

# Predicting Behavior from Cortical Activity Recorded through Widefield Transcranial Imaging

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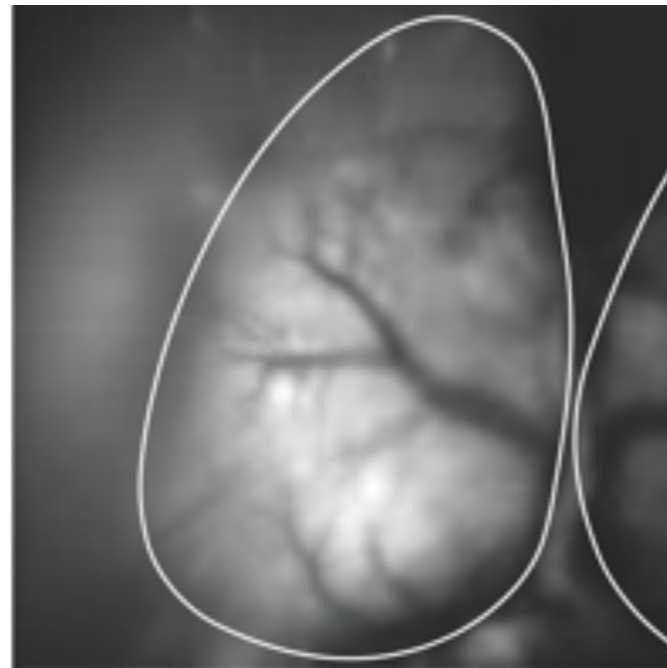
**This work was supported by Siemens, NSF, NJCBIR and NIH.**

05/16/2017

- **Introduction**
  - Background
  - Motivation
  - Overview
- **Experiment**
  - Setup
  - Data Collection
- **Analysis**
  - Visibility Graph
  - Feature Selection
  - Classification
- **Results and Conclusions**

- **Widefield Calcium Imaging**

- using GCaMP6f mice
- capable of imaging neural populations over large portions of the cerebral cortex
- enables longitudinal recording of neural activity
- offers high temporal resolution
- a powerful tool for studying the relationship between brain activity and behavior

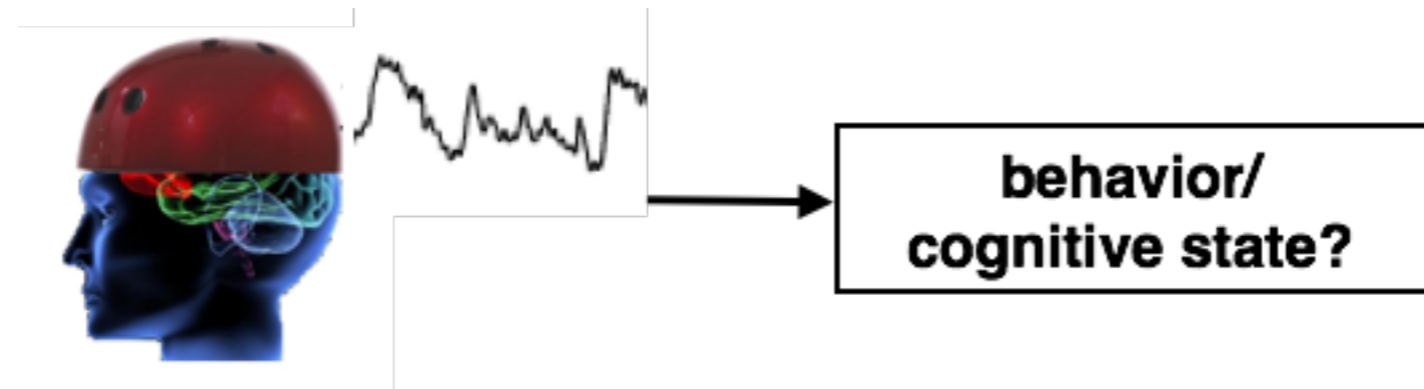


Minderer, Matthias, et al. "Chronic imaging of cortical sensory map dynamics using a genetically encoded calcium indicator." *The Journal of physiology* 590.1 (2012): 99-107.

Madisen, Linda, et al. "Transgenic mice for intersectional targeting of neural sensors and effectors with high specificity and performance." *Neuron* 85.5 (2015): 942-958.

