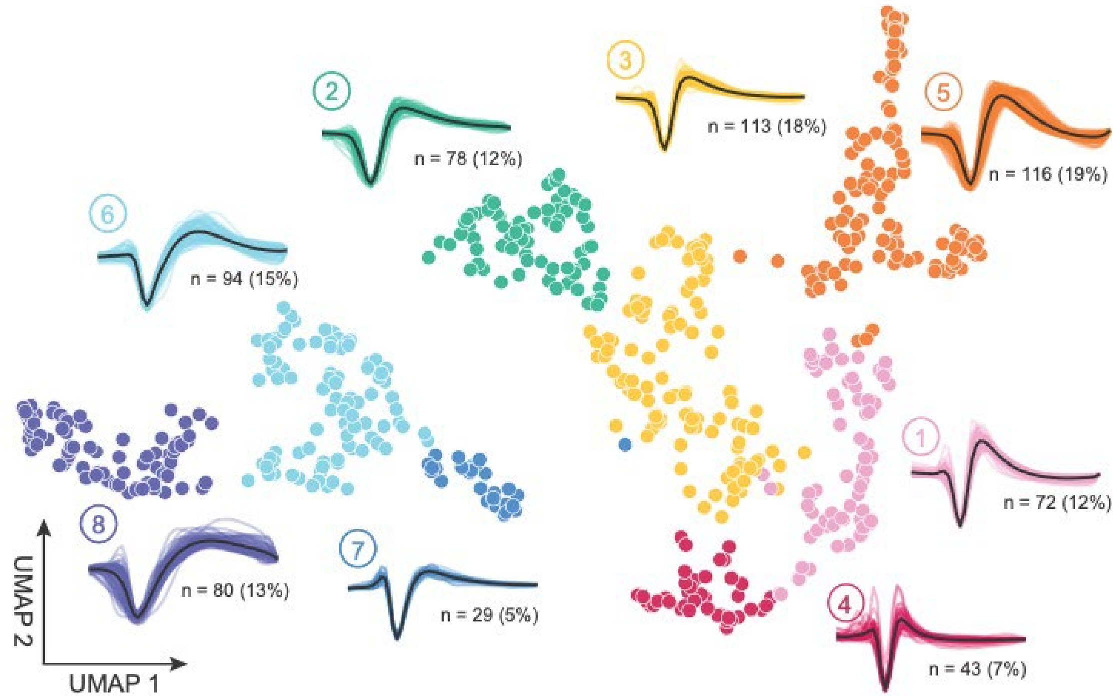
# Dimensionality Reduction Can Help Understand Distinct Roles of Various Brain Areas



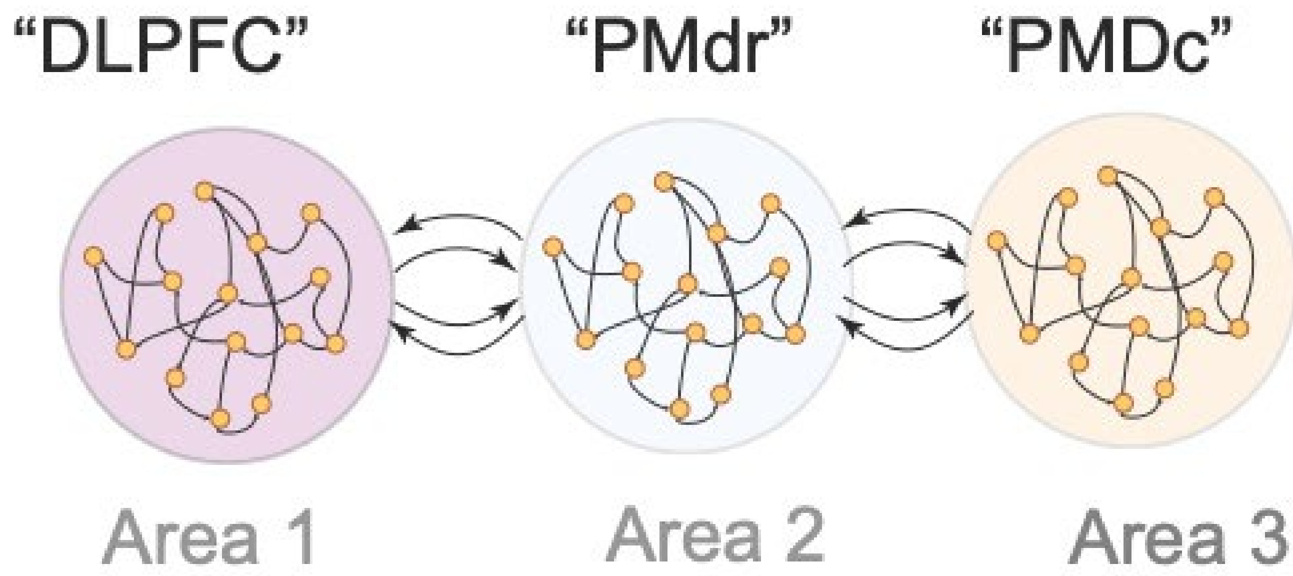
# Nonlinear dimensionality Reduction Can Identify Candidate Cell Types



