# Session III: Types of MVPA Analysis

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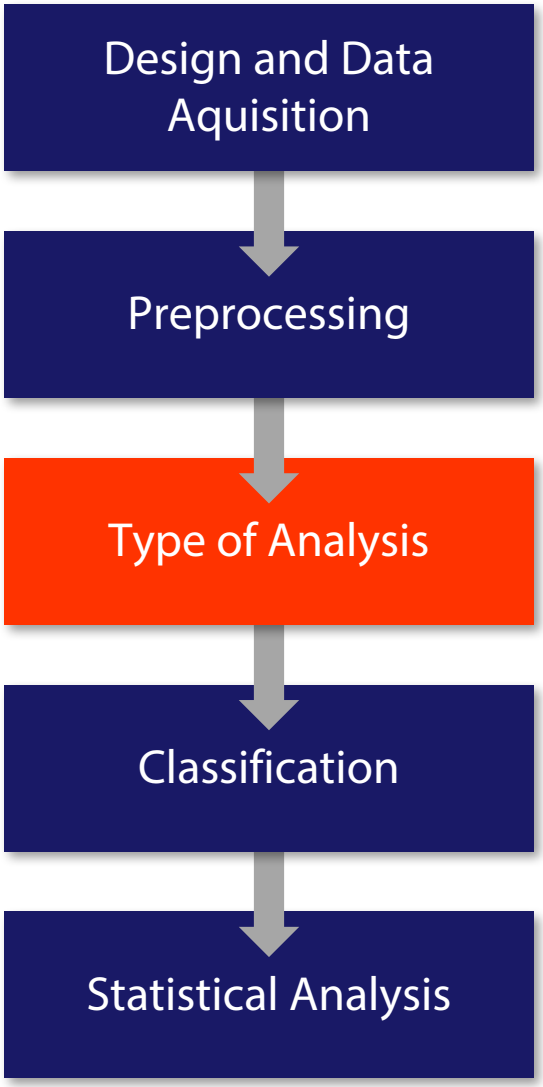
# MVPA Workflow



# Overview

Types of MVPA Analysis: Overview

Wholebrain Analysis

Region of Interest Analysis

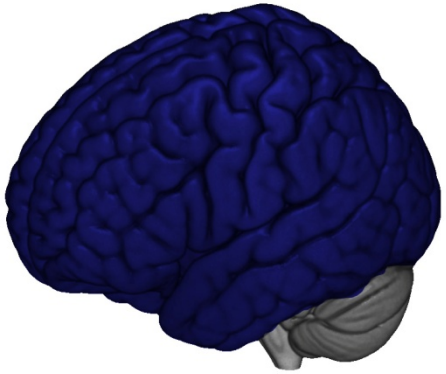
Searchlight Analysis

Multivariate Generalization (aka Cross-Decoding)

