



Brain Reading (MKI43)

Lecture 2: Discriminative decoding

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Radboud University Nijmegen



Decoding flavors



generative

Stimulus representation



Pixel luminance



Local contrast



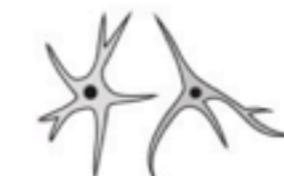
Object categories



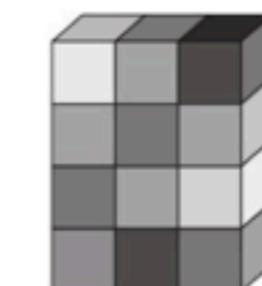
Grating orientations

touch, move, eat,
hear, smell, ...
Semantics

Type of brain activity



Neurons



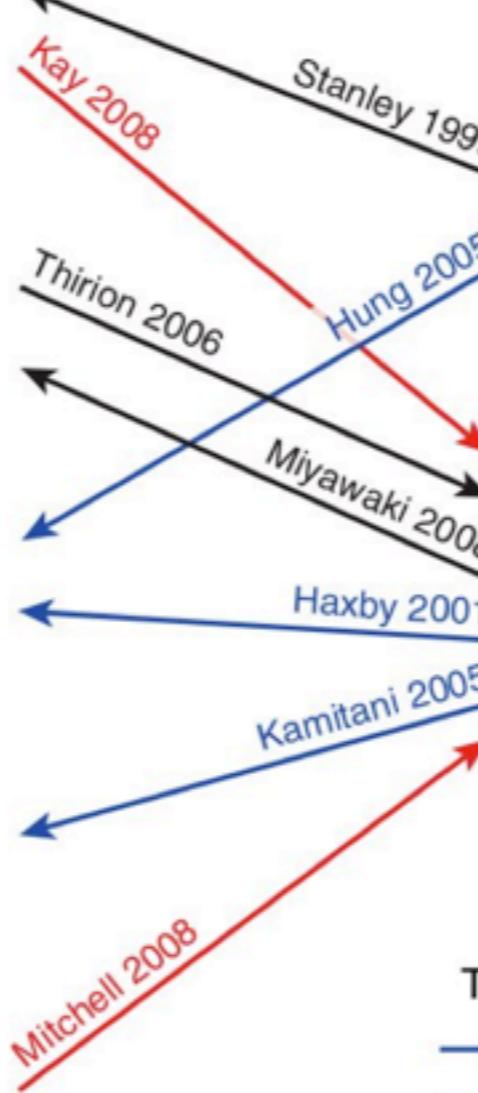
Voxels

Type of decoding

— Classification

— Identification

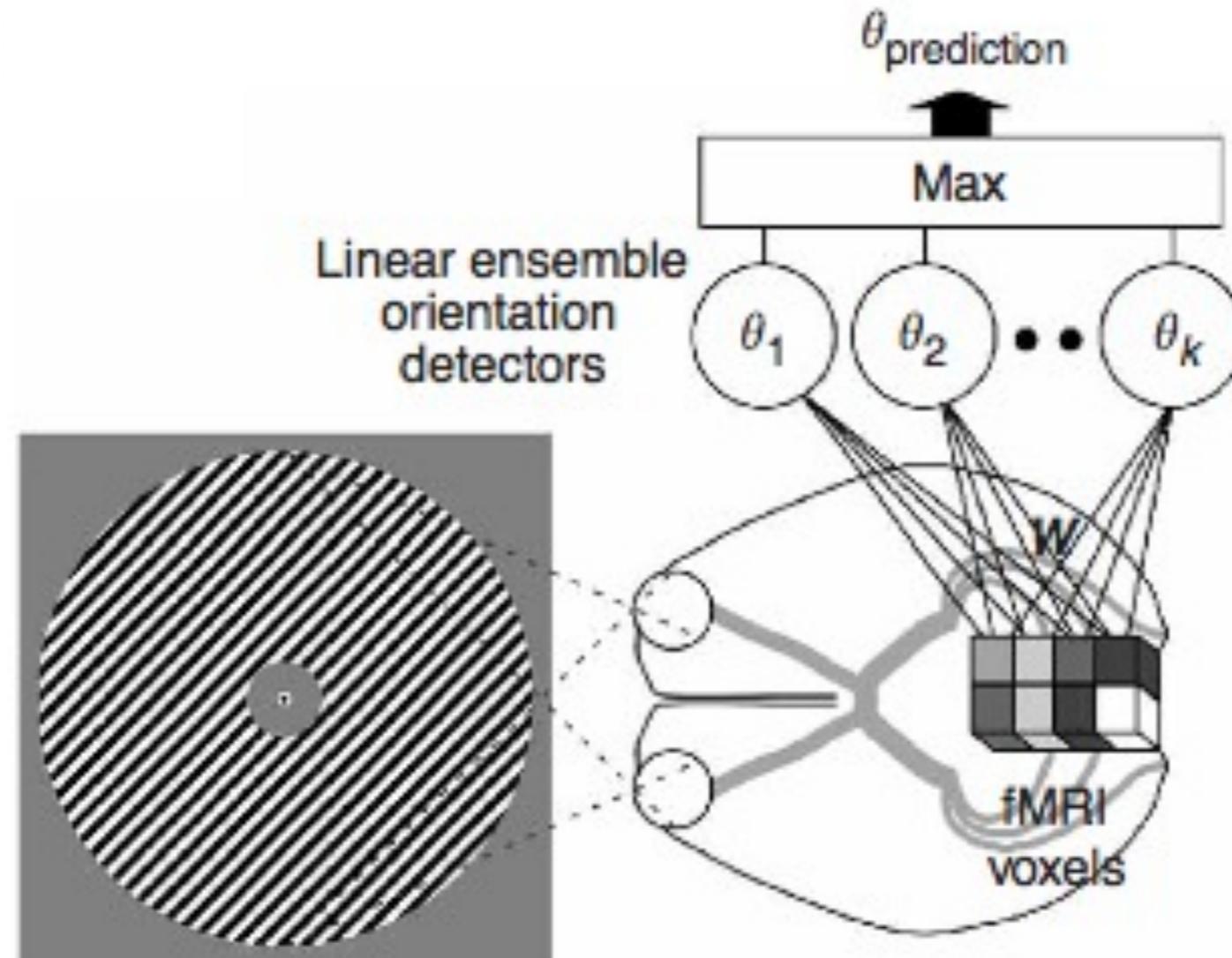
— Reconstruction



discriminative

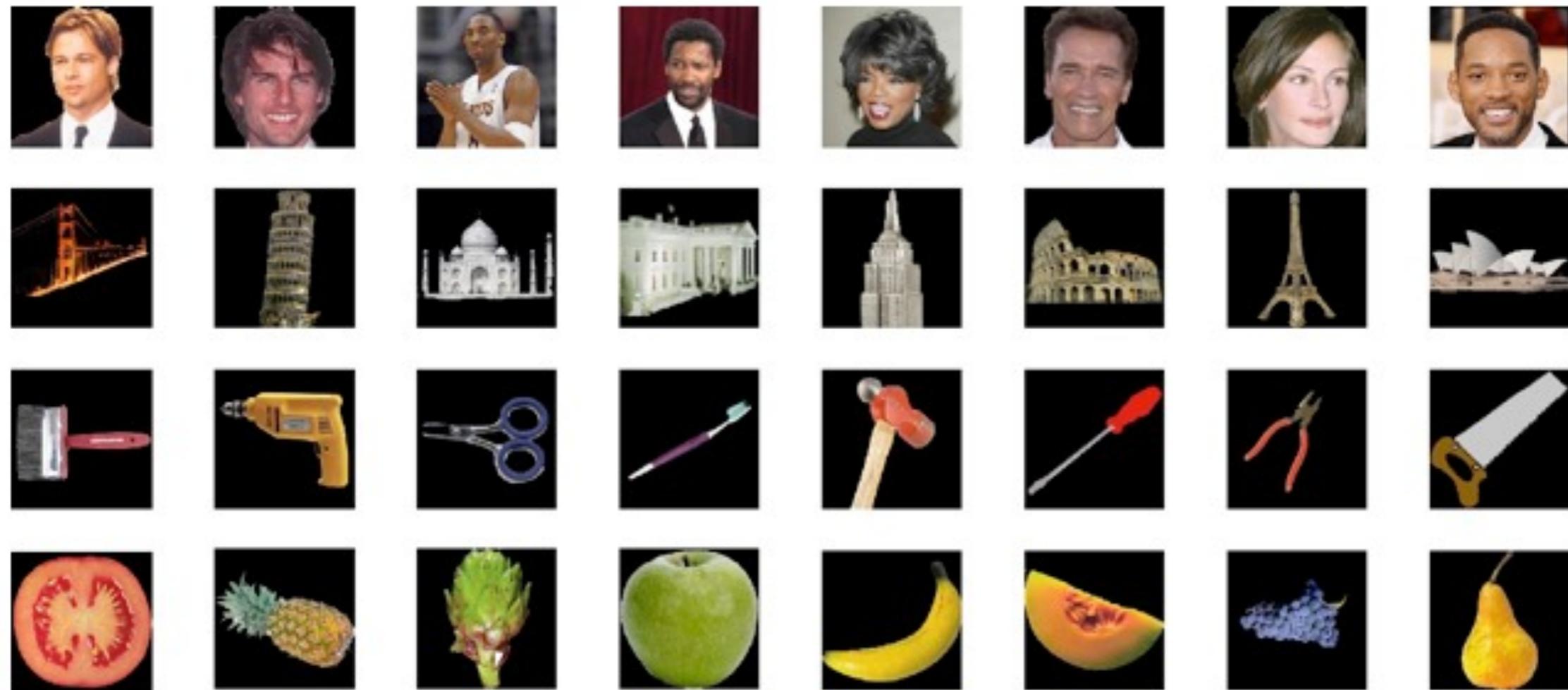
Kay and Gallant, Nature, 2009

Orientation decoding



Kamitani and Tong, Nature Neuroscience, 2005

Imagined category decoding

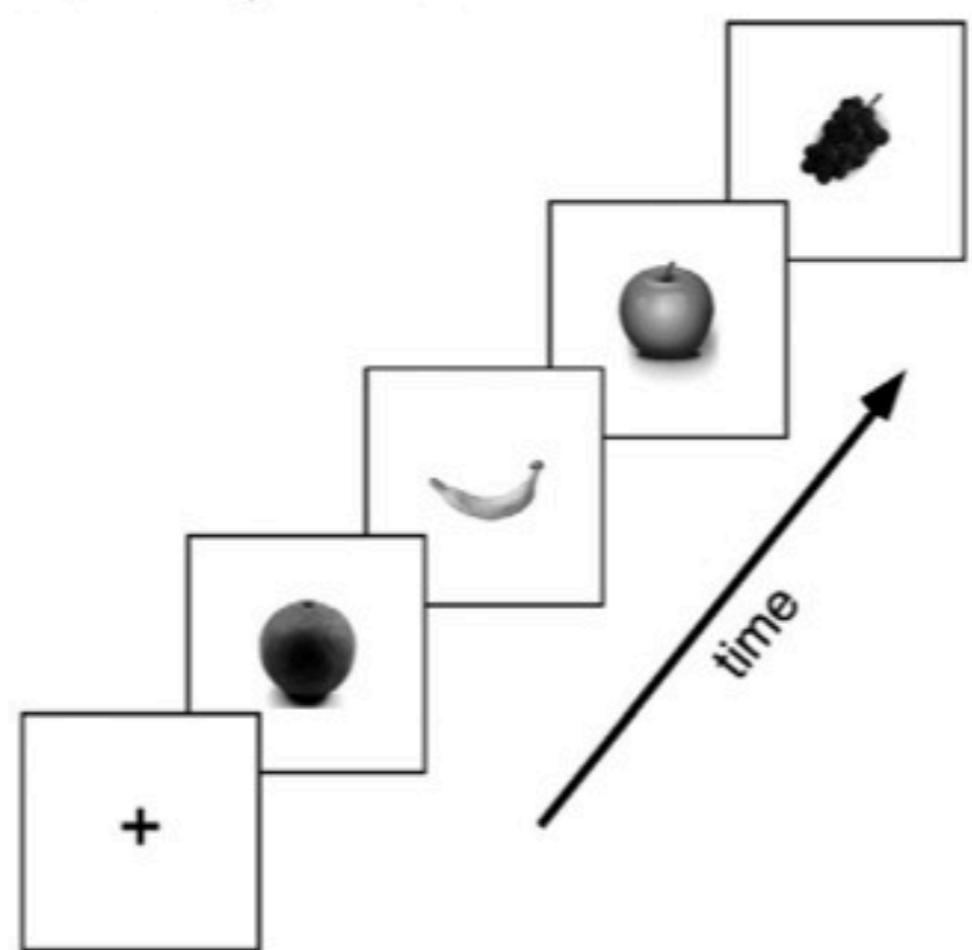


Reddy L, Tsuchiya N, Serre T. Reading the mind's eye: decoding category information during mental imagery. *Neuroimage*. 2010;50(2):818–825.

