Using population decoding to understand neural content and coding

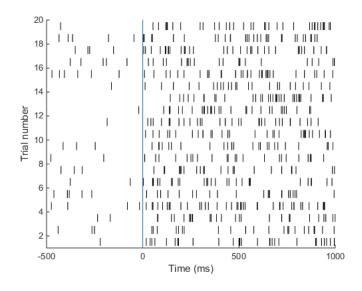


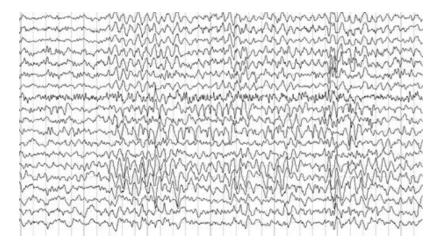


The Center for Brains, Minds & Machines

Motivation

We have some great theory about how the brain works We run an experiment and make neural recordings We get a bunch of data...





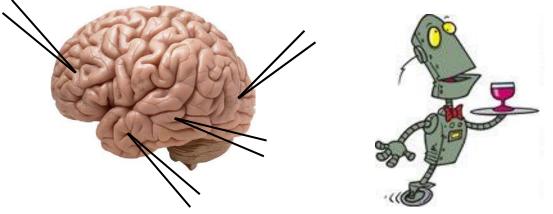
How can we convert data into answers?

What do I want from a data analysis method?

Clear answers to:

Neural content: What information is in a brain region?

<u>Neural coding</u>: What features of the activity contain information?



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What is population decoding?

Using decoding to understand neural content

Using decoding to understand **neural coding**

How to analyze your own data

Neural population decoding

Decoding: Predict stimulus/behavior from neural activity

f(neural activity) **—** stimulus

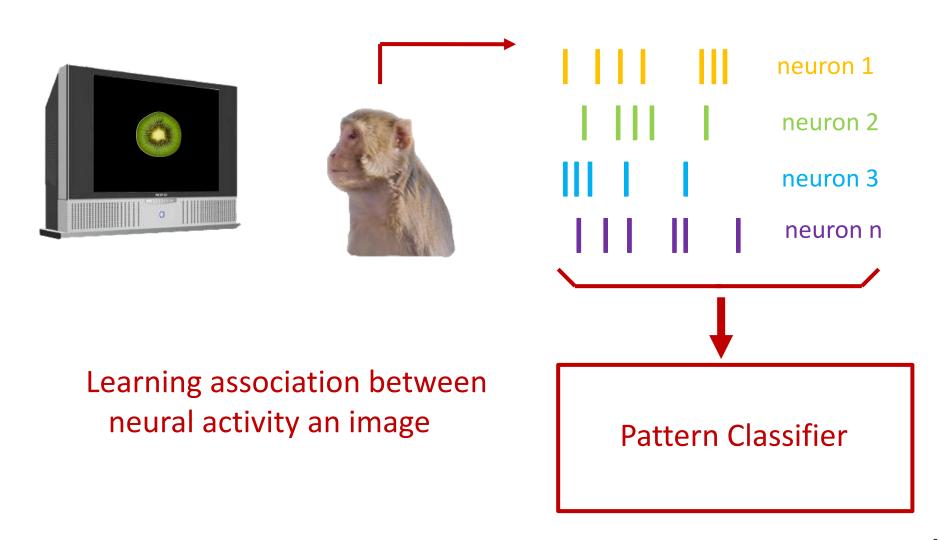
Decoding approaches have been used for 30 years

- Motor system: e.g., Georgopoulos et al, 1986
- Hippocampus: e.g., Wilson and McNaughton, 1993
- Computational work: e.g., Salinas and Abbott, 1994

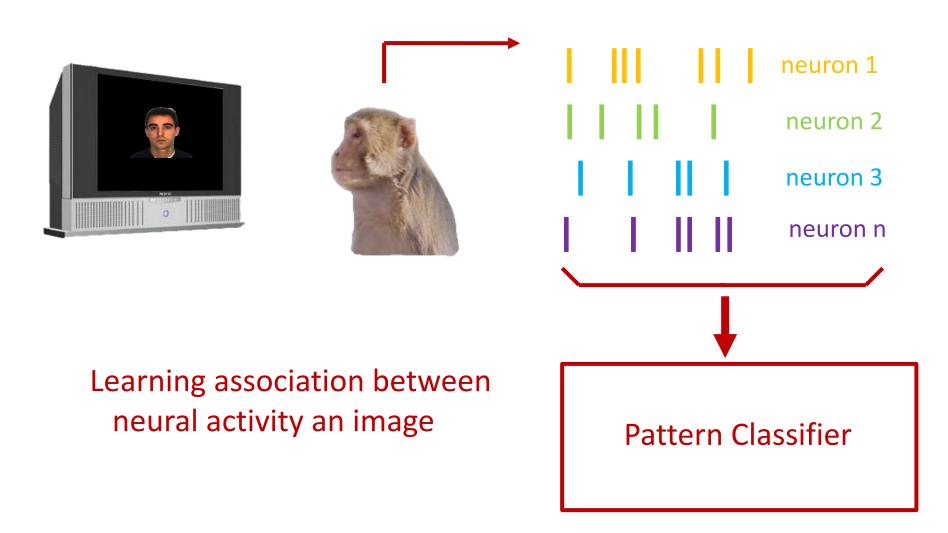
Alternative names for decoding:

- Multivariate Pattern Analysis (MVPA)
- Readout

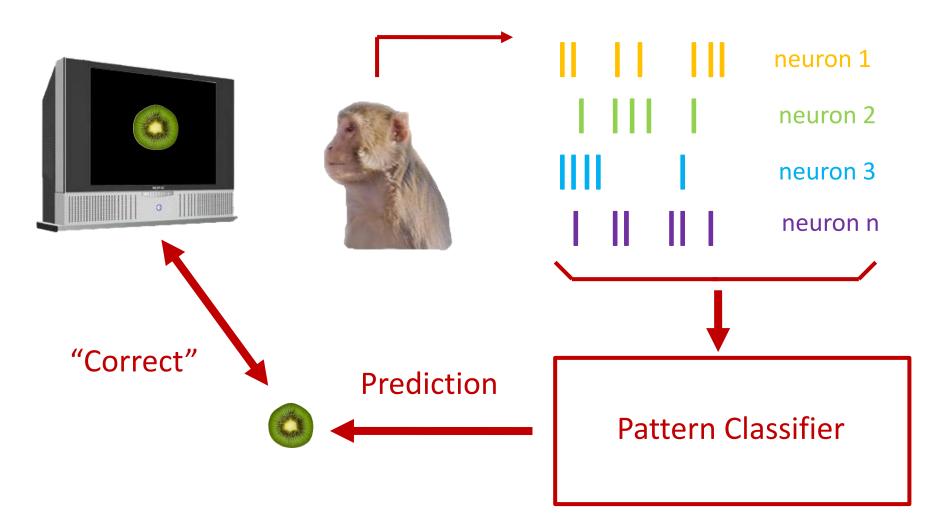
Training the classifier



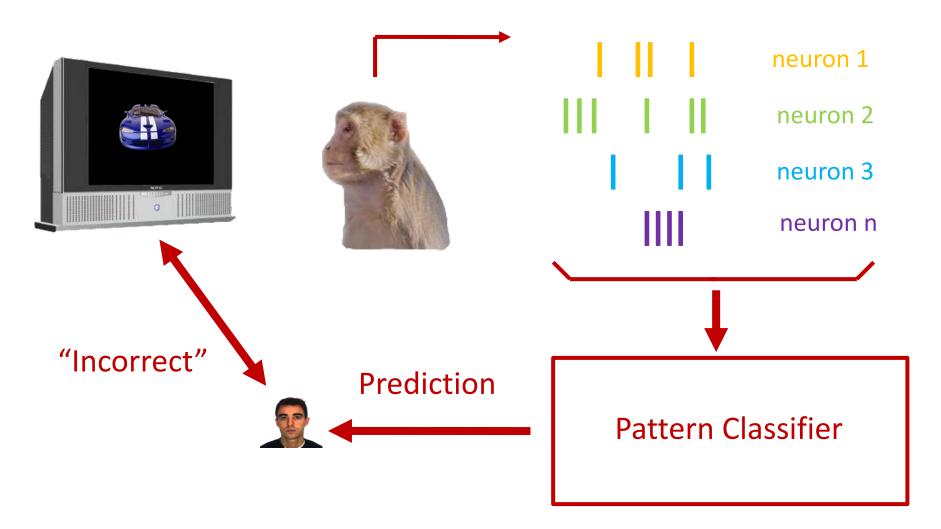
Training the classifier



Using the classifier

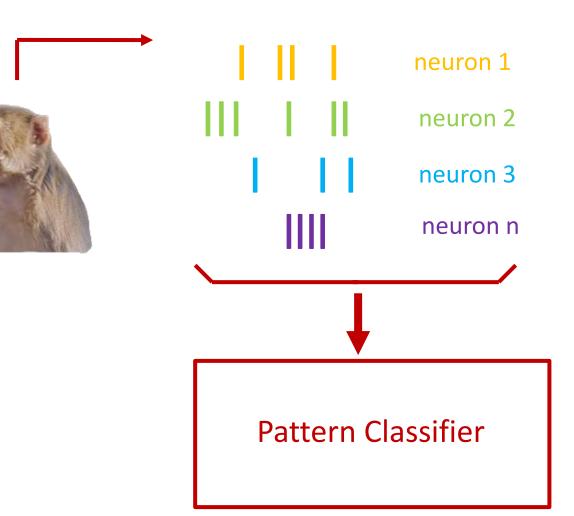


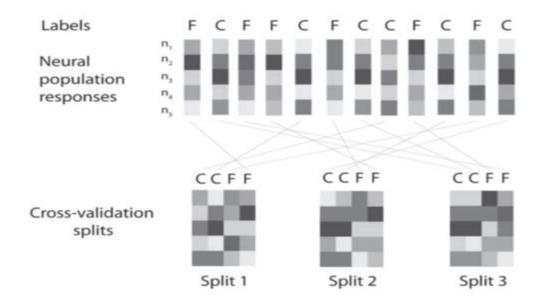
Using the classifier

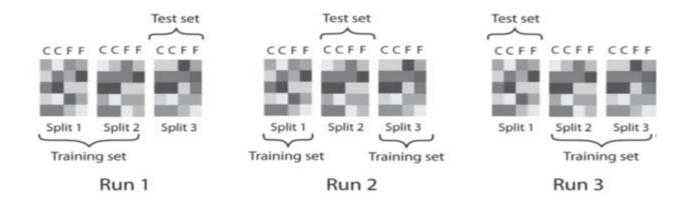


Using the classifier



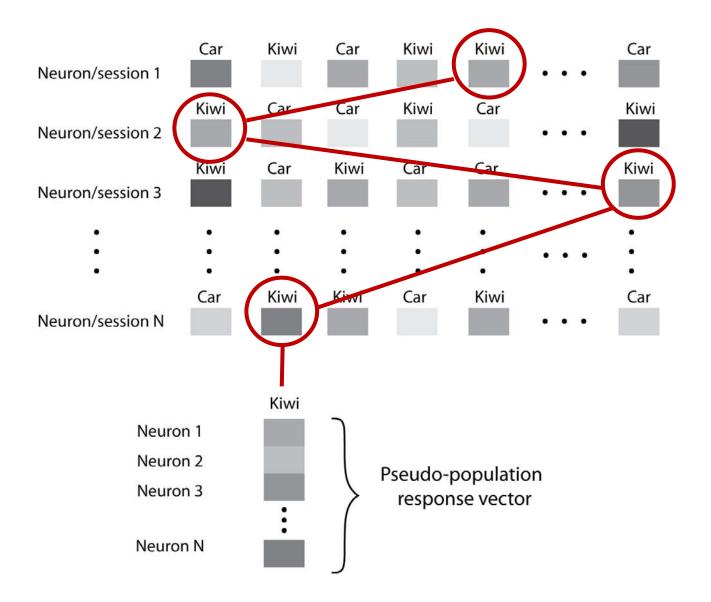




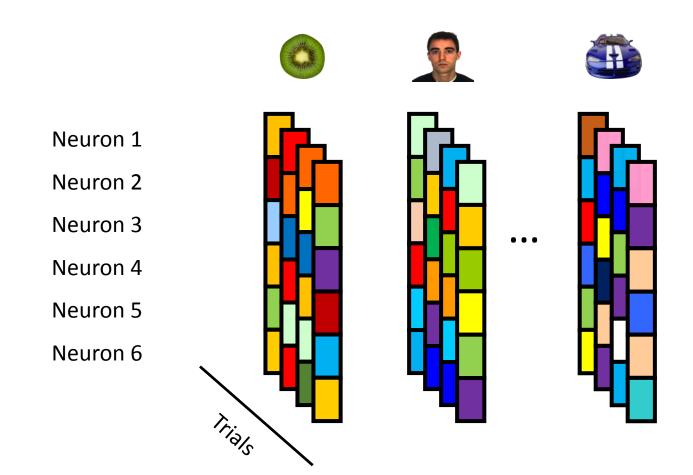


Courtesy of MIT Press. Used with permission. Source: Meyers, E. M., and Gabriel Kreiman. "Tutorial on pattern classification in cell recording." Visual Population Codes (2012): 517-538.

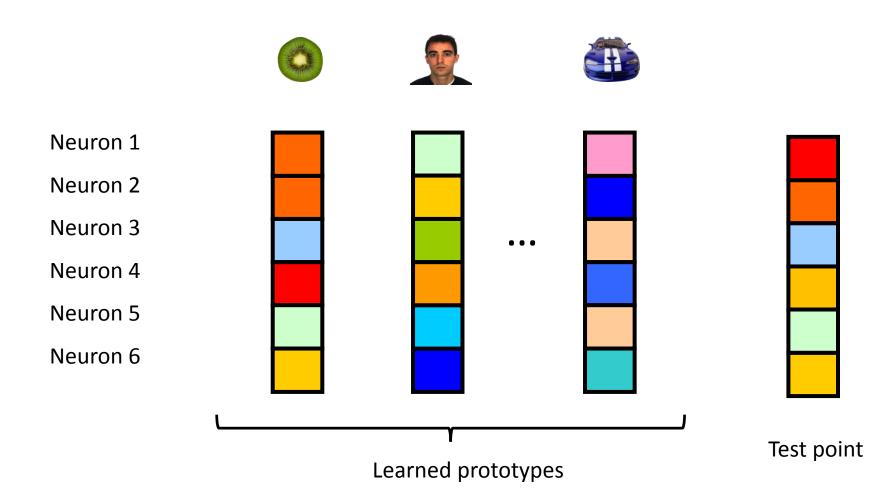
Pseudo-populations



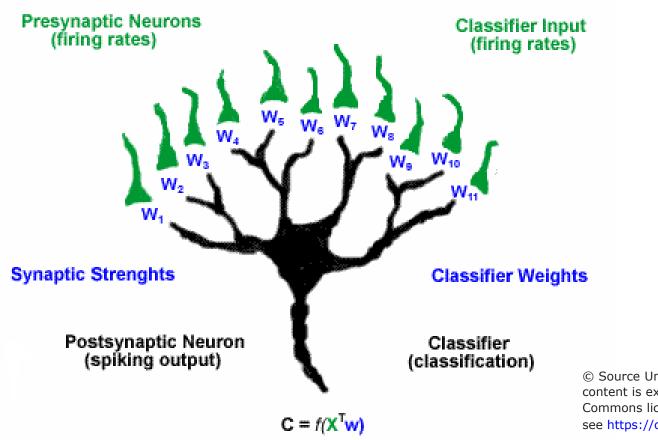
Maximum Correlation Coefficient Classifier



