Multivariate Pattern Analysis and Brain Decoding

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Neural Decoding of Visual Imagery During Sleep

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www.sciencemag.org SCIENCE VOL 340 3 MAY 2013

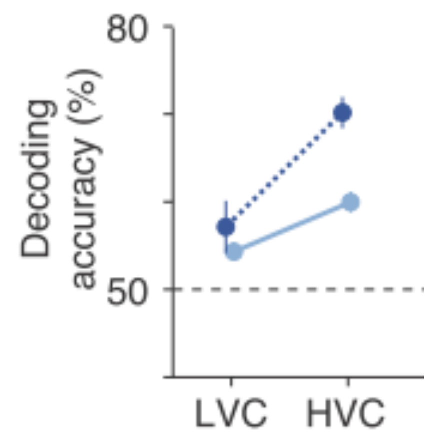
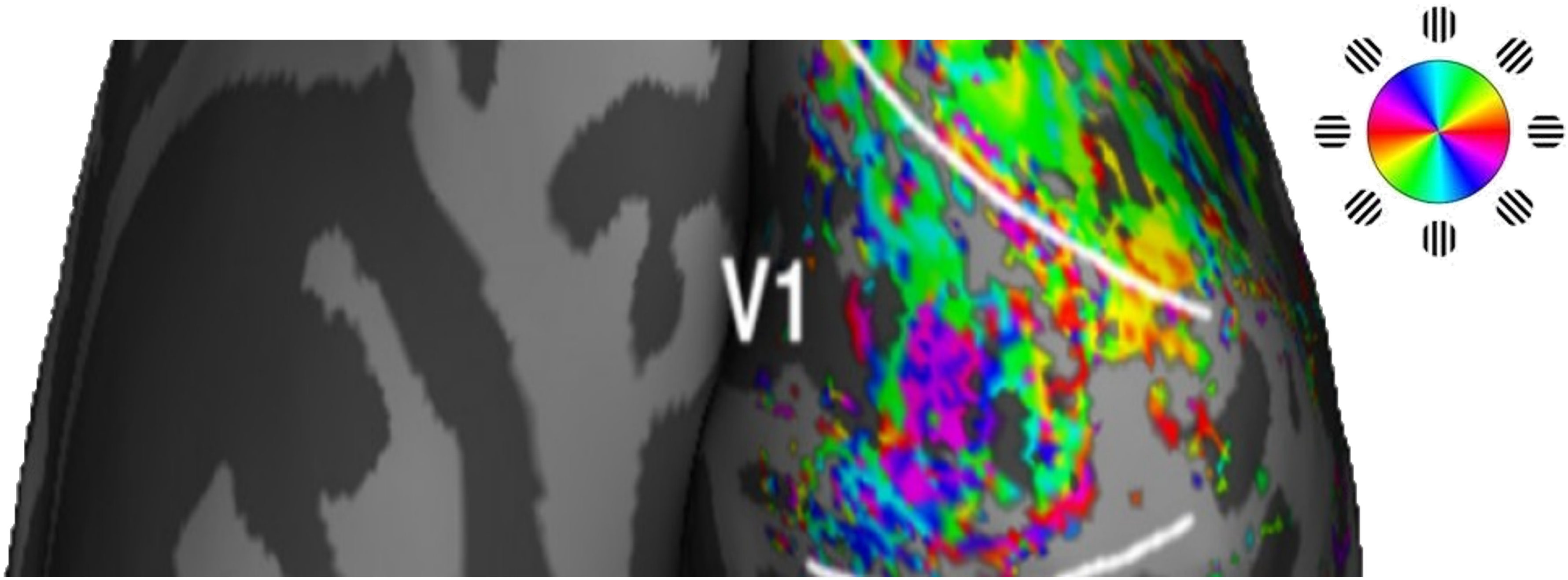


Image courtesy: David Castillo Dominici, http://www.freedigitalphotos.net

What is Multivariate Pattern Analysis?

Combined use of multiple variables measuring the brain (e.g. BOLD signal in multiple voxels) to predict or characterize states of the brain



Swisher et al. (2010) – J Neurosci

Central Questions for This Lecture

- What are the differences between classical univariate analysis and multivariate decoding?
- What is the difference between activity and information?
- How does MVPA work?
- What can MVPA be used for?

Why Multivariate Pattern Analysis?

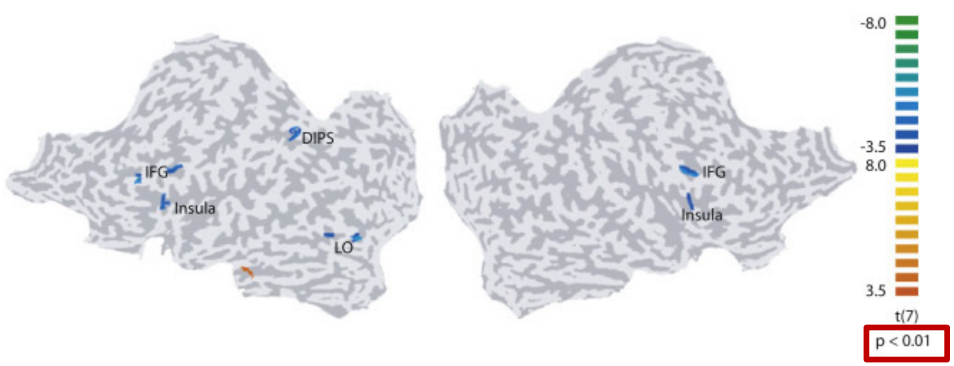
two reasons

Why Multivariate Pattern Analysis?

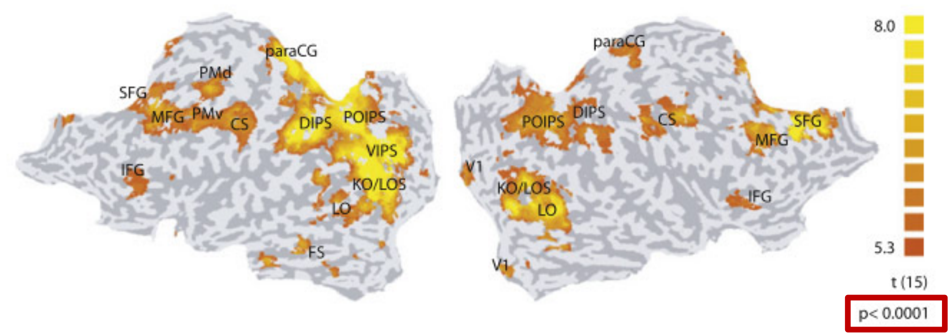
1. Higher sensitivity compared to classical univariate analysis

Example: Representation of perceptual choices

classical univariate analysis



multivariate decoding

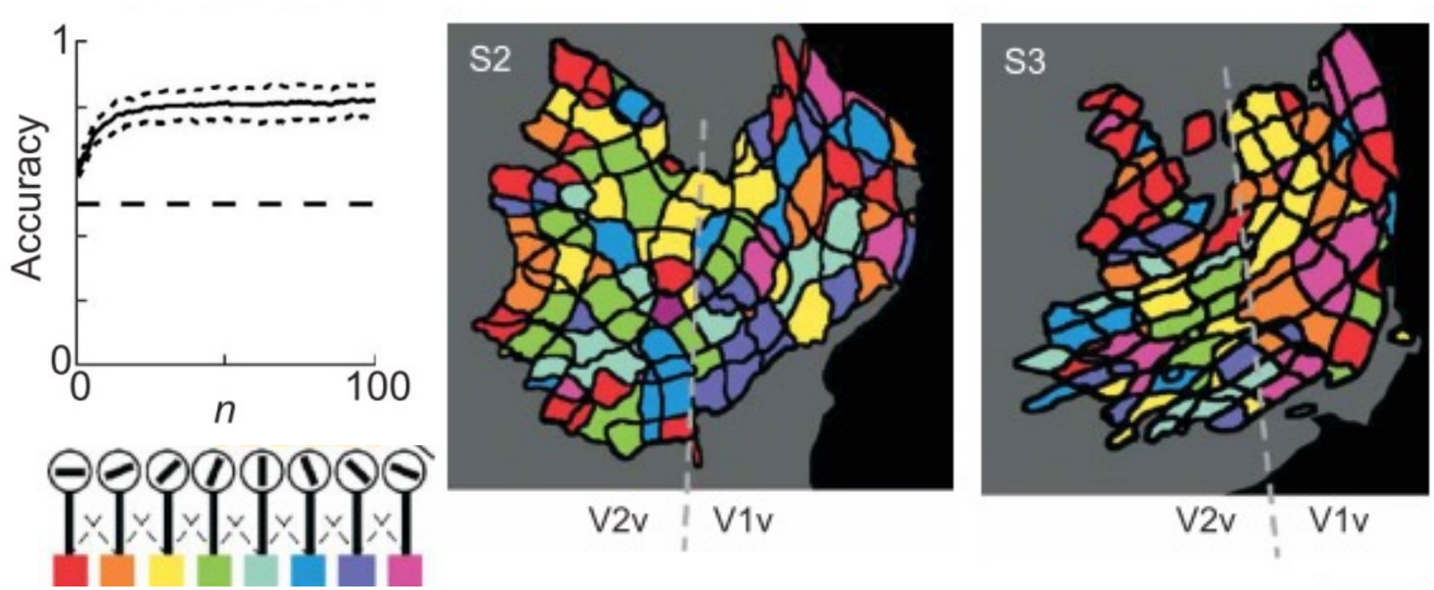


Li et al (2009) - Neuron

Why Multivariate Pattern Analysis?

2. Representational content in brain region rather than general activation can be studied

Example: Representation of orientations in visual cortex



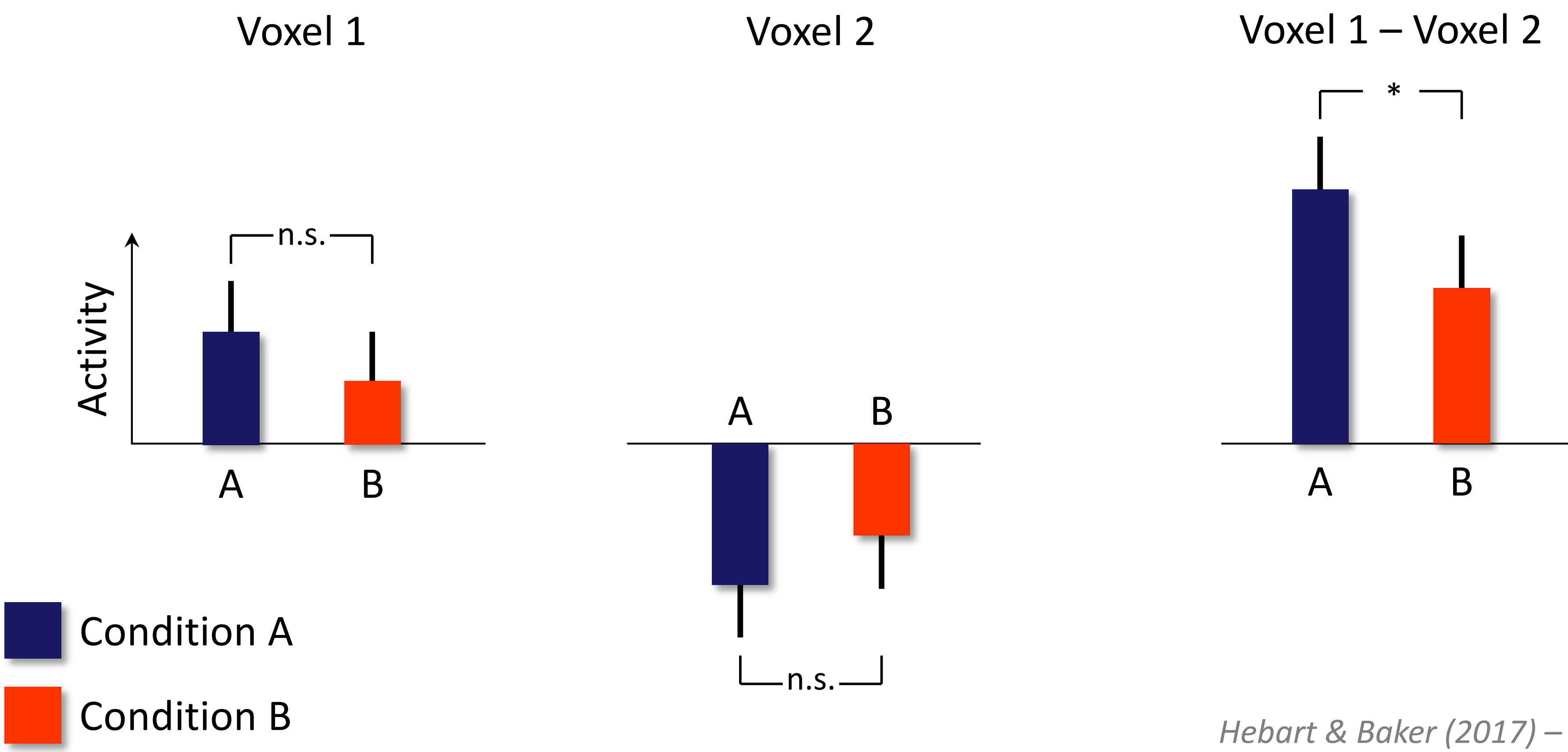
Kamitani & Tong (2005) – Nat Neurosci, Haynes & Rees (2005) – Nat Neurosci

How does MVPA work?

three principles

How Does Multivariate Pattern Analysis Work?