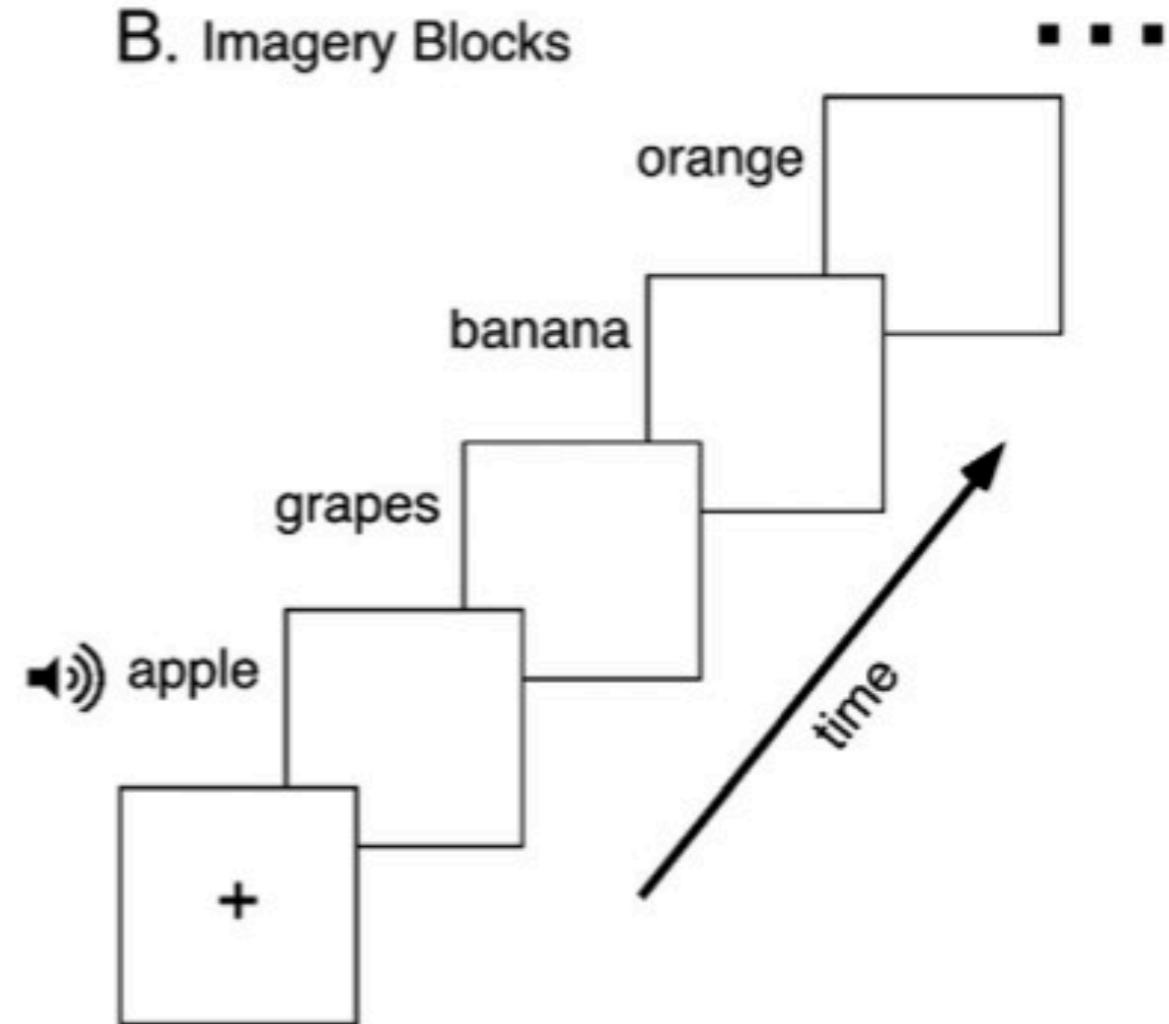
Imagined category decoding



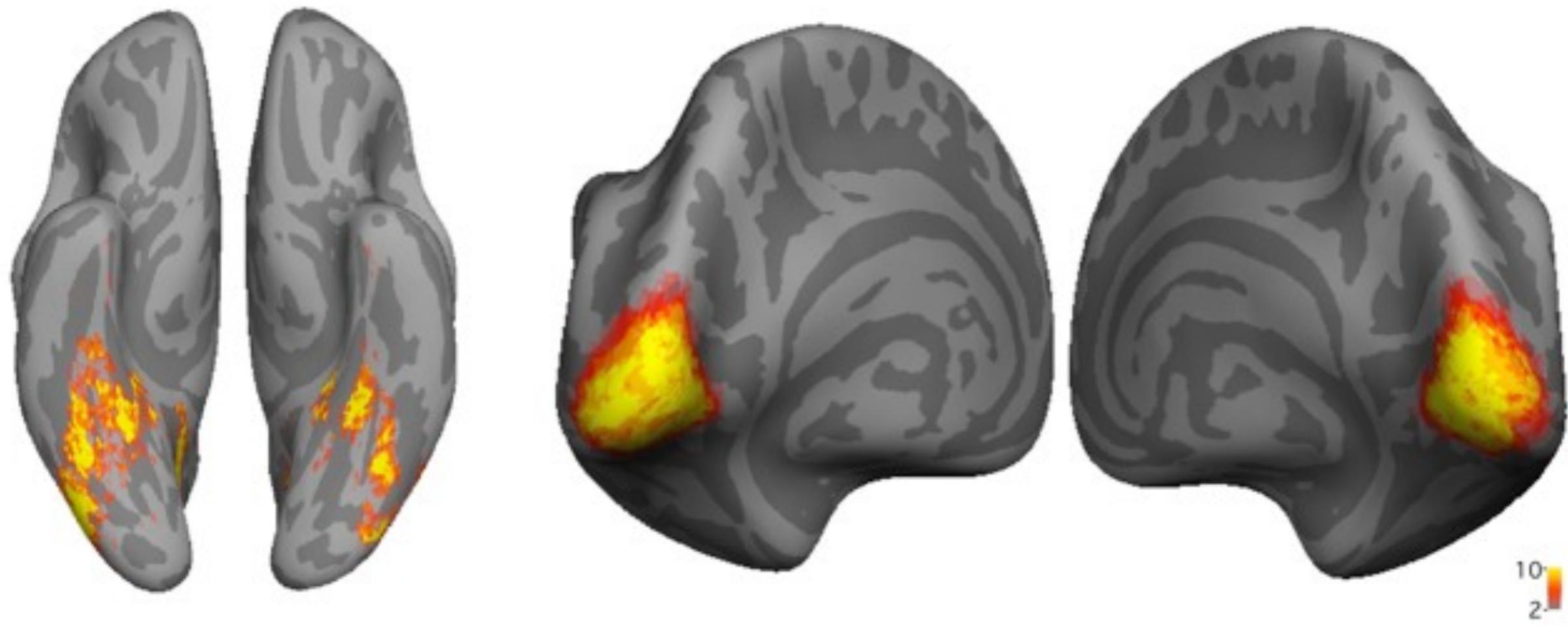
A. Perception Blocks



B. Imagery Blocks



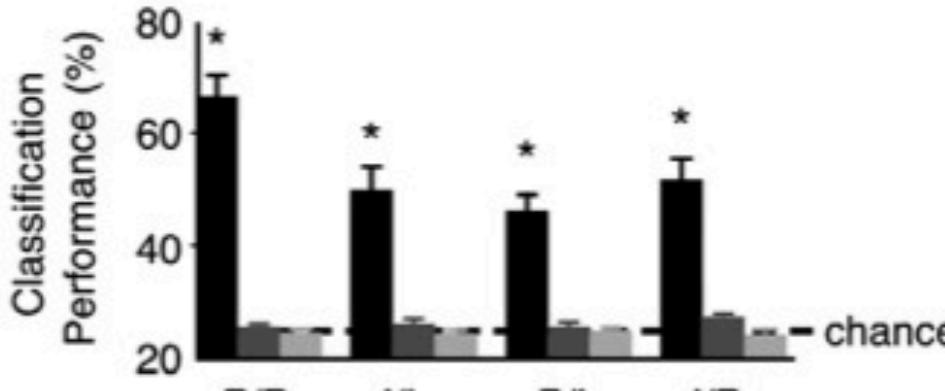
Imagined category decoding



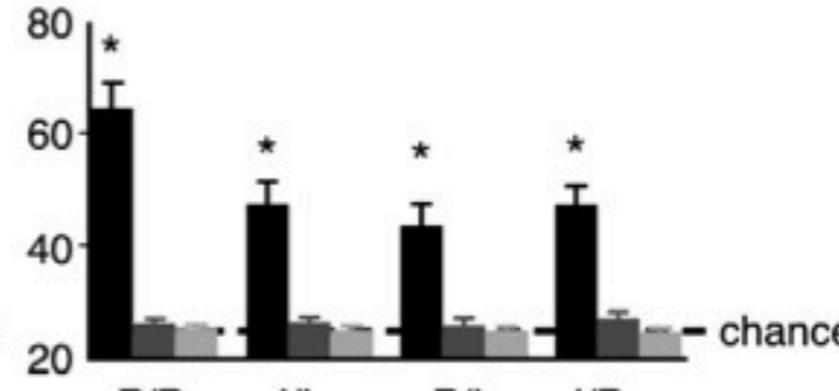
Imagined category decoding



A. OR Voxels



B. OR-FFA & PPA

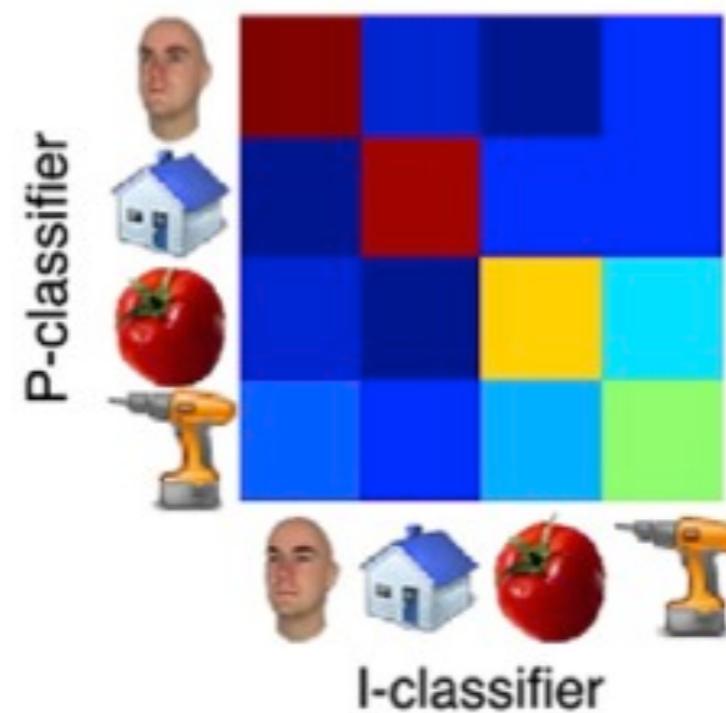


C. Retinotopic

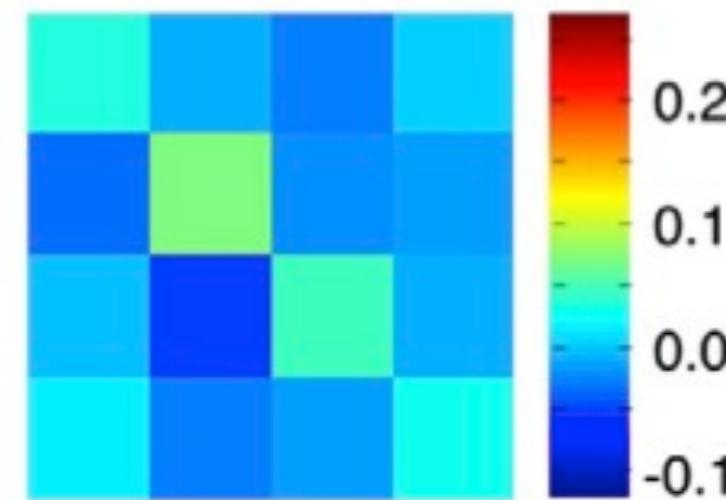


■ intact ■ scrambled voxels ■ shuffle labels

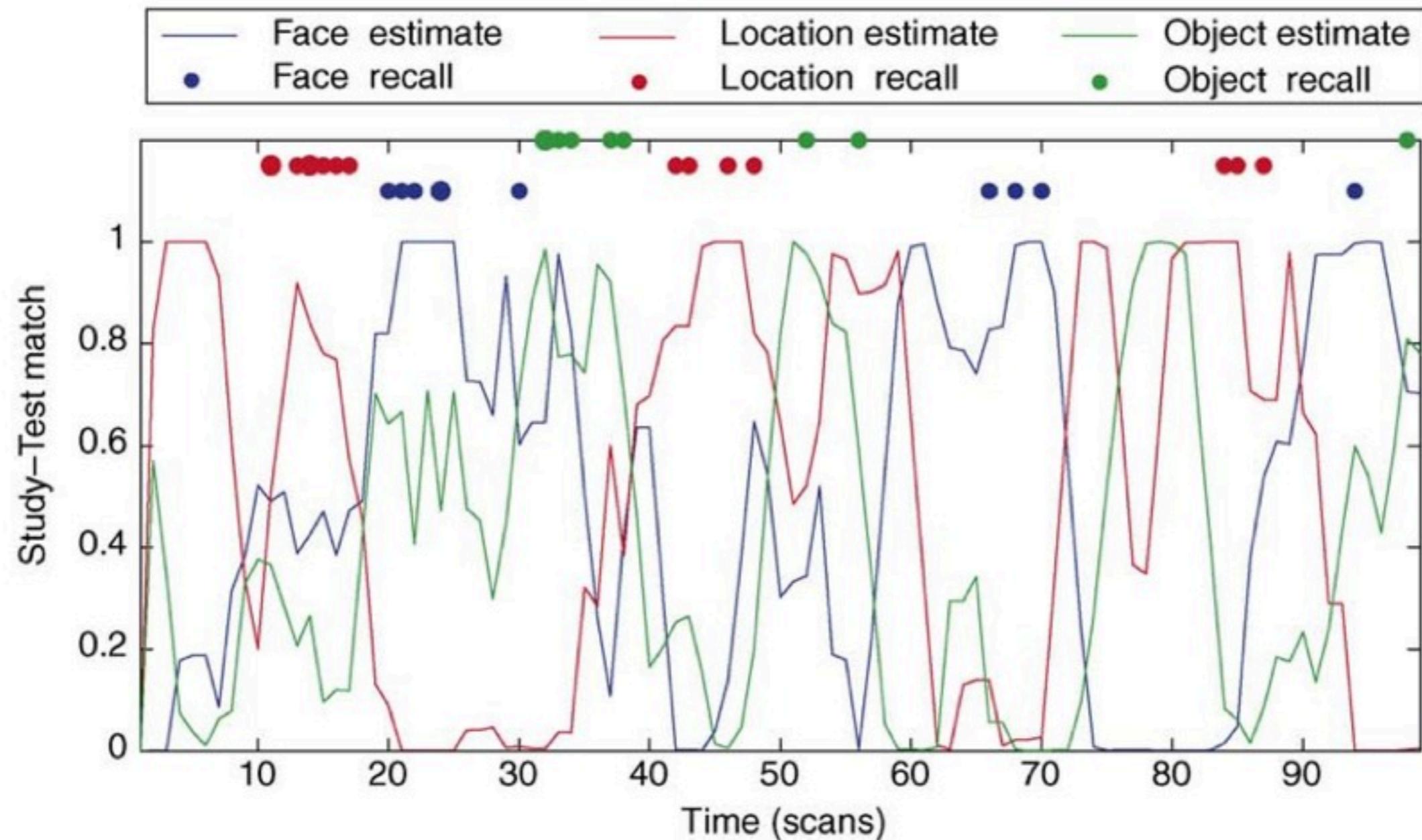
A. OR Voxels



B. Retinotopic Voxels

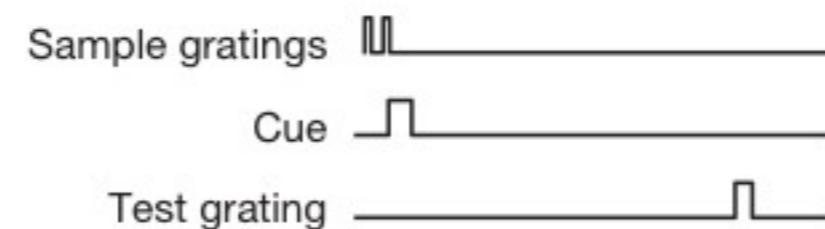
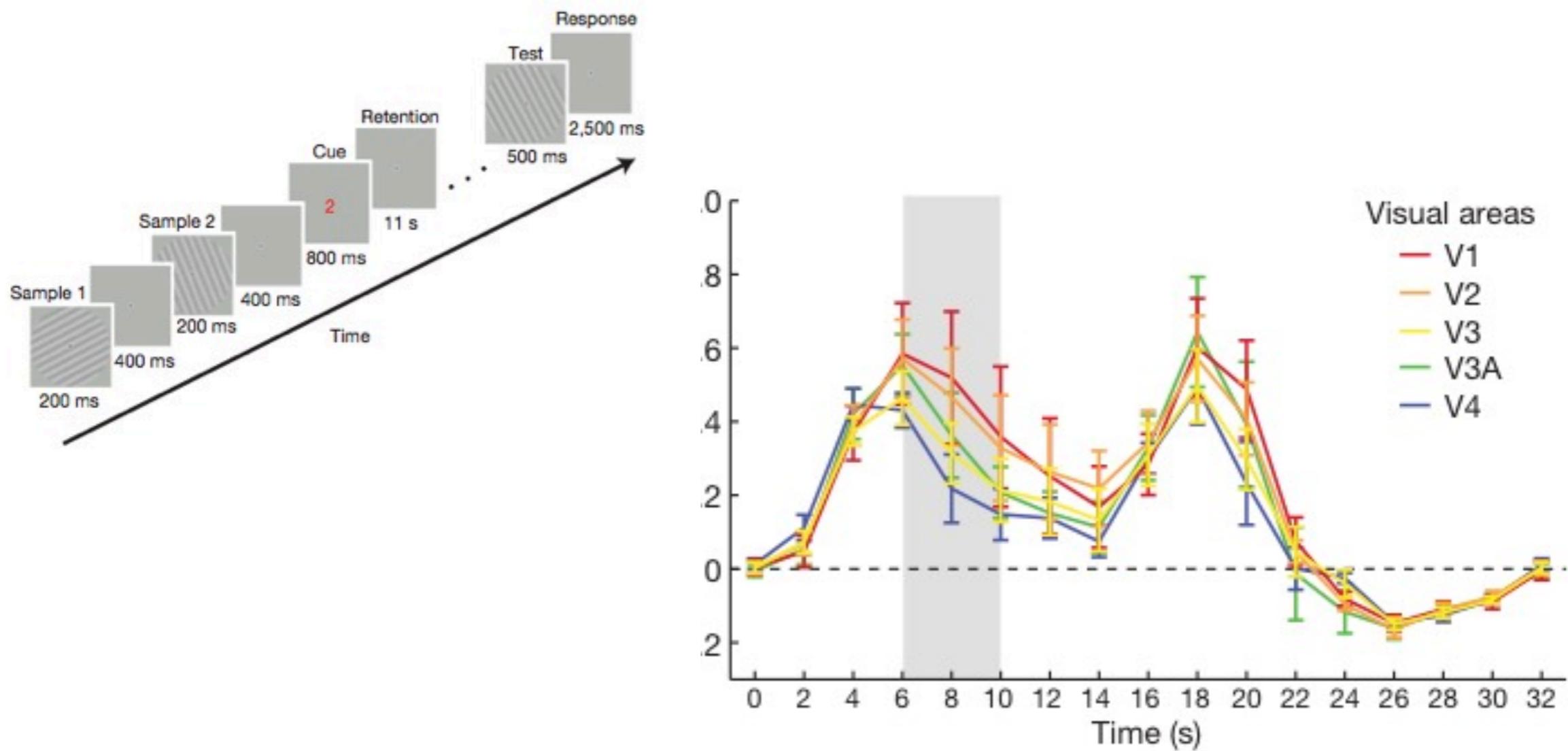


Memory search



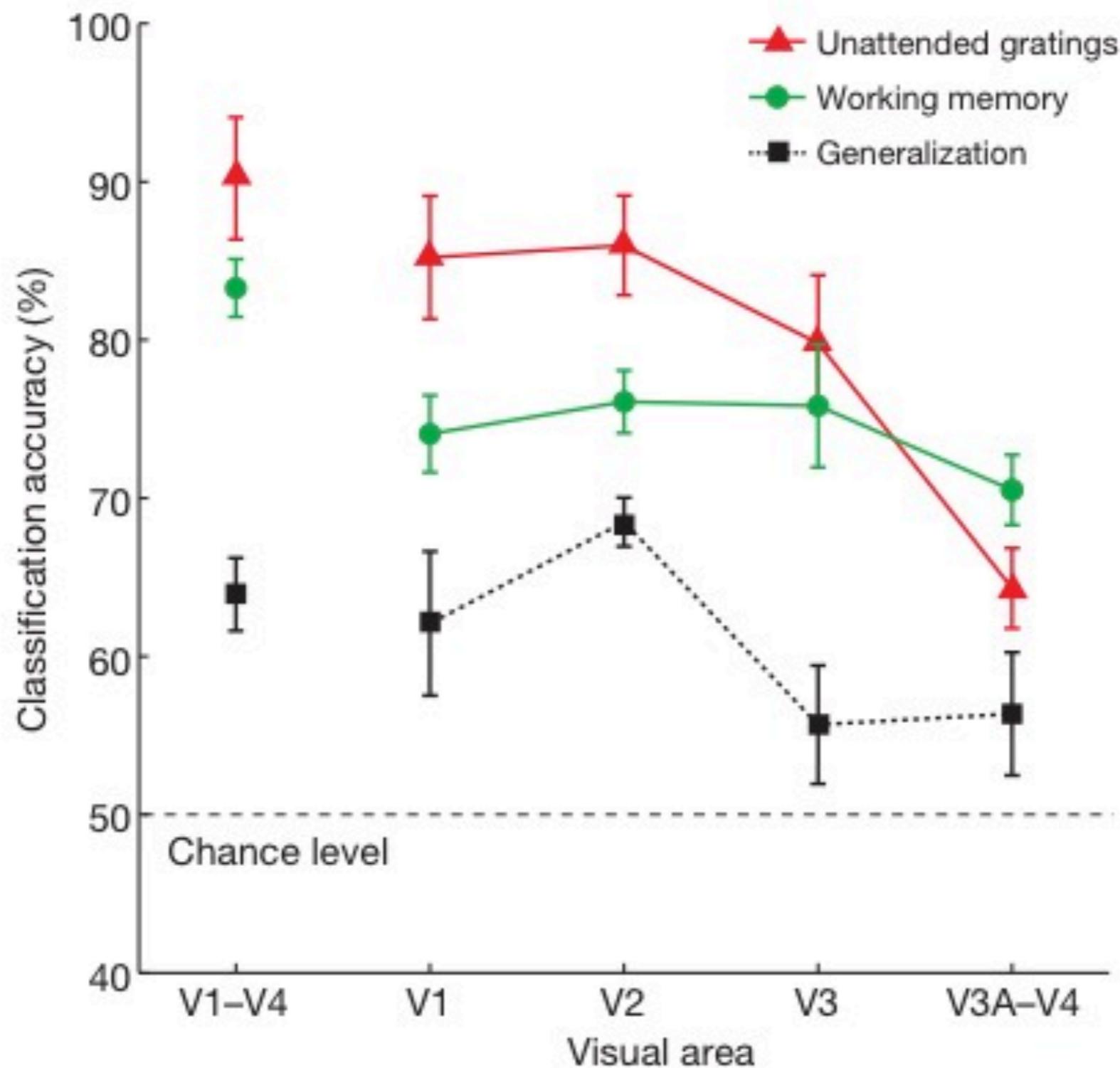
Norman et al. TICS, 2006

Decoding working memory

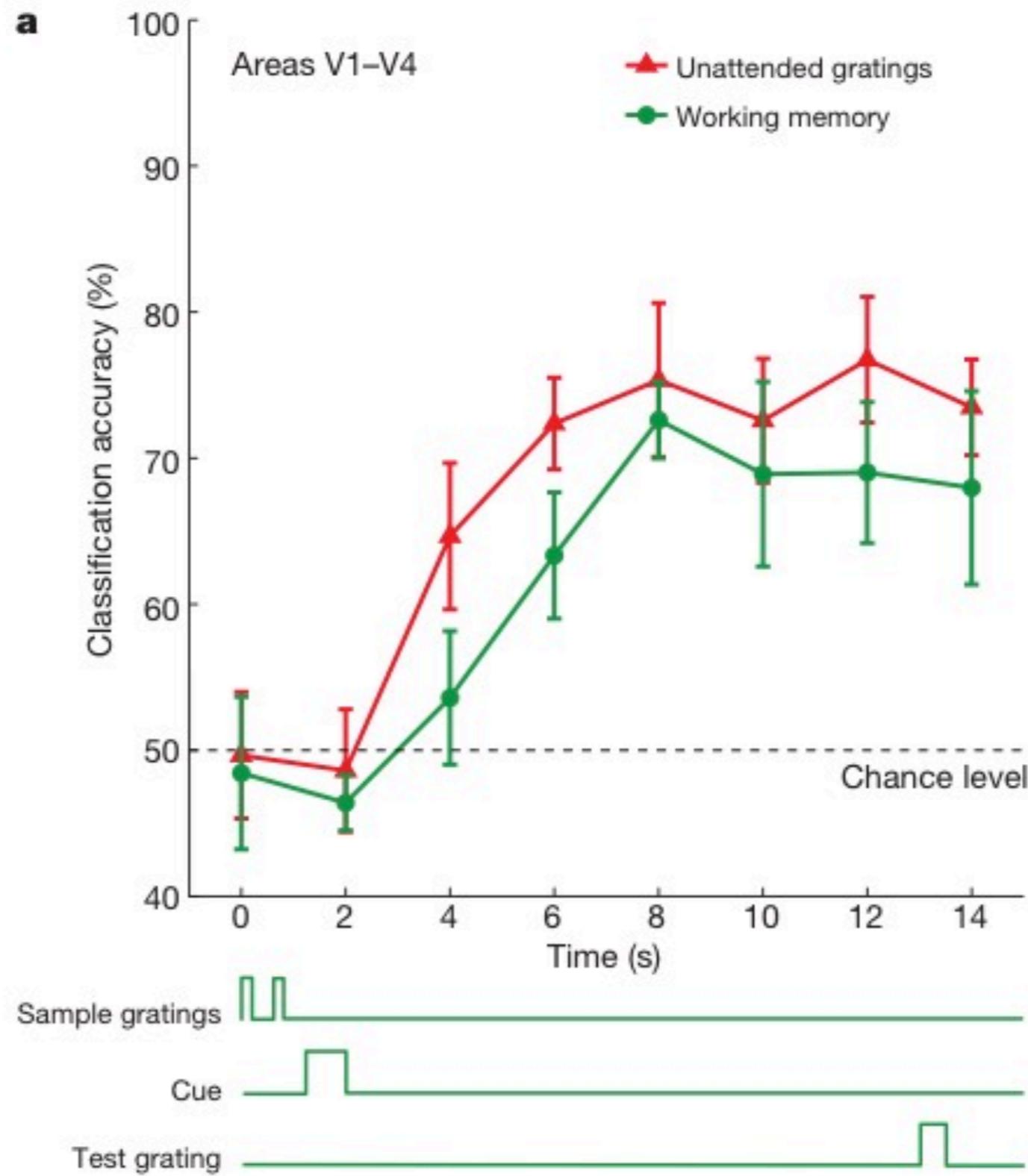


S. A. Harrison and F. Tong. Decoding reveals the contents of visual working memory in early visual areas. *Nature*, 458:632–635, 2009.