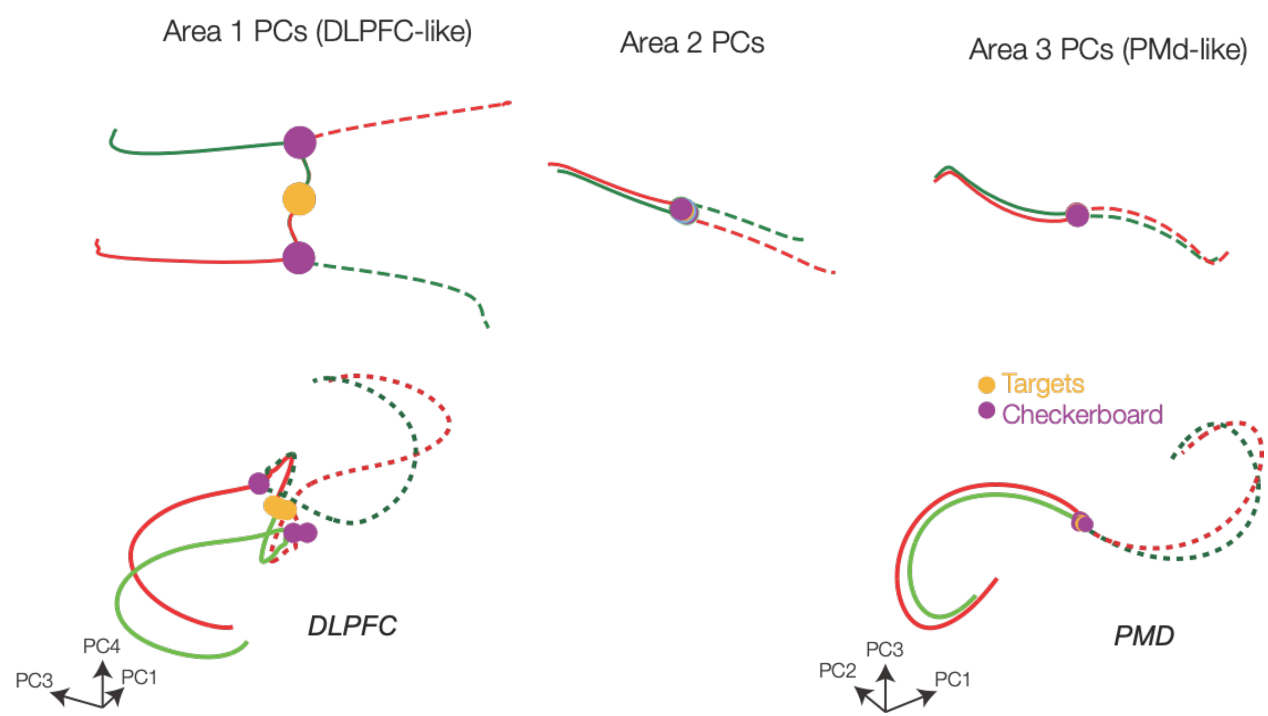



Models can help understand multi-area computation




Model

Data

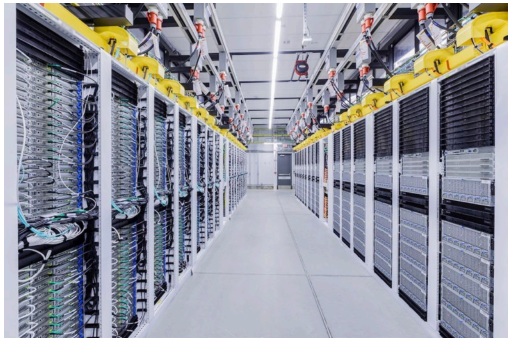


# Deciphering Neural Algorithms Using Machine Learning and Neural Networks

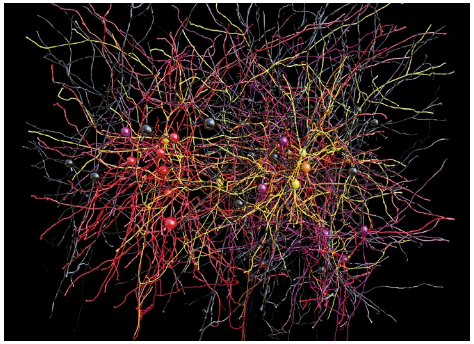

## Brian DePasquale

Assistant Professor
Department of Biomedical Engineering, College of Engineering

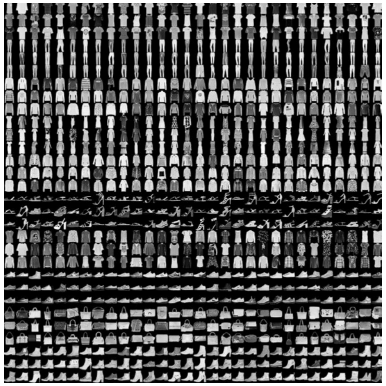
# Artificial and biological intelligence face **unique** challenges



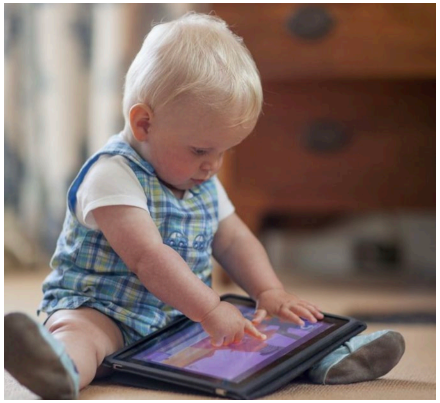
Lots of power



Low power



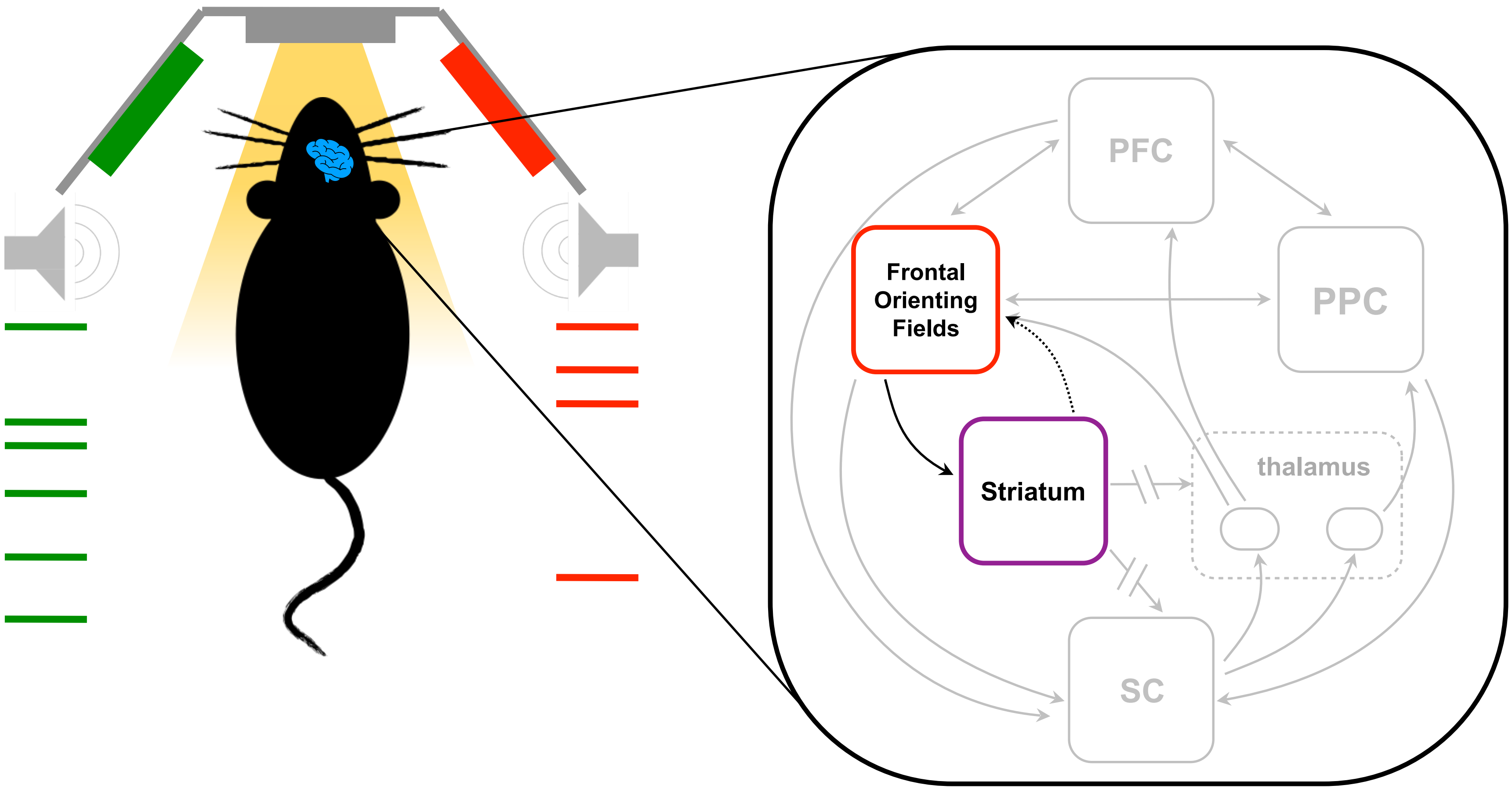
Lots of data



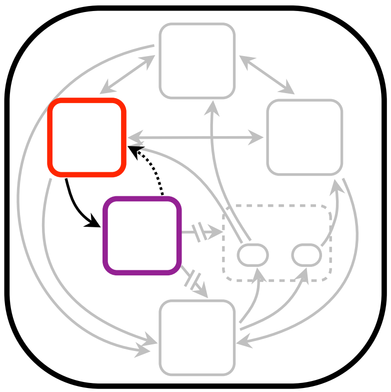
Fast learners

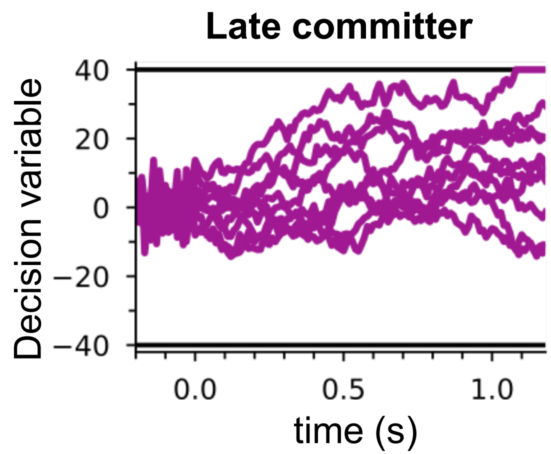
- What algorithms do neural circuits use?
- How do neural circuits instantiate these algorithms?