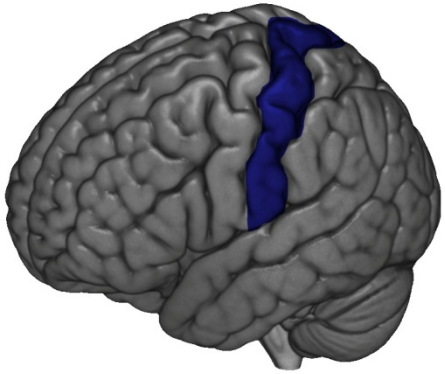
# TYPES OF MVPA ANALYSIS

# Types of MVPA Analysis

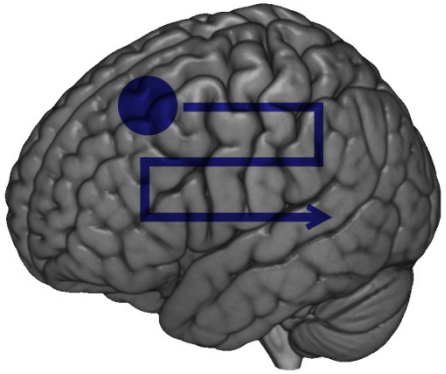
Wholebrain



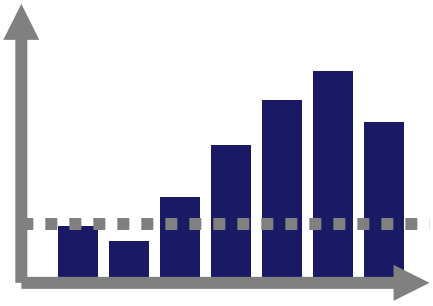
Region of Interest



Searchlight

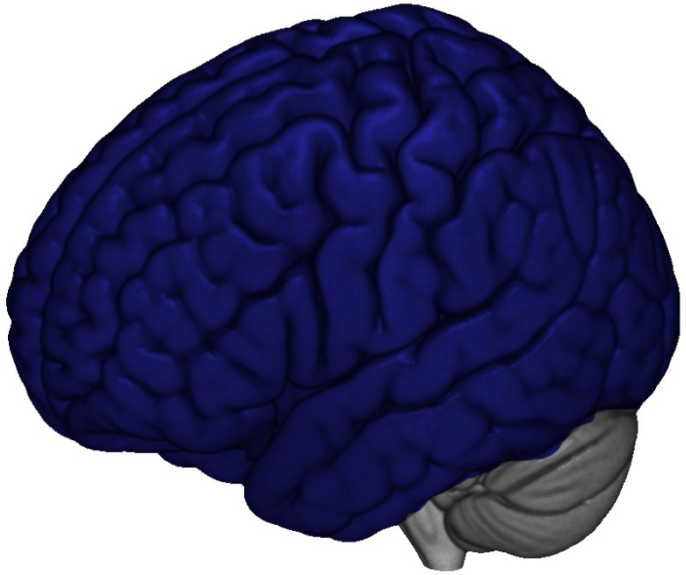


time-resolved



# Wholebrain Analysis

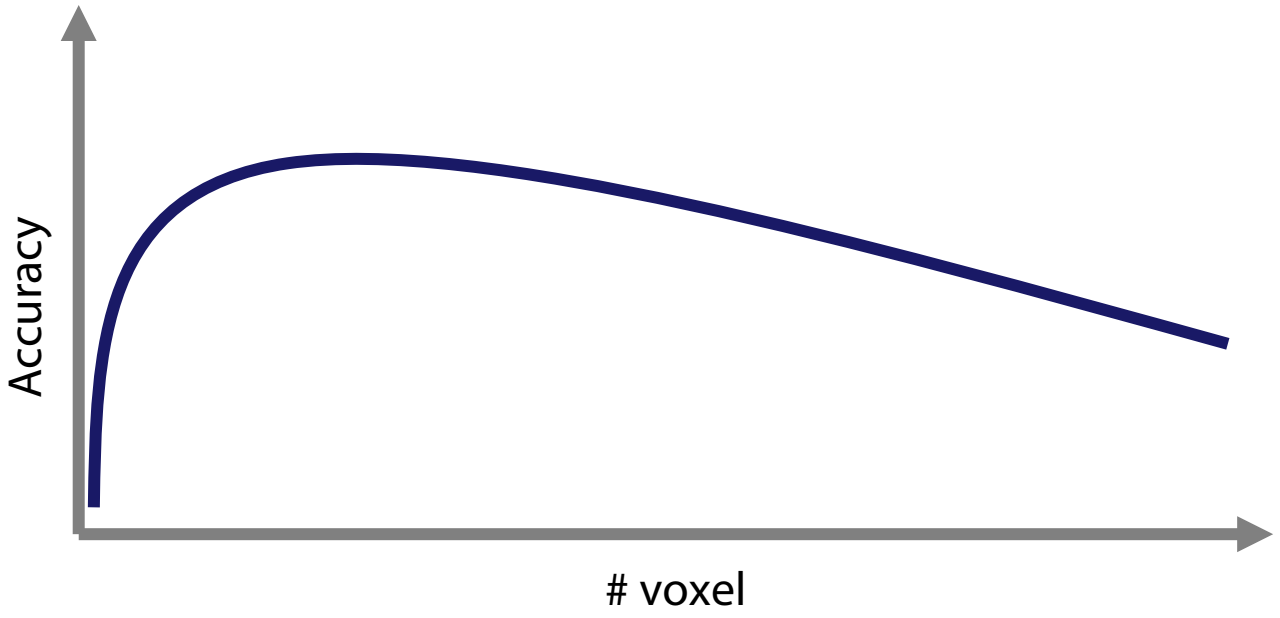
## All voxels are included into the classification



- All available spatial information is provided to the classifier
- No “multiple comparisons” problem
- Problem of overfitting
- No information about location of information possible

# Wholebrain Analysis: Problem of Overfitting

Reduction of accuracy with large number of voxels



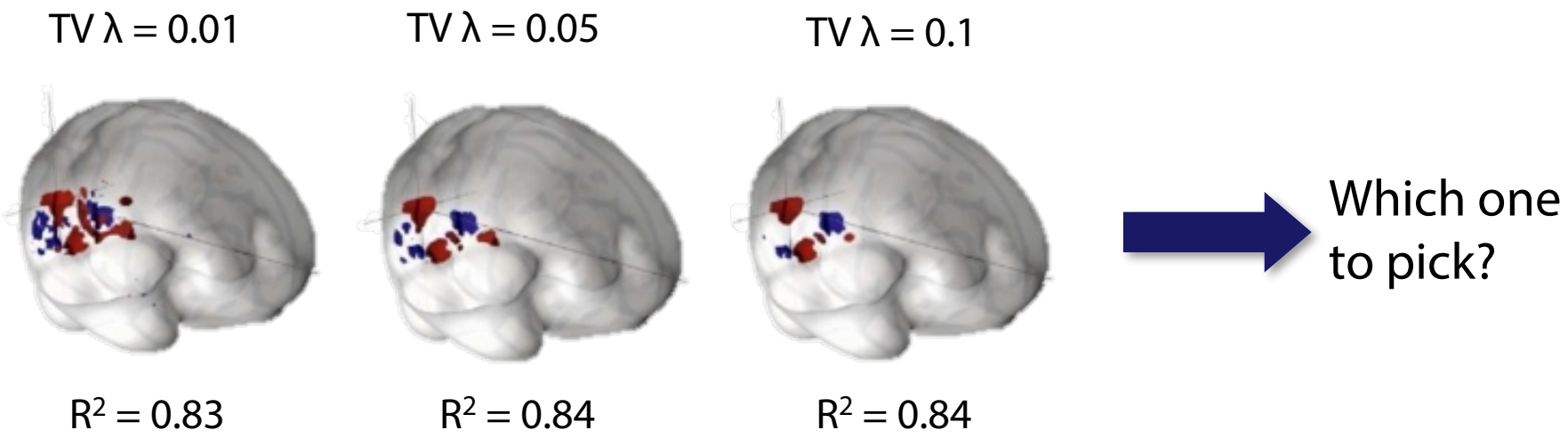
# Wholebrain Analysis: Problem of Overfitting