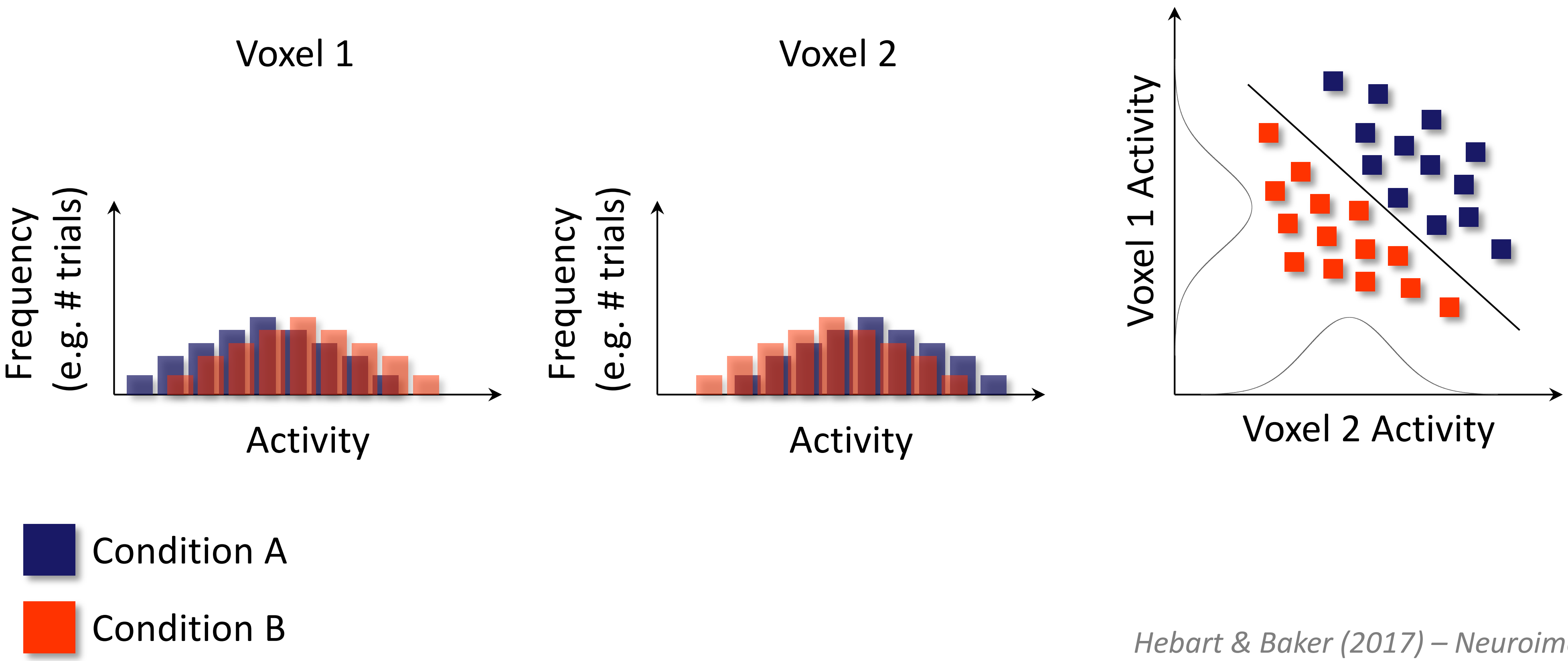
1. Information across multiple voxels can be combined



Hebart & Baker (2017) – Neuroimage

How Does Multivariate Pattern Analysis Work?

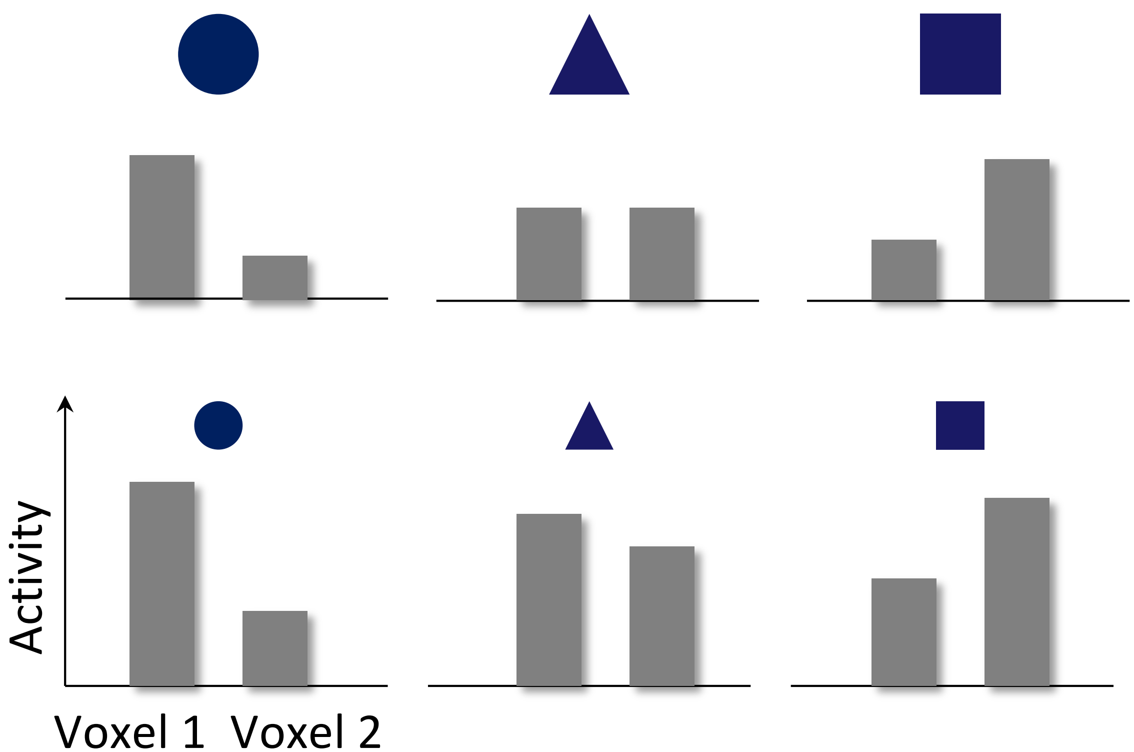
2. Covariation of voxel information can be used

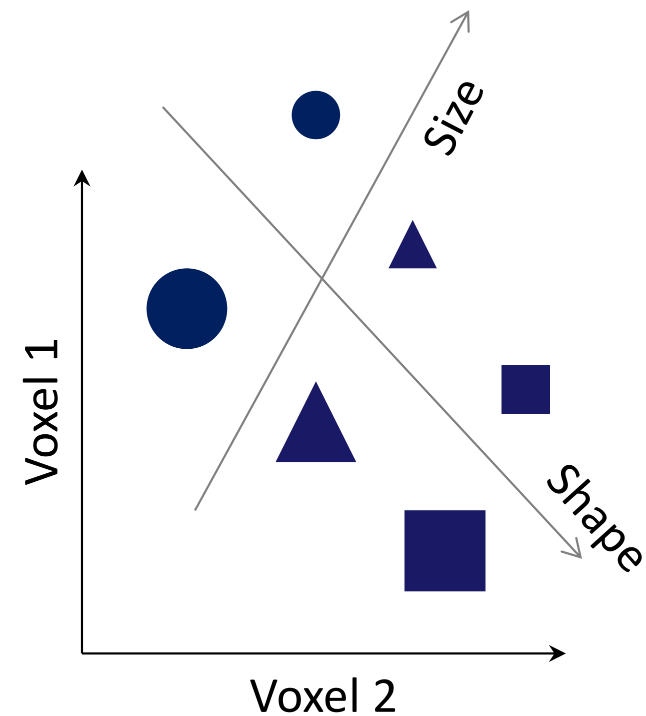


Hebart & Baker (2017) – Neuroimage

How Does Multivariate Pattern Analysis Work?

