Introduction into fMRI analysis. PsyMsc4 (Goethe 2021).

Session 1.

Multivariate analysis.

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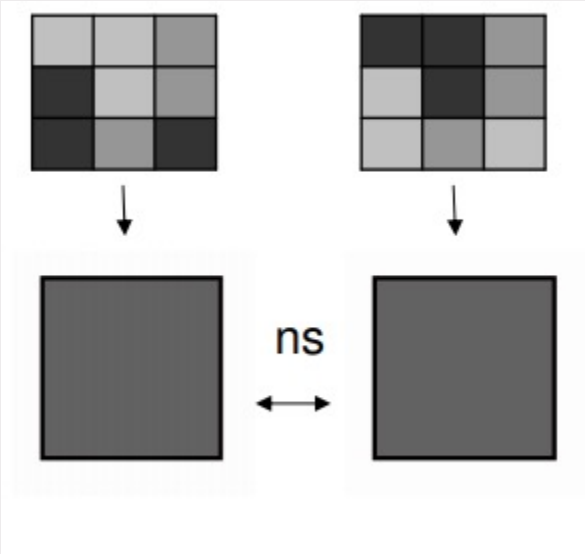
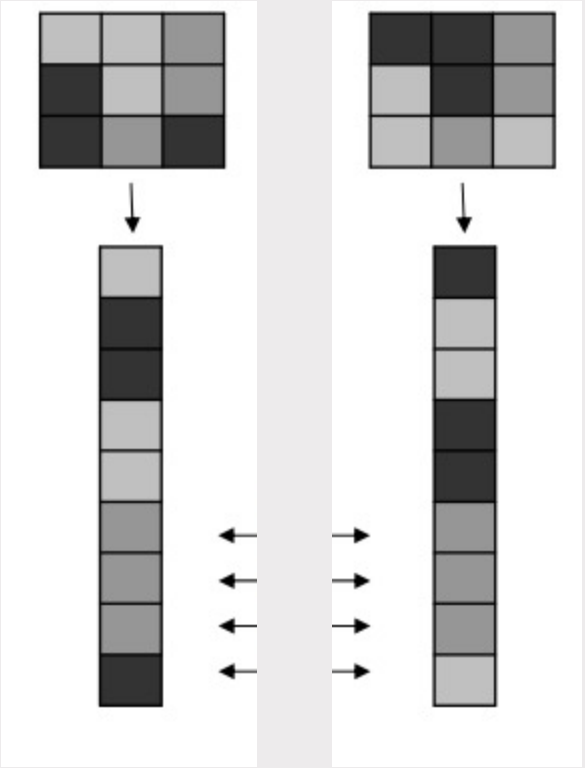
Multivariate in fMRI. Why?

Univariate:



Multivariate:



Multivariate in fMRI. What for?

Fine grained localization: *where in the brain it is possible to distinguish between class A and class B?* (e.g., stimulus categories? Stimulus identity?).

Representational content: what type of information is represented? (e.g., low level features vs. Categorical information? Detailed vs. Coarse representations?

Temporal dynamics: From and until when is a given type of information available? (note: BOLD signal might not be the best measure for small time scales).

Multivariate in fMRI. Two umbrella approaches.

Classification.

Representational Similarity Analysis.

Classification in fMRI. Key concepts.

Classifying: *Predict the type (i.e., class) of pattern that underlies a given dataset.*

Decoding: *From a given (brain) signal, figure out what caused the signal.*

MVPA (multivoxel/multivariate pattern analysis): *Collection of analyses that use several sources of variance in the data to study it*.