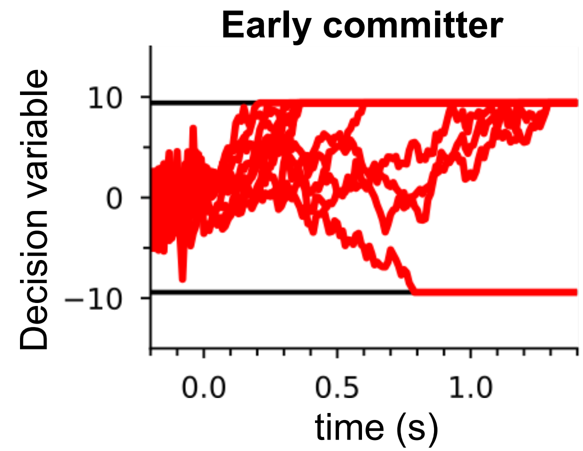
# Making decisions is a core neural computation



# Machine learning models show different strategies in different regions





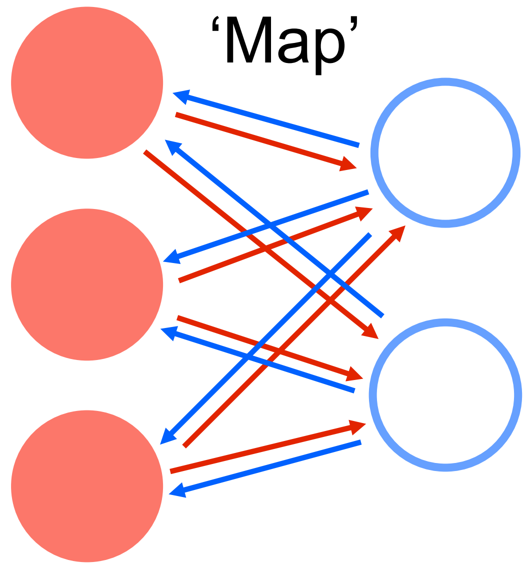




- Machine learning analysis can uncover neural algorithms
- Different regions use different, sometimes unconventional, algorithms
- Decisions are the result of multiple, interacting brain regions

# How do neural circuits <u>instantiate</u> these algorithms?

## Neural circuit implementation

- Spiking neurons
- Noise corrupted representations
- Sparse connections




## Artificial intelligence algorithms

- Interpretable
- Easier to implement *in silico*

- Frameworks for 'mapping' artificial intelligence models to <u>biologically realistic</u> artificial networks
- Artificial network analysis provides insight into <u>real</u> neural circuits

## Theoretical Cognitive Neuroscience

# Marc W. Howard

Professor
Psychological and Brain Sciences, CAS

# Towards a theory of the brain

4 August 1972, Volume 177, Number 4047 SCIENCE

## More Is Different

Broken symmetry and the nature of the hierarchical structure of science.

P. W. Anderson

less relevance they seem to have to the very real problems of the rest of science, much less to those of society.

The constructionist hypothesis breaks down when confronted with the twin difficulties of scale and complexity. The behavior of large and complex aggregates of elementary particles, it turns out, is not to be understood in terms of a simple extrapolation of the properties of a few particles. Instead, at each level of complexity entirely new properties appear, and the understanding of the new behaviors requires research which I think is as fundamental

Cognitive psychology

⇕

???

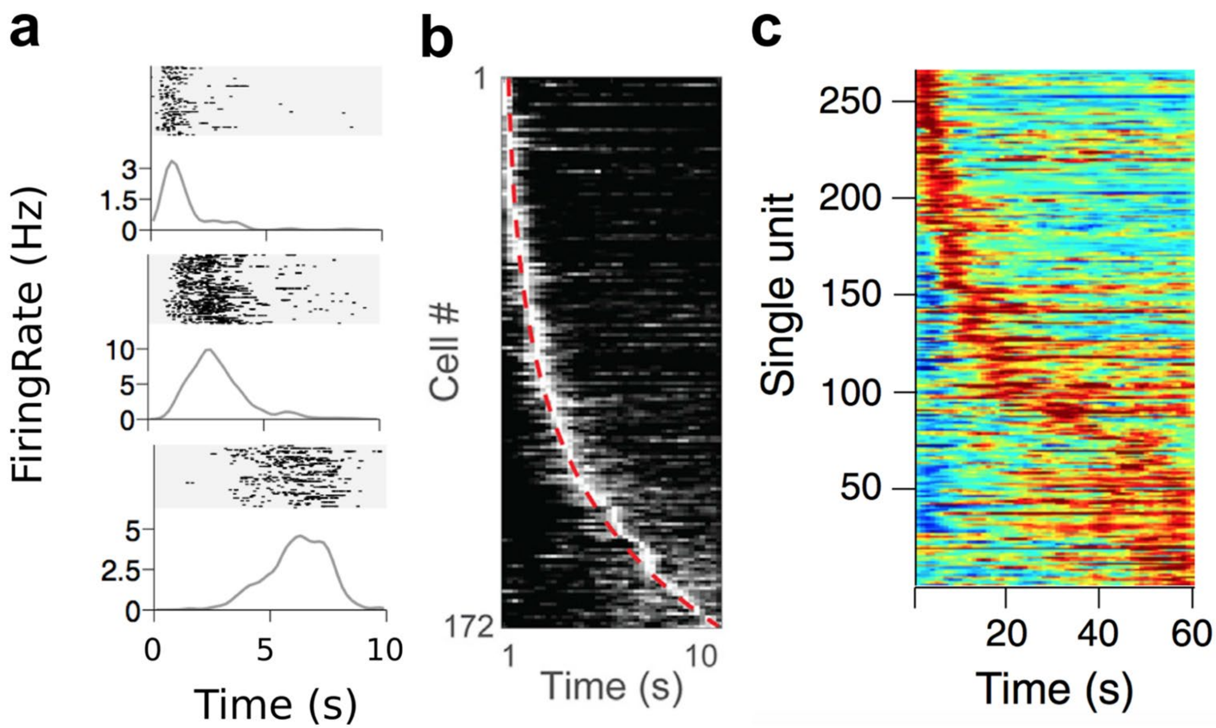
⇕

Neuroscience

- Function of the brain is to think
- Describe neural and cognitive data
- Equations you can take seriously