Maximum Correlation Coefficient Classifier



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

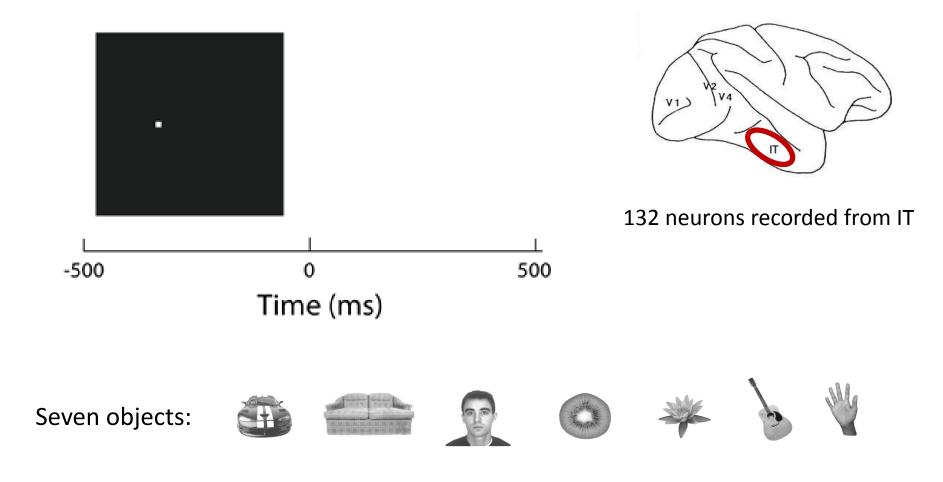


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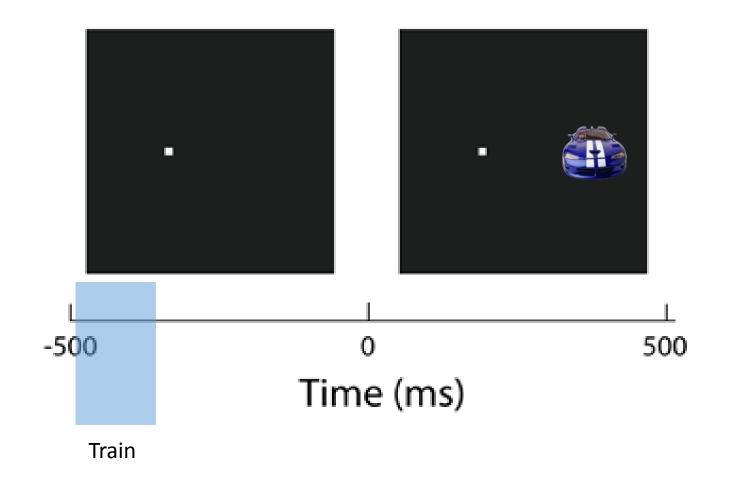
Neural content

