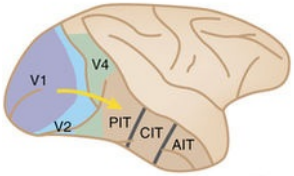
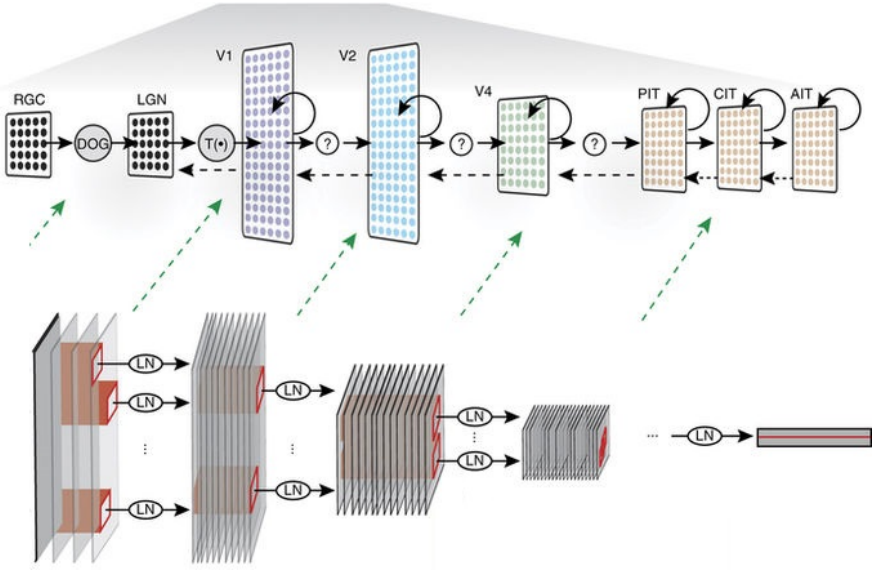
Decoding the neural algorithms that underlie behavior

Ethan Meyers

CENTER FOR
Brains
Minds+
Machines

Beyond feedforward processing

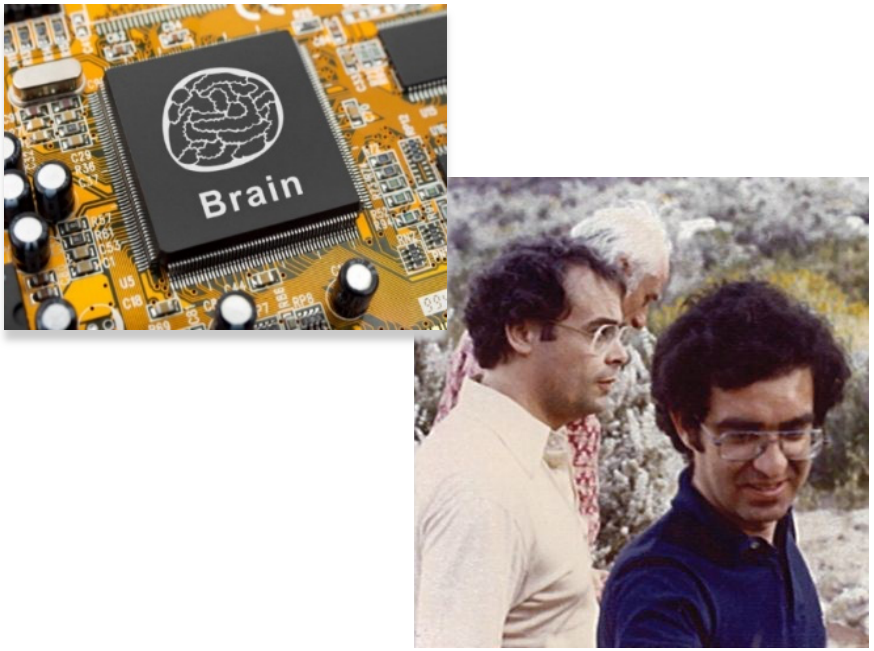


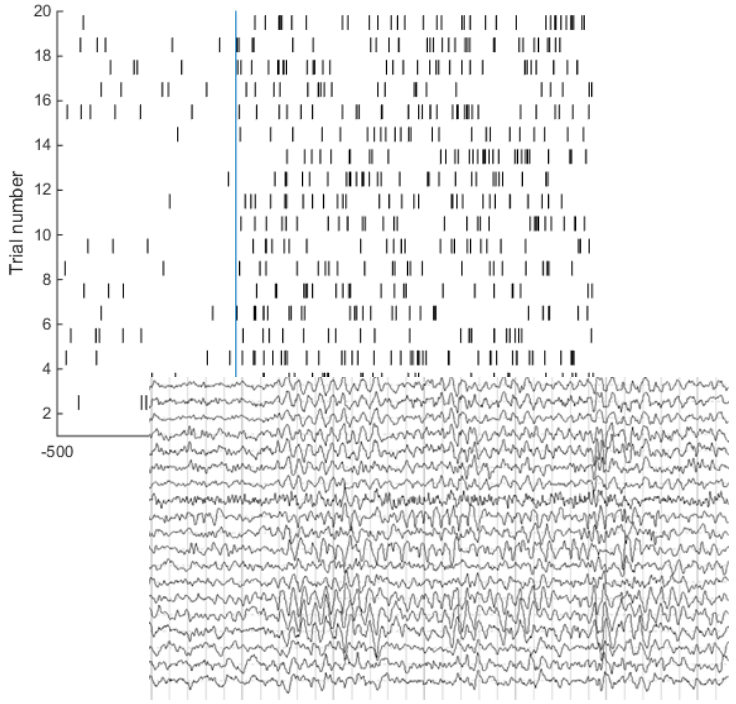


Yamins & DiCarlo, 2016
Serre et al, 2007

Homunculus in the Cartesian theater

Understanding neural algorithms





Understanding neural algorithms
that underlie behavior

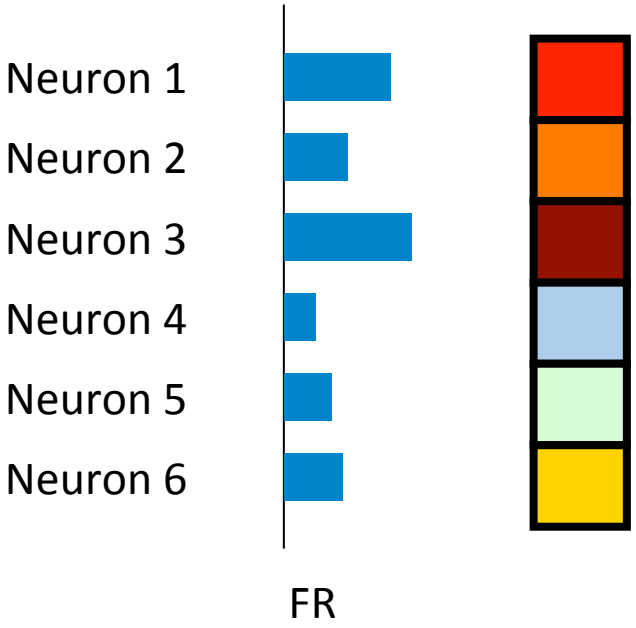
How can we convert messy data useful information?

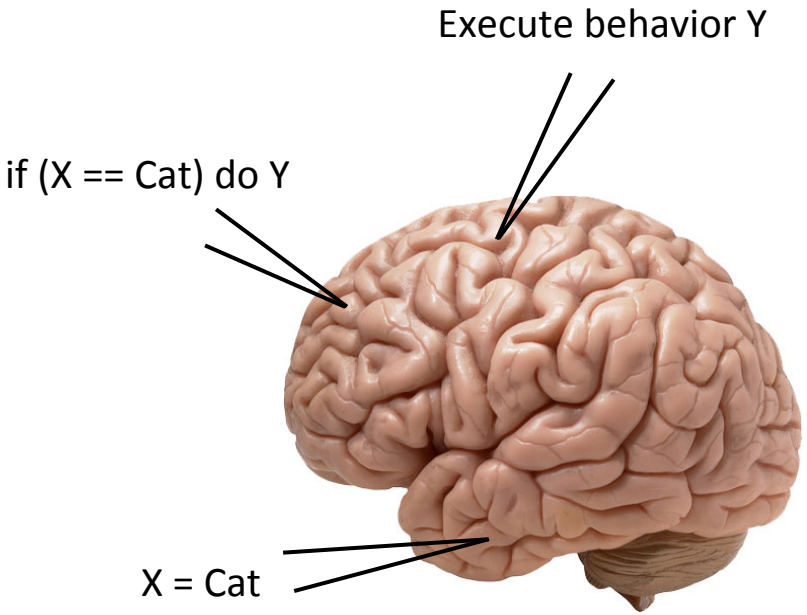
- Neural content: what information is in a brain region at a given time
- Neural coding: what features of neural activity contain information

Understanding neural algorithms

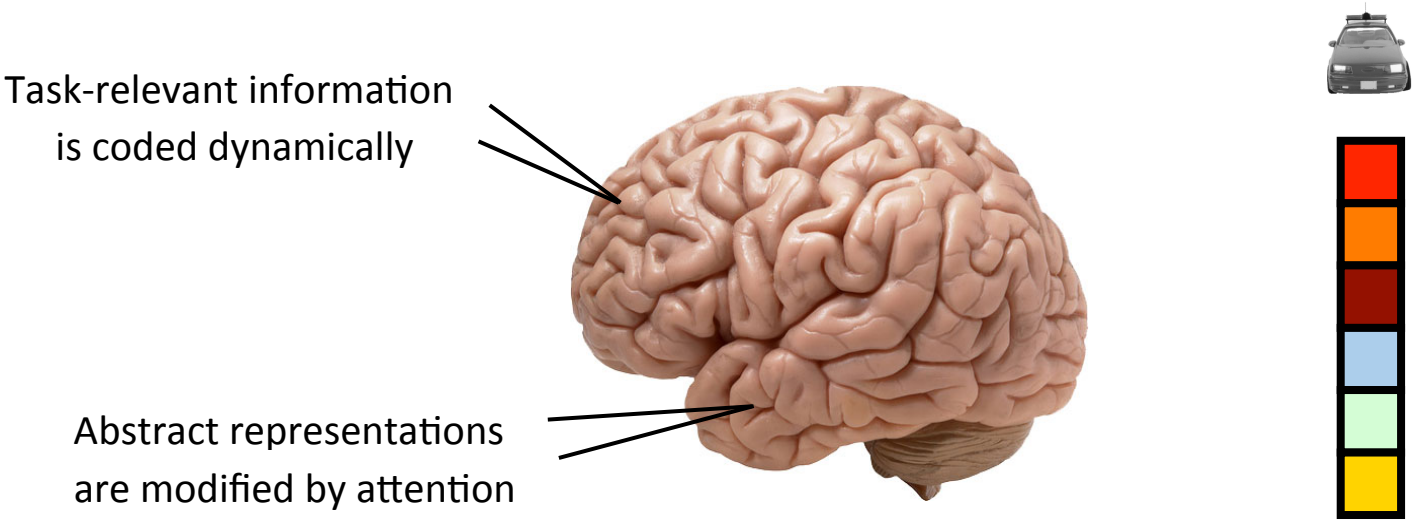
Information is contained in *patterns* of neural activity

We can use *neural decoding* to understand how information is being transformed as it travels through the brain



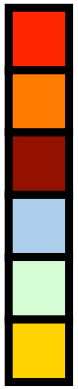


Talk outline



1. The basics of neural decoding
2. The sensory pathways create abstract representations
3. “Top-down attention” can modify these representations
4. Higher areas selectively represent task-relevant information
5. Information often is coded sparsely and dynamically
6. The flow of information can be traced through the brain

Talk outline



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Neural population decoding

Neural decoding predict stimuli/behavior from neural activity

f(neural activity) ⟶ stimulus

Decoding has been used for 30 years:

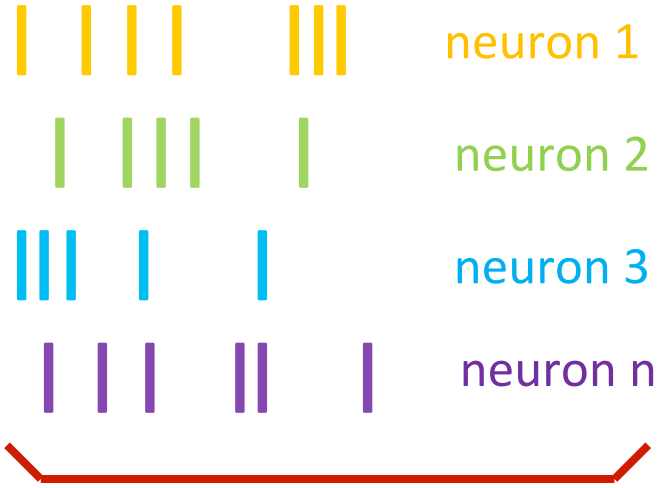
Motor system/BCIs
- e.g., Georgopoulos et al, 1986

Hippocampus
- e.g., Wilson and McNaughton, 1993

Computational work
- e.g., Salinas and Abbott, 1994

Decoding is called Multivoxel Pattern Analysis (MVPA) by the fMRI community

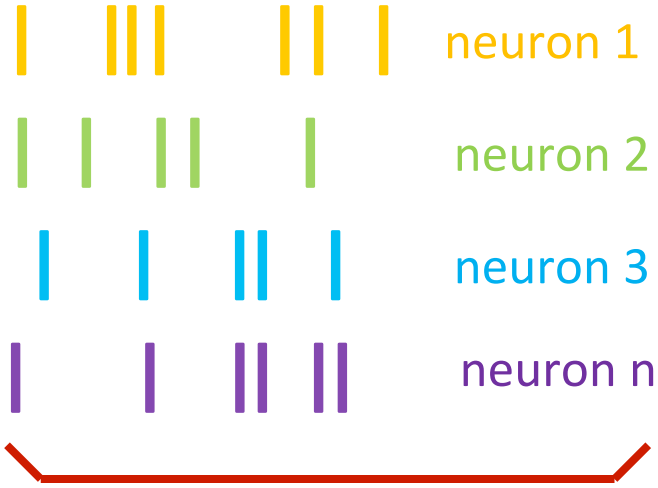
Training the classifier



Learning association between neural activity an image

Pattern Classifier

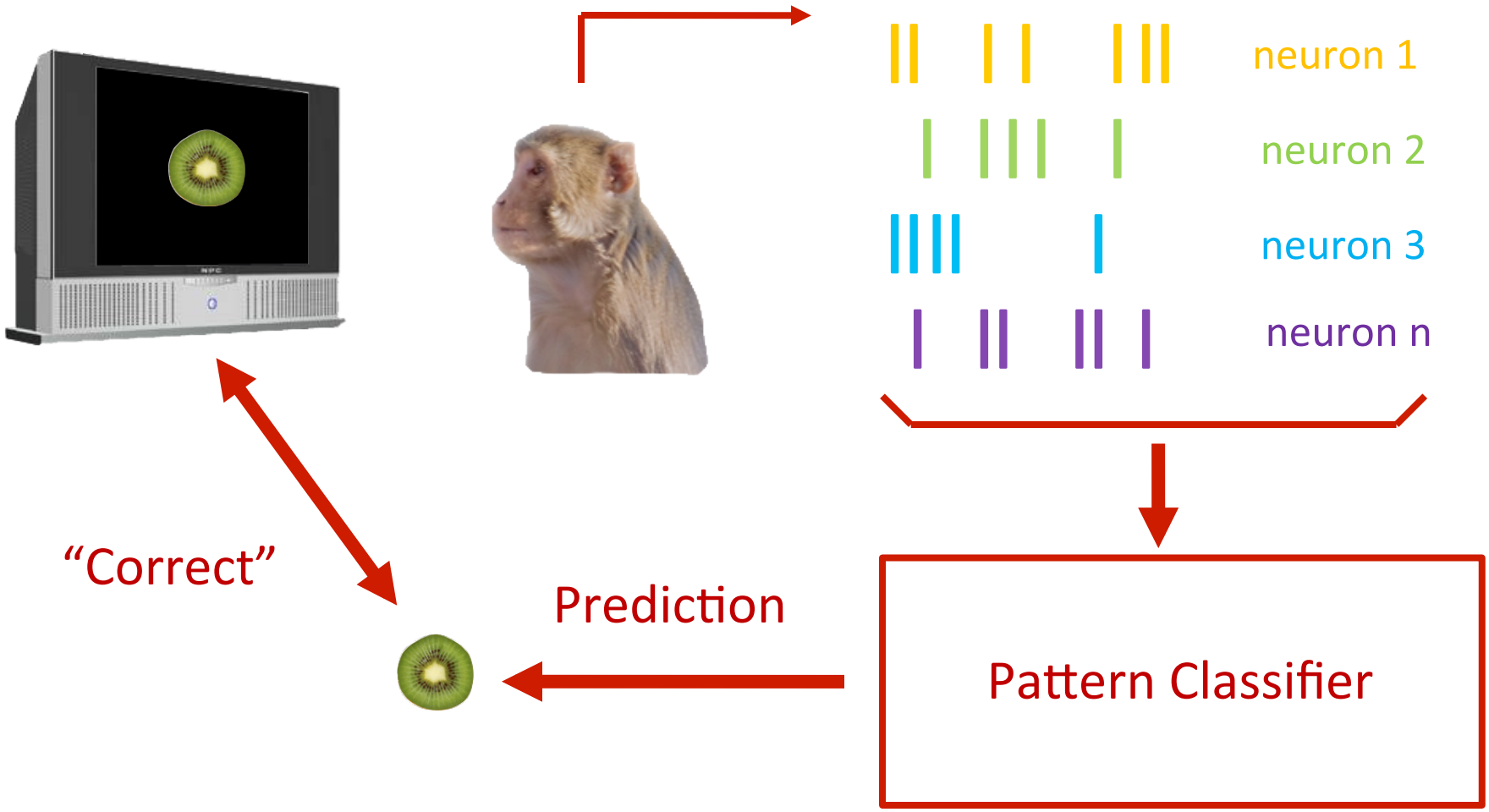
Training the classifier



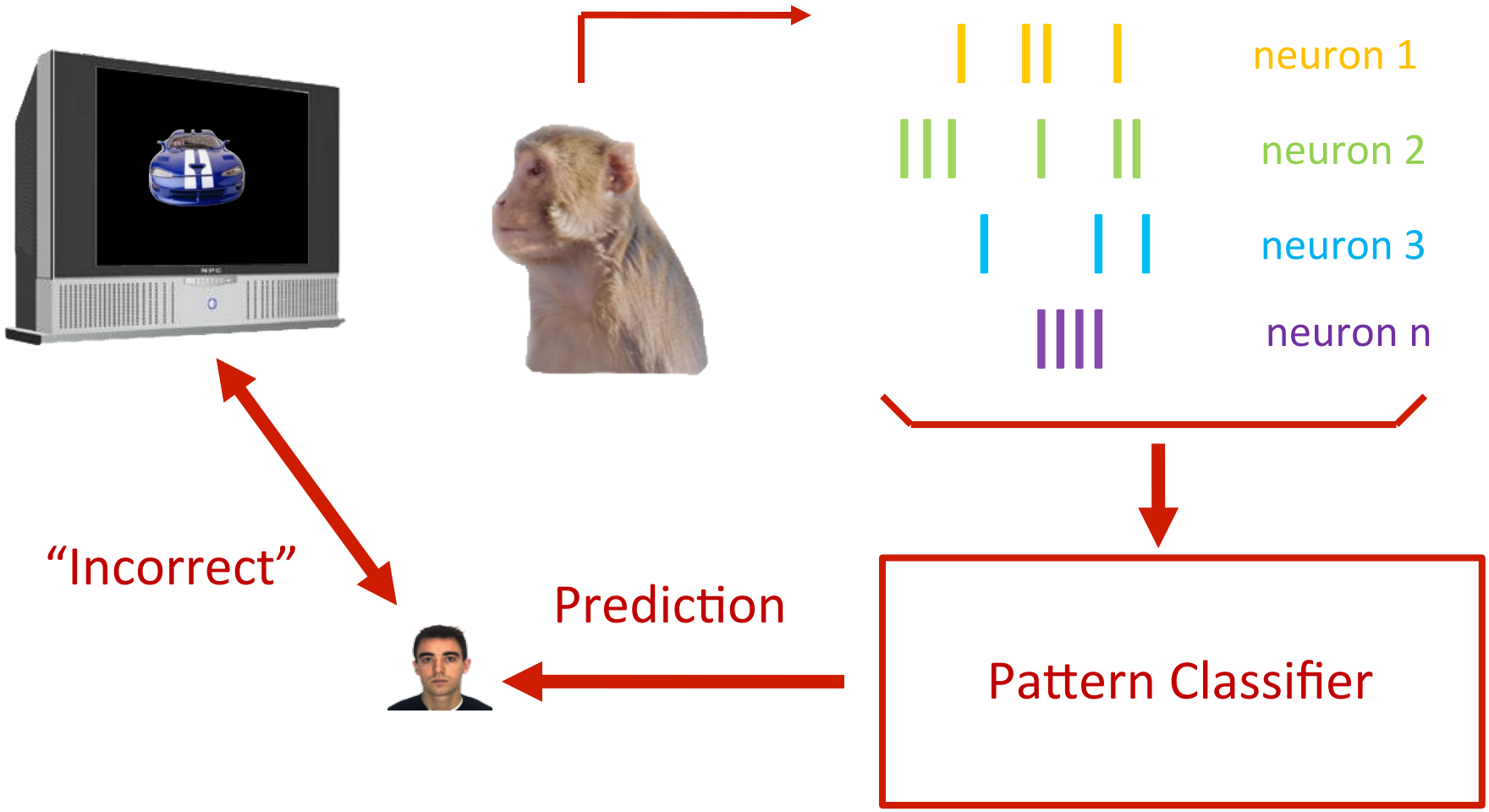
Learning association between neural activity an image

Pattern Classifier

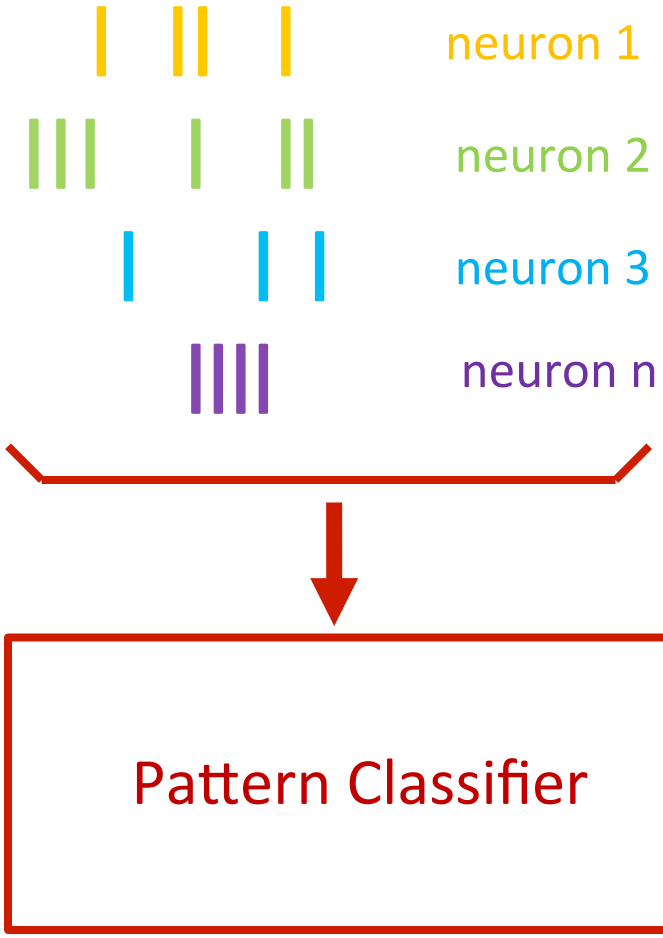
Using the classifier

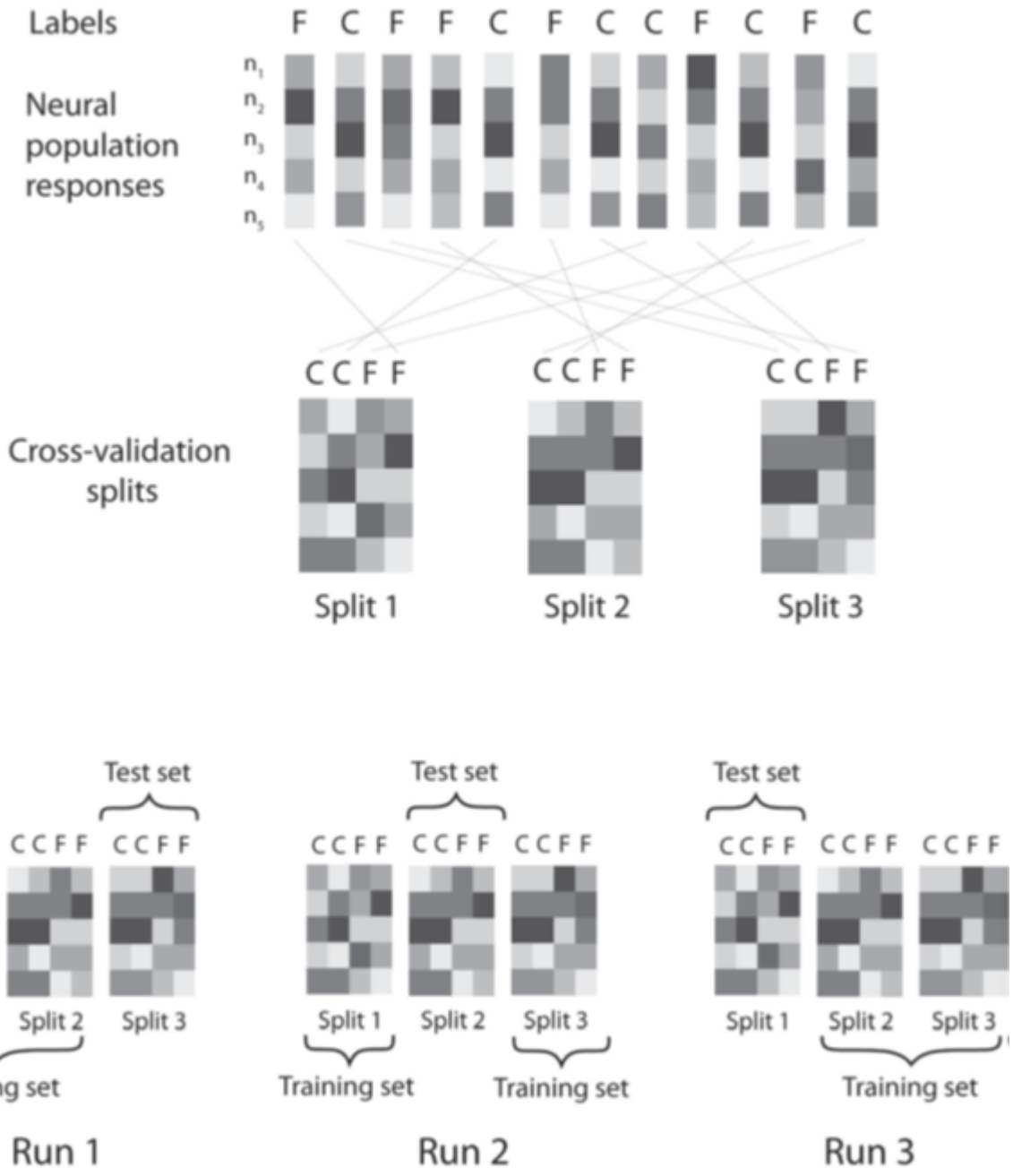


Using the classifier

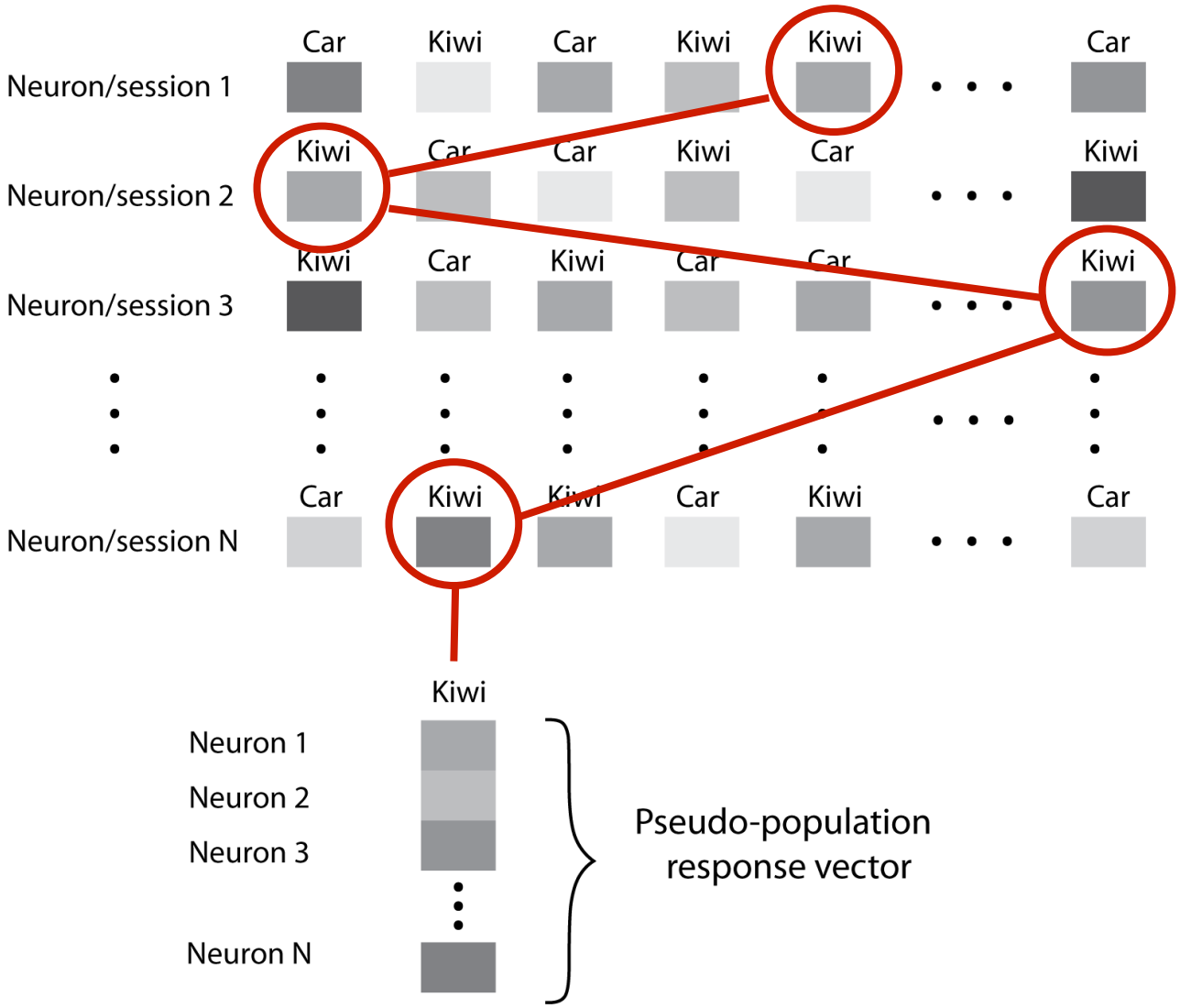


Using the classifier

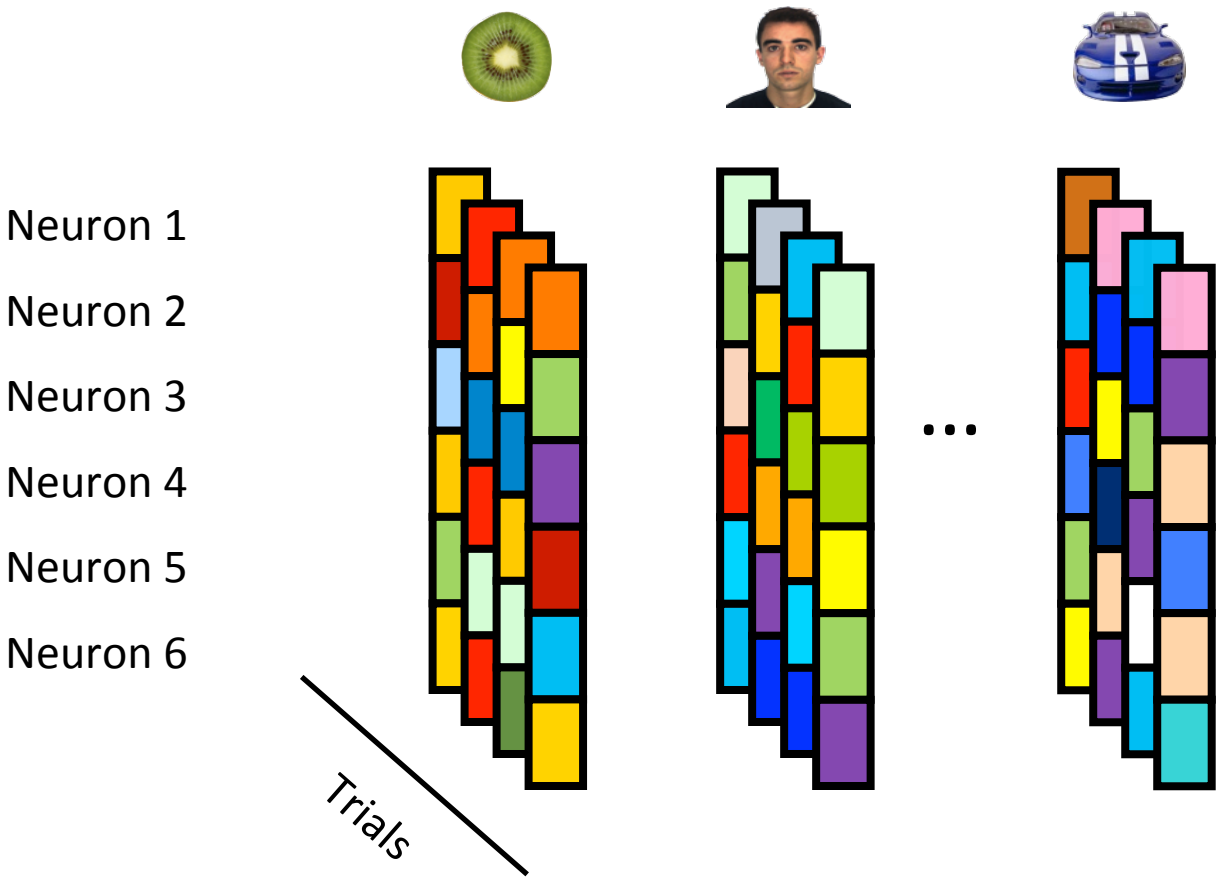



Labels
F C F F C F C C F C F C
Neural population responses
n1
n2
n3
n4
n5
Cross-validation splits
C C F F
C C F F
C C F F
Split 1
Split 2
Split 3
Test set
C C F F
C C F F
C C F F
Split 1
Split 2
Split 3
Training set
Run 1
Test set
C C F F
C C F F
C C F F
Split 1
Split 2
Split 3
Training set
Training set
Run 2
Test set
C C F F
C C F F
C C F F
Split 1
Split 2
Split 3
Training set
Run 3