3. Multidimensional representations encoded in distributed patterns of activity can be revealed





Hebart & Baker (2017) – Neuroimage

Multivariate Decoding

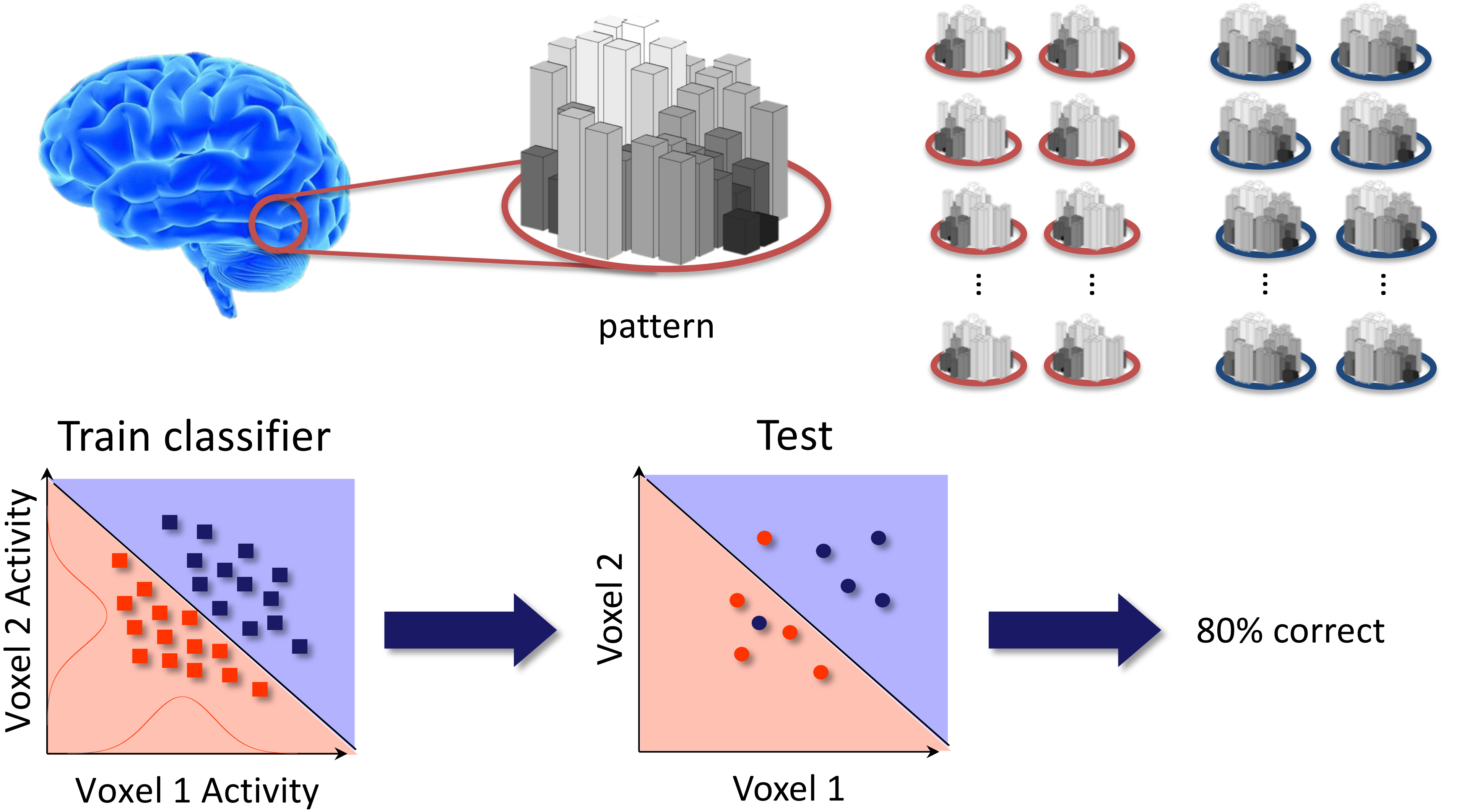
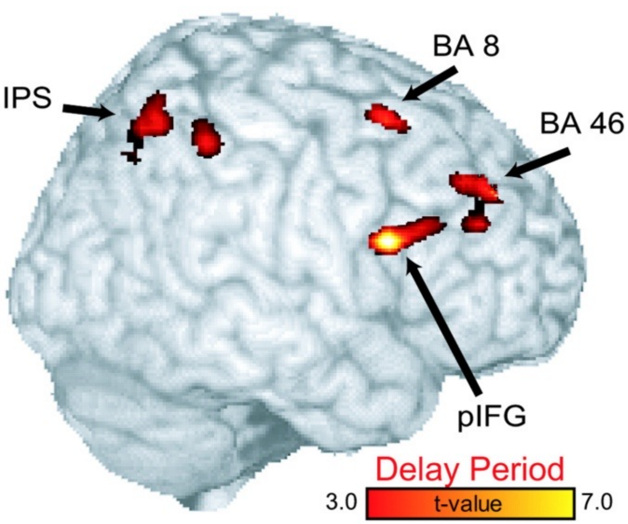
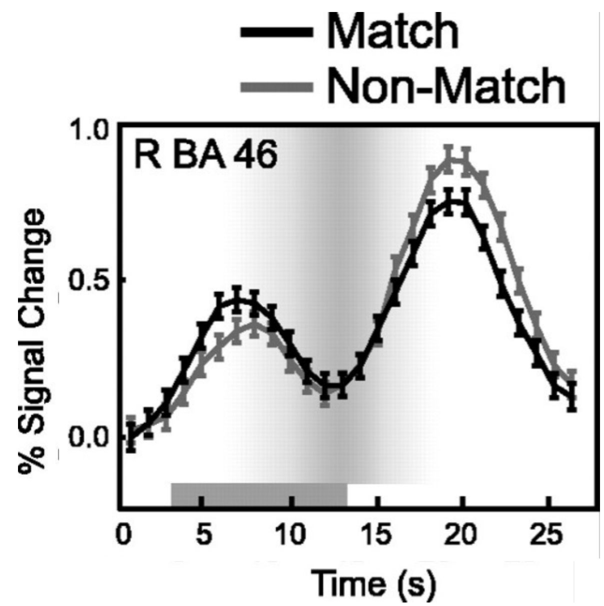


Image courtesy: Simone Brandt/imageBROKER/CORBIS

Activity vs. Information

Activity: Tells us about general involvement in cognitive function (e.g. working memory vs. no working memory)

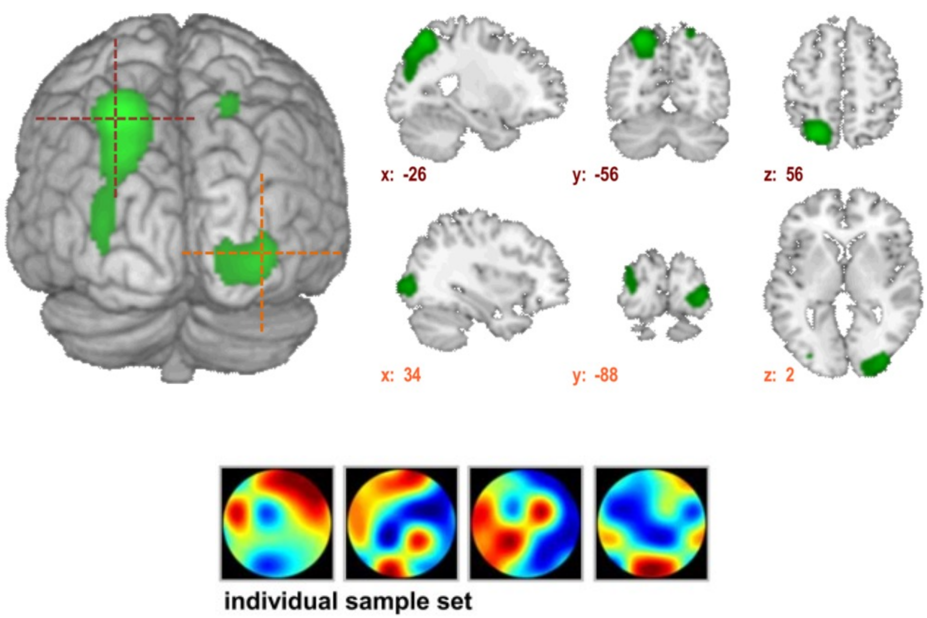


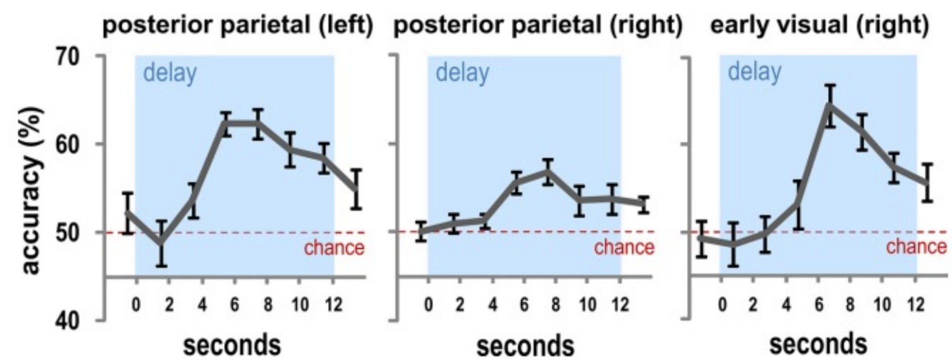


Curtis et al. (2004) – J Neurosci

Activity vs. Information

Information: Tells us about representational content (e.g. memory trace of A vs. memory trace of B)





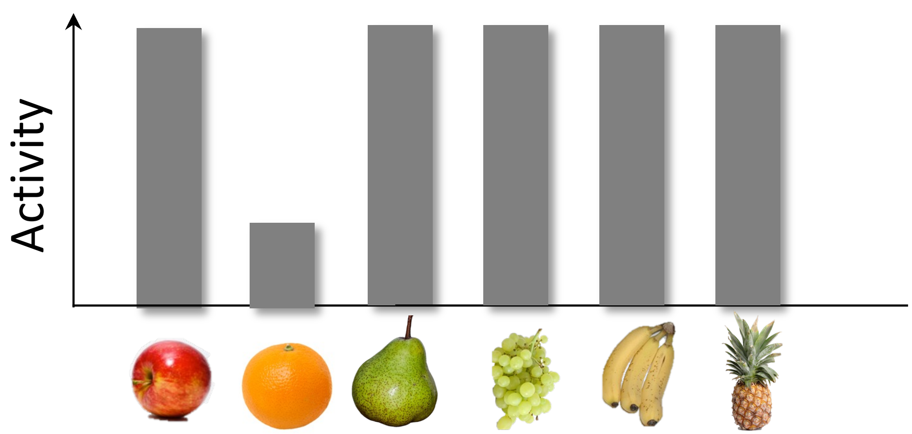
Christophel, Hebart, & Haynes (2012) – J Neurosci, see also Christophel et al (2017) – TiCS

Different Methodological Philosophies

Classical approach: More active = more involved

Multivariate decoding: More distinct = more involved

Thought experiment:



Classical approach: Brain region responds to all fruit but oranges

MVPA: Brain region carries information about oranges
(when contrasted with fruit)

Hebart & Baker (2017) – Neuroimage

Why Decoding?

two goals

Goals of Decoding

Prediction: Goal is to maximize future correct predictions

→ Any information is useful as long as it increases accuracy

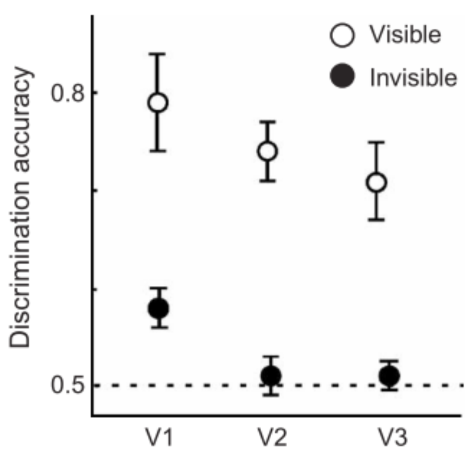
http://www.heise.de/tp/artikel/26/26759/26759_2.jpg, http://thinktechuk.files.wordpress.com/2011/10/97877.jpg, http://www.poly.edu/sites/polyproto.poly.edu/files/pressrelease/MRI_Alzheimers_Research.jpg

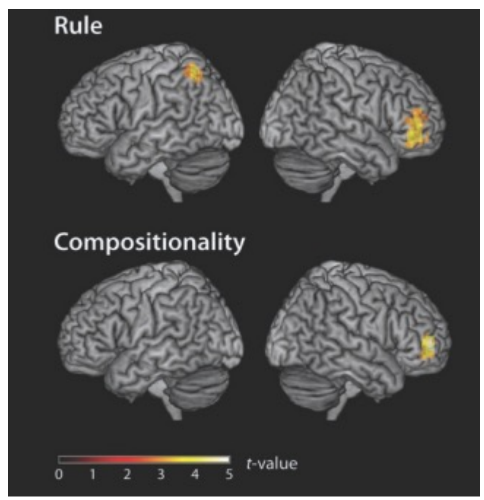
Goals of Decoding

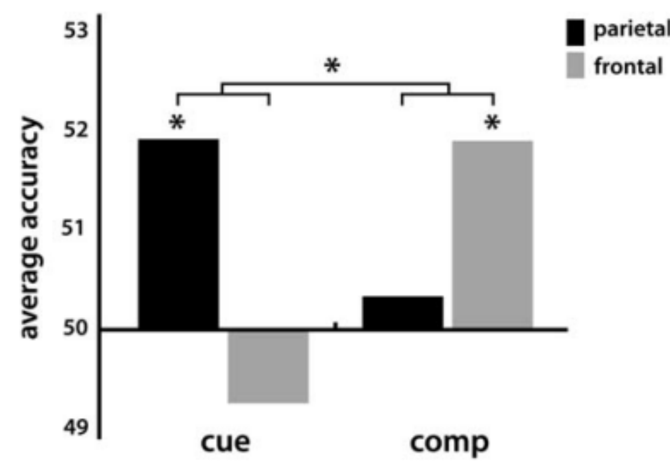
Interpretation: Is there information about XYZ?

→ Sufficient to show above chance accuracy (statistically!)