A simple experiment

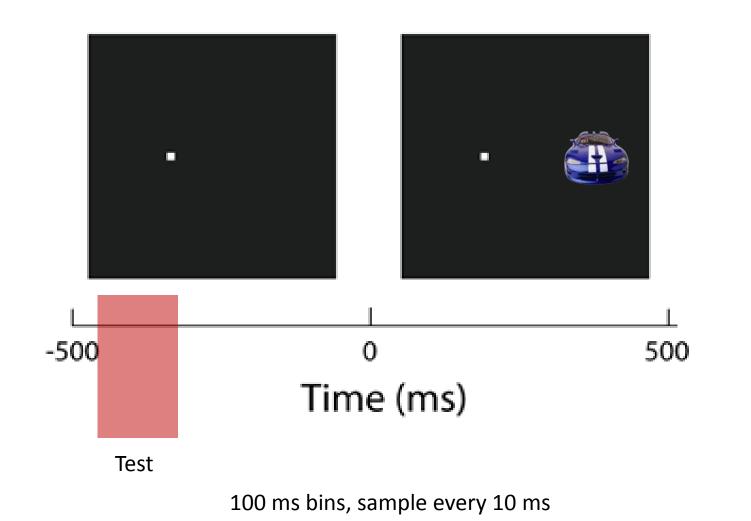


Zhang, Meyers, Bichot, Serre, Poggio, and Desimone, PNAS, 2011

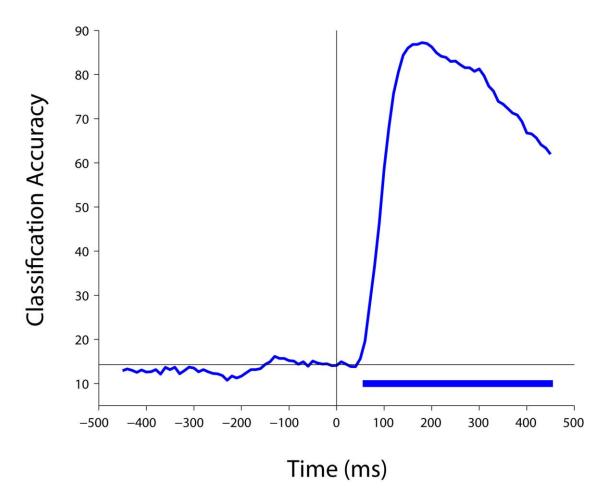
Applying decoding



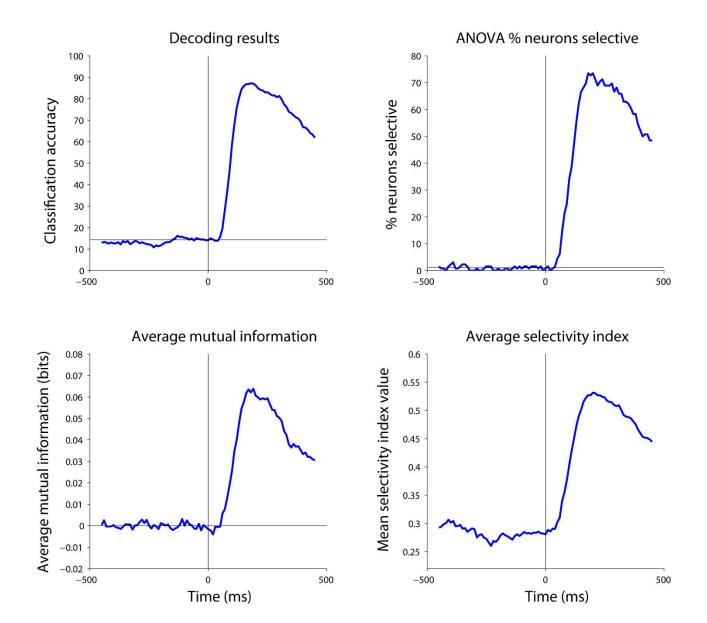
Applying decoding



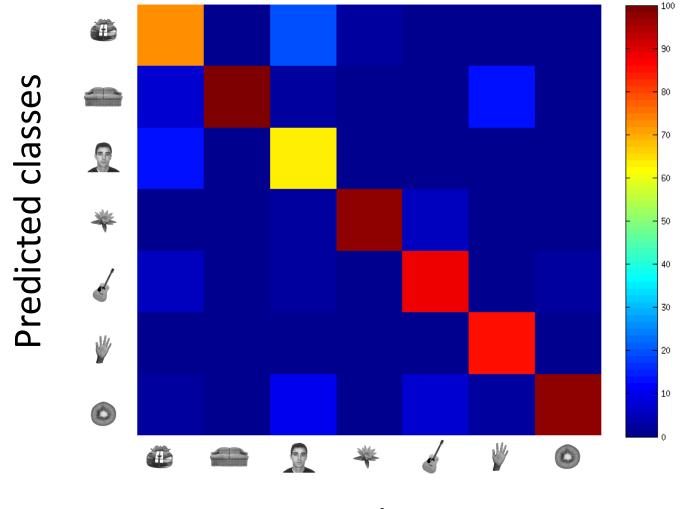
Basic decoding results



Basic results are similar to other methods

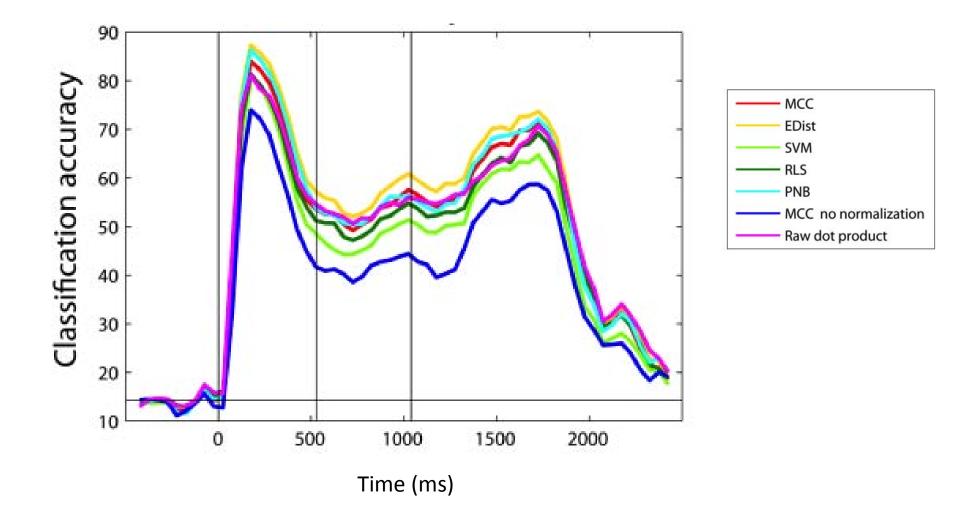


Confusion matrices



True classes

Generally robust to the choice of classifier



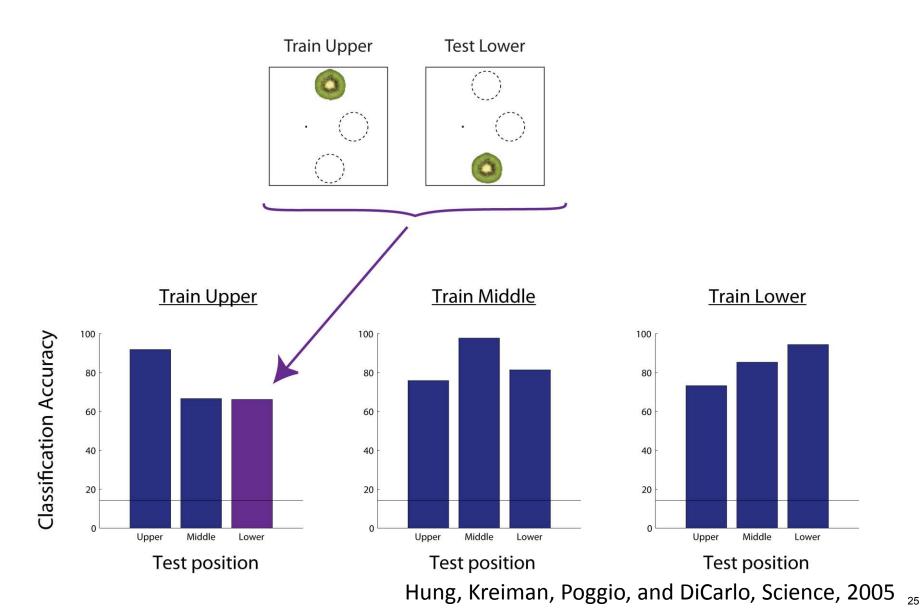
Abstract/invariant representations

The ability to form abstract representations is essential for complex behavior

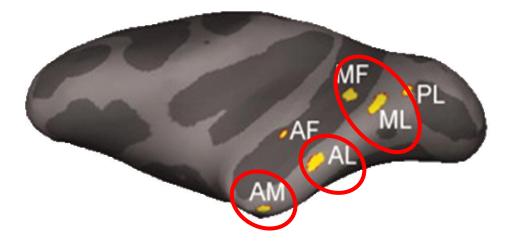


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Example: position invariance



Face identification invariant to head pose

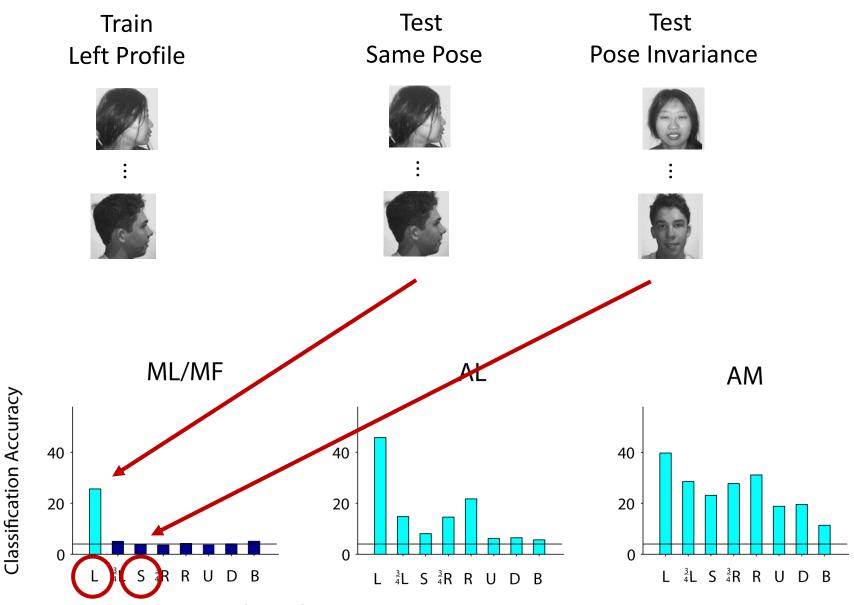


Stimulus set: 25 individuals, 8 head poses per individual



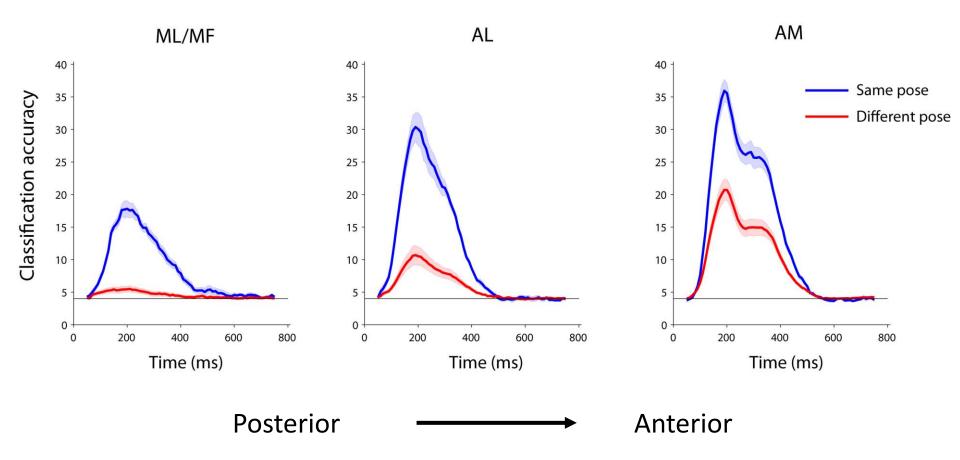
Meyers, Borzello, Freiwald, Tsao, J Neurosci, 2015

Face identification invariant to head pose



Courtesy of Society for Neuroscience. License CC BY. Source: Meyers, Ethan M., Mia Borzello, Winrich A. Freiwald, and Doris Tsao. "Intelligent information loss: the coding of facial identity, head pose, and non-face information in the macaque face patch system." Journal of Neuroscience 35, no. 18 (2015): 7069-7081.

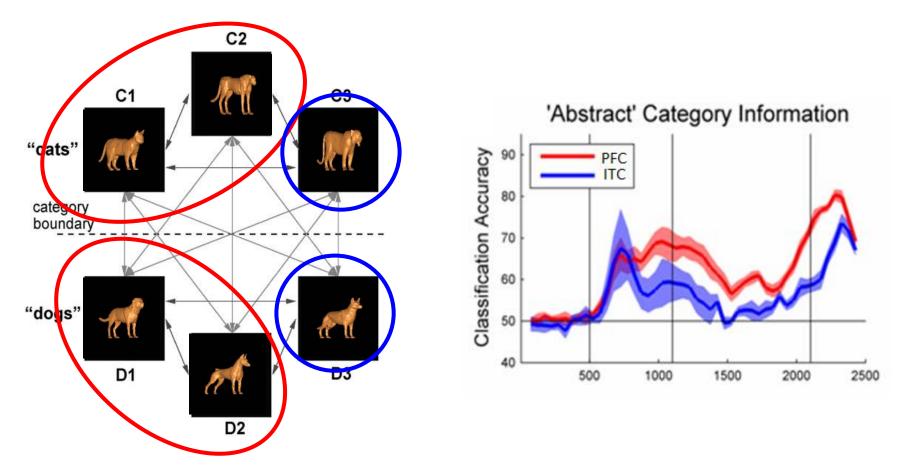
Face identification invariant to head pose



Courtesy of Society for Neuroscience. License CC BY.