- **Decoding Behavior**

- *goal*: inferring brain states/behavior from neuroimaging data

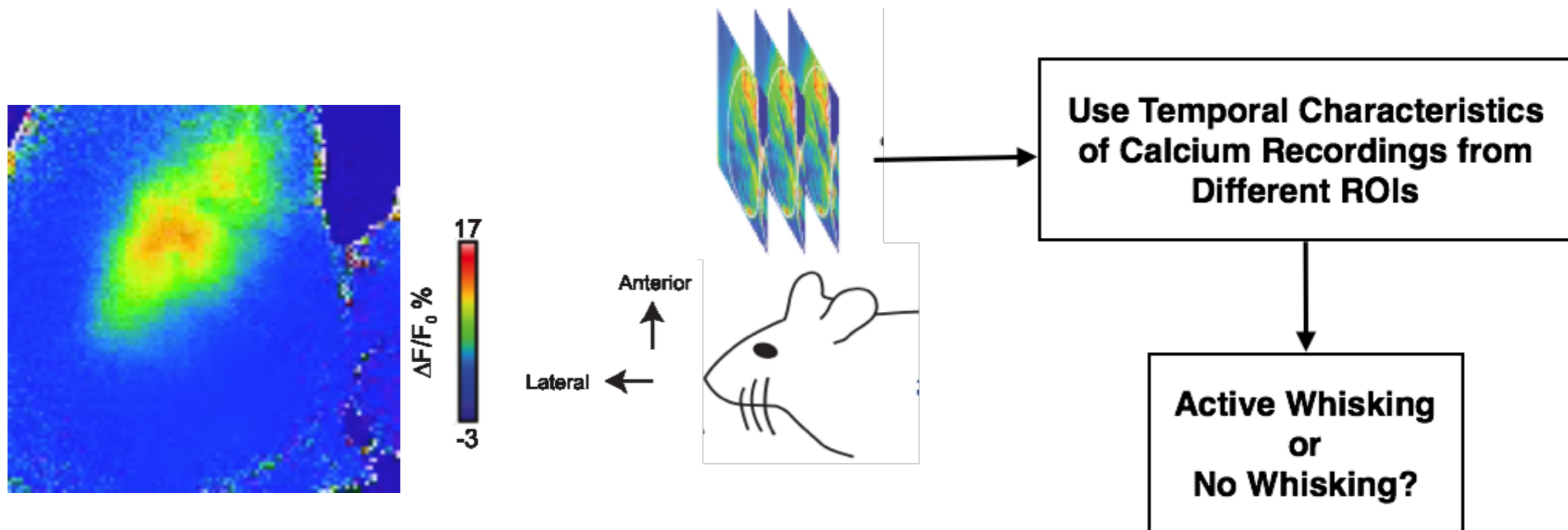


- many applications
  - helps in understanding the brain function and relationship to behavior
  - helps in developing predictive models of brain function
  - helps in identifying biomarkers of brain-related disorders
- several challenges
  - most existing work have looked at functional specificity
  - spatial information will aid only to decode few “distinct” cognitive processes
  - brain is dynamic and time variant

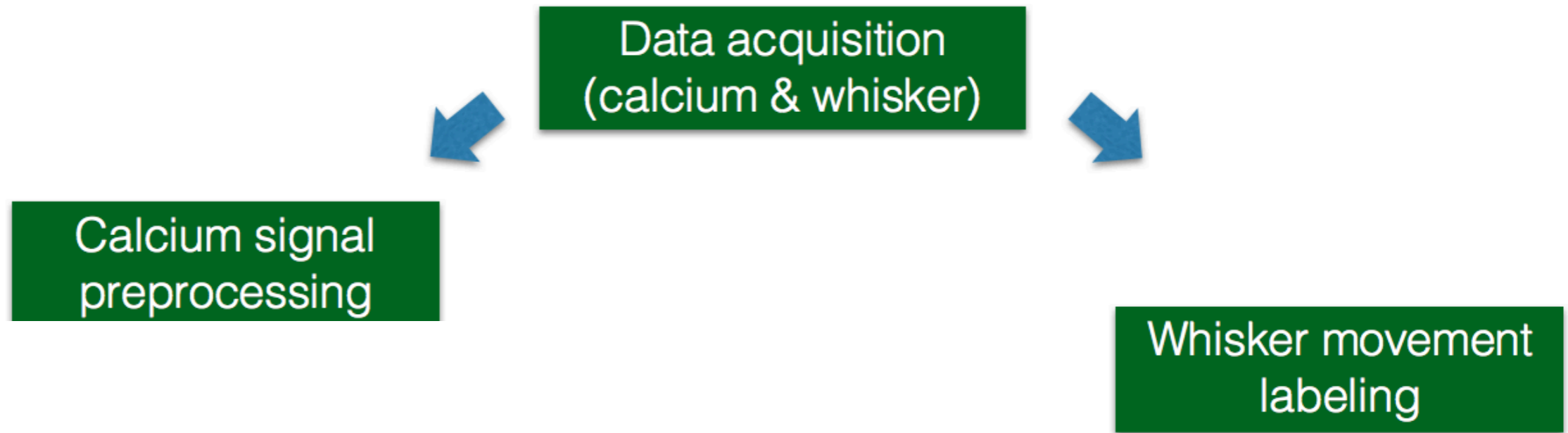
# Motivation

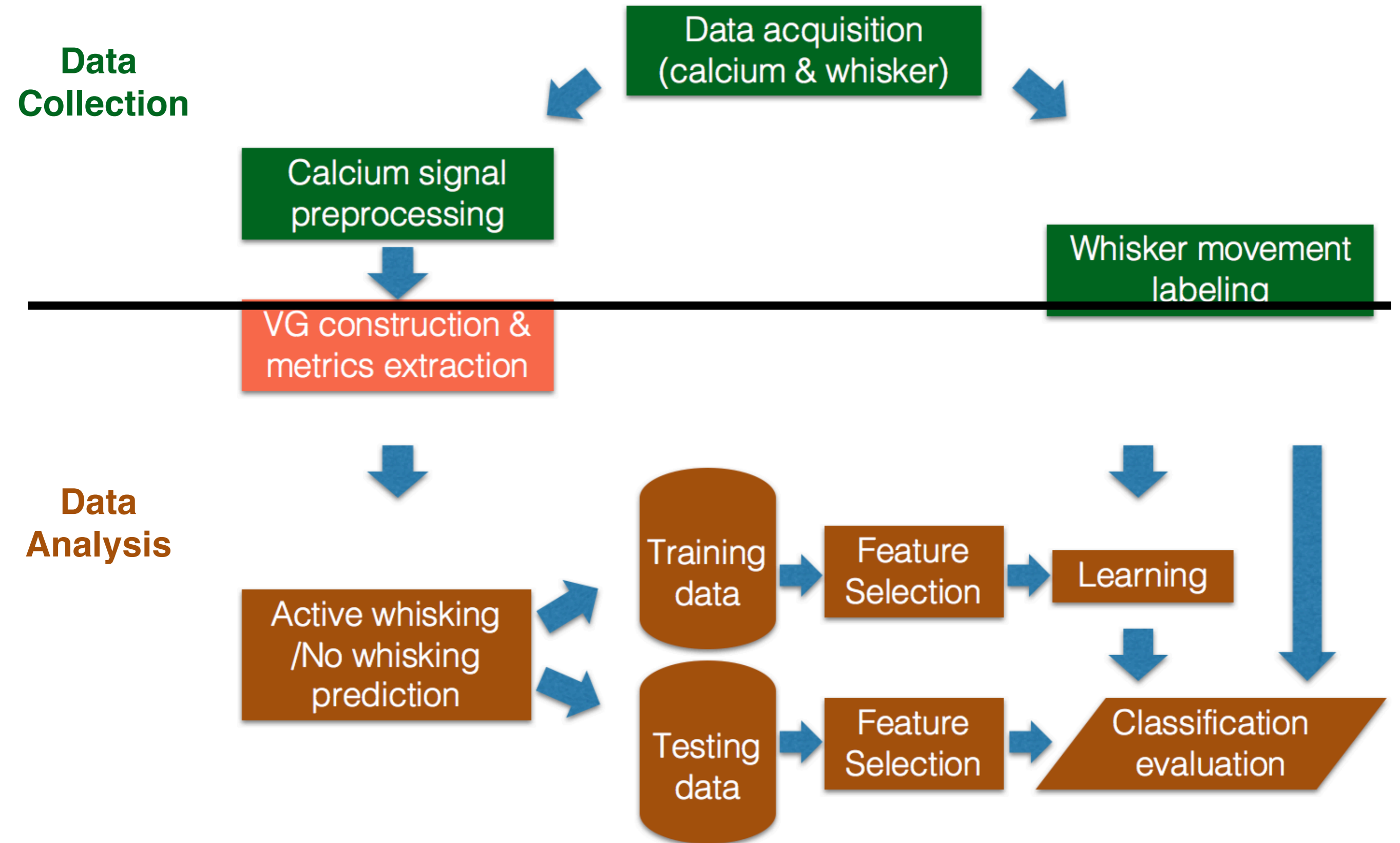
## • Decoding Behavior from Calcium Recordings

