

fMRI classification analysis: a conceptual introduction

Marieke Mur
CBU, april 2016

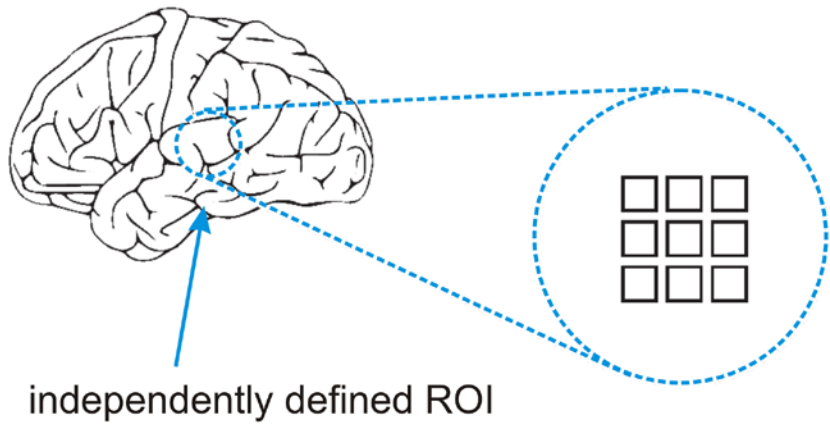
Overview

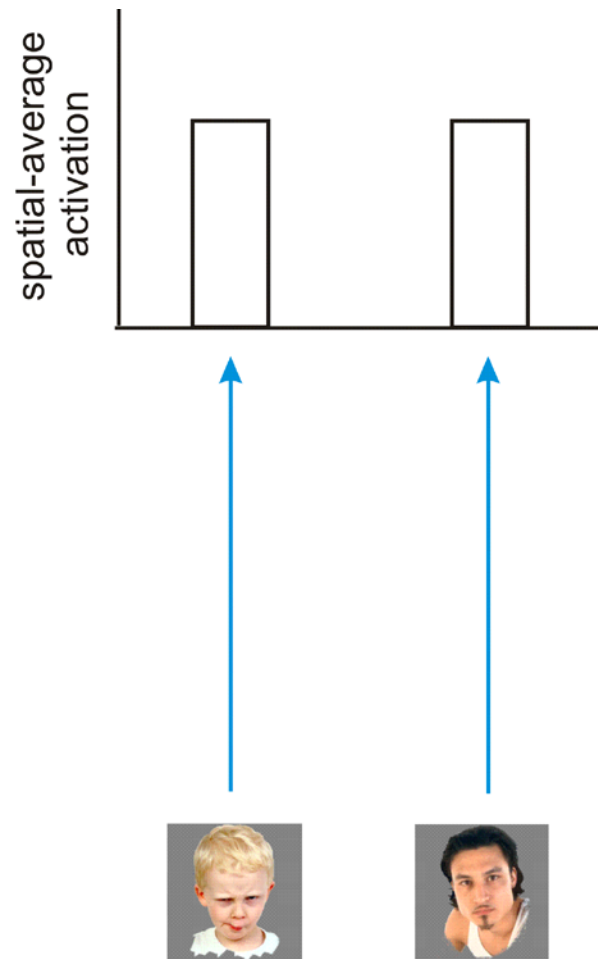
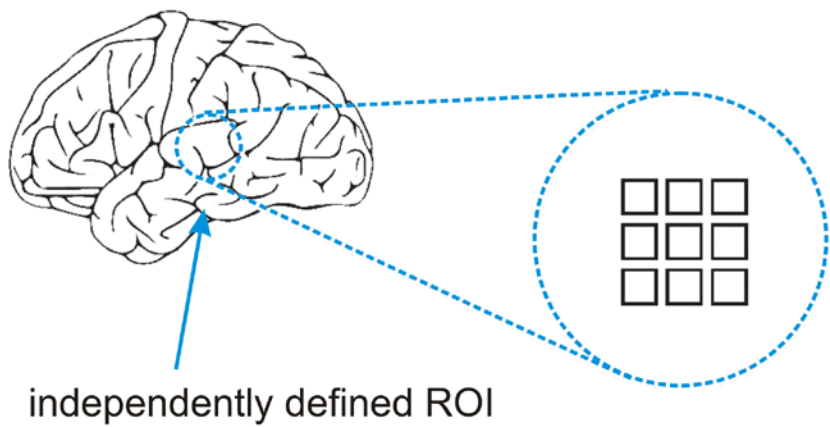
- Why classification analysis?
- Linear classification: the basic idea
- Linear classification: different classifiers
- Do it yourself: six steps
 - step 1: preprocess and split data
 - step 2: estimate single-subject activity patterns
 - step 3: select voxels
 - step 4: train the classifier
 - step 5: test the classifier
 - step 6: statistical inference
- Toolboxes
- Literature

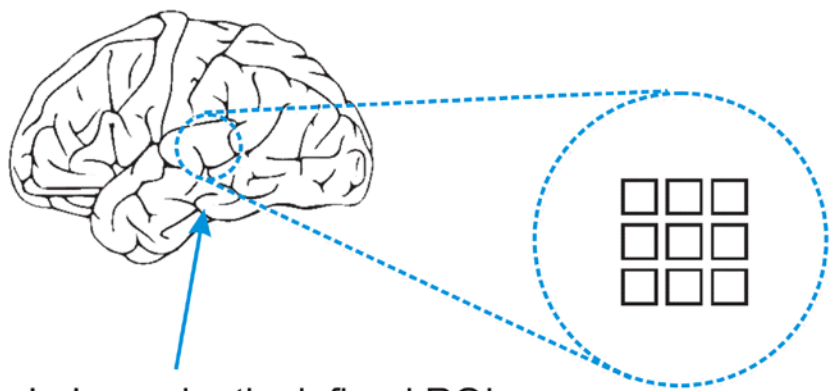
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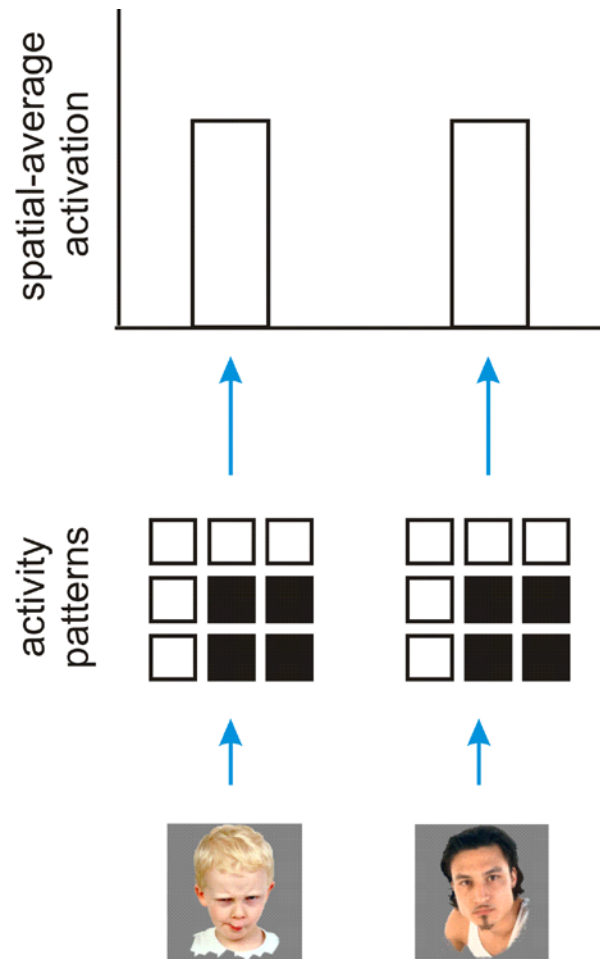
Activation-based analysis



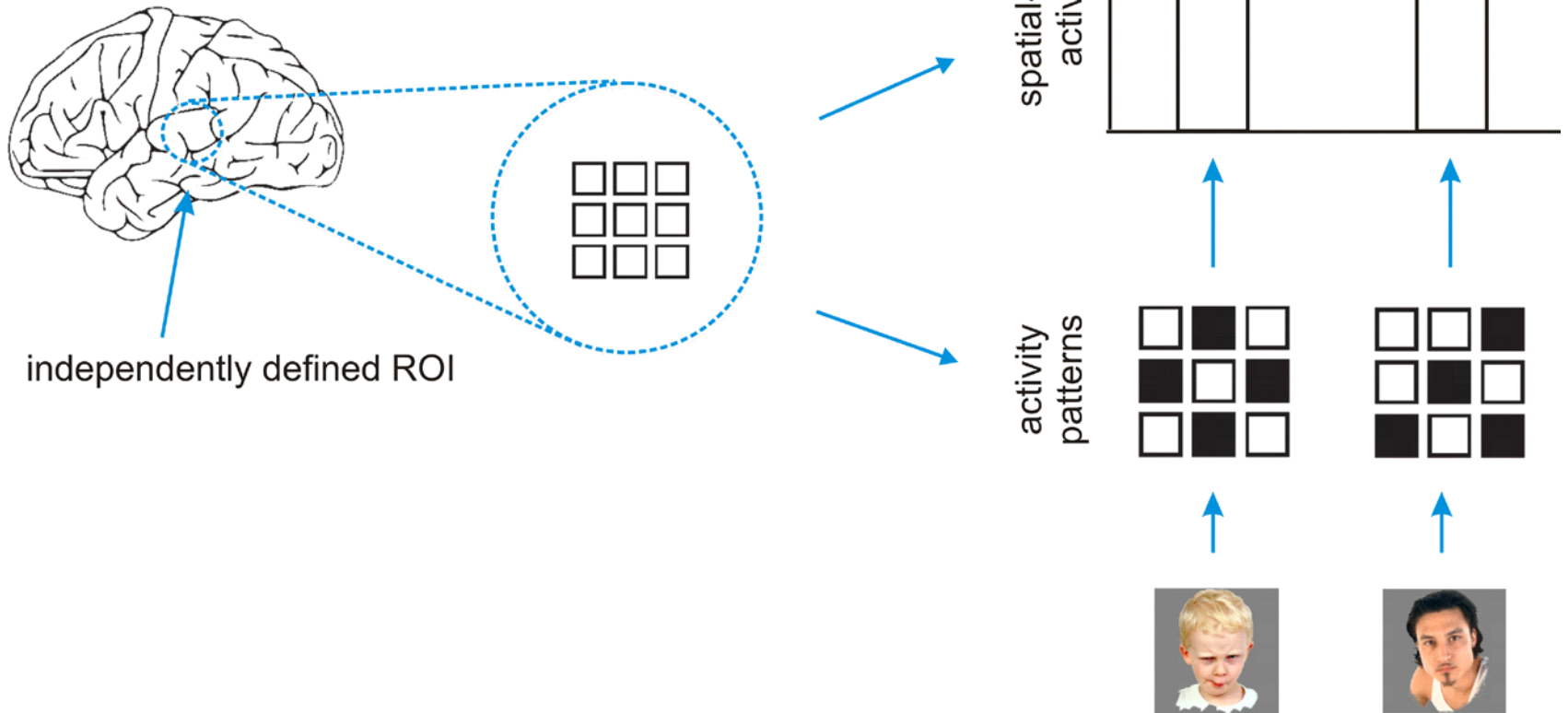




independently defined ROI



Pattern-information analysis



Pattern-information analysis

Goal

Determine whether activity patterns elicited by different conditions are statistically discriminable.

How?

Multivariate analysis of variance (MANOVA)?

Pattern-information analysis

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Multivariate analysis of variance (MANOVA)?

Pattern-information analysis

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Determine whether activity patterns elicited by different conditions are statistically discriminable.

How?

Approach pattern analysis as a classification problem.

Pattern classification

IF

we can classify the experimental conditions on the basis of the activity patterns better than chance

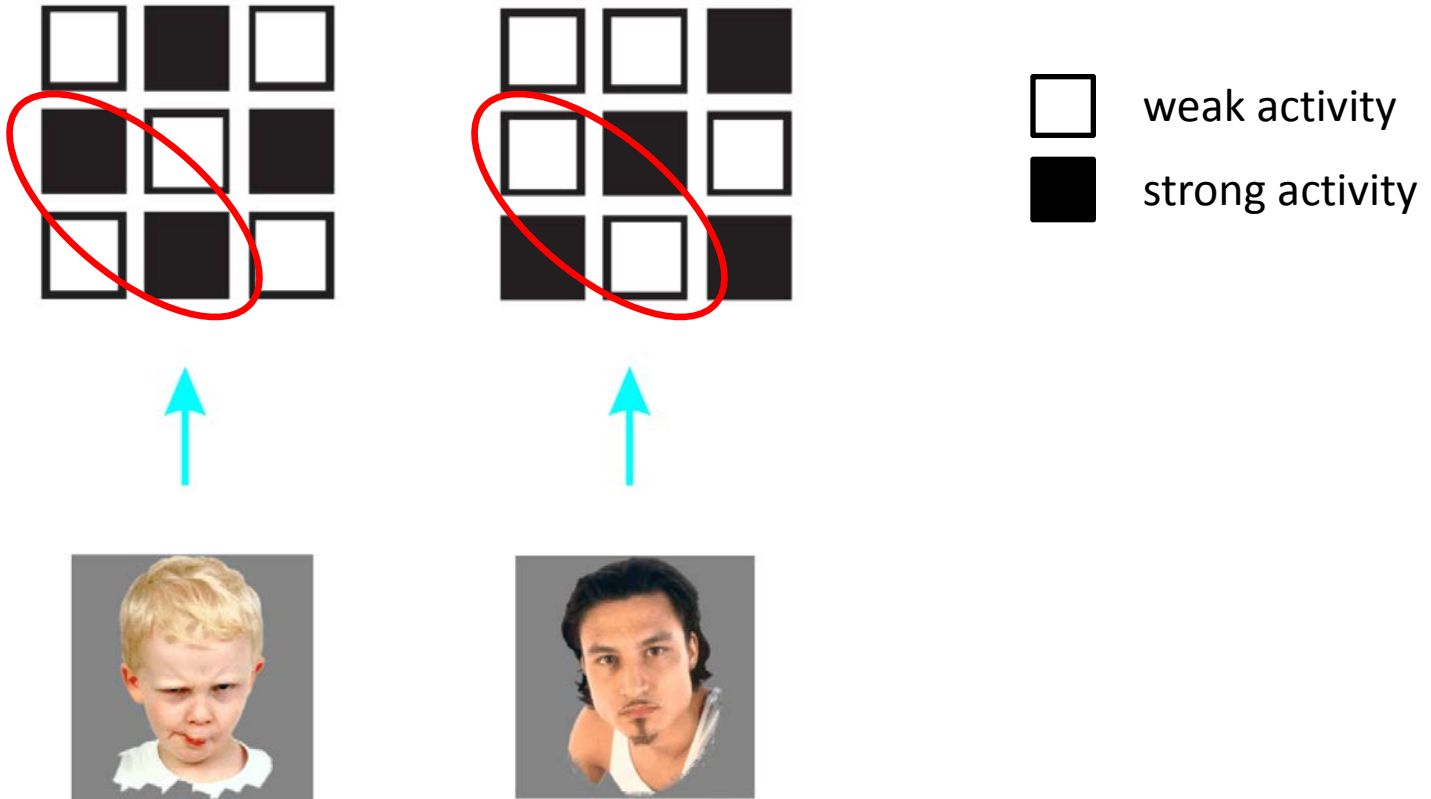
THEN

this indicates that the activity pattern carries information about the experimental conditions.