Source: Meyers, Ethan M., Mia Borzello, Winrich A. Freiwald, and Doris Tsao. "Intelligent information loss: the coding of facial identity, head pose, and non-face information in the macaque face patch system." Journal of Neuroscience 35, no. 18 (2015): 7069-7081.

Learning abstract category information



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

Summary of neural content

Decoding offers a way to clearly see information flow over time

For assessing basic information, decoding often yields similar results as other methods

Decoding allows one to assess whether information is contained in an abstract/invariant format, which is not possible with other methods

Neural coding

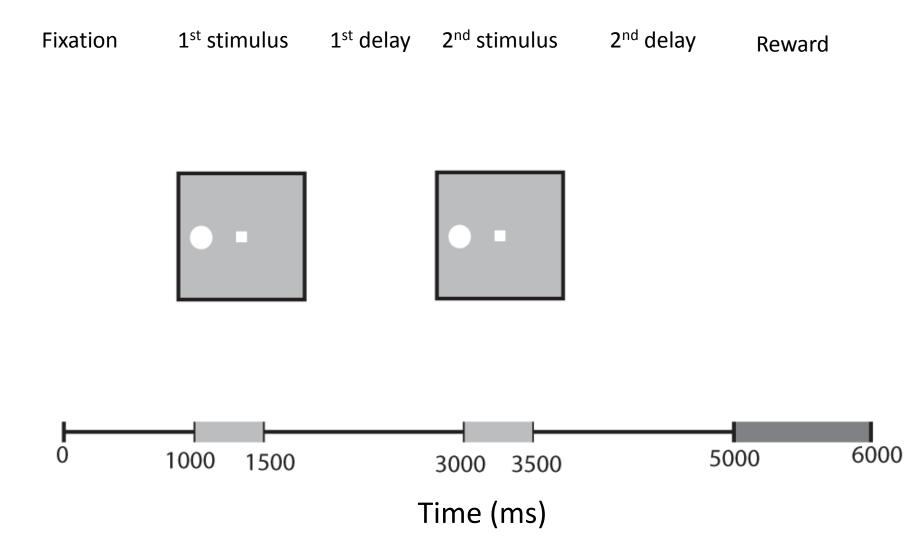
Motivating study



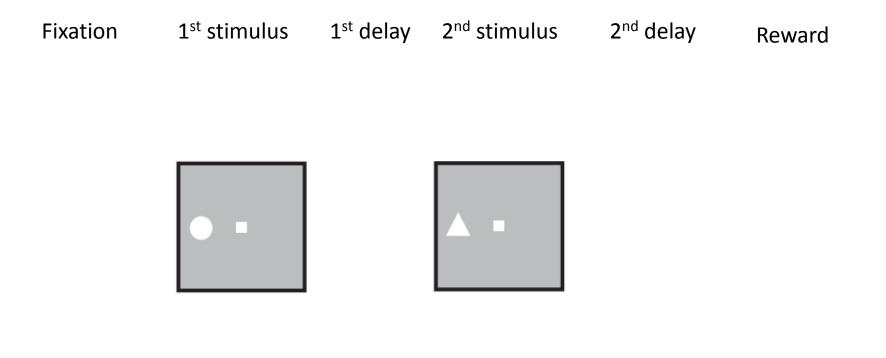
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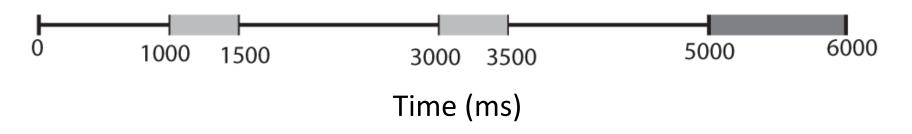
Meyers, Qi, Constantinidis, PNAS, 2012

Monkeys were first trained to passively fixate

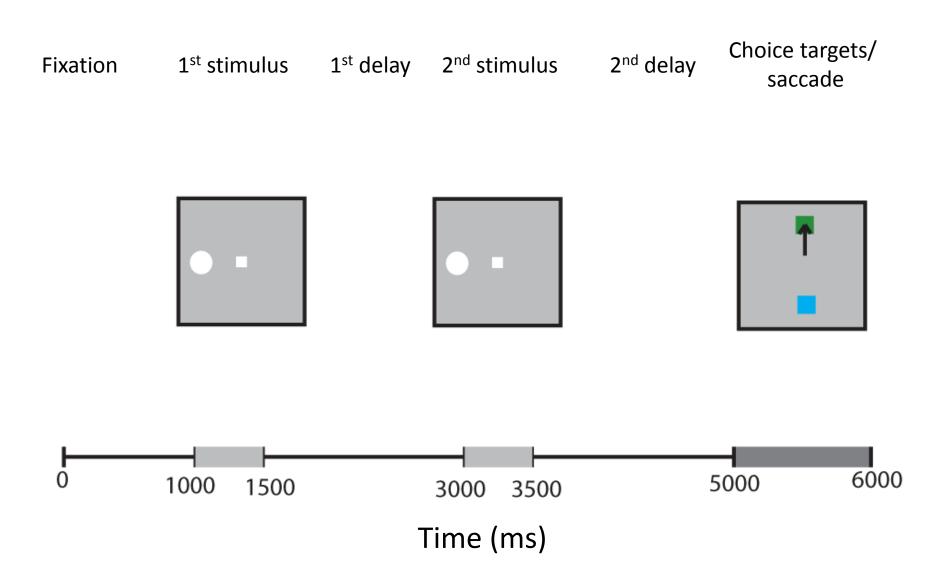


Monkeys were first trained to passively fixate

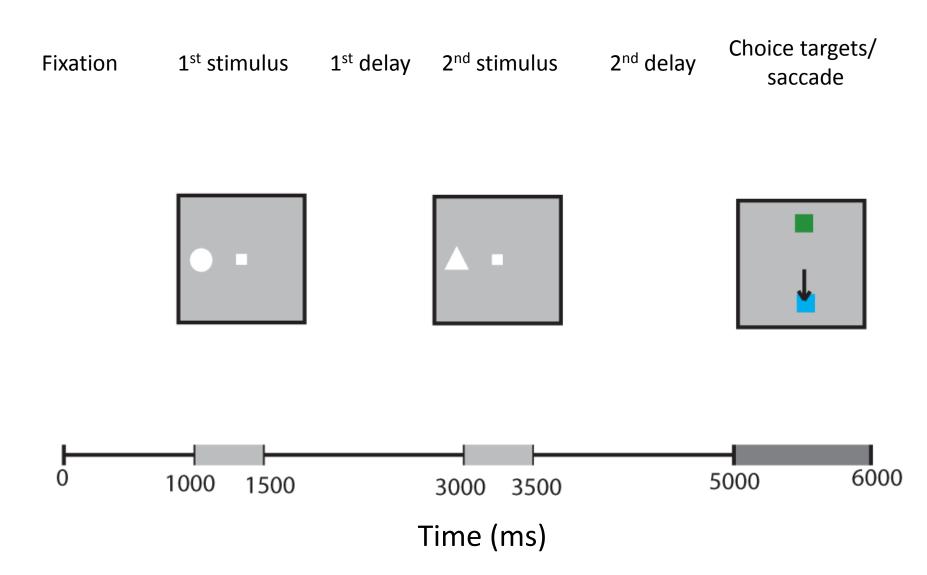




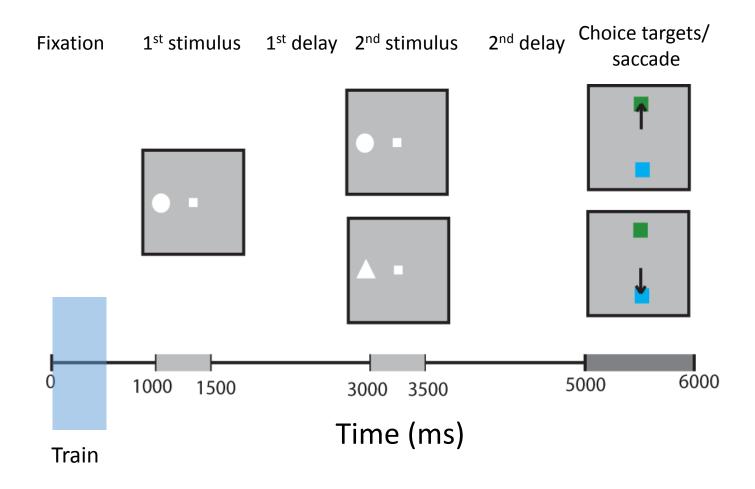
Monkeys then engaged in a delayedmatch-to-sample task (DMS task)