- can *temporal* characteristics of calcium recordings be used to predict behavior?
- behavior
  - active whisking (AW)
  - no whisking (NW)



## Data Collection





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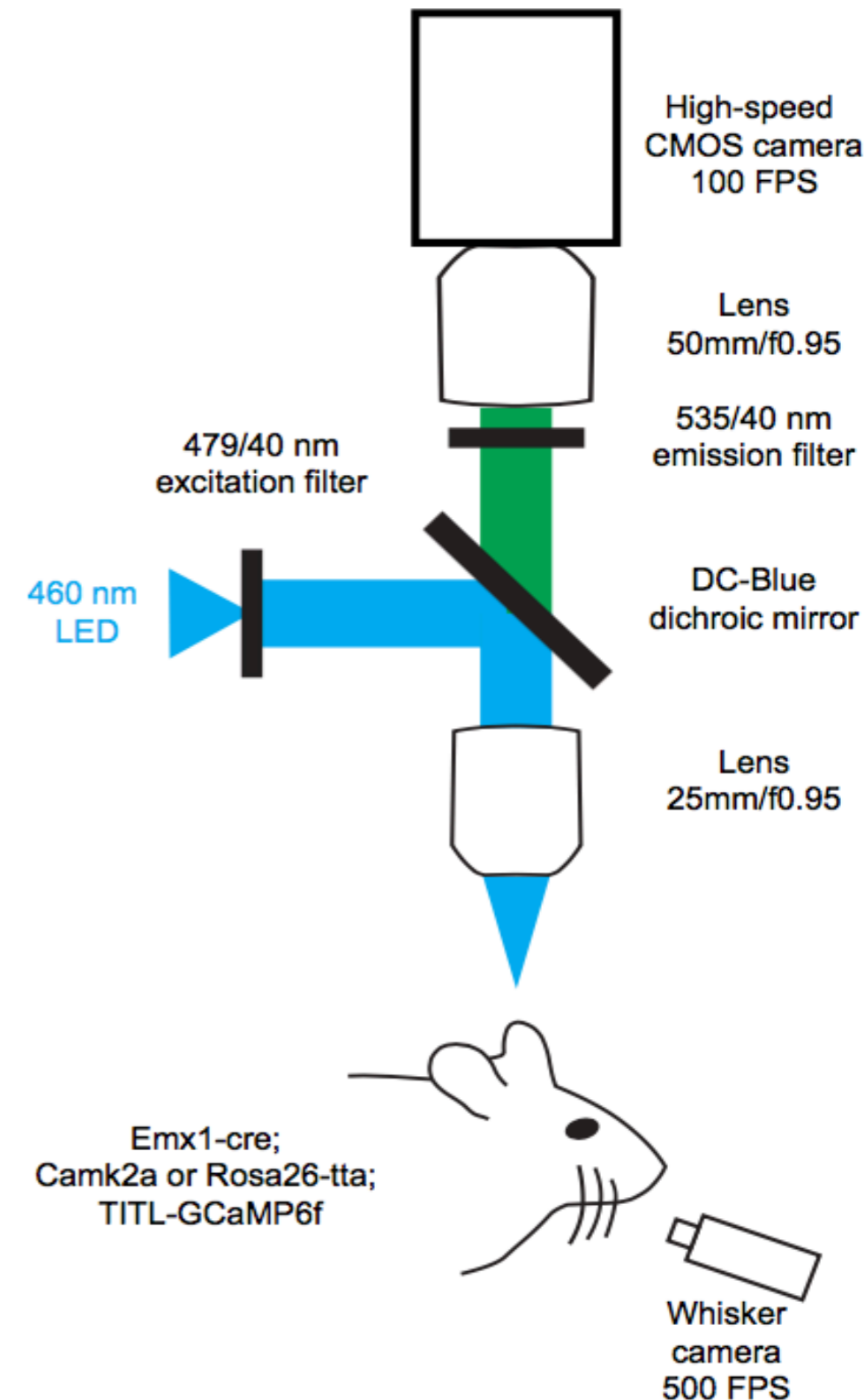
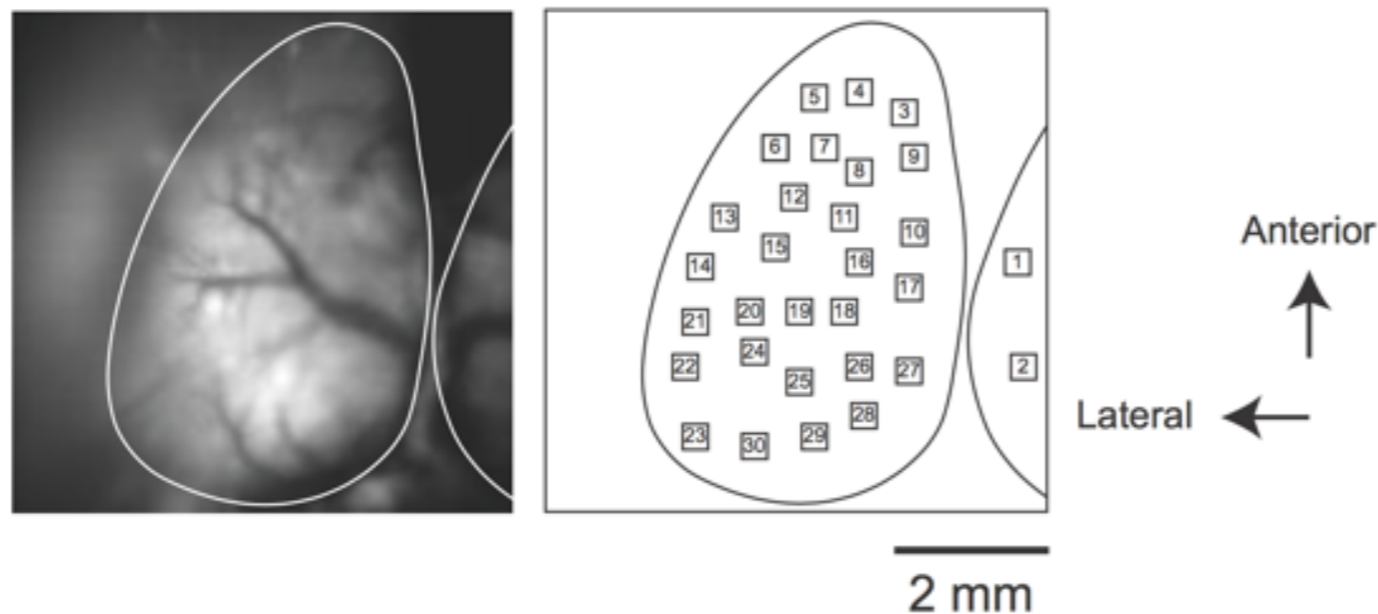
- **Results and Conclusions**