→ Not all information sources ok, need to rule out confounds







Haynes & Rees (2005) – Nat Neurosci; Reverberi, Görgen, & Haynes (2012) – Cereb Cortex

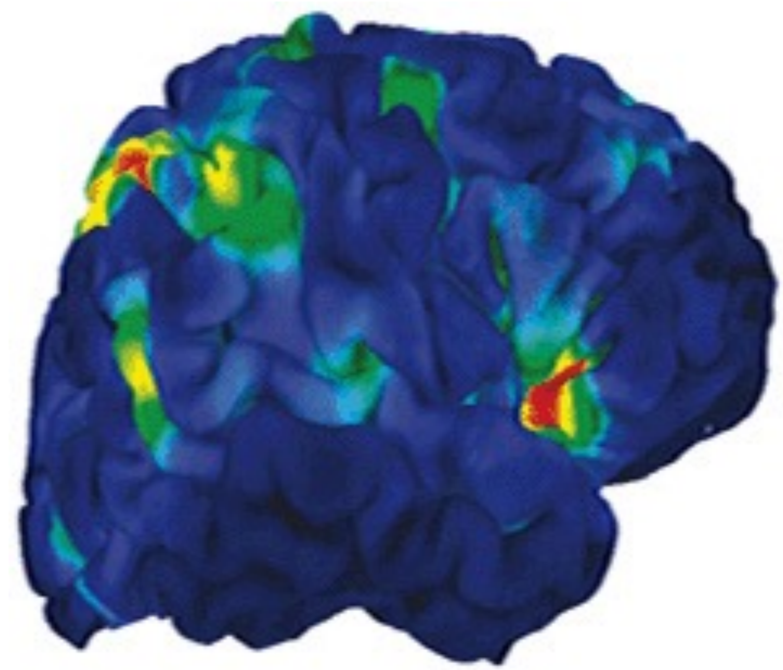
Encoding vs. Decoding

what we normally do
in univariate analyses

Cognitive Function

Encoding g: X → Y

Decoding h: Y → X



X: Explaining variable

Example: Stimulus, response, cognitive condition

Y: Measured data

Example: BOLD signal, EEG signal, VBM intensity

Overview Over Analysis Methods

	Encoding	Decoding
univariate	GLM Model-based	Simple Classification
multivariate	MANOVA Similarity Analysis	Multivariate Decoding

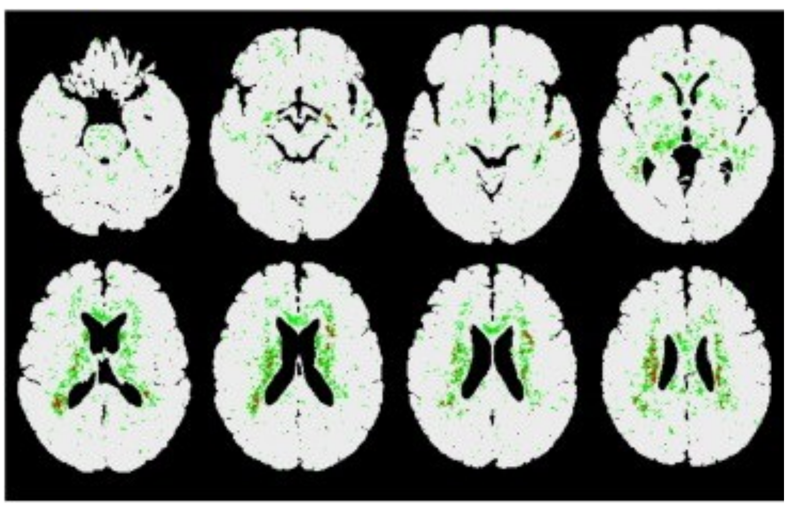
What Questions can you Address with Multivariate Decoding?

five types of questions

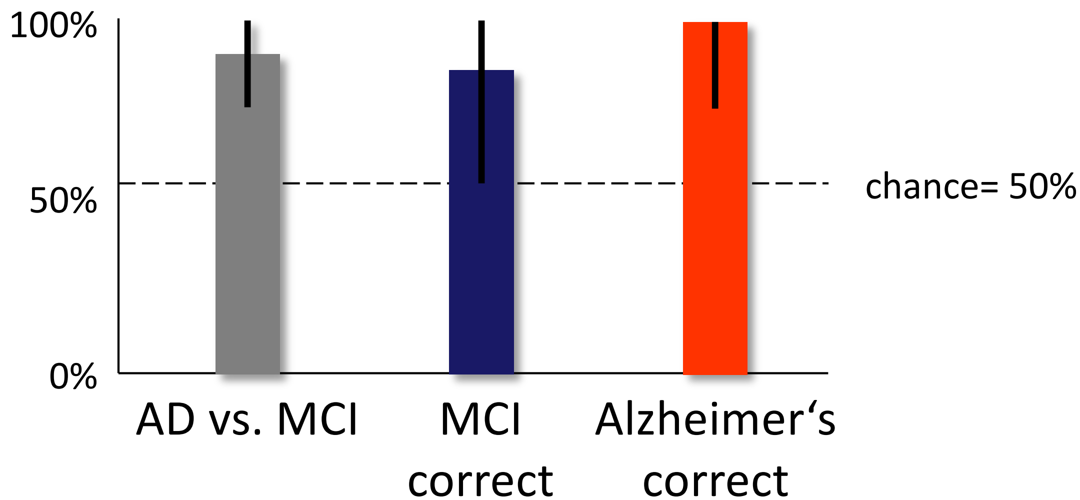
Types of Questions for MVPA

1. Presence of Information

Example: Will a patient with mild cognitive impairment develop Alzheimer's 2 ½ years later?



structural data

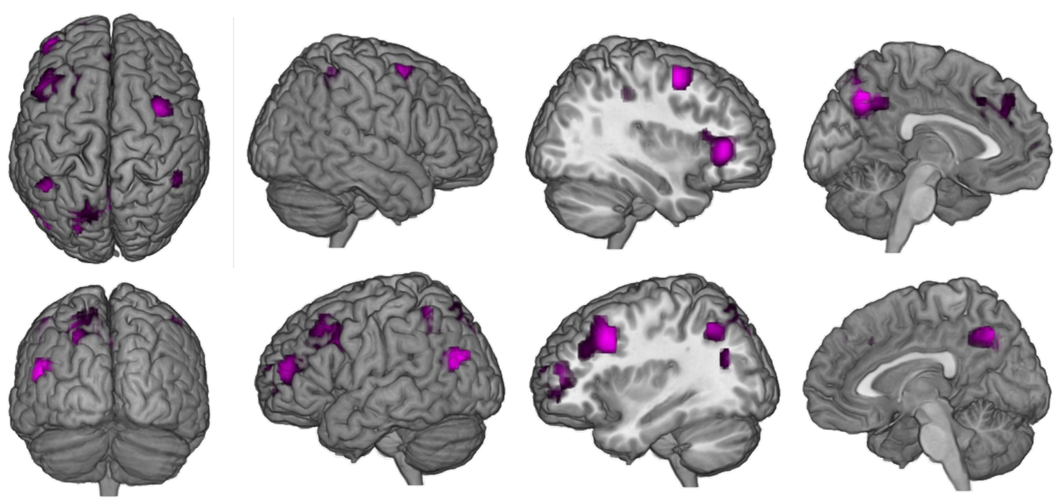


Plant et al. (2010) – Neuroimage

Types of Questions for MVPA

2. Localization of Information

Example: Which brain regions carry information about perceptual decision variables irrespective of the response format?



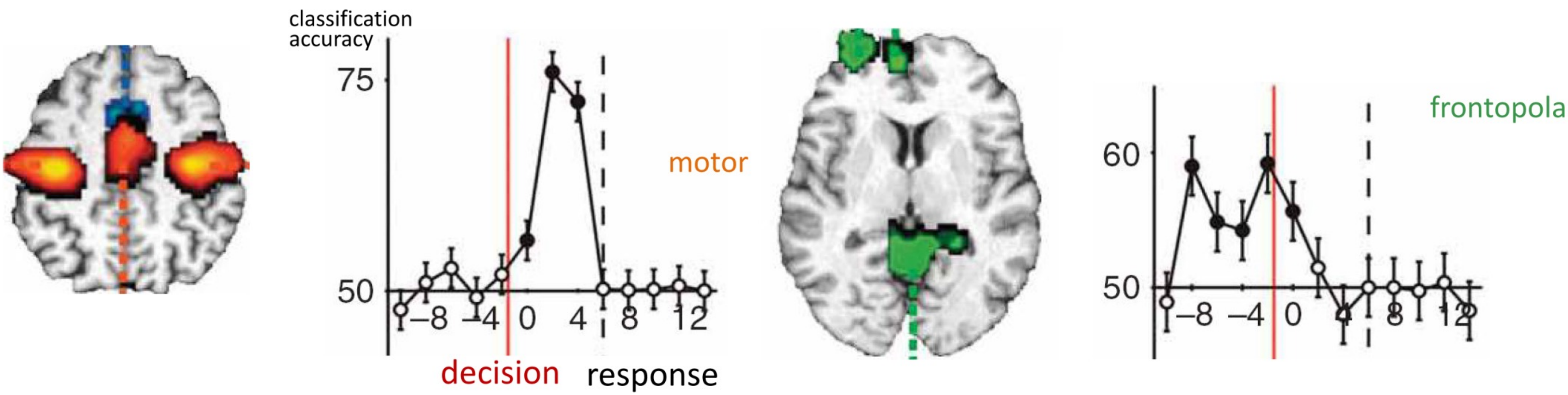
$p < 0.0001$, cluster-corrected FWE $p < 0.05$

Hebart et al. (2012) – Neuroimage, Hebart et al. (2014) – Cereb Cortex

Types of Questions for MVPA

3. Time Course of Information

Example: At what time do you find information about “free” decision of a person?