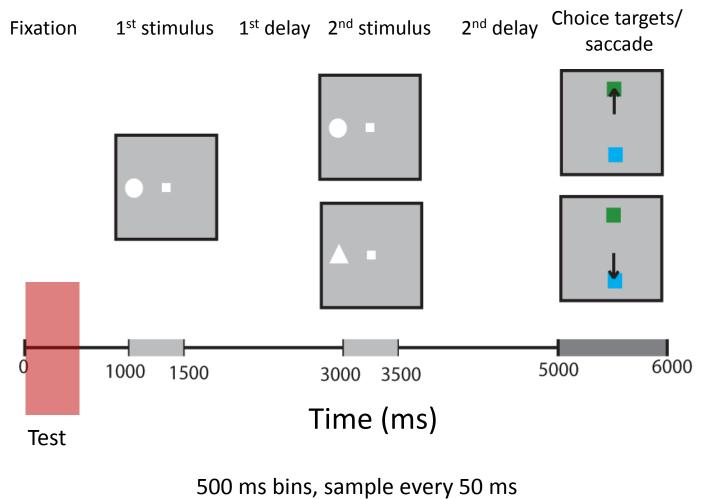
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Decoding applied

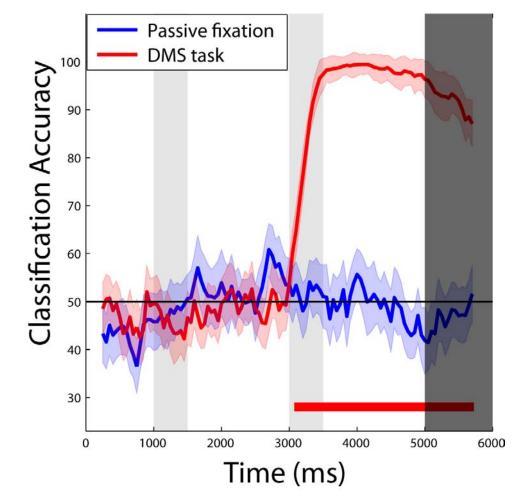


Decoding applied



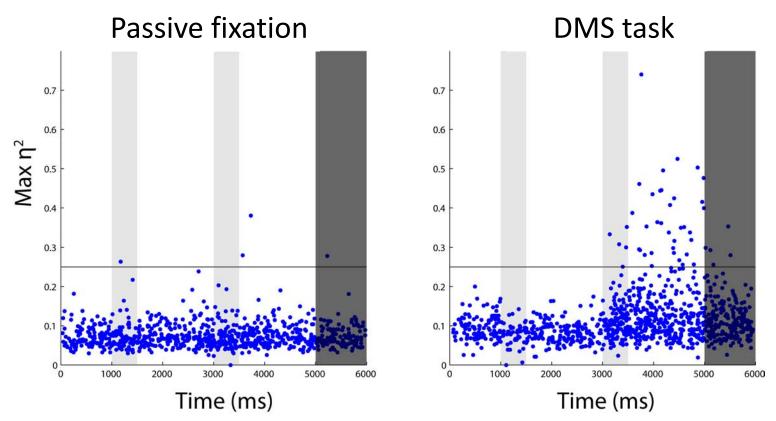
Decoding is based on 750 neurons

Decoding match/nonmatch information

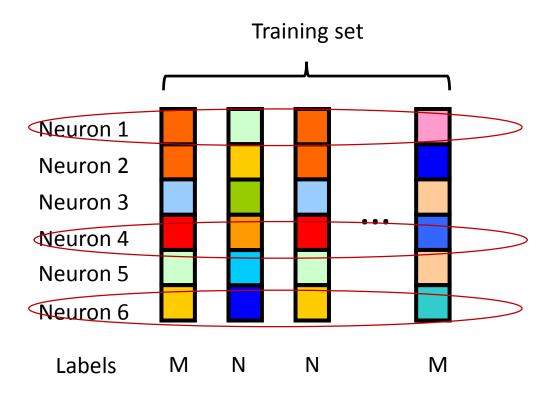


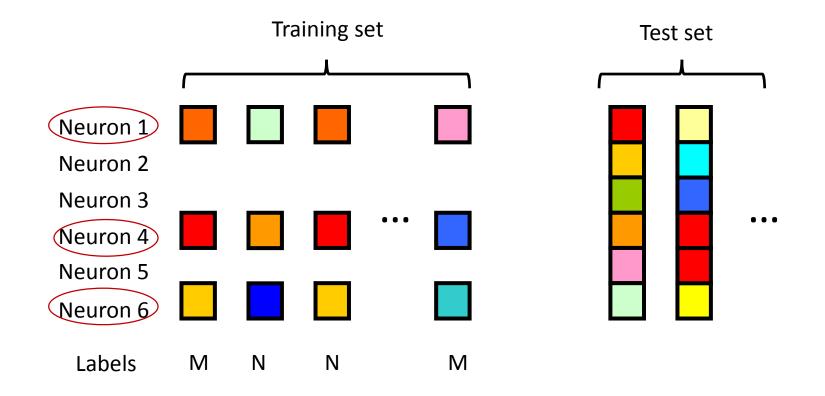
Courtesy of Proceedings of the National Academy of Sciences. Used with permission. Source: Meyers, Ethan M., Xue-Lian Qi, and Christos Constantinidis. "Incorporation of new information into prefrontal cortical activity after learning working memory tasks." Proceedings of the National Academy of Sciences 109, no. 12 (2012): 4651-4656.

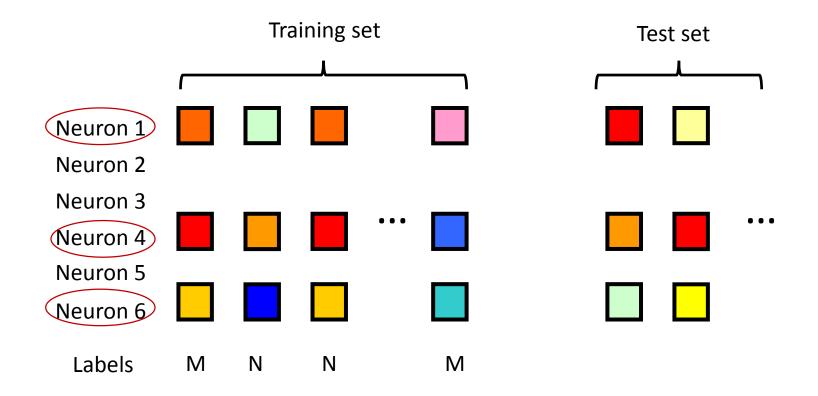
Is the new information widely distributed?

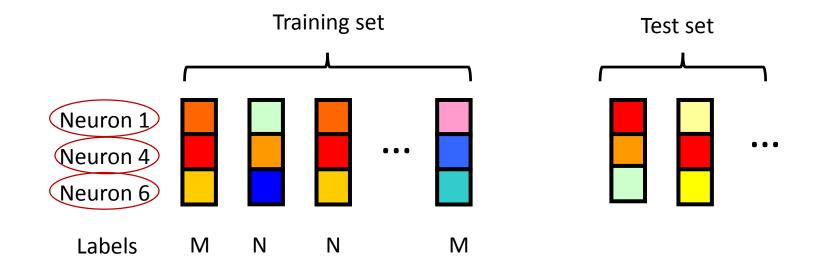


Courtesy of Proceedings of the National Academy of Sciences. Used with permission. Source: Meyers, Ethan M., Xue-Lian Qi, and Christos Constantinidis. "Incorporation of new information into prefrontal cortical activity after learning working memory tasks." Proceedings of the National Academy of Sciences 109, no. 12 (2012): 4651-4656.