Pseudo-populations



Maximum Correlation Coefficient Classifier



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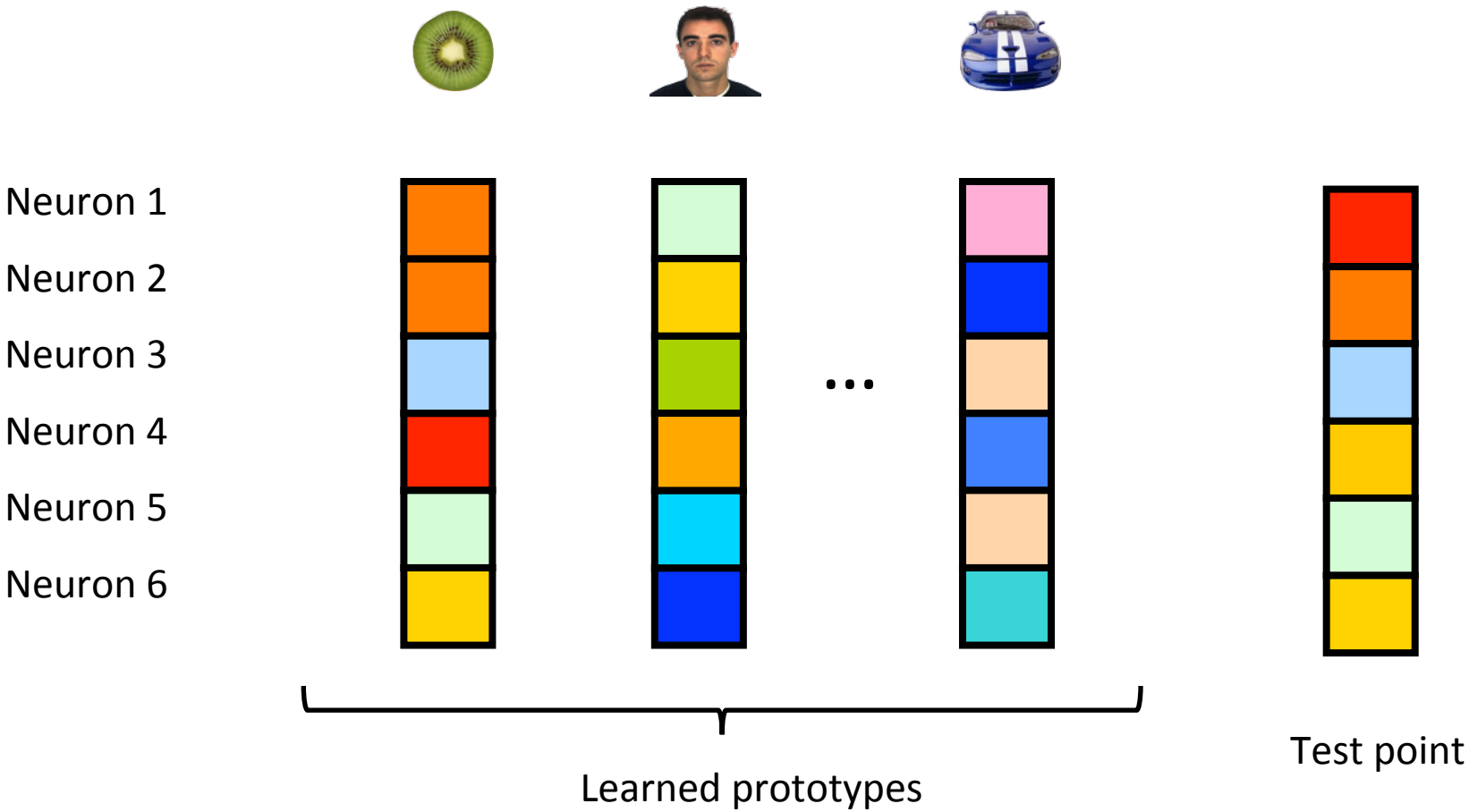
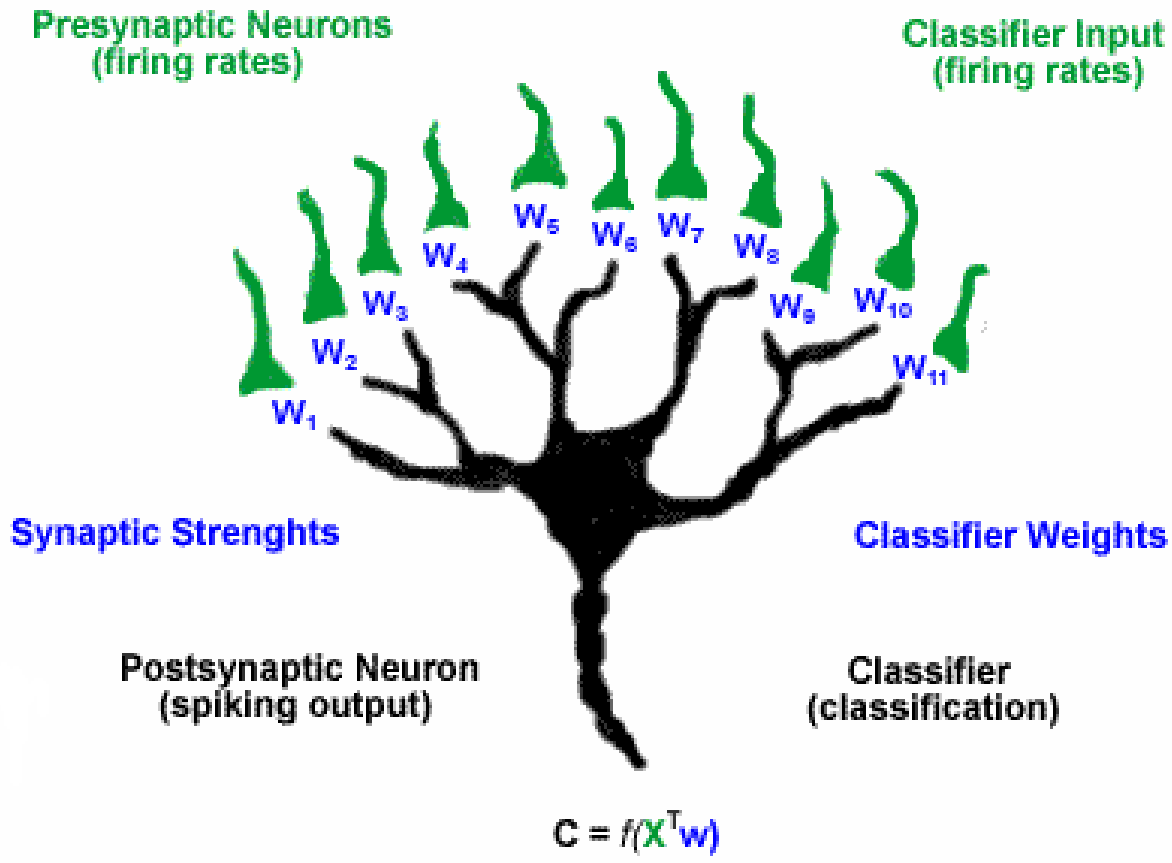
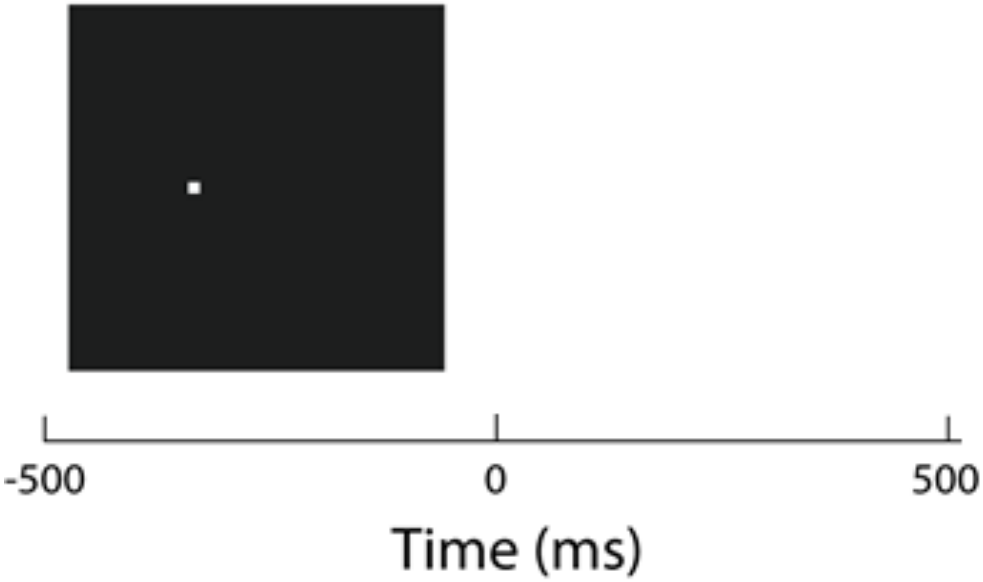
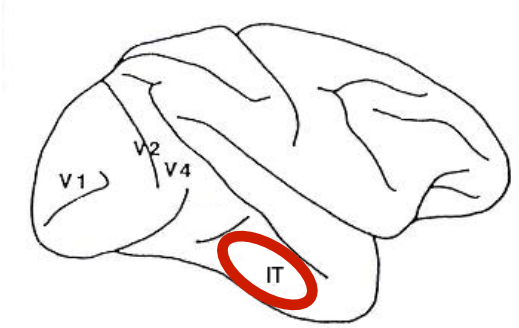


Decoding can be viewed as assessing the information available to downstream neurons



Decoding basics: A simple experiment



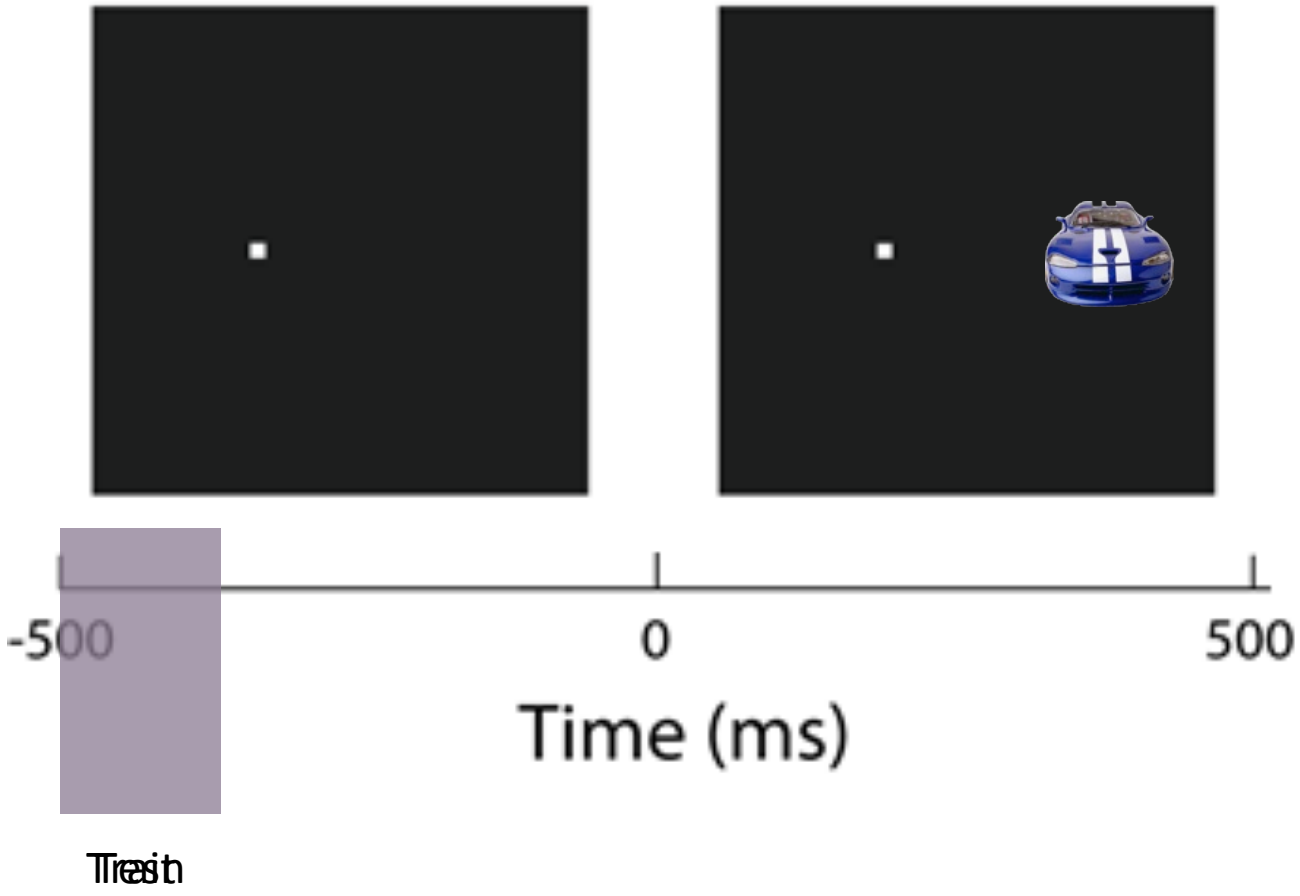


132 neurons recorded from IT

Seven objects:

Zhang, Meyers, Bichot, Serre, Poggio, and Desimone, PNAS, 2011

Applying decoding



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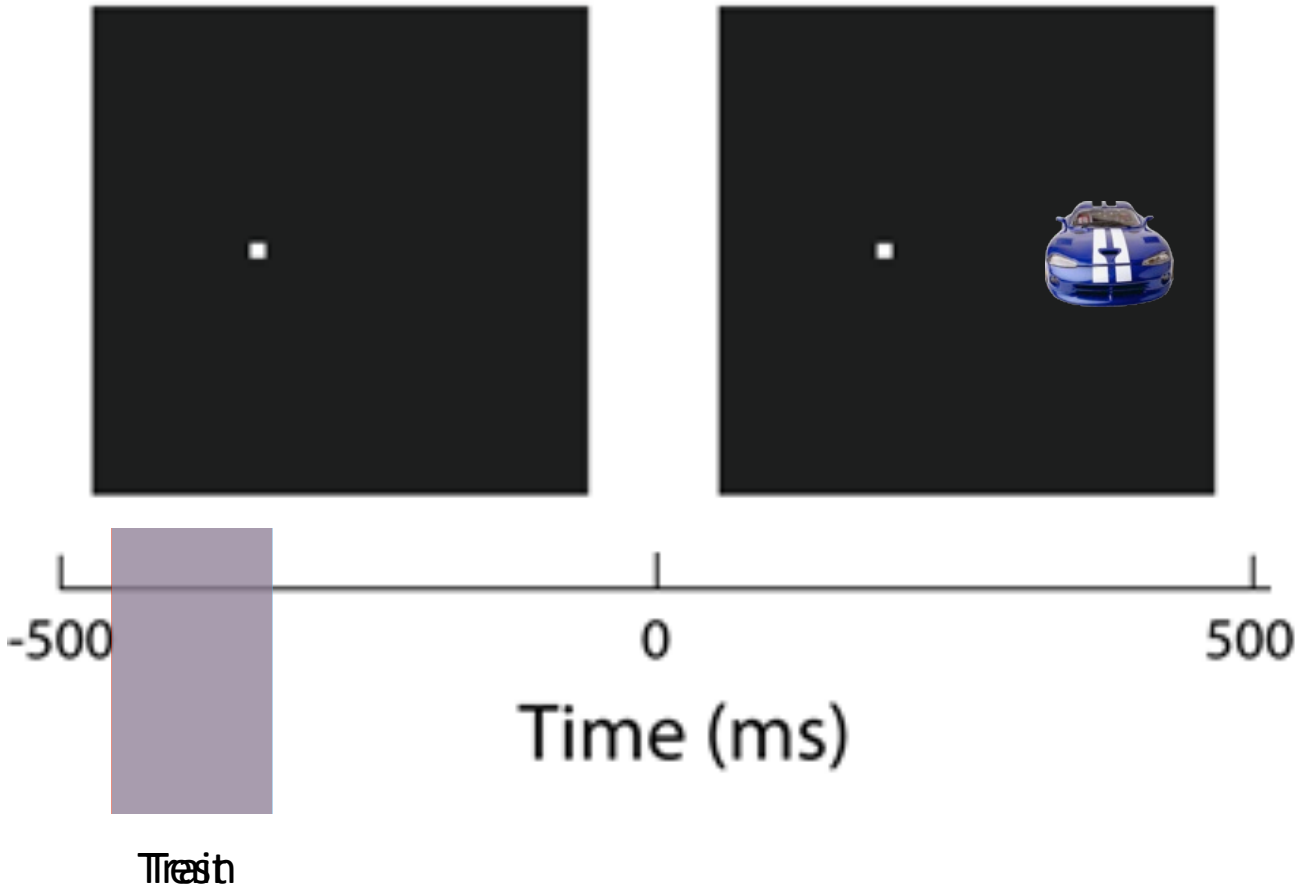
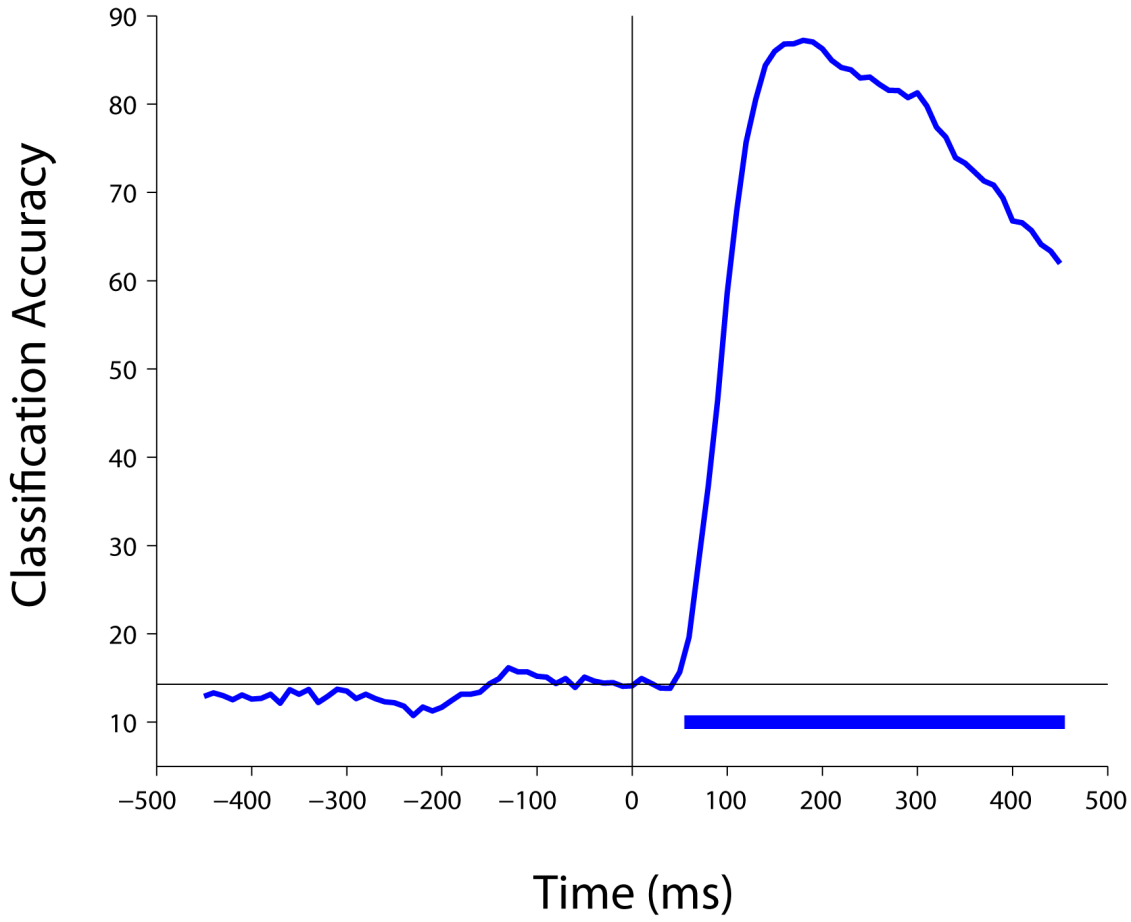
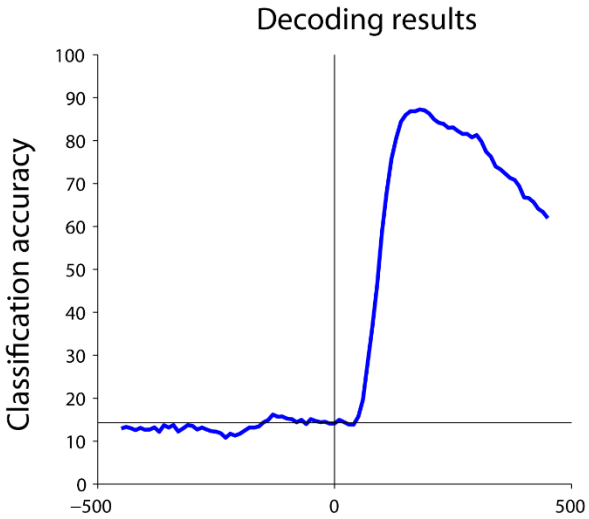


100 ms bins, sample every 10 ms

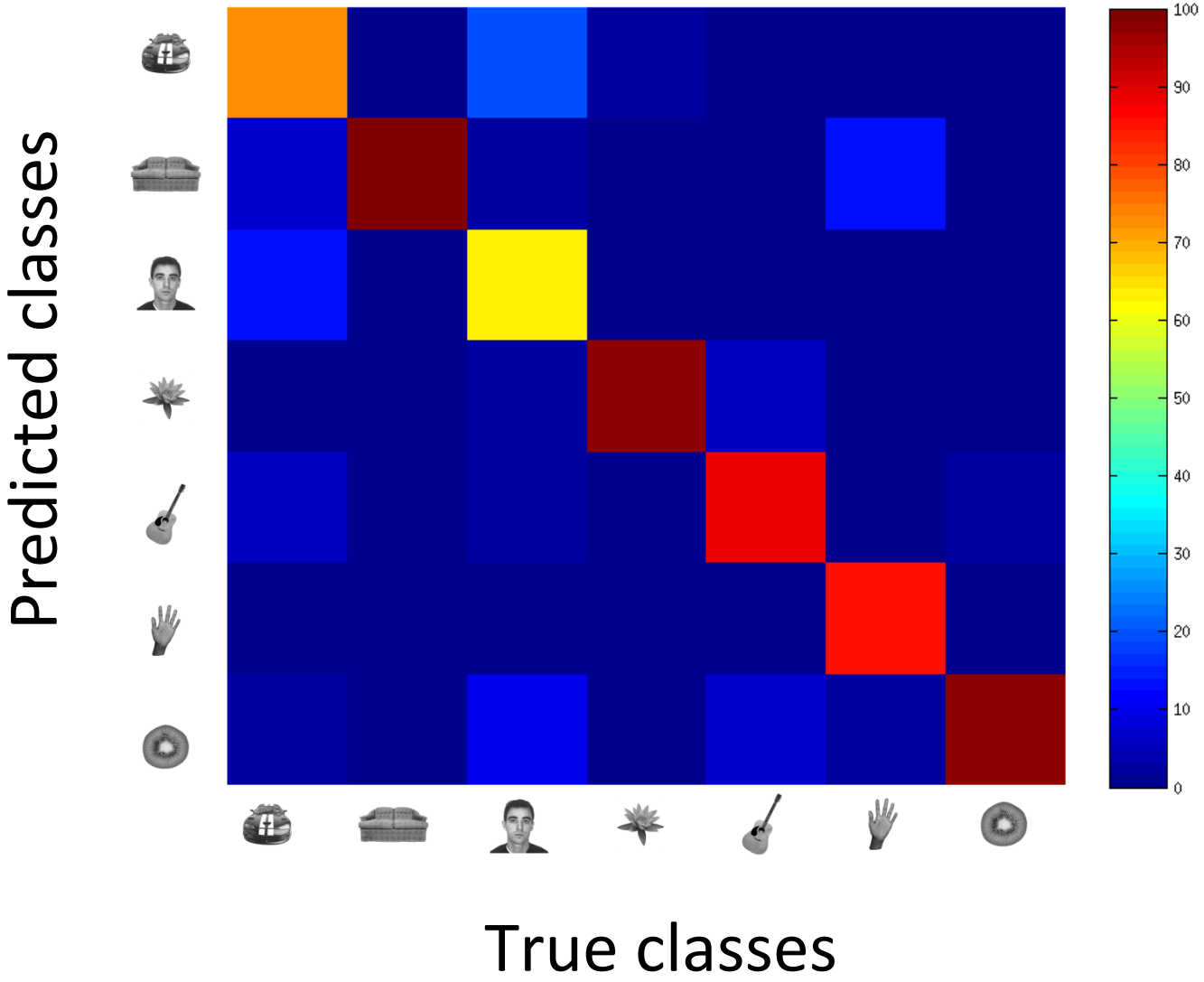
Basic decoding results



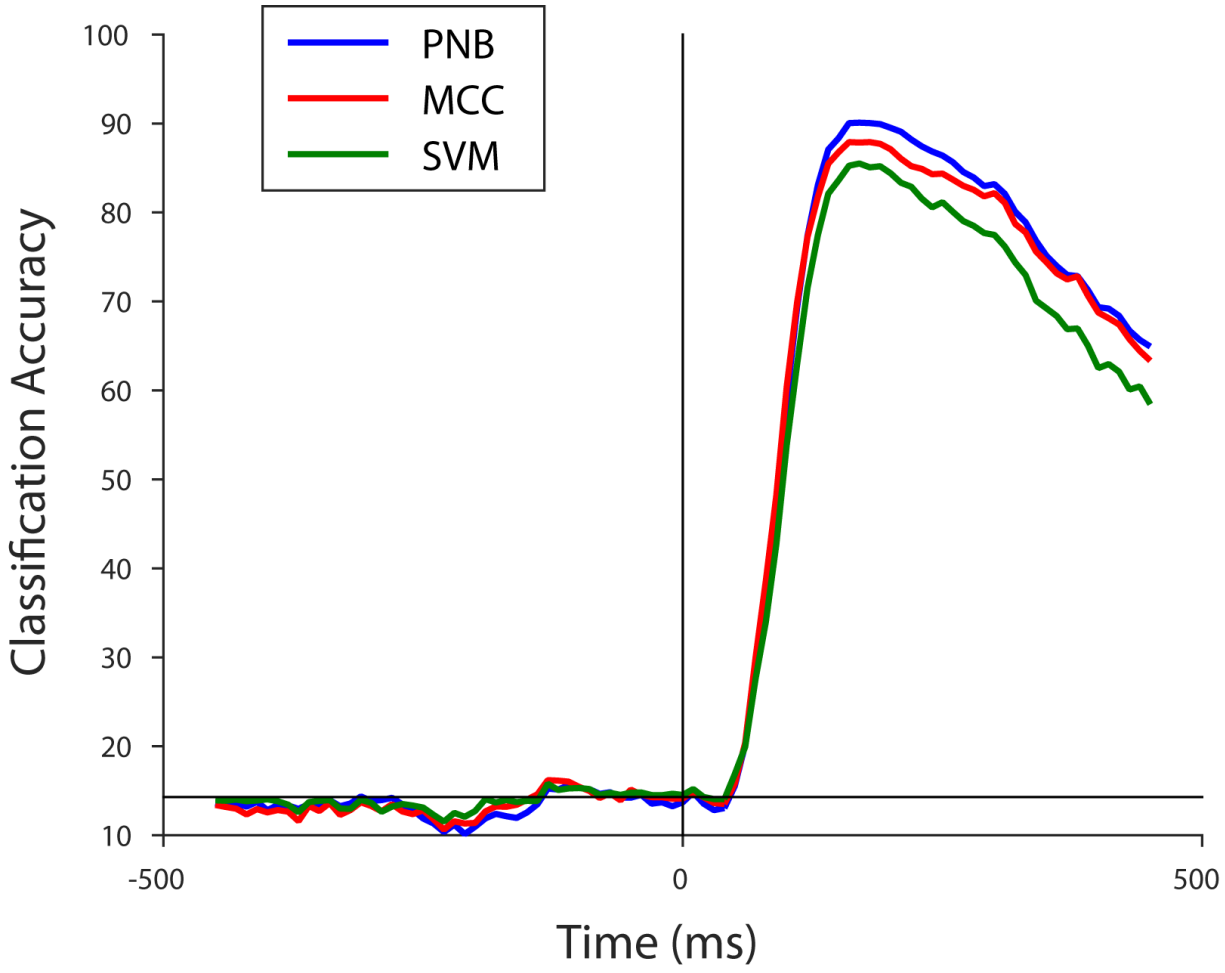
Basic results are similar to other methods