# Experimental Setup

## • Widefield Calcium Imaging

- head-fixed GCaMP6f mice
- entire left and mediate right hemisphere
- 100 x 100 pixels per frame
- sampling rate at 100 frames per second
- 30 ROI locations (5x5 pixels) were selected

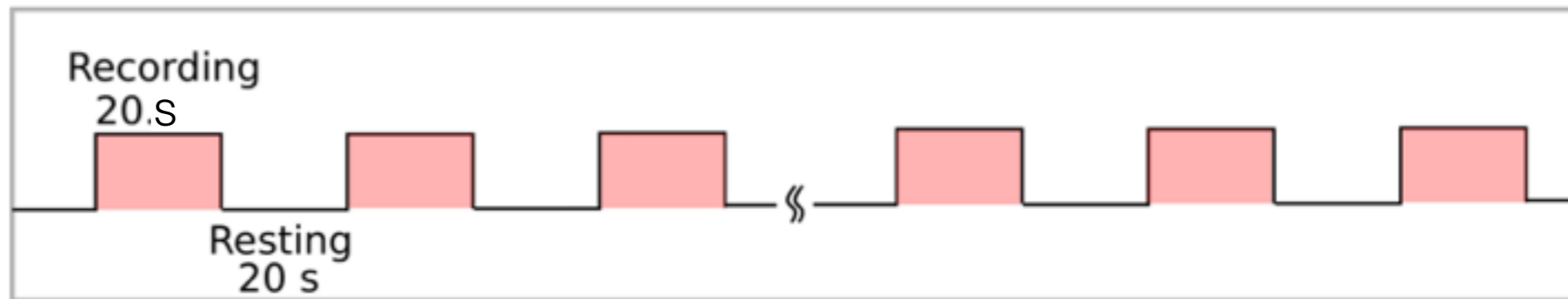


## • Whisker Movement Recoding

- simultaneously recorded at 500 frames per second

- **Paradigm**

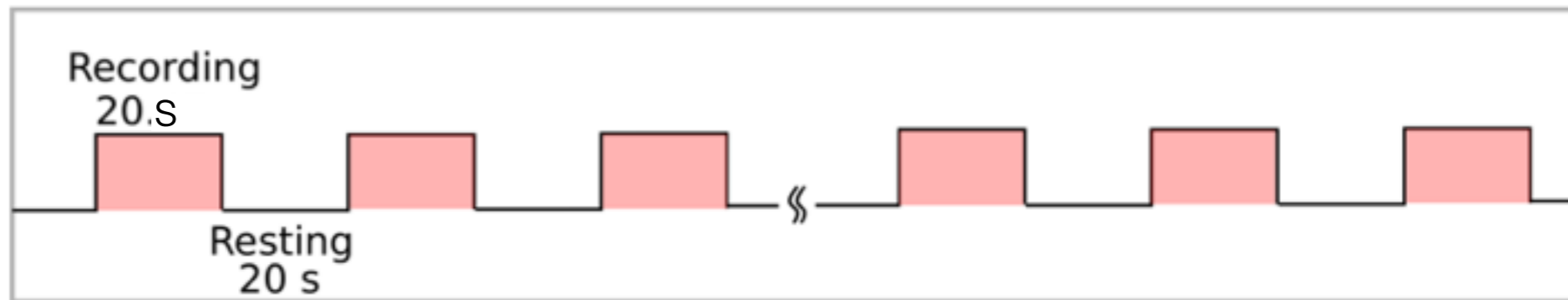
- 32 blocks with 20 second rest in between
- 6 mice participated