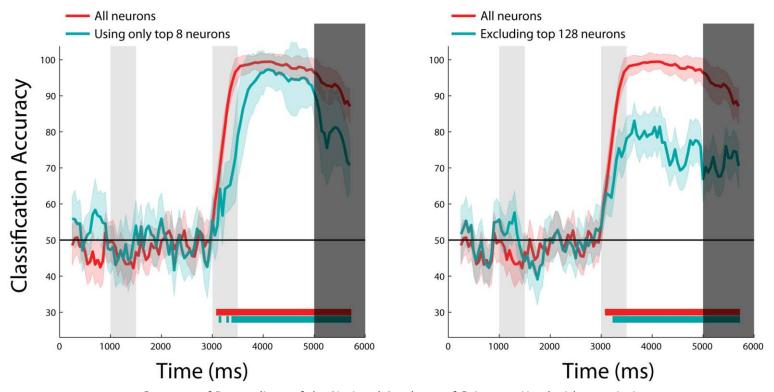




Is the new information widely distributed?

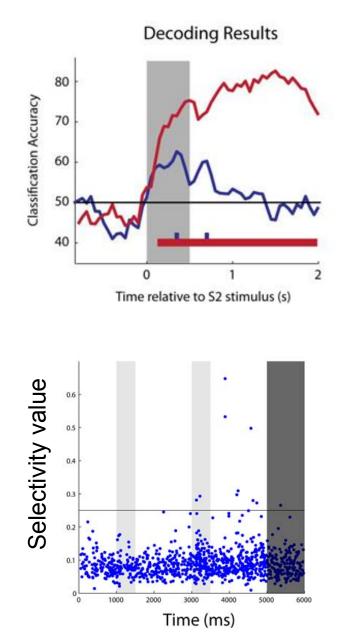
Using only the 8 most selective neurons

Excluding the 128 most selective neurons

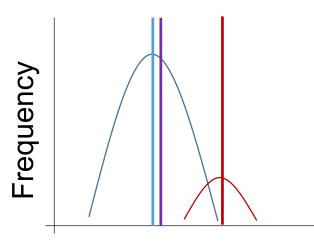


Courtesy of Proceedings of the National Academy of Sciences. Used with permission. Source: Meyers, Ethan M., Xue-Lian Qi, and Christos Constantinidis. "Incorporation of new information into prefrontal cortical activity after learning working memory tasks." Proceedings of the National Academy of Sciences 109, no. 12 (2012): 4651-4656.

Implications for analyzing data

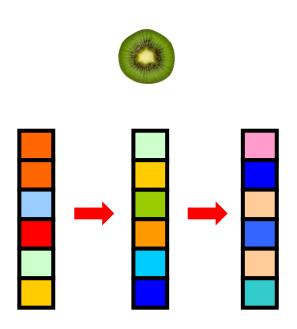


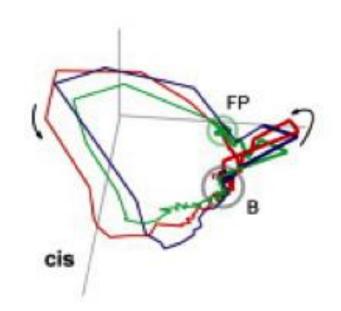
Averaged ROC Results



Selectivity value

Is information contained in a dynamic population code?



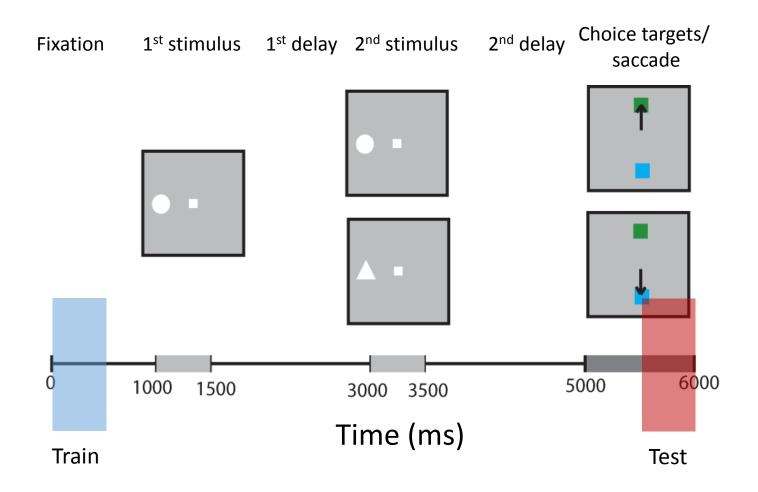


Time

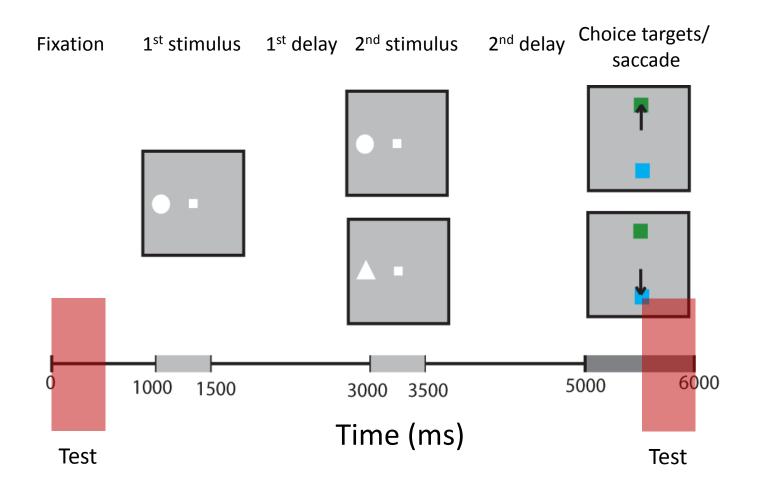
Courtesy of Elsevier, Inc., http://www.sciencedirect.com. Used with permission. Source: Mazor, Ofer, and Gilles Laurent. "Transient dynamics versus fixed points in odor representations by locust antennal lobe projection neurons." Neuron 48, no. 4 (2005): 661-673.