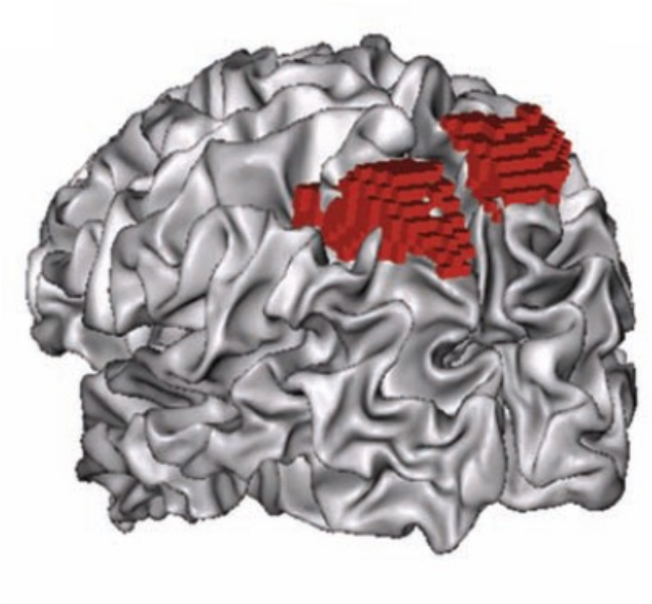


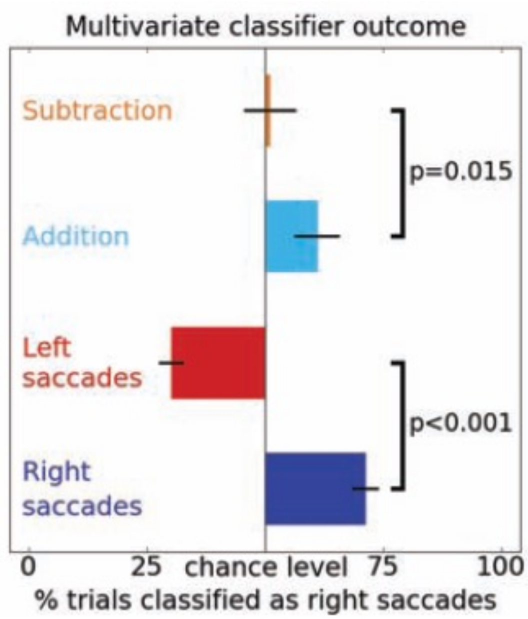
Soon et al. (2008) – Nat Neurosci

Types of Questions for MVPA

4. Association of Cognitive Functions

Example: Generalization of eye movements to calculations



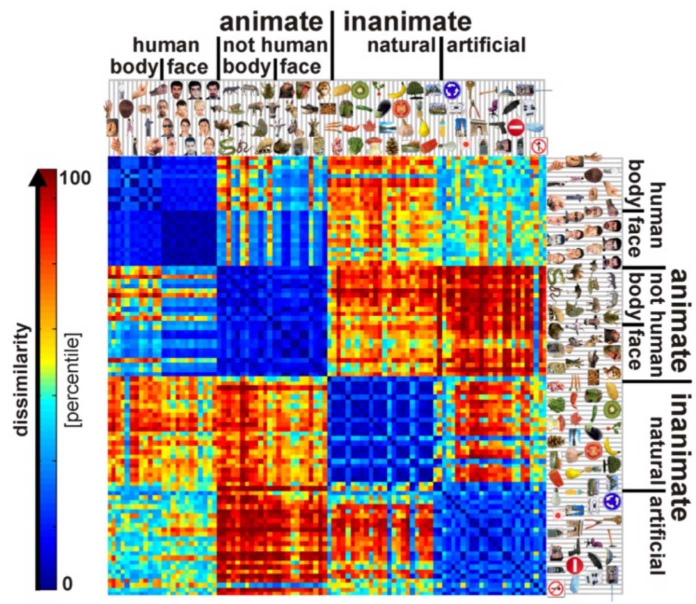


Knops et al. (2009) – Science

Types of Questions for MVPA

5. Characterization of Activation Patterns

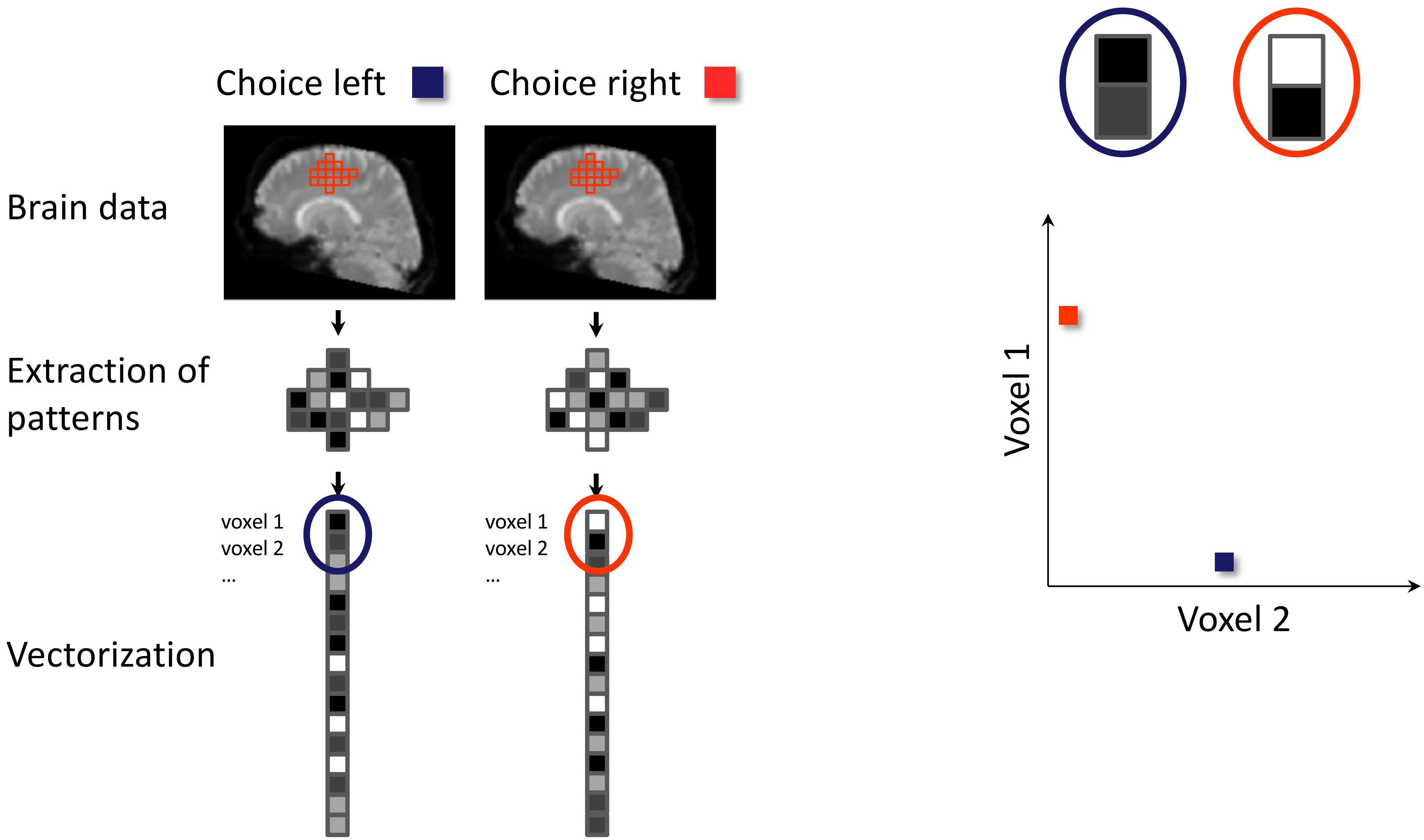
Example: Representational Similarity Analysis



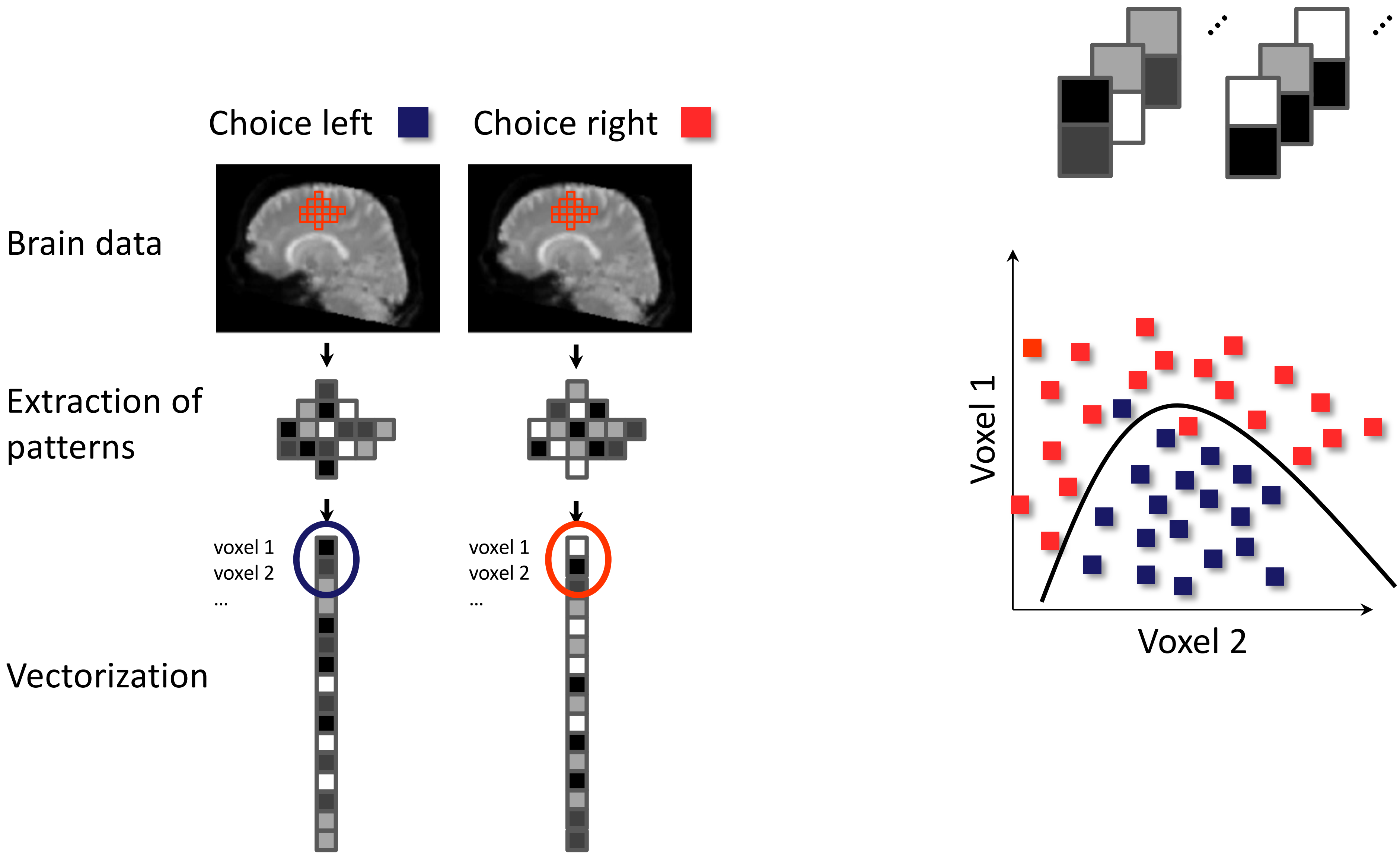
Edelman et al (1998) – Psychobiology; Kriegeskorte et al. (2008) – Neuron; Kriegeskorte & Kievit (2013) – TICS

How Does Classification Work?