Possible solution: Use sparse models (e.g. LASSO)

- But: Sparse models find only subset of voxels with information → we miss a lot of relevant voxels

Alternative solution: Use prior to regularize smoothness

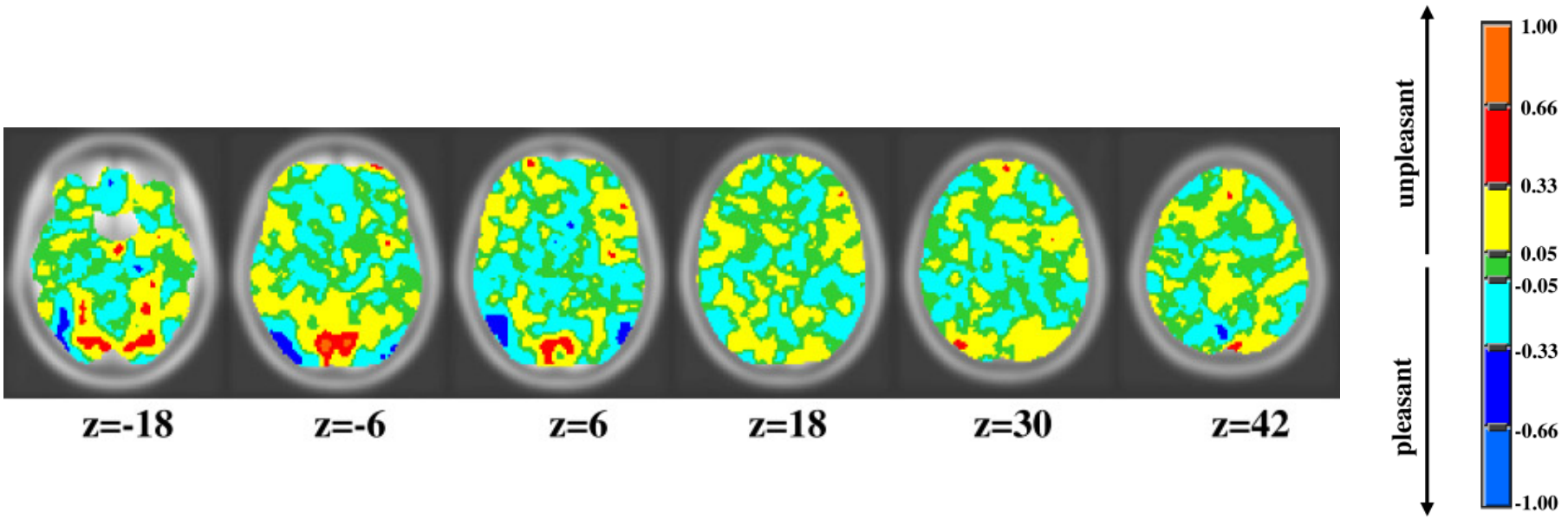
- But: unclear if prior is correct




*Michel et al. (2011) – IEEE Trans Med Imaging*

# Wholebrain Analysis

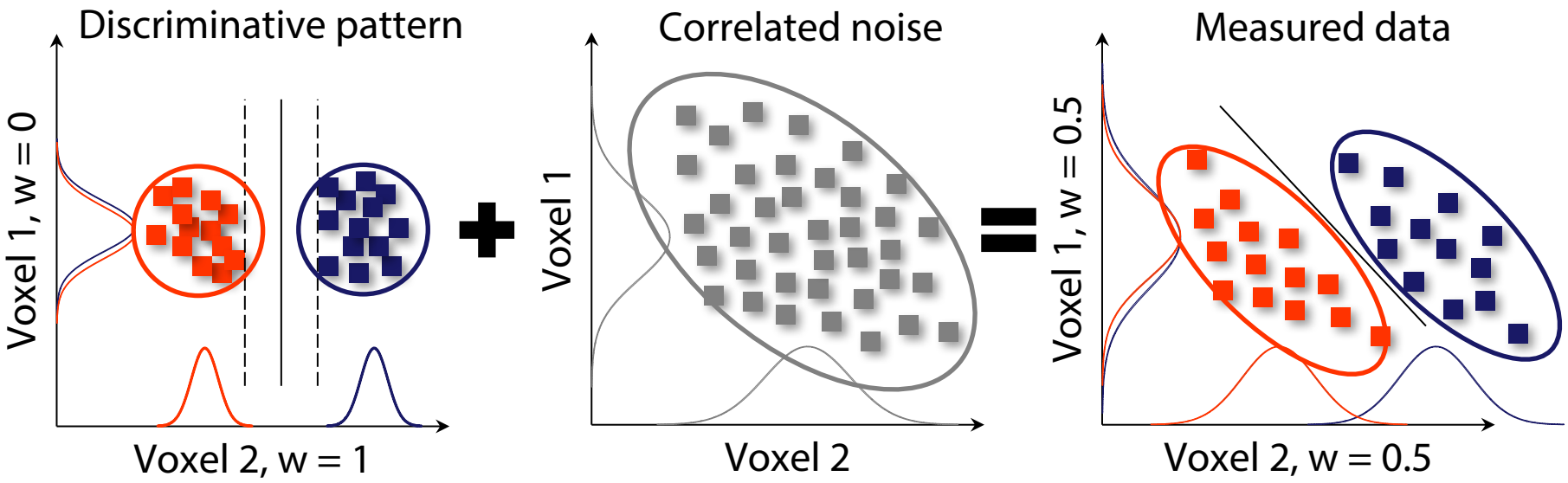
Weight maps: Solution to inability to localize information?