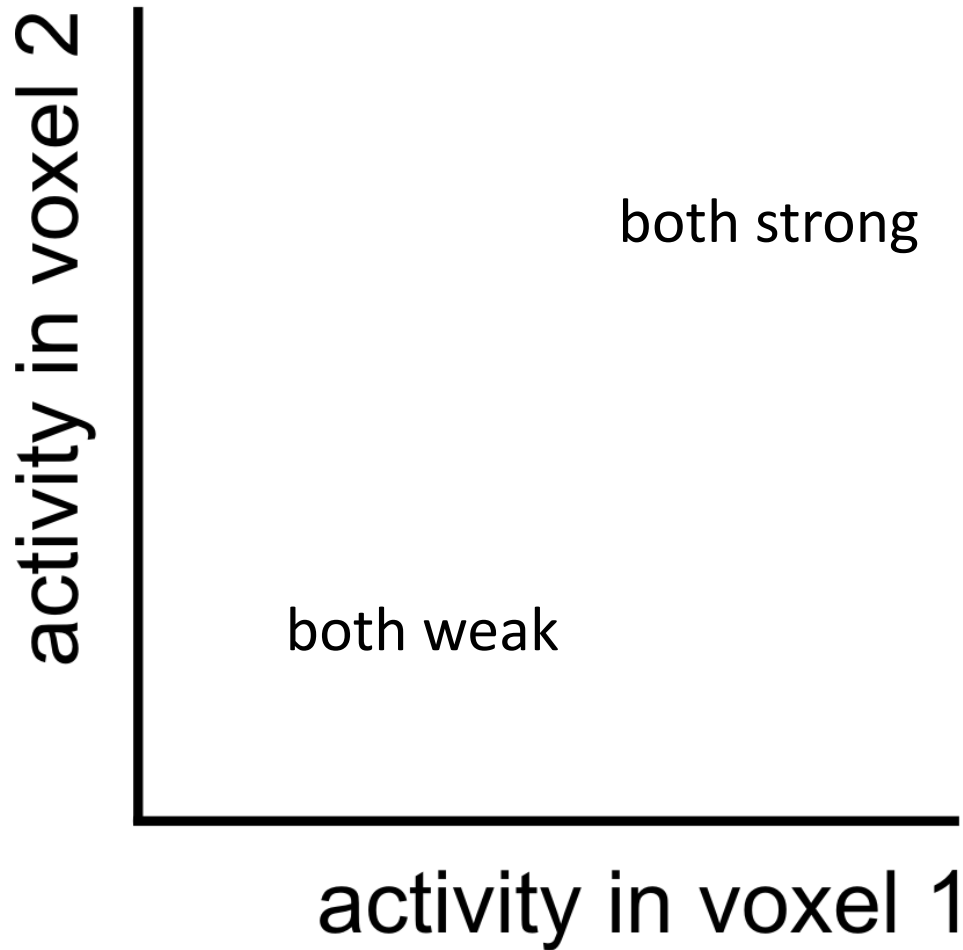
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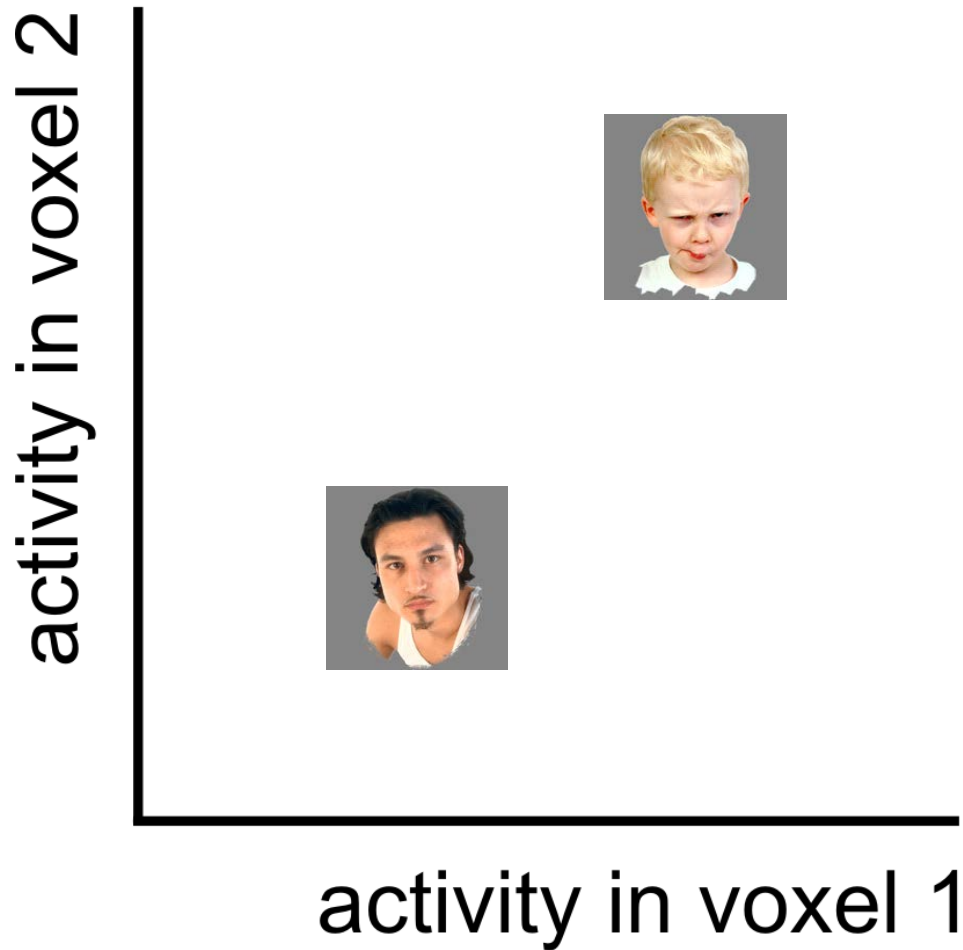
Linear classification: the basic idea



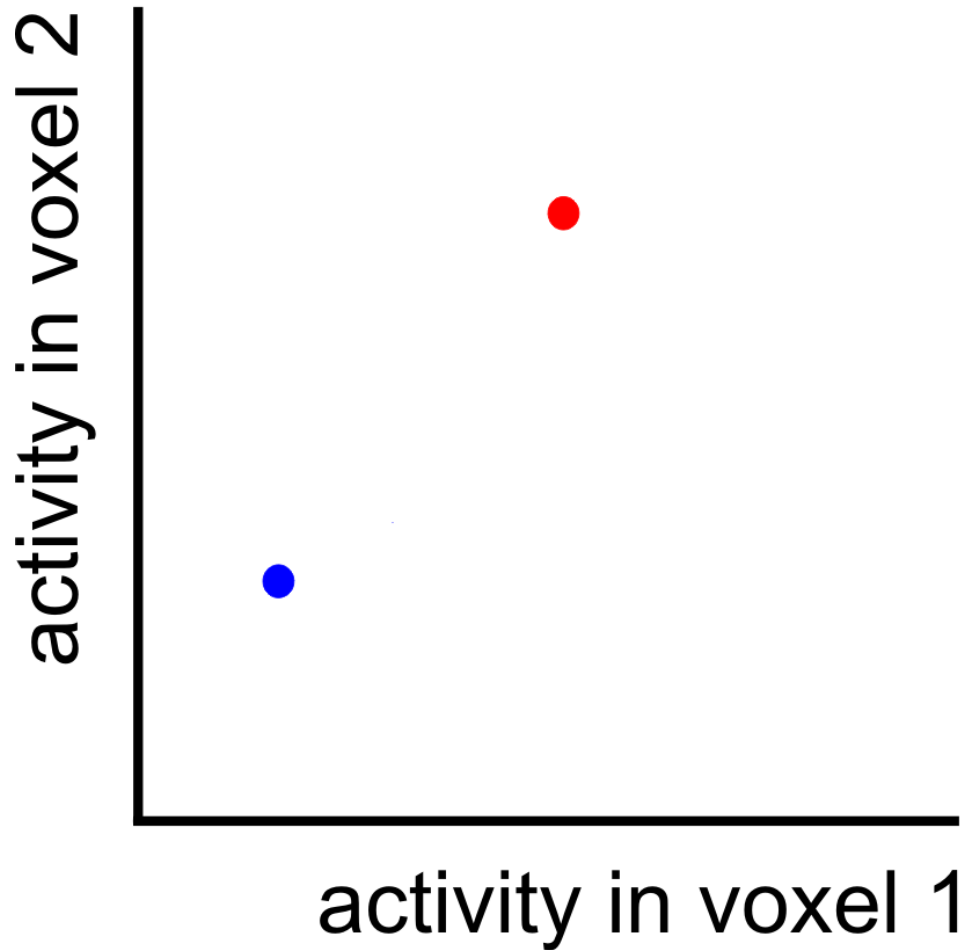
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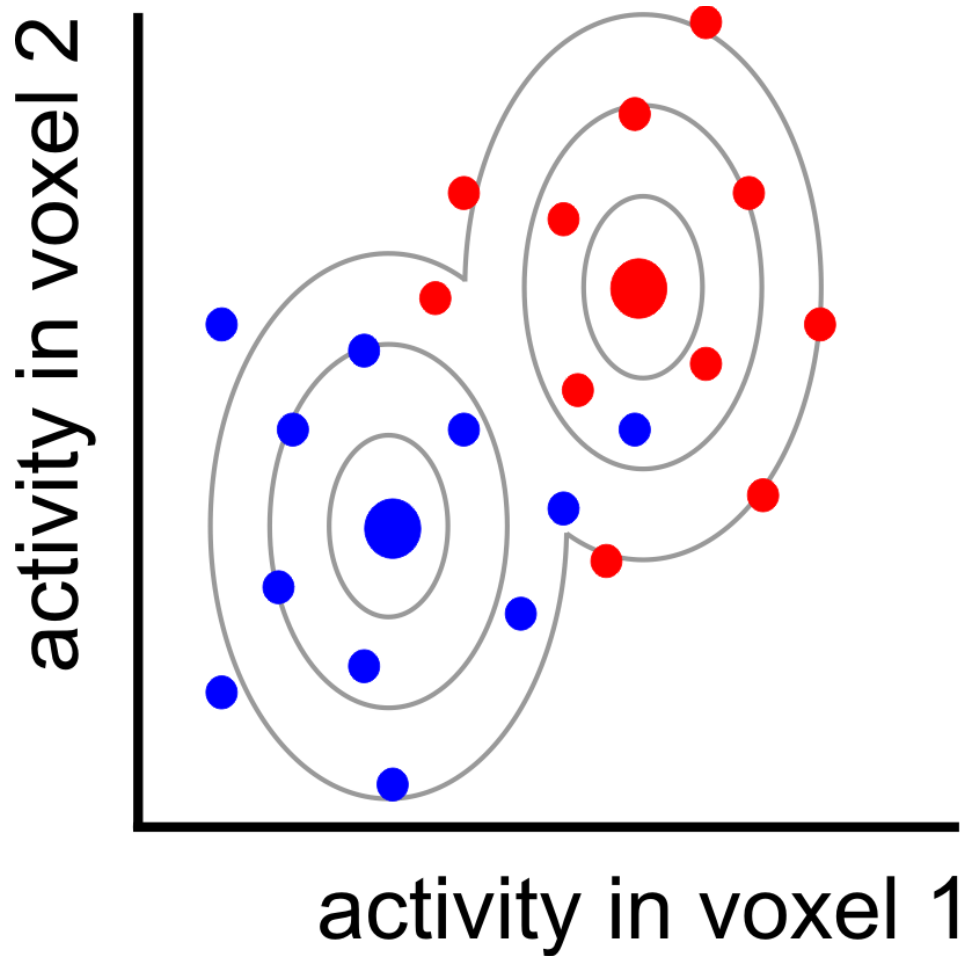
Linear classification: the basic idea