Confusion matrices



Generally robust to the choice of classifier



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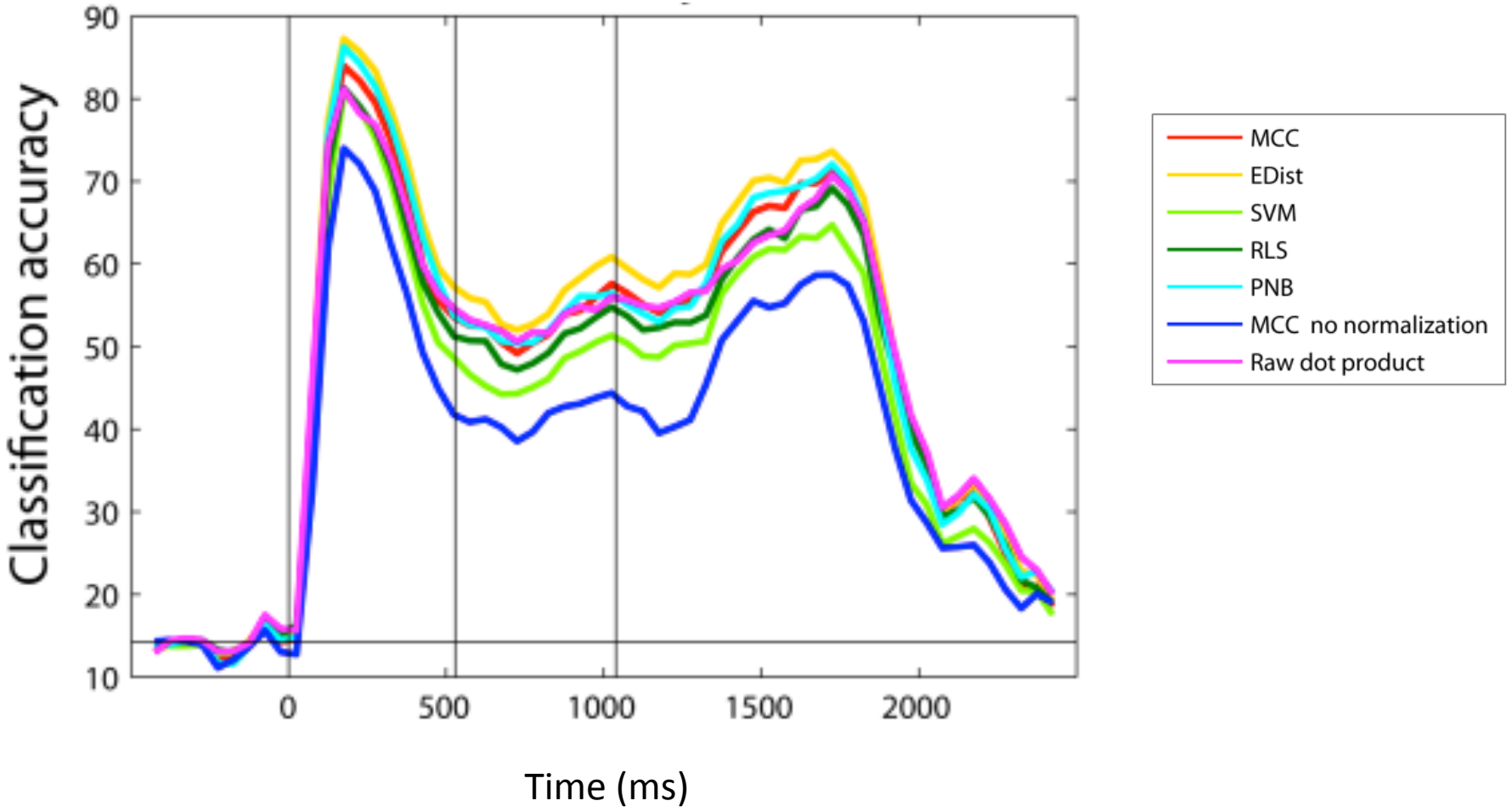
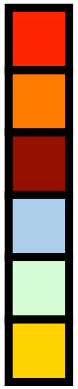


Talk outline



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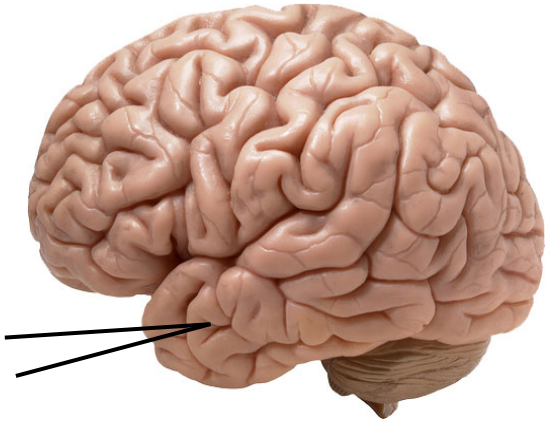

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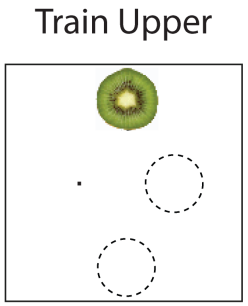
Abstract/invariant representations

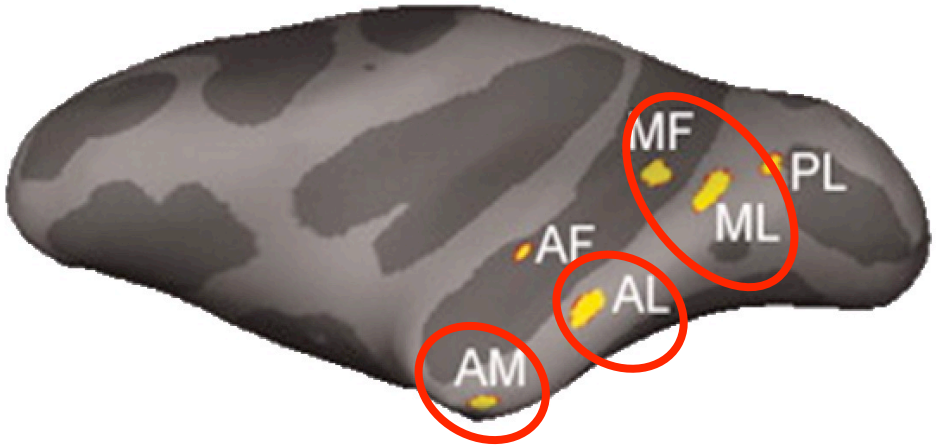
The ability to form abstract representations is essential for complex behavior

Example: position invariance

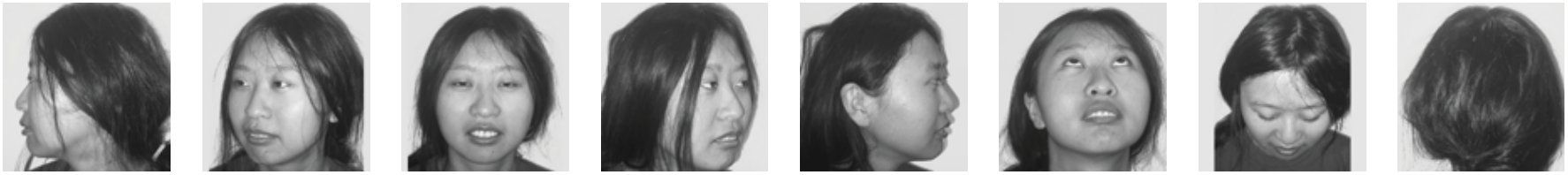


Hung, Kreiman, Poggio, and DiCarlo, Science, 2005

Face identification invariant to head pose

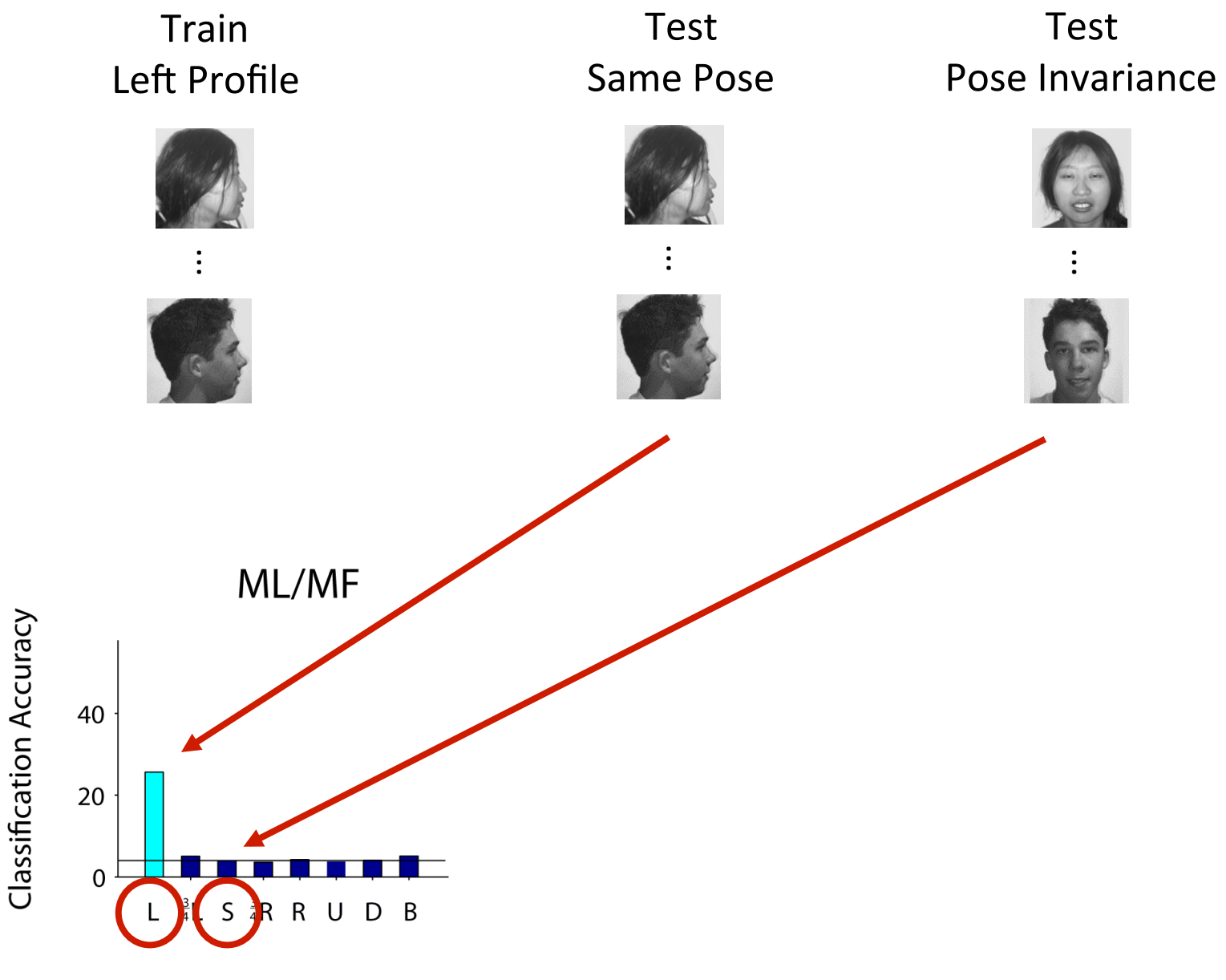


Stimulus set: 25 individuals, 8 head poses per individual



Meyers, Borzello, Freiwald, Tsao, J Neurosci, 2015

Face identification invariant to head pose



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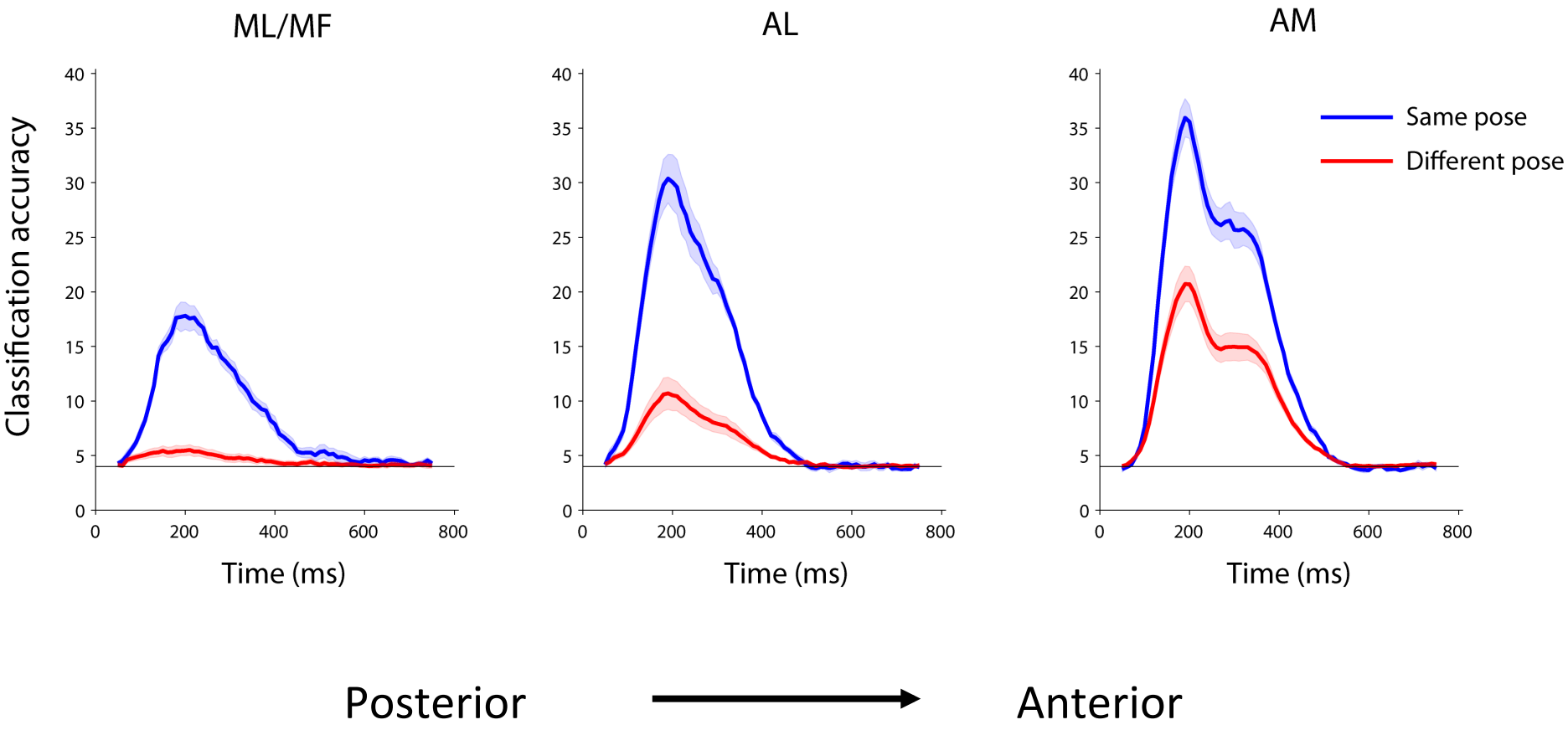
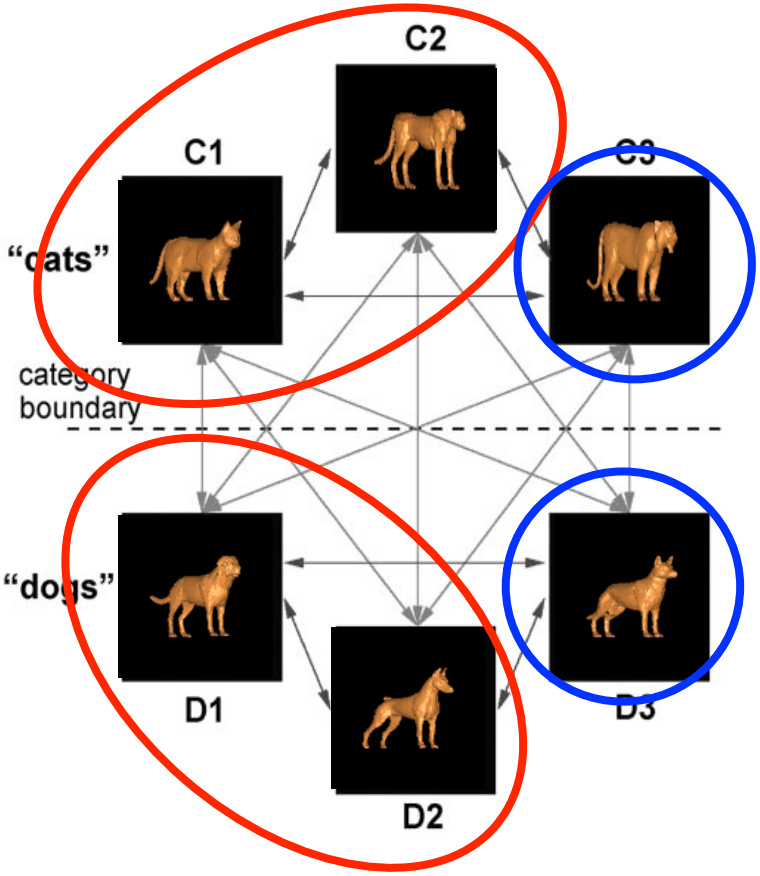
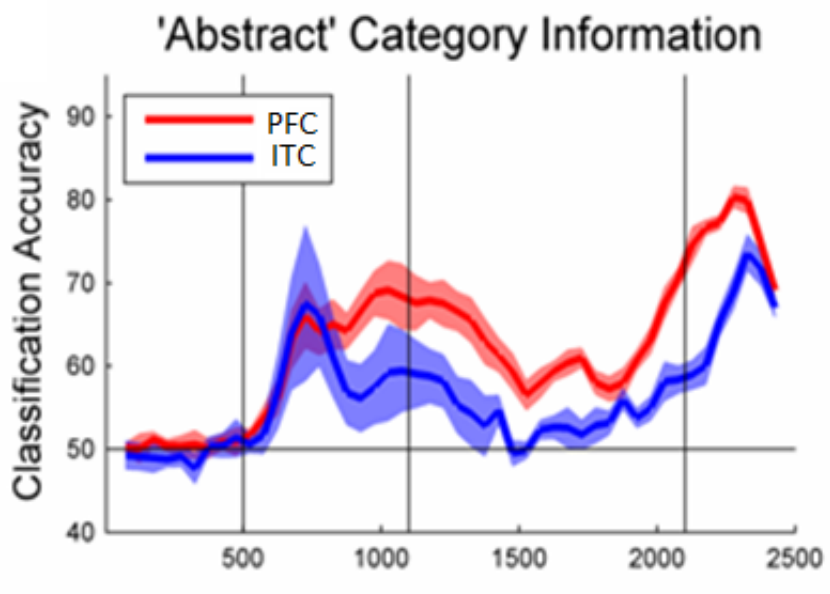


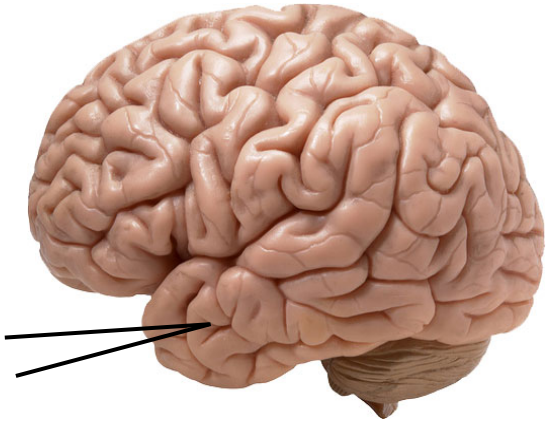
Learning abstract category information





Meyers, Freedman, Kreiman, Poggio, Miller, J Neurphys, 2008

Talk outline



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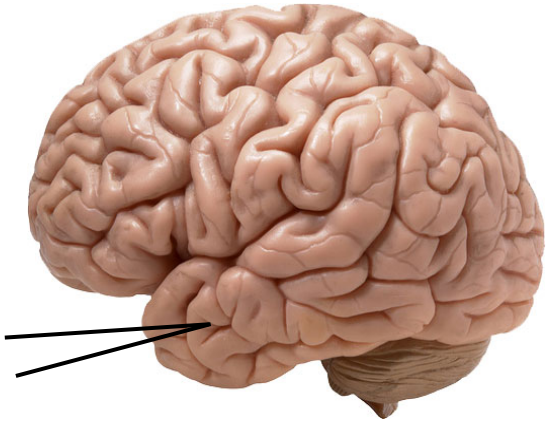

Abstract representations
are modified by attention

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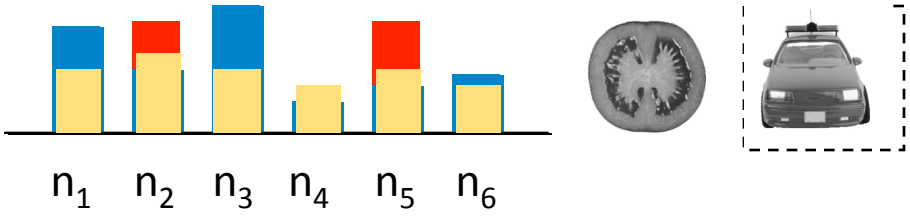
Attention's effects on visual representations

The ability to rapidly recognize objects is degraded by visual clutter

Visual attention can improve recognition clutter

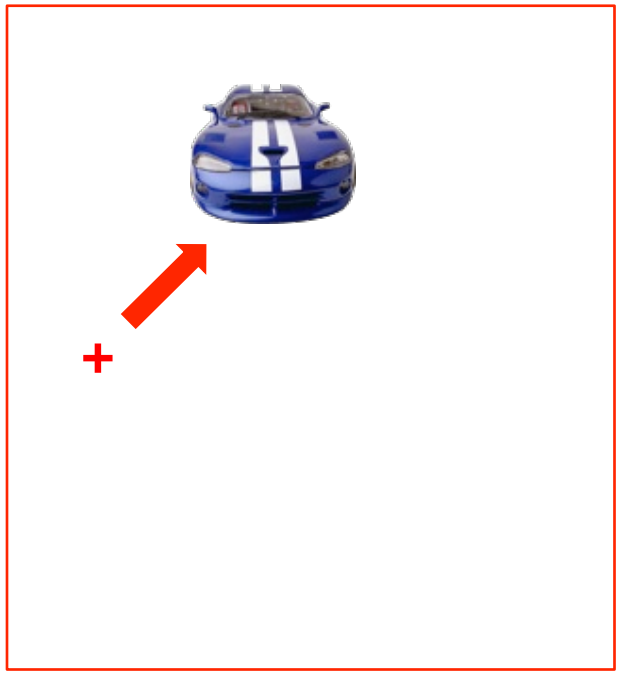
Attention's effects on visual representations

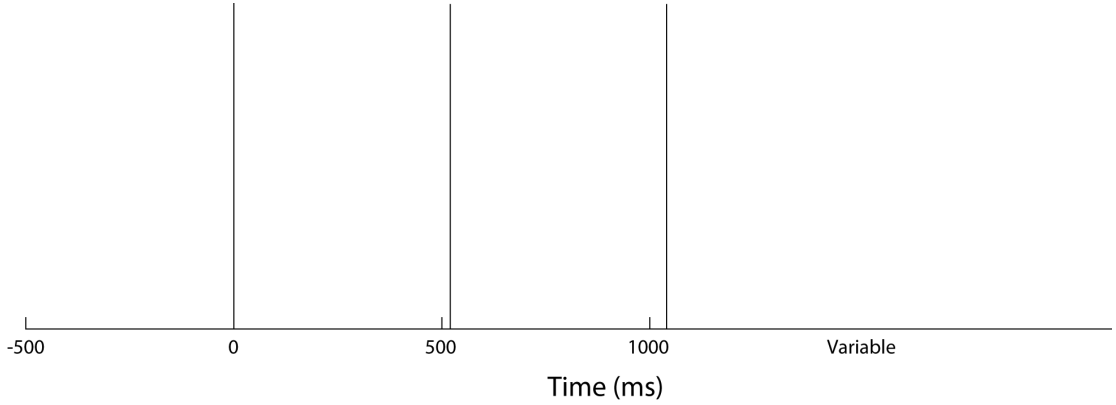


Basic idea:

- Objects are represented in IT by patterns of activity across a population neurons
- Clutter degrades these neural representations
- Attending to an object restores its neural representation

Experiment design





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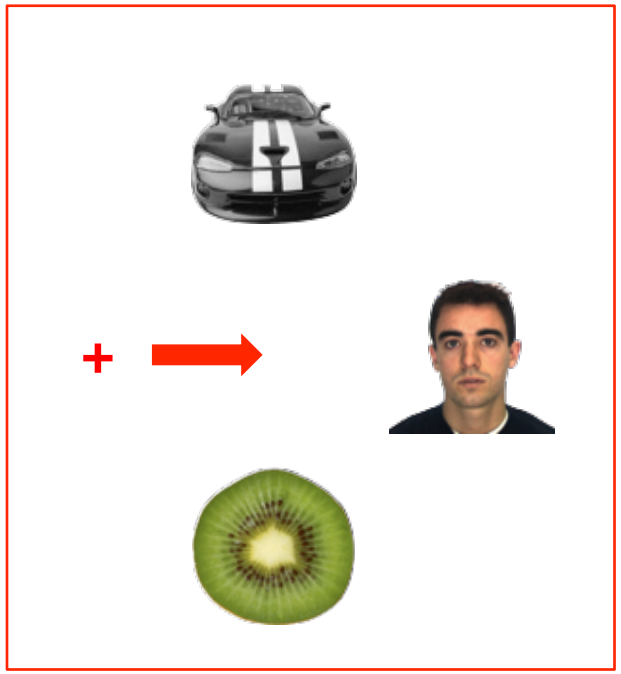
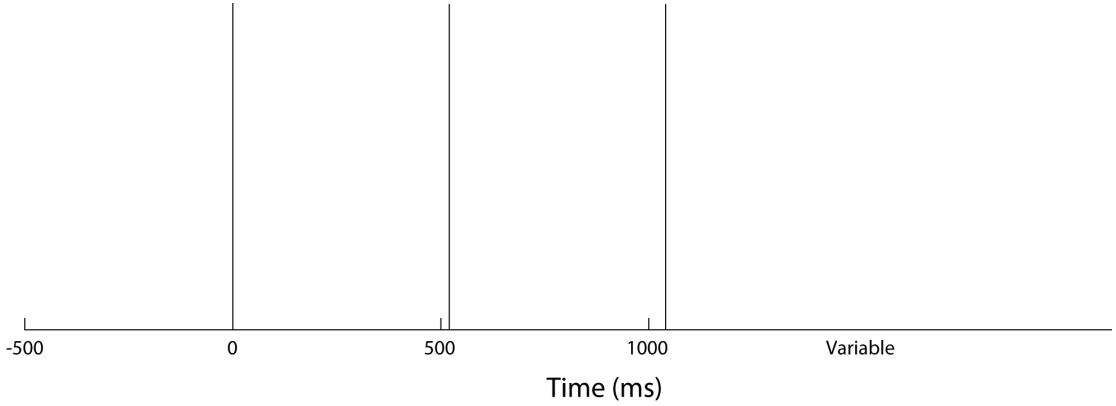
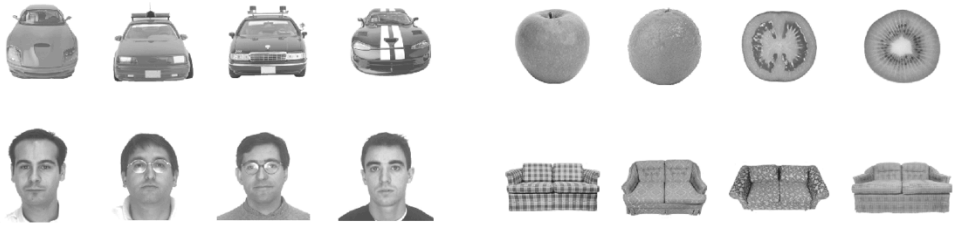
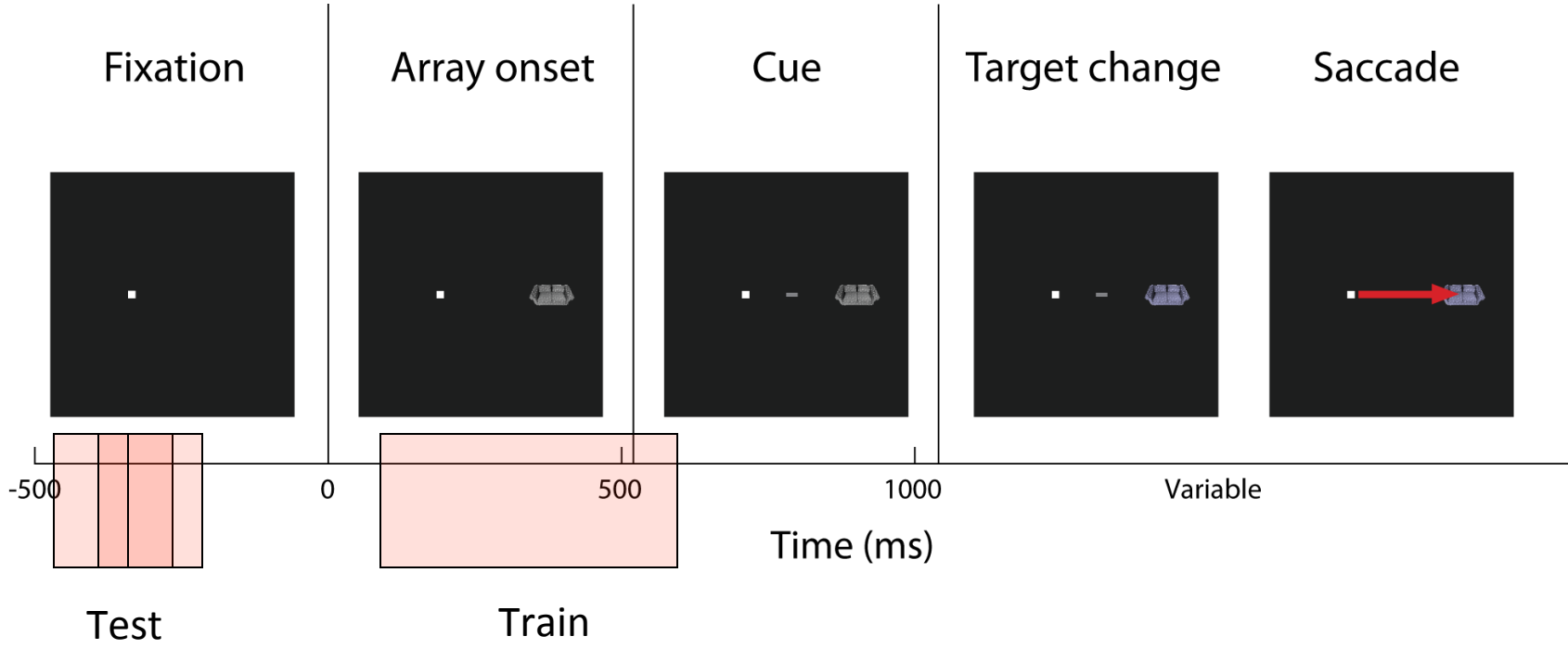