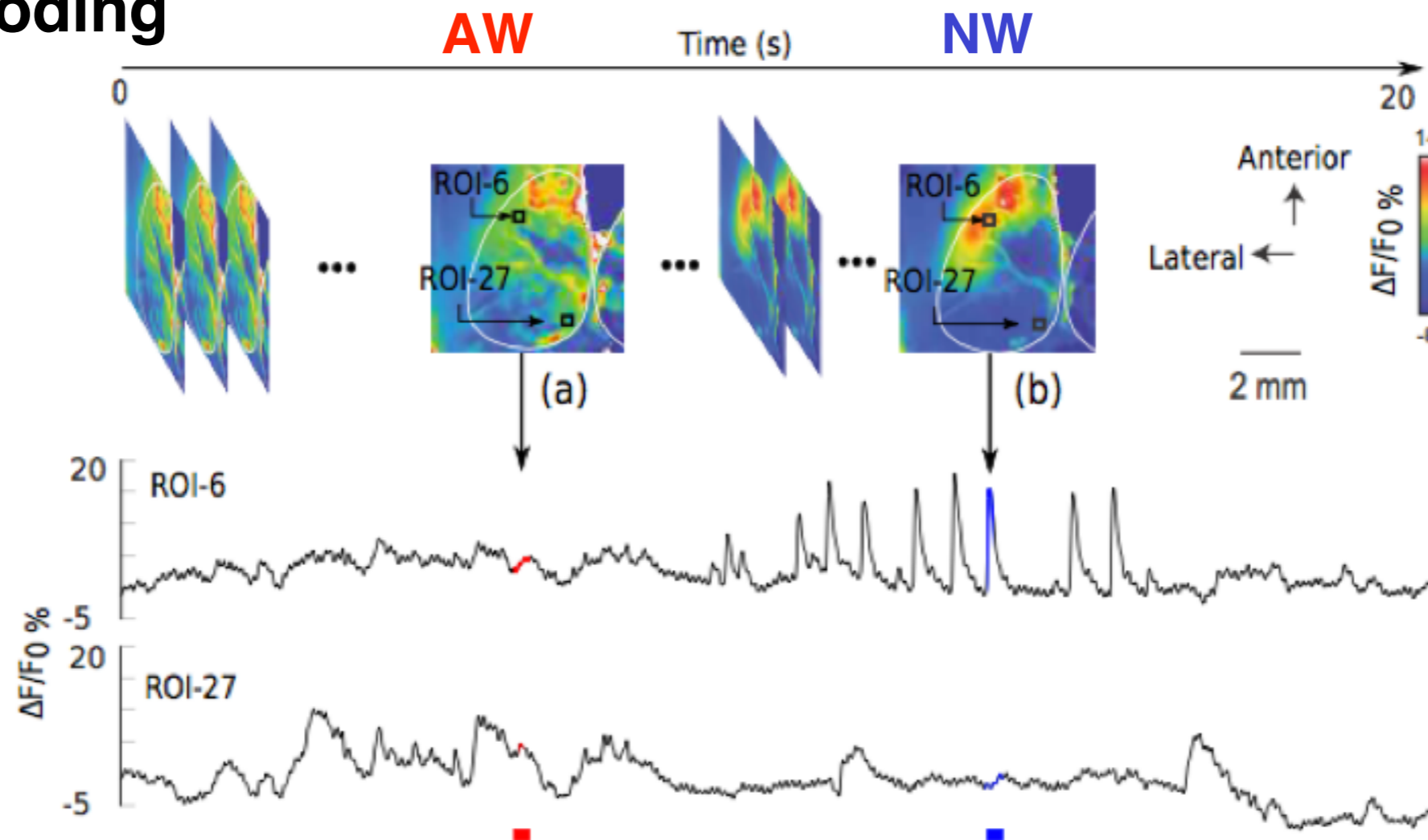
# Data Collection

- **Paradigm**

- 32 blocks with 20 second rest in between
- 6 mice participated



- **Sample Recoding**



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# Visibility Graph

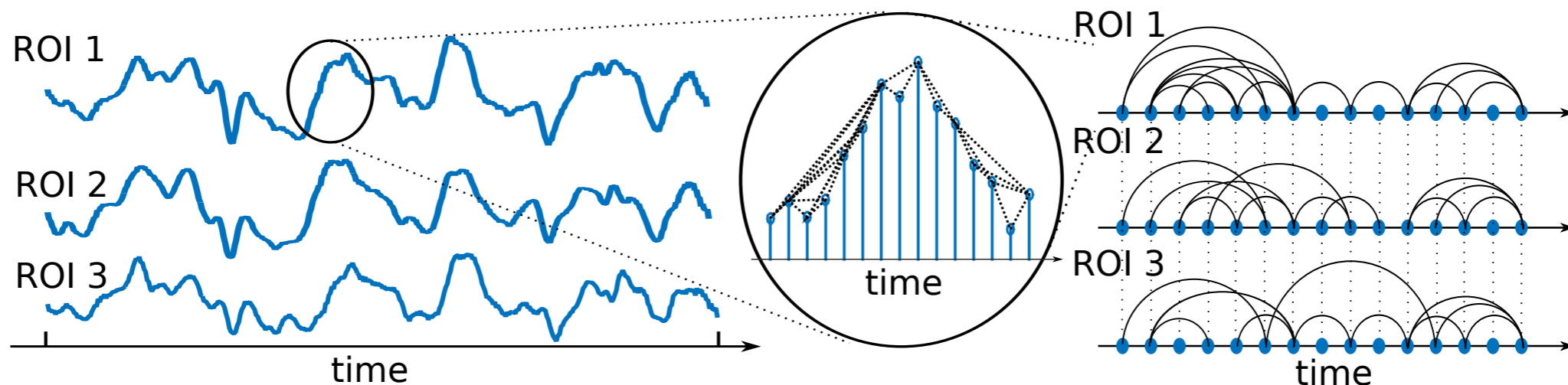
- **Maps a Time Series into a Graph**

- each point in time serves as a node in the graph
- nodes  $h$  and  $l$  are connected if for any point  $p$  ( $h < p < l$ ), we have

$$x(p) < x(l) + [x(h) - x(l)] \left[ \frac{t_l - t_p}{t_l - t_h} \right]$$

- **Reveals Dynamic Properties of Time Series**

- periodic signals result in regular graphs
- fractal time series result in scale-free networks

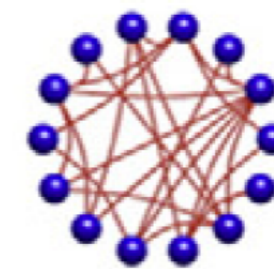


## • Topological Metrics of VG Quantify Characteristics of Time Series

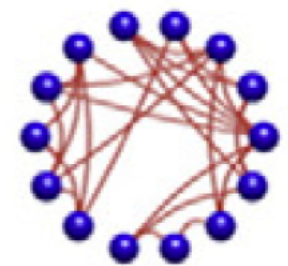
- edge density (K):

▸ related to number of existing edges in the graph

$$K = \frac{1}{N(N-1)} \sum_{i,j} a_{i,j}$$



high

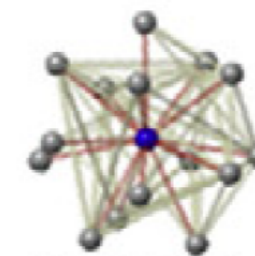


low

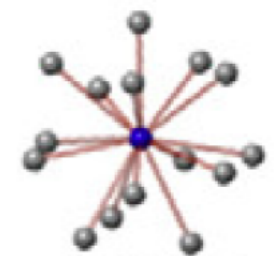
- averaged clustering coefficient (C):