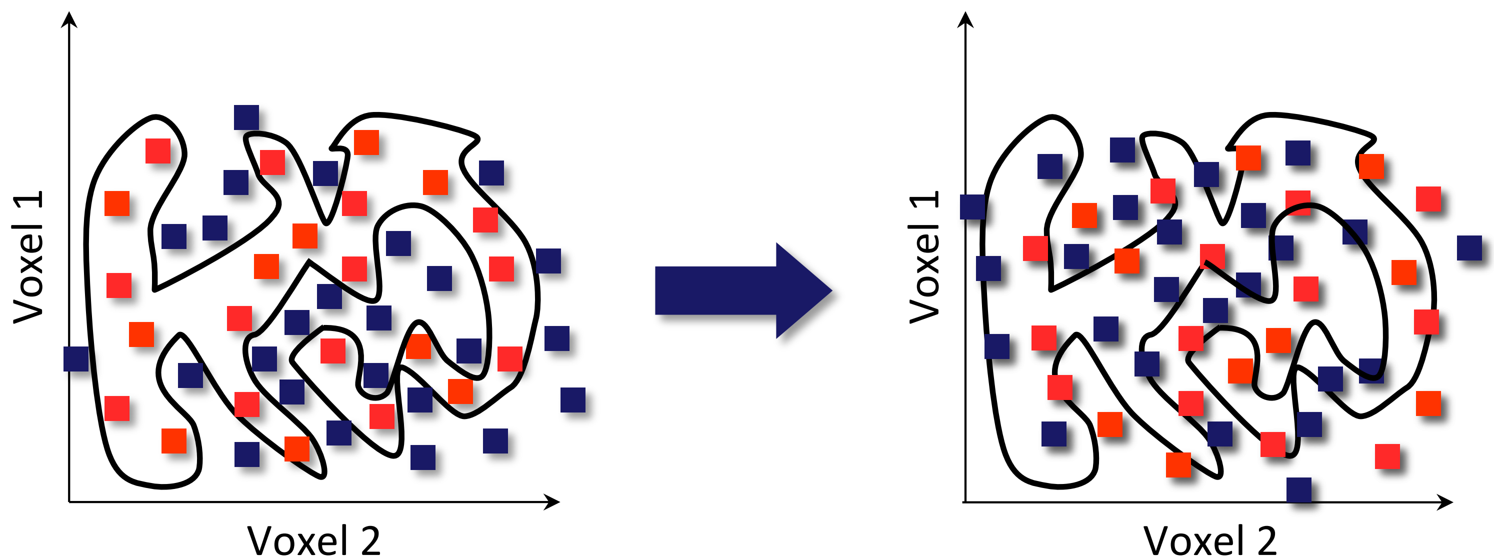
Classification Overview: Example



Classification Overview: Example

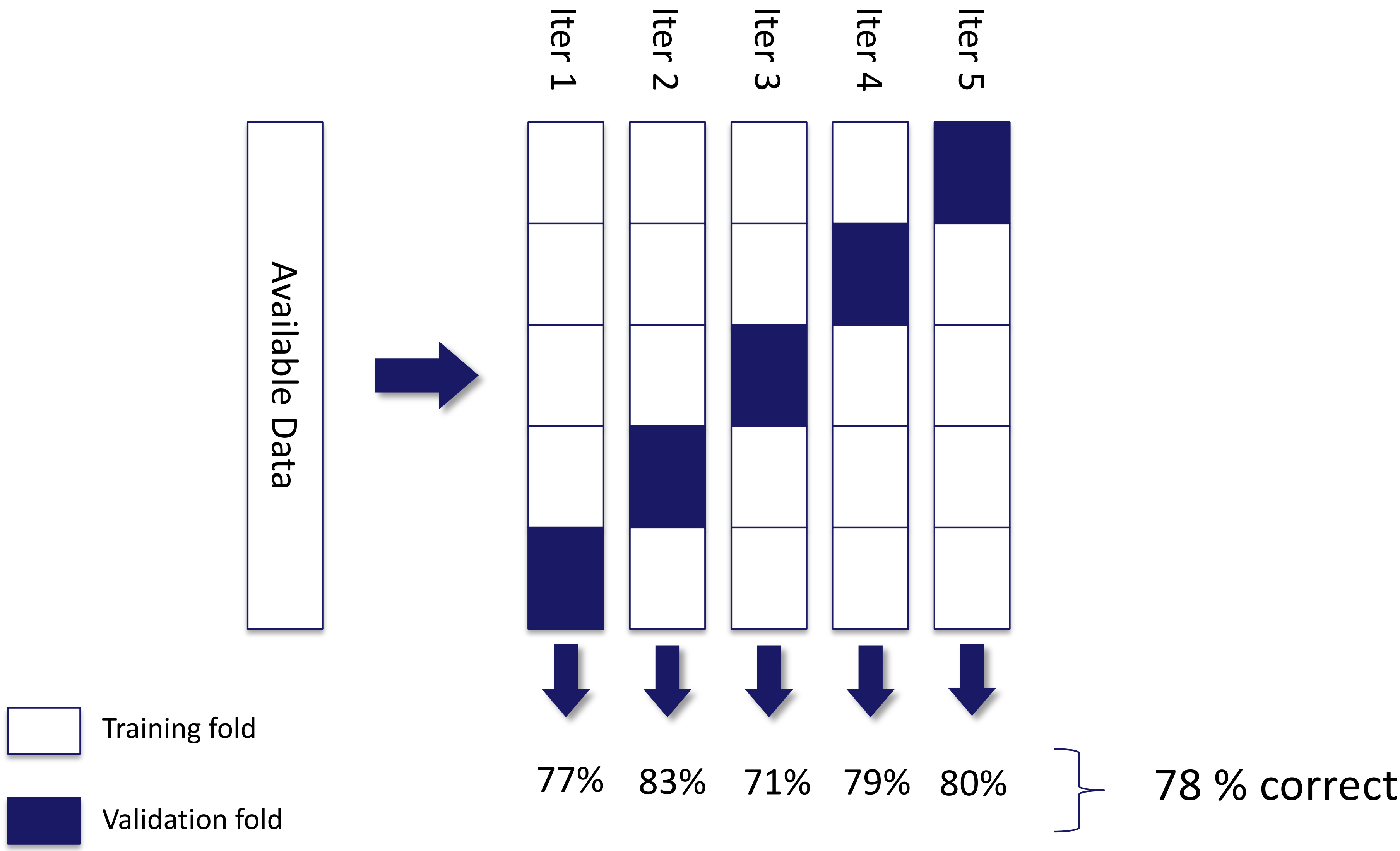


Why Train and Test a Classifier?

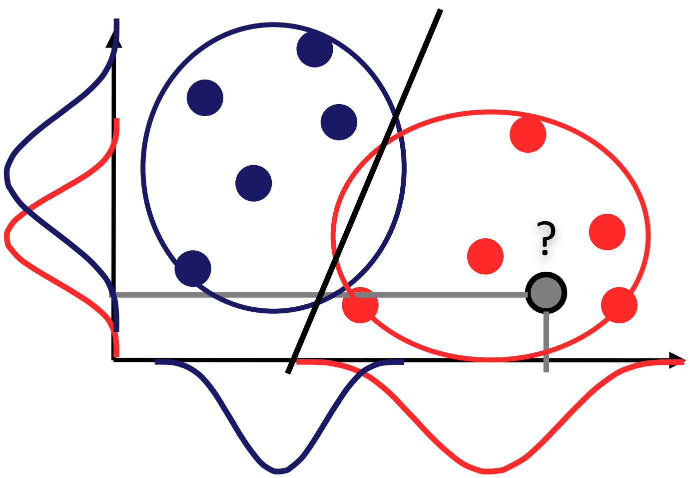
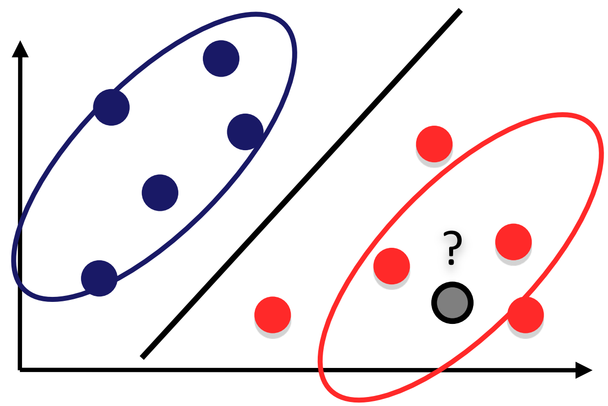
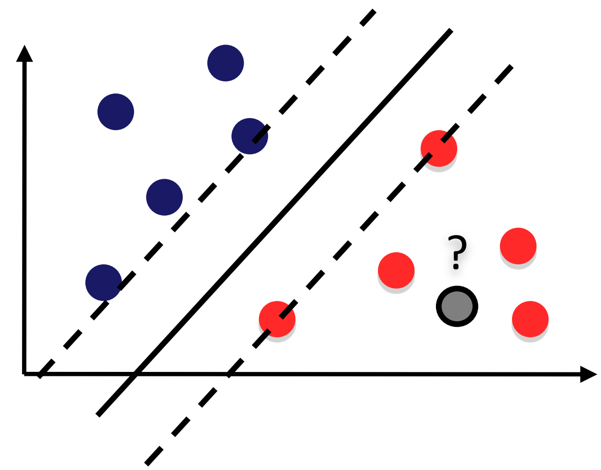


- Goal of classification: Finding a general model beyond noise in the data
- Way of testing generalization: Training and testing classifier

Cross-validation



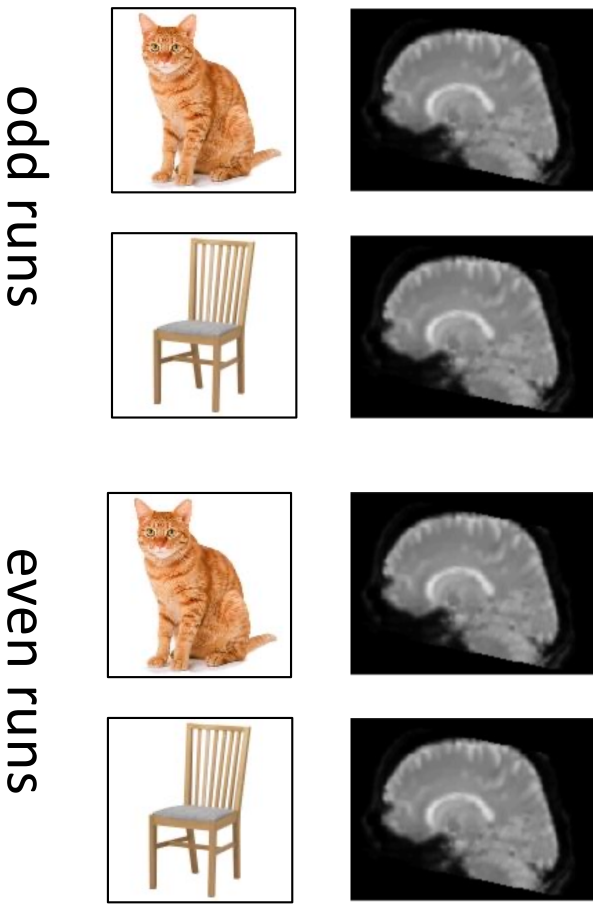
Typical linear classifiers

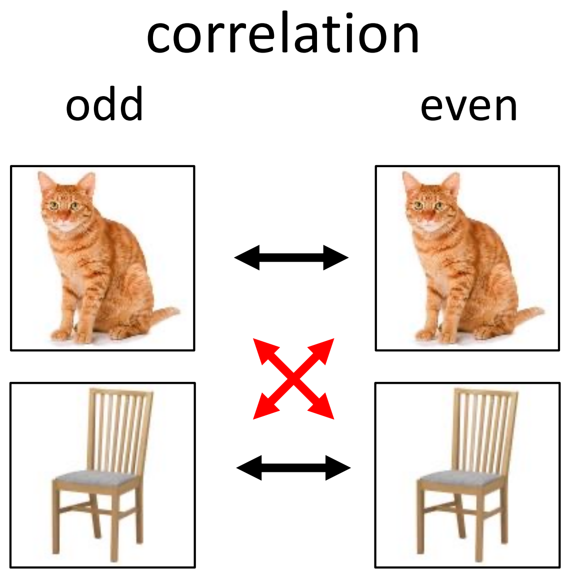
Gaussian Naïve Bayes	Linear Discriminant Analysis	Support Vector Machine
		
Ignores covariance between voxels	Considers covariance between voxels	Maximizes margin (distance between closest points of different classes)

- Linear classifiers are the most commonly used classifiers in MVPA
- All share the same formula $y = \Sigma w_i x_i$ but differ in how they find parameters w

Correlation-based classifier

Very simple classifier: find maximal pattern correlation





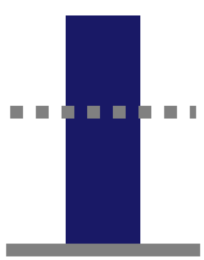
$r_{withincategory} > r_{betweencategory}$?