Decoding working memory



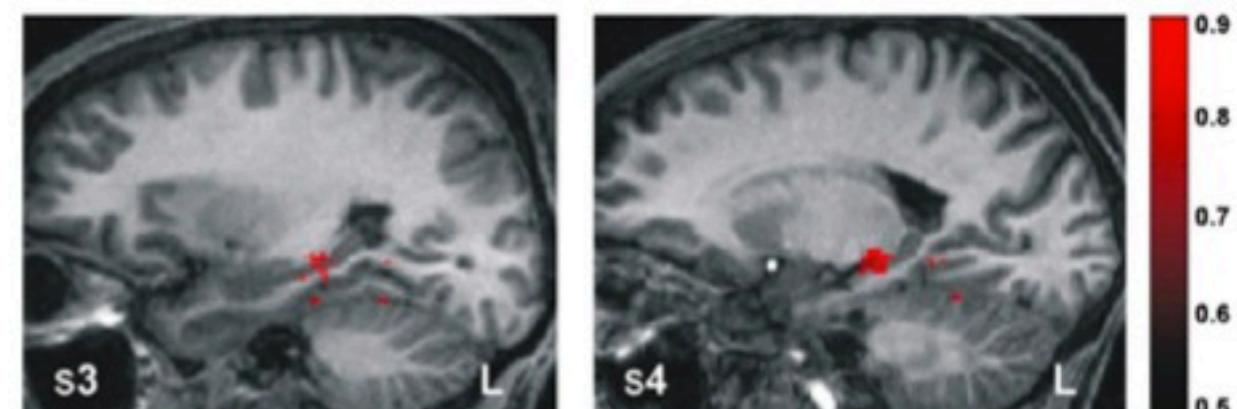
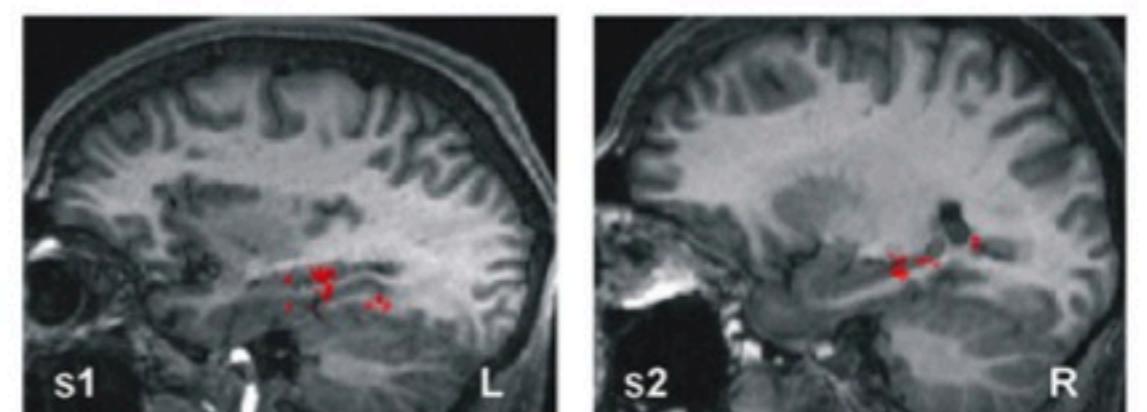
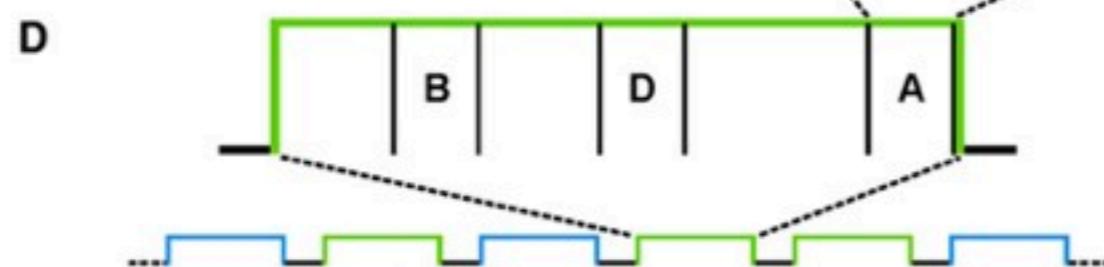
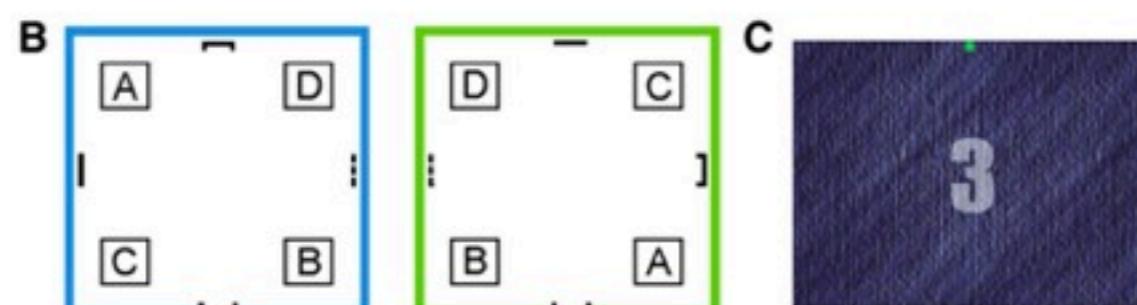
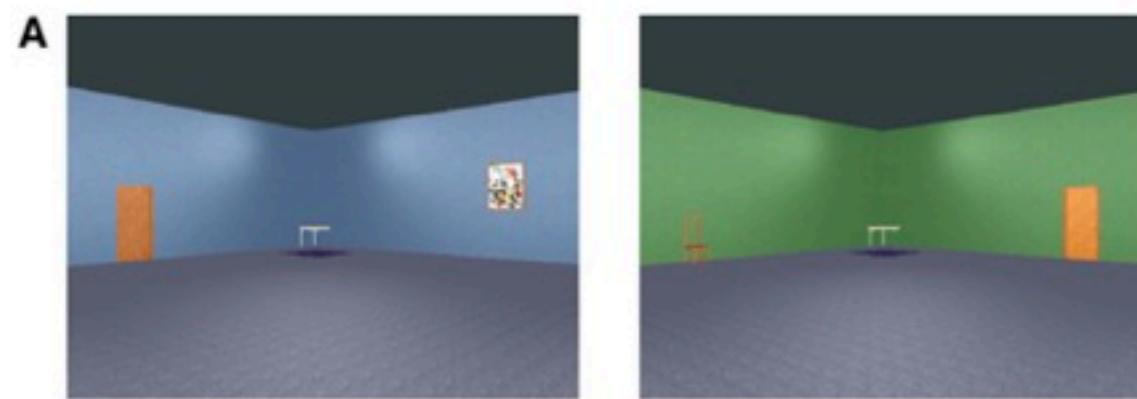
Decoding working memory





Decoding Neuronal Ensembles in the Human Hippocampus

Demis Hassabis,^{1,*} Carlton Chu,¹ Geraint Rees,^{1,2}
Nikolaus Weiskopf,¹ Peter D. Molyneux,³
and Eleanor A. Maguire^{1,*}



Current Biology, 2009

Episodic memory decoding



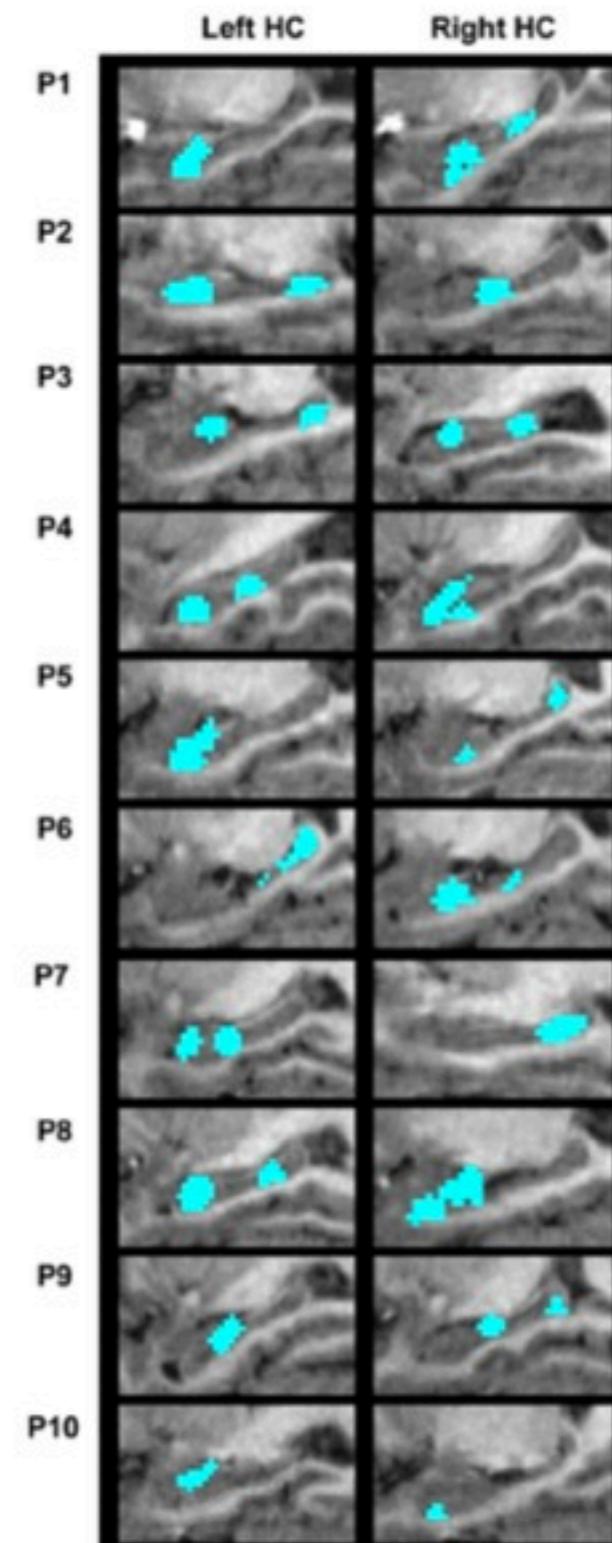
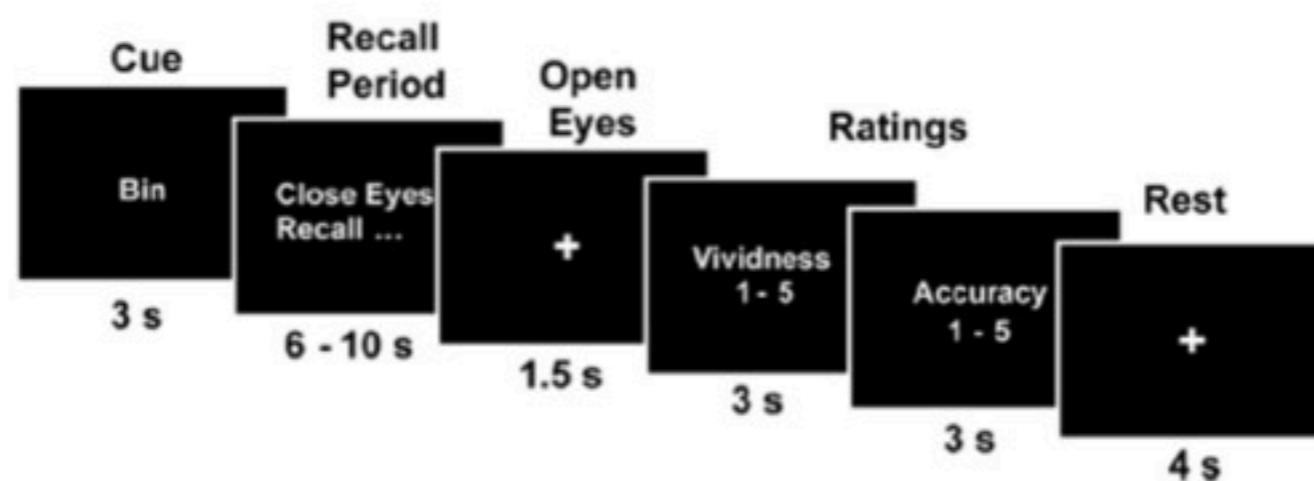
Decoding Individual Episodic Memory Traces in the Human Hippocampus

Martin J. Chadwick,^{1,2} Demis Hassabis,^{1,2}
Nikolaus Weiskopf,¹ and Eleanor A. Maguire^{1,*}

A



B



Current Biology, 2010

Donders Institute
for Brain, Cognition and Behaviour

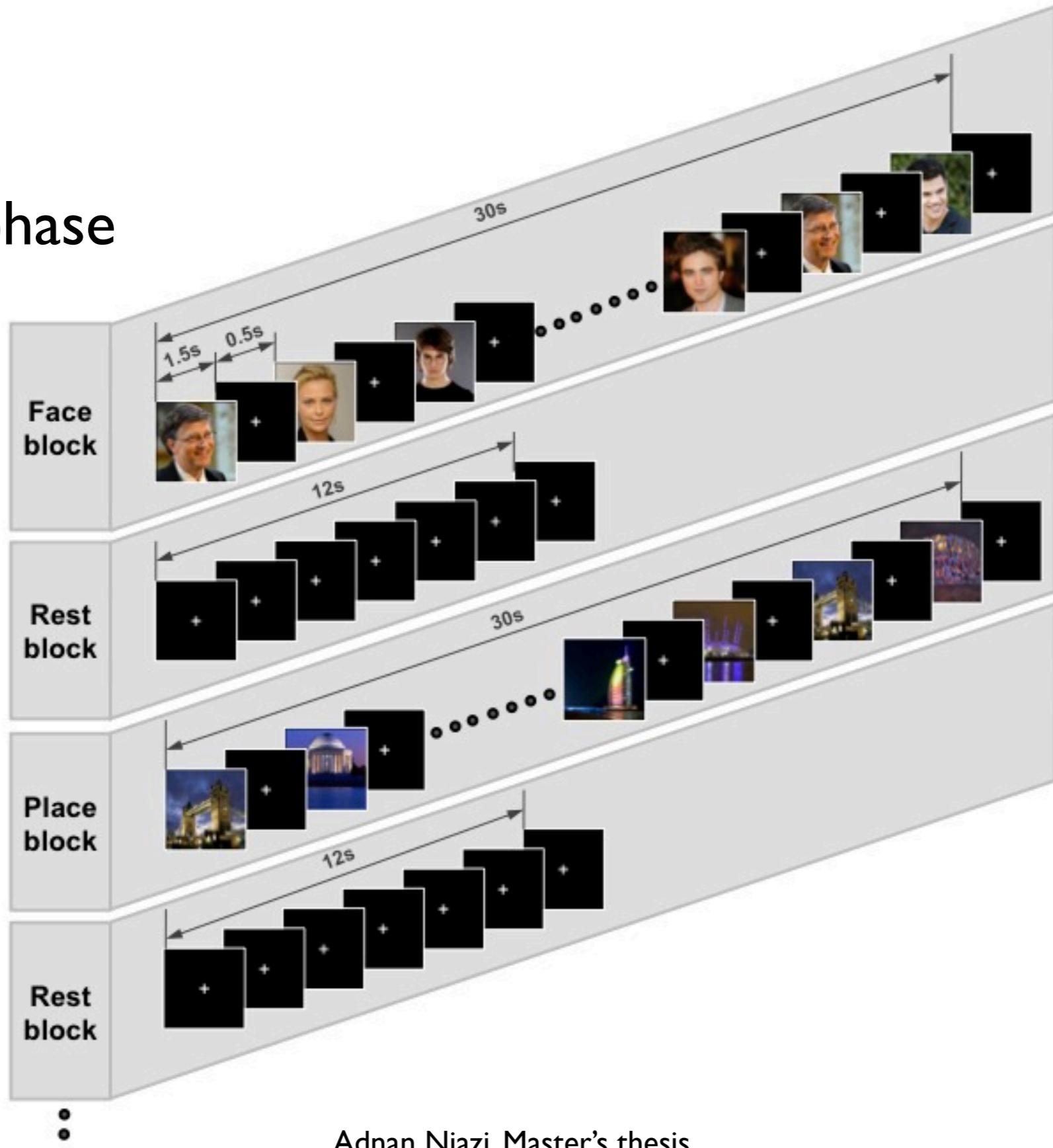


Radboud University Nijmegen



Real-time decoding of attended object categories

training phase



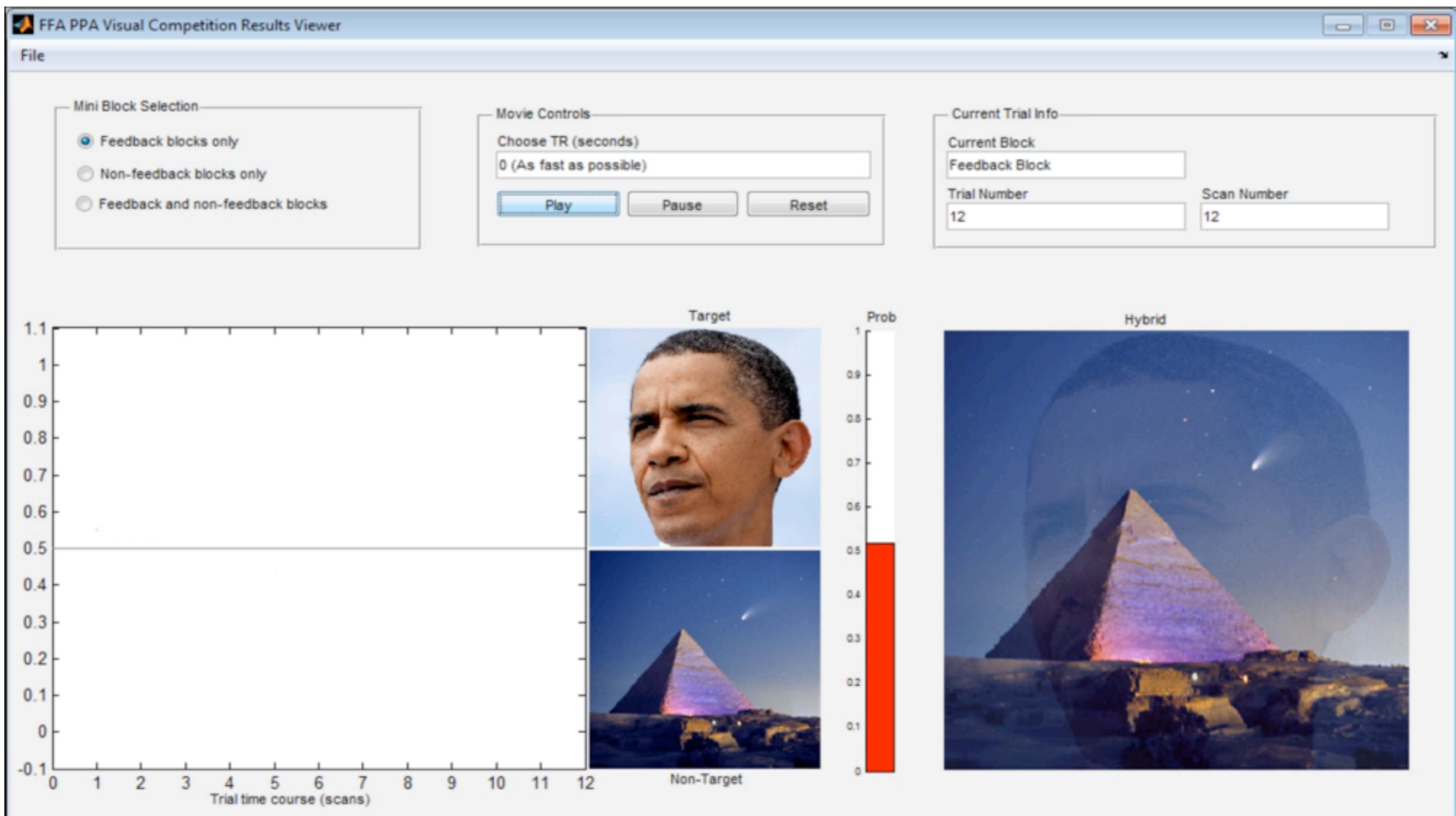
Adnan Niazi. Master's thesis

Real-time decoding of attended object categories

accuracy ~ 75%

Adnan Niazi. Master's thesis

Real-time decoding of attended object categories

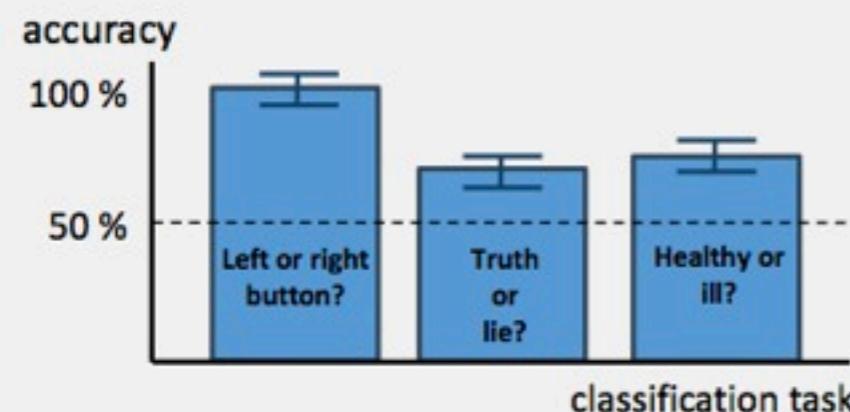


accuracy ~ 75%

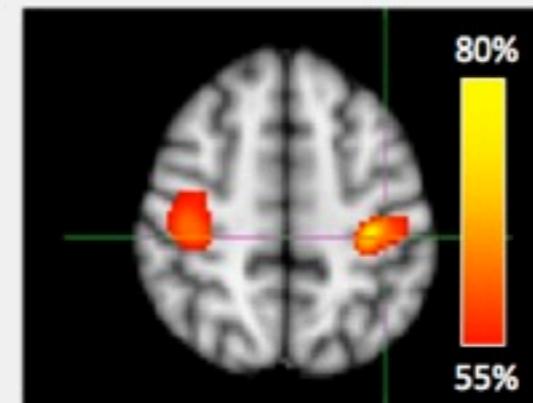
Adnan Niazi. Master's thesis



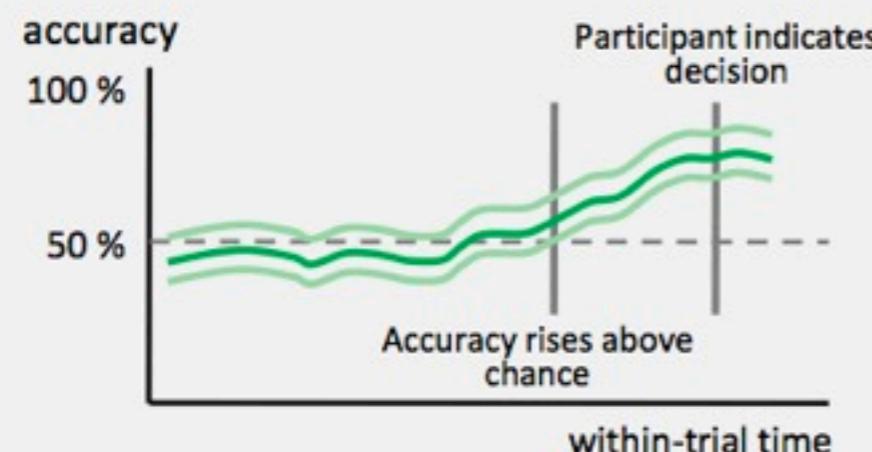
Overall classification accuracy



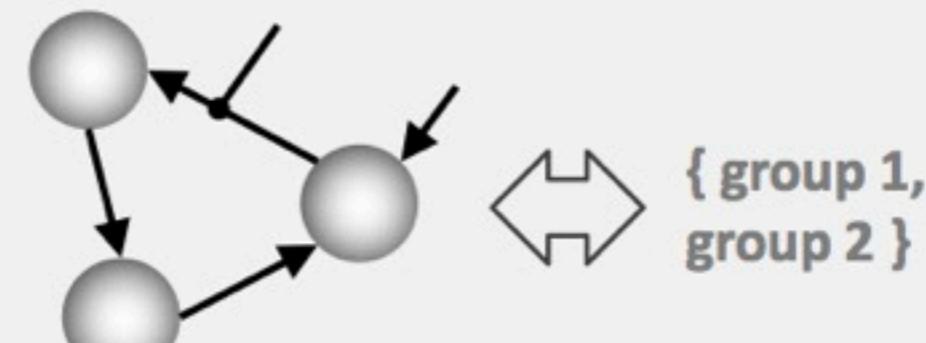
Spatial deployment of discriminative regions