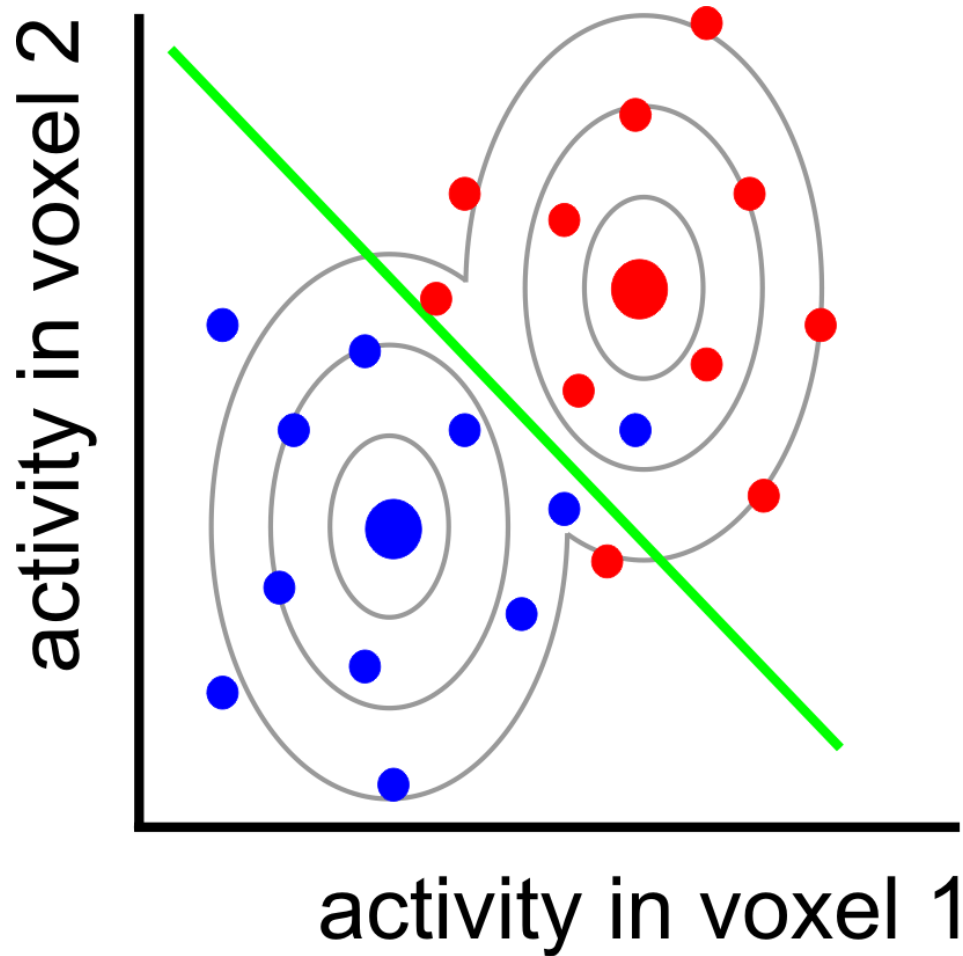
Linear classification: the basic idea



Linear classification: the basic idea



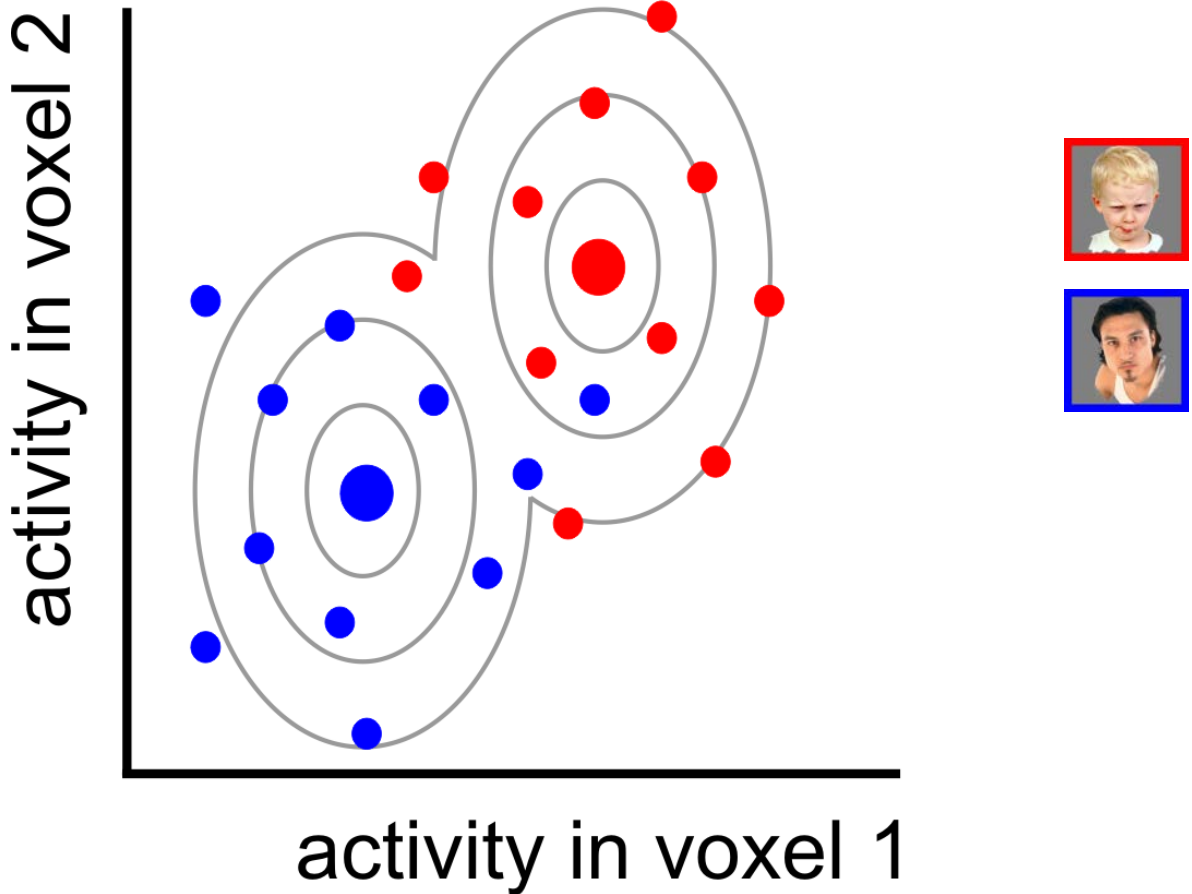
Linear classification: the basic idea



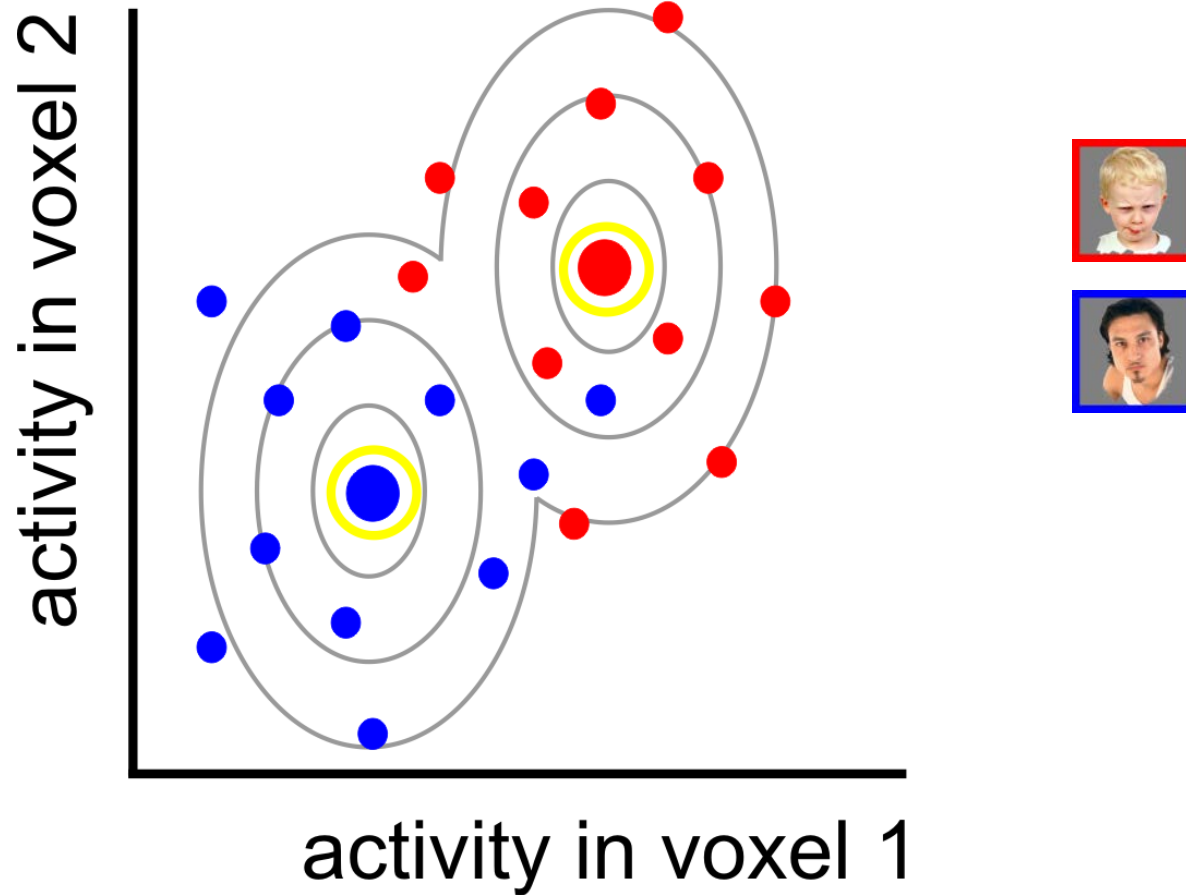
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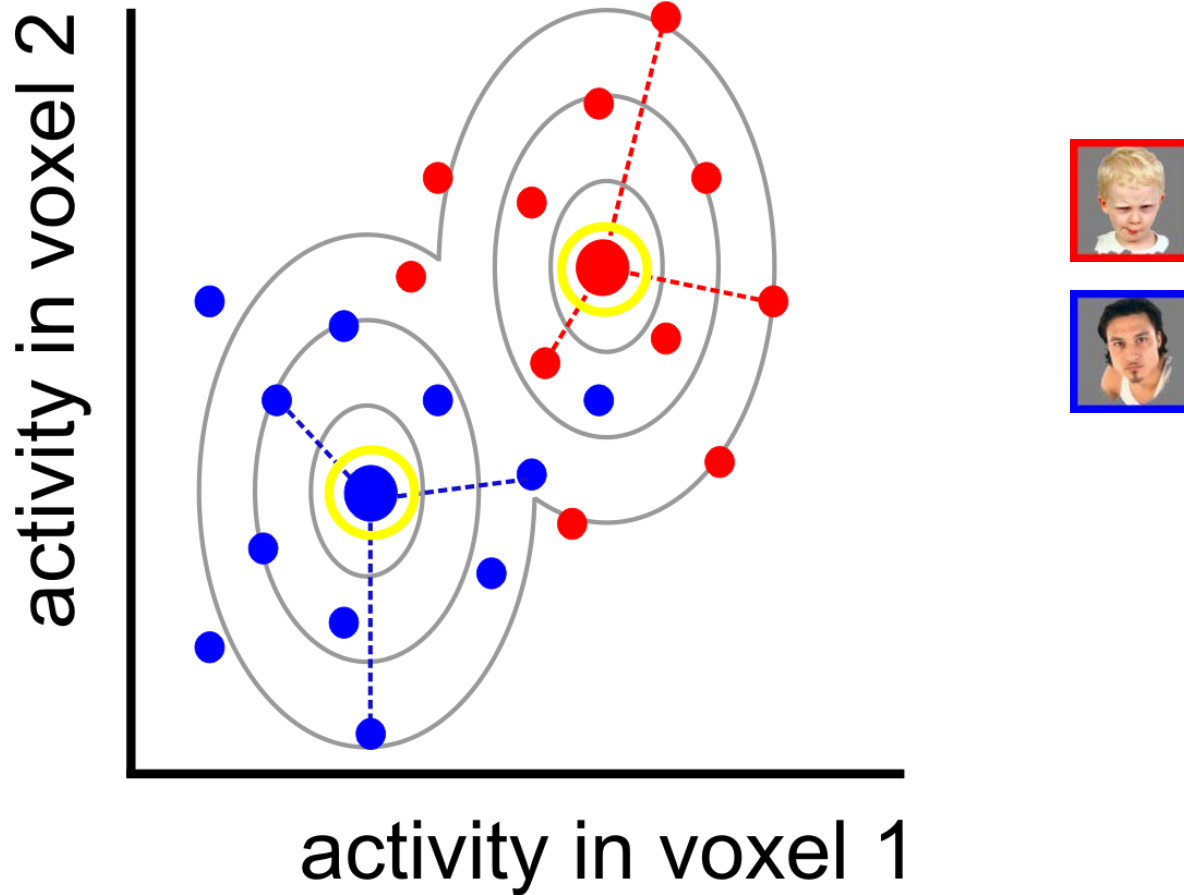
Linear classification: different classifiers



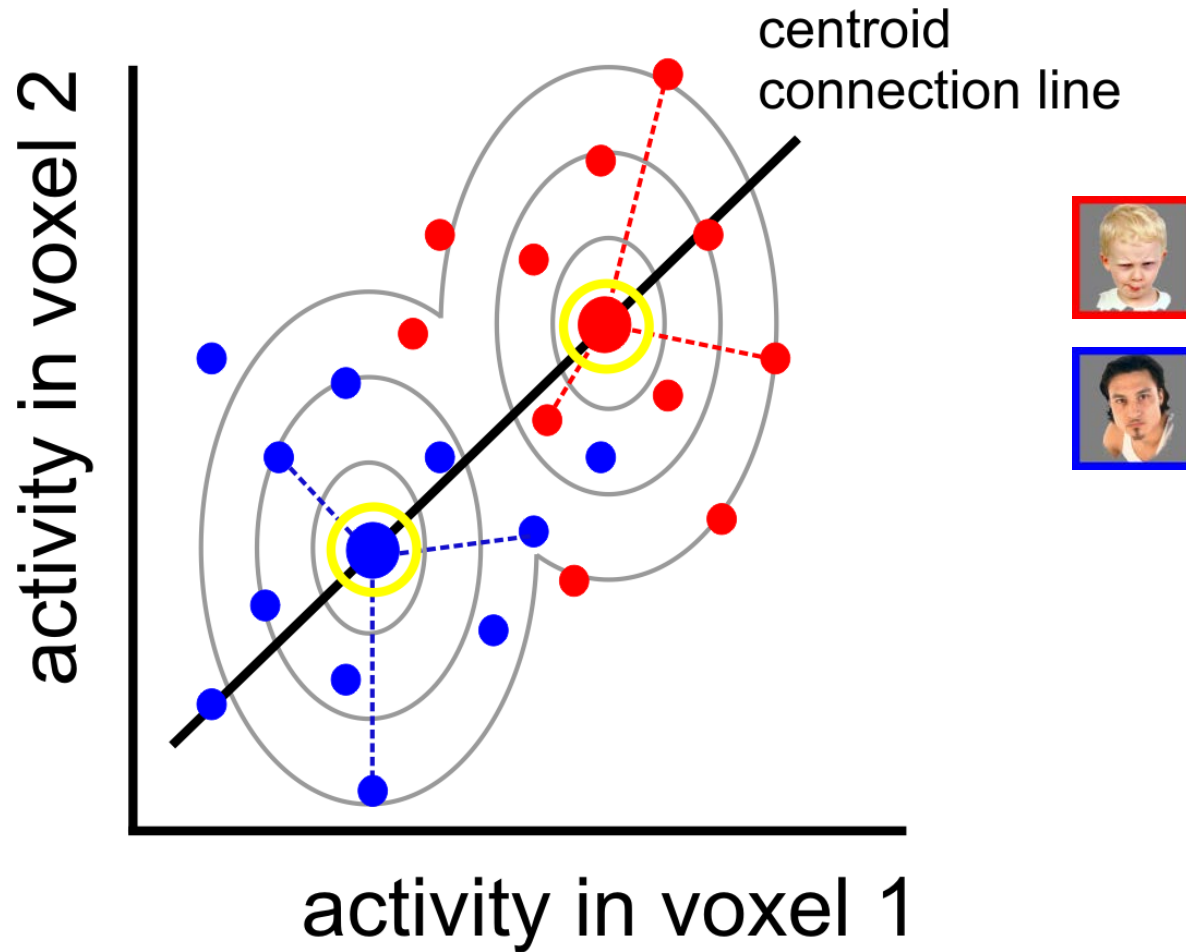