*Mourao-Miranda et al. (2006) – Neuroimage*

# Wholebrain Analysis

Problem: Voxel weights reflect signal (= source) and unspecific noise



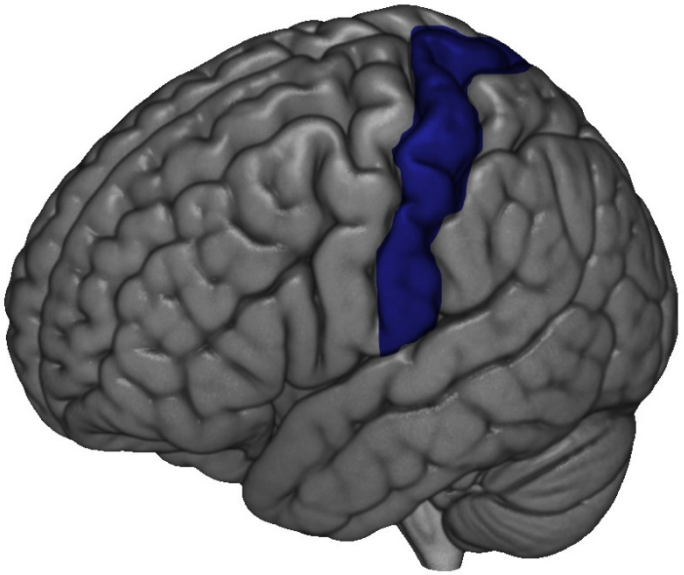

Weights do not indicate source of information

But: source of information can be reconstructed

*Haufe et al. (2014) – Neuroimage; Hebart & Baker (2017) – Neuroimage*

# Region of Interest Analysis

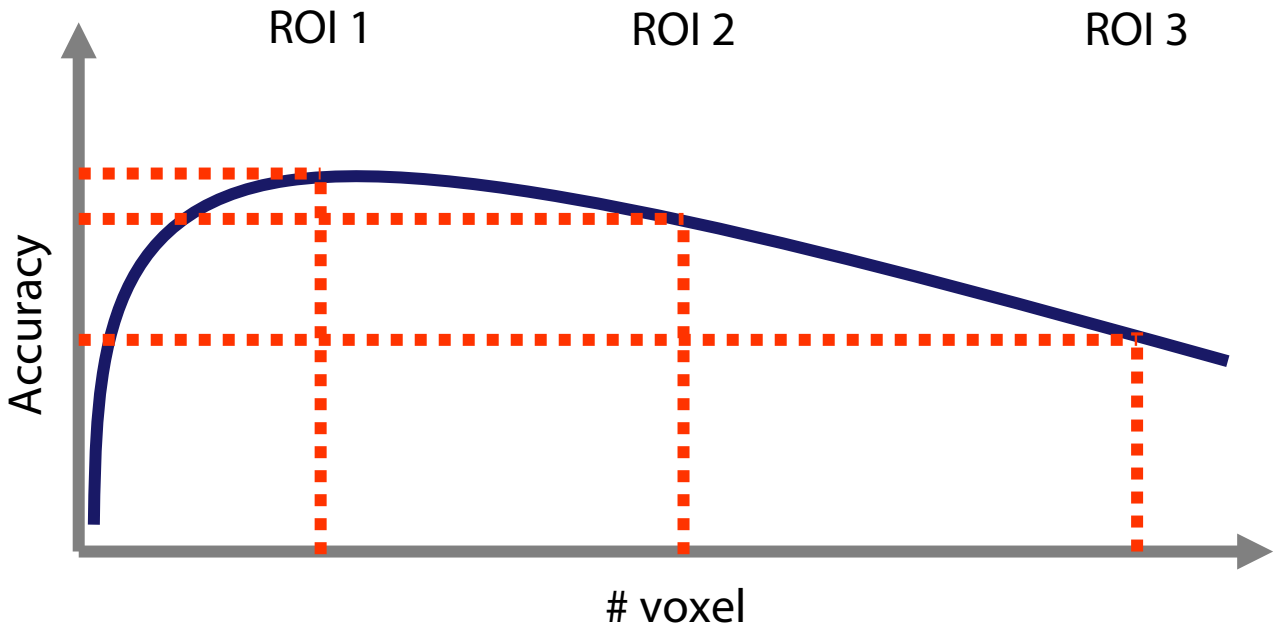
## Voxels are selected using spatial criteria