Stimulus set



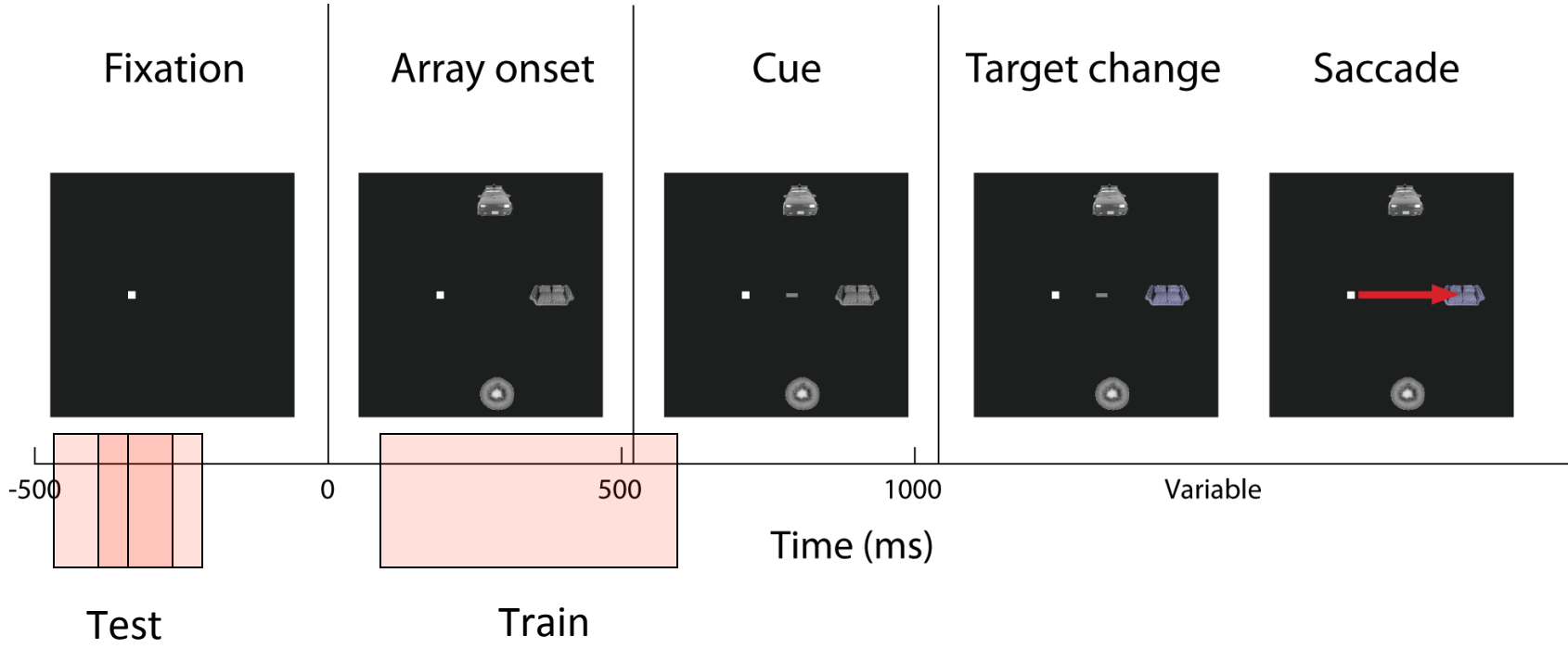
Population decoding attention experiment



Testing using 150 ms bins, sampled every 50 ms

Training using 500 ms bins, sampled every 50 ms

Population decoding attention experiment

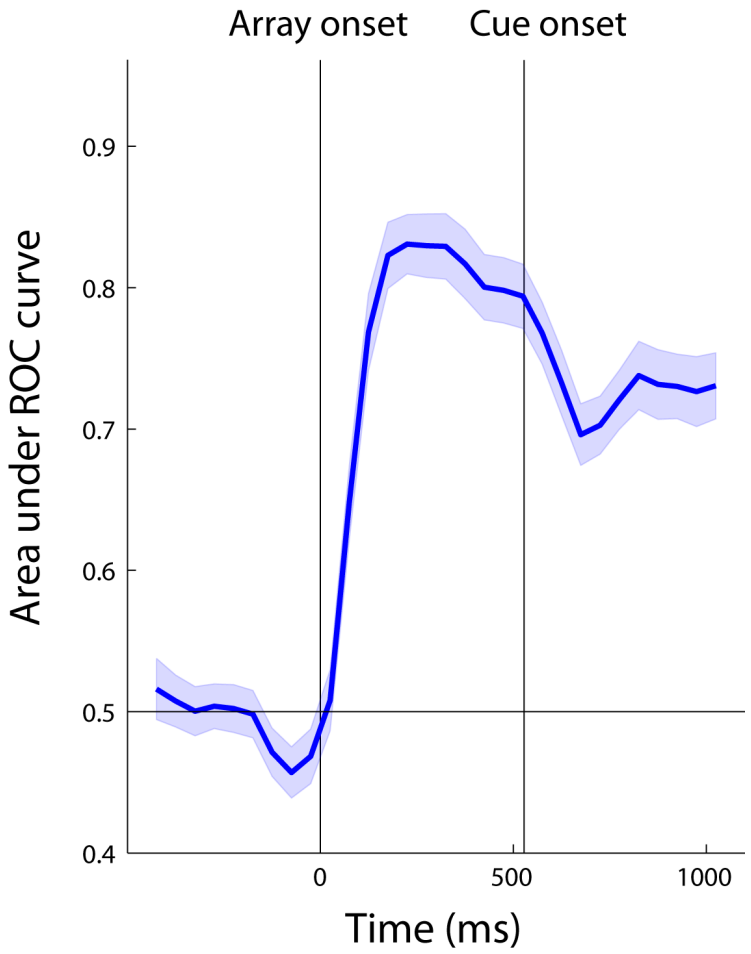


Area under ROC curve measure used

1 = Perfect classification

0.5 = Chance classification

Decoding results



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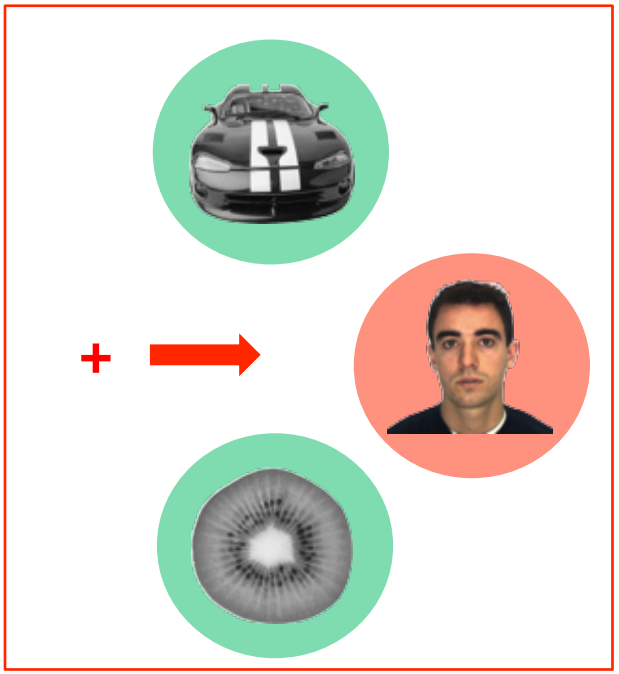
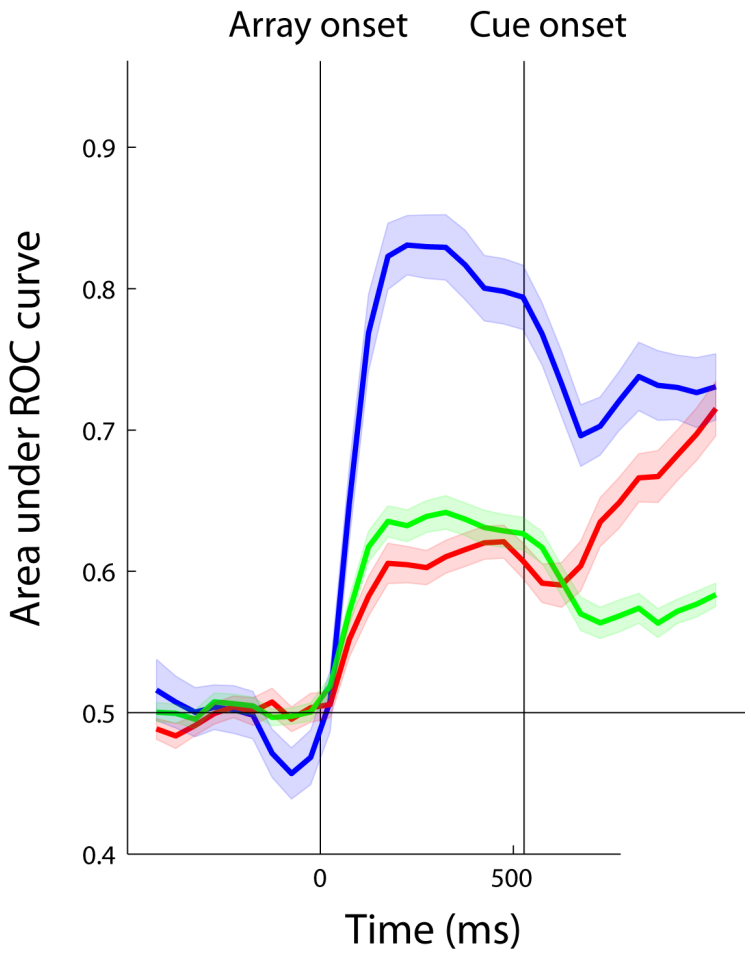
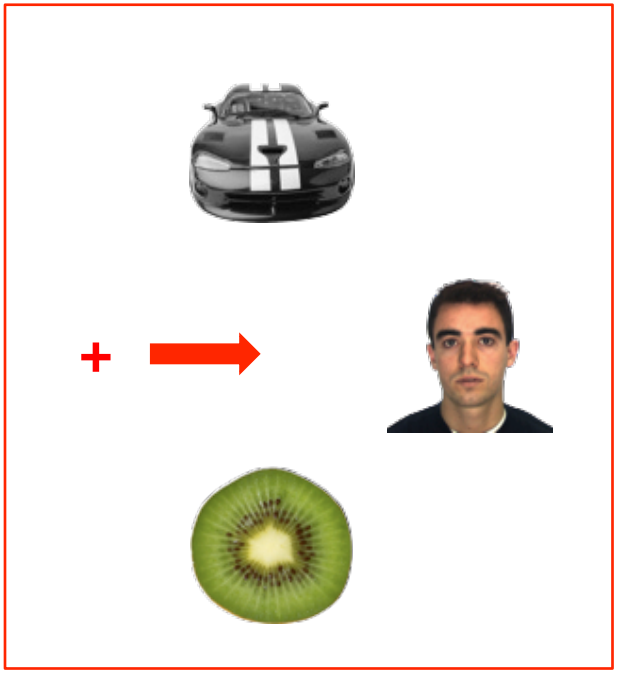
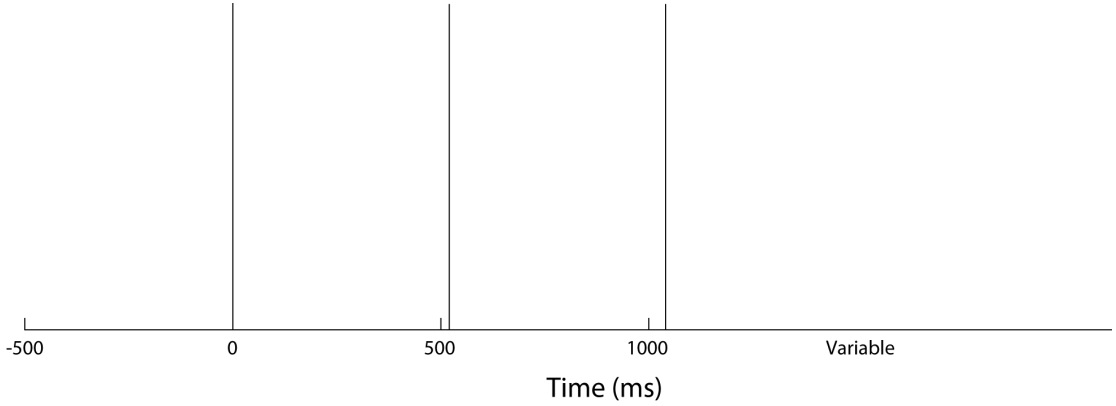


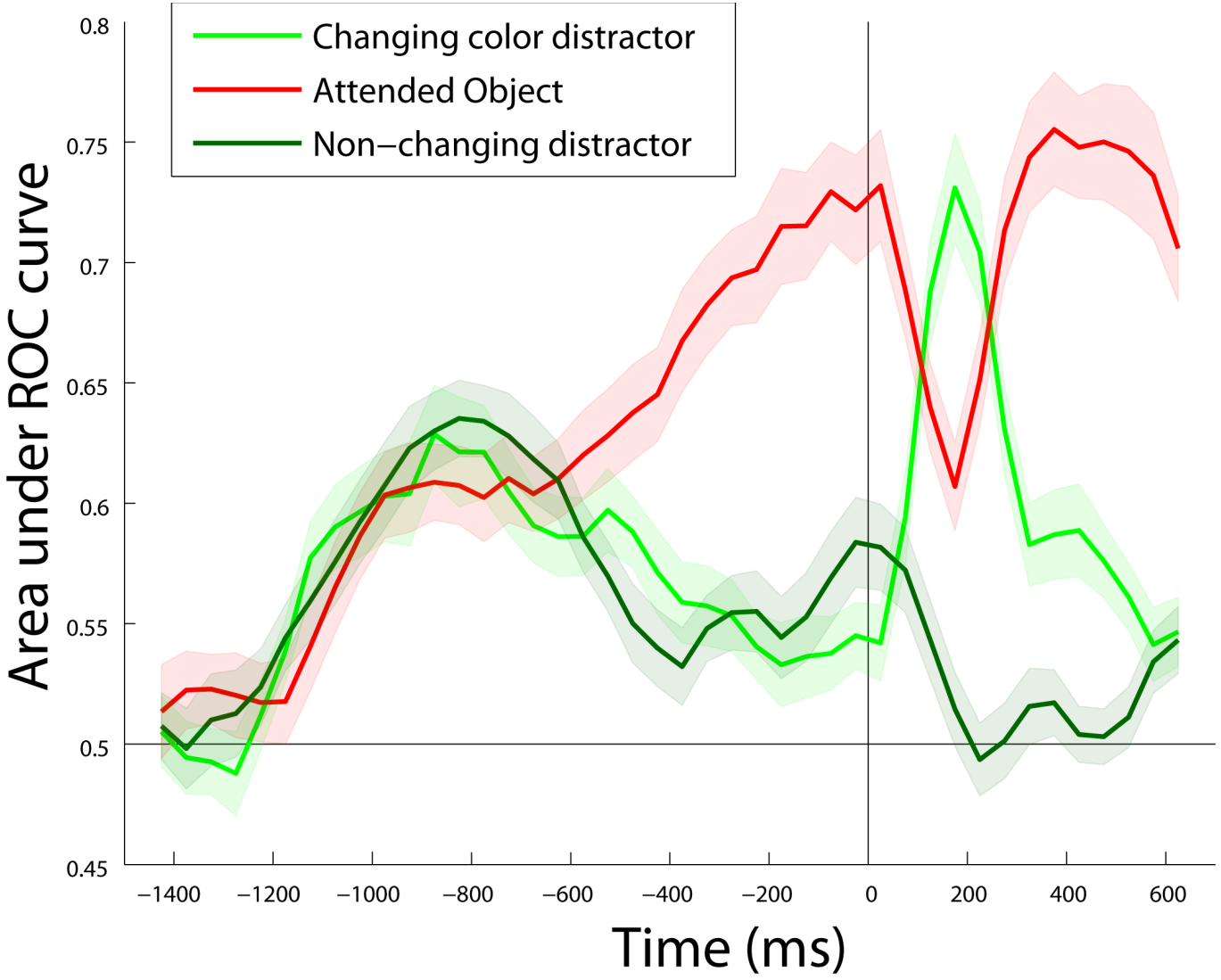


How does the color change of a distractor influence information in IT?





Decoding the distractor



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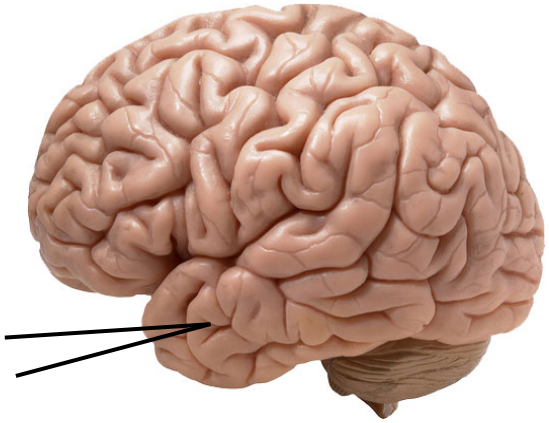

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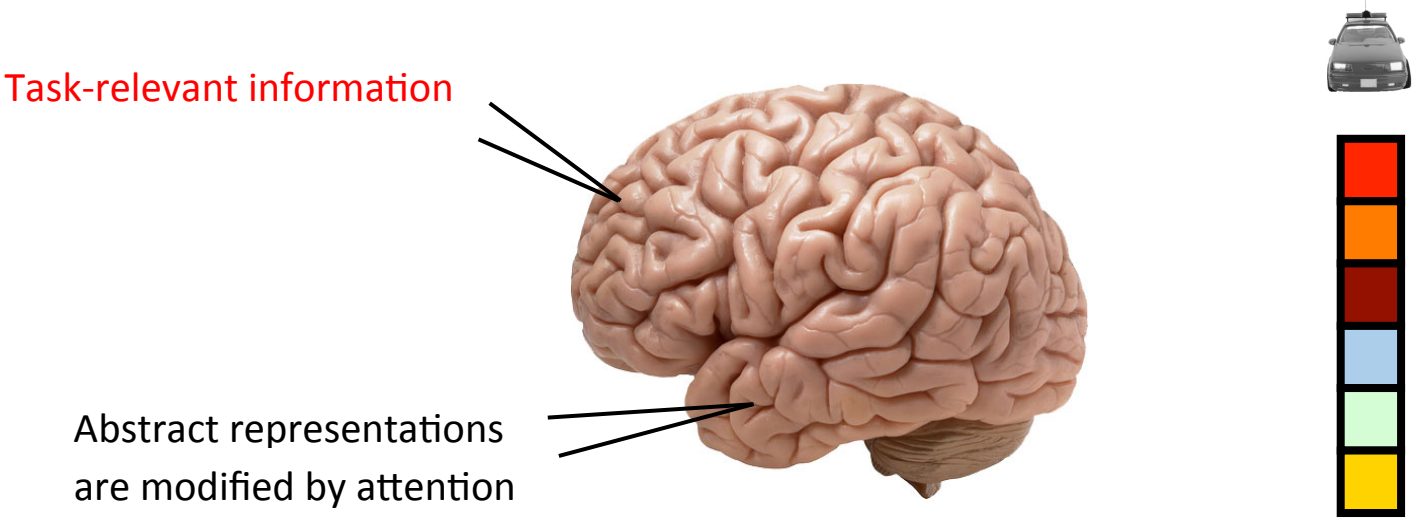

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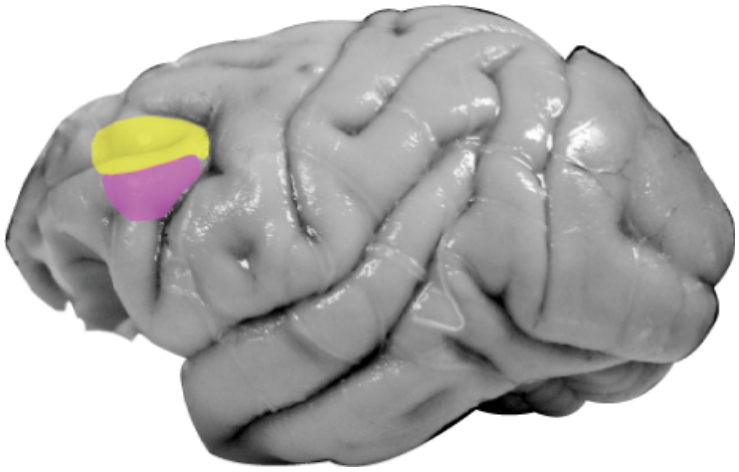
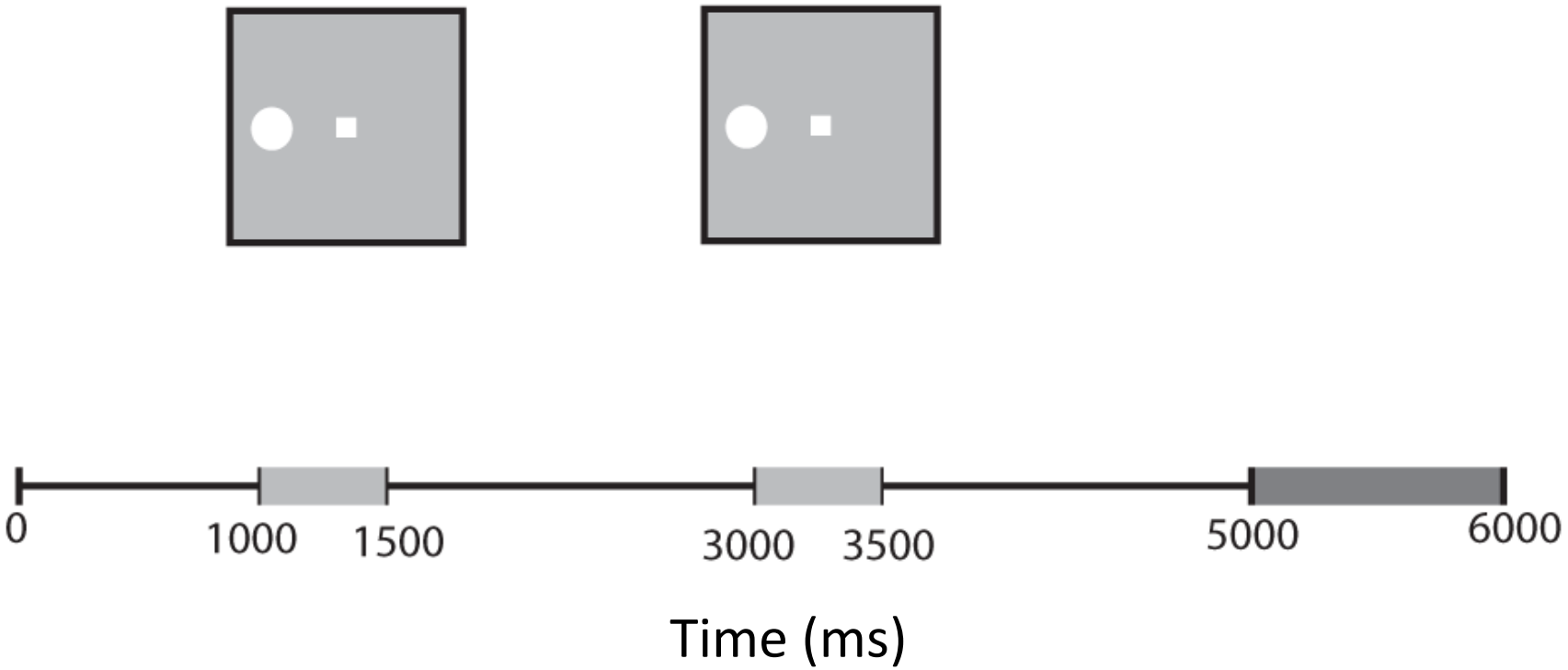
Learning new tasks changes neural processing



Meyers, Qi, Constantinidis, PNAS, 2012

Monkeys were first trained to passively fixate

Fixation 1st stimulus 1st delay 2nd stimulus 2nd delay Reward



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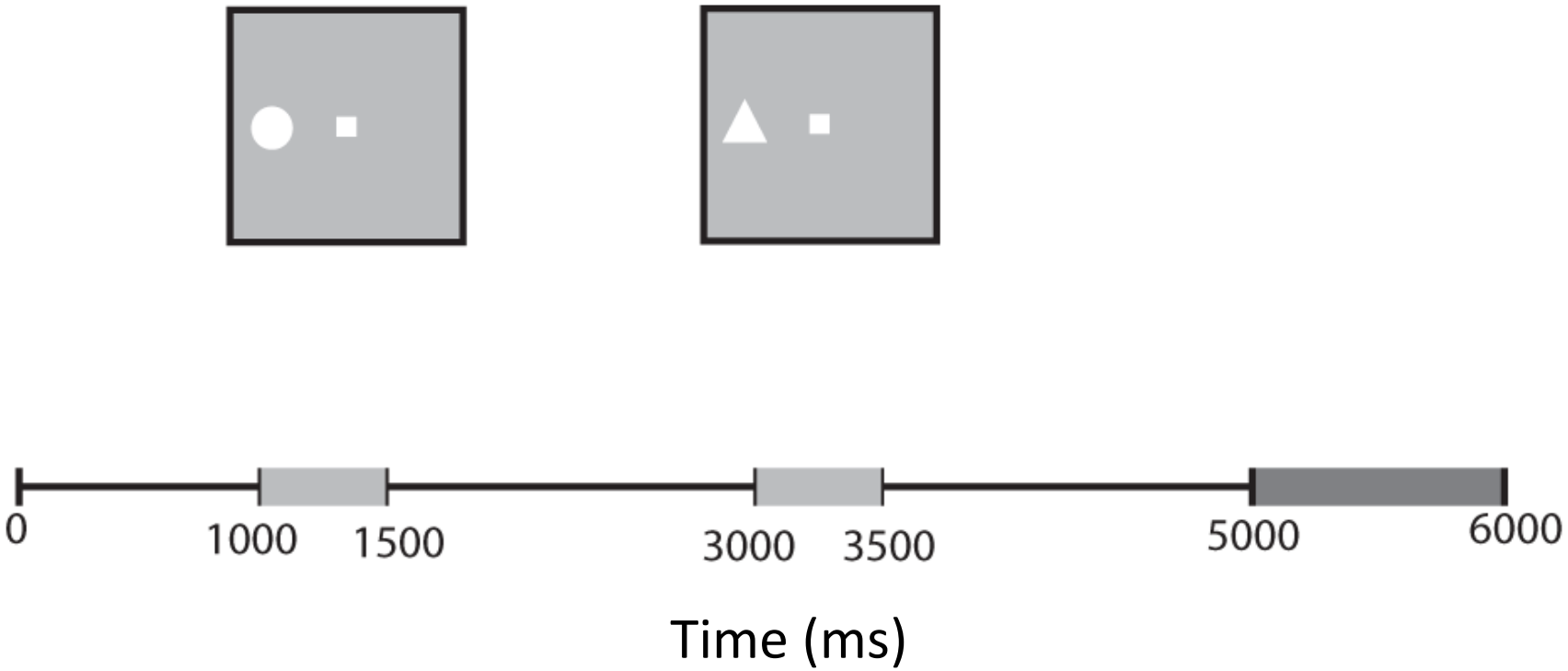
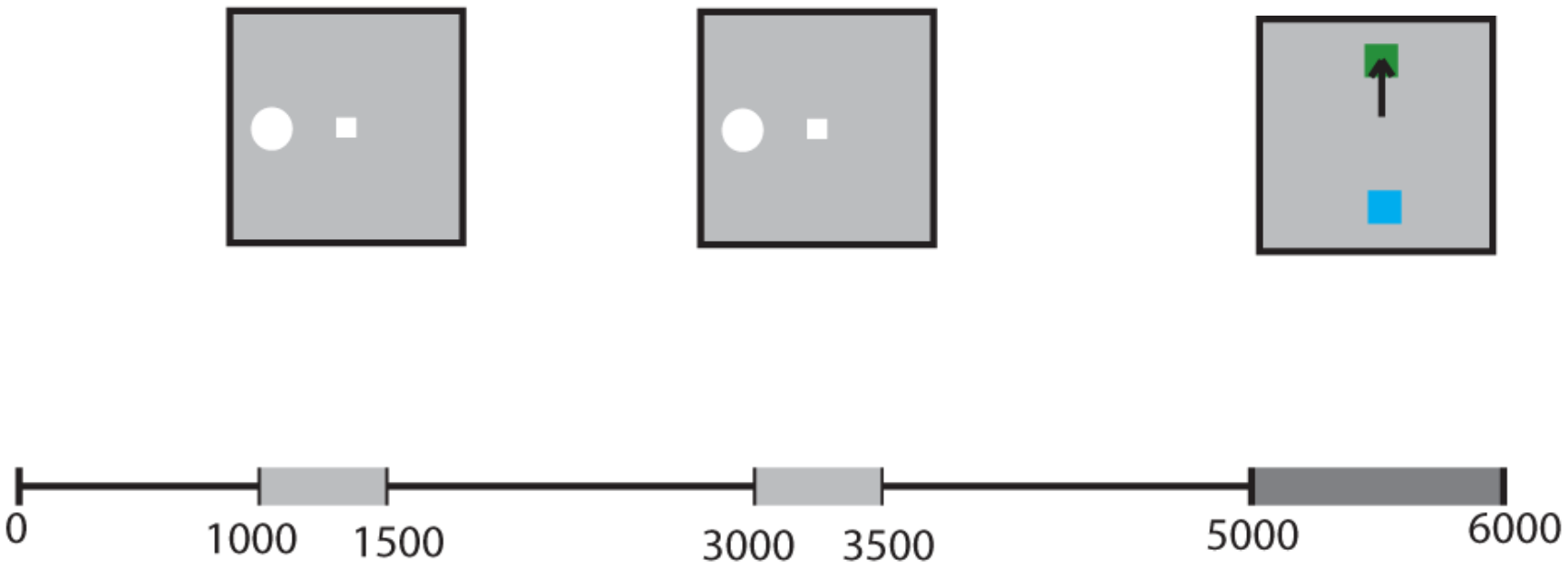