Linear classification: minimum-distance



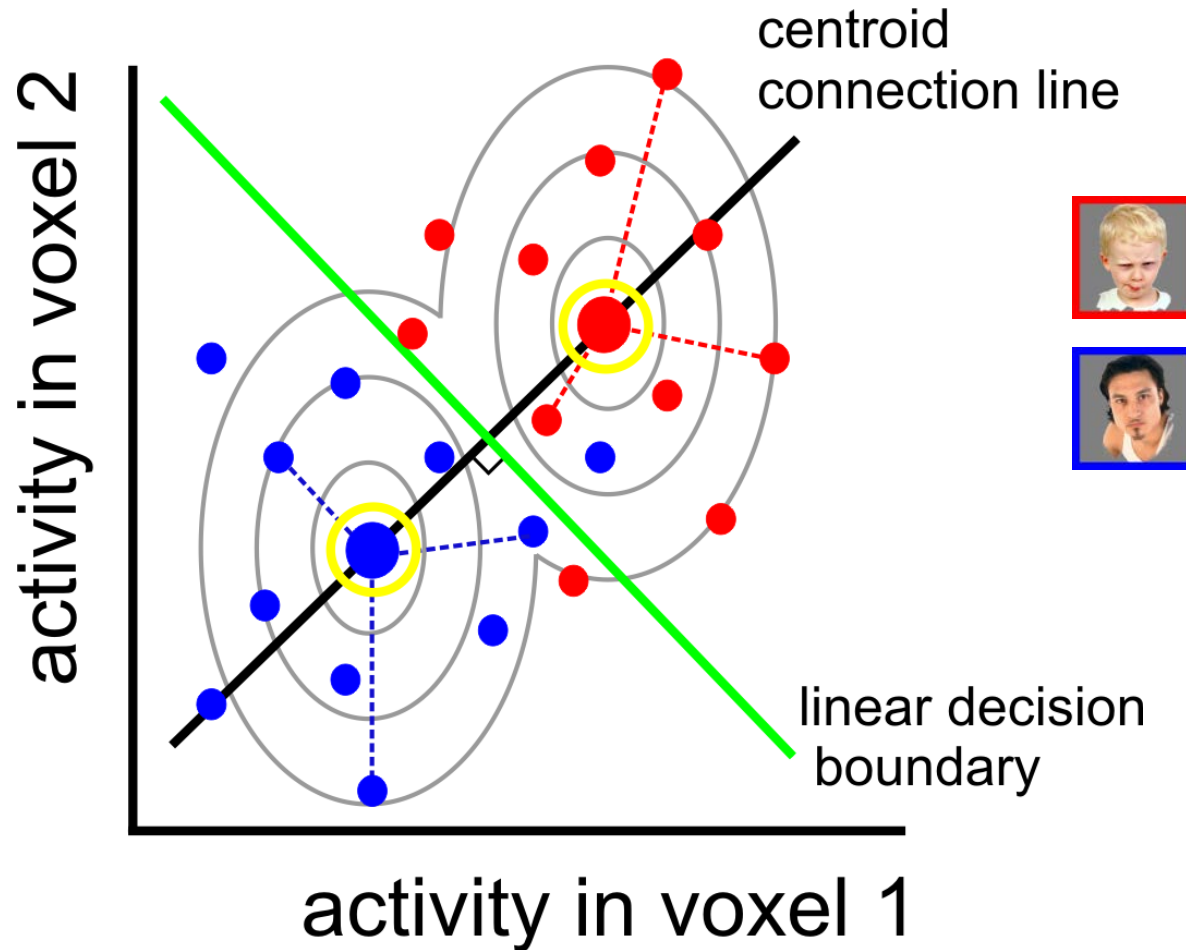
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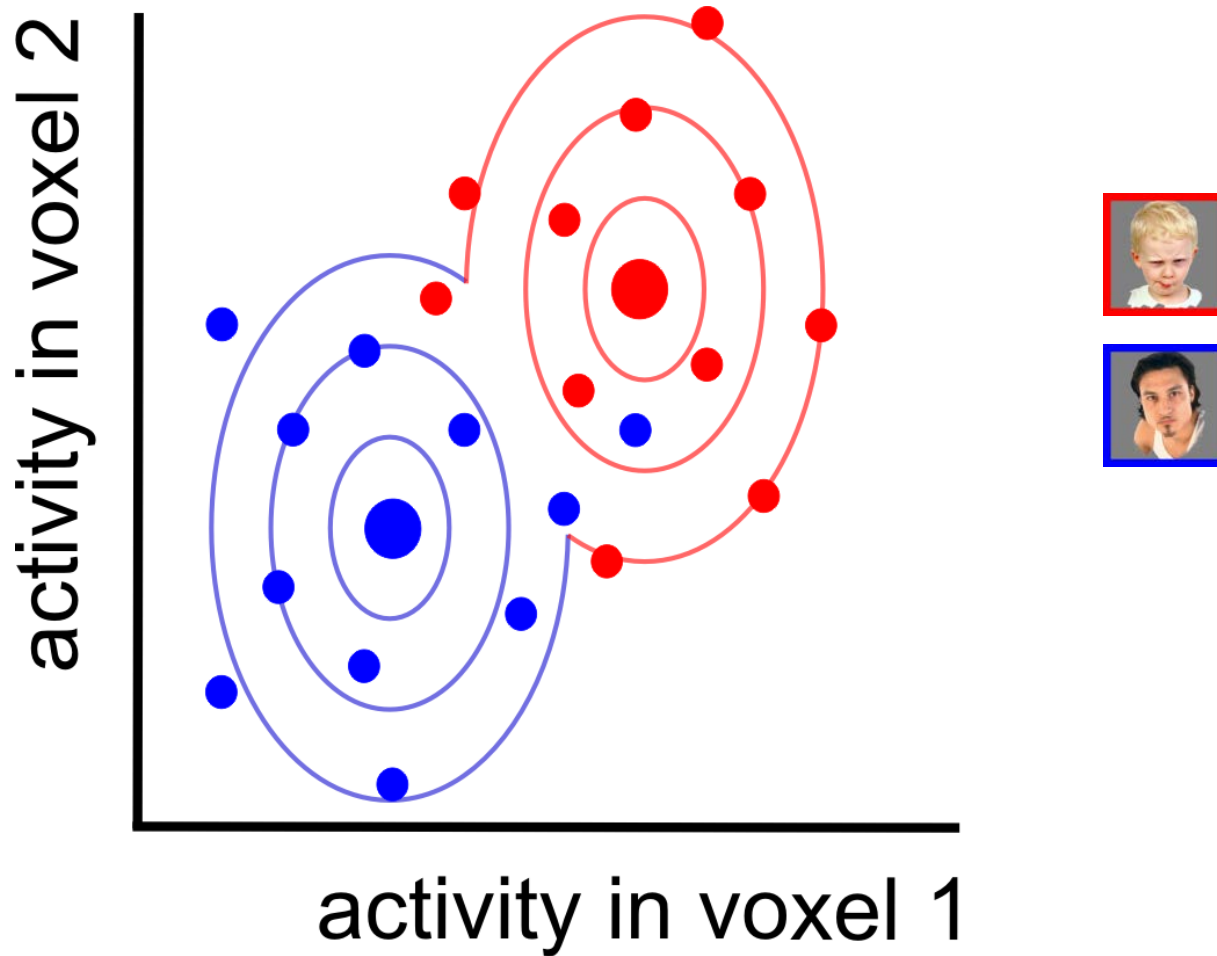
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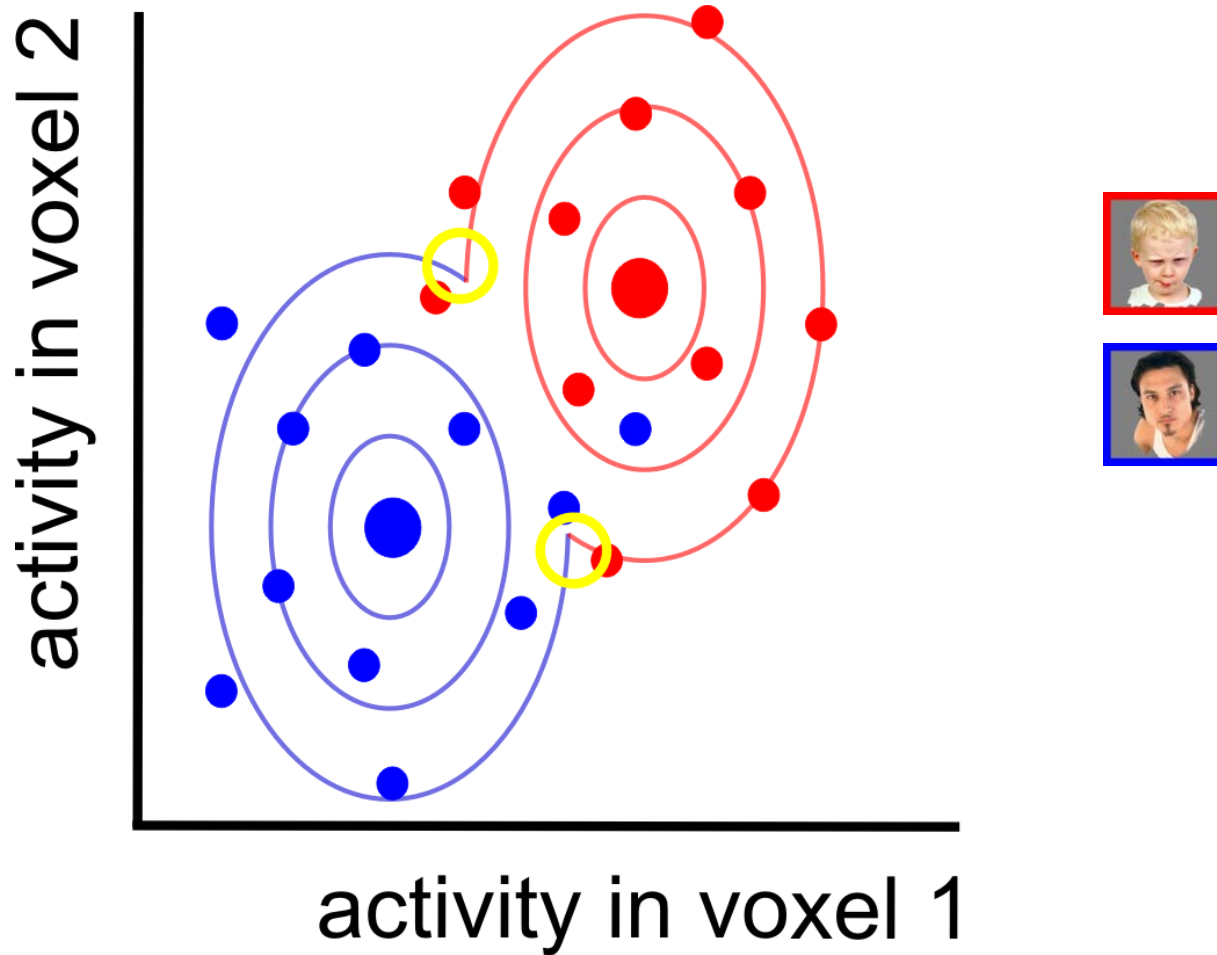
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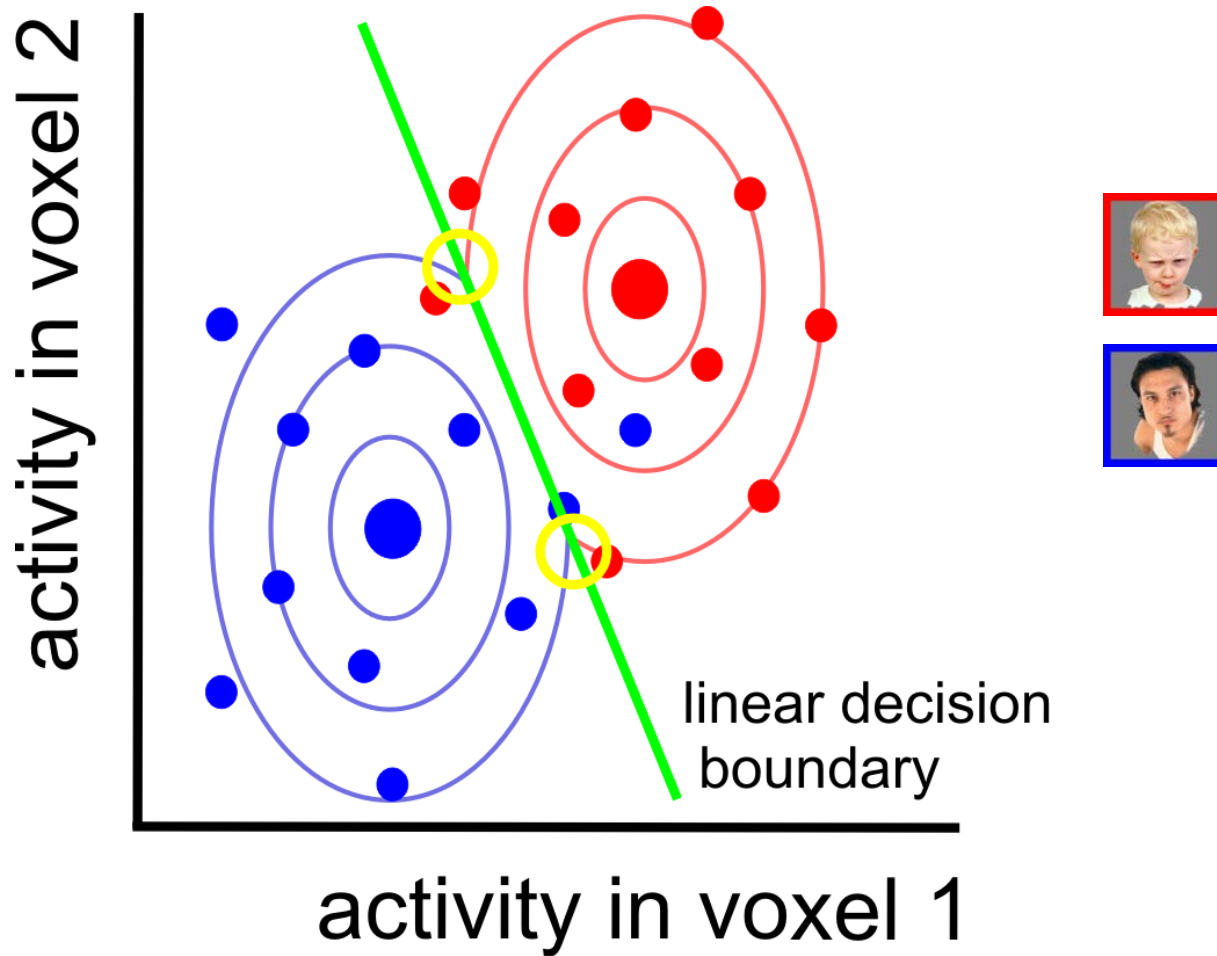
Linear classification: FLDA