Temporal evolution of discriminability



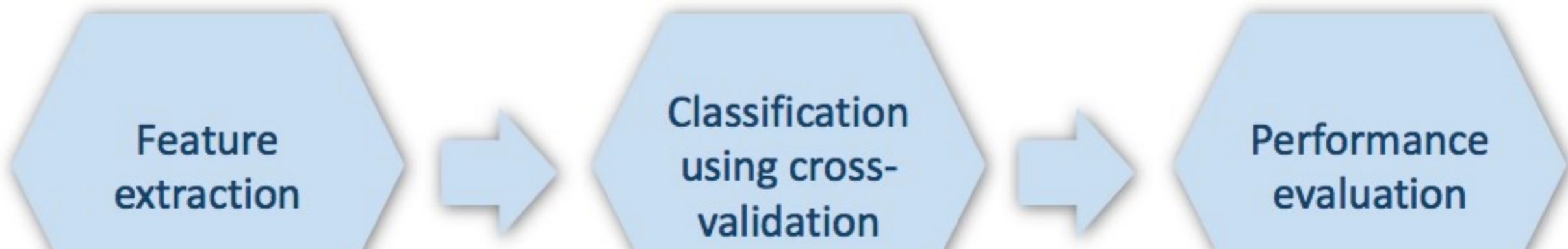
Model-based classification



Slide courtesy Kai Brodersen



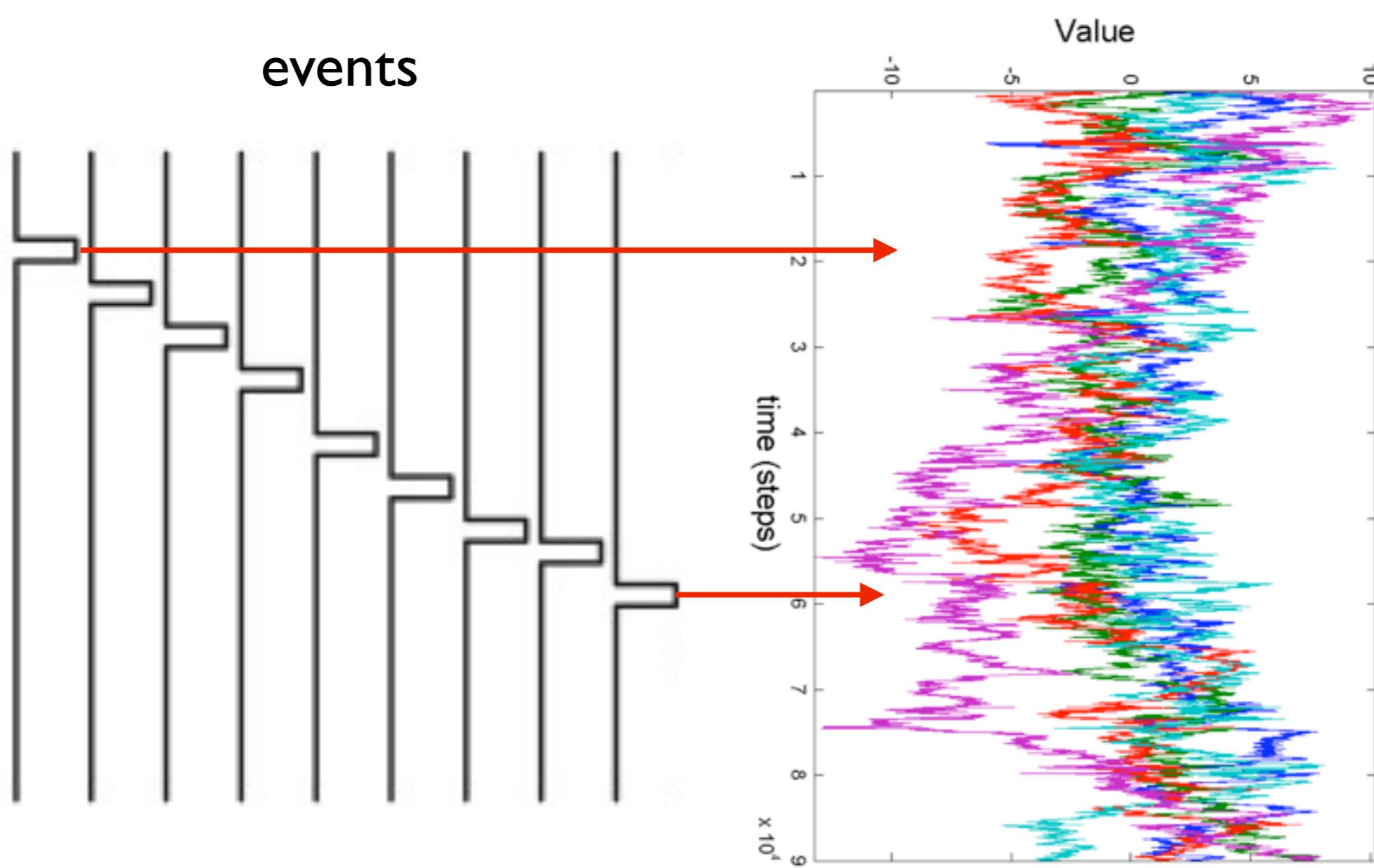
predicting one from a discrete set of cognitive states from measured data (e.g. perceived animal versus tool, patient versus control)



Note:

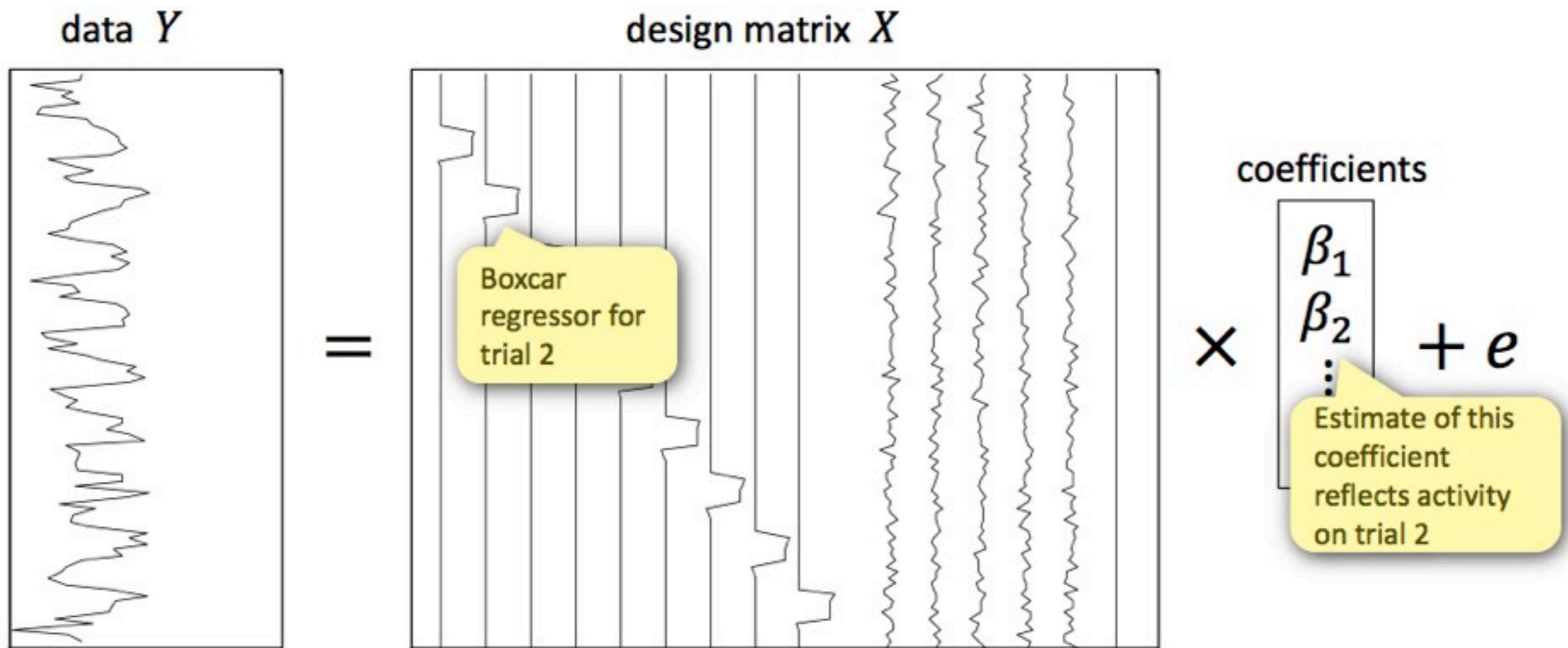
if the cognitive state is a continuous quantity then we are dealing with a regression problem (e.g. level of arousal)

What's the input?





We can obtain trial-wise estimates of neural activity by filtering the data with a GLM.



Slide courtesy Kai Brodersen





A principled way of designing a classifier would be to adopt a probabilistic approach:



In practice, classifiers differ in terms of how strictly they implement this principle.

Generative classifiers

use Bayes' rule to estimate
 $p(X_t | Y_t) \propto p(Y_t | X_t)p(X_t)$

- *Gaussian Naïve Bayes*
- *Linear Discriminant Analysis*

Discriminative classifiers

estimate $p(X_t | Y_t)$ directly without Bayes' theorem

- *Logistic regression*
- *Relevance Vector Machine*

Discriminant classifiers

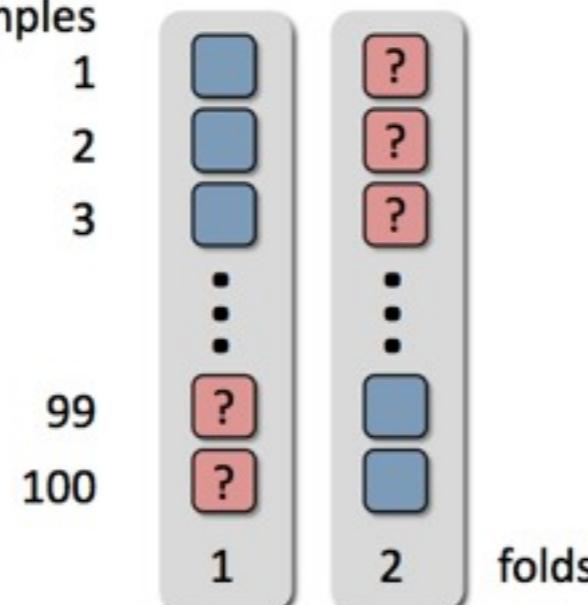
estimate $f(Y_t)$ directly

- *Fisher's Linear Discriminant*
- *Support Vector Machine*





2-fold: examples



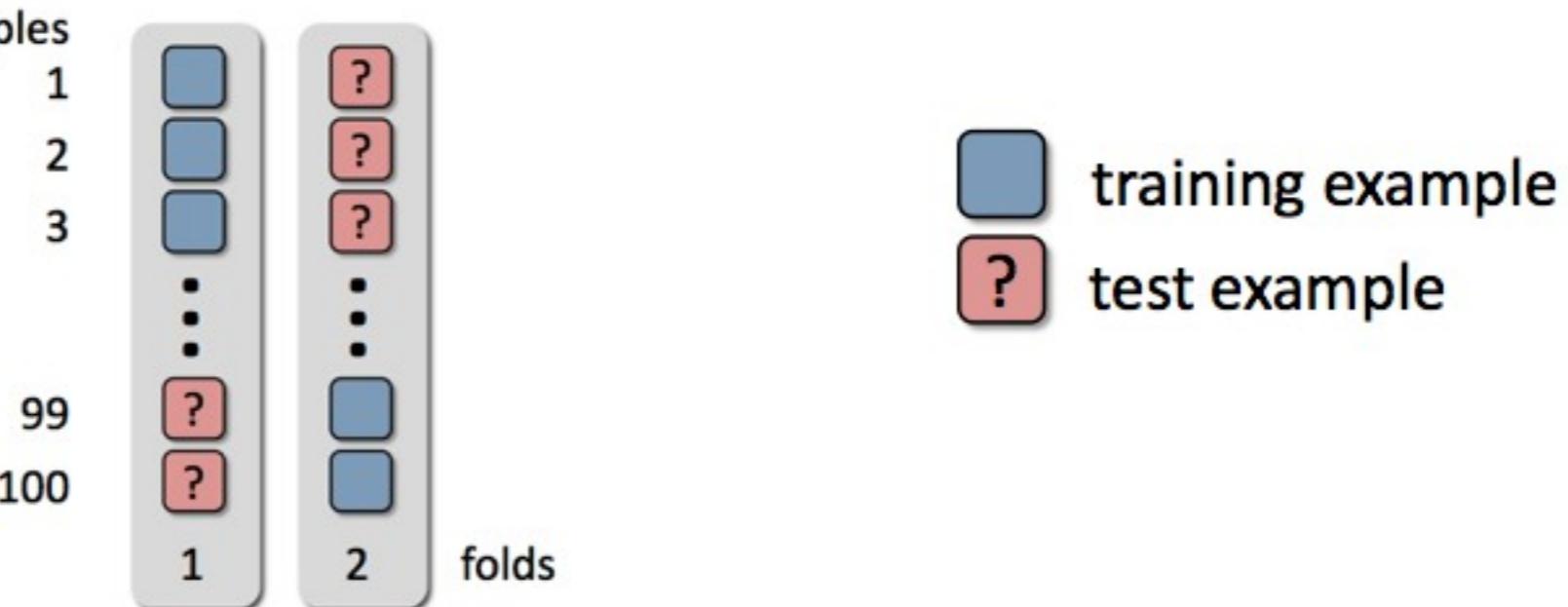
- training example
- test example

Slide courtesy Kai Brodersen

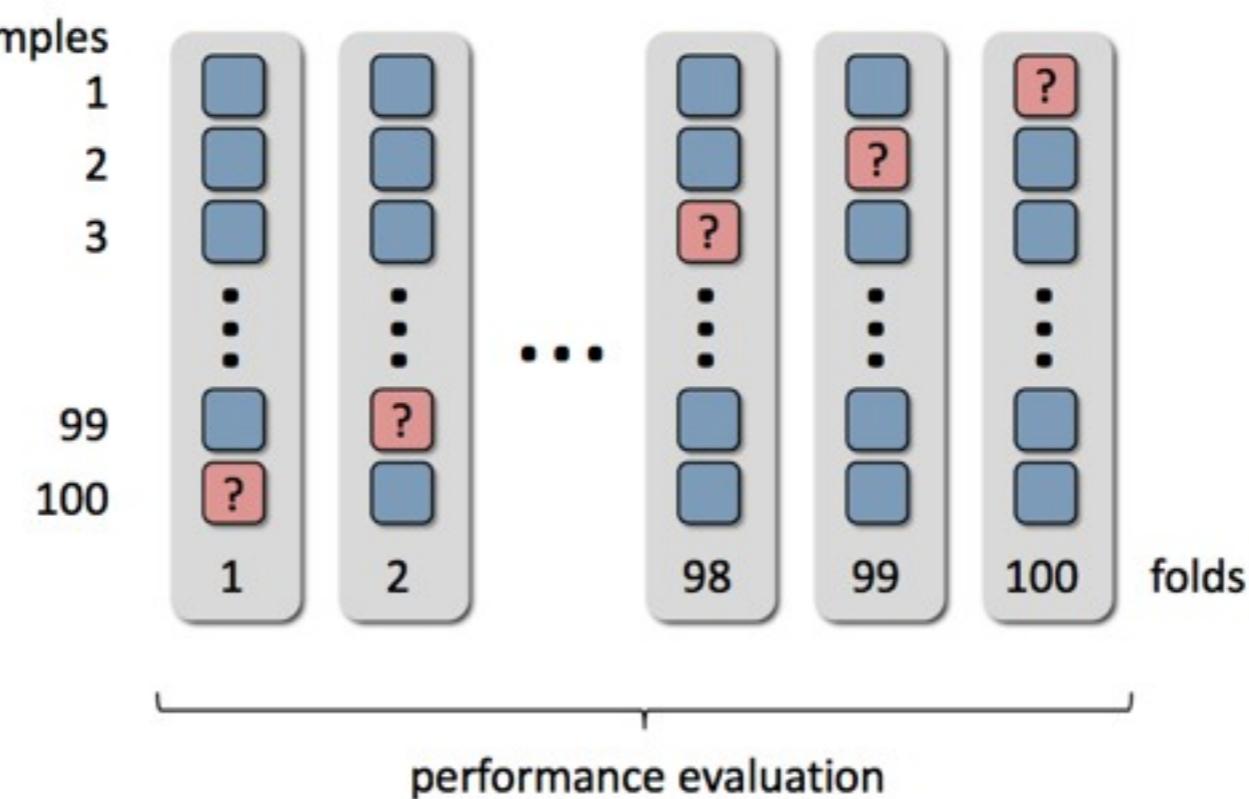




2-fold:



leave-one-out:



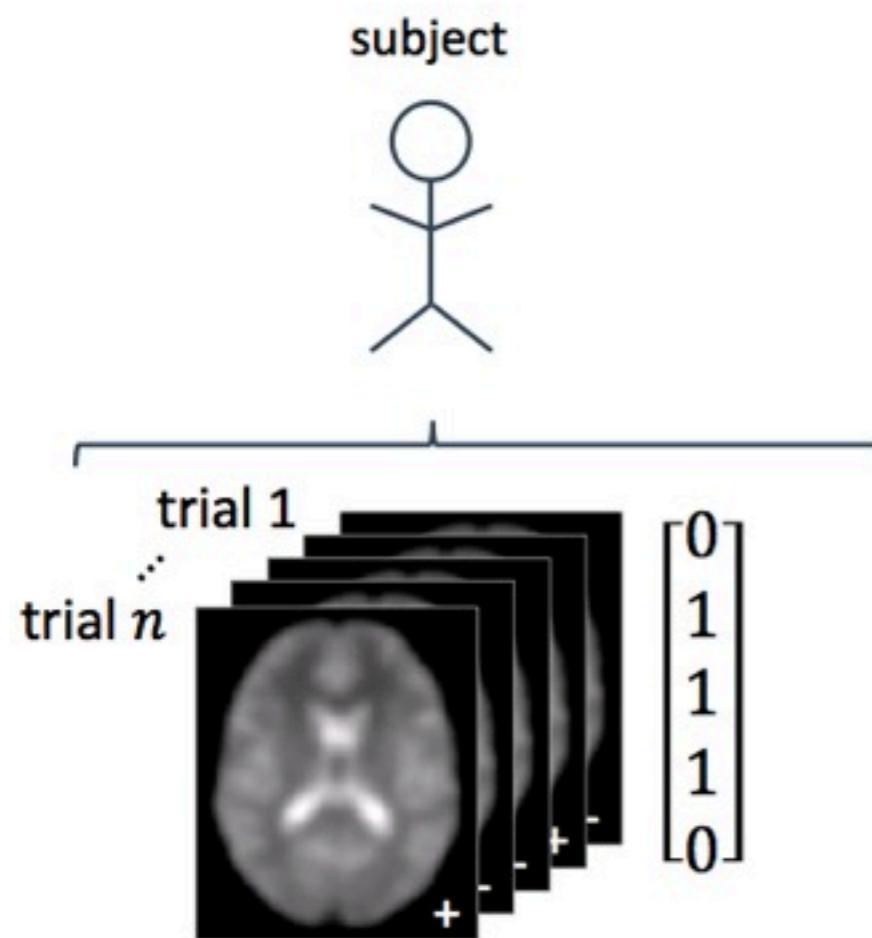
Slide courtesy Kai Brodersen





⌚ Single-subject study with n trials

The most common approach is to assess how likely the obtained number of correctly classified trials could have occurred by chance.