Monkeys then engaged in a delayed-match-to-sample task (DMS task)

Fixation | 1st stimulus | 1st delay | 2nd stimulus | 2nd delay | Choice targets/ saccade



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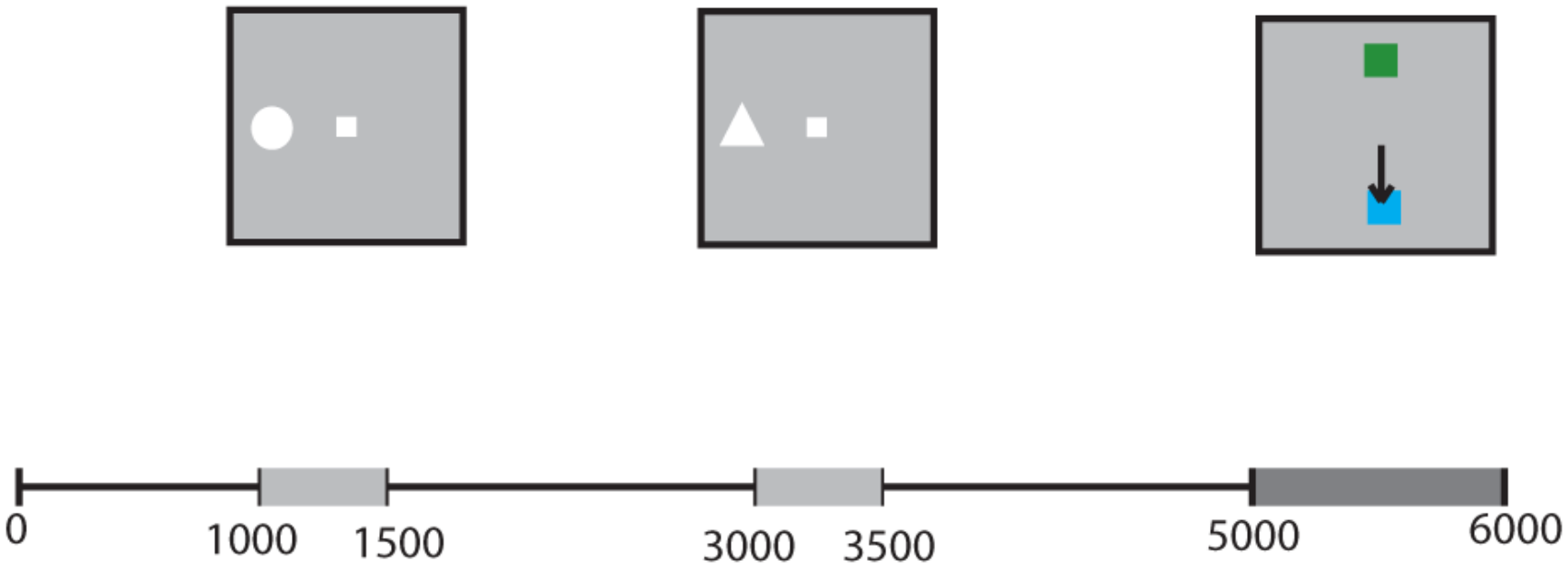
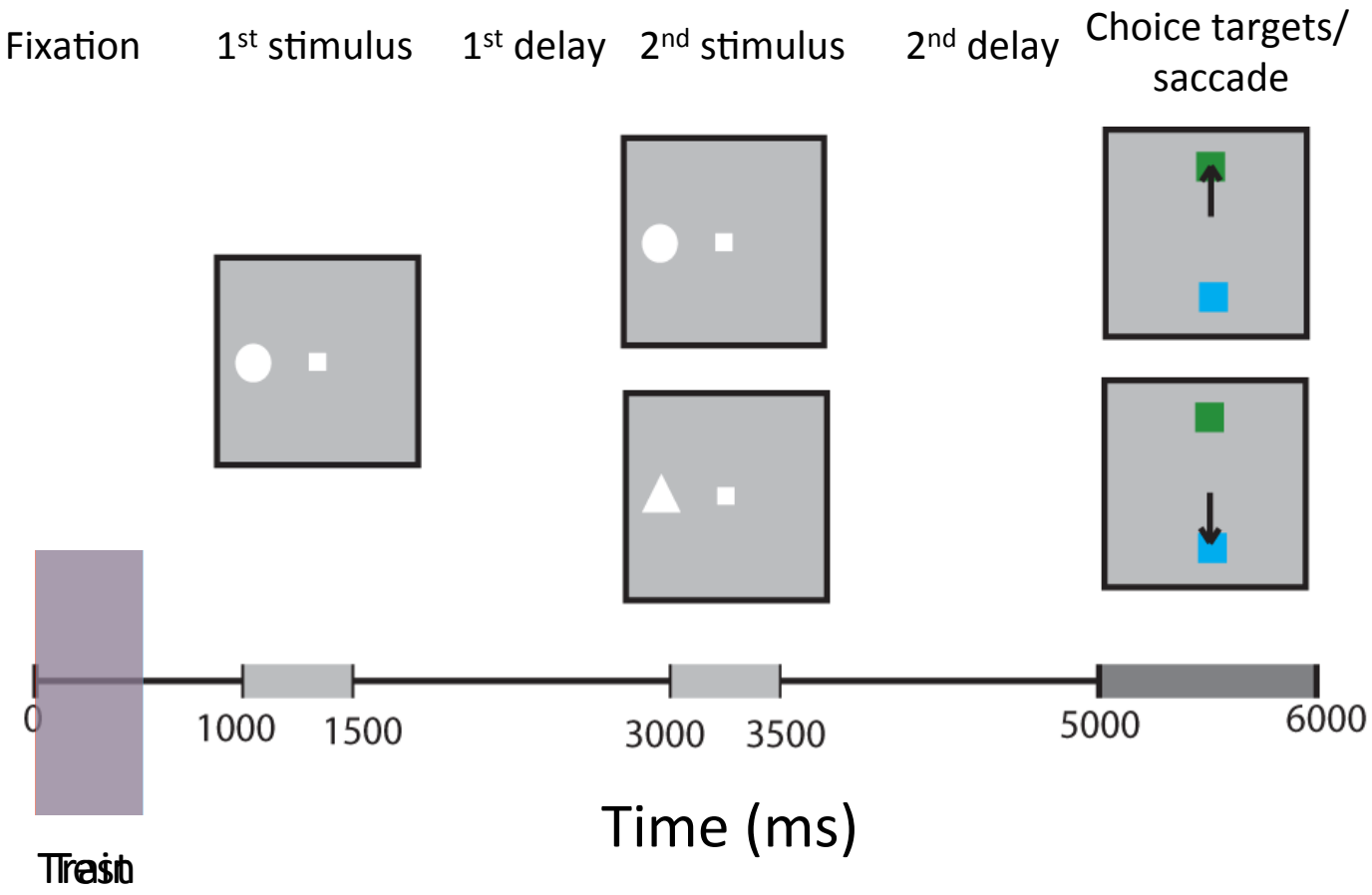


Decoding applied



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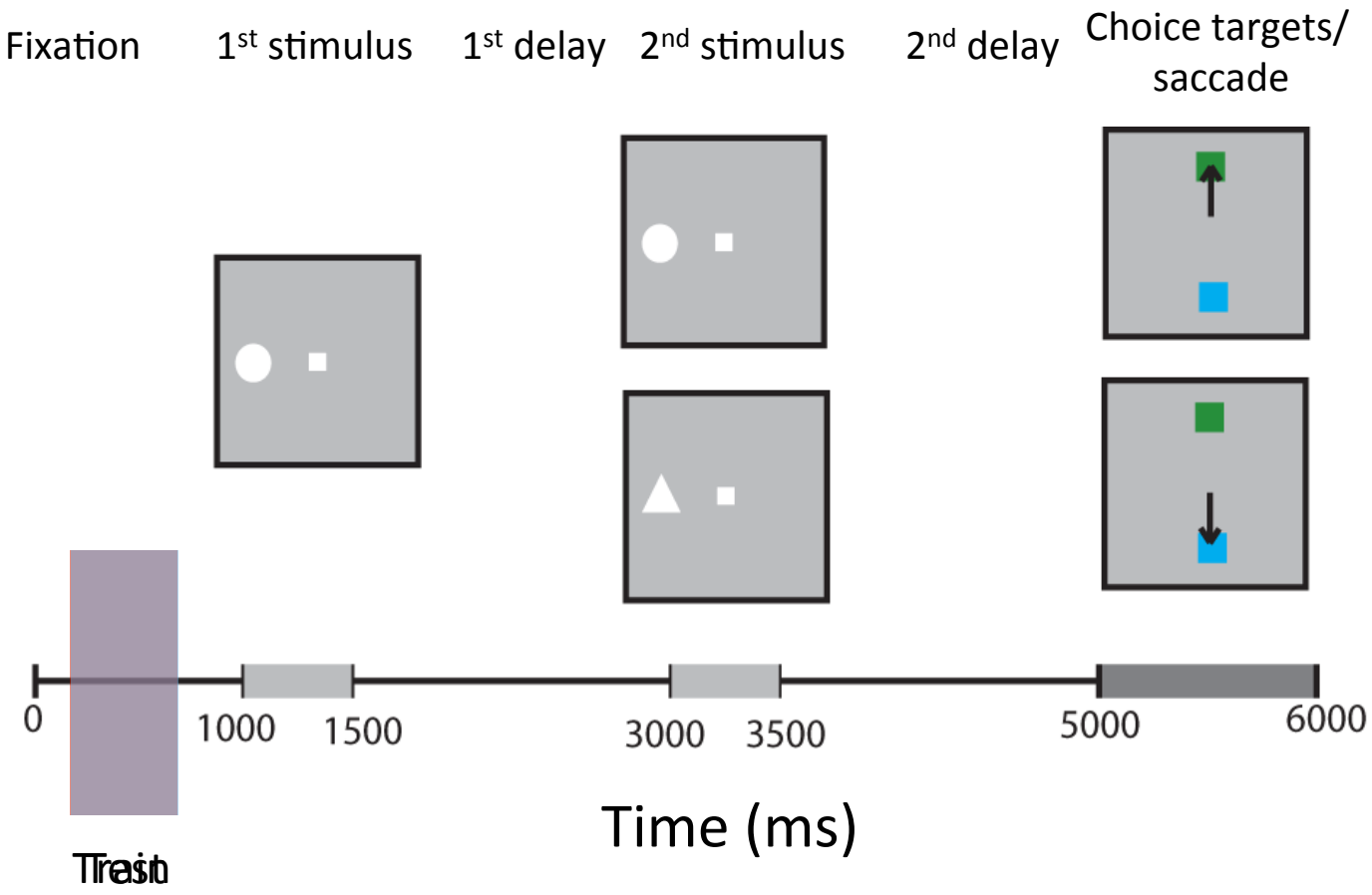
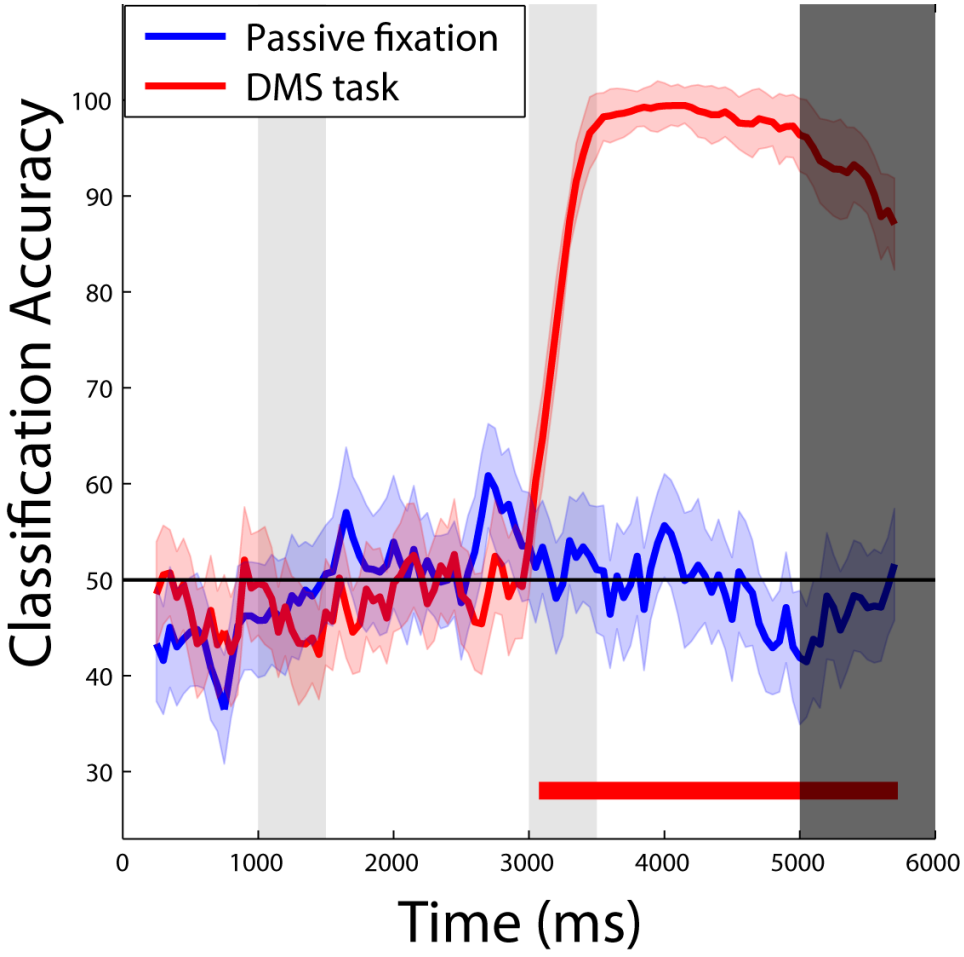
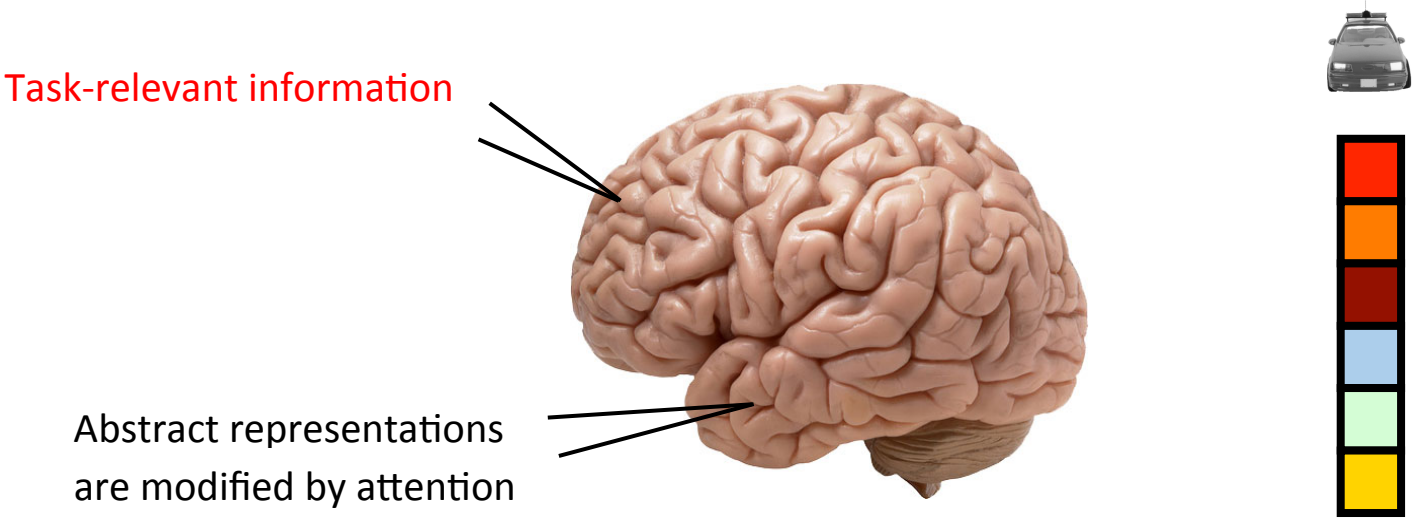


500 ms bins, sample every 50 ms
Decoding is based on 750 neurons

Decoding match/nonmatch information



Talk outline



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Task relevant information
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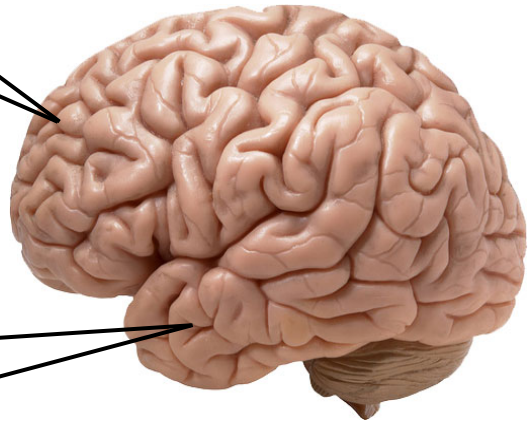

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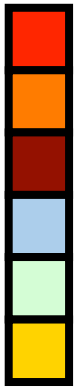

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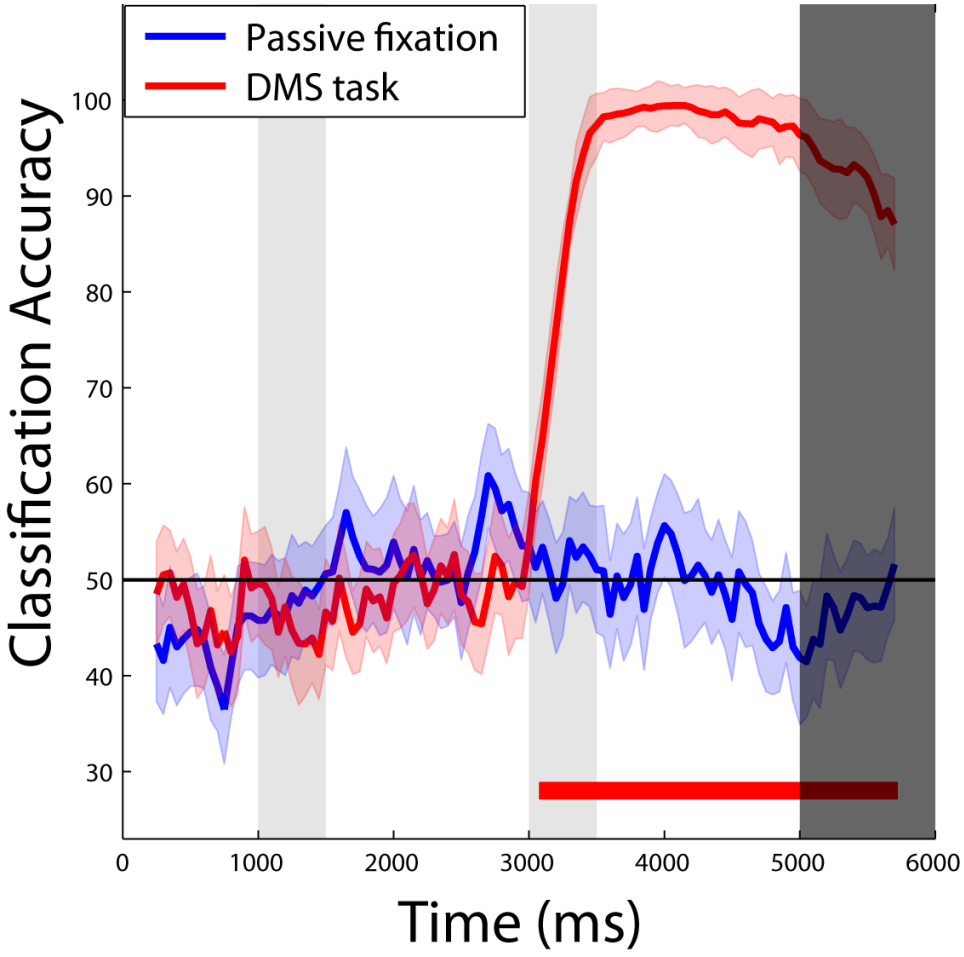
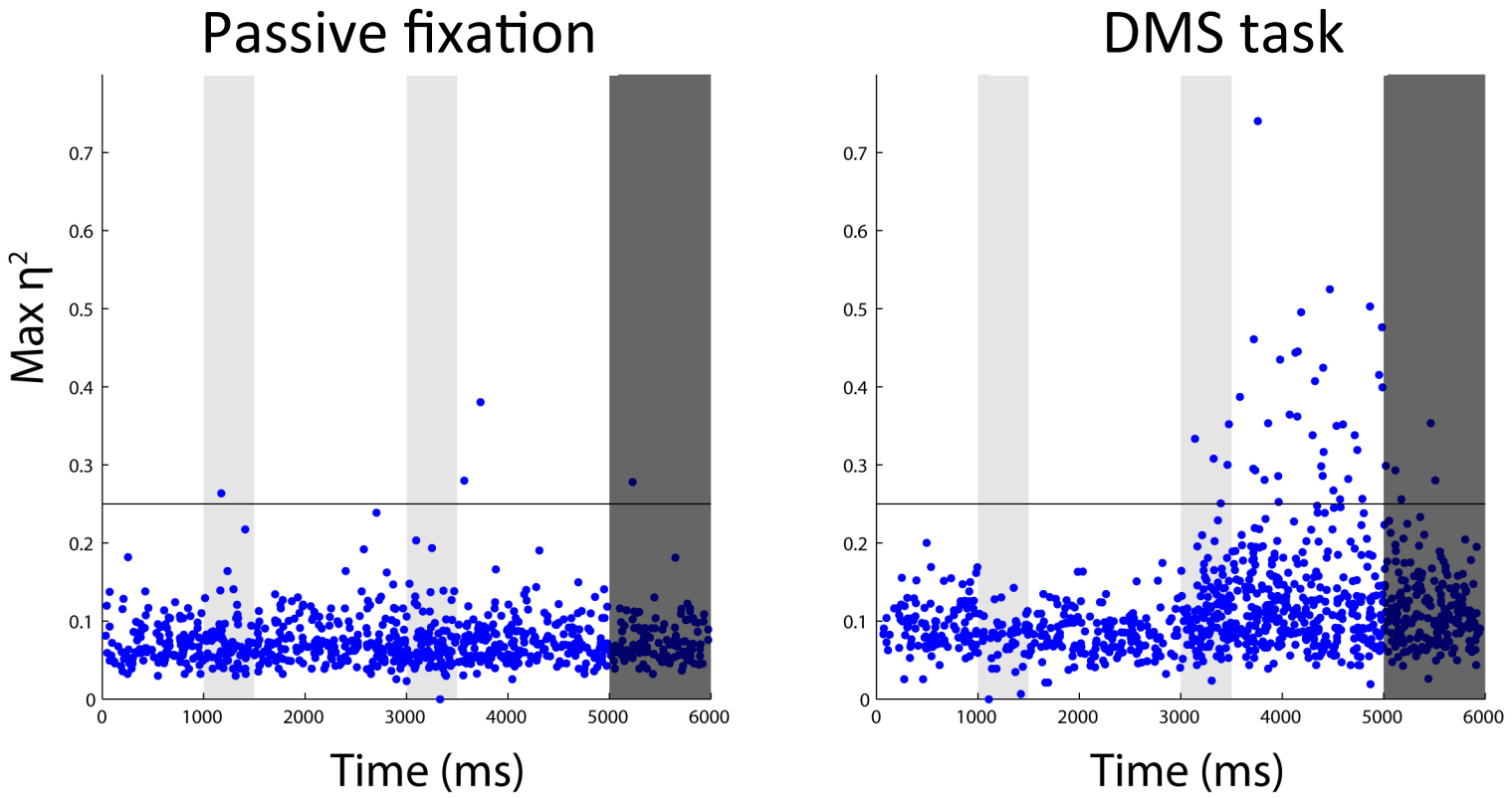
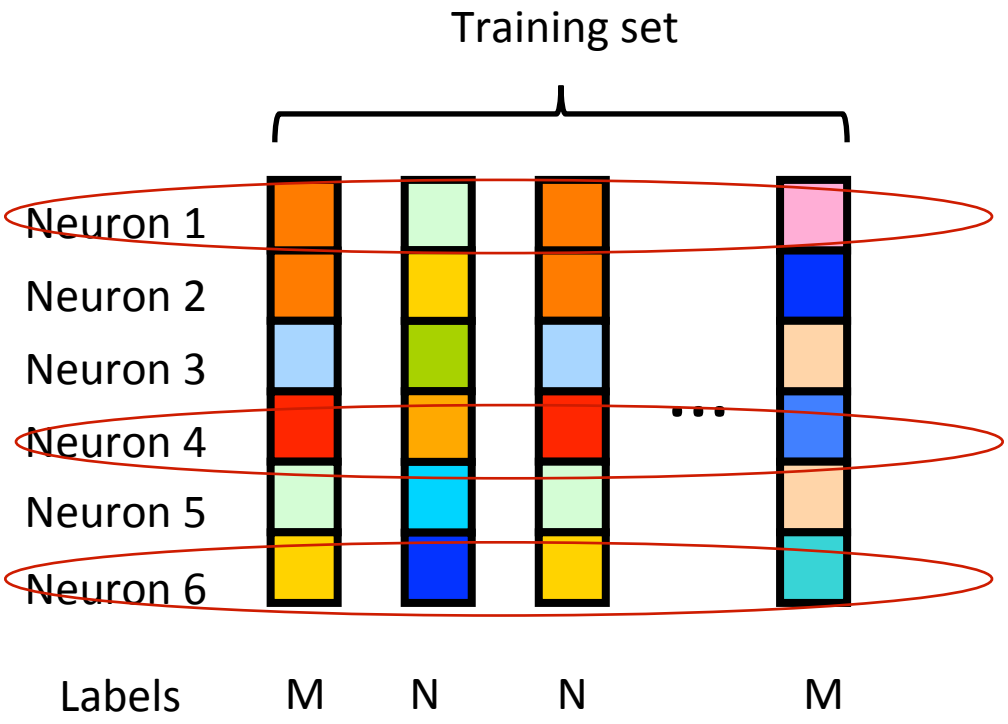


Is the new information widely distributed?