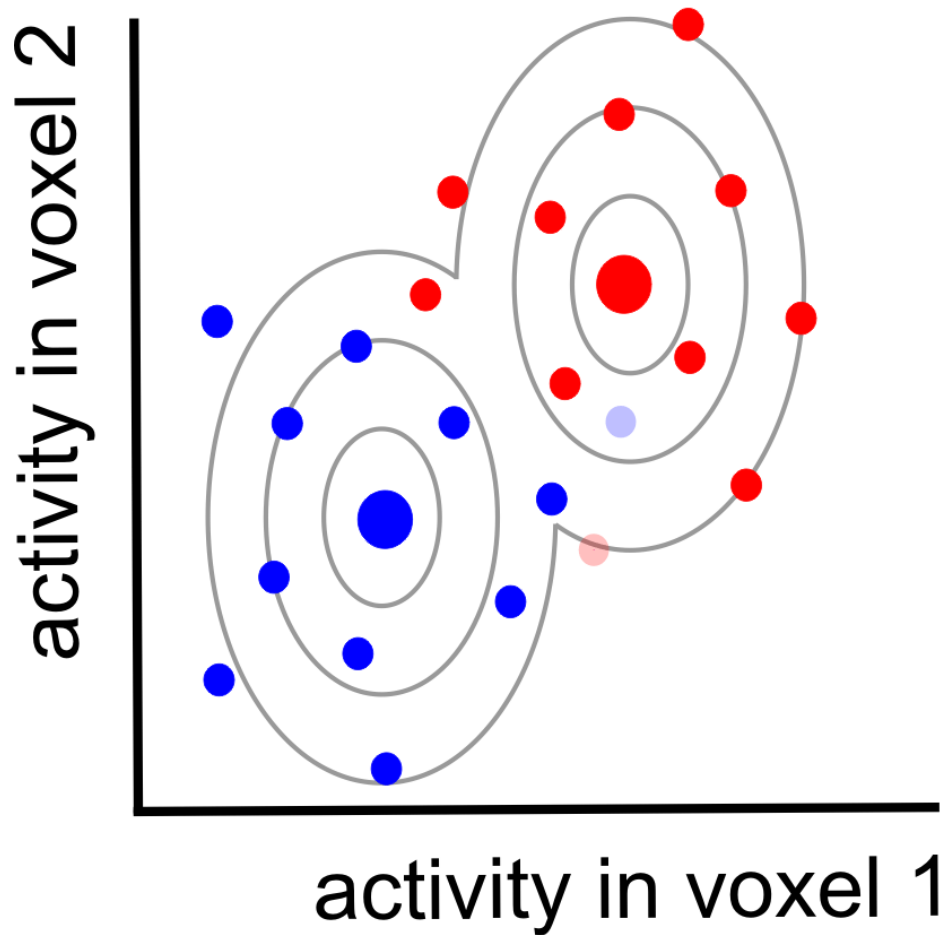
Linear classification: FLDA



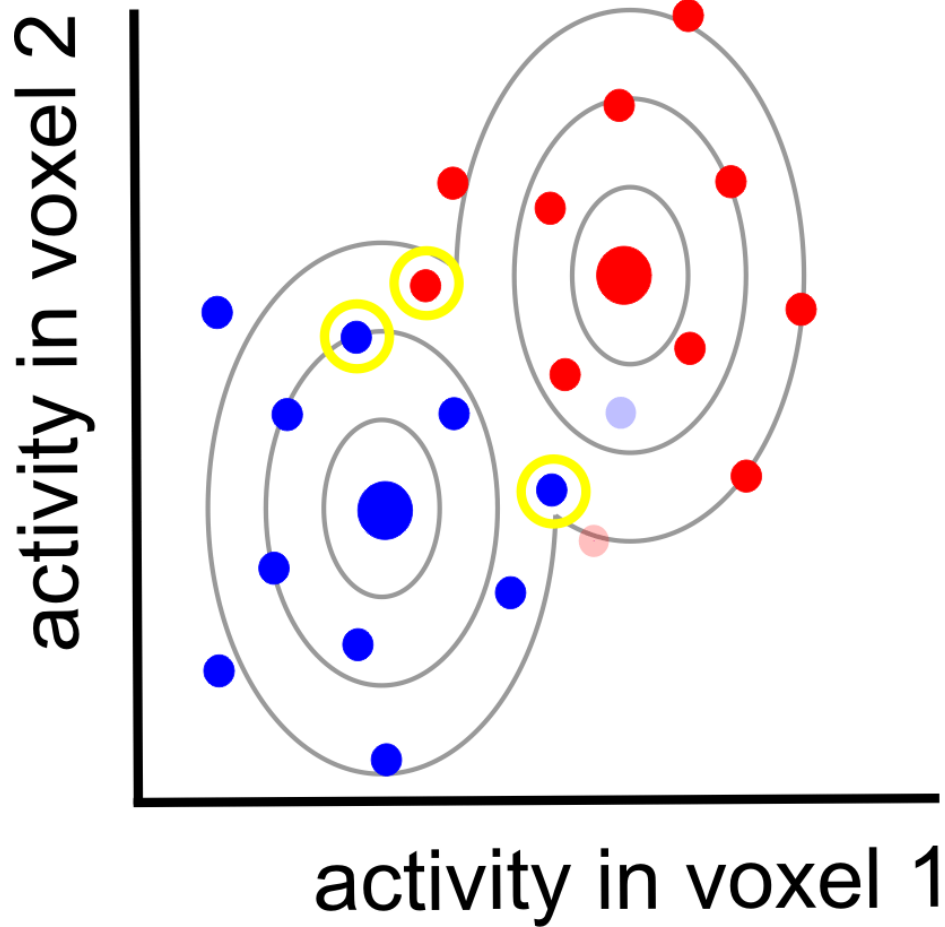
Linear classification: FLDA



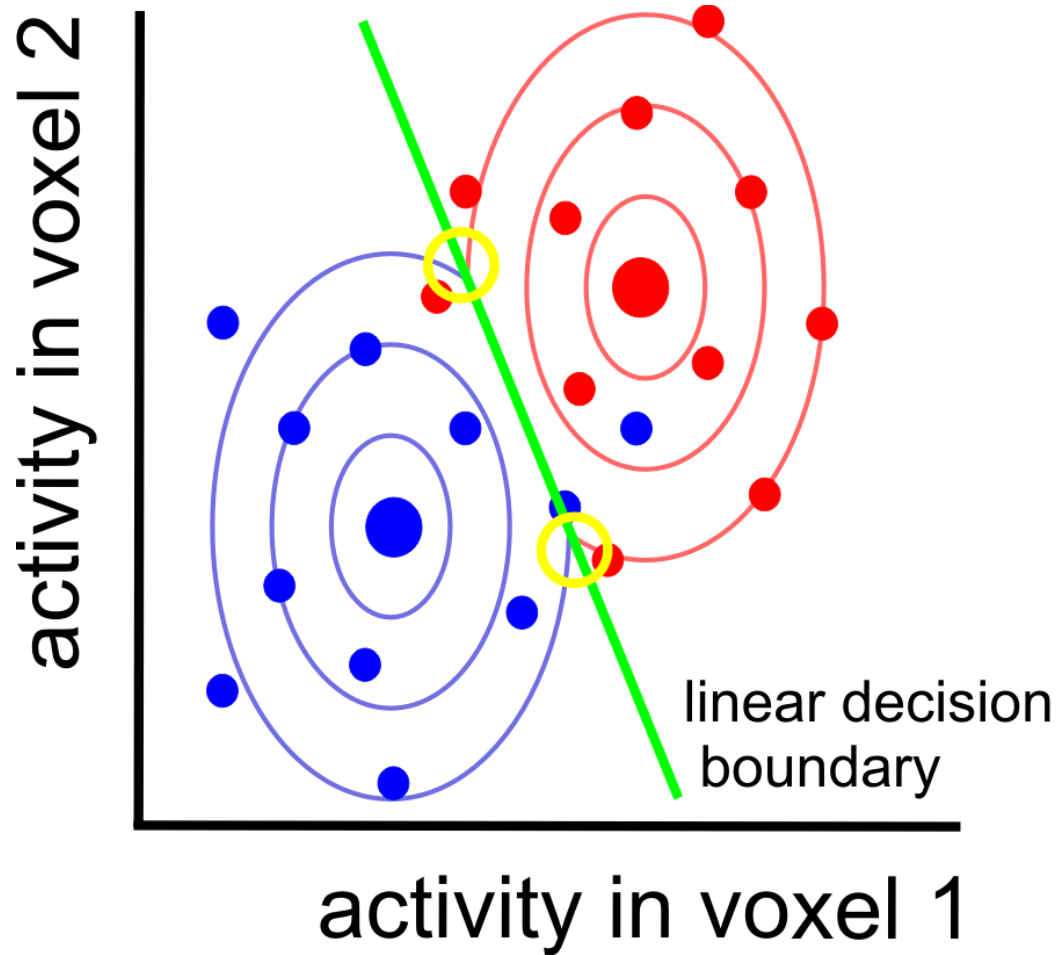
Linear classification: linear SVM



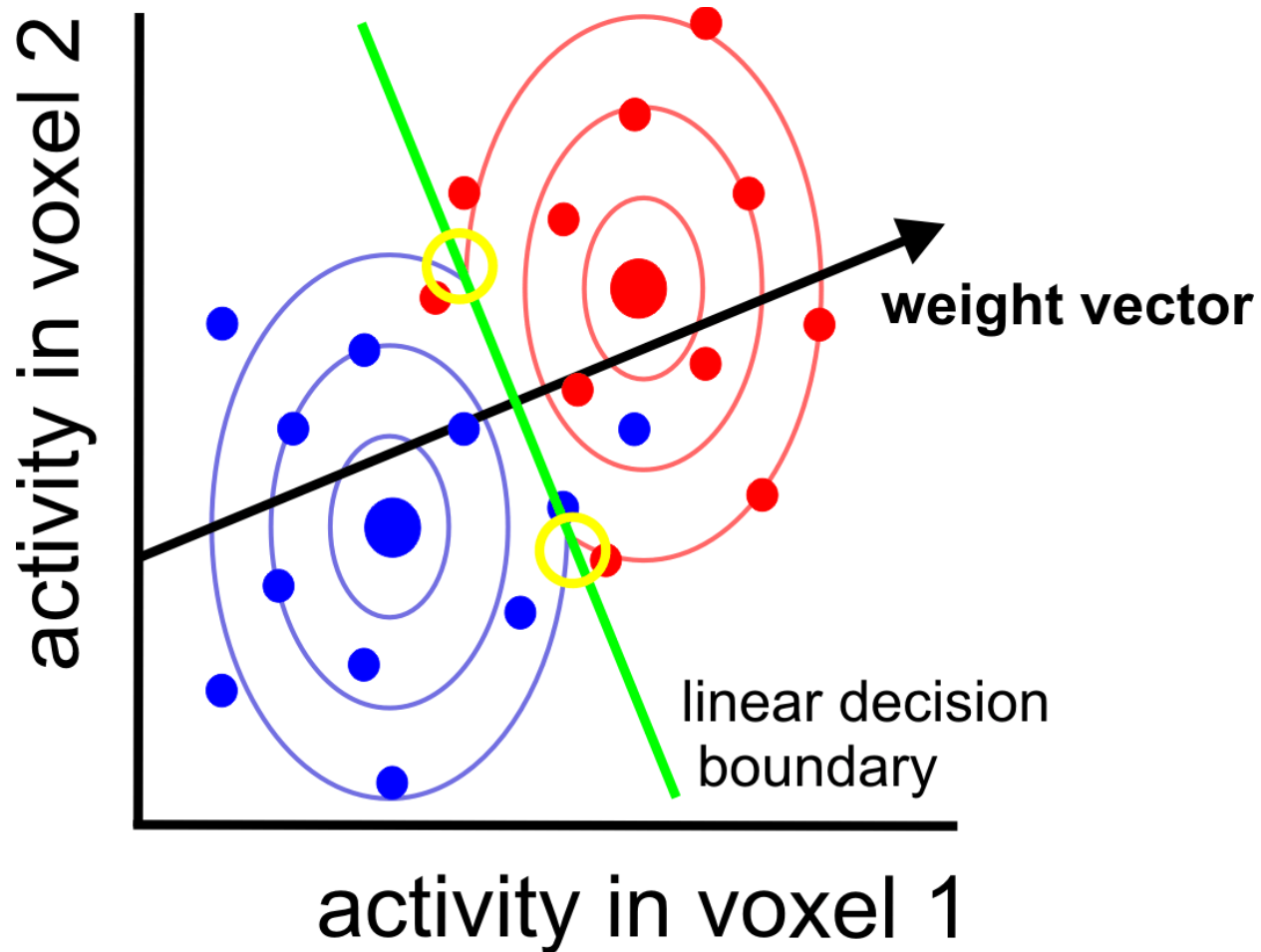
Linear classification: linear SVM



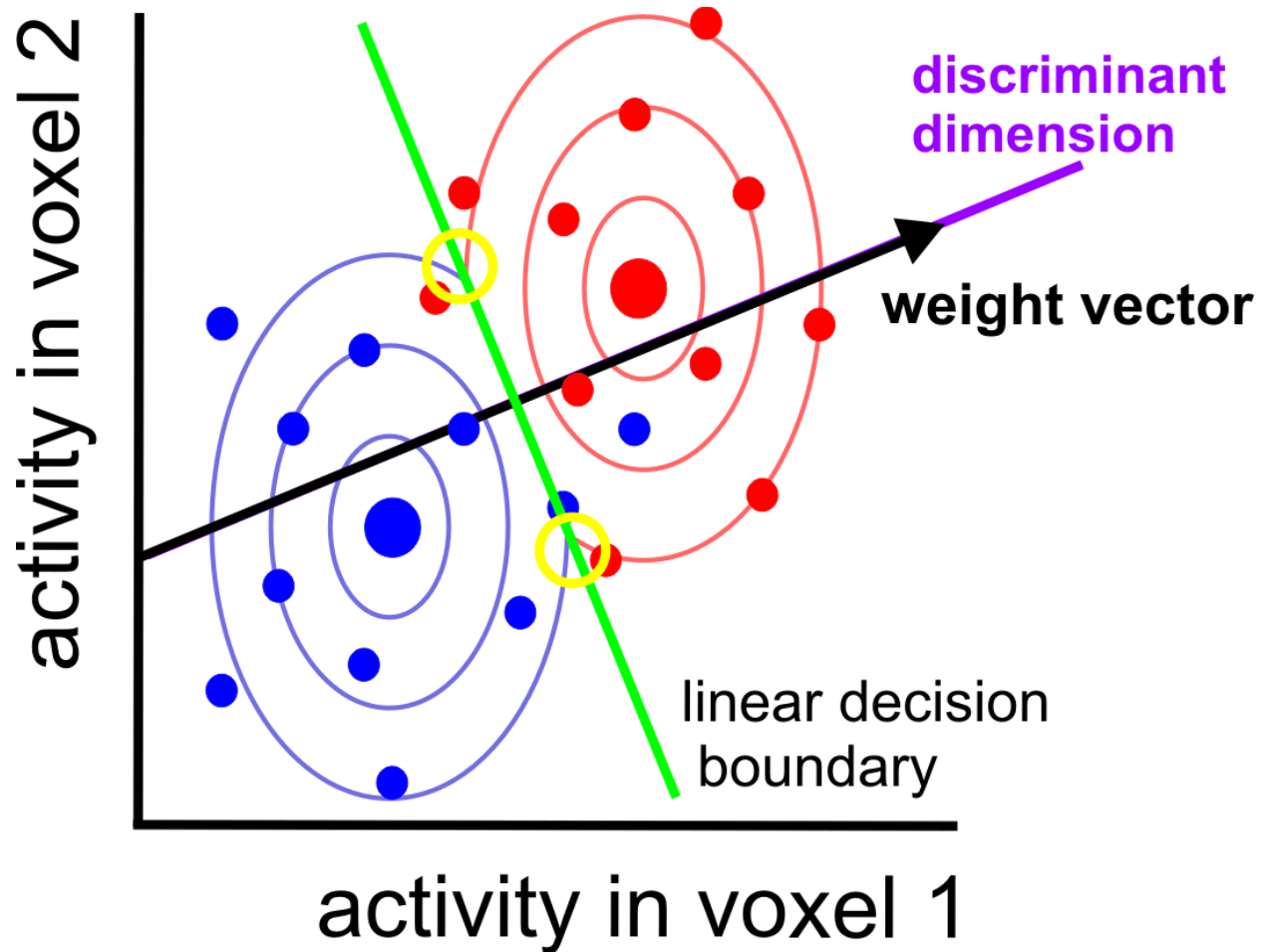
Boundary placement: some more detail



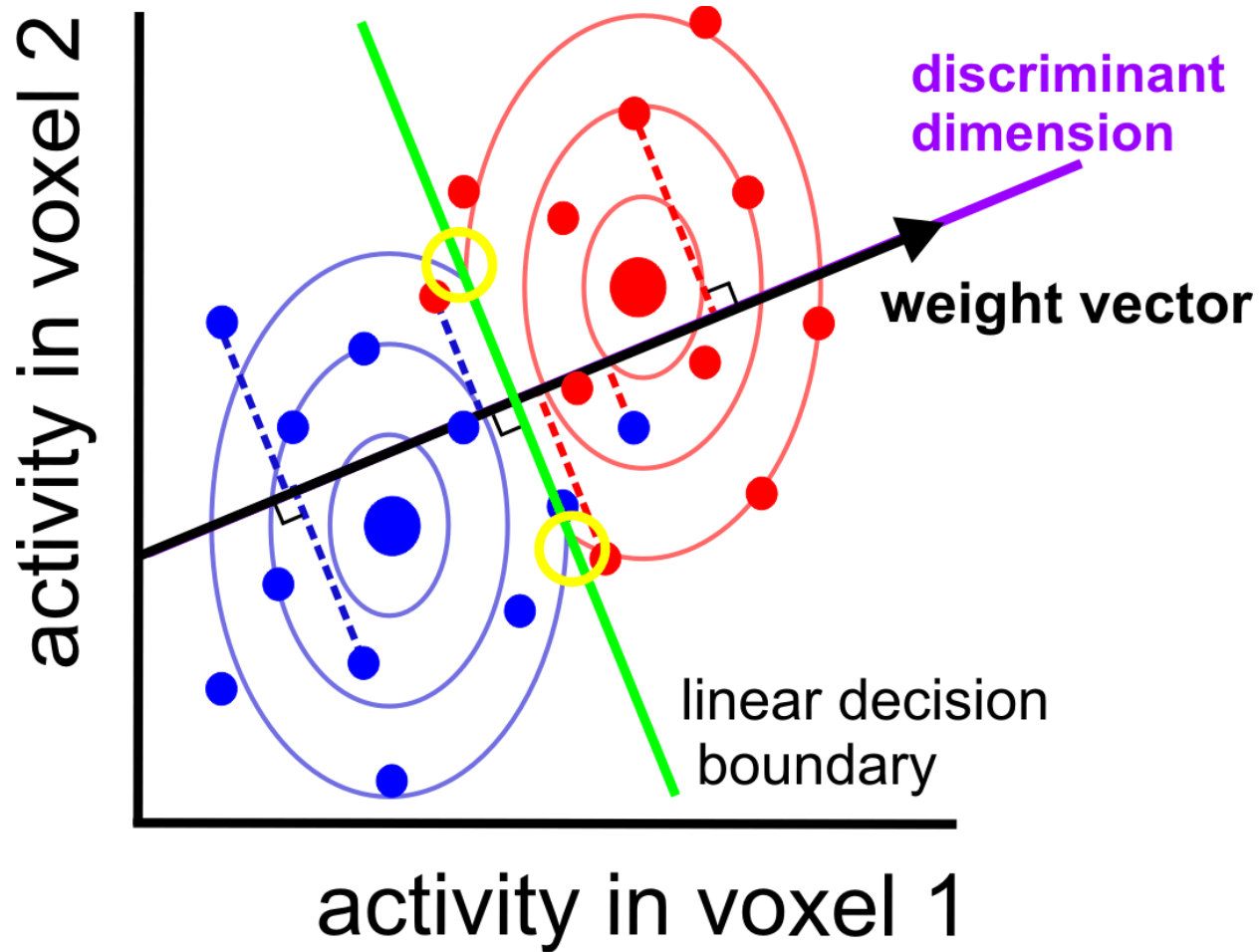
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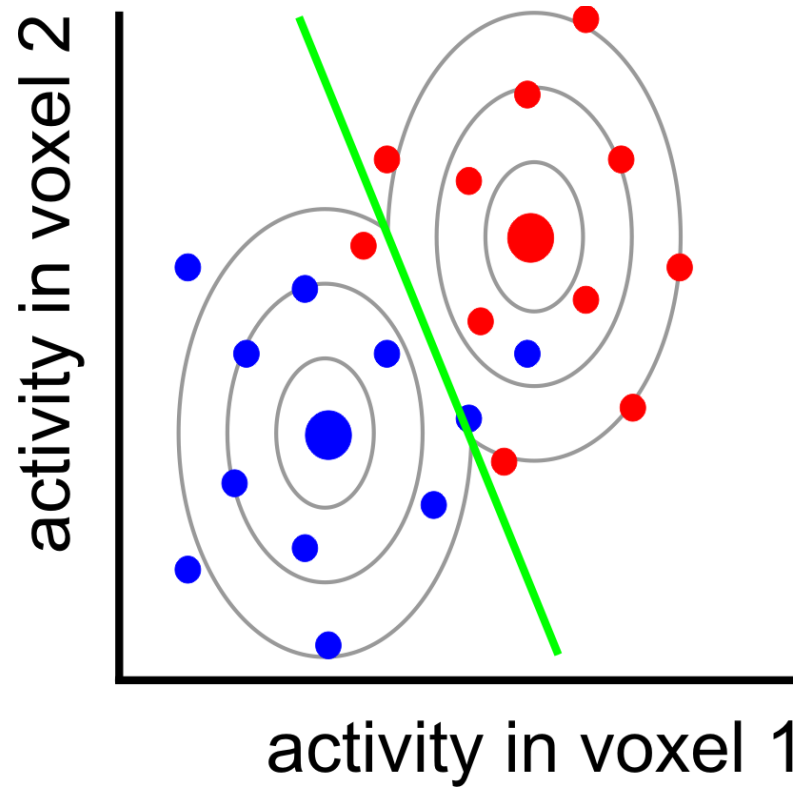
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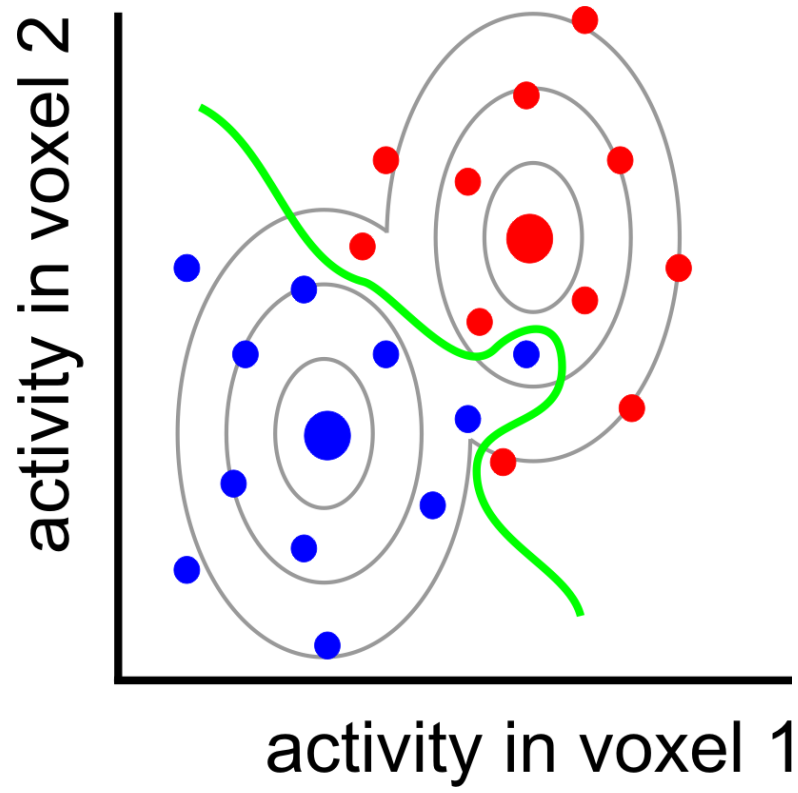


Boundary placement: some more detail



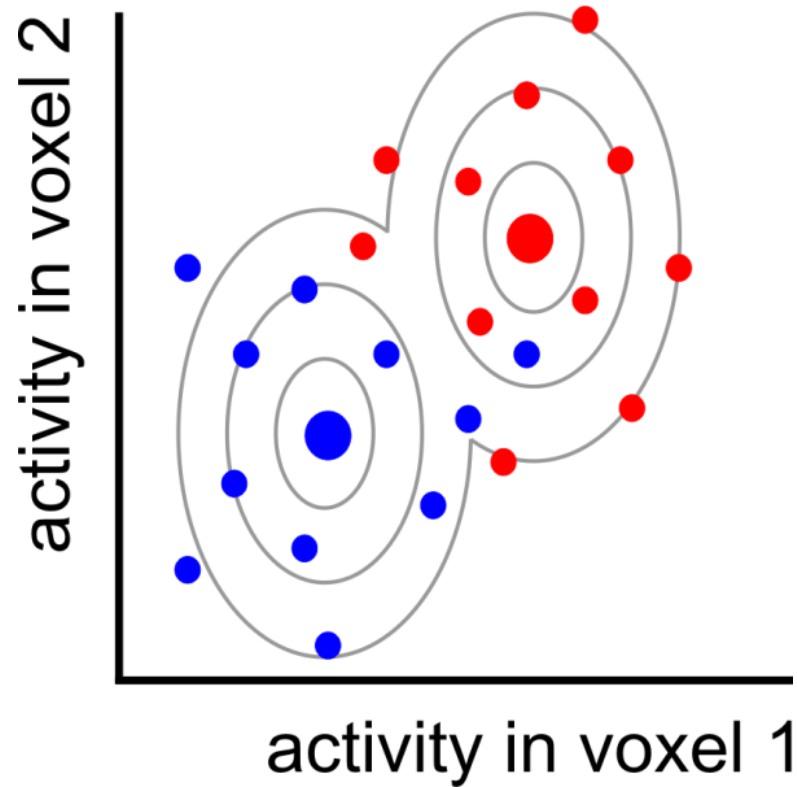
Can we do better?