Binomial test

$$p = P(X \geq k | H_0) = 1 - \Pr(X \leq x - 1)$$

In MATLAB:

```
p = 1 - binocdf(k-1,n,pi_0)
```

k number of correctly classified trials

n total number of trials

π_0 chance level (typically 0.5)

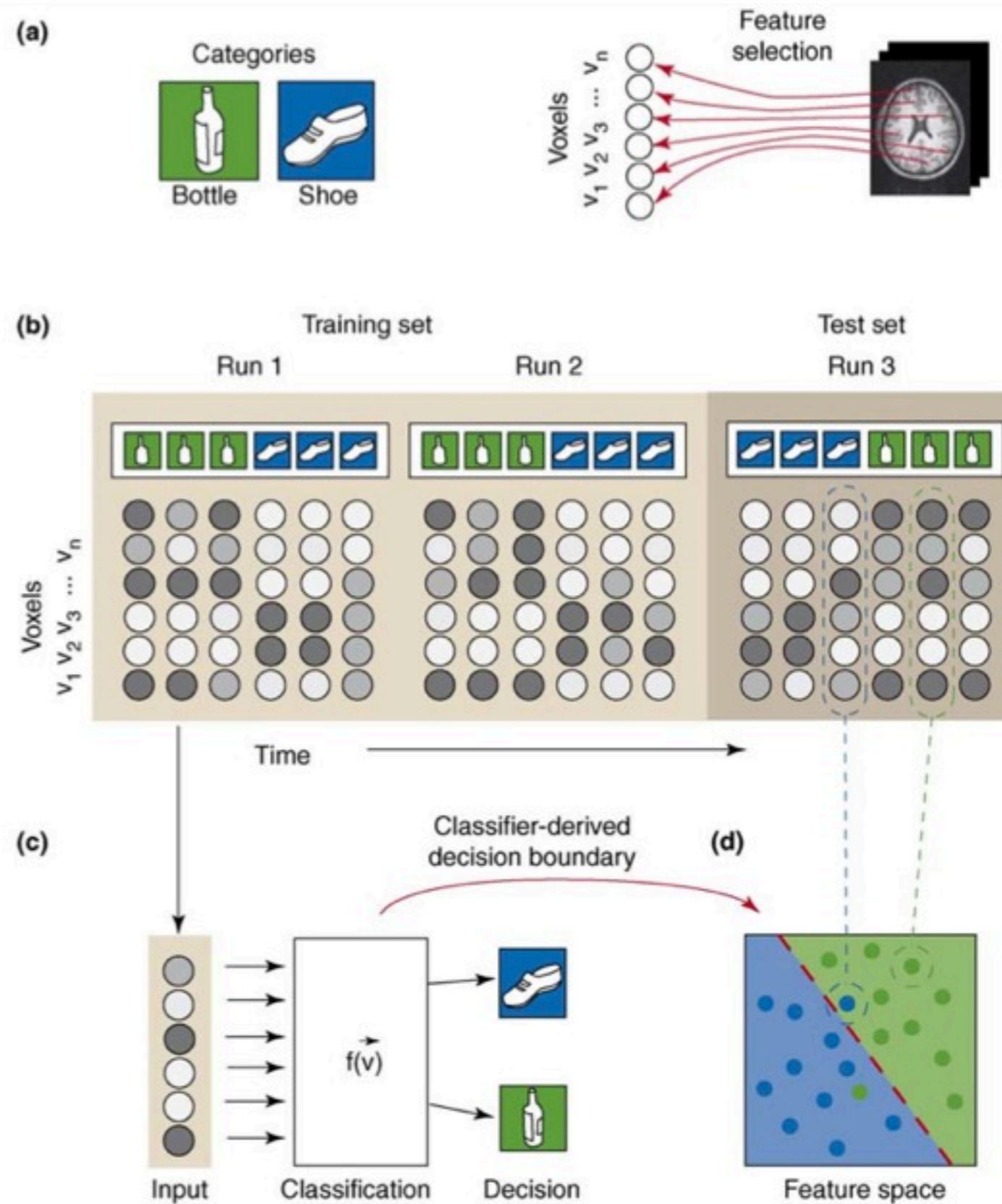
B binomial cumulative density function



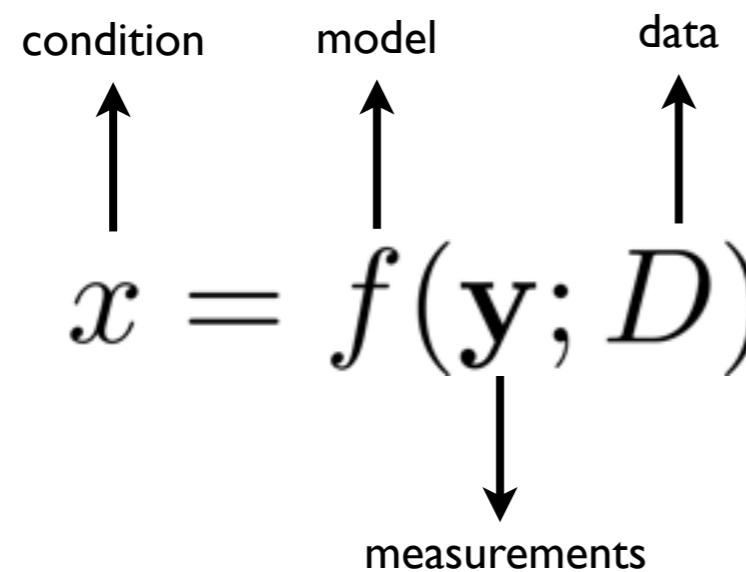
- compute number of subjects s from population of n that are significant under a certain p value
- compute probability of observing such a result, again under a binomial distribution:

```
pvalue = 1 - binocdf(s-1,n,p);
```

Classification of neuroimaging data

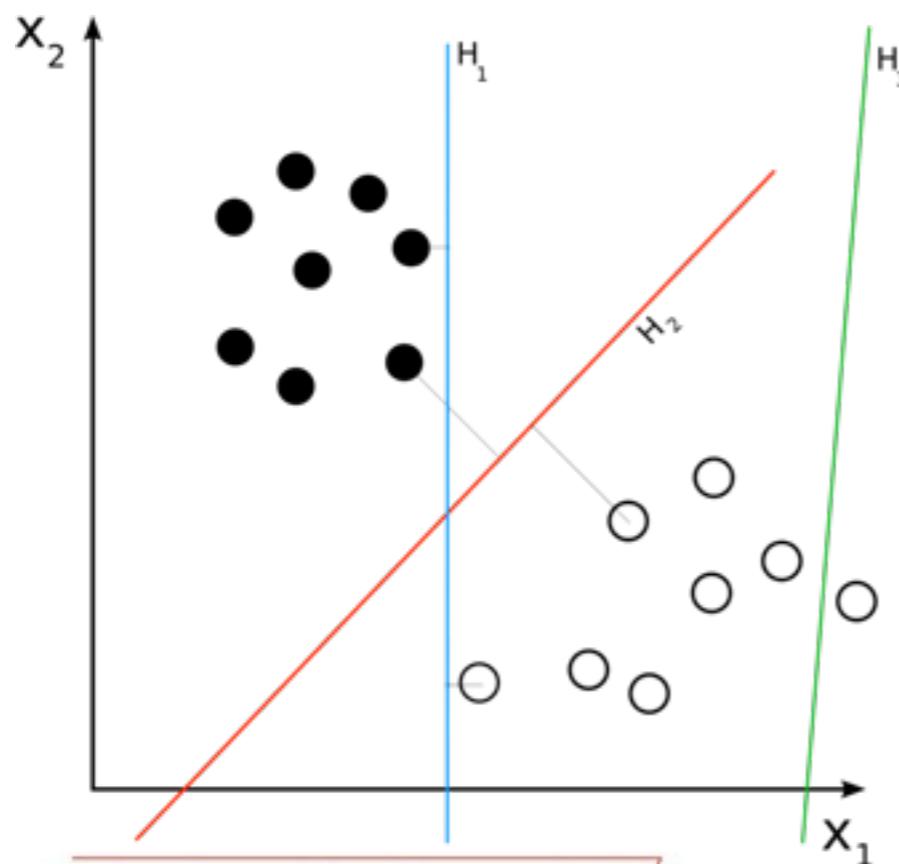


TRENDS in Cognitive Sciences



E.g. Linear support vector machine

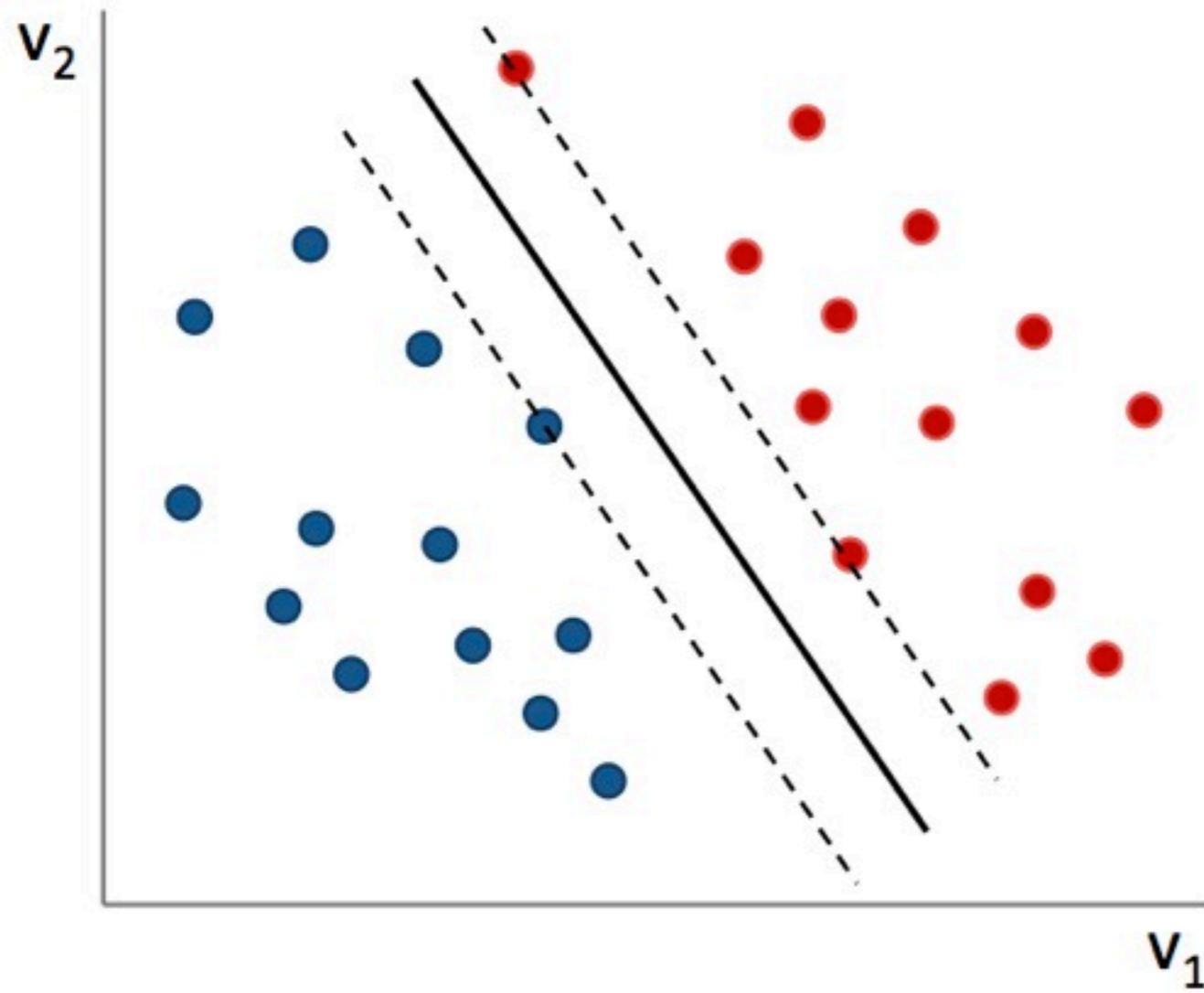
hyperplane maximizes distance between classes



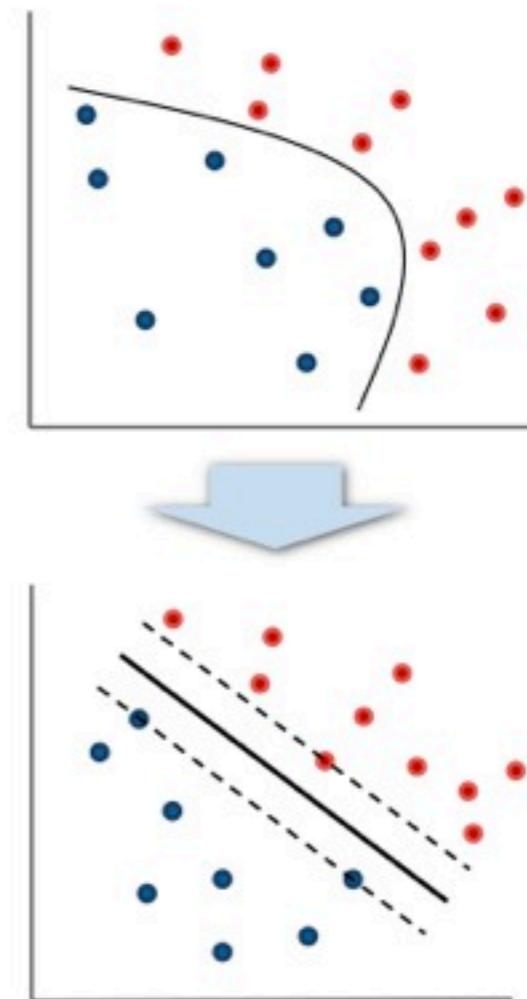
- very popular approach in neuroimaging:
- fast
 - robust
 - easy-to-use packages



Linear SVM



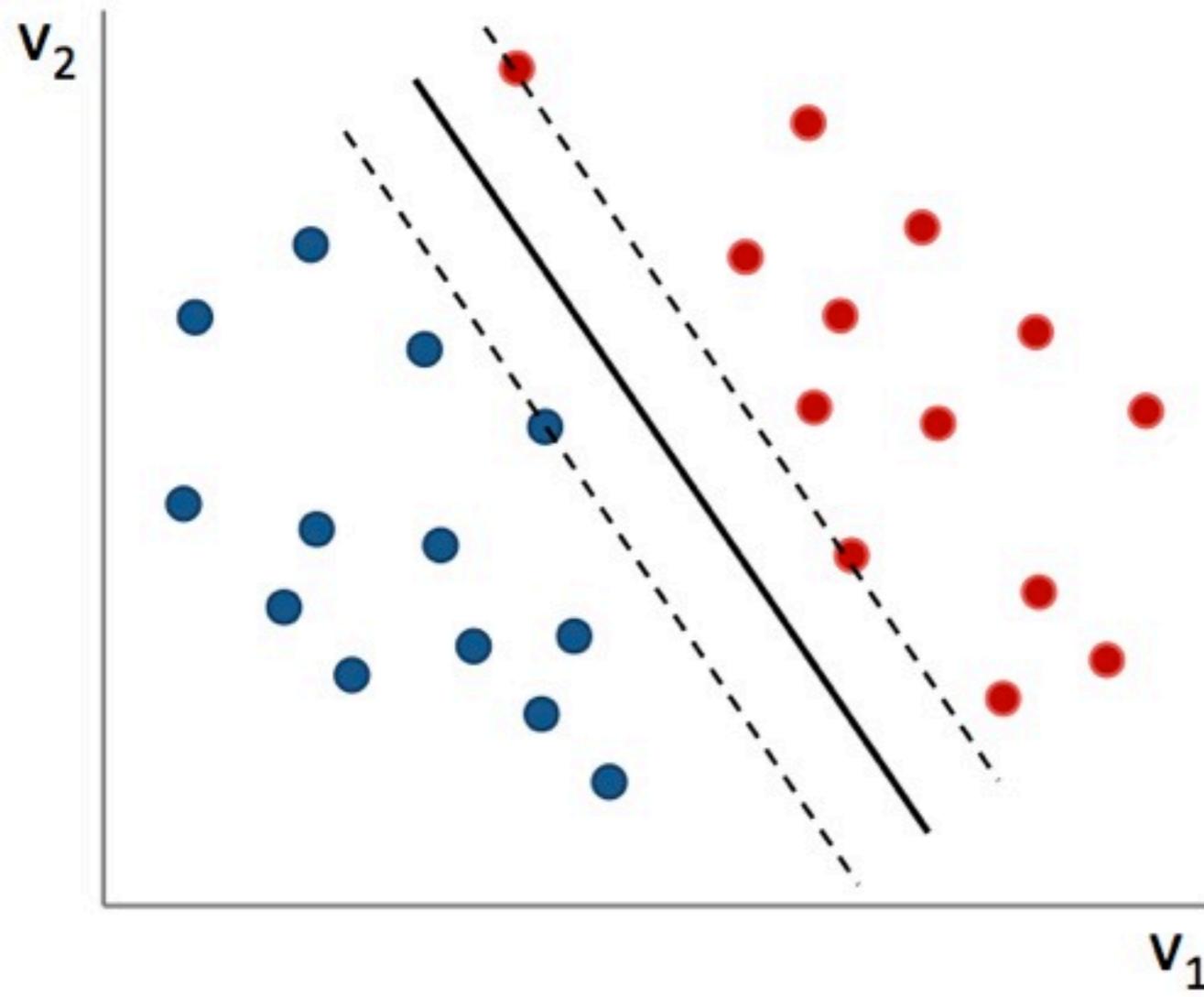
Nonlinear SVM



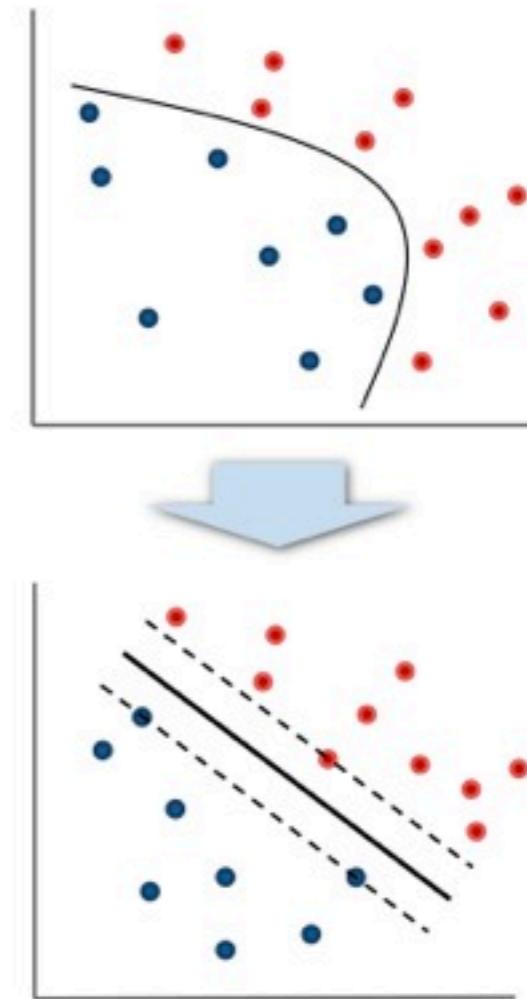
Vapnik (1999) Springer; Schölkopf et al. (2002) MIT Press