Compact/sparse coding of information



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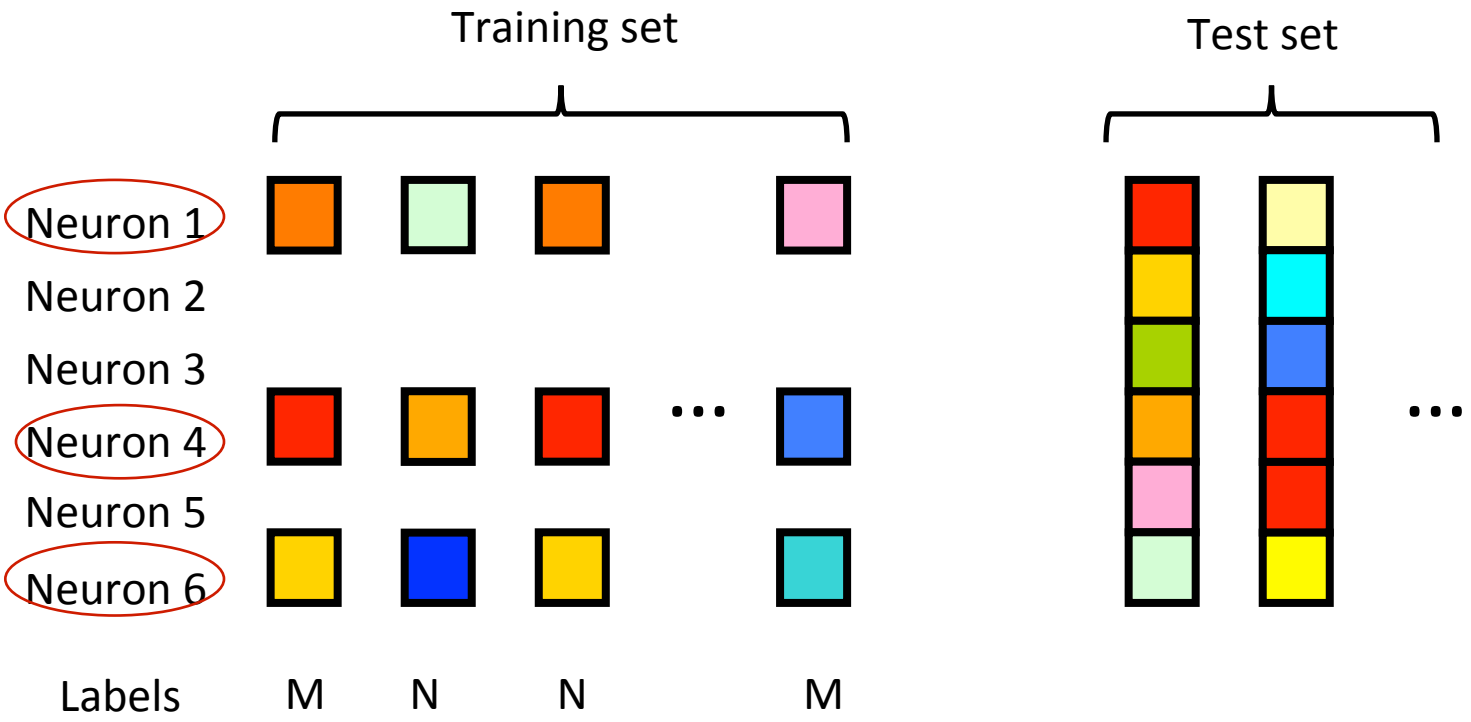

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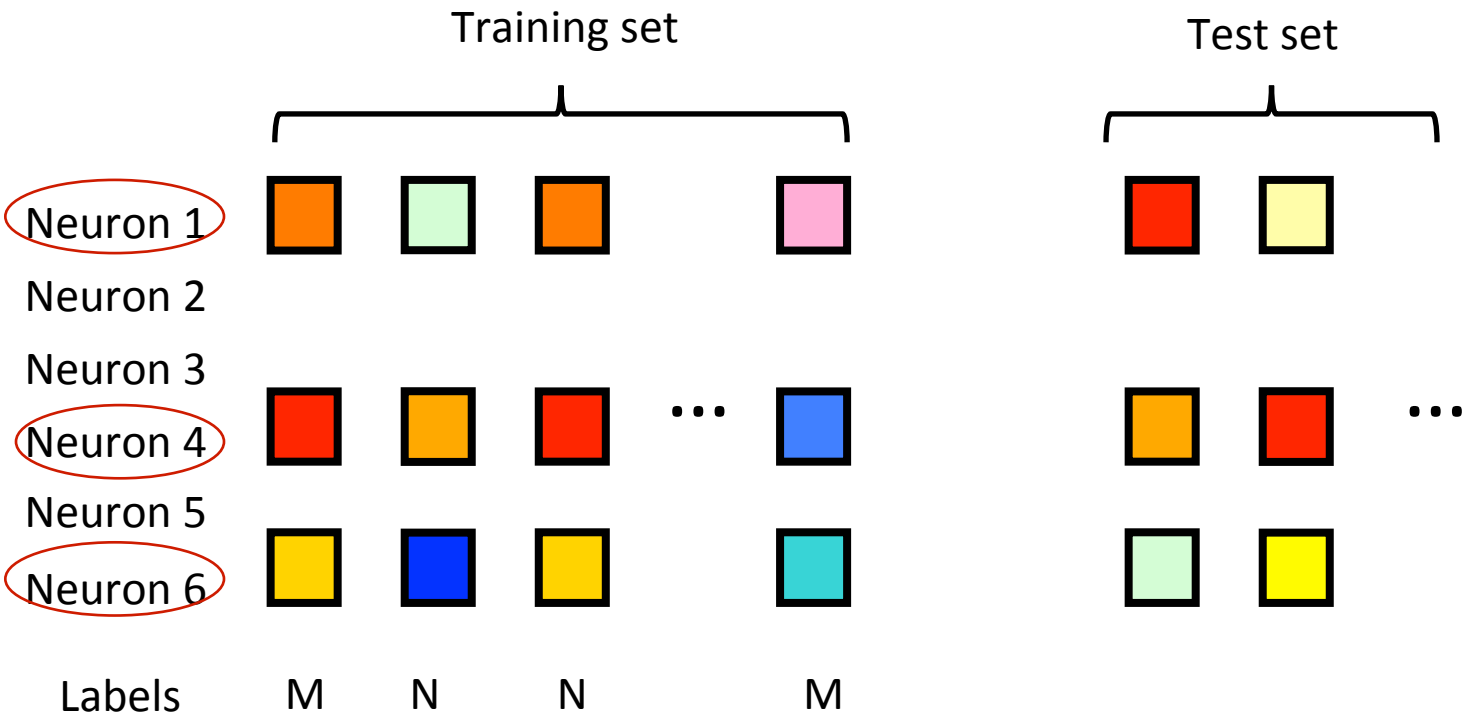

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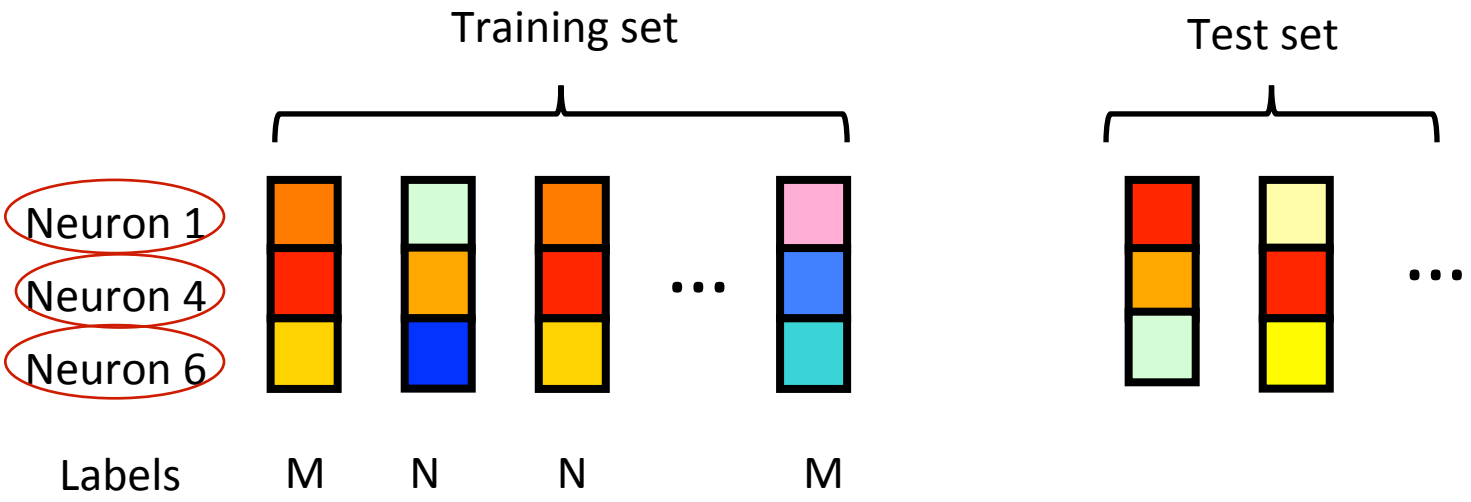
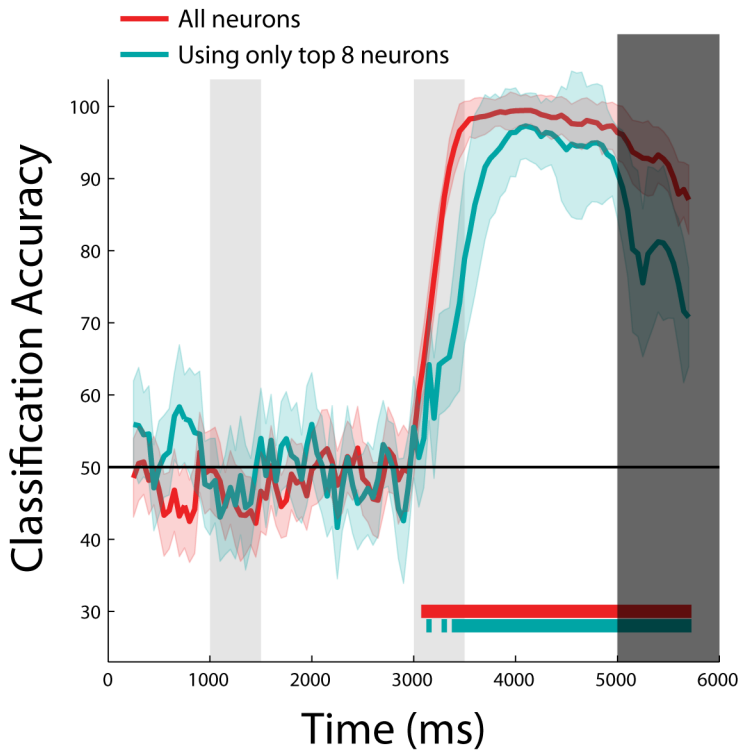


Is the new information widely distributed?

Using only the 8 most selective neurons



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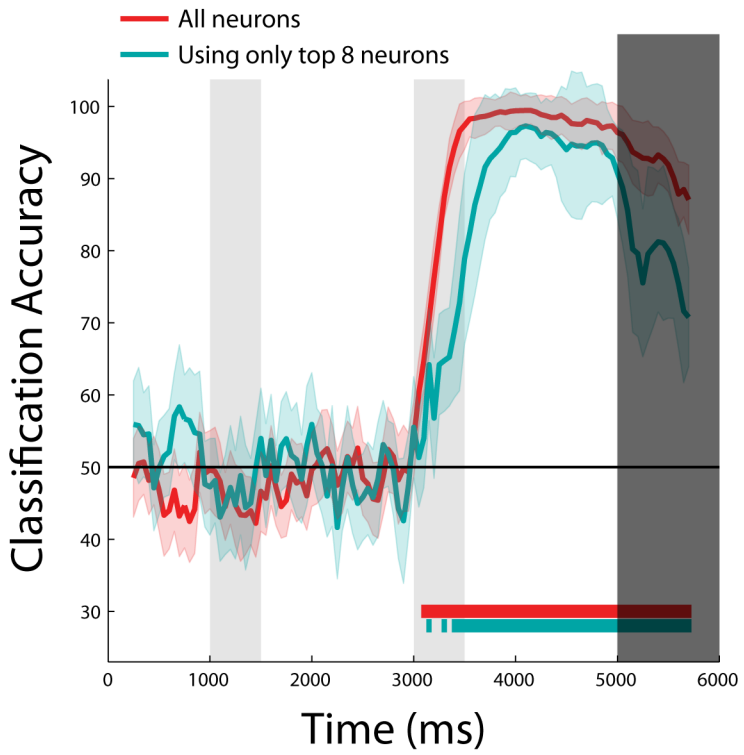
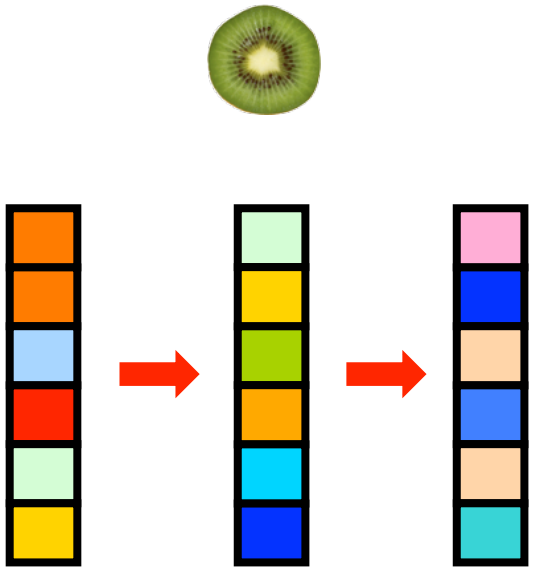
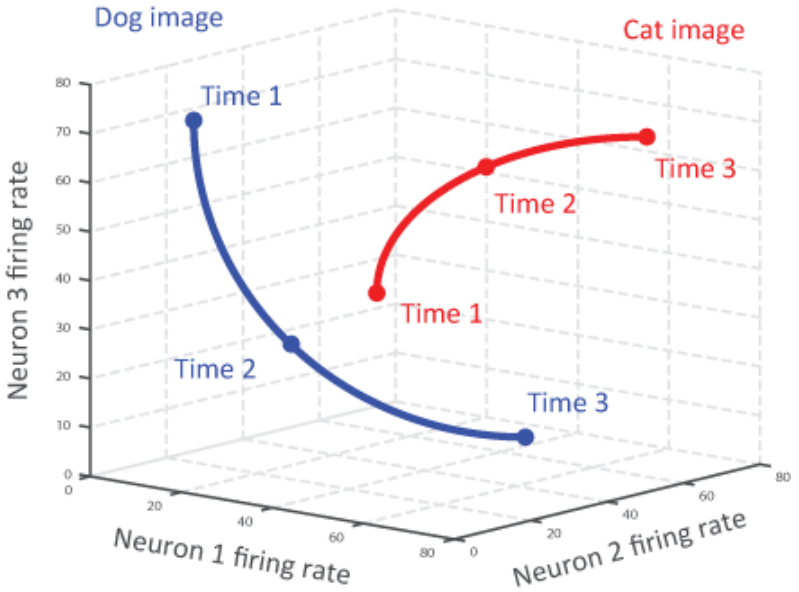


Excluding the 128 most selective neurons

Is information contained in a dynamic population code?

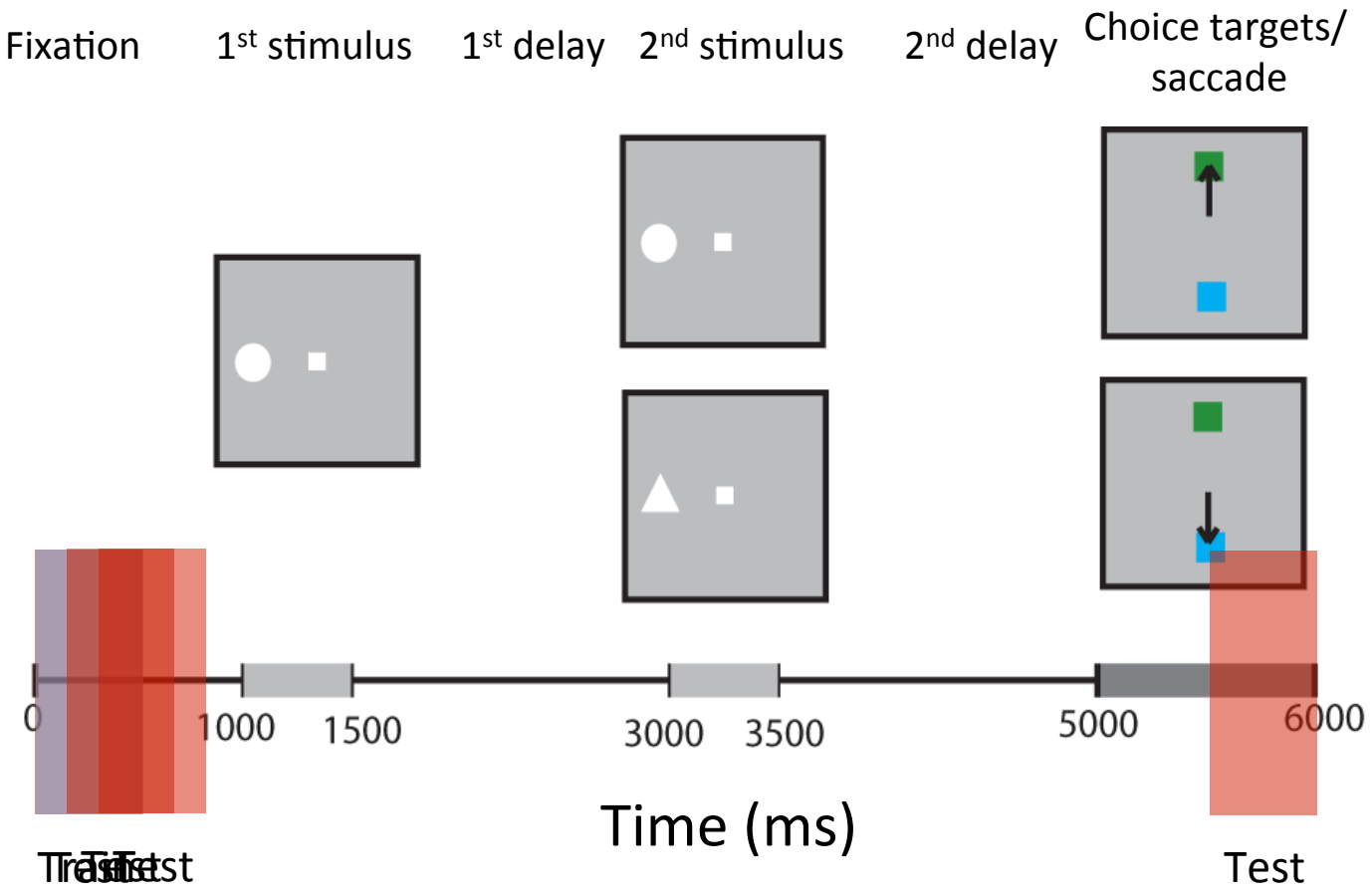


Time



Meyers et al, 2008; King and Dehaene 2014; Meyers 2018 in press

Temporal generalization method



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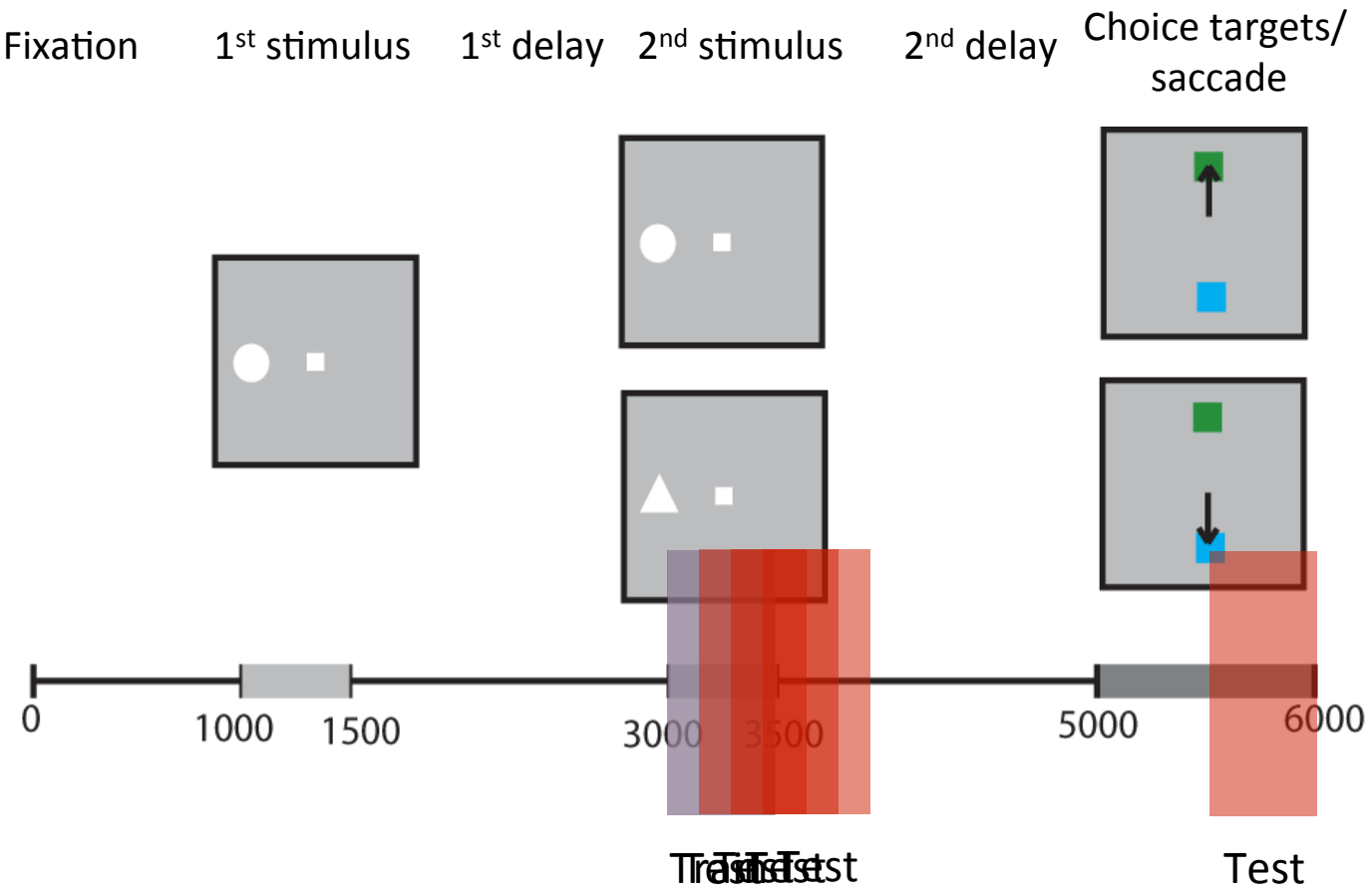
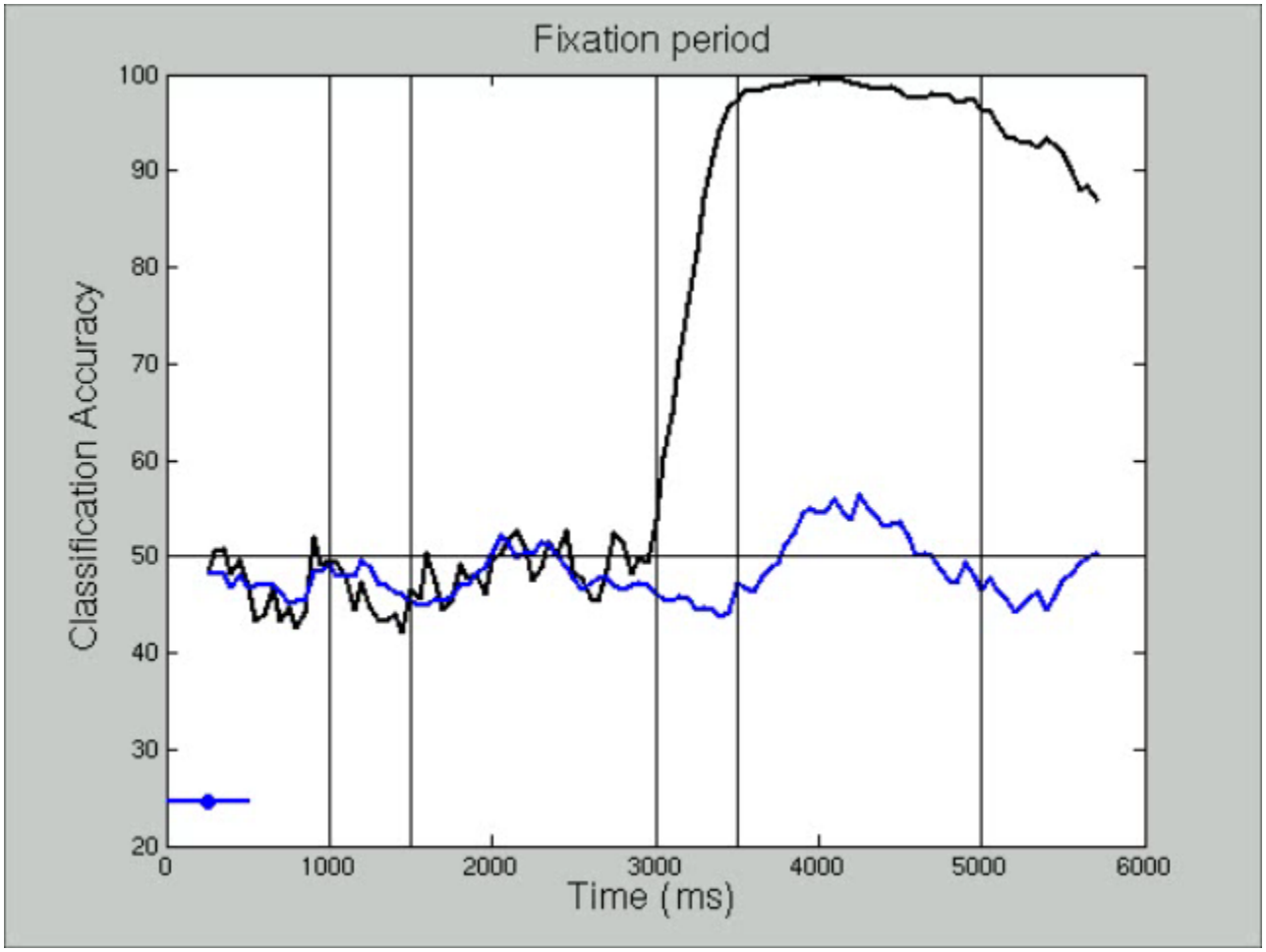


Dynamic population coding



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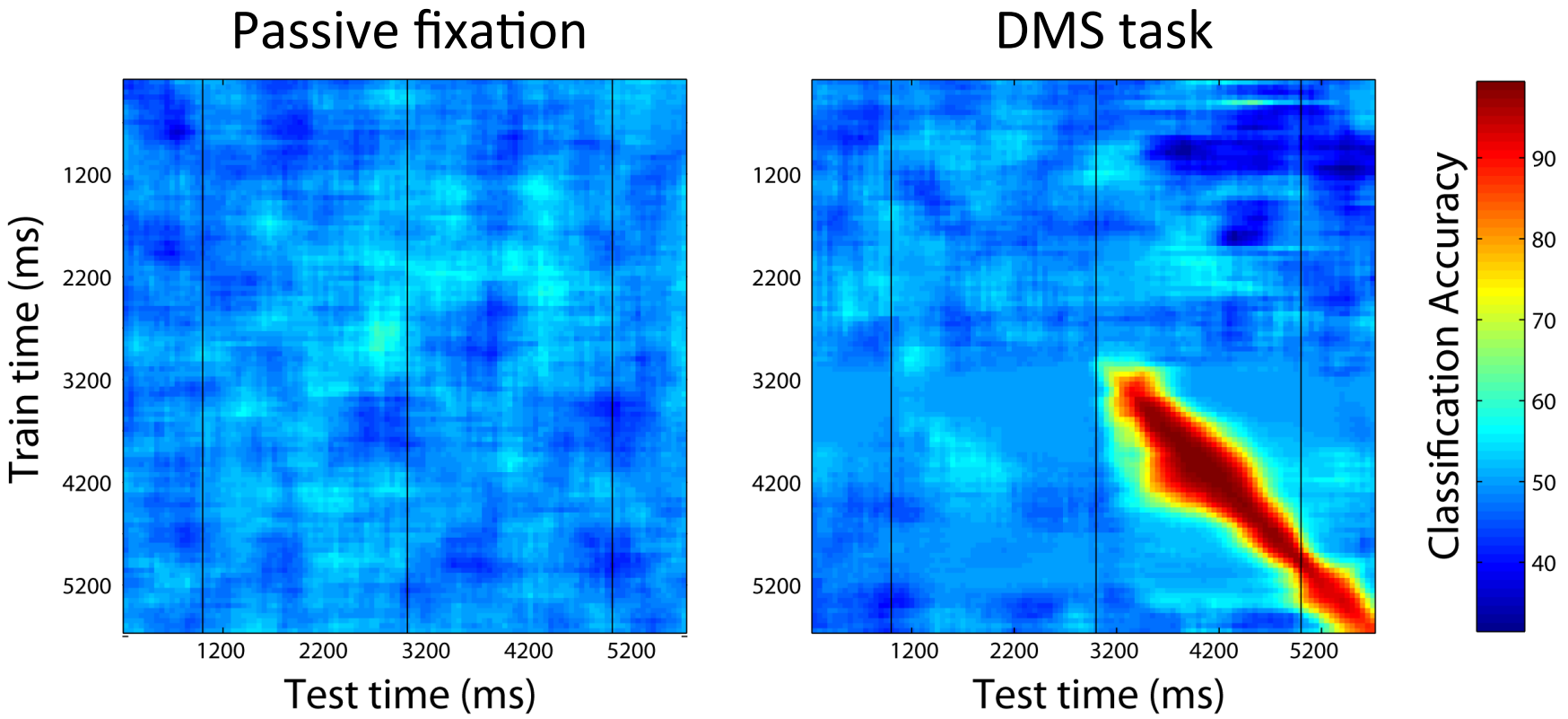
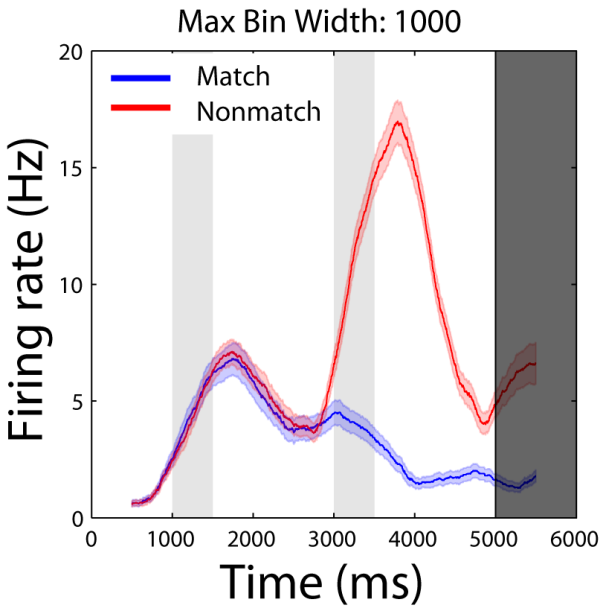
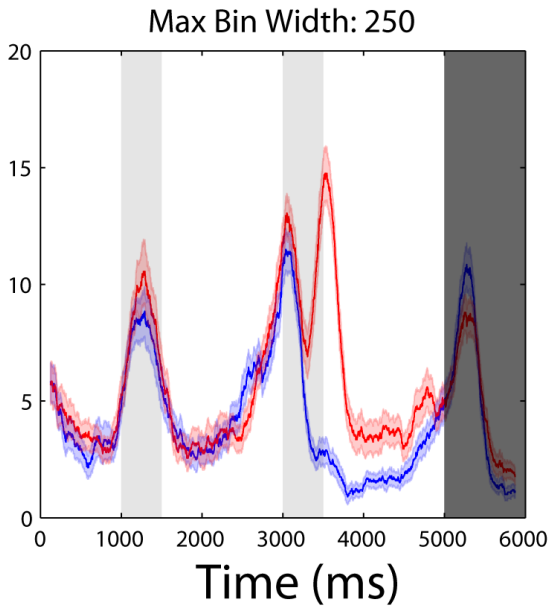


The dynamics can be seen in individual neurons

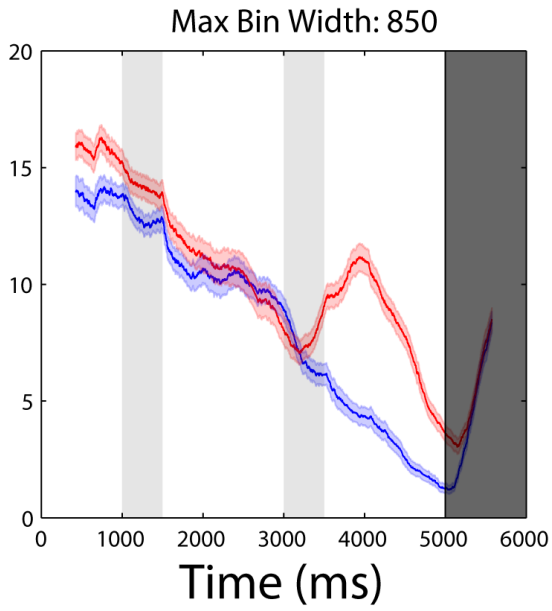
Neuron 1



Neuron 2



Neuron 3



Talk outline

Task-relevant information
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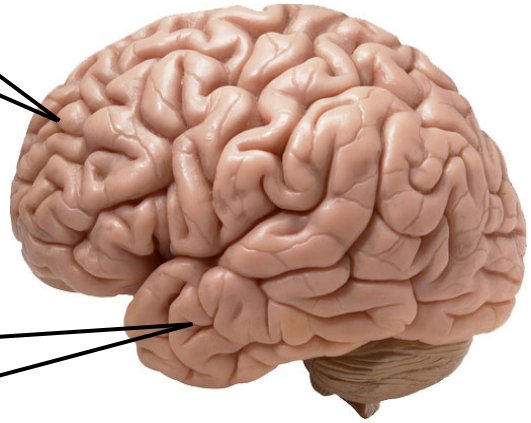