▸ average of local clustering coefficients

$$C = \frac{1}{N} \sum_{i=1}^N C_i = \frac{1}{N} \sum_{i,j,l} \frac{a_{ij}a_{il}a_{jl}}{K_i(K_i-1)}$$



high

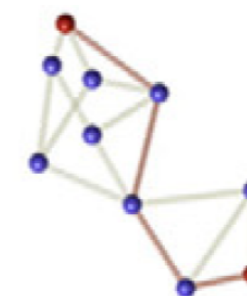


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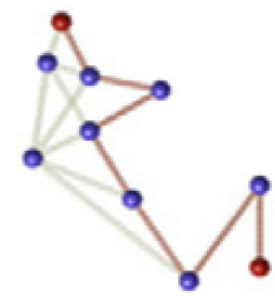
- characteristic pathlength (L):

▸ averaged shortest pathlength between all node pairs

$$L = \frac{1}{N(N-1)} \sum_{i,j} l_{i,j}$$



short

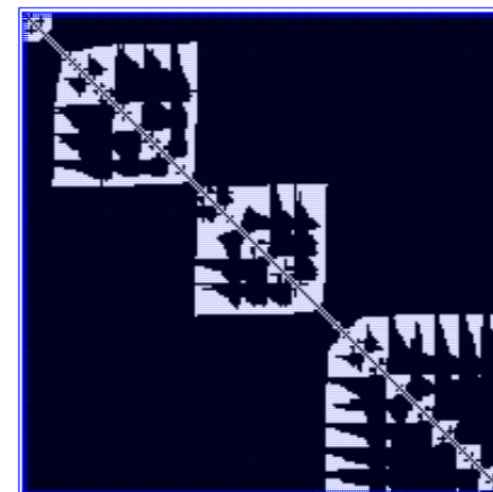
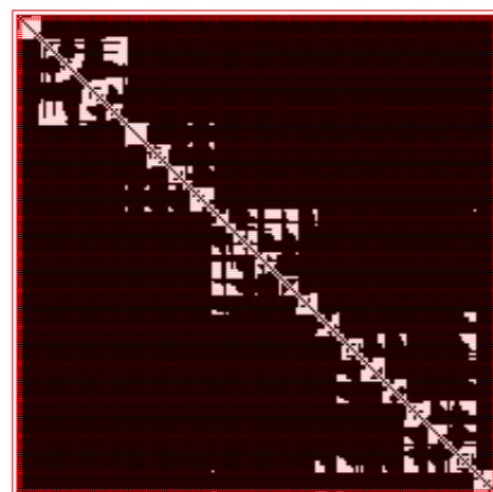
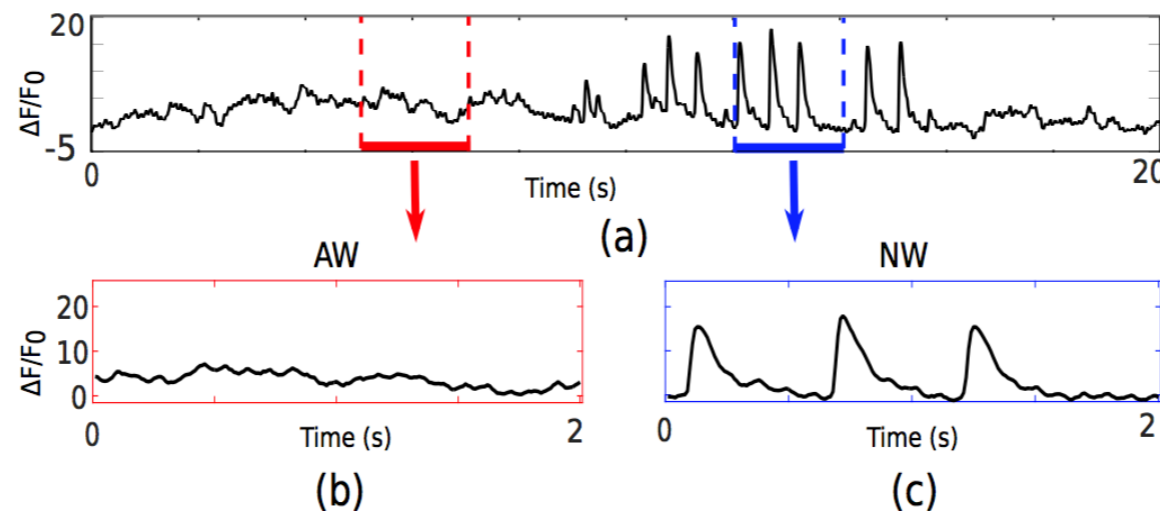
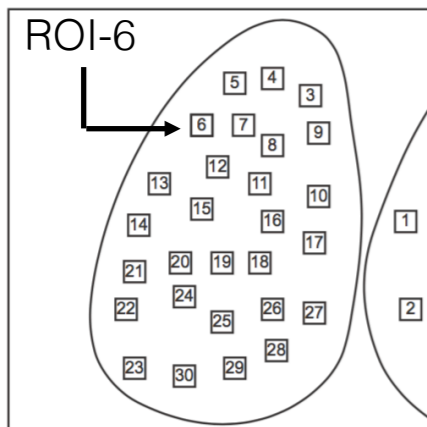


long

# Feature Selection

## • Procedure

- calcium recordings were first segmented using sliding windows
  - window length: 2 s
  - window step: 0.5 s
- VG was constructed for each segment and each ROI
- graph metrics were extracted from each VG