# Time cells maintain a record of what happened when

- Sequence of firing
- many regions
- many species

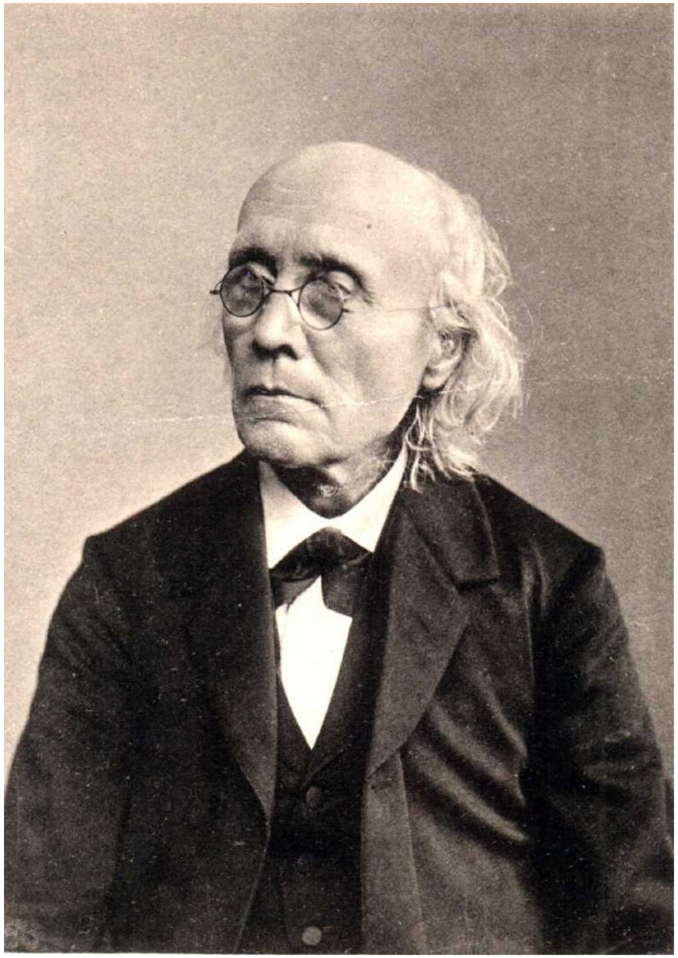



Can build elegant cognitive models of many memory tasks.

# The Weber-Fechner Law: An equation you can take seriously

- Sensations are on a log scale.
- What about time?
- Time cells in the rodent hippocampus form a log scale for what happend when.

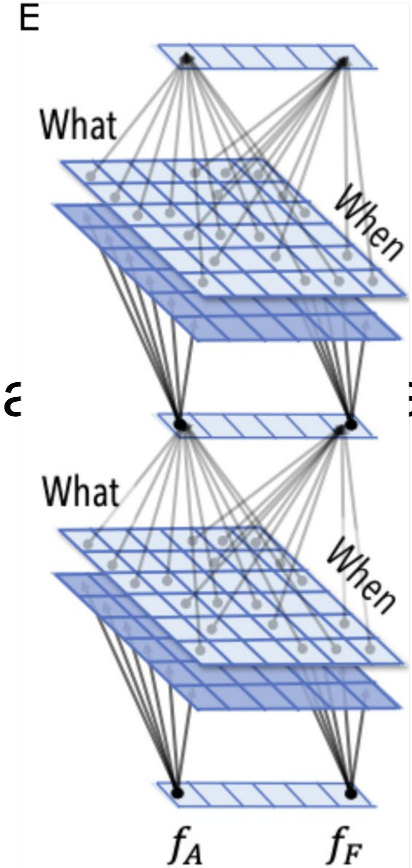
Cao, Bladon et al., (2022, *eLife*)

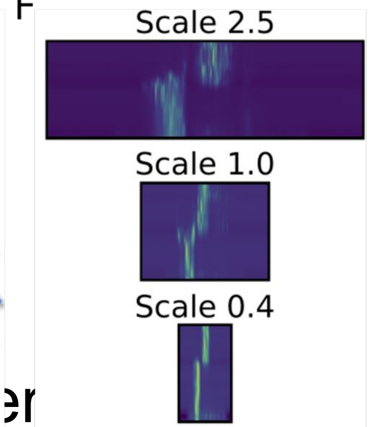


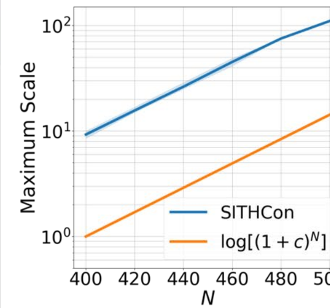
# These equations let you build deep networks with human like properties

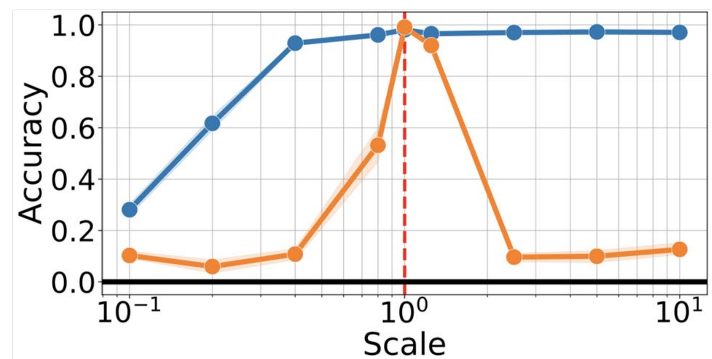
- Deep CNN of time cells.
- Train on speech
- Test on faster or slower speech
- Network generalizes.