Mazor and Laurent 2005; Meyers et al, 2008; King and Dehaene 2014

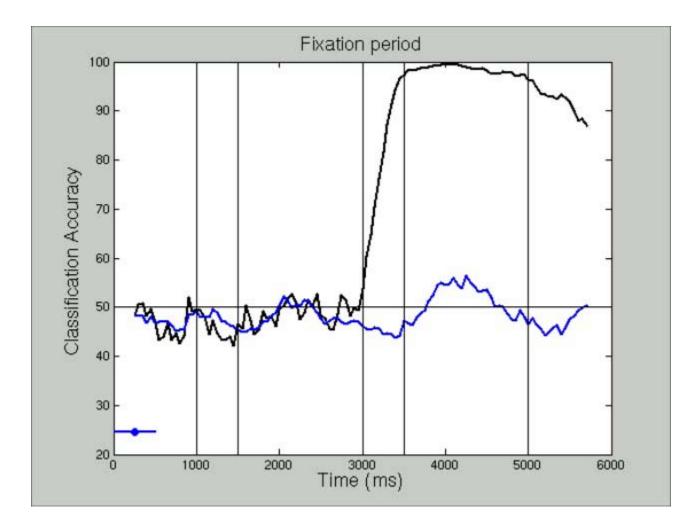
Decoding applied



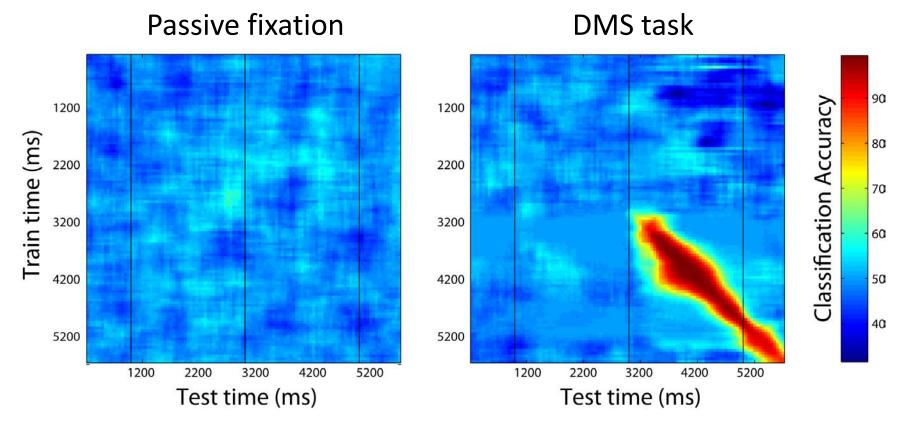
Decoding applied



Dynamic population coding



Dynamic population coding



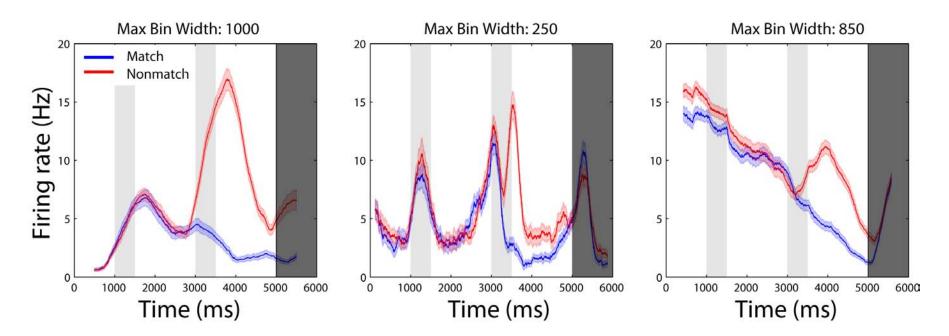
Courtesy of Proceedings of the National Academy of Sciences. Used with permission. Source: Meyers, Ethan M., Xue-Lian Qi, and Christos Constantinidis. "Incorporation of new information into prefrontal cortical activity after learning working memory tasks." Proceedings of the National Academy of Sciences 109, no. 12 (2012): 4651-4656.

The dynamics can be seen in individual neurons

Neuron 1

Neuron 2

Neuron 3



Courtesy of Proceedings of the National Academy of Sciences. Used with permission. Source: Meyers, Ethan M., Xue-Lian Qi, and Christos Constantinidis. "Incorporation of new information into prefrontal cortical activity after learning working memory tasks." Proceedings of the National Academy of Sciences 109, no. 12 (2012): 4651-4656. Is information coded in high firing rates or patterns?

Decision Rule

 $\underset{c}{\operatorname{arg\,max}} \log(\mathbf{w_c})^T \mathbf{x} - n\overline{w}_c$

$$\underset{c}{\operatorname{arg\,max}} \frac{\mathbf{w_c}^T \mathbf{x}}{\|\mathbf{w_c}\| \| \mathbf{x} \|}$$

$$\underset{c}{\arg\max} |\overline{w}_c - \overline{x}|$$

w_c are the classification weights for class c
x is the test point to be classifier

Poisson Naïve Bayes Classifier

Total activity and pattern

Minimum Angle Classifier

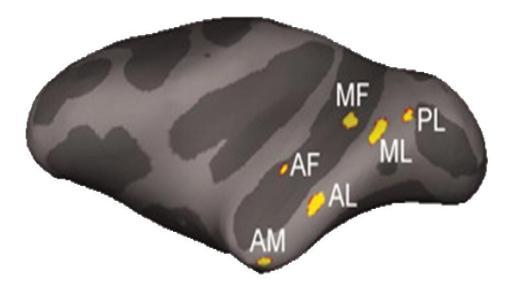
Pattern only

Total Population Activity Classifier

Total activity only

Is information coded in high firing rates or patterns?

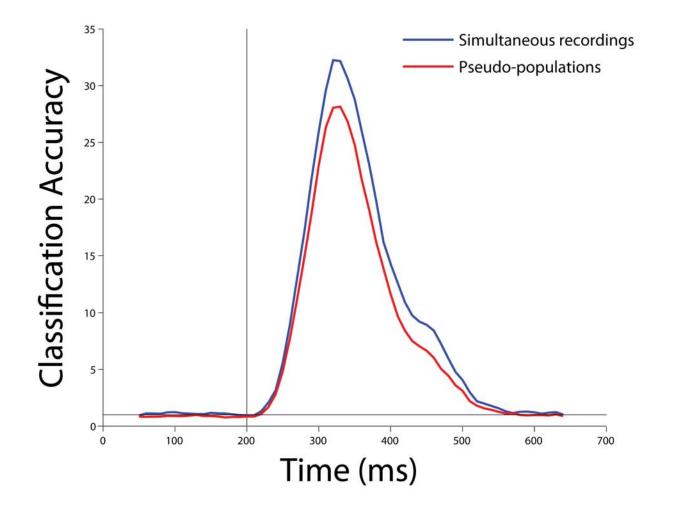
Pose specific face identification



Poisson Naïve Bayes – Total activity and pattern Minimum Angle – Pattern only Total Population Activity - Total activity only

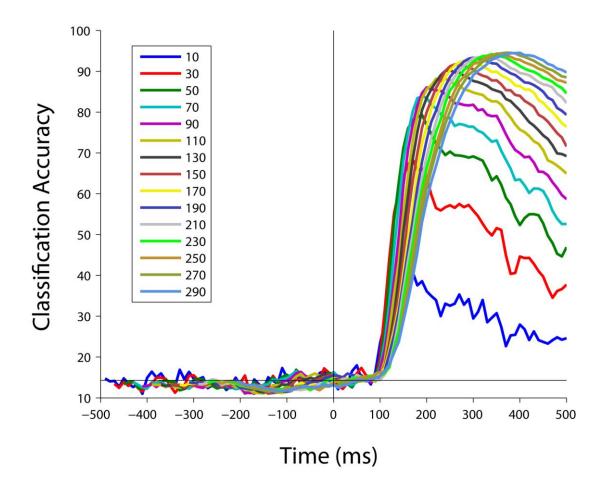
Meyers, Borzello, Freiwald, Tsao, 2015

Independent neuron code?



Data courtesy of the DiCarlo lab; see Ami Patel's MEng thesis

Precision of the neural code (temporal coding)



Summary of neural coding

Decoding allows you examine many questions in neural coding including:

- Compact/sparse coding
- Dynamic population coding
- Independent neural code
- Temporal precision/temporal coding

Decoding can be applied to other types of data

MEG/EEG (LFPs, ECog)

New tutorial on readout.info

fMRI

- Princeton-mvpa-toolbox
- PyMVPA
- The decoding toolbox

Figure removed due to copyright restrictions. Please see the video. Source: Figure 2, Isik, Leyla, Ethan M. Meyers, Joel Z. Leibo, and Tomaso Poggio. "The dynamics of invariant object recognition in the human visual system." Journal of neurophysiology 111, no. 1 (2014): 91-102.

Continuous decoding

• nSTAT

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

Limitations of decoding

Hypothesis based – could be overlooking information that is not explicitly tested for

Just because information is present, doesn't mean it's used

Decoding focuses on the computational and algorithmic/representational levels, does not give a mechanistic explanation of the phenomena

Decoding methods can be computationally intensive, analyses can be slow to run

The Neural Decoding Toolbox (NDT)

Makes it easy to do decoding in MATLAB:

- 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

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'

Figure removed due to copyright restrictions. Please see the video or Figure 3 from Meyers, Ethan M. "The neural decoding toolbox." Frontiers in neuroinformatics 7 (2013).



Funding: The Center for Brains, Minds and Machines, NSF STC award CCF-1231216

Acknowledgements:

Narcisse Bichot, Mia Borzello, Christos Constantinidis, Jennie Deutsch, Jim DiCarlo, Robert Desimone, David Freedman, Winrich Freiwald, Leyla Isik, Gabriel Kreiman, Andy Leung, Joel Liebo, Earl Miller, Ami Patel, Tomaso Poggio, Xue-Lian Qi, Doris Tsao, Ying Zhang

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Resource: Brains, Minds and Machines Summer Course Tomaso Poggio and Gabriel Kreiman

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