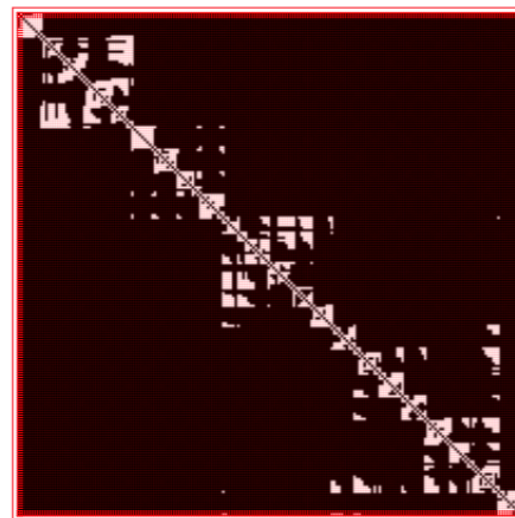
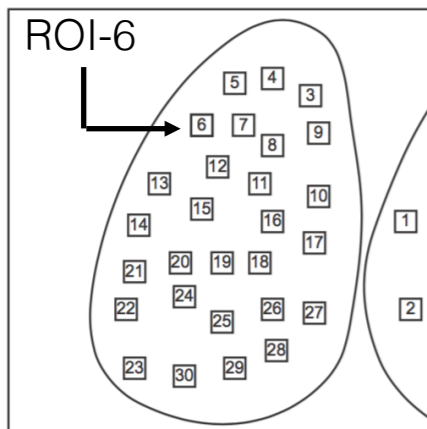




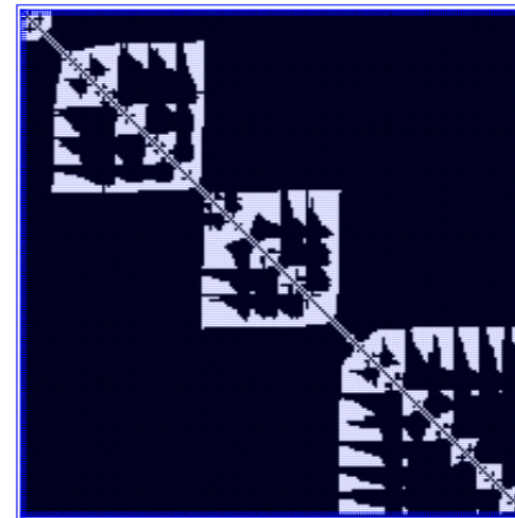
# Feature Selection

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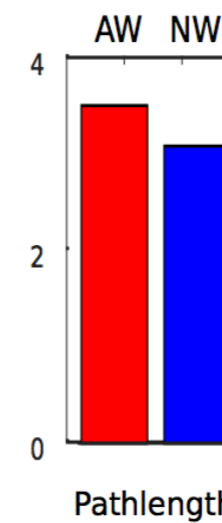
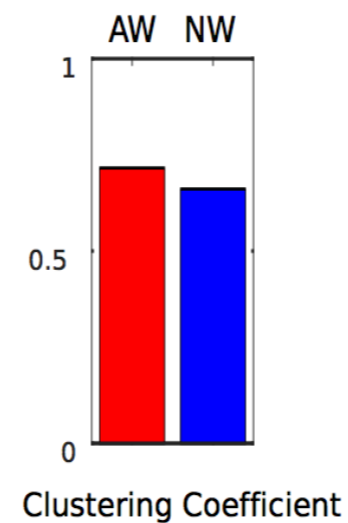
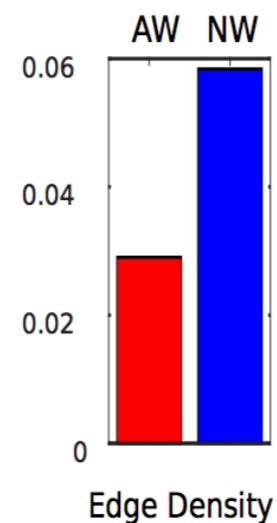
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(d)



(e)

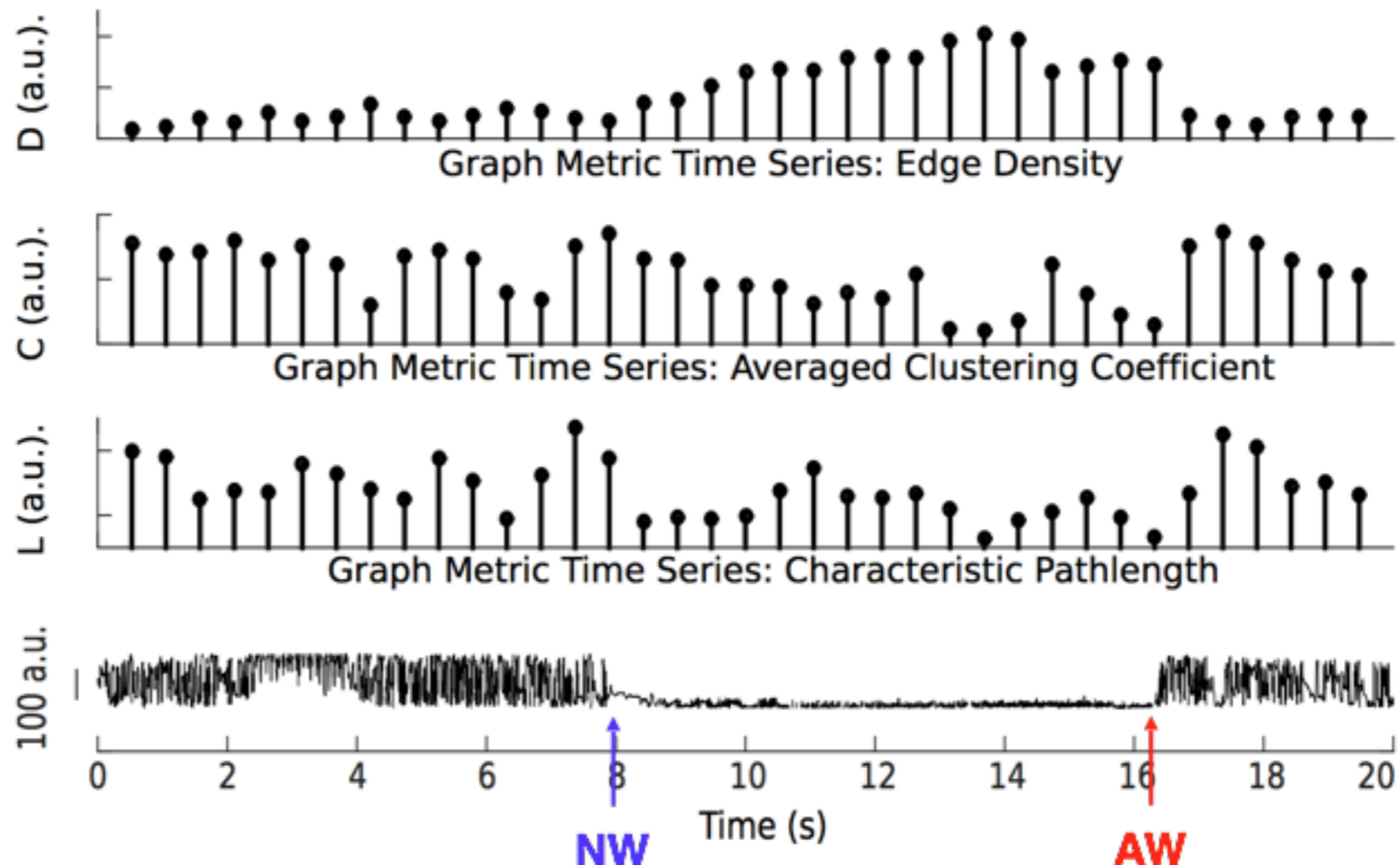
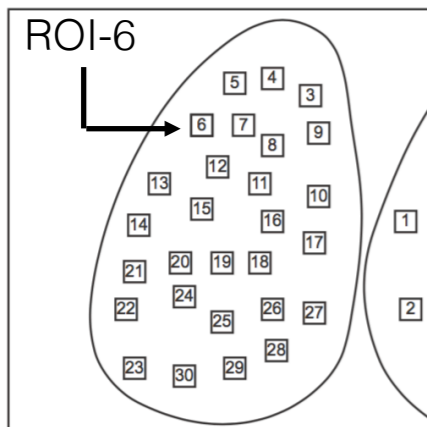