Let's do a … er



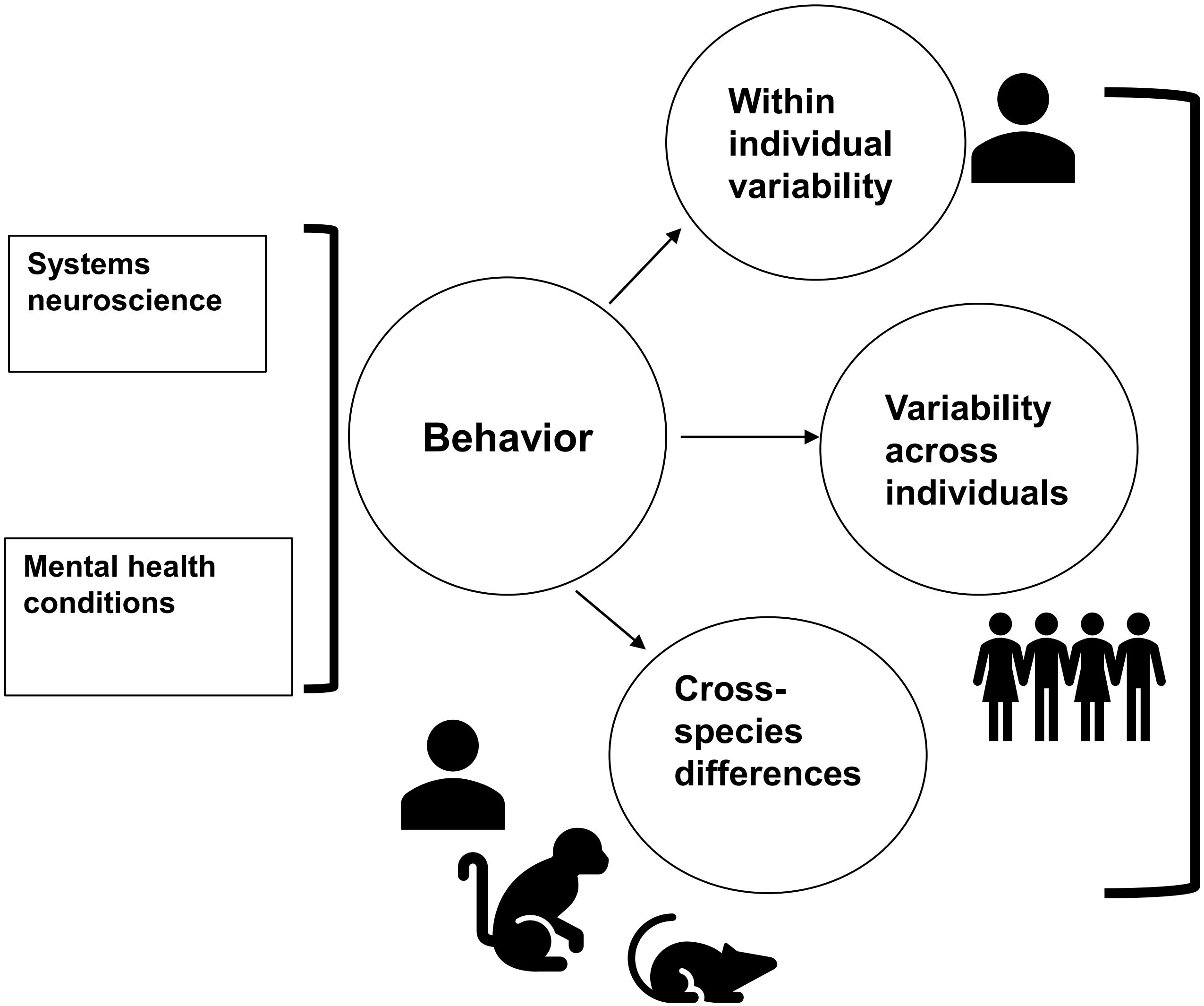



# Data Science Approach for the Study of Behavior

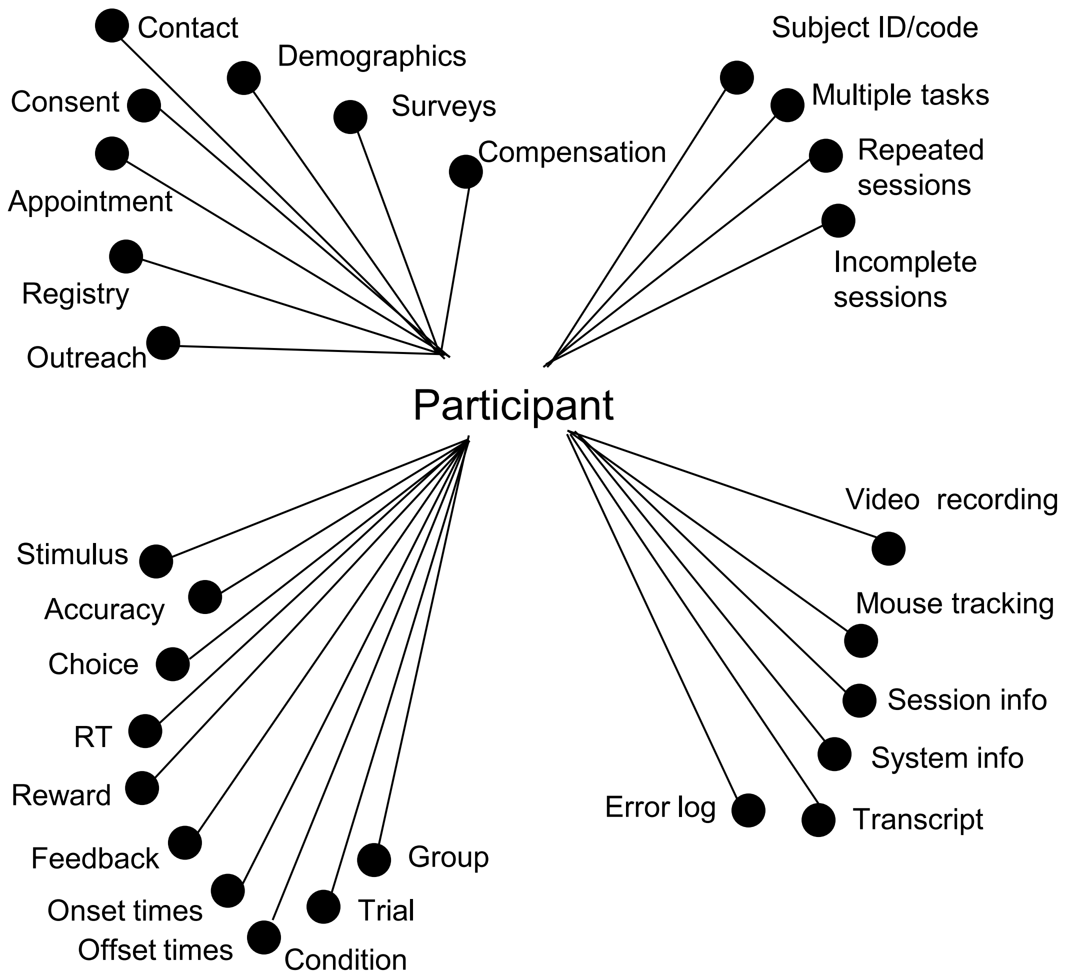

## Sucheta Chakravarty

Postdoctoral Research Associate
Psychological & Brain Sciences, CAS




- New data collection tools
- Advanced quantitative models

## Data are high-dimensional




## Datasets are large

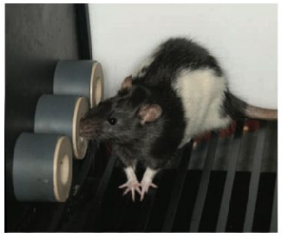
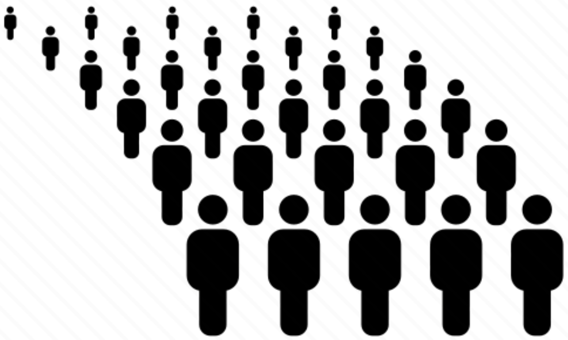


Photo: Nature.com


Photo: A. Akrami

>10 million trials from over 50 rats



>2000 participants

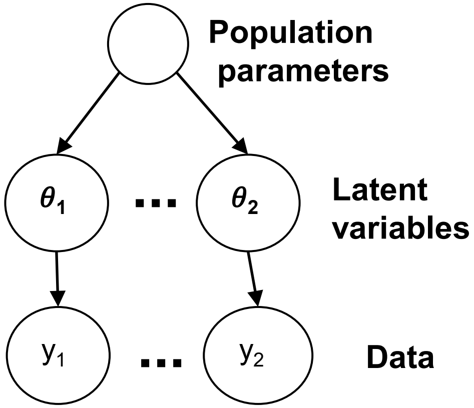
# Behavioral data science for ASD

## Goal

- Inclusion
- Objective biomarkers
- Translation
- Scalable

## Approach

- Online video game
- Non-verbal training pipeline
- HB modeling of individuals

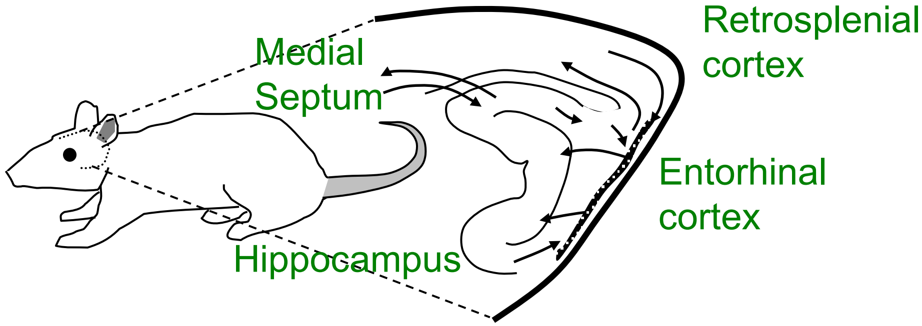
# Coding of Space for Guiding Behavior

Michael Hasselmo

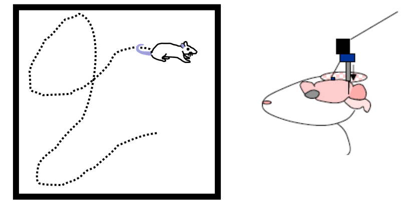
Director
Center for Systems Neuroscience