➡ Geometric interpretation: smallest angular distance from centroid

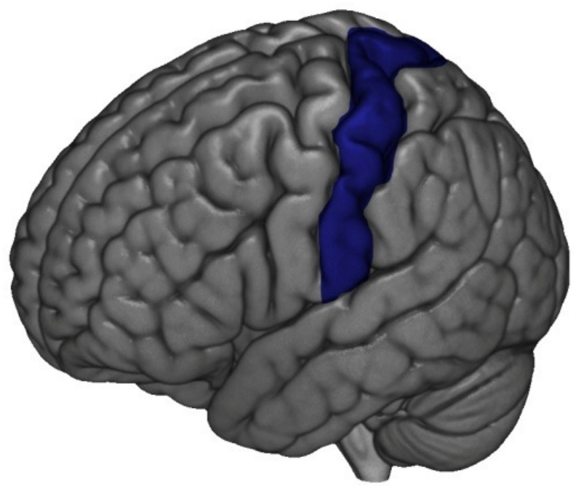
Levels of MVPA Analyses

Wholebrain

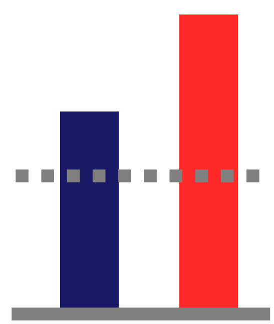
One value per brain



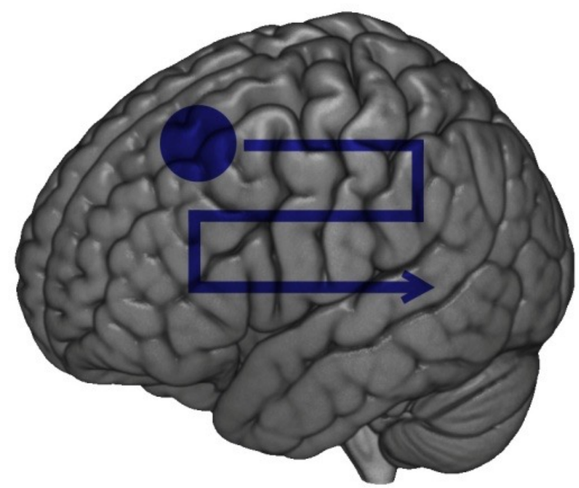
Region of Interest



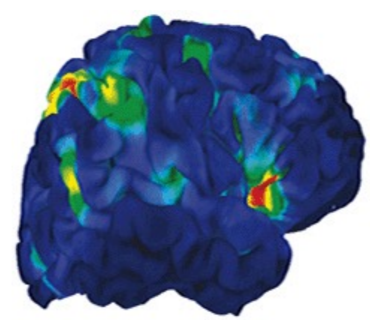
One value per ROI



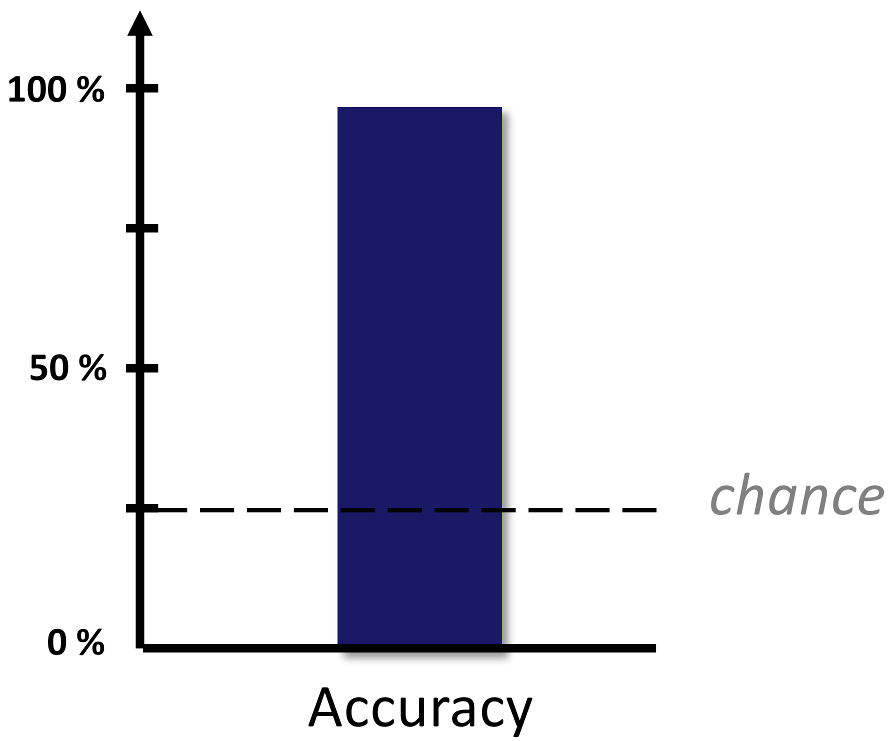
Searchlight



A value per searchlight, i.e. a map of values



Great Finding?

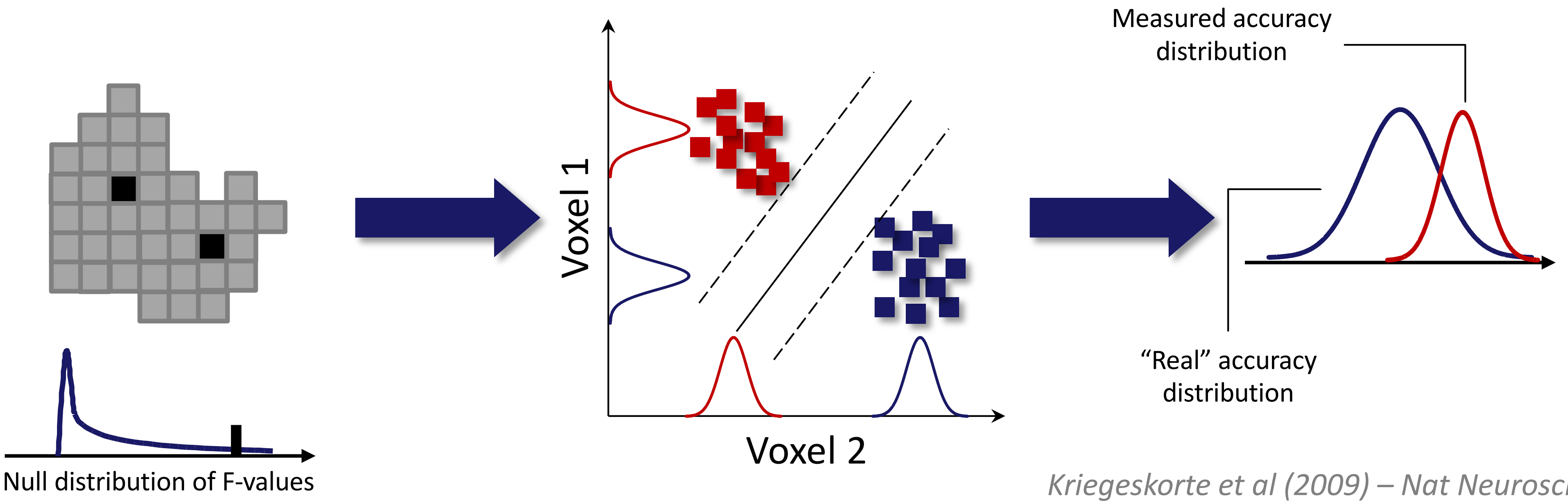


http://www.smallbiztechnology.com/wp-content/uploads/2012/12/success.jpg

Non-independence and Double Dipping

For classification: Information about class membership leaks from training set to test set

Example: Voxel selection prior to classification that is
(1) based on label (red vs. blue) and (2) uses **all data**

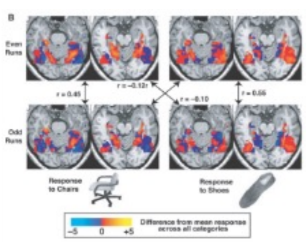


Kriegeskorte et al (2009) – Nat Neurosci

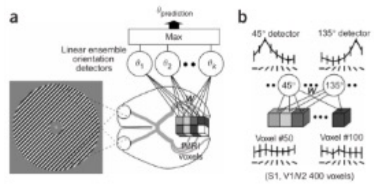
Milestones of MVPA

Edelman et al (1998)

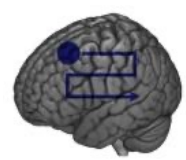
Haxby et al (2001)



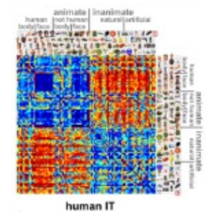
Kamitani & Tong (2005)
Haynes & Rees (2005)



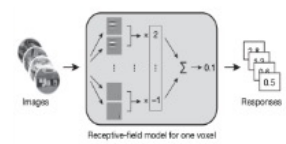
Kriegeskorte et al (2006)



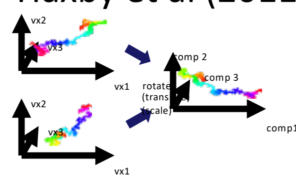
Kriegeskorte et al (2008)



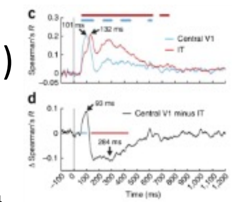
Kay & Gallant (2008)



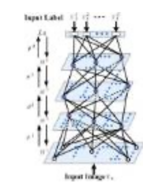
Haxby et al (2011)



Cichy et al (2014)



e.g. Di Carlo



1998 — 2001 — 2005 — 2006 — 2008 — 2011 — 2014 — 2015/2016

“first” MVPA study

first multivariate decoding study

popularization of multivariate decoding

searchlight approach

representational similarity analysis

model-based encoding methods

hyperalignment

combination of fMRI and MEG using RSA

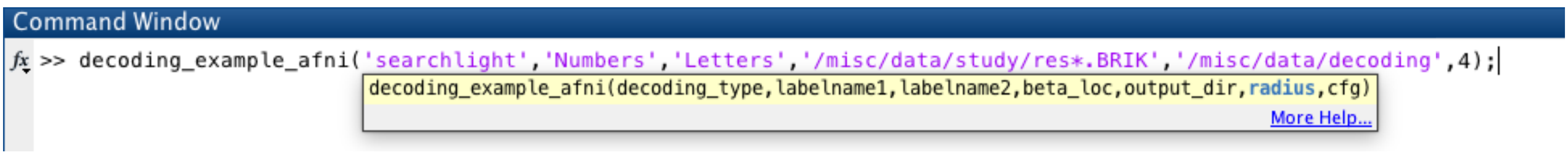
Demonstration of homologies in feed-forward architecture btw artificial neural networks and visual cortex

Summary

- MVPA is more sensitive than classical univariate approaches and can reveal representational content
- MVPA works by combining information across voxels and using their covariation
- Investigating brain activity vs. informational content are two different approaches
- We use cross-validation to reduce avoid bias from overfitting

The Decoding Toolbox

- Fast and easy to use MVPA software package in Matlab (for Python, we recommend PyMVPA, Scikit-Learn, and MNE Python)
- Provides searchlight, ROI and wholebrain analyses
- Comes with a wide range of options, classifiers and similarity analysis
- Runs with SPM and AFNI



https://sites.google.com/site/tdtdecodingtoolbox/

Hebart MN*, Görgen K*, Haynes JD (2015). The Decoding Toolbox (TDT): A versatile software package for multivariate analyses of functional imaging data. Front. Neuroinform. 8:88.

Thank you for your attention

Suggested Readings

Beginners

Tong & Pratte (2012) – Decoding patterns of human brain activity
Haxby et al (2014) – Decoding neural representational spaces
Haynes (2015) – A primer on pattern-based approaches

More Advanced

Pereira et al (2009) – Machine learning classifiers and fMRI: a tutorial
Hebart & Baker (2017) – Deconstructing multivariate decoding

Representational models

Kriegeskorte & Kievit (2013) – Representational geometry
Diedrichsen & Kriegeskorte (2017) – Representational models: A common framework for understanding encoding, pattern-component, and representational-similarity analysis