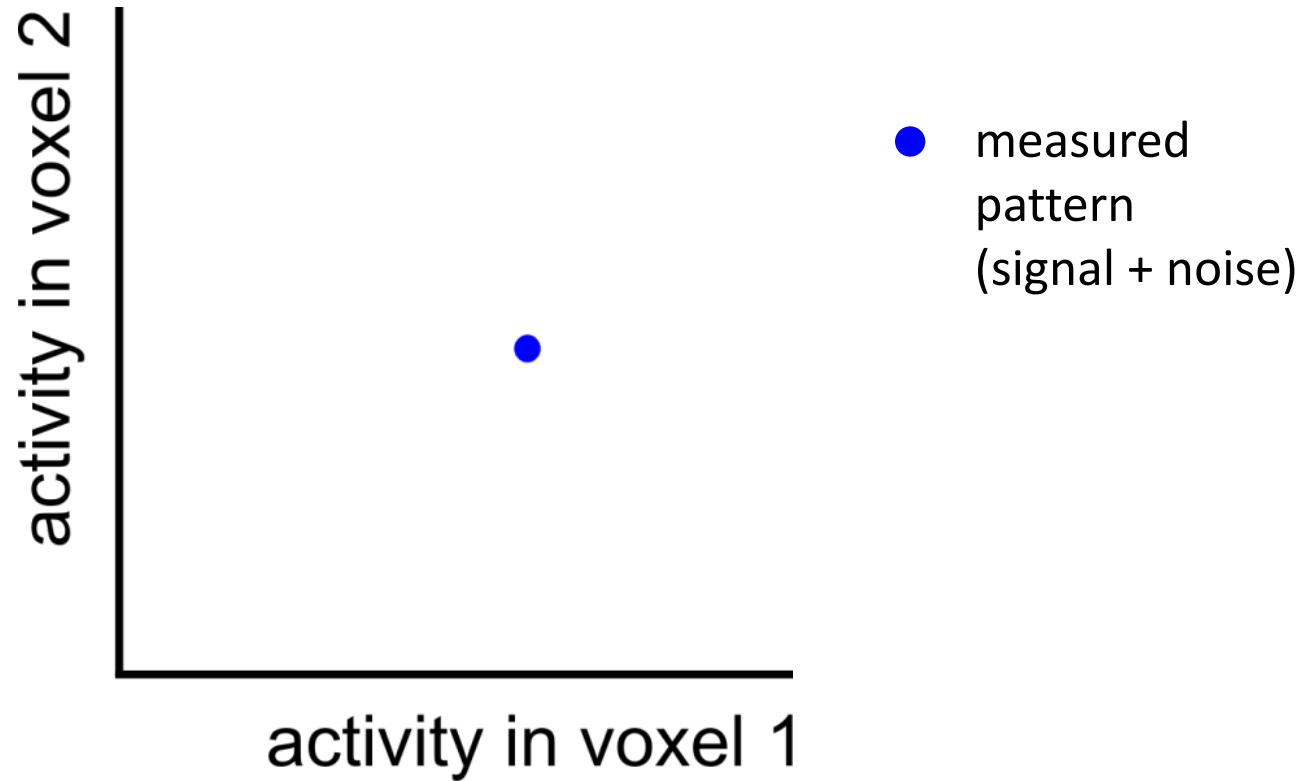


nonlinear
classifier

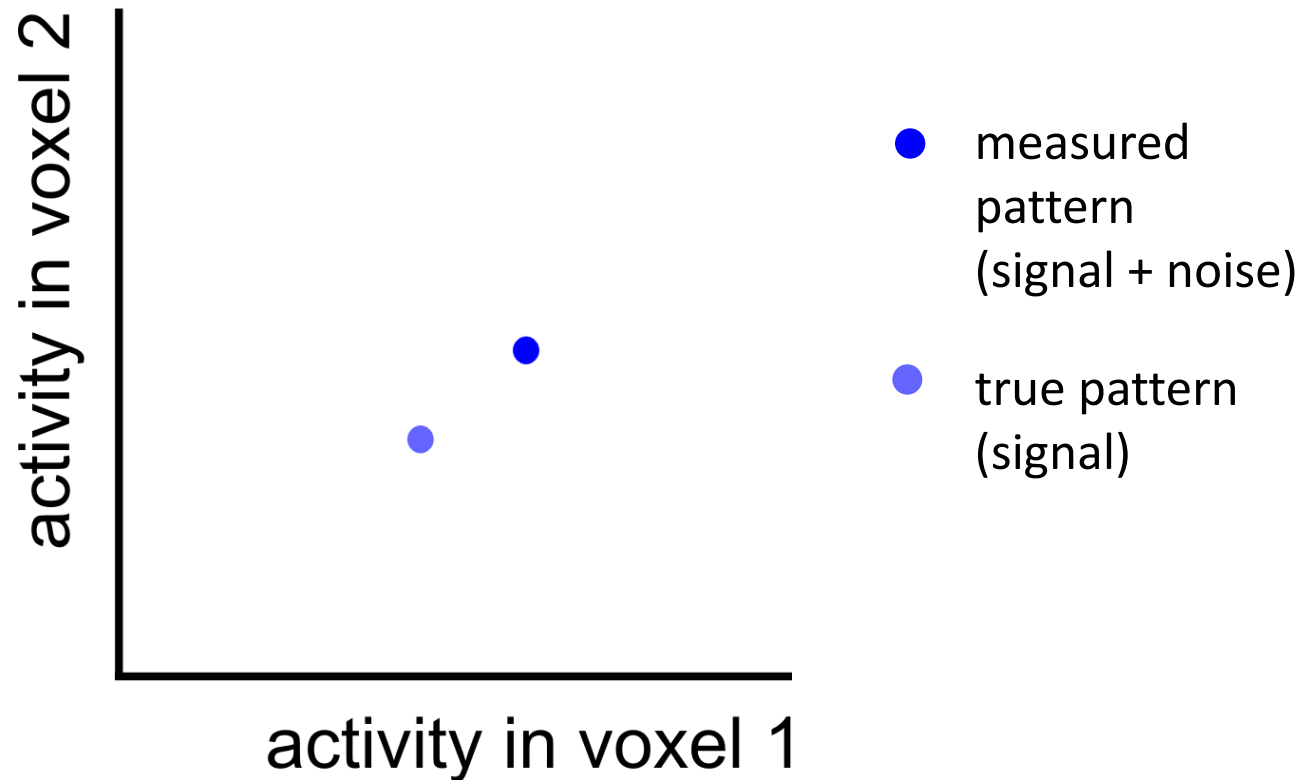
Pattern = signal + noise



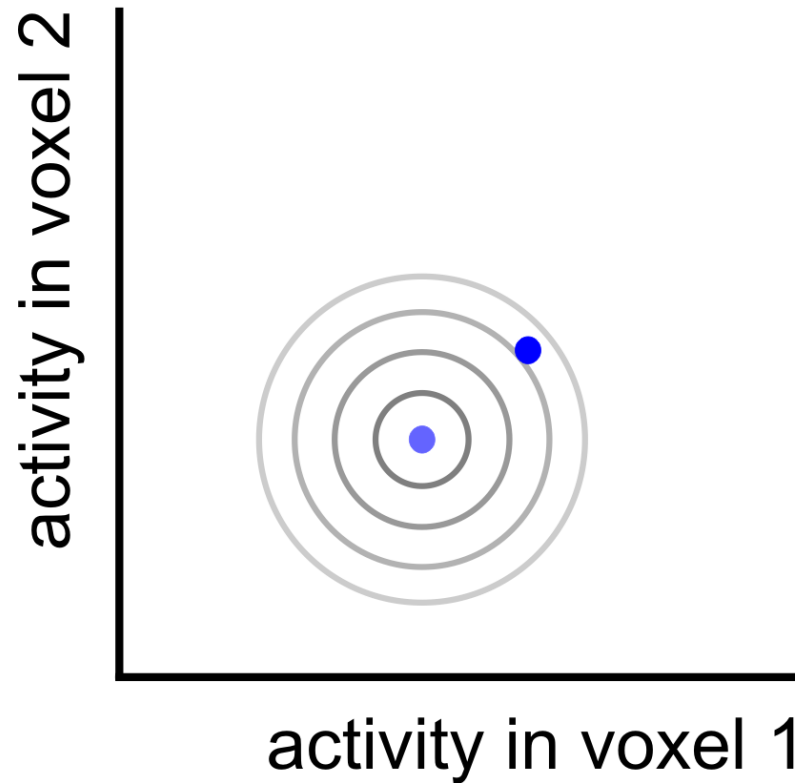
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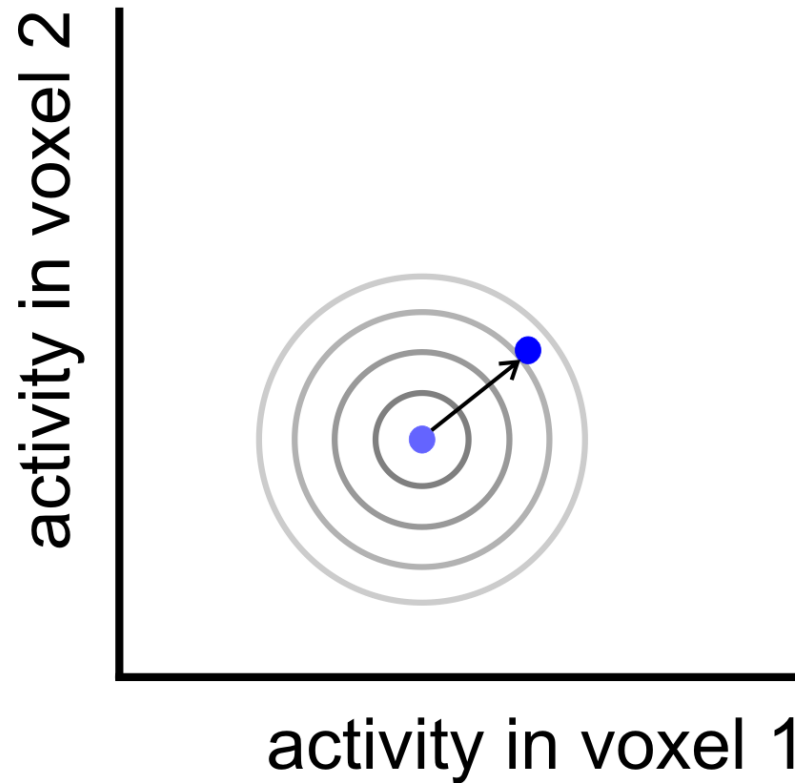


Pattern = signal + noise



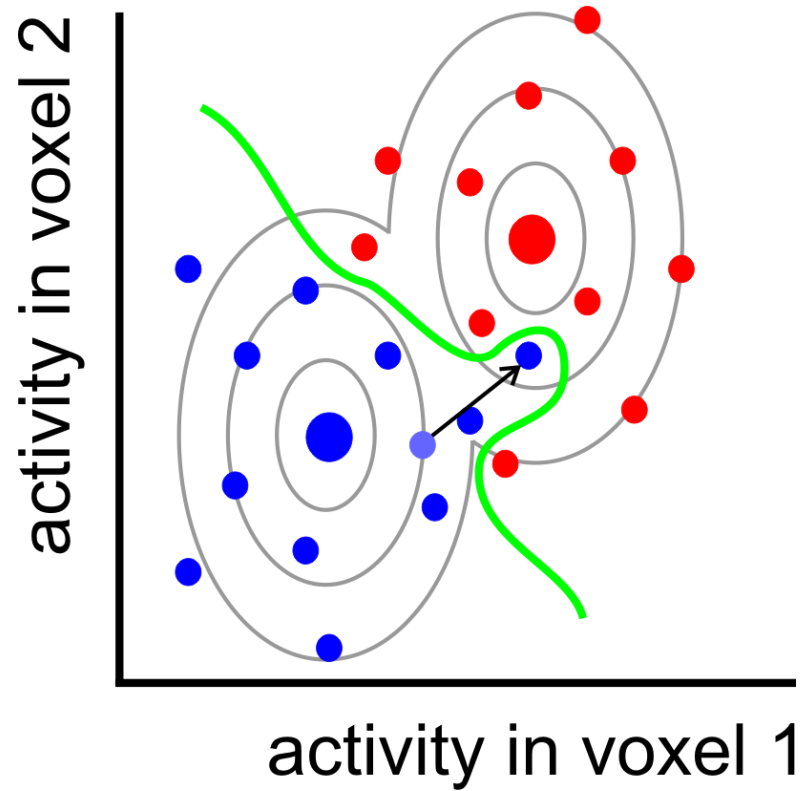
- measured pattern (signal + noise)
- true pattern (signal)

Pattern = signal + noise



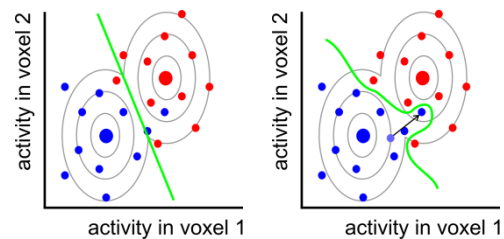
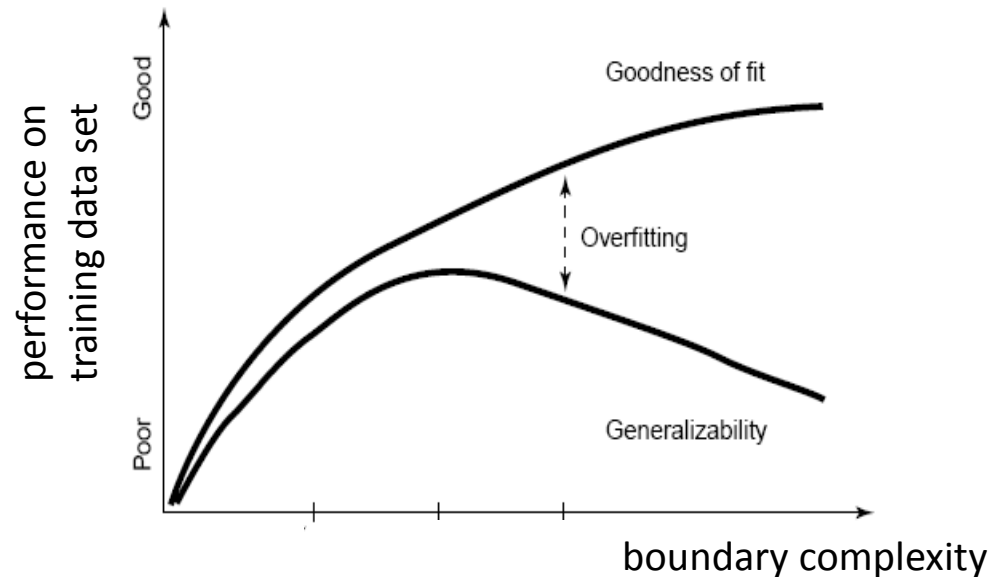
- measured pattern (signal + noise)
- true pattern (signal)
- ↗ noise displacement

Overfitting



Overfitting

After determining the decision boundary, we need to test how well the boundary generalises to new data (cross validation).



Overfitting

After determining the decision boundary, we need to test how well the boundary generalises to new data (cross validation).

Linear classifiers usually perform better on fMRI data than nonlinear classifiers.

Overfitting can be further reduced by:

- regularisation
- dimensionality reduction of the activity patterns (e.g. voxel selection)

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Step 1a: preprocess

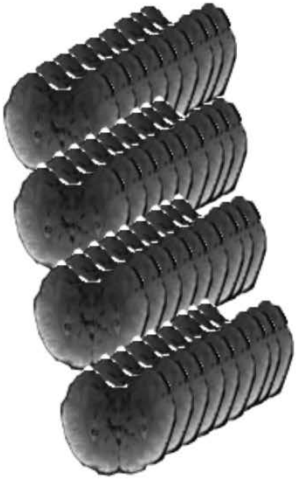
For each run:

- slice-scan-time correction
- motion-correction

Optional:

- normalisation to template (if random-effects searchlight analysis across subjects)
- spatial smoothing (to increase signal, sensitive to larger-scale spatial patterns)

Step 1b: split data



full data set



Make sure that training and test data are independent.

Do it yourself: six steps

Step 1: preprocess and split data

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Step 5: test the classifier

Step 6: statistical inference

Step 2: estimate single-subject activity

patterns

training data set

(e.g. runs 1-3)

data



t patterns
preferred over
beta patterns
(Misaki et al.
2010)

Do it yourself: six steps

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Step 3: select voxels

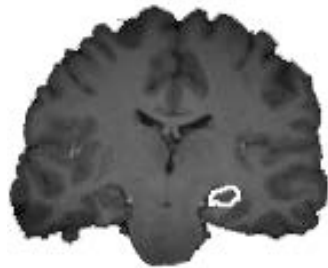
Make sure that voxel selection is based on data independent from test data set.

Most common ways of voxel selection:

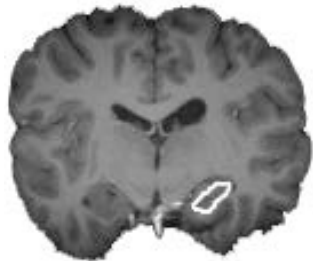
- structural selection (anatomy)
- functional selection (activity)
 - univariate (activation differences)
 - multivariate (pattern differences)

Step 3: select voxels

anatomy



subject 1



subject 2



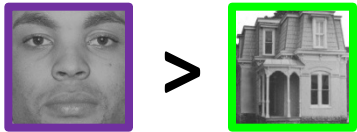
subject n

For example:
hippocampus

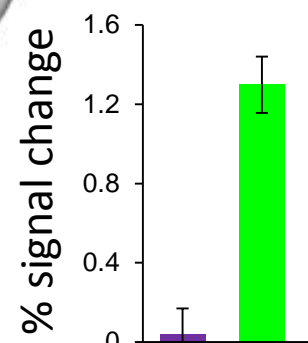
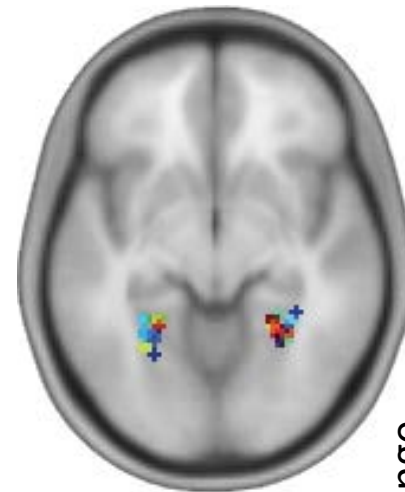
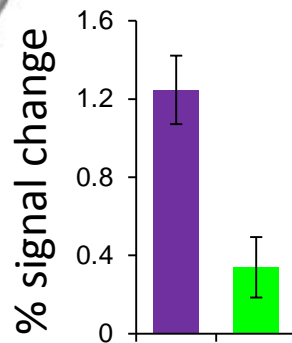
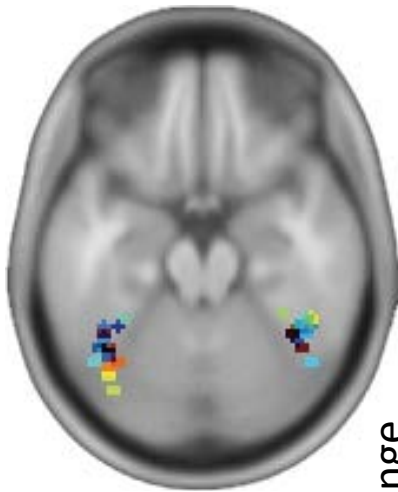
Step 3: select voxels

function (activation differences)

FFA

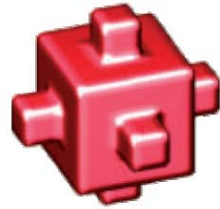


PPA



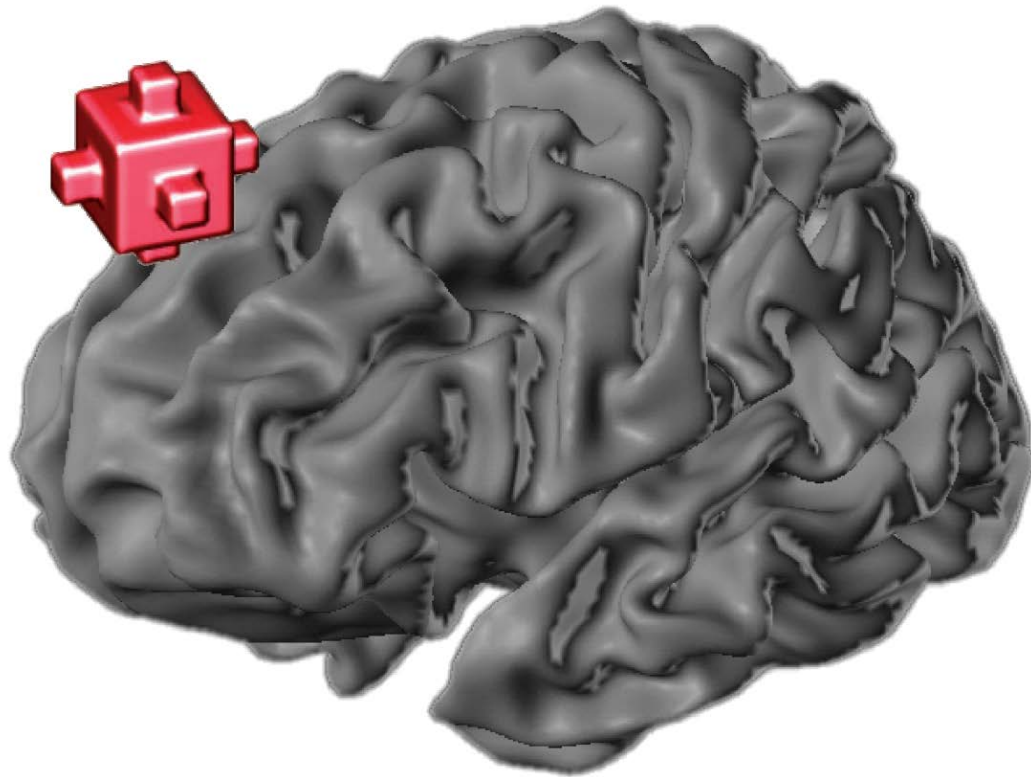
Step 3: select voxels

multivariate searchlight (pattern differences)



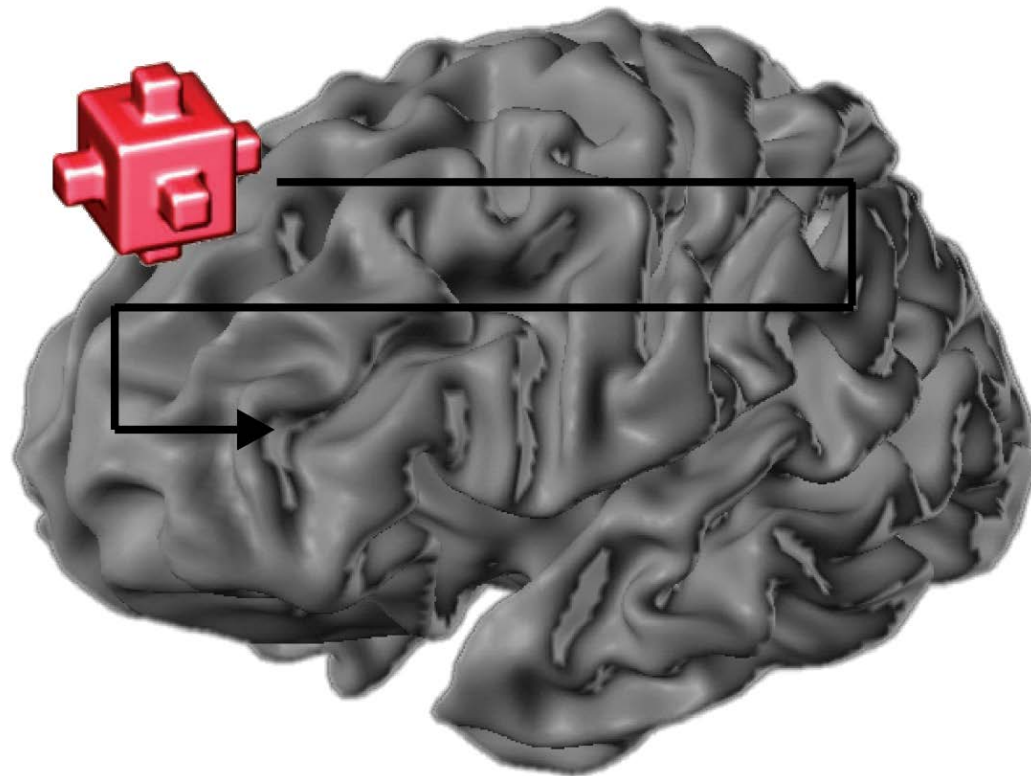
Step 3: select voxels

multivariate searchlight (pattern differences)



Step 3: select voxels

multivariate searchlight (pattern differences)



Step 3: select voxels

How many voxels?