Linear SVM



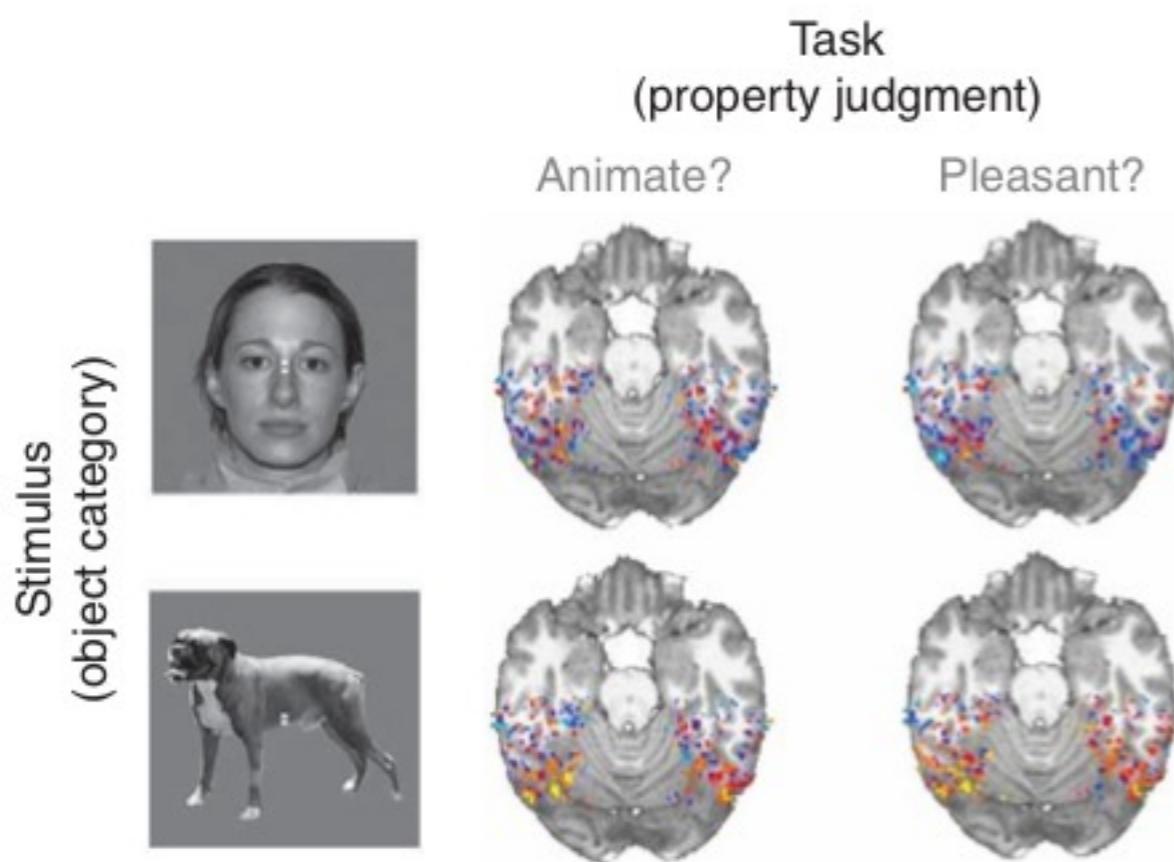
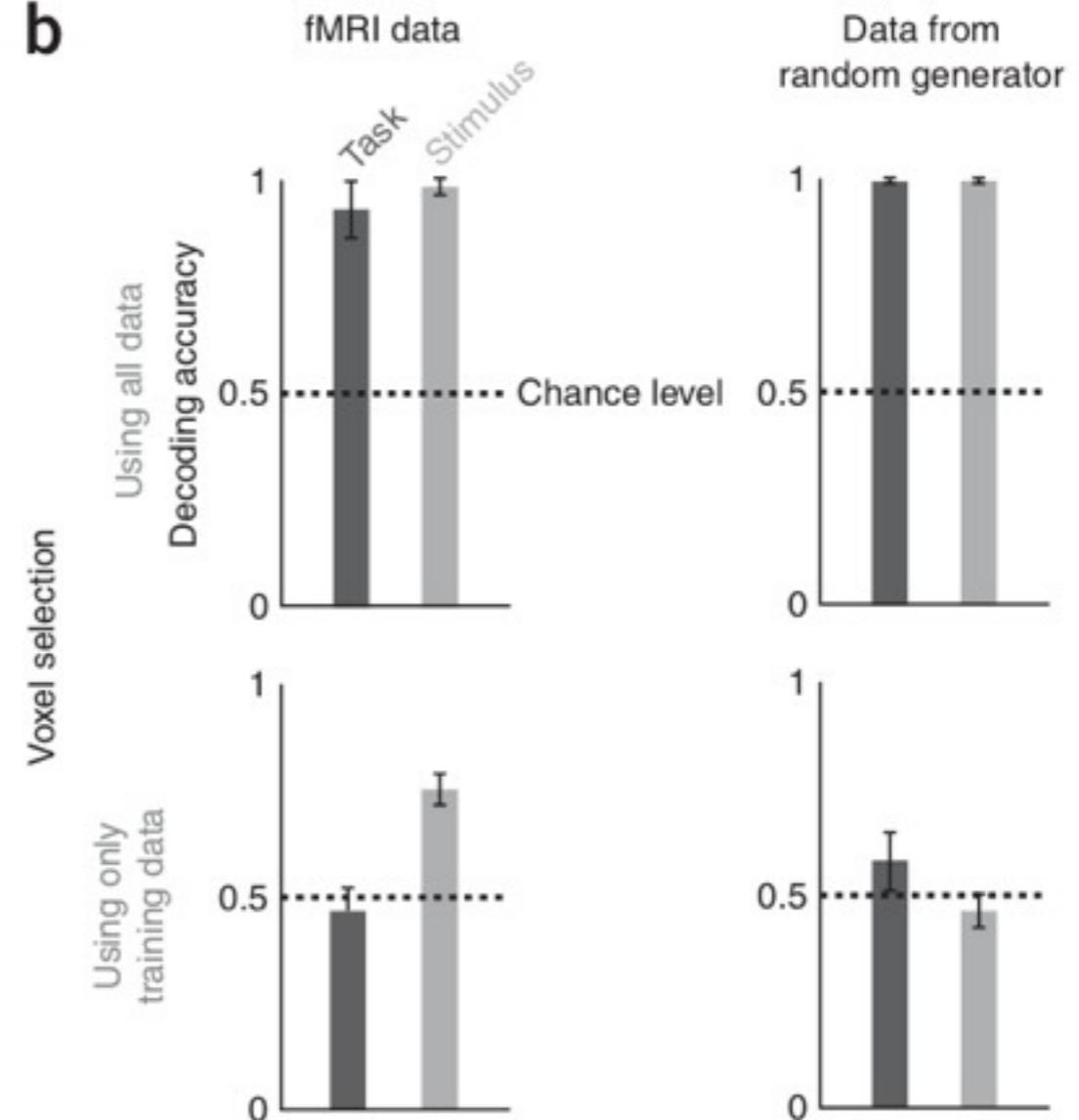
Nonlinear SVM



Vapnik (1999) Springer; Schölkopf et al. (2002) MIT Press

Linear classifiers are more often used in neuroimaging:
Robust in case of small sample sizes

How to cheat with classifiers

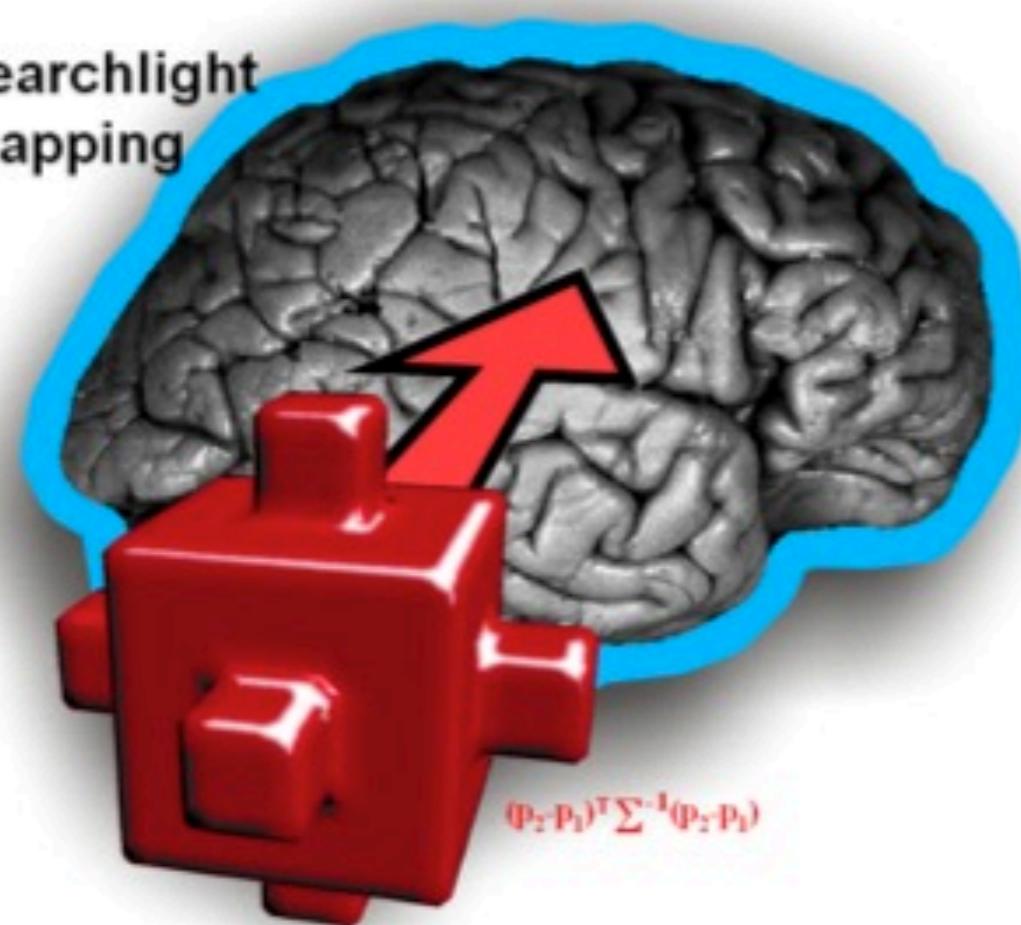
**a****b**

Kriegeskorte N, Simmons WK, Bellgowan PSF, Baker CI. Circular analysis in systems neuroscience: the dangers of double dipping. *Nat Neurosci.* 2009;12(5):535–540.



How to use classifiers to find which regions are functionally involved?

Searchlight
mapping



In each “sphere”:

Support Vector Machine classifier

- classification accuracy
- classification significance



local classification performance ~ voxel relevance

1. select voxels within radius
2. train
3. test
4. set estimated significance to center voxel
5. correct for multiple comparisons

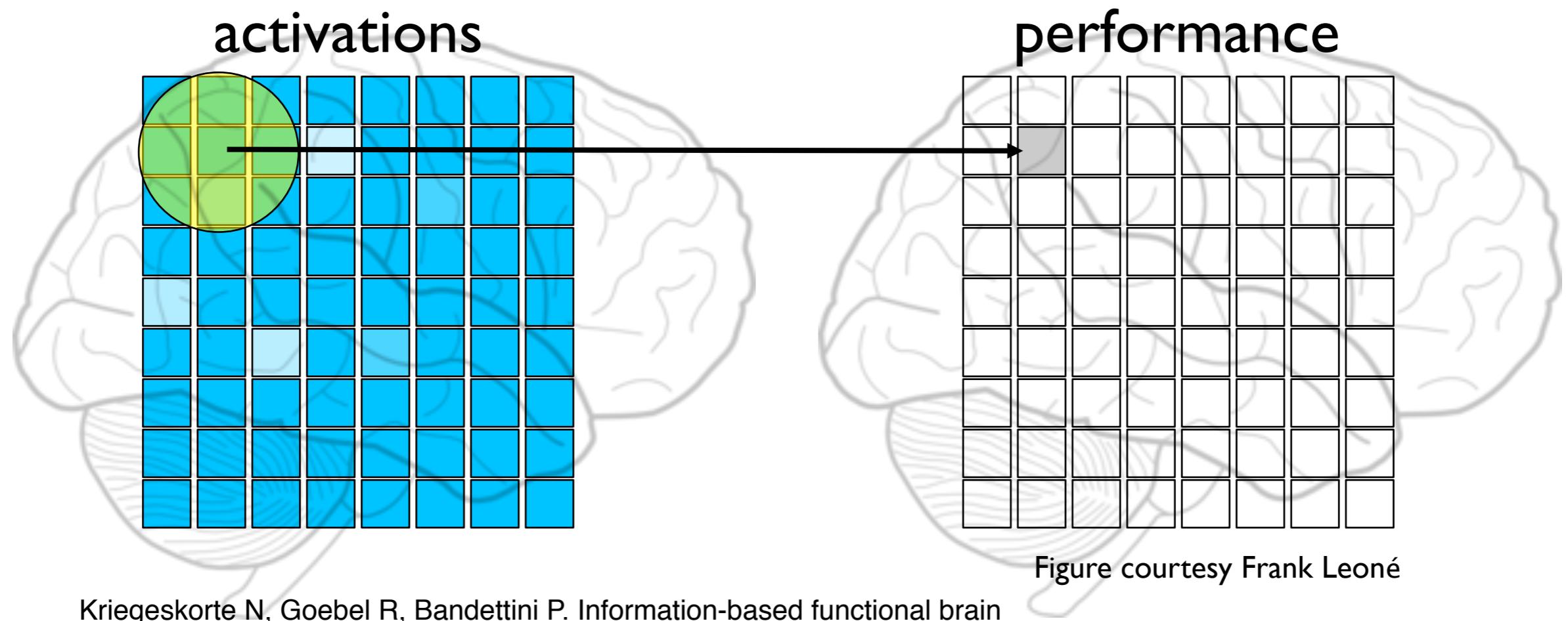


Figure courtesy Frank Leoné

Kriegeskorte N, Goebel R, Bandettini P. Information-based functional brain mapping. Proc Natl Acad Sci U S A. 2006 Mar.;103(10):3863–3868.



local classification performance ~ voxel relevance

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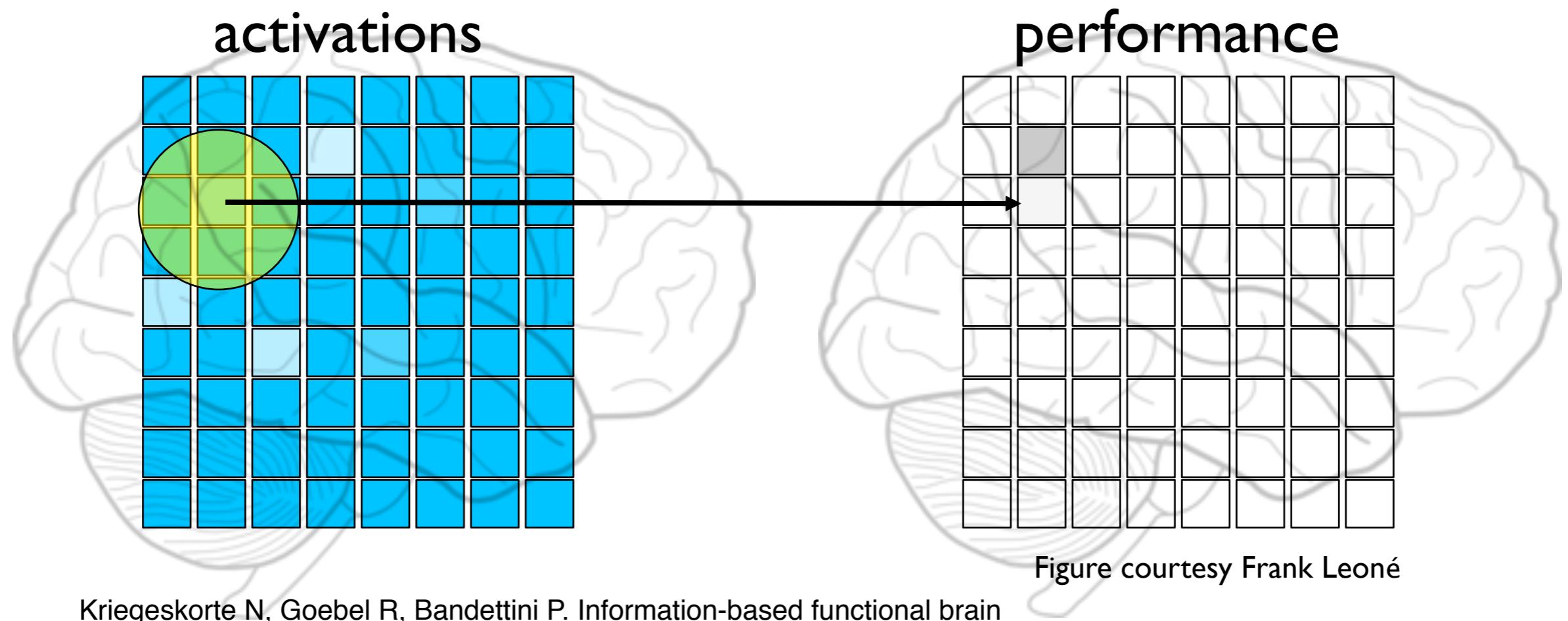


Figure courtesy Frank Leoné

Kriegeskorte N, Goebel R, Bandettini P. Information-based functional brain mapping. Proc Natl Acad Sci U S A. 2006 Mar.;103(10):3863–3868.



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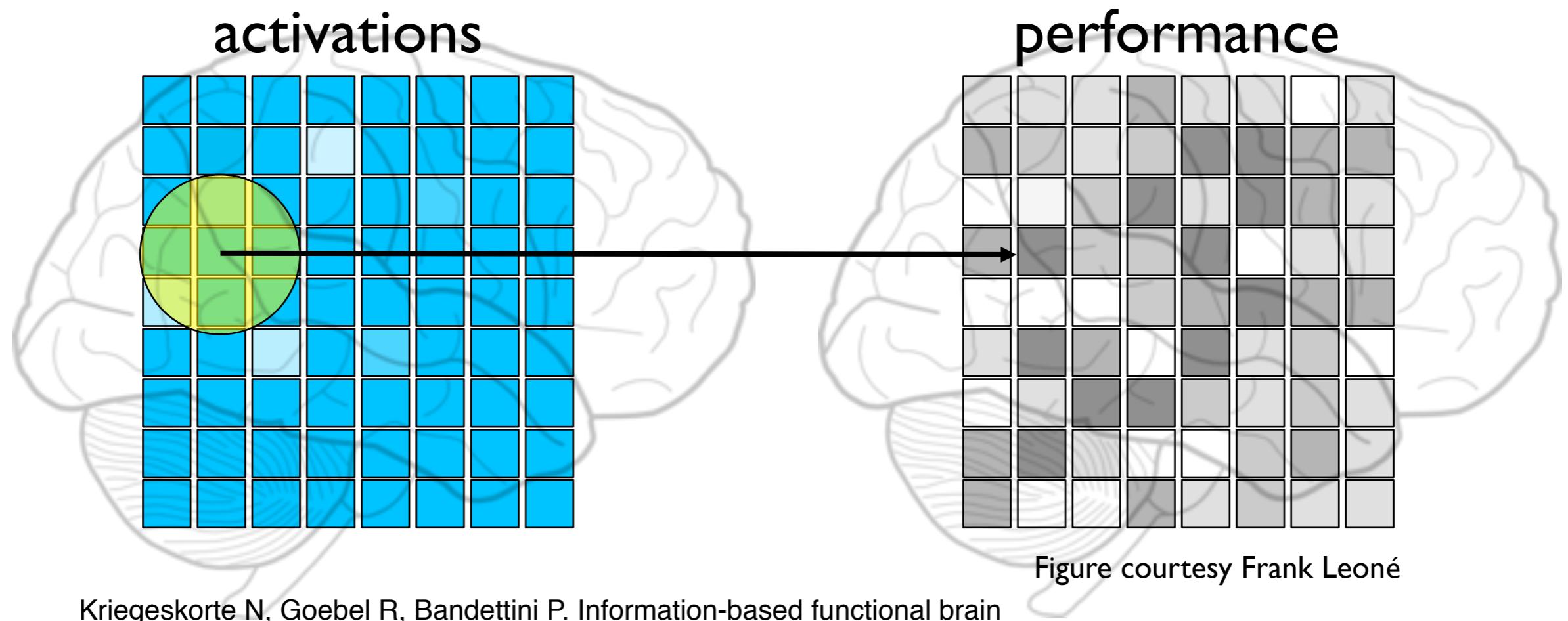
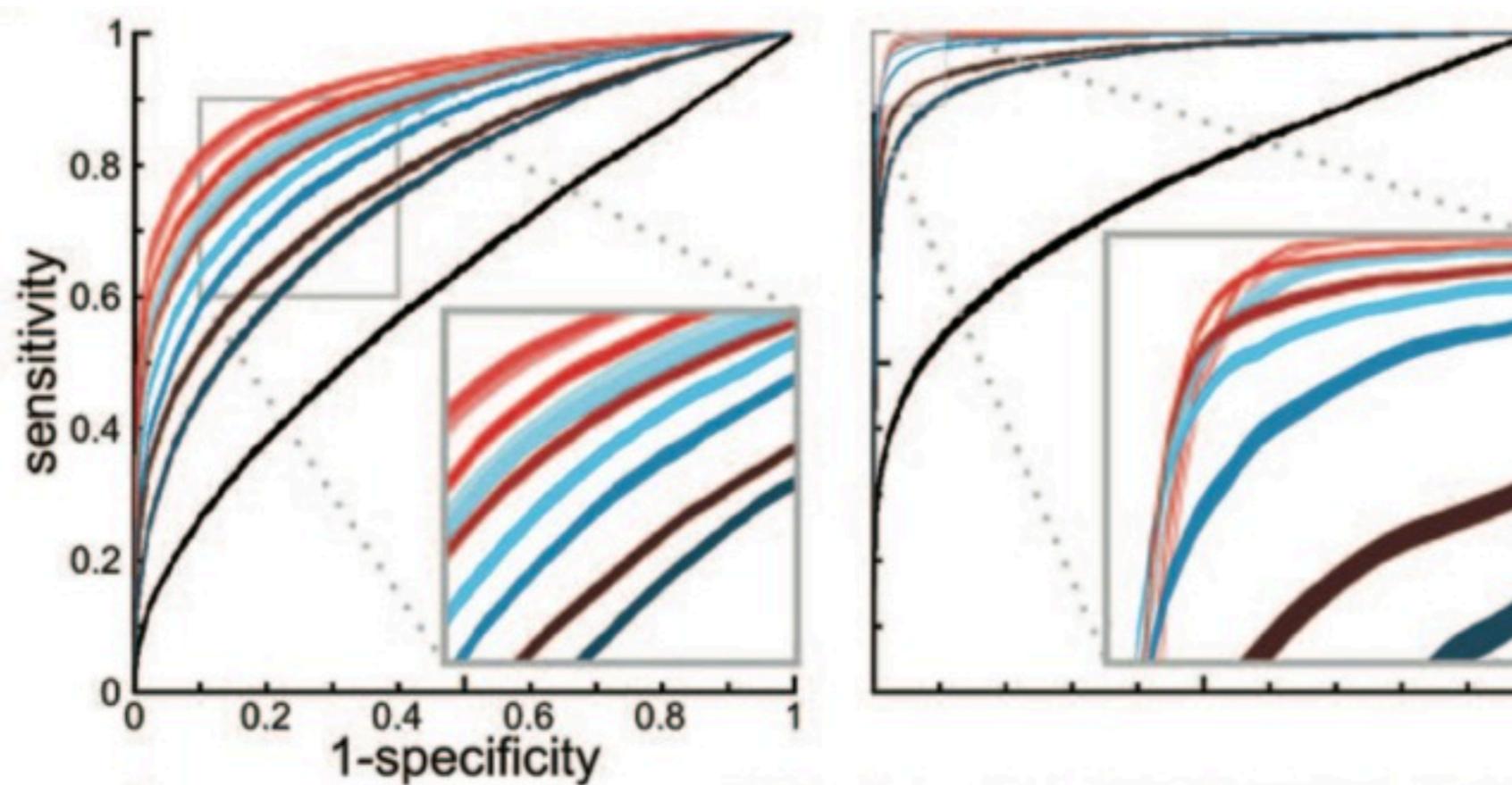