# Egocentric coding of boundaries

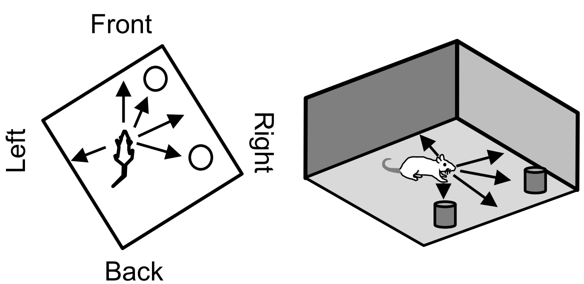
## Structures for episodic memory and navigation

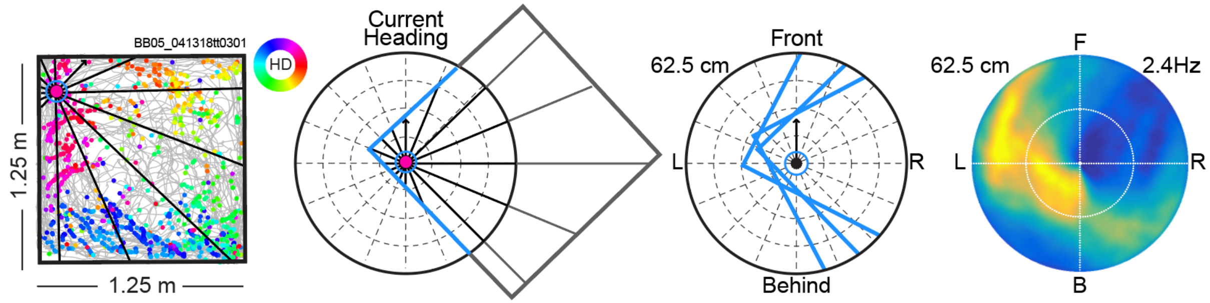



## Hasselmo lab: recording of neuronal spiking activity during spatial behavior (foraging)

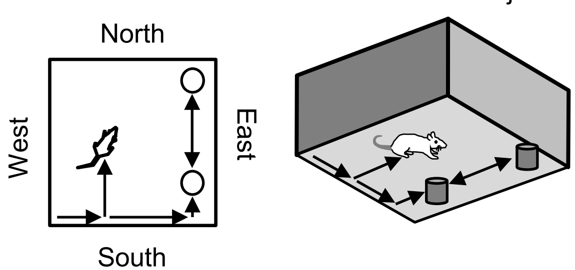


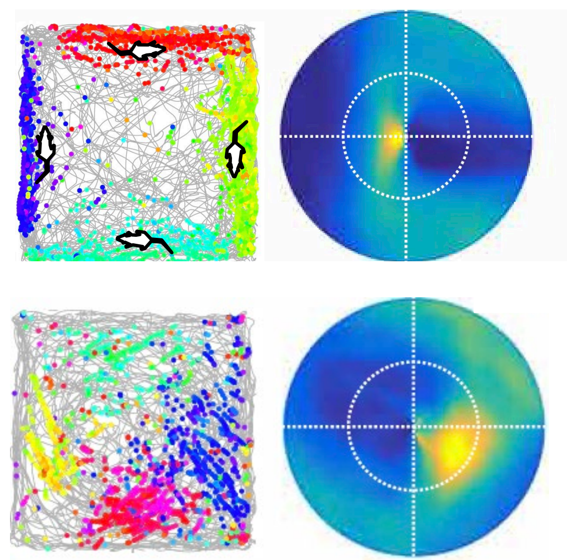
Egocentric coordinates – barriers/objects to self




Allocentric coordinates – self to barriers/objects



Research by former post-docs:
Alexander et al., 2020
Hinman et al., 2019

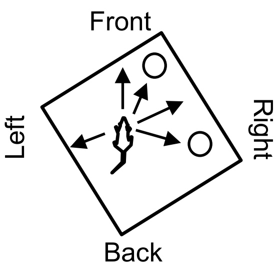
Andy Alexander (faculty at UCSB)
Jake Hinman (Univ. Illinois)

Current lab members:
Patrick LaChance, Jake Wilmot
Jennifer Robinson, Quan Do
Lucas Carstensen, Kelton Wilmerding
Samantha Malmberg, Tudor Dragoi

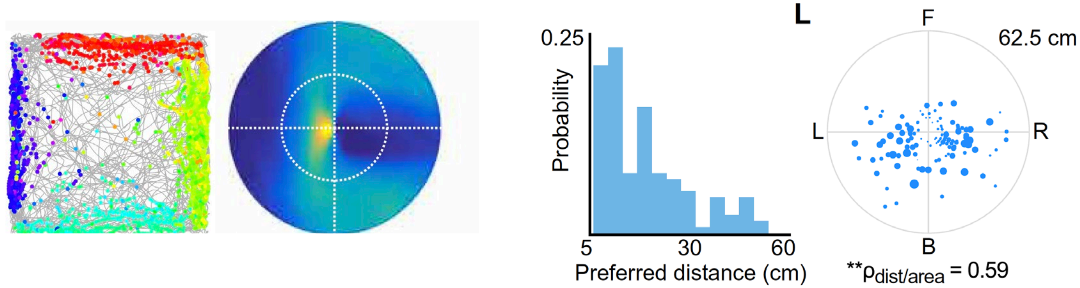
Funding: NIH R01 MH120037; NIH R01 MH052090; ONR MURI N00014-16-1-2832; ONR MURI N00014-19-1-2571

# How transform egocentric to allocentric coordinates?

Egocentric
barriers/objects to self




Egocentric coding of barriers at different angles and distances



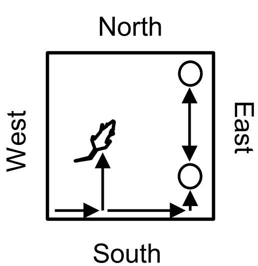

Egocentric boundary cells

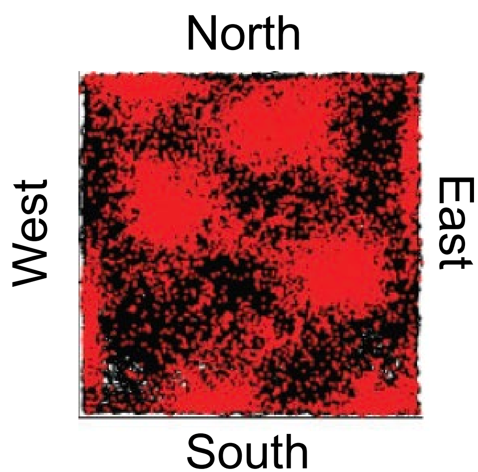
Allocentric grid cells

Model: Array of grid cells may code current affine transformations mediated by oscillatory phase shifts