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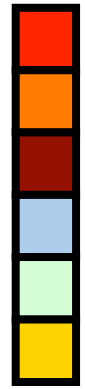

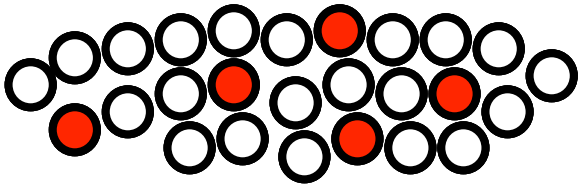

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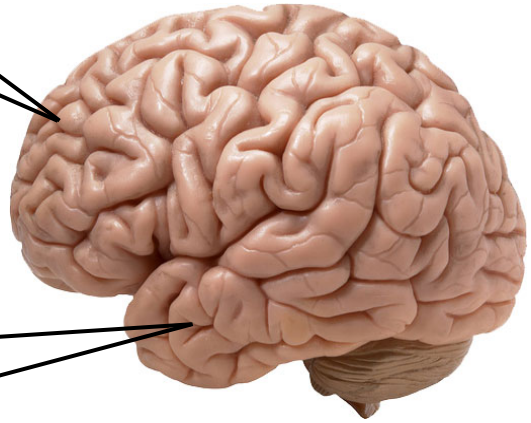

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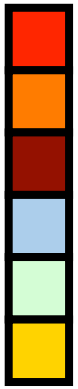

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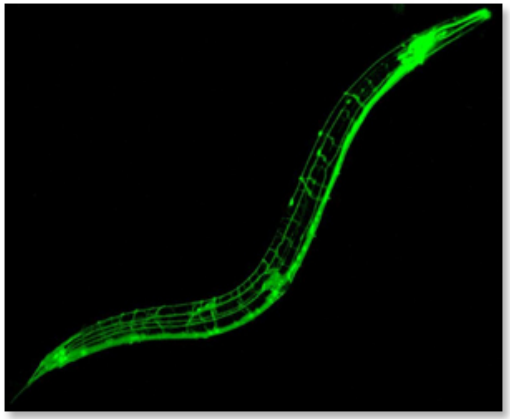
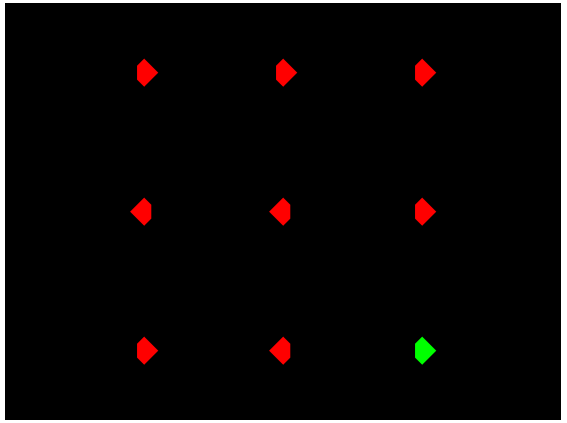
Toward and understanding of neural algorithms

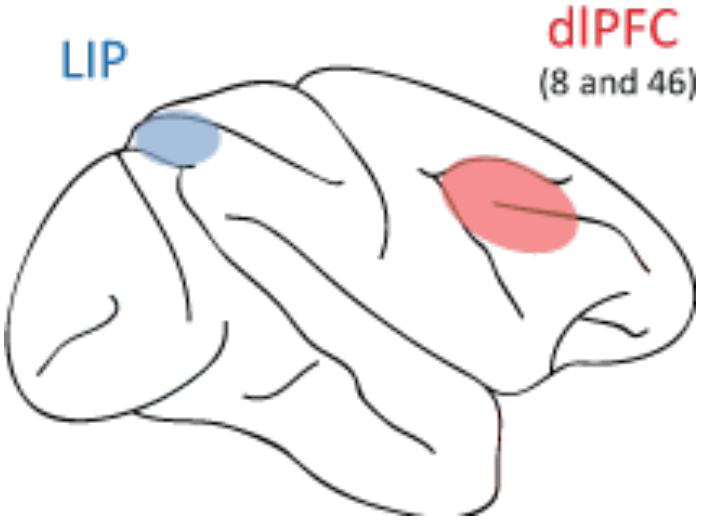
A useful approach to understanding complex problems: start with simpler systems and build up from there

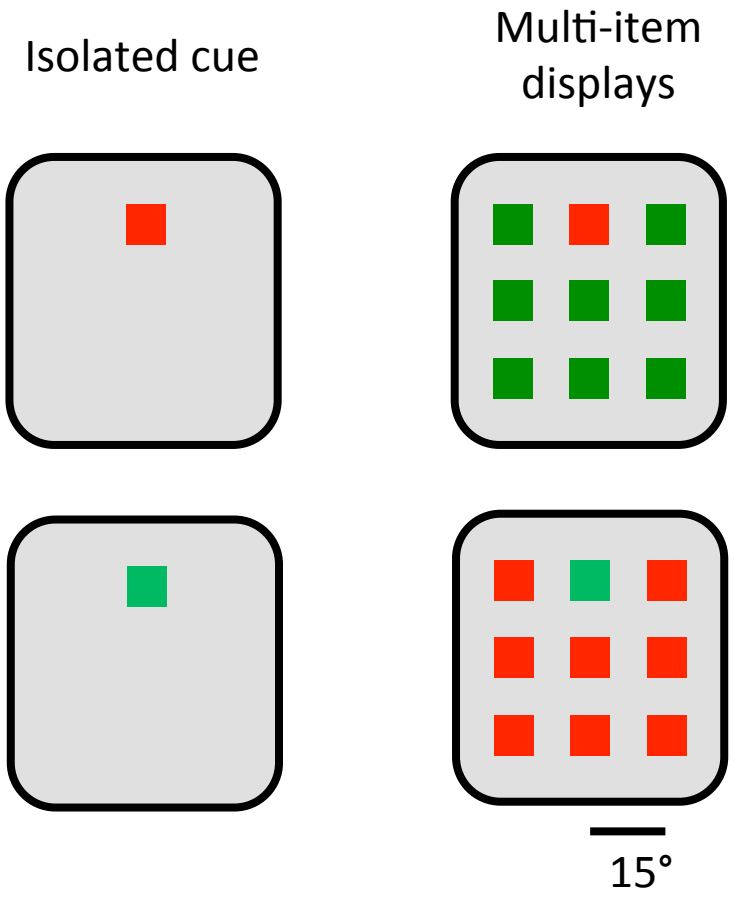




A relatively simple behavior: locating a 'pop-out' item

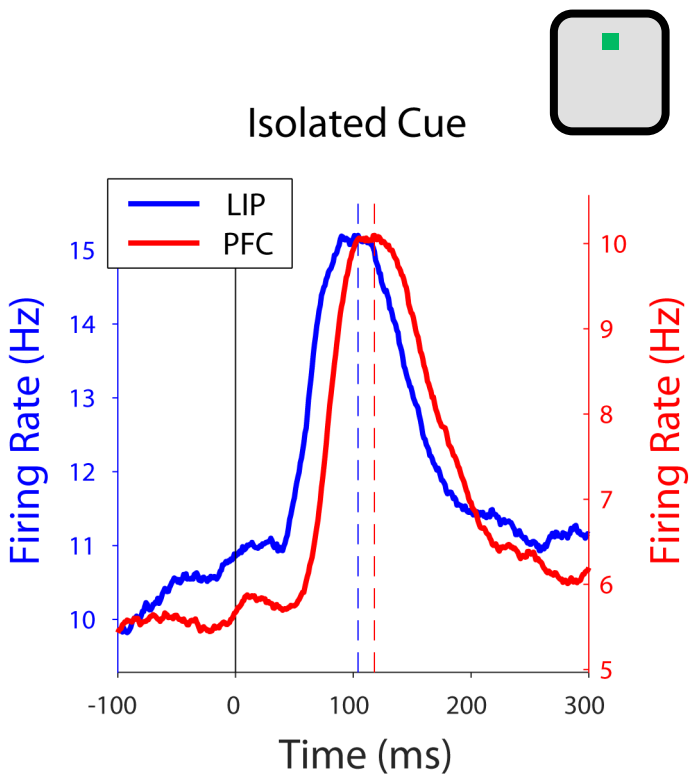
Relating neural activity to behavior

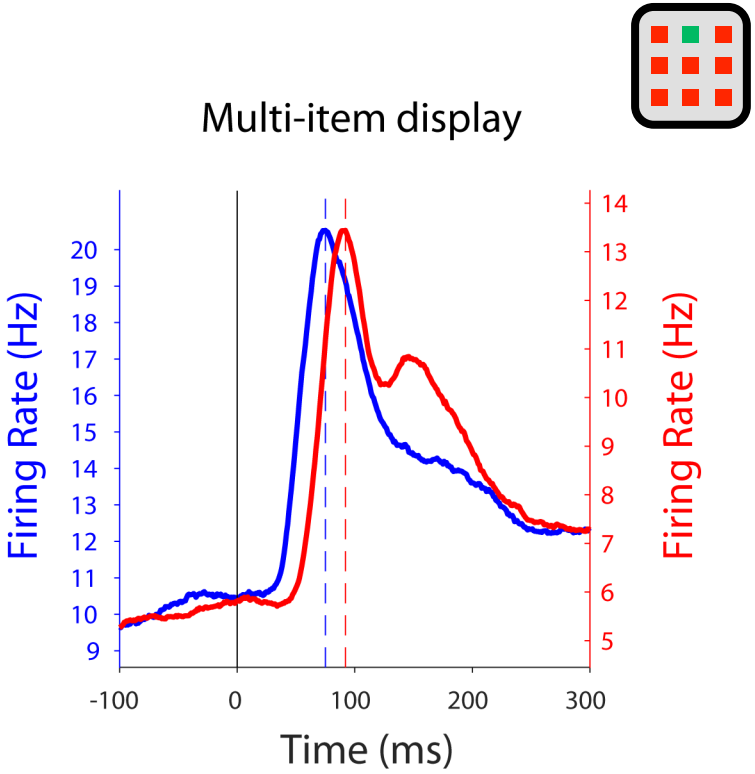




Meyers, Liang, Katsuki and Constantinidis (2017)

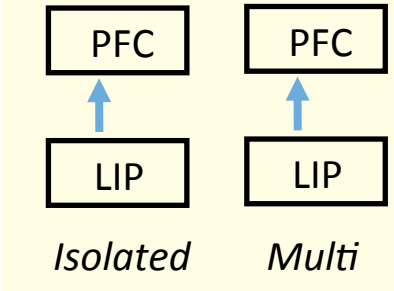
Firing rate analysis



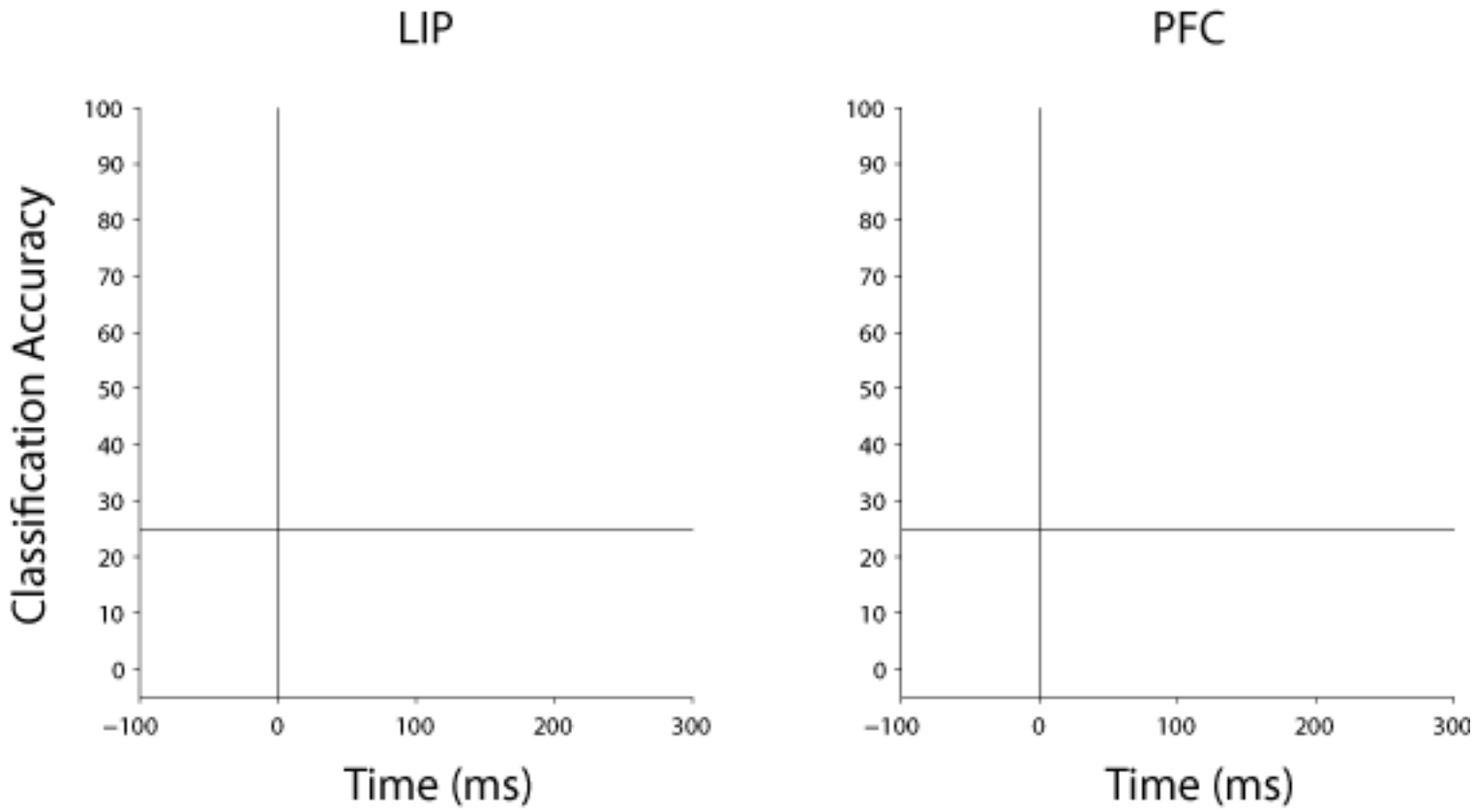


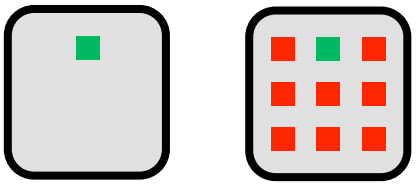
Firing rates in LIP increase (~15 ms) before PFC

This is consistent with feed-forward increases in firing rates



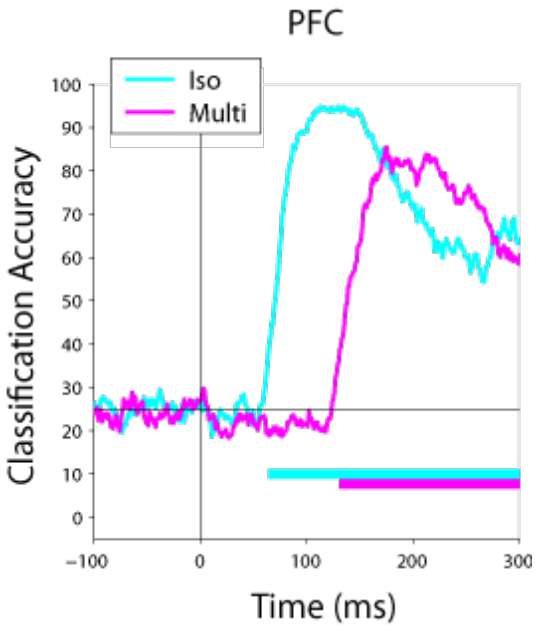
Comparing isolated and multi-item displays

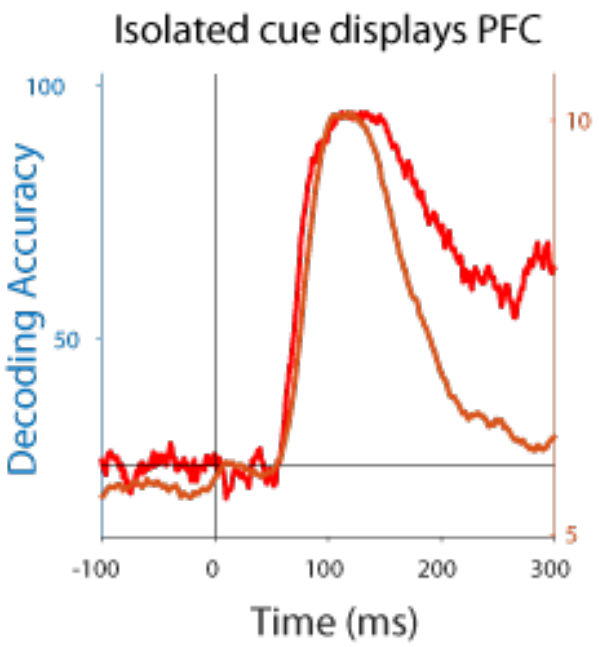


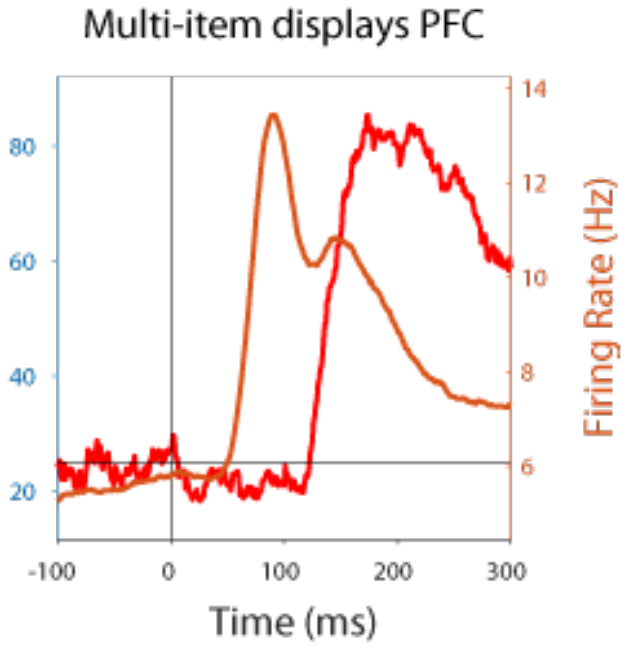


Multi-item displays are processed slower than isolated stimuli

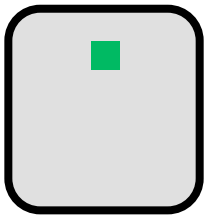
Relating information to firing rates (PFC)

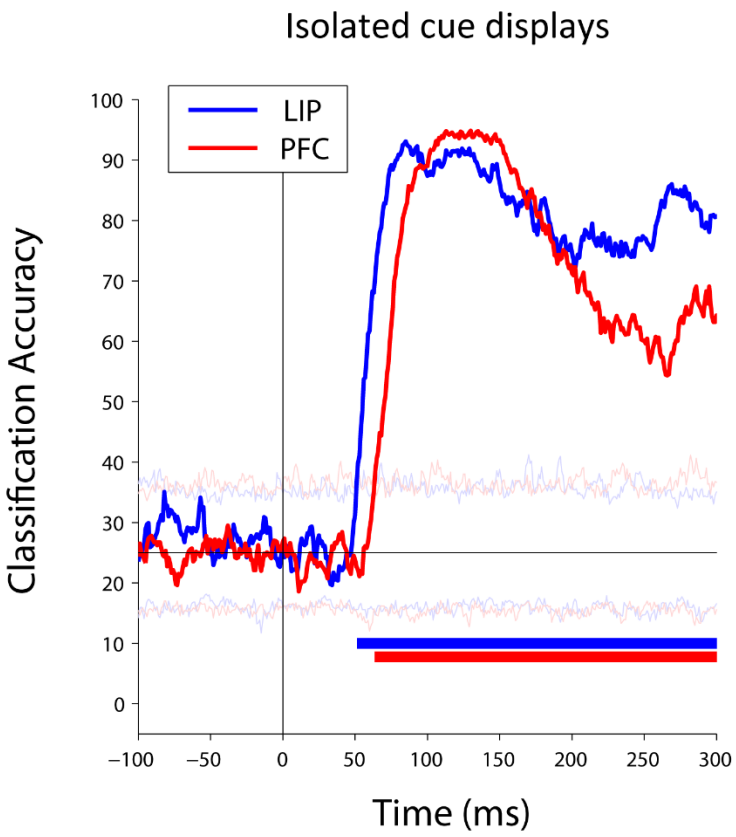






Information analysis: isolated cue displays





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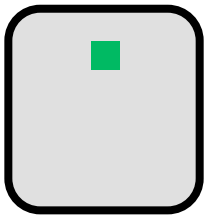

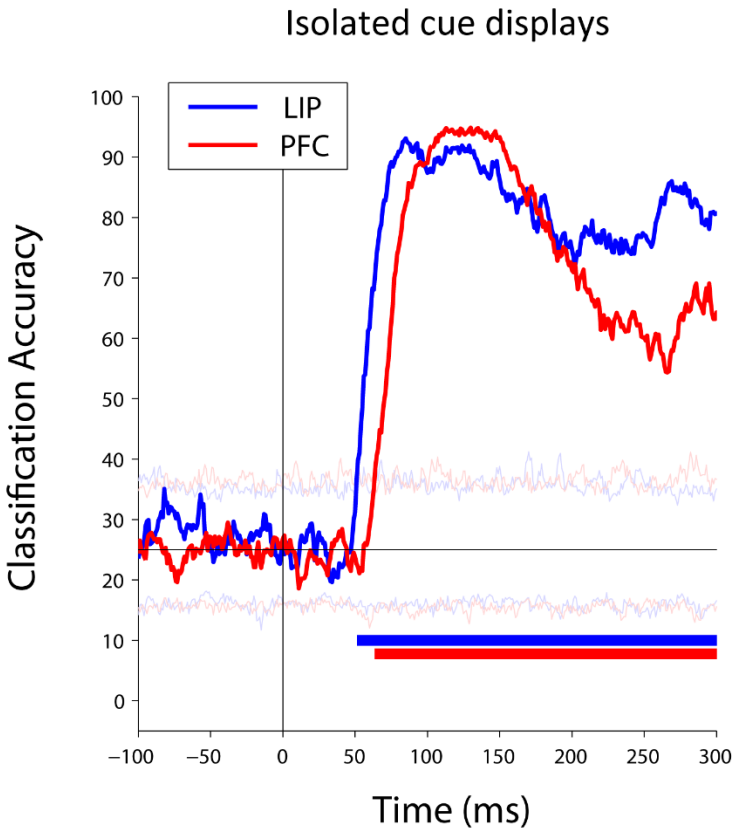

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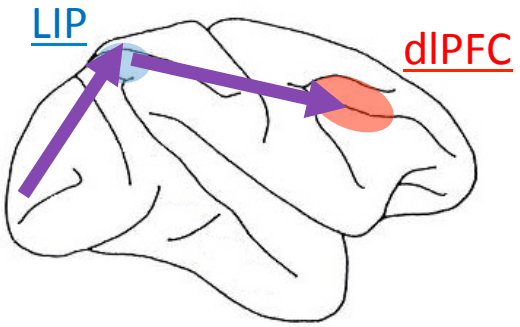
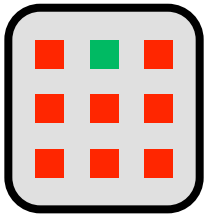
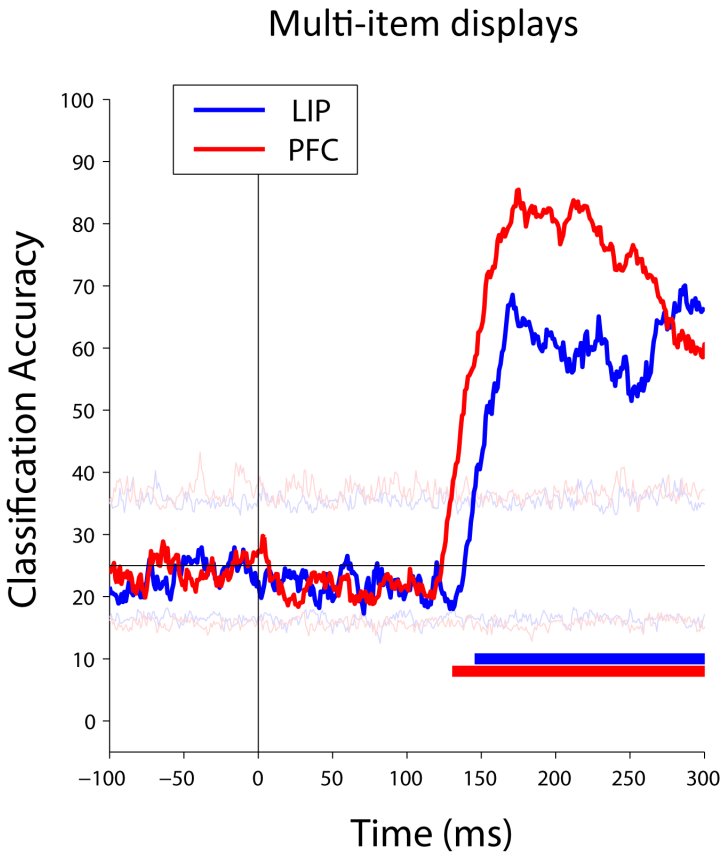
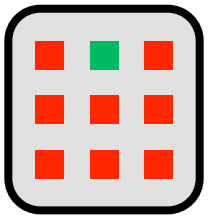


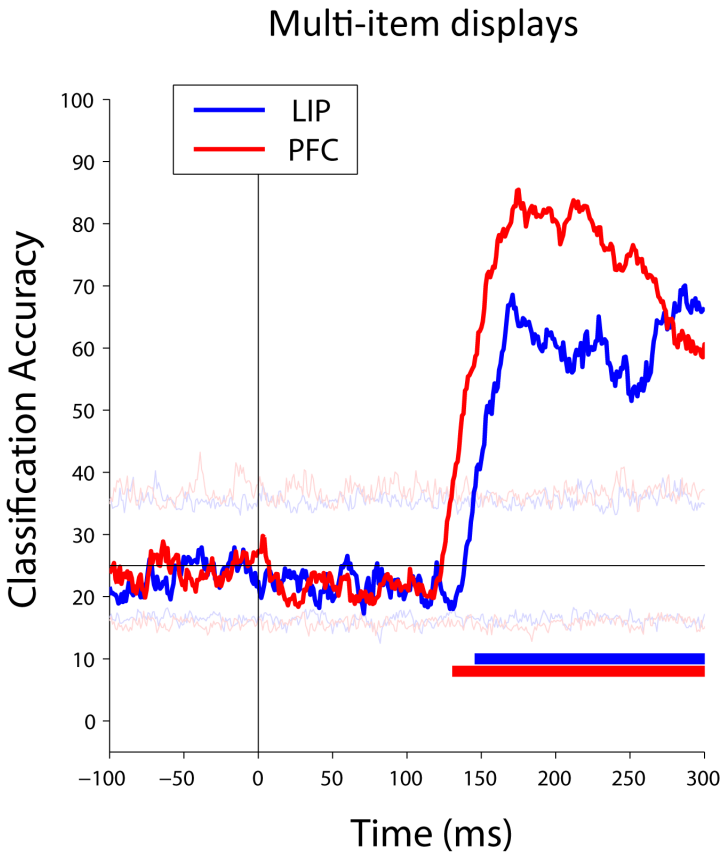
Information analysis: multi-item displays