- 👍 Relatively precise localization of information
- 👍 Small ”multiple comparisons” problem
- 👎 Selection of regions required in advance (bias?)
- 👎 Information encoded only across the distance gets lost
- 👎 Limited comparability between ROIs

# Region of Interest Analysis

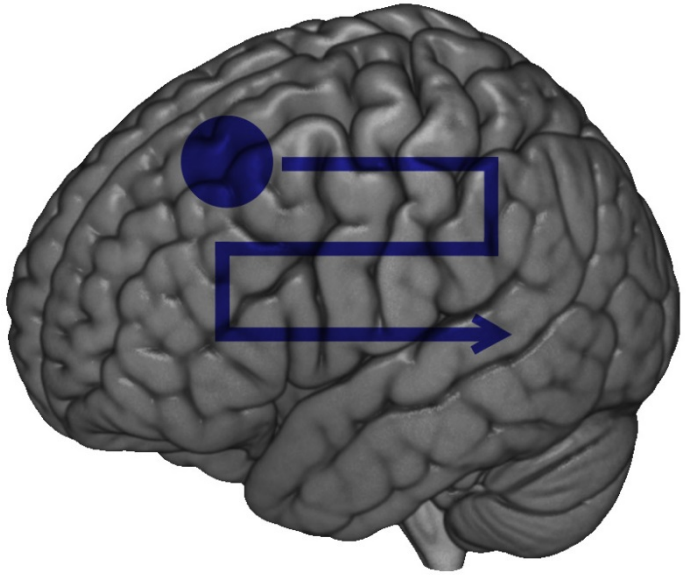
ROIs with very different size difficult to compare




*Haushofer et al (2008) – PLoS biol; Schreiber & Krekelberg (2013) – PLoS One*

# Searchlight Analysis

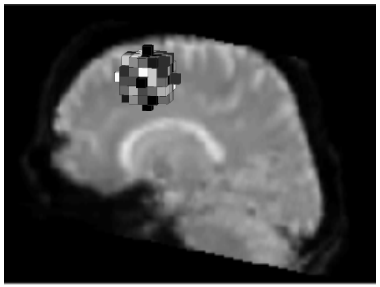
Sphere of voxels is moved through brain as ROI

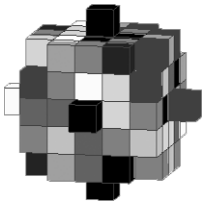


- 👍 Very precise localization of information
- 👍 Maximization of local information
- 👍 Good for group comparisons analogous to SPM
- 👎 Informative regions possibly inflated
- 👎 “multiple comparisons” problem
- 👎 Ideal shape and size of searchlight unknown
- 👎 Information encoded only across the distance gets lost