Alexander, Robinson, Stern, Hasselmo (2023)

Allocentric
self to barriers/objects




Allocentric coding of location by grid cells

Dannenberg et al., 2020

General principles for cortical learning

ONR MURI linking neural circuits to robotic navigation (PI: Yannis Paschalidis, Chantal Stern, Betke, Bailleul, Tron)

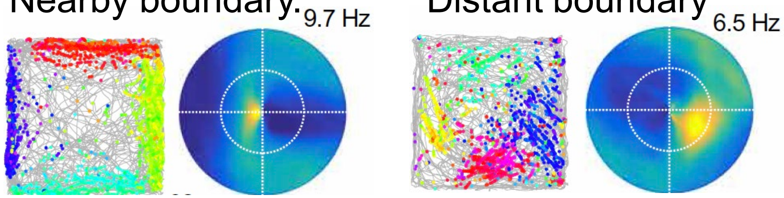
New application for additional MURI

ONR MURI grant on cortical rule learning (w. Chantal Stern, Marc Howard)

# Model egocentric responses to visual input (retinotopic image coordinates)

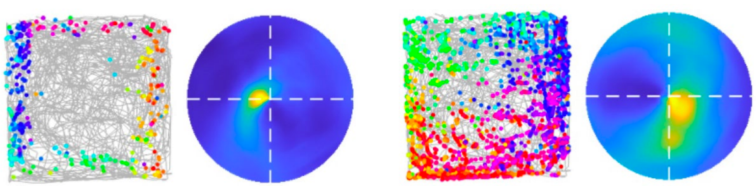
Neuronal data:

Nearby boundary. Distant boundary



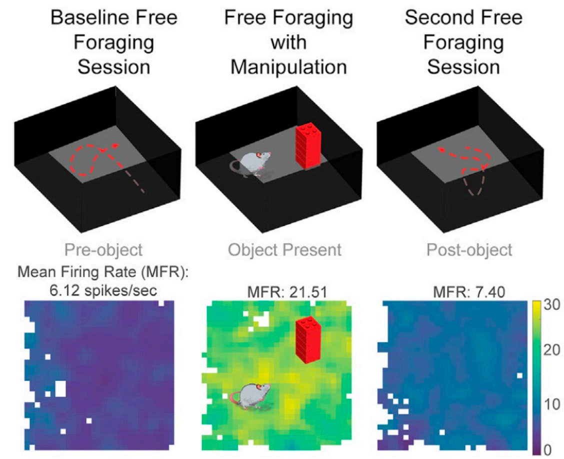

Sparse coding model

Nearby boundary. Distant boundary



Lian, Williams, Alexander, Hasselmo, Burkitt (2022)

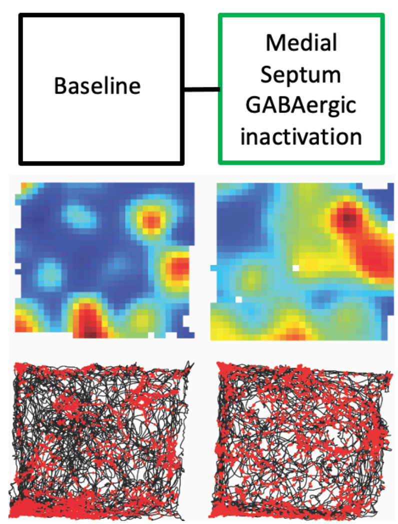
# How do neurons respond to novel objects or barriers?



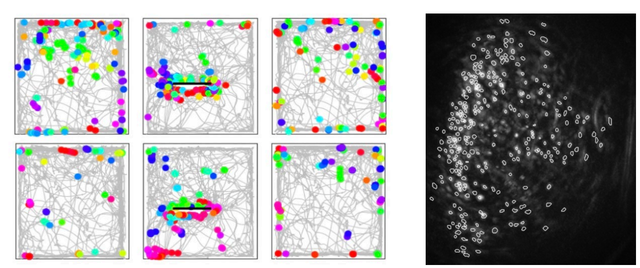

Carstensen, Alexander, Chapman, Lee, Hasselmo (2021)

# Loss of grid cell allocentric coding with optogenetic inactivation of medial septum

Robinson, Brandon, Hasselmo (2022)




# Calcium imaging of responses to inserted barriers



Malmberg, Cartsensen, Hasselmo

Alexander et al., 2022

## Summary

1. Neural data shows coding of space in both egocentric and allocentric coordinates
2. Models show neural mechanisms for transformation from retinotopic to egocentric to allocentric coordinates
3. Neurally inspired models explore brain properties not found in deep learning (e.g. phase coding instead of rate coding, transformations via phase shifting)
4. Ongoing interaction of Neuroscience and Data science can develop neurally-inspired models that are more efficient than deep learning in use of data and energy.

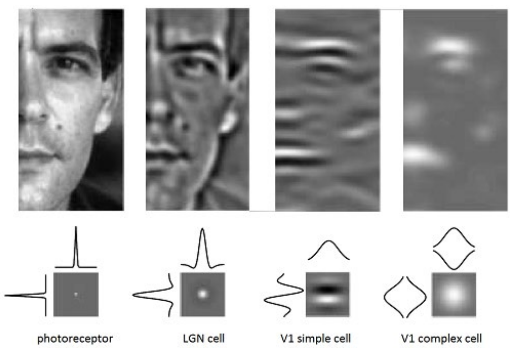
Funding: NIH R01 MH120037; NIH R01 MH052090;
ONR MURI N00014-16-1-2832; ONR MURI N00014-19-1-2571
Kilachand Fund Award

# Learned Dynamics Encode Temporal Expectations, and Also Something About ACh

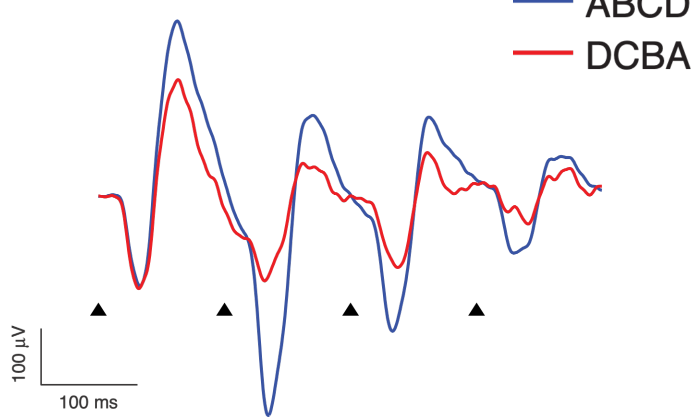

## Jeff Gavornik

Assistant Professor
Biology, CAS

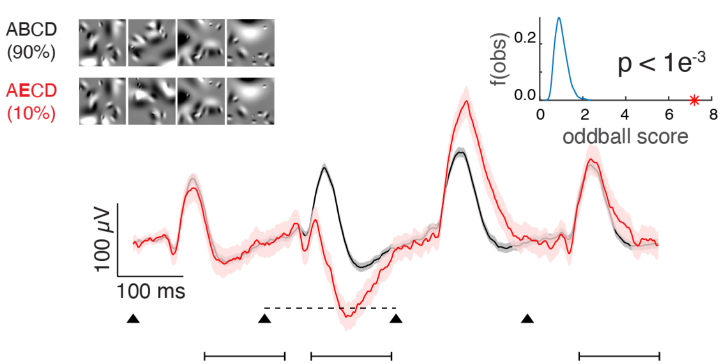
## Activity in the visual cortex represents features in visual space