Depends on the expected spatial extent of effects.

Find the right balance:

too few → risk of missing signal

too many → risk of overfitting (too noisy)

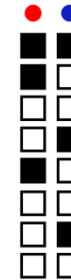
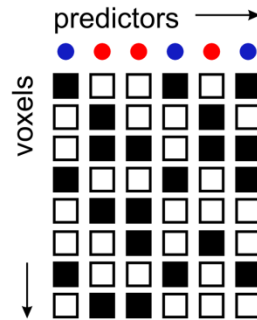
Common practice: select the same number of voxels in each subject, and for each region of interest.

Step 3: select voxels

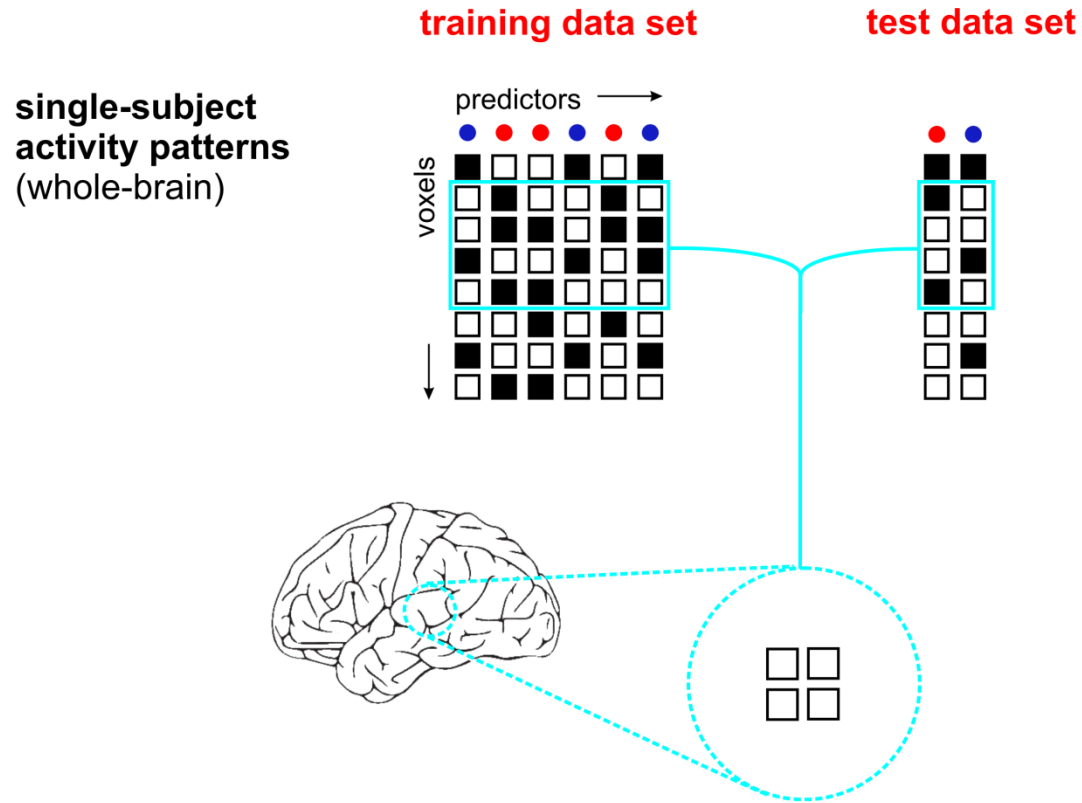
training data set

test data set

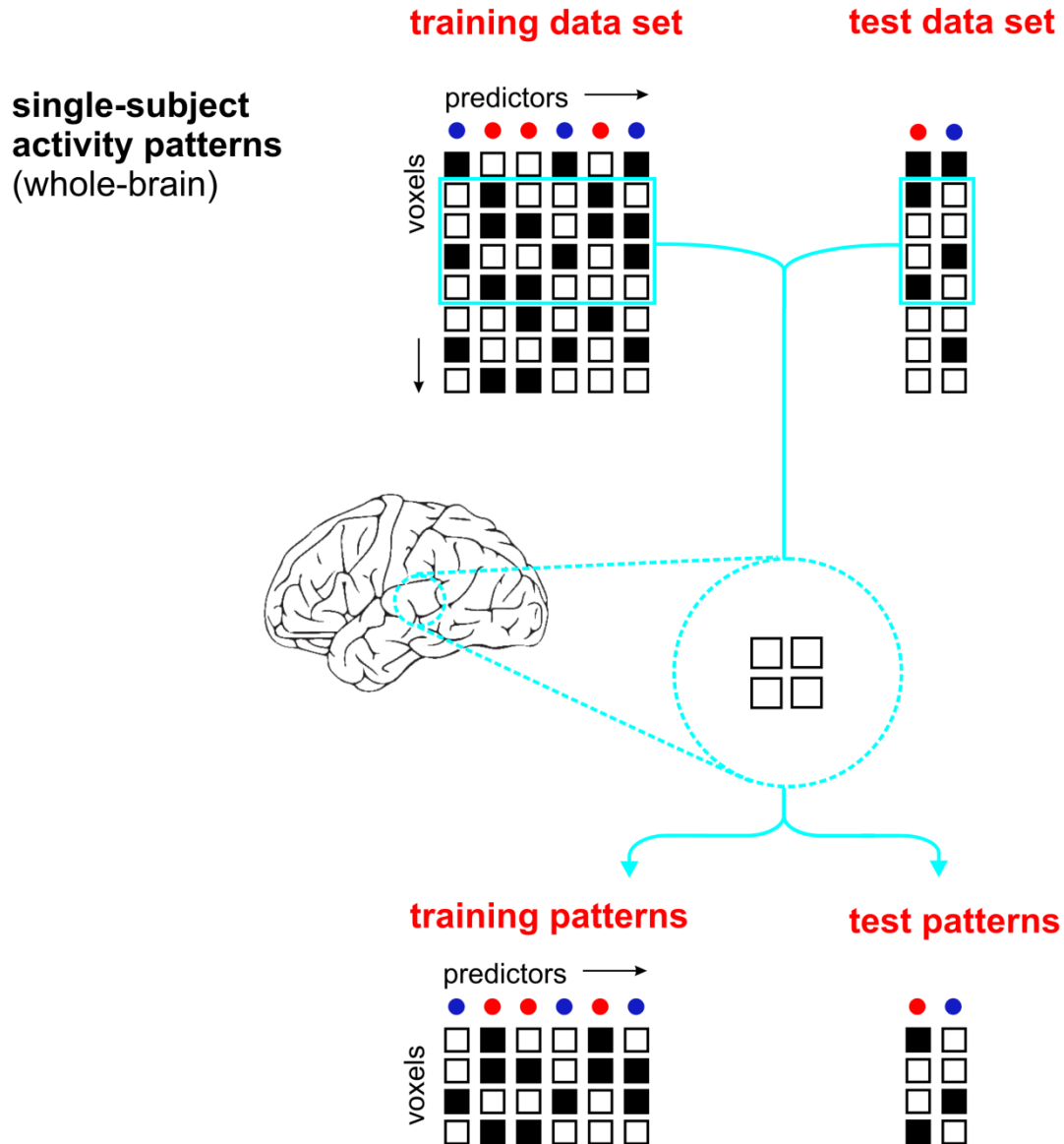
single-subject
activity patterns
(whole-brain)



Step 3: select voxels



Step 3: select voxels



Do it yourself: six steps

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Step 3: select voxels

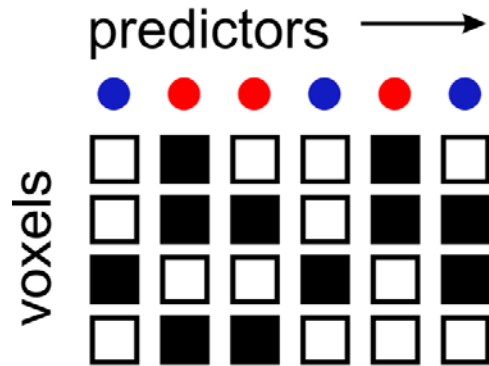
Step 4: train the classifier

Step 5: test the classifier

Step 6: statistical inference

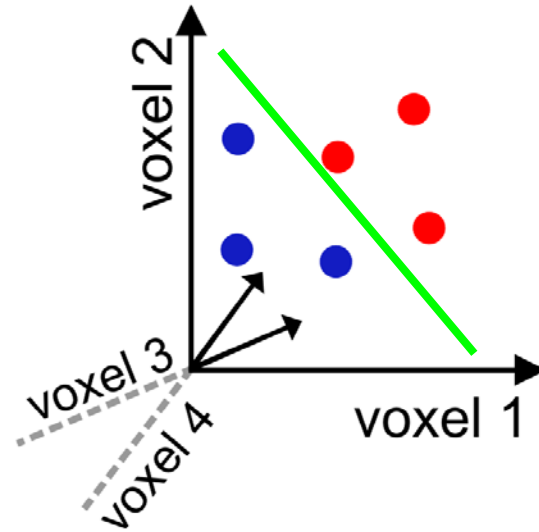
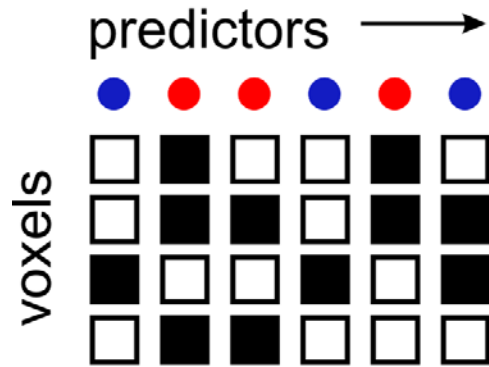
Step 4: train the classifier

training patterns



Step 4: train the classifier

training patterns



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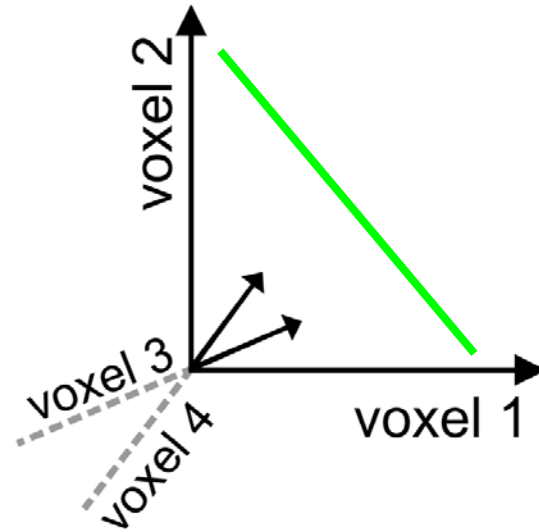
Step 3: select voxels

Step 4: train the classifier

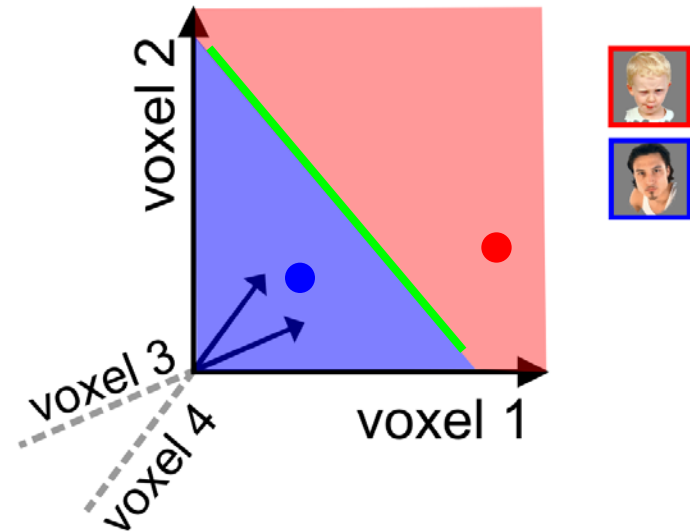
Step 5: test the classifier

Step 6: statistical inference

Step 5: test the classifier



Step 5: test the classifier



classification accuracy
for this fold = 100%

Cross-validation: generalise to....?

- different run (leave-run-out)
- different subject (leave-subject-out)
- different stimulus pair (leave-stimulus-pair-out)
- different block/trial within run (leave-block/trial-out)

Common procedure: use each run/subject etc as test data once.

For example: 4 runs → repeat cross validation 4 times (= 4-fold cross validation) → average accuracy across the 4 folds.

Do it yourself: six steps

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Step 6: statistical inference

Step 6: statistical inference

Dominant in the literature:

Random-effects analysis across subjects using a standard one-sample right-sided t test.

$$H_0: \mu = 50\%$$

$$H_a: \mu > 50\%$$

Step 6: statistical inference

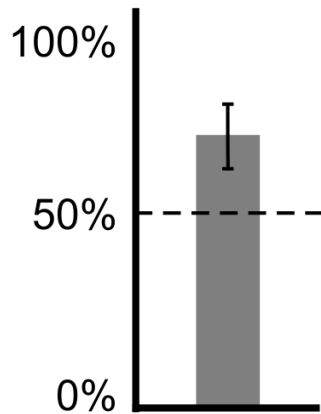
**single-subject
classification accuracy**

error bars
= standard error
across *folds*

error bar
= standard error
across *subjects*

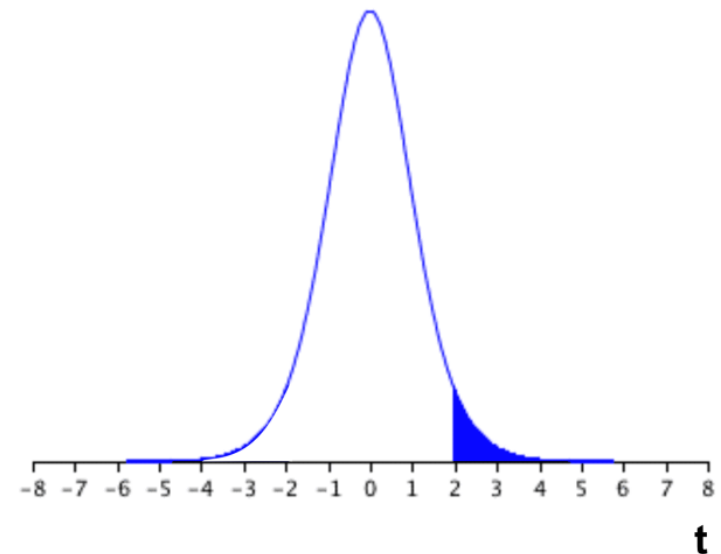
Step 6: statistical inference

subject-average
classification accuracy



$$t = \frac{\bar{x} - \mu_0}{s / \sqrt{n}}$$

student's t distribution



If the computed t value falls within
the top 5% (blue) of the t distribution
→ reject H_0 .

Step 6: statistical inference

However:

- can we always assume a t distribution?
- are we sure that the accuracy is 50% under H_0 ?

→ use a permutation test: create a null distribution by randomly shuffling the condition labels during training.

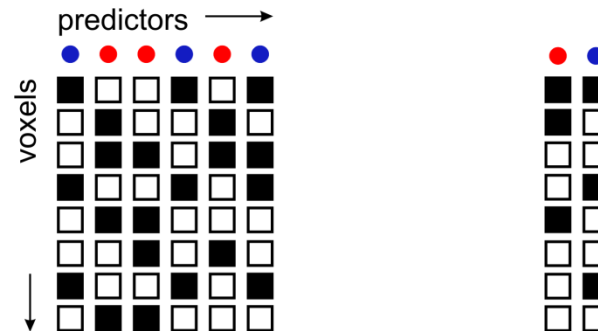
Generally used if number of subjects < 15 .

Step 6: statistical inference

training data set
(e.g. runs 1-3)

test data set
(e.g. run 4)

**single-subject
activity patterns**
(whole-brain)



Step 6: statistical inference

training data set

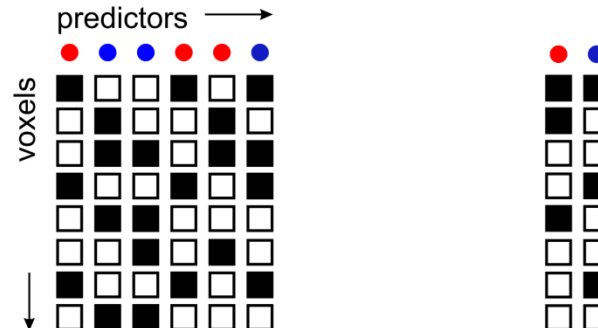
(e.g. runs 1-3)

test data set

(e.g. run 4)

Remove the
relationship
between conditions
and patterns.

**single-subject
activity patterns
(whole-brain)**



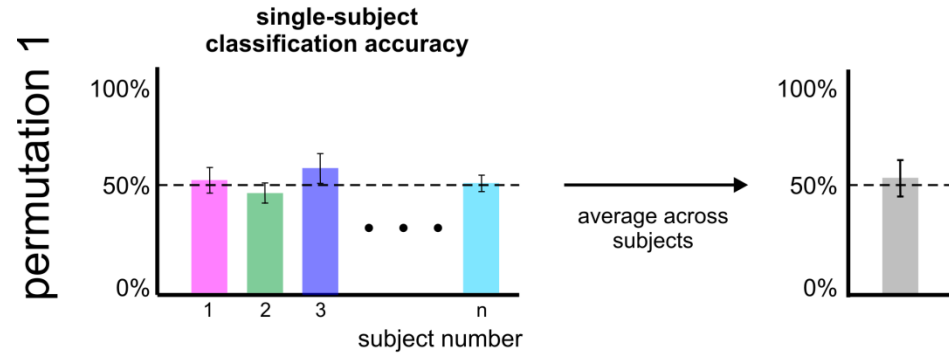
Step 6: statistical inference

Repeat step 4 & 5 after randomly reshuffling the condition labels.