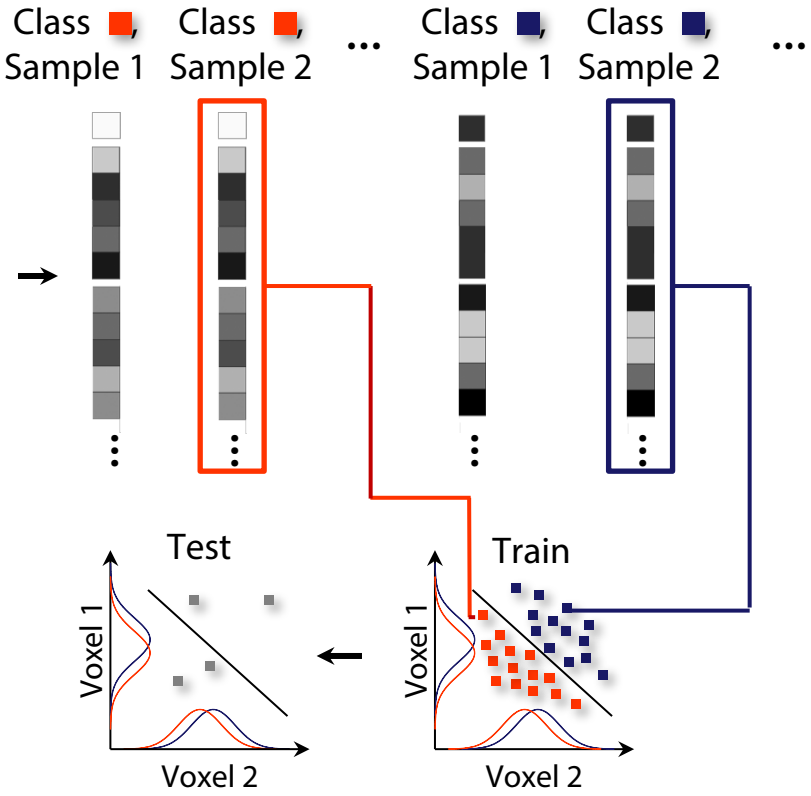
# Searchlight Analysis

Step 1: Select current searchlight position





Step 2: Extract local pattern from functional images

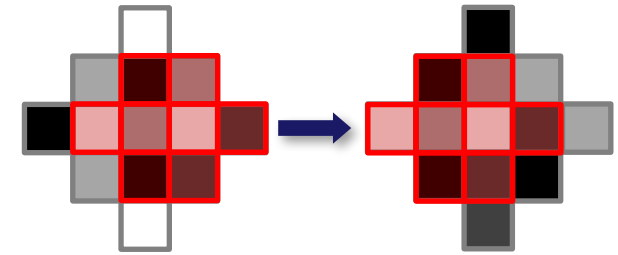


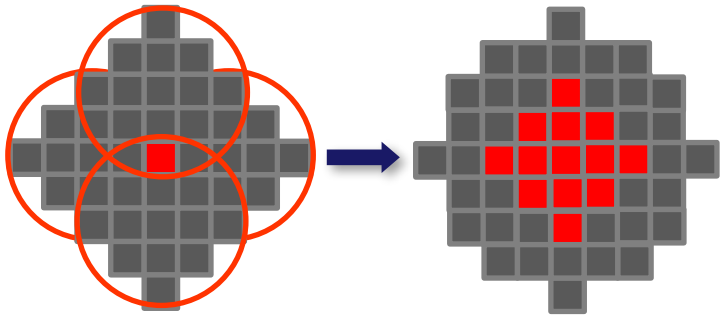

Step 3: Perform classification

Step 4: Fill-in classification output at central voxel in result image

Output (z.B. Accuracy: 60%)

# Searchlight Analysis





- Searchlight analysis acts as spatial smoothing
- Reason: Neighboring searchlights overlap a lot, i.e. have very similar information
- Extreme example: One highly informative voxel creates high accuracy in size of searchlight