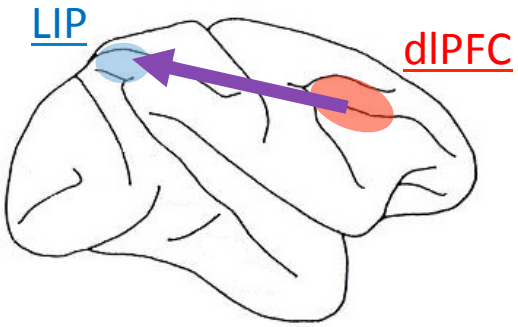




Information analysis: multi-item displays



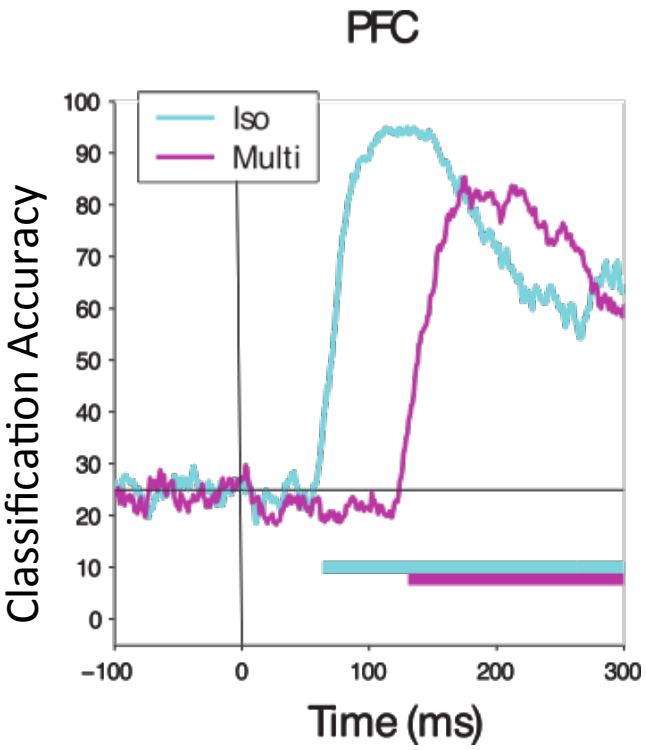


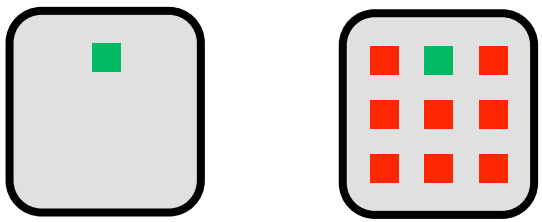


Information in PFC increase (~15 ms) before LIP

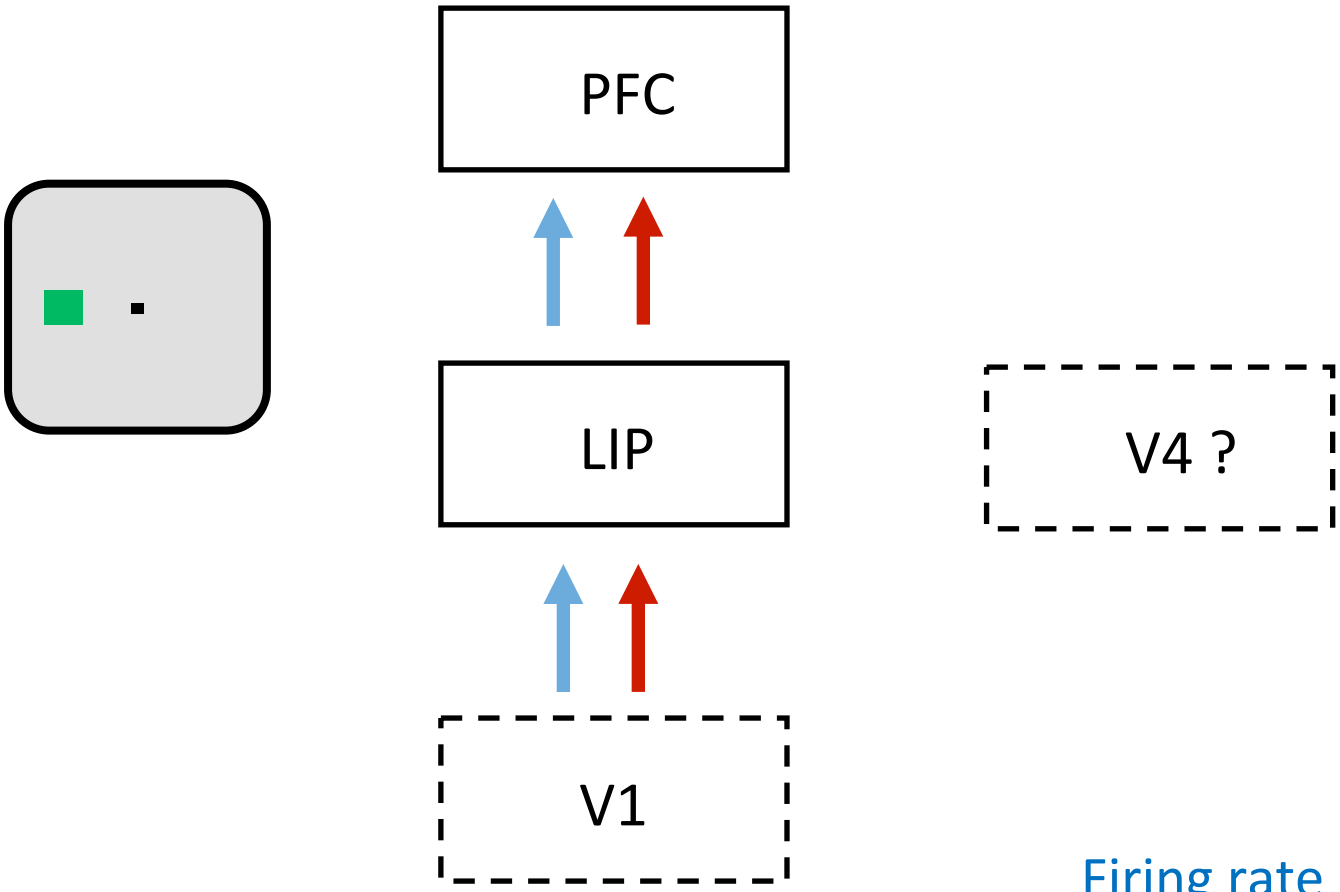
This is consistent with **feed-back** increases in information

Relating neural activity to behavior





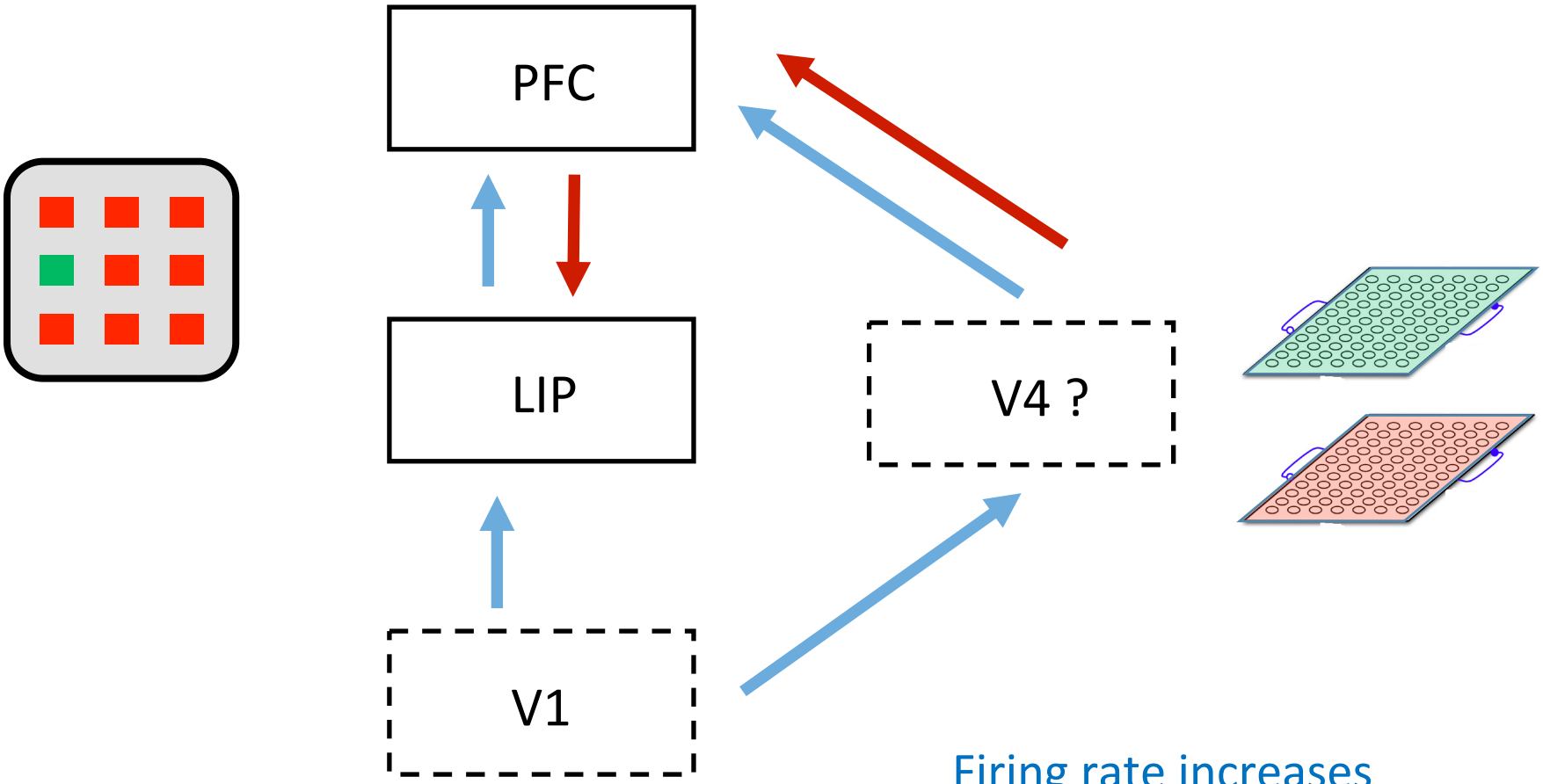
Model that summarizes the results



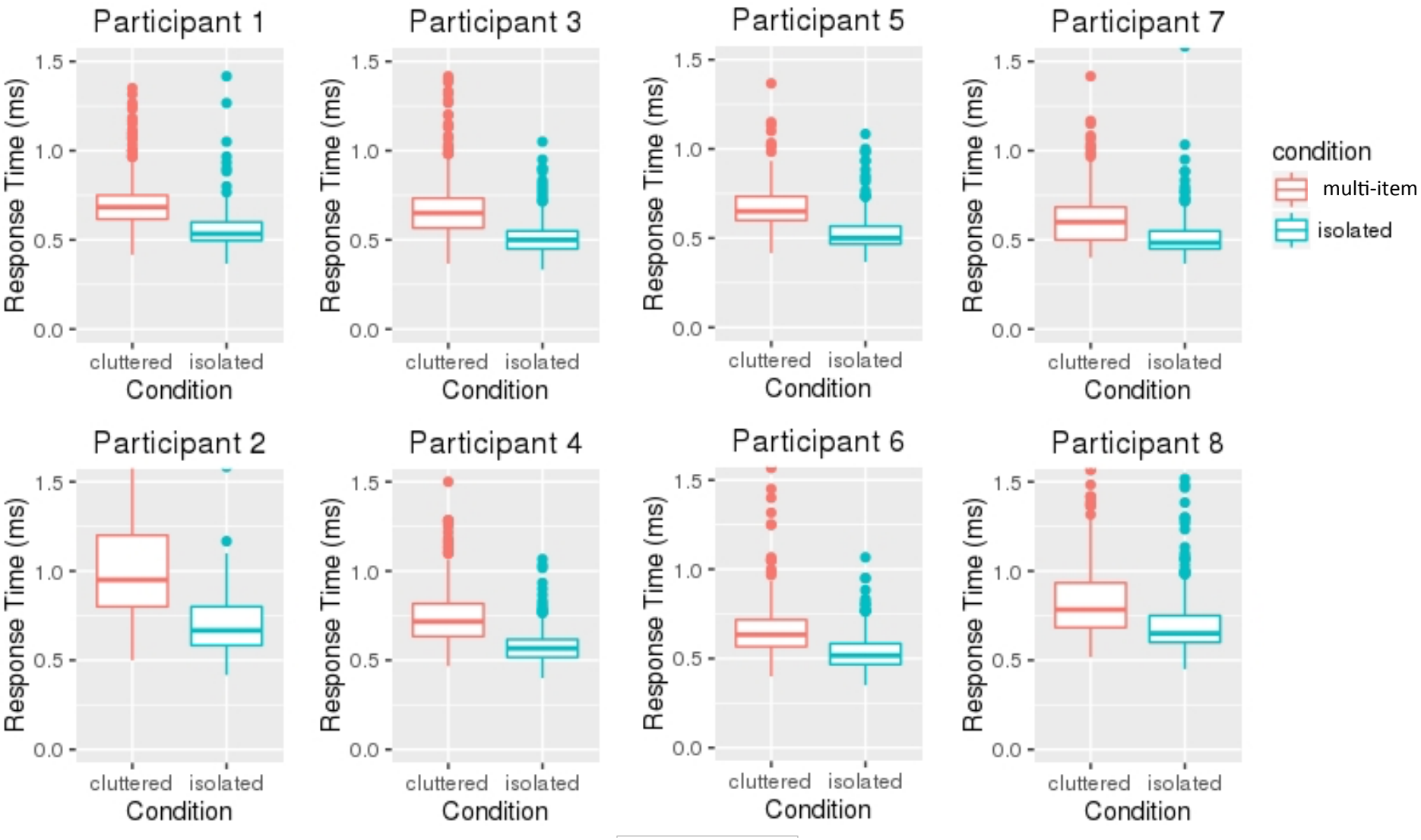
Firing rate increases

Cue location information

Model that summarizes the results



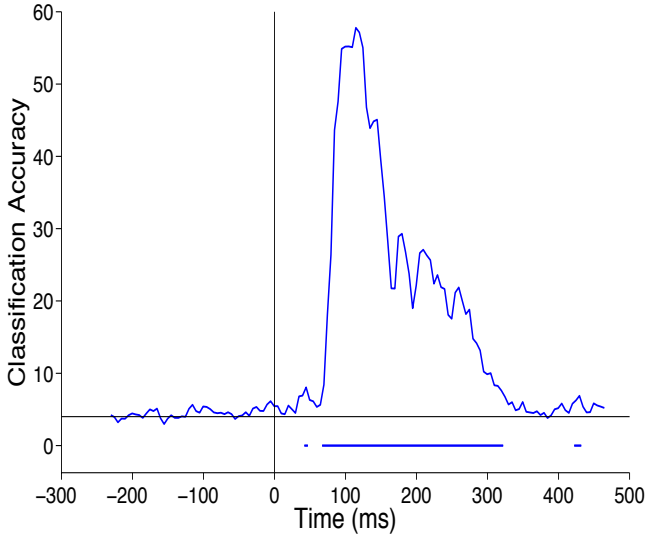
Results from human brain activity and behavior



Decoding can be applied to other types of data

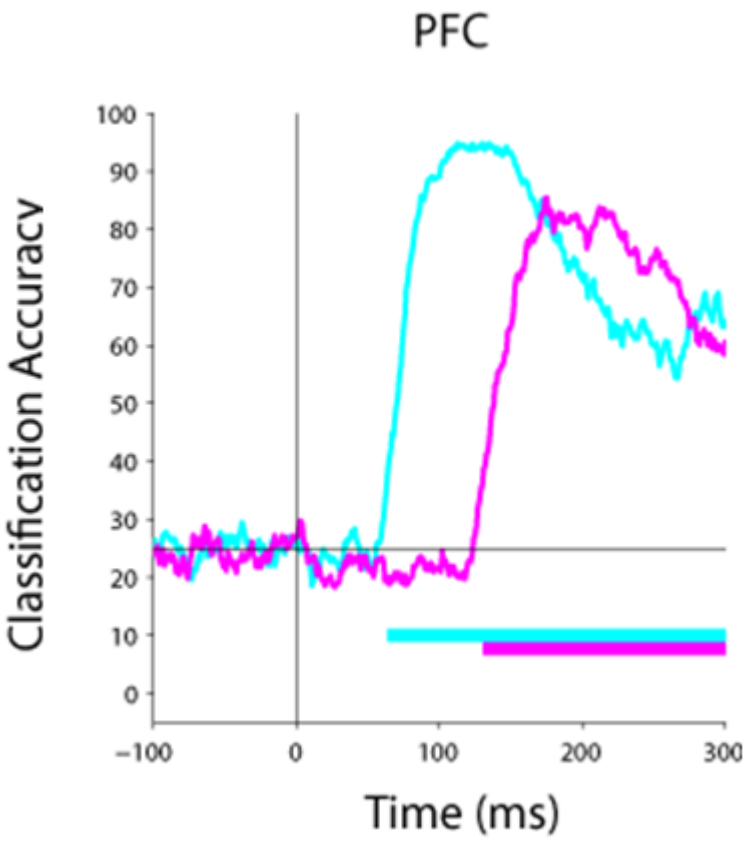
MEG Decoding

A	B	C	D	E
F	G	H	I	J
K	L	M	N	O
P	Q	R	S	T
U	V	W	X	Y

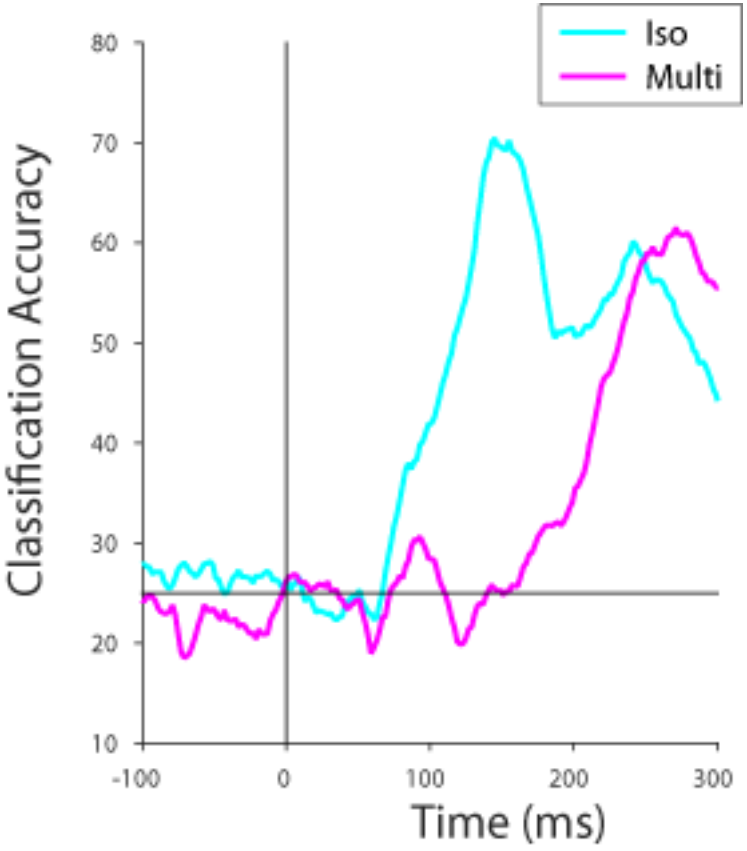


Isik, Meyers, Liebo, Poggio, J. Neurophys, 2014

EEG results average across subjects

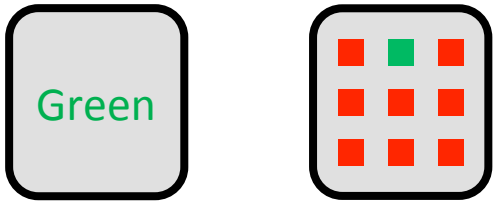


Monkeys



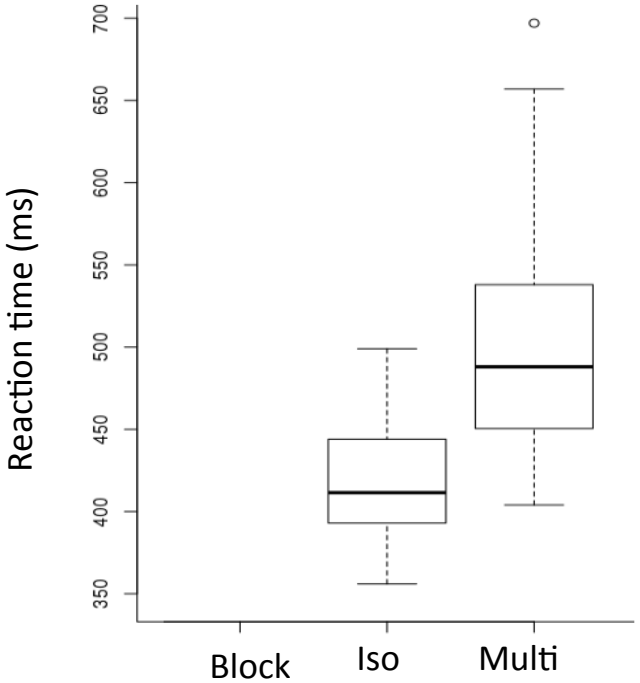
Hampshire Students

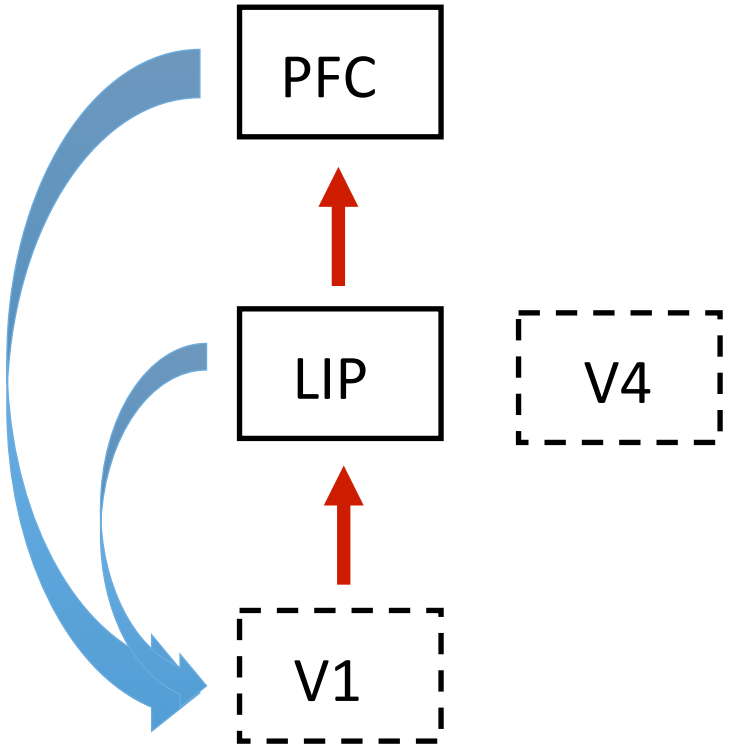
Next step: examining anticipation effects



Pre-cuing causes top-down anticipatory filtering in early visual areas

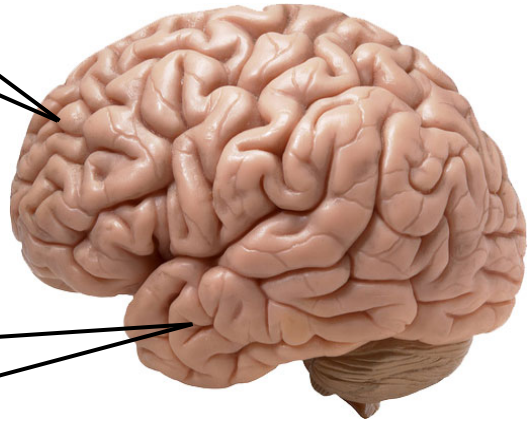
Humans – reaction times



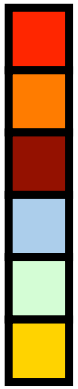


Talk outline

Task relevant information
is coded dynamically



Abstract representations
are modified by attention



1. The basics of neural decoding
2. The sensory pathways create abstract representations
3. “Top-down attention” can modify these representations
4. Higher areas selectively represent task-relevant information
5. Information often is coded dynamically and sparsely
6. The flow of information can be traced through the brain

Try this at home: The Neural Decoding Toolbox (NDT)

The neural decoding toolbox makes it easy to do decoding in MATLAB:

```
1   binned_file = 'Binned_data.mat';
2   ds = basic_DS(binned_file, 'stimulus_ID', 20);
3   cl = max_correlation_coefficient_CL;
4   fps{1} = zscore_normalize_FP;
5   cv = standard_resample_CV(ds, cl, fps)
6   DECODING_RESULTS = cv.run_cv_decoding;
```

Open Science philosophy: open source for reproducible results

- The code open source for reproducible results
- Hope to encourage open science culture, so please share your data

www.readout.info

Meyers, Font Neuroinfo, 2013

The Neural Decoding Toolbox Design

Toolbox design: 4 abstract classes

1. **Datasource**: creates training and test splits
   - E.g., can examine the effects from different binning schemes

2. **Preprocessors:** learn parameters from training data apply them to the training and test data
   - E.g., can examine sparse/compact coding

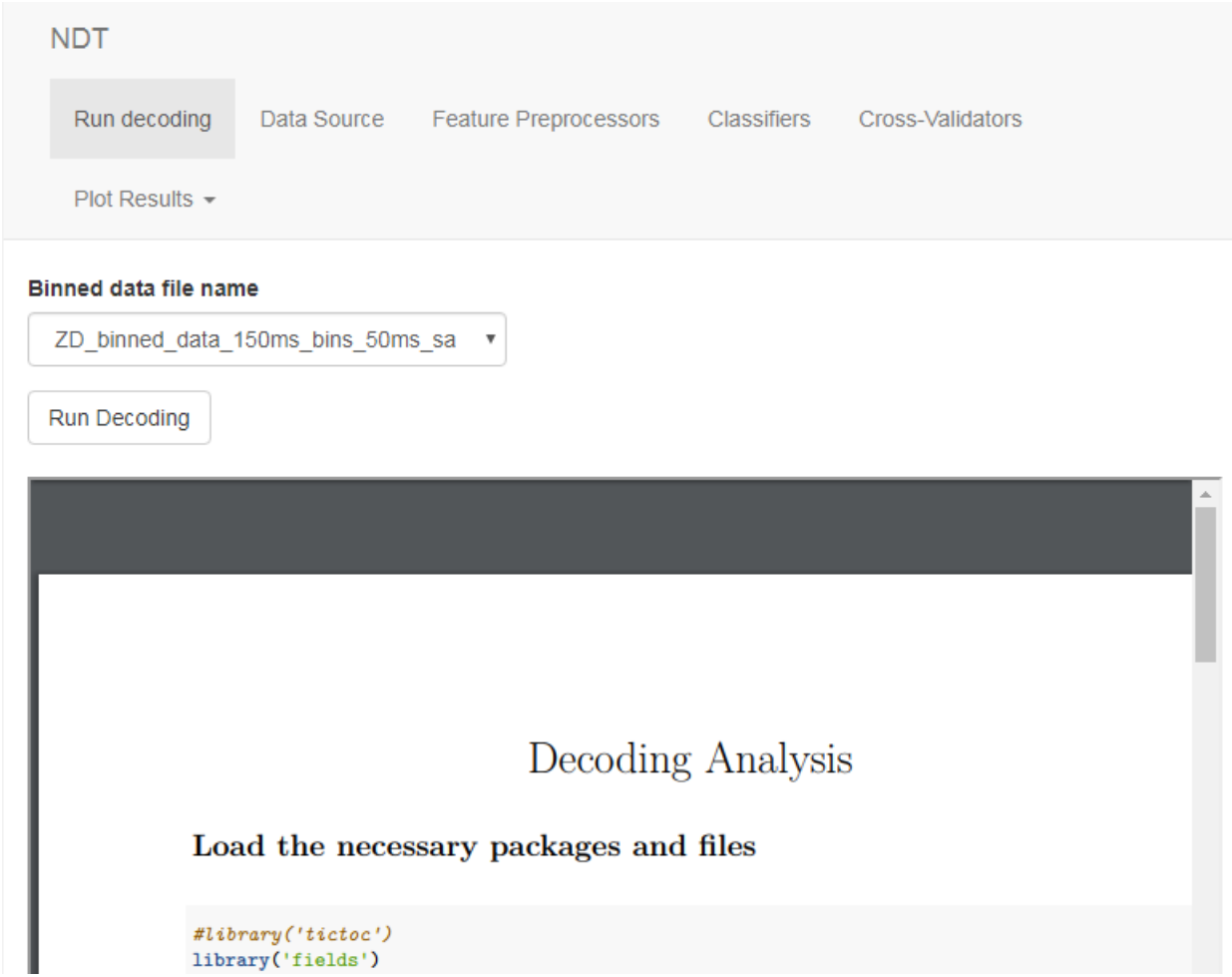
3. **Classifiers**: learn from training data and make predictions on test data
   - E.g., can examine whether information is in high firing rates or patterns

4. **Cross-validators:** run the training/test cross-validation cycle

Getting started with your own data

You can use the NDT on your own data by putting your data into ‘raster format’

Coming soon: The Neural Decoding Toolbox in R (NDTr)



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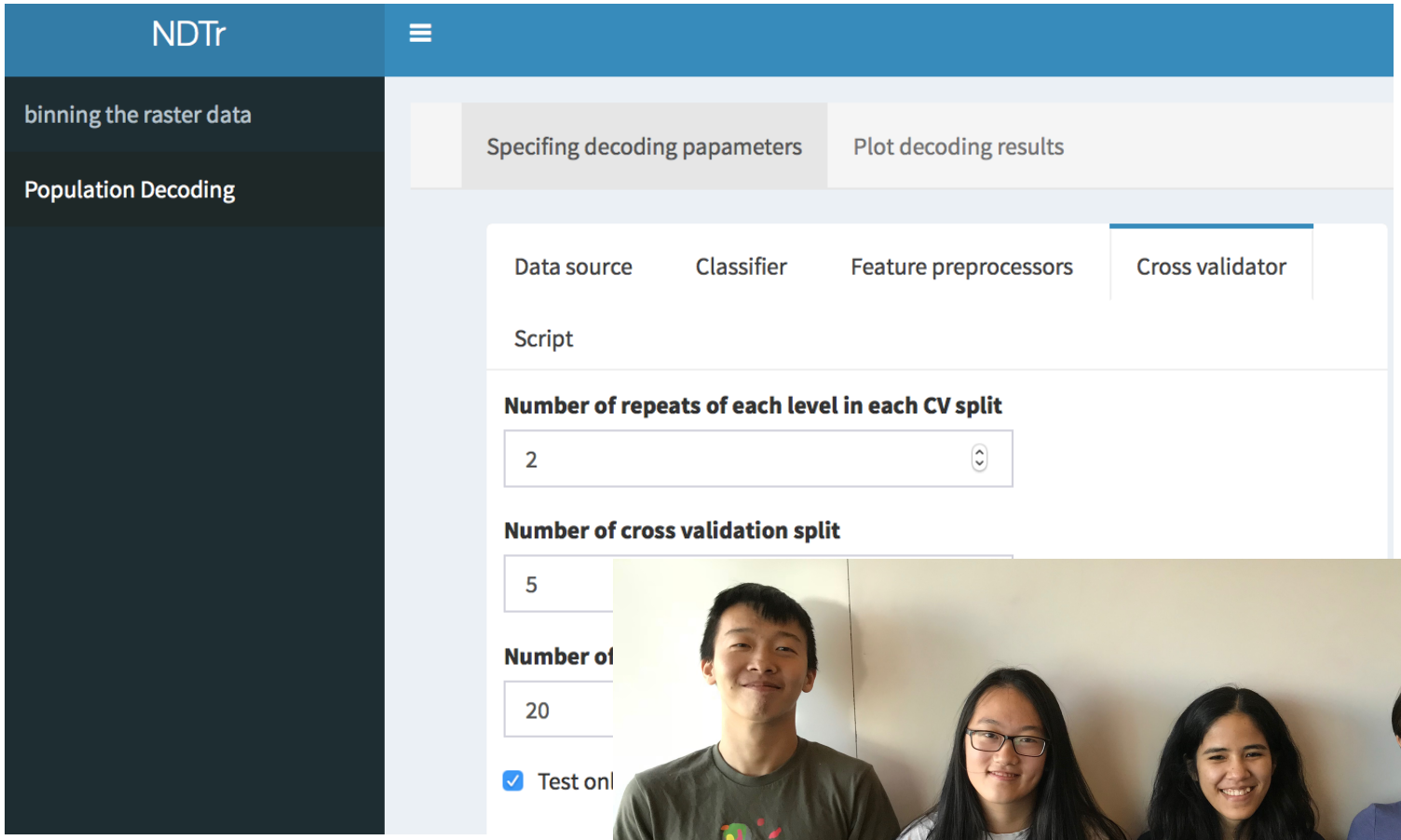
neuraldata.net

Coming soon: The Neural Decoding Toolbox in R (NDTr)



Demo

Questions

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