# Feature Selection

## • Procedure

- for each block, and each ROI, three new time series are obtained
- at each point, for each ROI, seven types of features are extracted
  - *individual metrics*: K or C or L
  - *joint metrics*: K&C or K&L or C&L or K&C&L
- feature vectors were formed by stacking selected graph metrics across ROIs



- **Classifier**
  - logistic regression with  $l_2$  regularization
- **Classification Experiments**
  - 10-fold cross validation: data were randomly partitioned into ten subsamples
  - nine subsamples were used to estimate the model parameters
  - remaining subsample was used to evaluate the performance
  - this procedure was repeated ten times
- **Evaluation Measures**
  - Accuracy
    - measure of correctly identified samples
  - Sensitivity
    - measure of correctly identified AW samples
  - Specificity
    - measure of correctly identified NW samples

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- **Overall**

- classification experiments delivered better-than-naive-classifier results

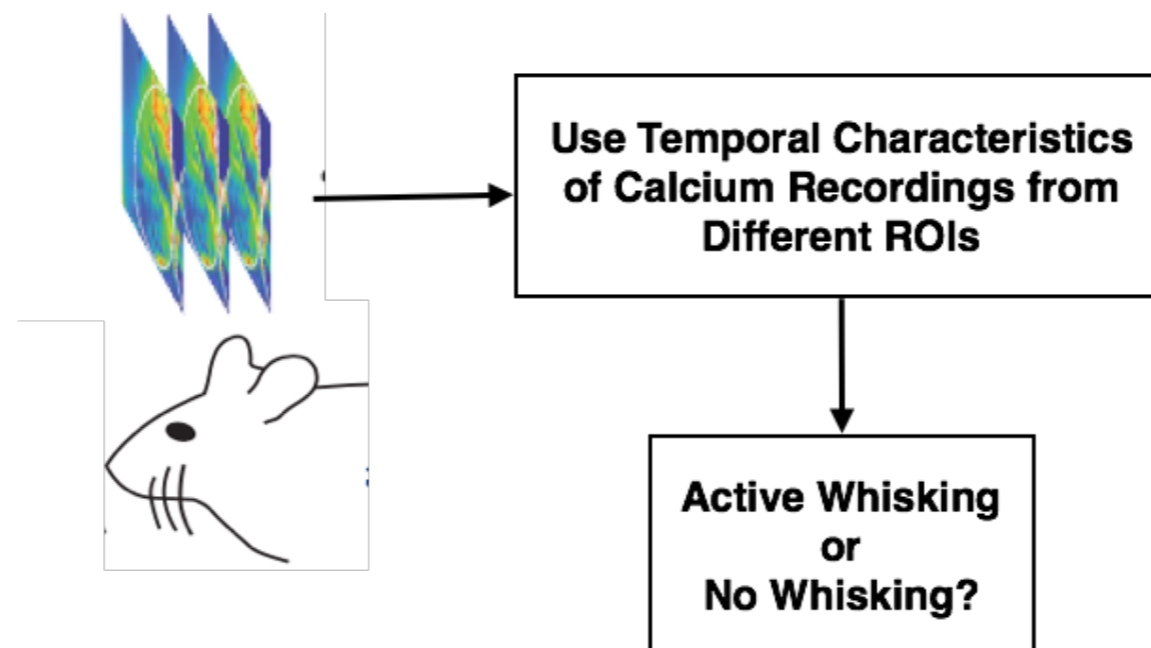
- **Features**

- edge density delivered the best performance

- results suggest that edge density carries the strongest discriminatory information among the three metrics

	Subject						Mean	SD
	1	2	3	4	5	6		
<b>Accuracy (%)</b>	89.66	88.75	88.14	84.70	88.39	91.83	<b>88.59</b>	2.33
<b>Sensitivity (%)</b>	72.36	89.54	67.53	75.89	68.30	55.58	<b>71.53</b>	11.18
<b>Specificity (%)</b>	94.02	88.37	93.64	89.43	93.89	97.49	<b>92.81</b>	3.36
<b>Feature</b>	<b>K</b>	<b>K&amp;C</b>	<b>K&amp;C&amp;L</b>	<b>K&amp;C</b>	<b>K&amp;C</b>	<b>K&amp;C</b>		

- **Widefield Imaging Was Used to Record Cortical Activity in GCaMP6f Mice during Active Whisking and No Whisking**
- **A VG-based Approach Was Proposed for Predicting the Behavior from Recorded Calcium Signals**
- **We Demonstrated that Temporal Characteristics of Calcium Recordings can be Utilized to Predict Behavior**
- **Future Work Include Considering a More Diverse Range of Behavior**



***Thank You!***