Related “problem” in spatial smoothing

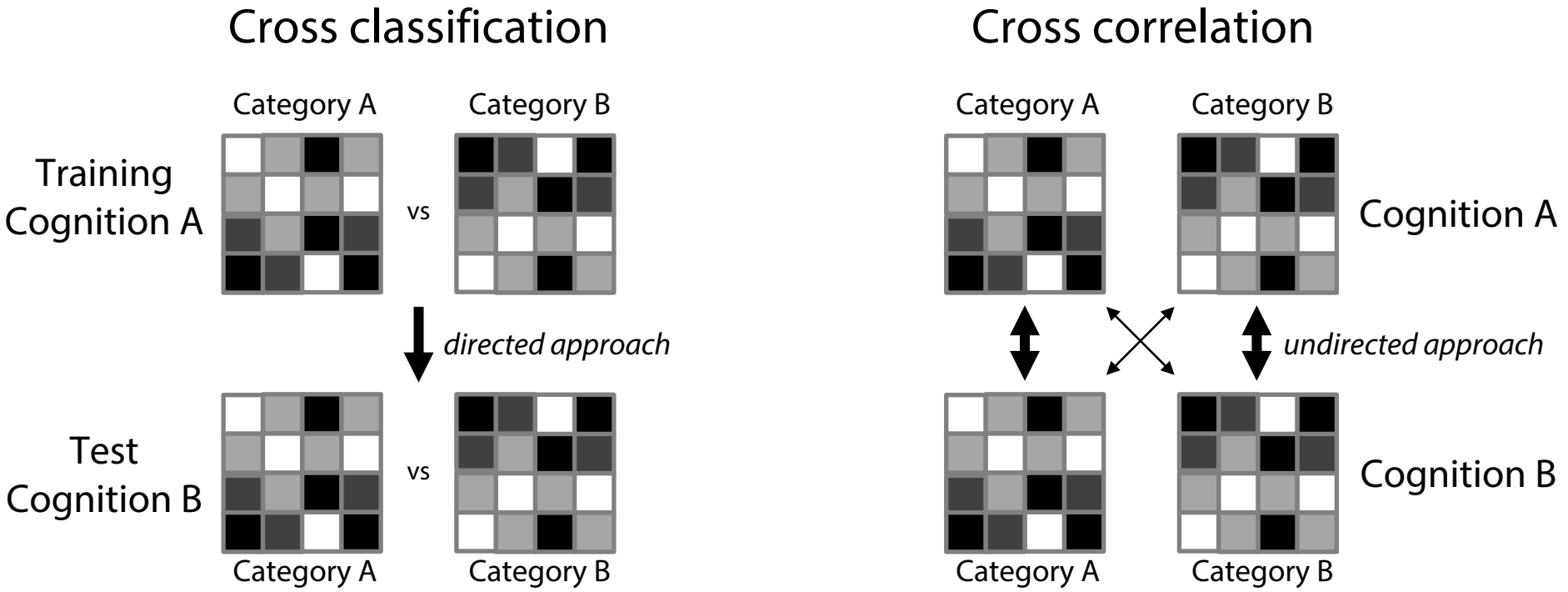
*Etzel et al (2013) – Neuroimage*

# Interim Summary

- There are three main types of analysis:
  Wholebrain, ROI, and searchlight
- Each type has specific advantages and disadvantages
- For most disadvantages there are potential solutions

# Multivariate Generalization

Approach that is growing in popularity to test association of cognitive states

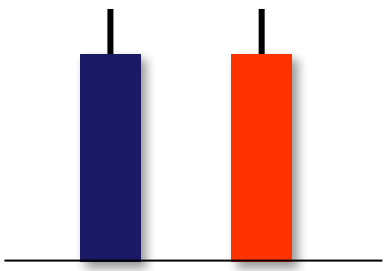


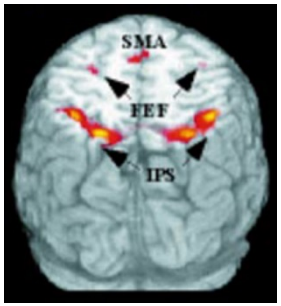
# Multivariate Generalization

## Multivariate equivalent to conjunction analysis

### Conjunction analysis

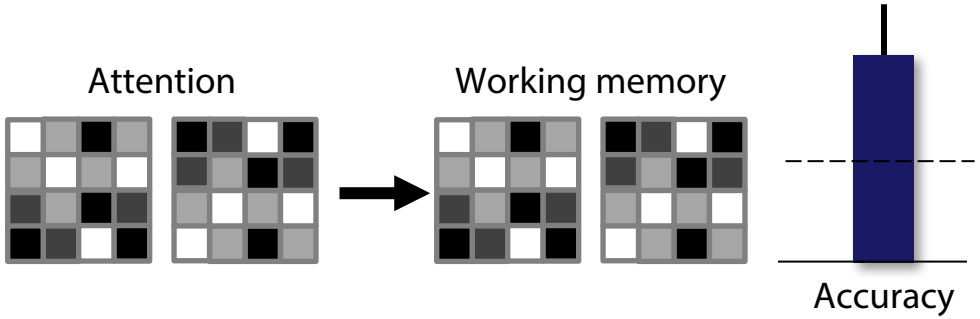
Results: Attention and working memory activate the same regions