- step 4: train the classifier
- step 5: test the classifier

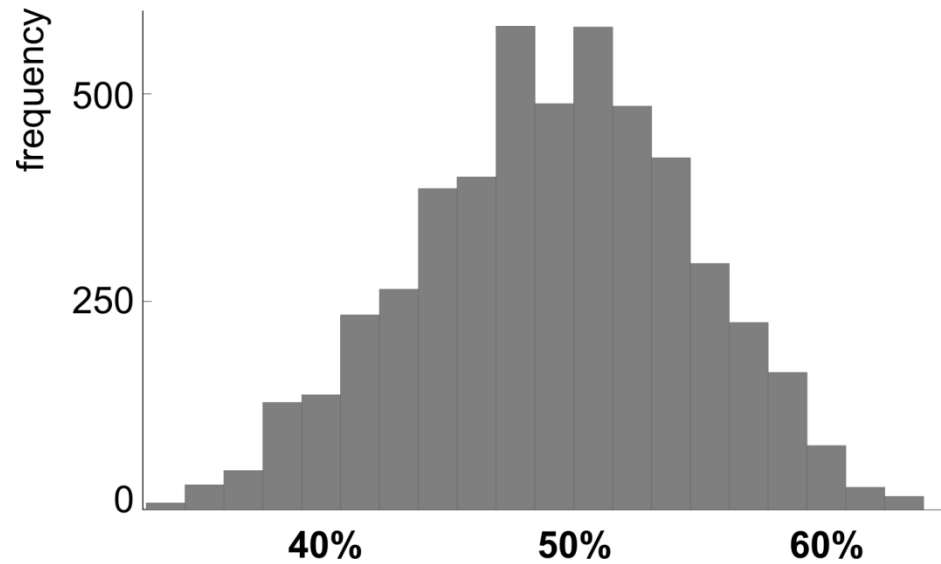
Do this many (e.g. 1000) times to create a null distribution.

Step 6: statistical inference

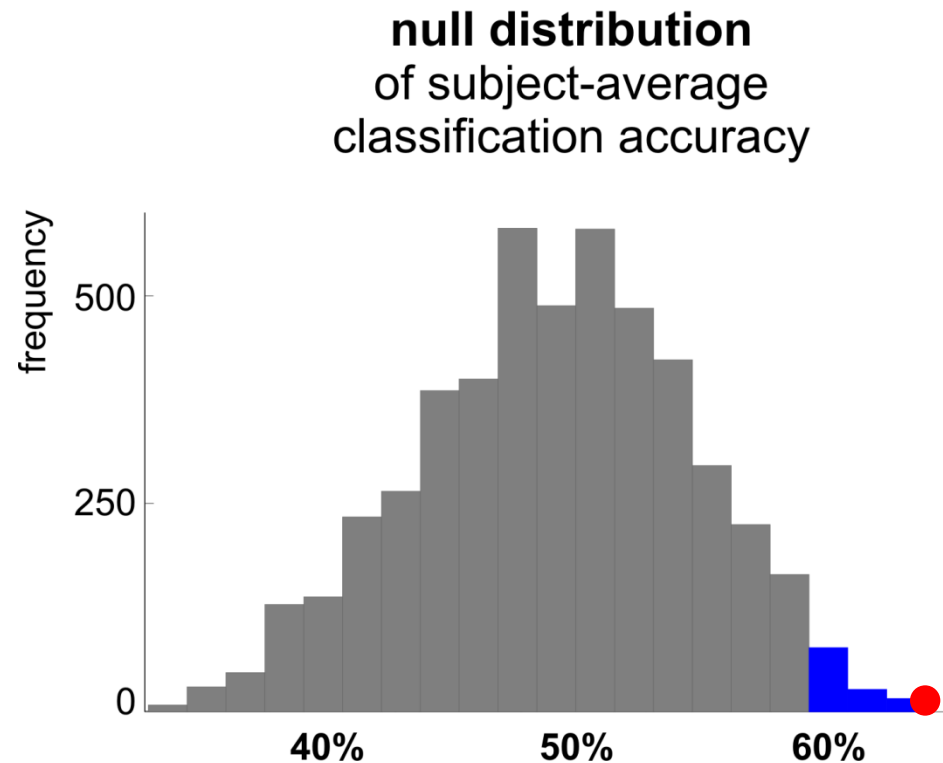


Step 6: statistical inference

null distribution
of subject-average
classification accuracy



Step 6: statistical inference

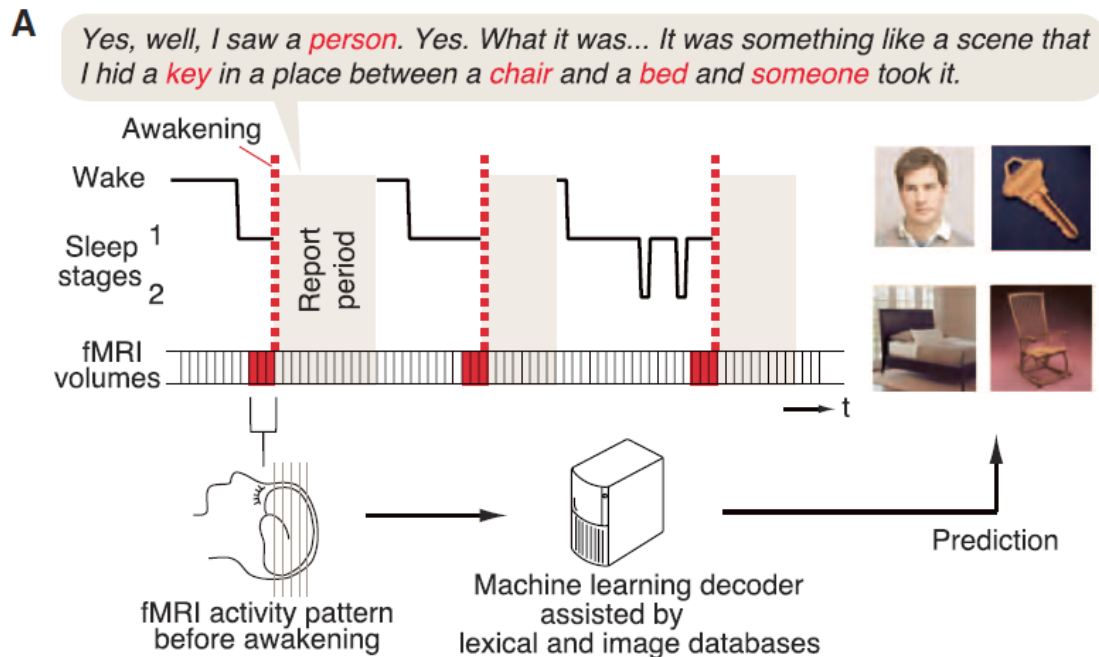


If the actual subject-average classification accuracy falls within the top 5% (blue) of the null distribution \rightarrow reject H_0 .

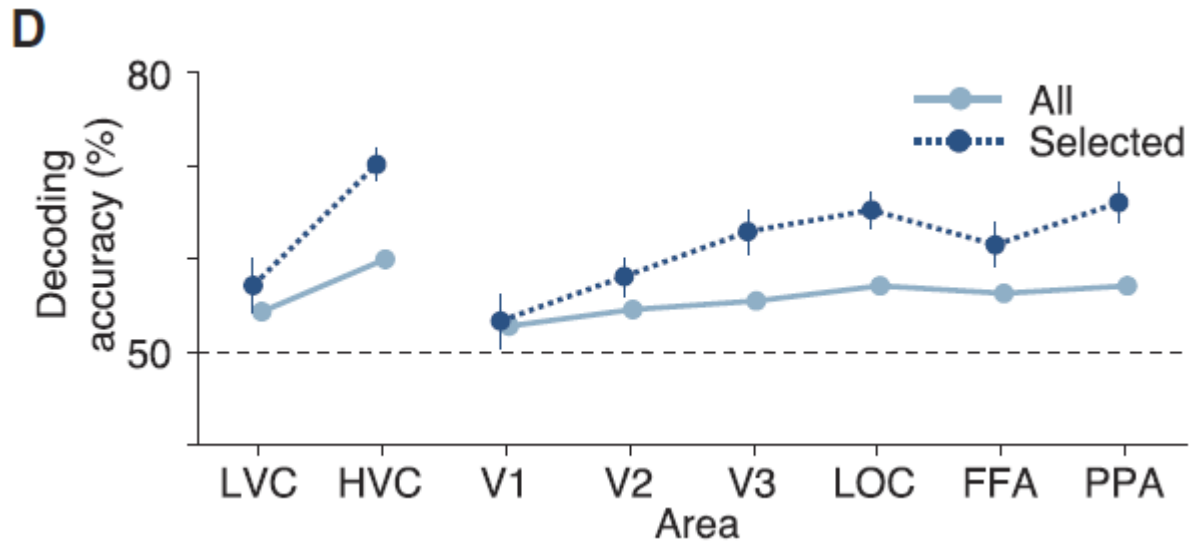
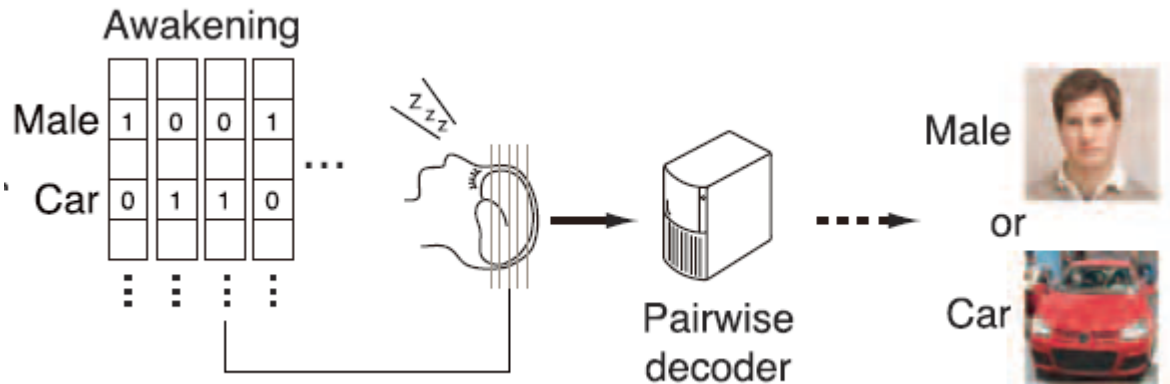
Applications: dream content

Neural Decoding of Visual Imagery During Sleep

T. Horikawa,^{1,2} M. Tamaki,^{1*} Y. Miyawaki,^{3,1†} Y. Kamitani^{1,2‡}



Applications: dream content



Overview

- Why classification analysis?
- Linear classification: the basic idea
- Linear classification: different classifiers
- Do it yourself: six steps
 - step 1: preprocess and split data
 - step 2: estimate single-subject activity patterns
 - step 3: select voxels
 - step 4: train the classifier
 - step 5: test the classifier
 - step 6: statistical inference
- **Toolboxes**
- Literature

Toolboxes

- PRoNTTo (SPM)

<http://www.mlnl.cs.ucl.ac.uk/pronto/>

- LIBSVM

<http://www.csie.ntu.edu.tw/~cjlin/libsvm/>

- PyMVPA

<http://www.pymvpa.org/>

- CoSMo MVPA

<http://cosmomvpa.org/>

Overview

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- **Literature**

Literature

Linear classification tutorials

Mur M et al. (2009) *Soc Cogn Affect Neurosci* 4: 101-109. [conceptual introduction]

Pereira F et al. (2009) *Neuroimage* 45(1 Suppl): S199-S209. [introduction]

Schreiber K, Krekelberg B (2013) *PLoS ONE* 8(7): e69328. [cautionary comments on statistical inference]

Kriegeskorte N et al. (2006) *PNAS* 103(10): 3863-3868. [multivariate searchlight]

Linear classification reviews

Norman KA et al. (2006) *Trends Cogn Sci* 10(9): 424-430.

Haynes JD, Rees G (2006) *Nat Rev Neurosci* 7: 523-534.

Linear classification: applications in neuroscience

Kamitani Y, Tong F (2005) *Nat Neurosci* 8(5): 679-685. [vision: classify orientations]

Formisano E et al. (2008) *Science* 322: 970-973. [voices: classify speakers & vowels]

Haynes JD et al. (2007) *Curr Biol* 17(4): 323-328. [cognitive control: task preparation]

Literature

Recursive feature elimination (RFE)

De Martino F et al. (2008) *Neuroimage* 43: 44-58.

Kernels

Jäkel F et al. (2009) *Trends Cogn Sci* 13: 381-388.

Which classifiers & preprocessing options are best?

Mourao-Miranda J et al. (2005) *Neuroimage* 28: 980-995. [SVM vs FLDA]

Kriegeskorte et al. (2009) *Nat Neurosci* 12(5): 535-540. [how to prevent selection bias]

Misaki M et al. (2010) *Neuroimage* 53: 103-118. [compares 6 different classifiers]

Garrido L et al. (2013) *Front Neurosci* 7(174): 1-4. [subtract the mean pattern?]

Relationships between classification (decoding), encoding, and RSA

Naselaris T et al. (2011) *Neuroimage* 56: 400-410.

Kriegeskorte N (2011) *Neuroimage* 56: 411-421.

PRACTICAL

Unique semantic space in the brain of each beholder predicts perceived similarity

Ian Charest^{a,1}, Rogier A. Kievit^a, Taylor W. Schmitz^a, Diana Deca^b, and Nikolaus Kriegeskorte^{a,1}



Set up your laptop

XX = laptop number

Log in

- Username: trainXXuser
- Password: *****

TurboVNCviewer



- Double-click on desktop shortcut
- VNCserver: loginXX:51
- Click connect

Set up your laptop

Matlab

- Right-click to open terminal
- Type `matlab_r2009a`, hit enter

- Set matlab current directory to `/imaging/trainXXlinux/Workshop/Material`
- Open `rsa_tutorial.m`

Do it yourself: six steps

Step 1: preprocess and split data

Step 2: estimate single-subject activity patterns

Step 3: select voxels

Step 4: train the classifier

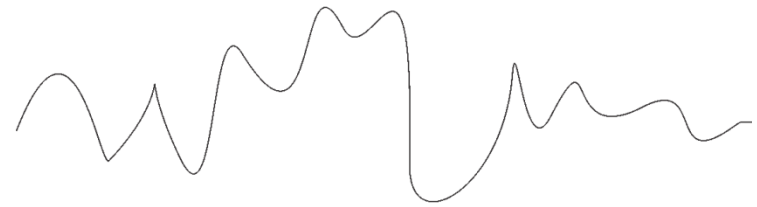
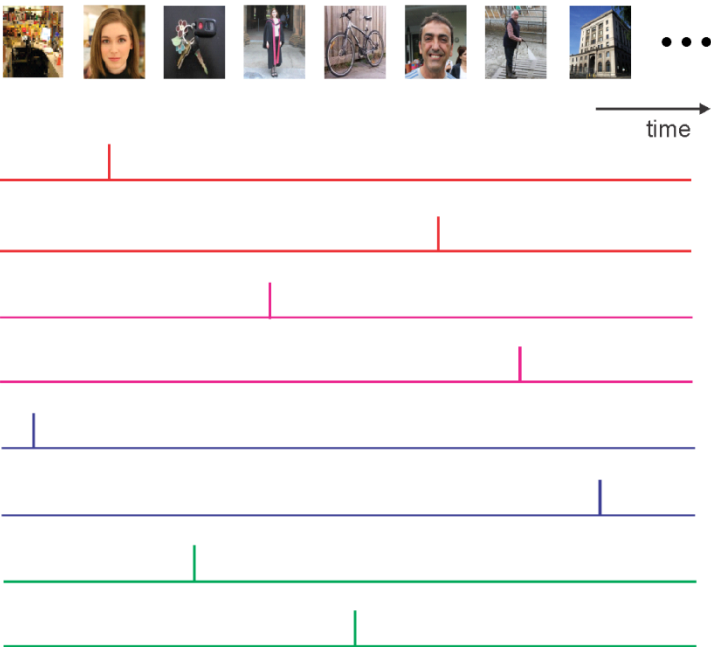
Step 5: test the classifier

Step 6: statistical inference

General linear model (GLM)



General linear model (GLM)



Do it yourself: six steps

Step 1: preprocess and split data

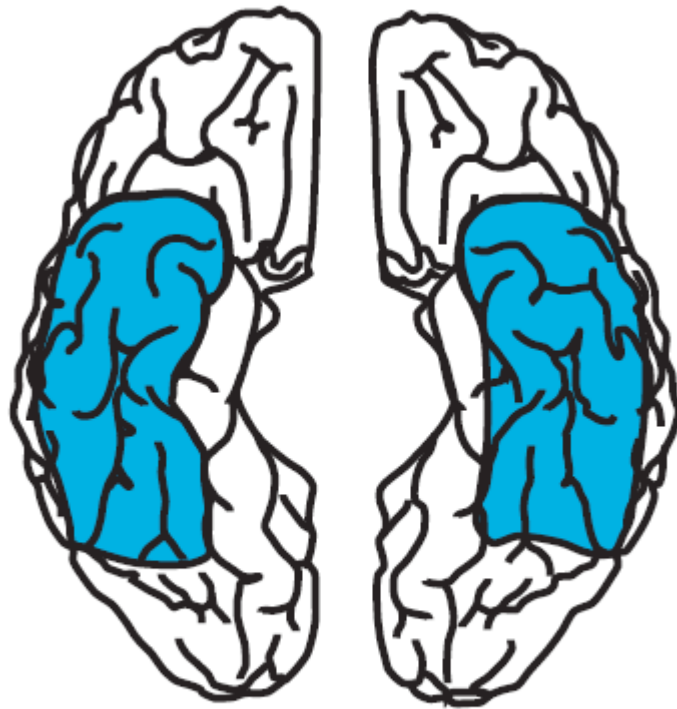
Step 2: estimate single-subject activity patterns

Step 3: select voxels

Step 4: train the classifier

Step 5: test the classifier

Step 6: statistical inference



hIT

Do it yourself: six steps

Step 1: preprocess and split data

Step 2: estimate single-subject activity patterns

Step 3: select voxels

Step 4: train the classifier

Step 5: test the classifier

Step 6: statistical inference

Parameters:

nu-SVM

linear SVM

Leave-session-out cross-validation:

(1) Train on session 1, test on session 2

(2) Train on session 2, test on session 1

Do it yourself: six steps

Step 1: preprocess and split data

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Step 4: train the classifier

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