More Recent Developments

Idea of a representational geometry

Human fMRI

Monkey recordings

Measurement level

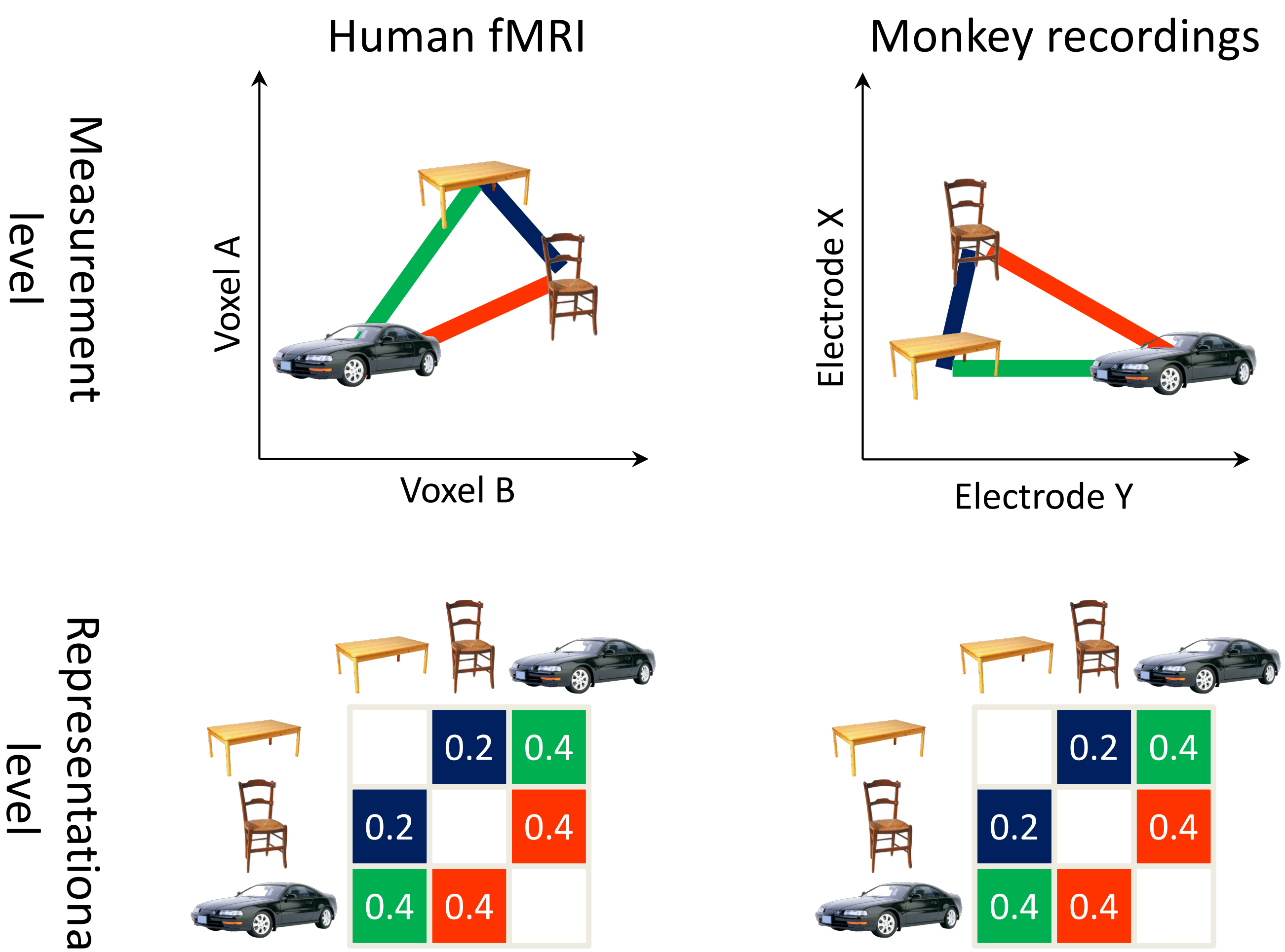
seconds

milliseconds

Kriegeskorte & Kievit (2013) – TICS

More Recent Developments

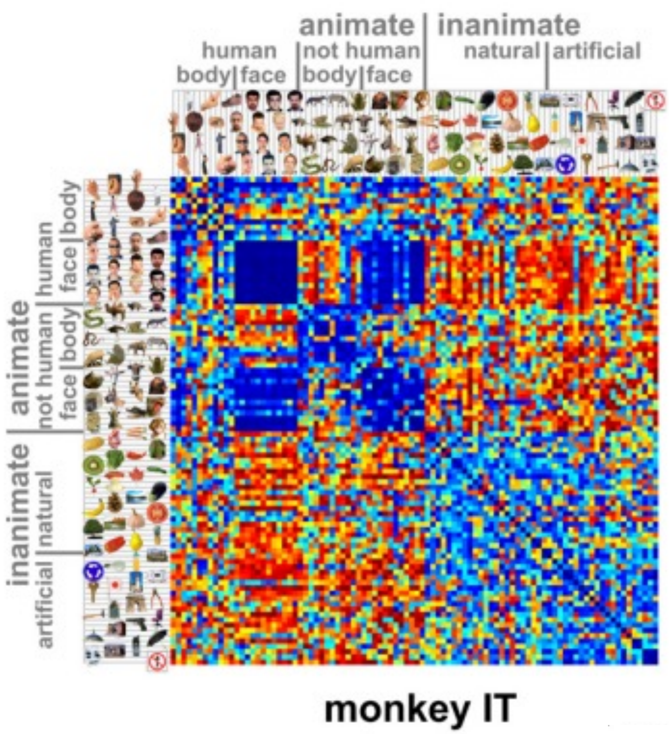
Idea of a representational geometry



Kriegeskorte & Kievit (2013) – TICS

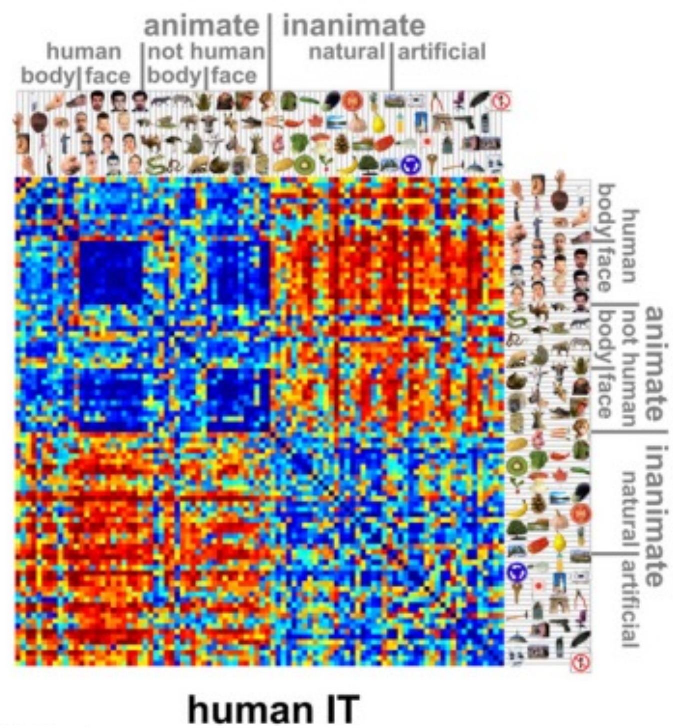
Representational Similarity Analysis

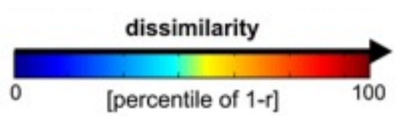
Monkey Dissimilarity Matrix



Comparison

Human Dissimilarity Matrix

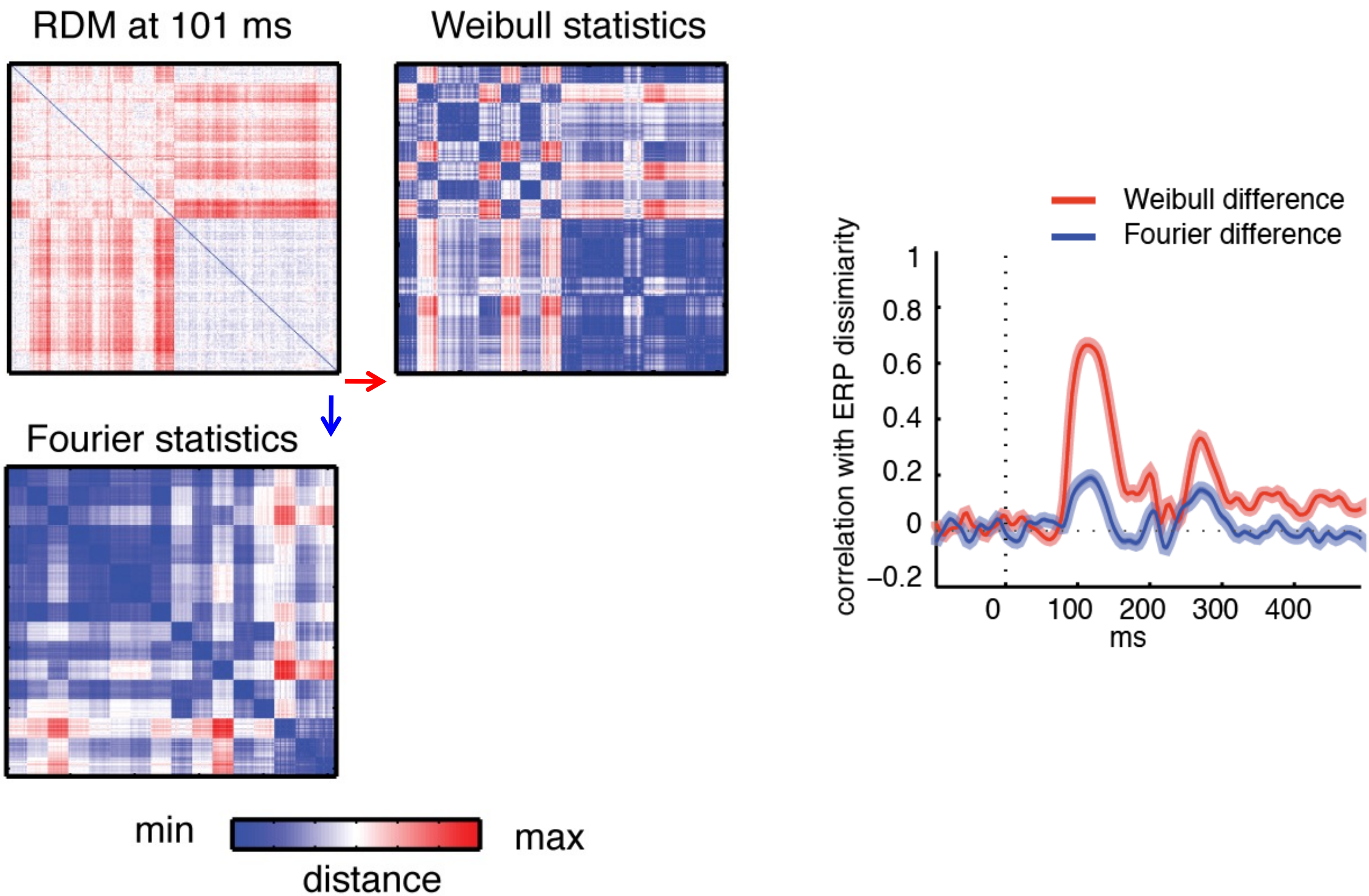




Relative similarity of pairs of patterns can be compared

Kriegeskorte et al (2008) – Neuron

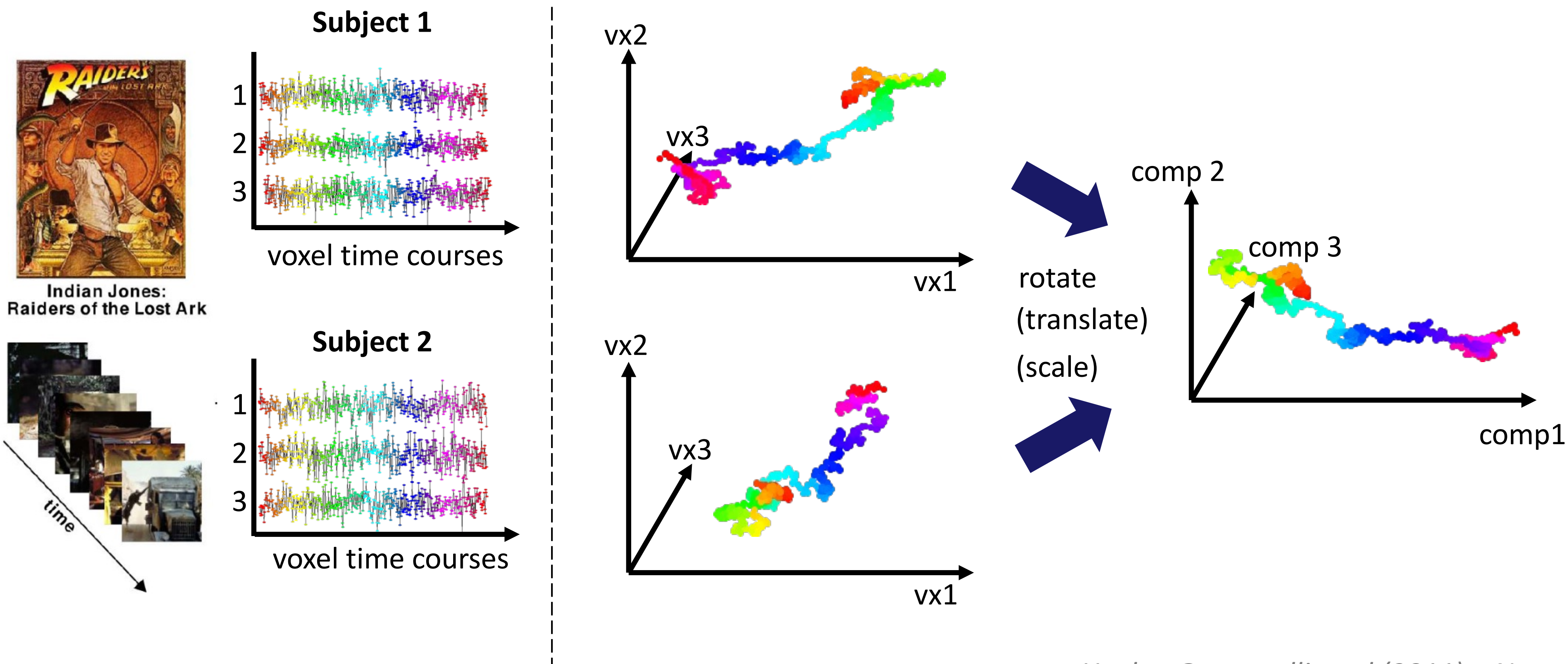
EEG-based Model Comparison



Groen et al (2012) – PLoS Comput Biol

Hyperalignment

- Brings subjects functionally in common space
- Allows predicting one brain from another



Haxby, Guntupalli et al (2011) – Neuron