Figure courtesy Frank Leoné

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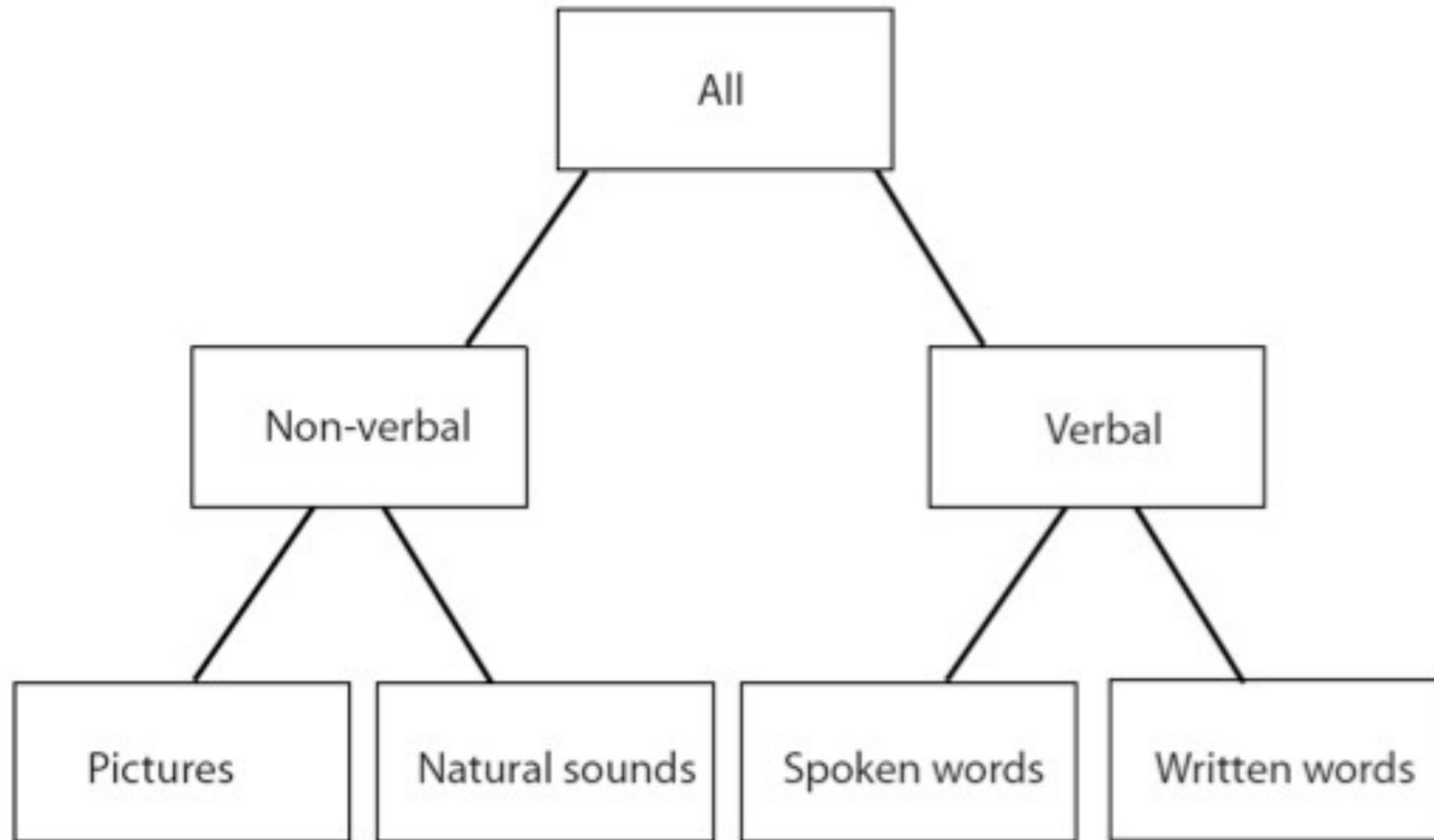
Searchlight analysis



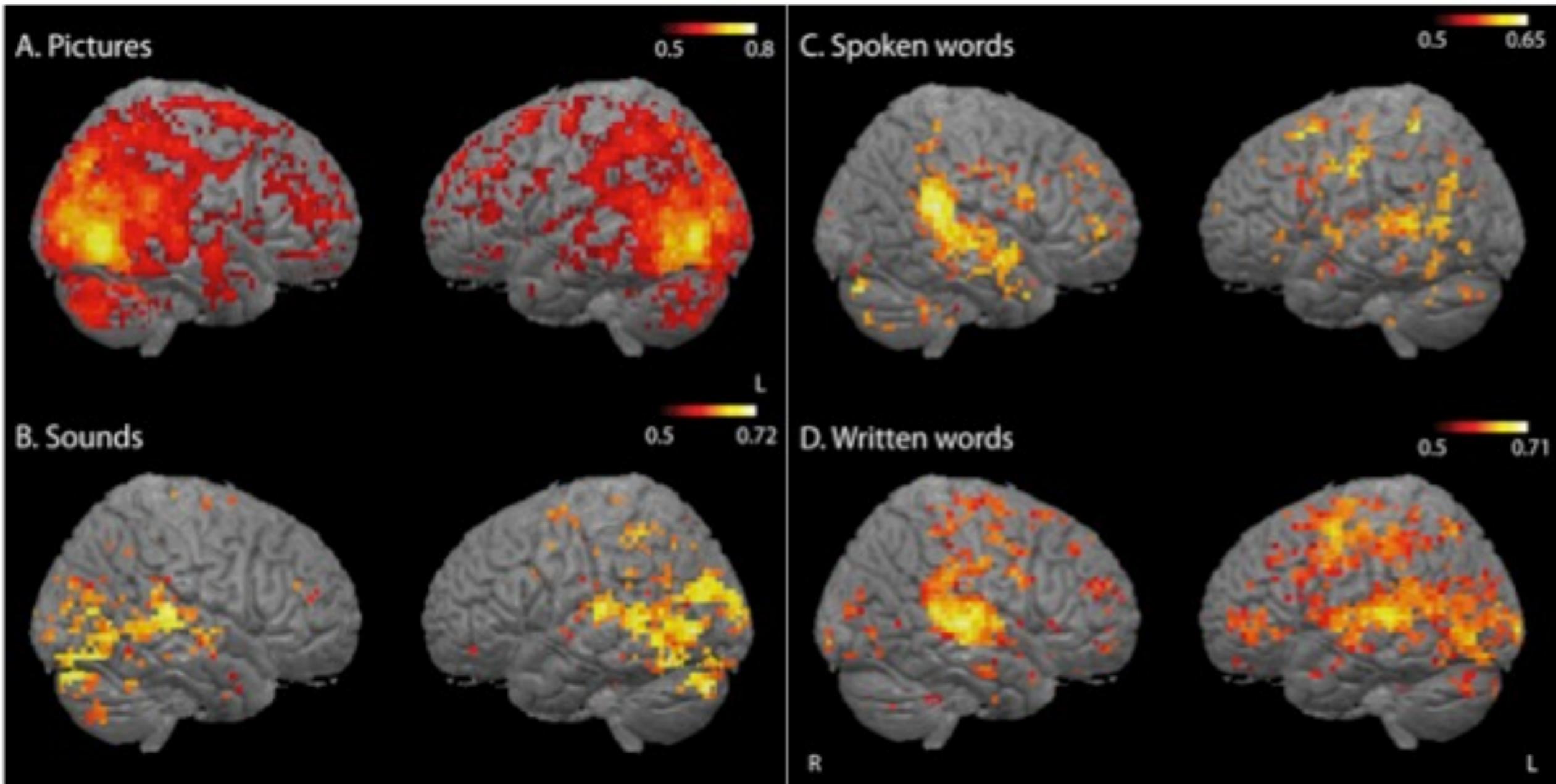
D Color coding of mapping techniques

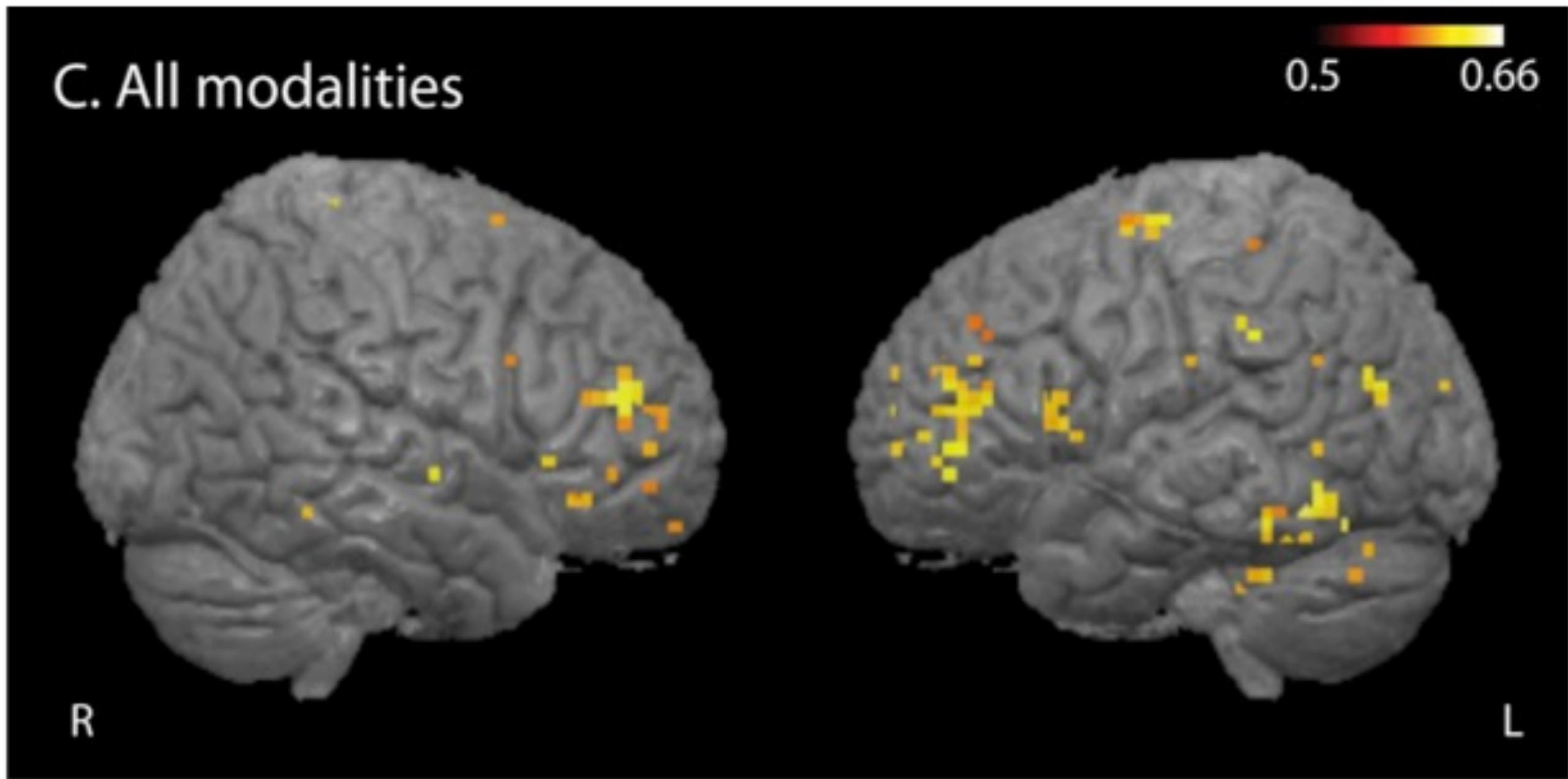


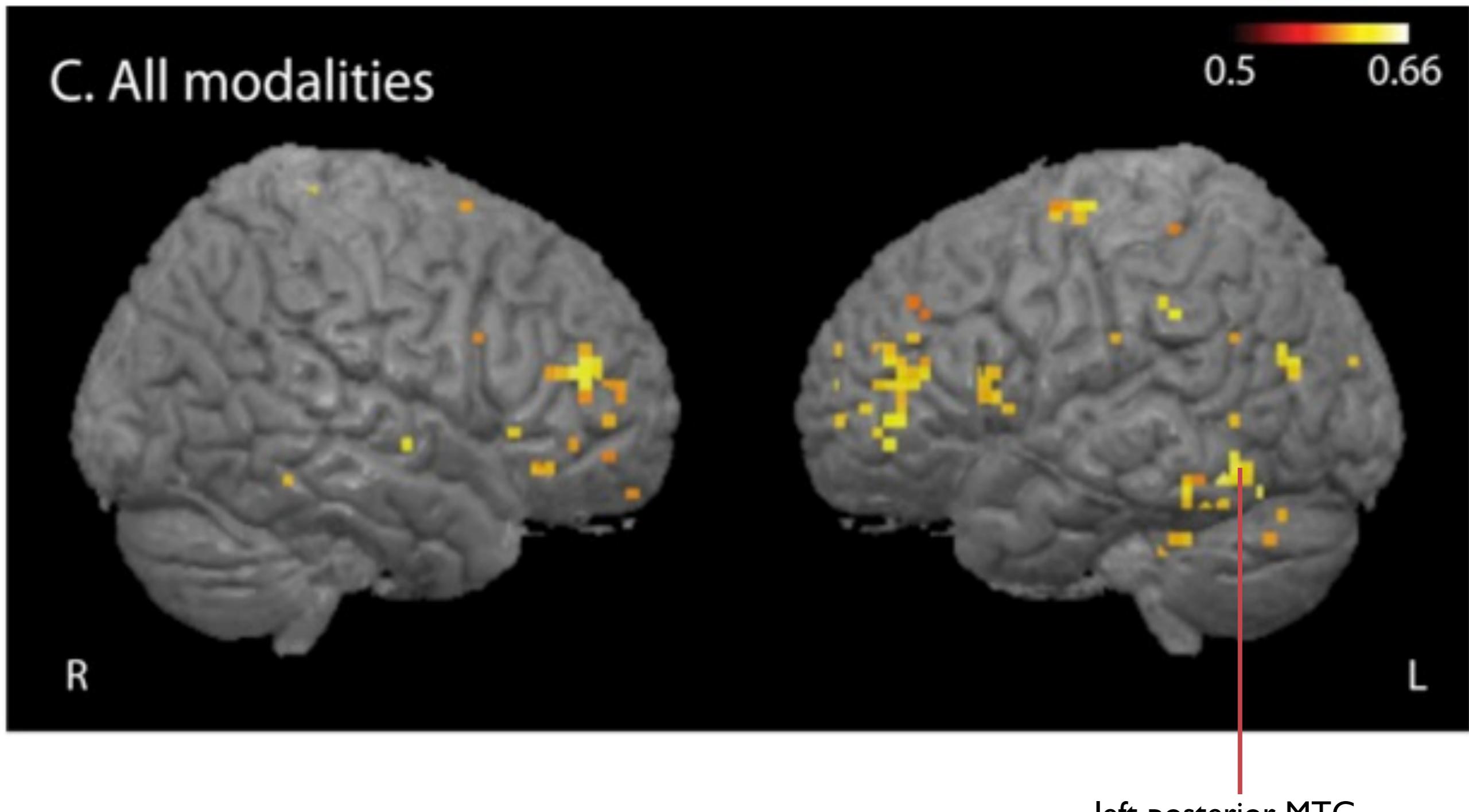
Kriegeskorte N, Goebel R, Bandettini P. Information-based functional brain mapping. Proc Natl Acad Sci U S A. 2006 Mar.;103(10):3863–8.

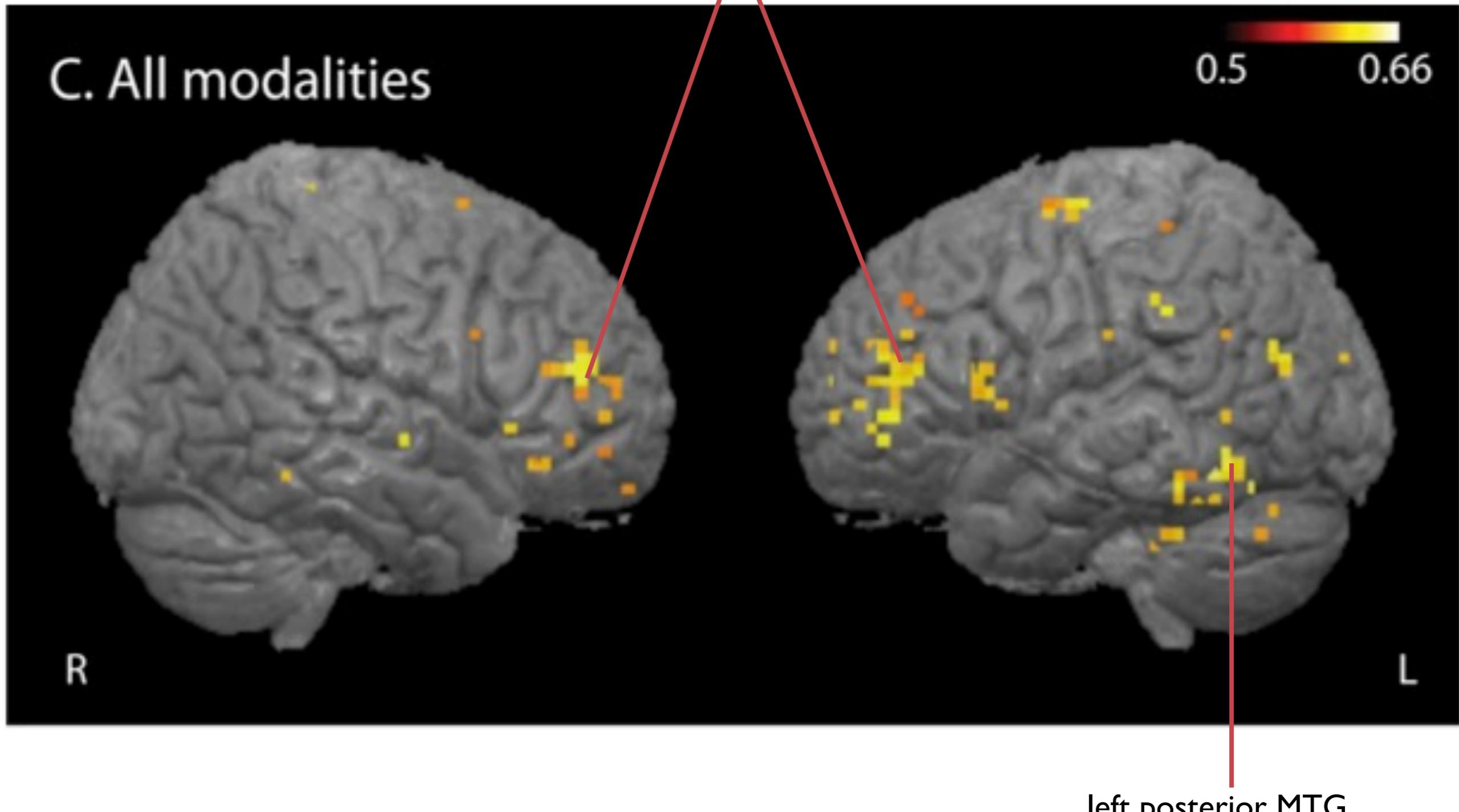


Single modalities











- correct p-value for m comparisons!
- use Bonferroni or FDR correction on single or group p-values

Bonferroni:

- $p_{\text{new}} = p/m$
- conservative

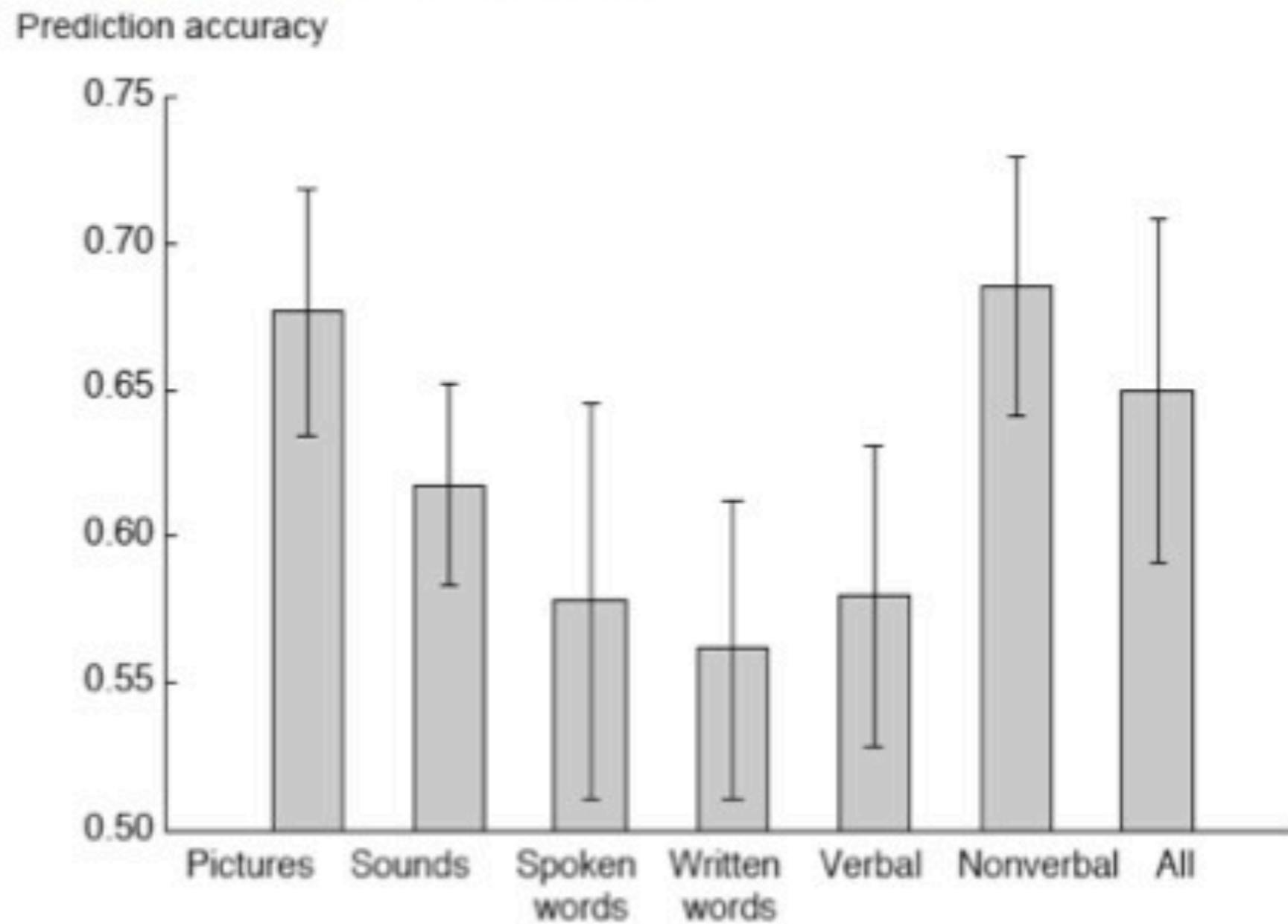
False discovery rate:

1. choose alpha
2. $H_1 \dots H_m$ hypotheses with $P_{(1)} \dots P_{(m)}$ p-values ordered in increasing order
3. find largest k such that $P_{(k)} \leq \frac{k}{m} \alpha$
4. reject null hypotheses $H_1 \dots H_k$

alpha gives expected proportion of false positives among all significant hypotheses

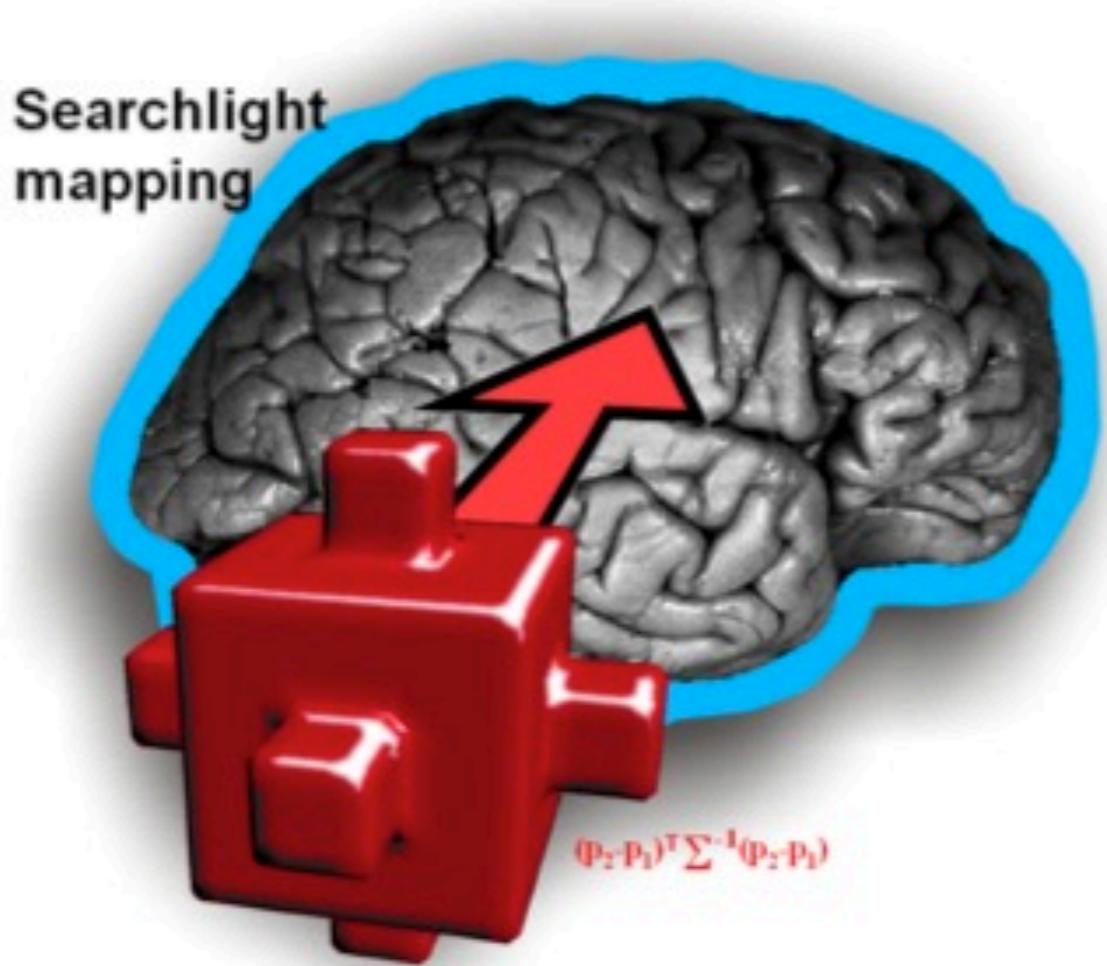


Think about all **animals** that you have seen during the experiment...
OR
Think about all **tools** that you have seen....



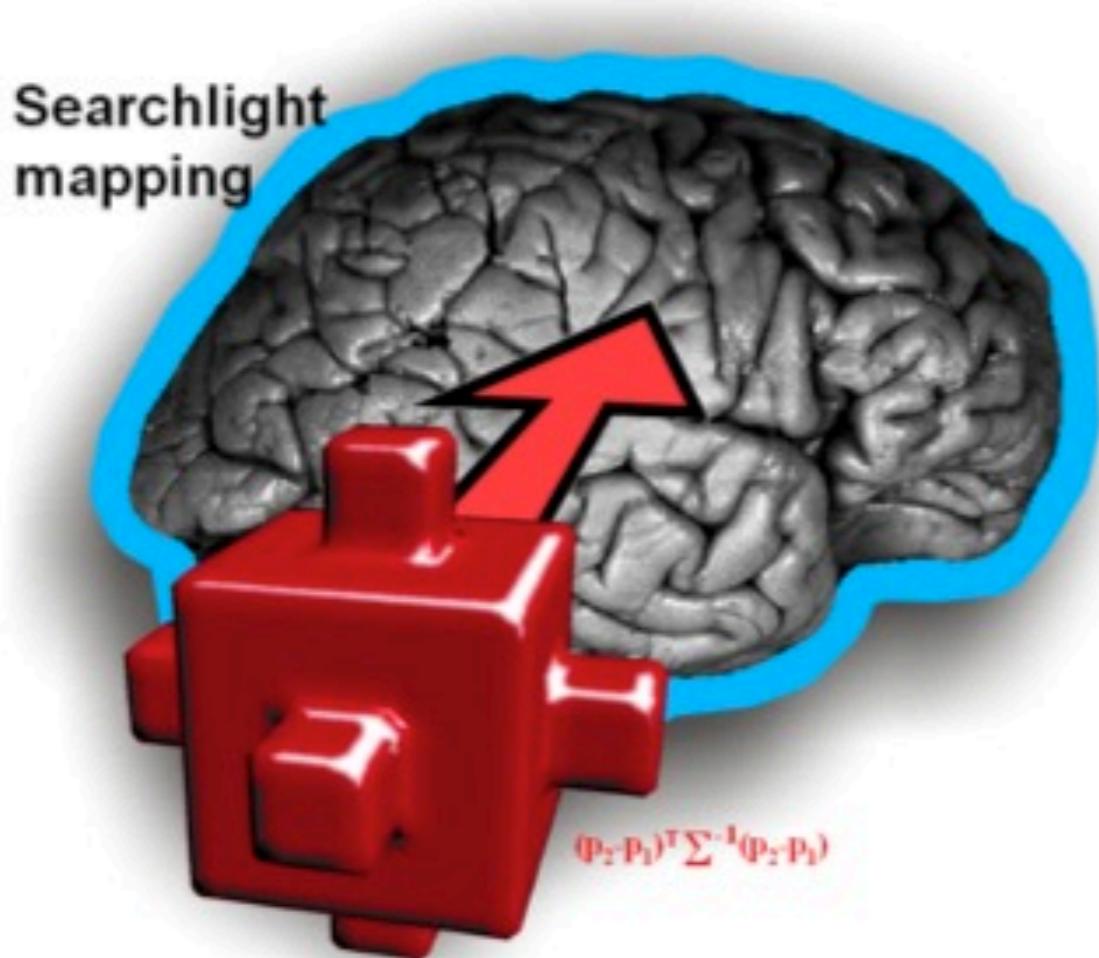


How to use classifiers to find which regions are functionally involved?





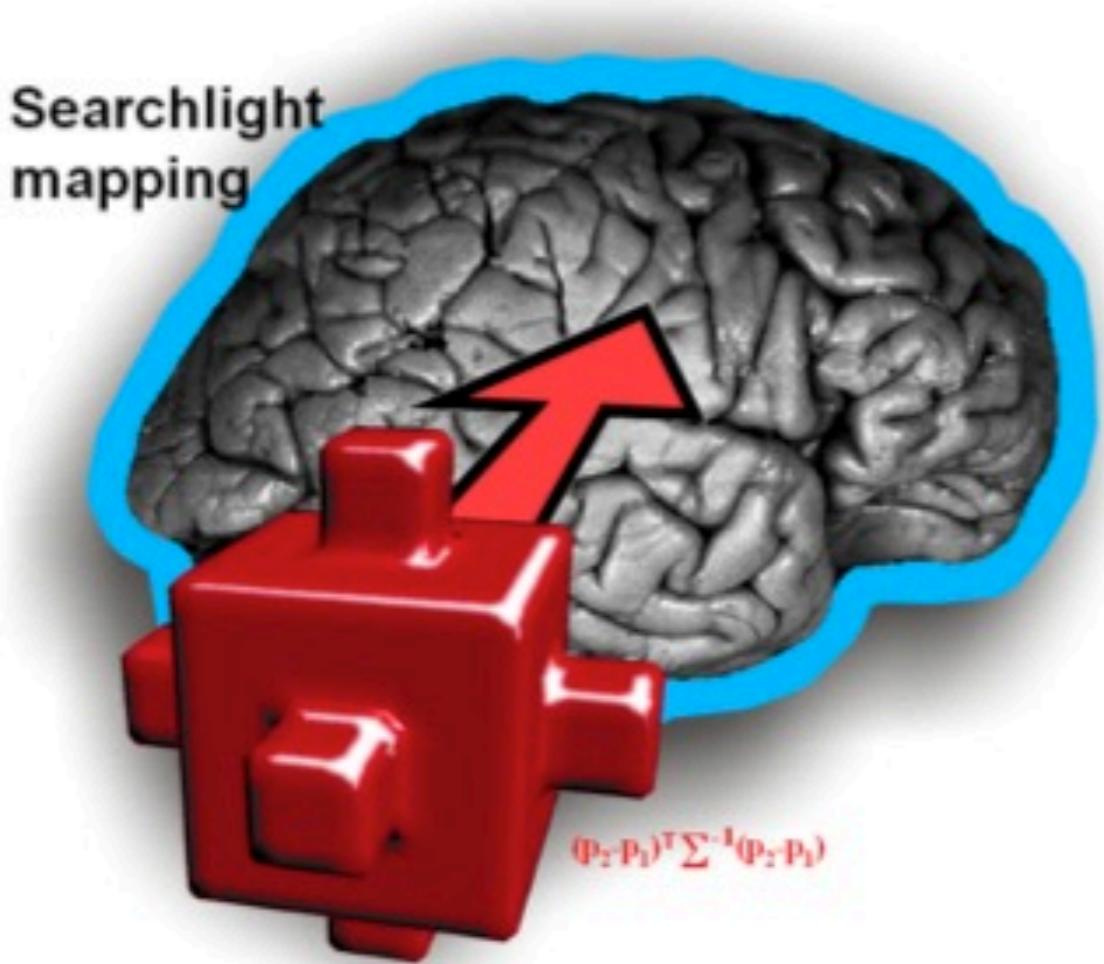
How to use classifiers to find which regions are functionally involved?



- nice estimate of local decoding performance



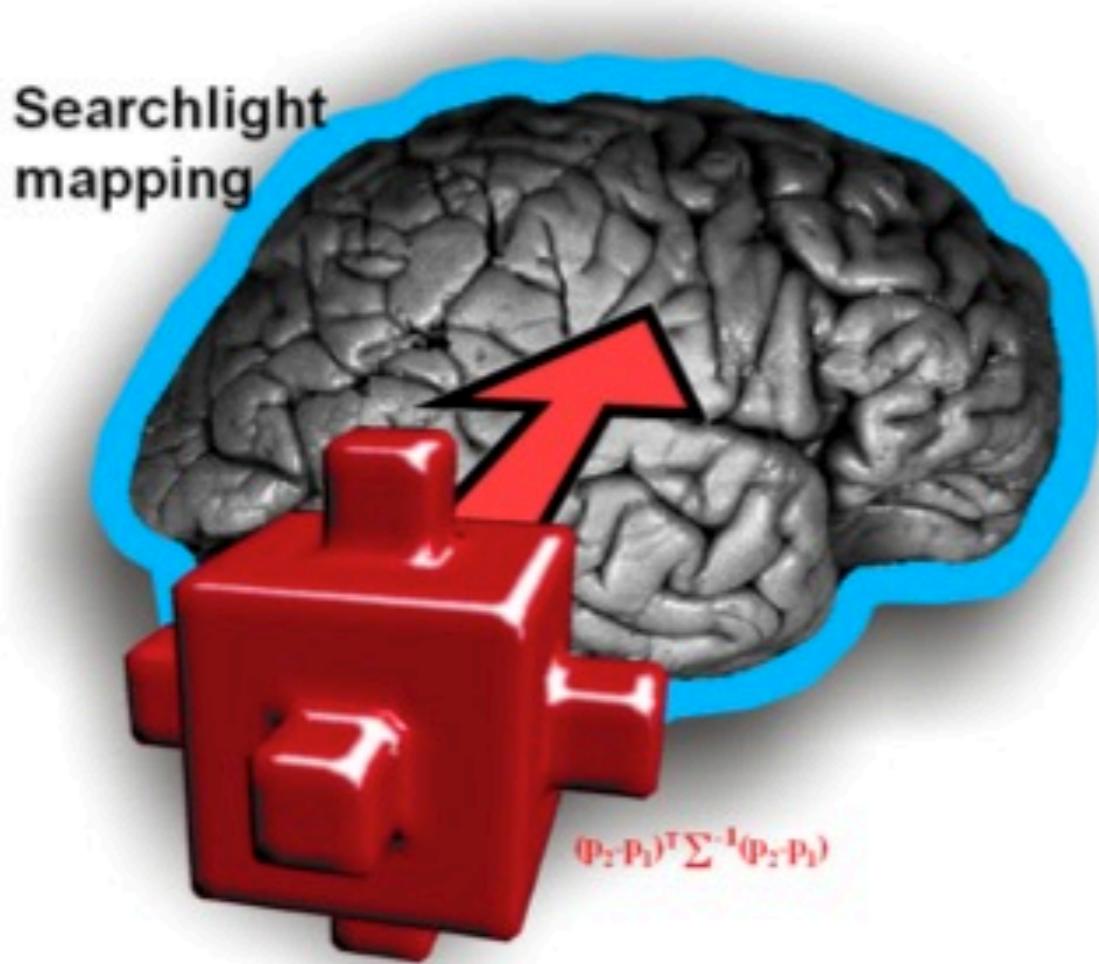
How to use classifiers to find which regions are functionally involved?



- nice estimate of local decoding performance
- naive approach to feature selection



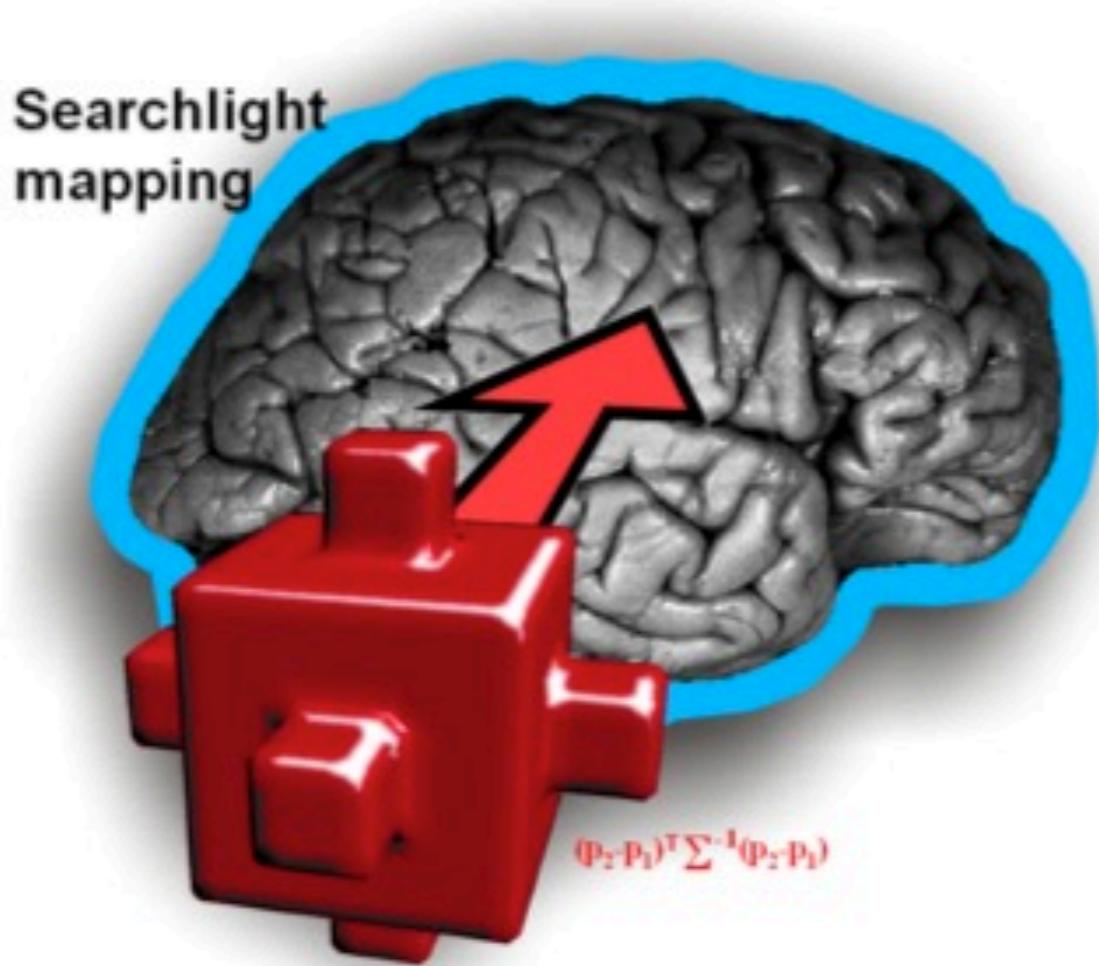
How to use classifiers to find which regions are functionally involved?



- nice estimate of local decoding performance
- naive approach to feature selection
- huge multiple comparison problem



How to use classifiers to find which regions are functionally involved?



- nice estimate of local decoding performance
- naive approach to feature selection
- huge multiple comparison problem
- closely related to mass-univariate approach