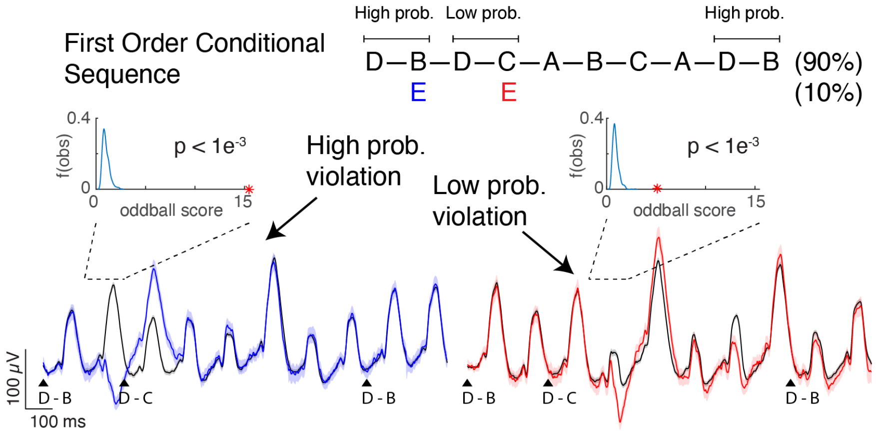

## But activity is also shaped by experience-dependent expectation



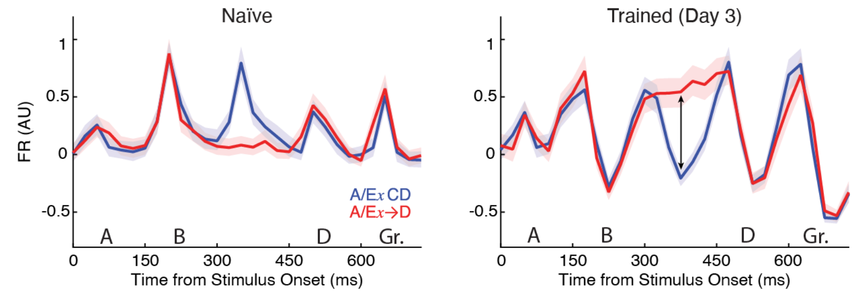

## At multiple timescales



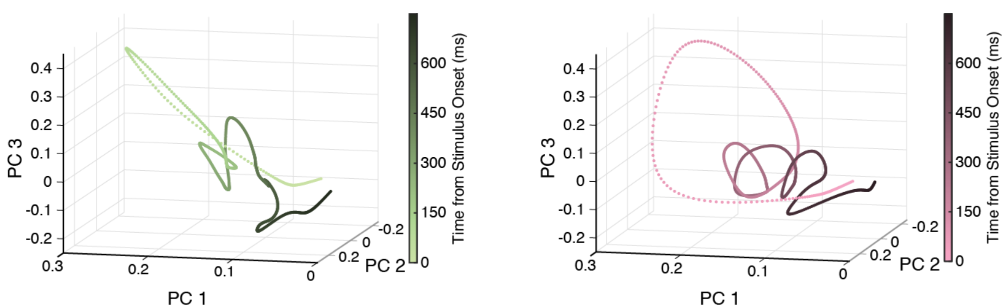
# May directly represent probability

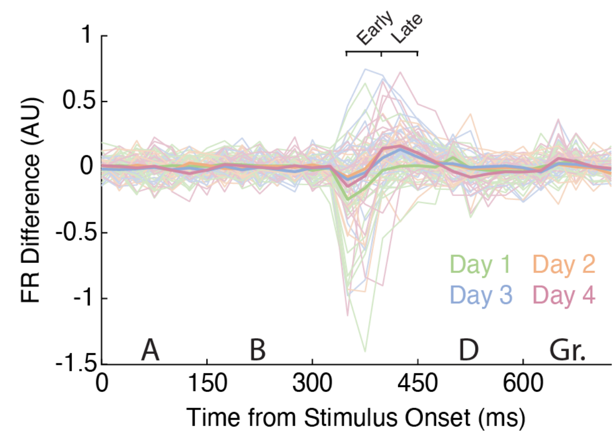



# Predict temporal content through local network mechanisms

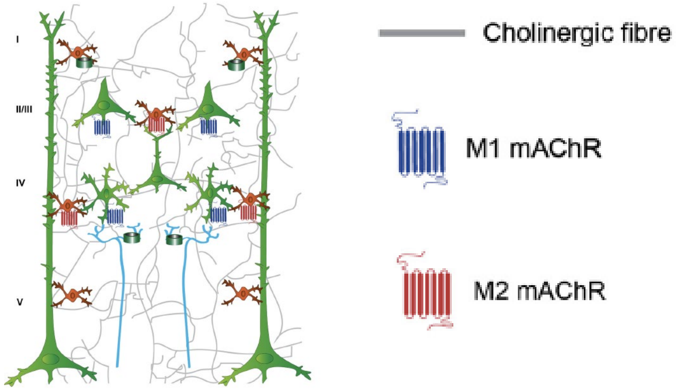


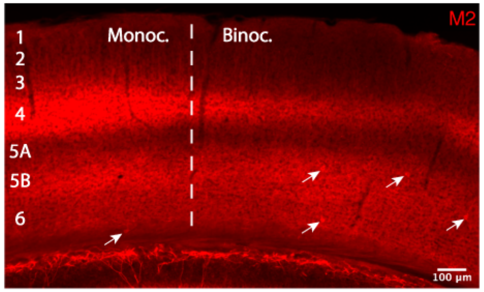

# May create temporal bases

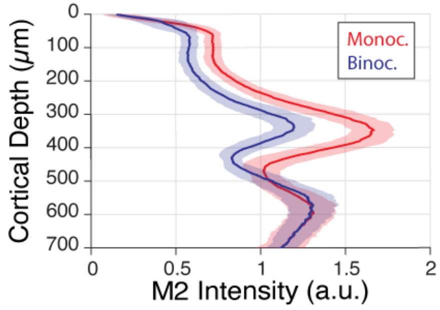


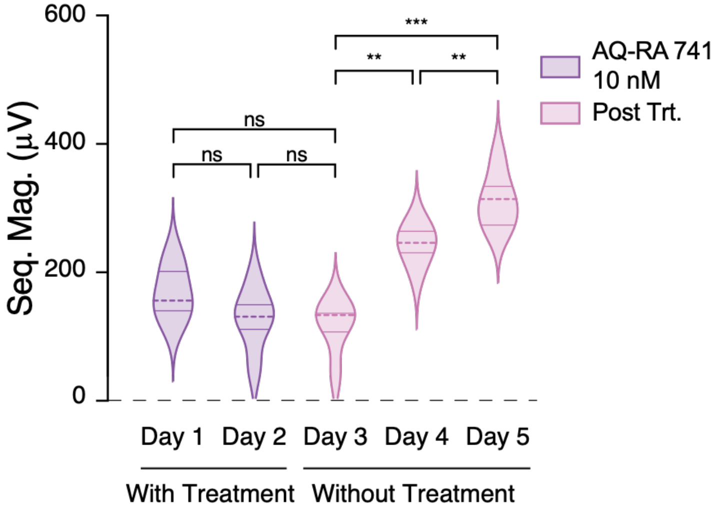



# Multi-day plasticity requires M2 ACh receptors




## And ACh activity in V1 is… interesting

# THANK YOU!