### Generalization (multivariate)

Result: Attention and working memory <u>content</u> are encoded similarly

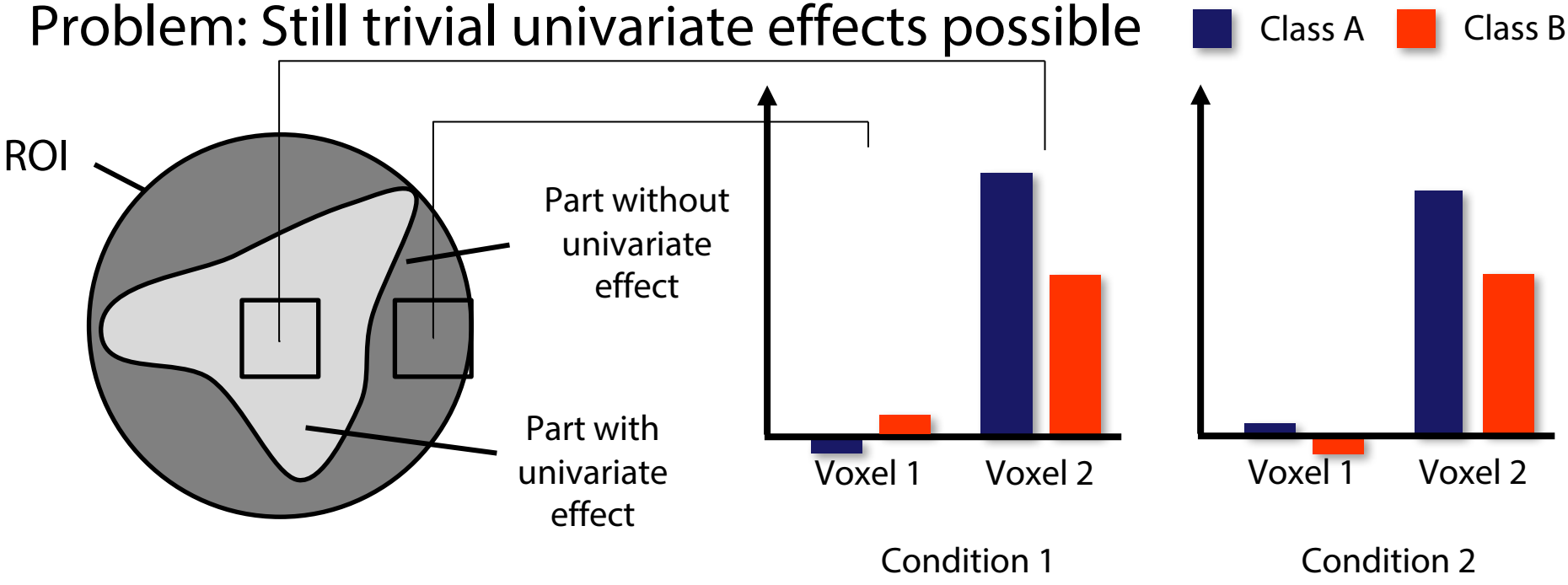



*LaBar et al (1999) – Neuroimage*

# Cross-Classification

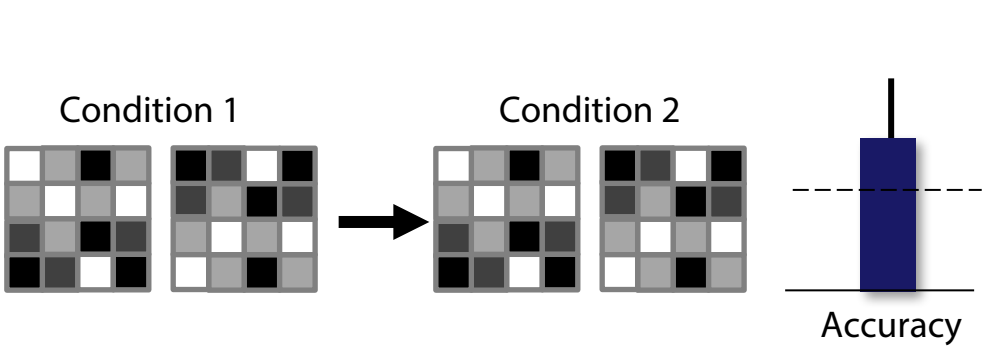
Idea: Cross-classification is more specific than conjunction analysis, because pattern needs to be similar in both cases

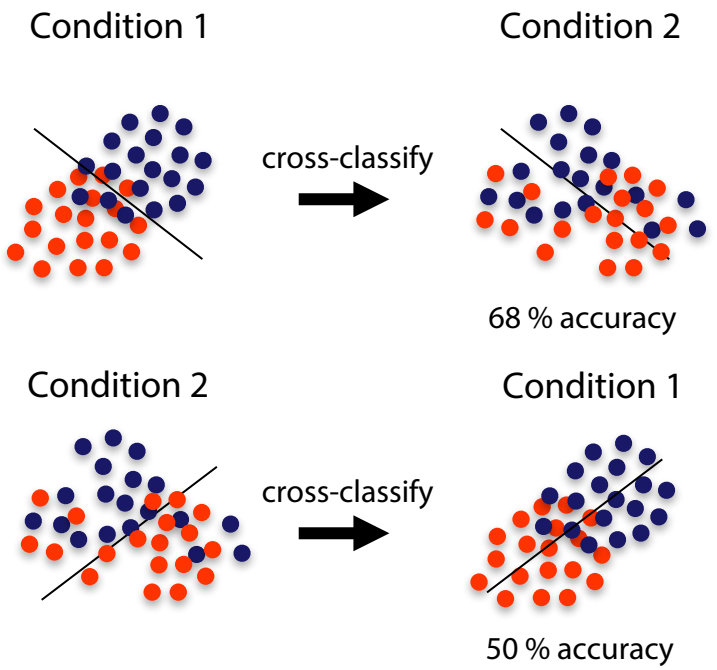
Problem: Still trivial univariate effects possible



# Cross-Classification

## Why does cross-classification sometimes work better one way than the other?




→ Cond 2 has some information of Cond 1 in same direction but more in orthogonal direction

→ Orthogonality more likely in higher dimensionality (i.e. more voxels)

*Hebart & Baker (2017) – Neuroimage*

# Summary

- Generalization is a good approach for testing associations
- Cross classification is directed, cross-correlation in undirected
- Trivial explanations remain possible

# Study questions

You are interested in studying consumer preferences (i.e. whether you would prefer buying A or B) and have some a priori assumptions about where in the brain you would expect this to be encoded.

Question 1: Compare these two approaches:

(a) Run an analysis combining these ROIs and (if significant) removing individual ROIs (so called “virtual lesioning” approach)

(b) Run individual ROI analyses

Question 2: What are the pros and cons of restricting yourself to grey matter voxels only?