Class: *Each "pattern" that we want find (we need at least two).*

Observations: *Each one of the items inside a class that we will use in our analysis.*

Features: *Each element inside an observation.*

Introduction to machine learning classifiers.

```
%% Practical example (human learning)
% If you see the following data sets that correspond to two conditions or classes,
% 1 and 2, can you see a pattern that distinguishes them?
array1 = [51; 53; 55; 57; 59; 61; 63; 65];
array2 = [32; 34; 36; 38; 40; 42; 44; 46];
labels1 = [1; 1; 1; 1; 1; 1; 1; 1];
labels2 = [2; 2; 2; 2; 2; 2; 2; 2];

% What is the best way of knowing whether you learn the pattern or not? Test your self:
test_observation(1)=34;

% Is test_observation a member of 1 or 2? Replace the "[]" with your answer.
your_prediction(1)=[];
```

Introduction to machine learning classifiers.

```
%% Can machines do that?
% Put all of the 'training' observations together
train_data=[array1; array2];
train_labels=[labels1;labels2];

% Train the model
model = fitcsvm(train_data, train_labels);

% Test its knowledge
model_prediction=predict(model, test_observation)
sprintf('The model thinks the observation "%d" belongs to class %d', ...
    test_observation(1), model_prediction)

% Compute performance
acc=model_prediction==test_label;
```

It very likely that the classifier agrees with your prediction. Do you know which pattern has it learned?

Introduction to machine learning classifiers.

Validation is the process of using fine tuned tests to discover the pattern that the algorithm as learned.

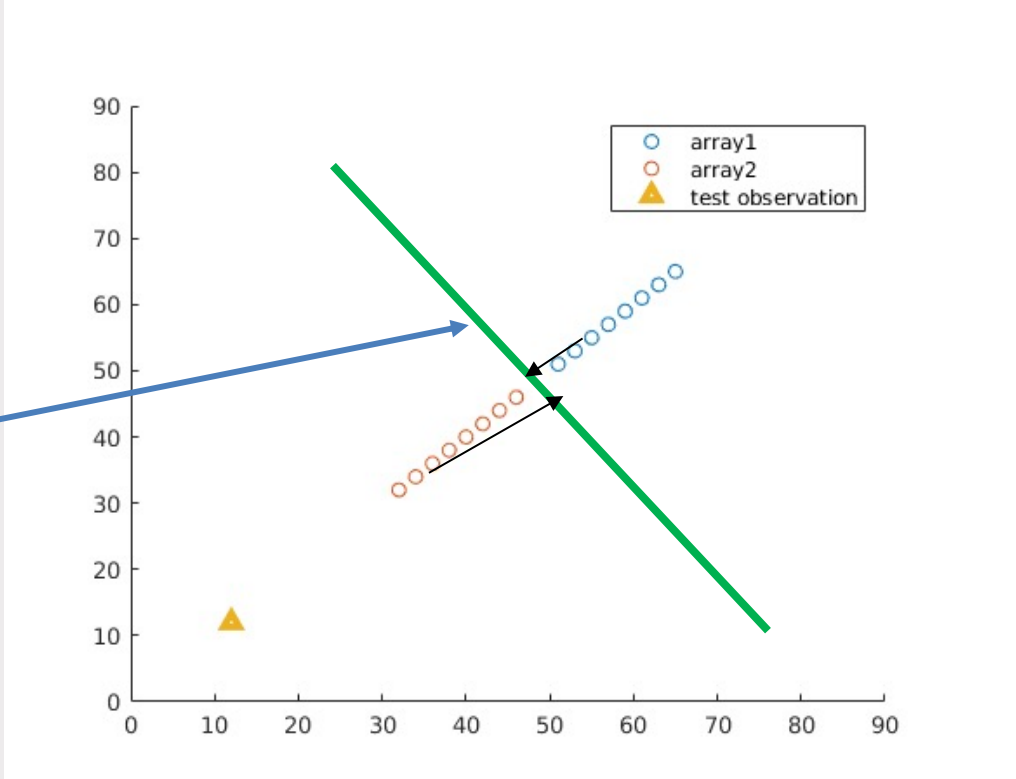
Let's do an exercise on independent validation.

```
%% Validation
% There is yet a better (more restrictive) way of assessing learning:
% Test on observations that are different from the study sets.
test_observation(2)=12;
test_label(2)=2;

% Is test_observation a member of 1 or 2? Replace the "[]" with your answer
your_prediction(2)=[];
```

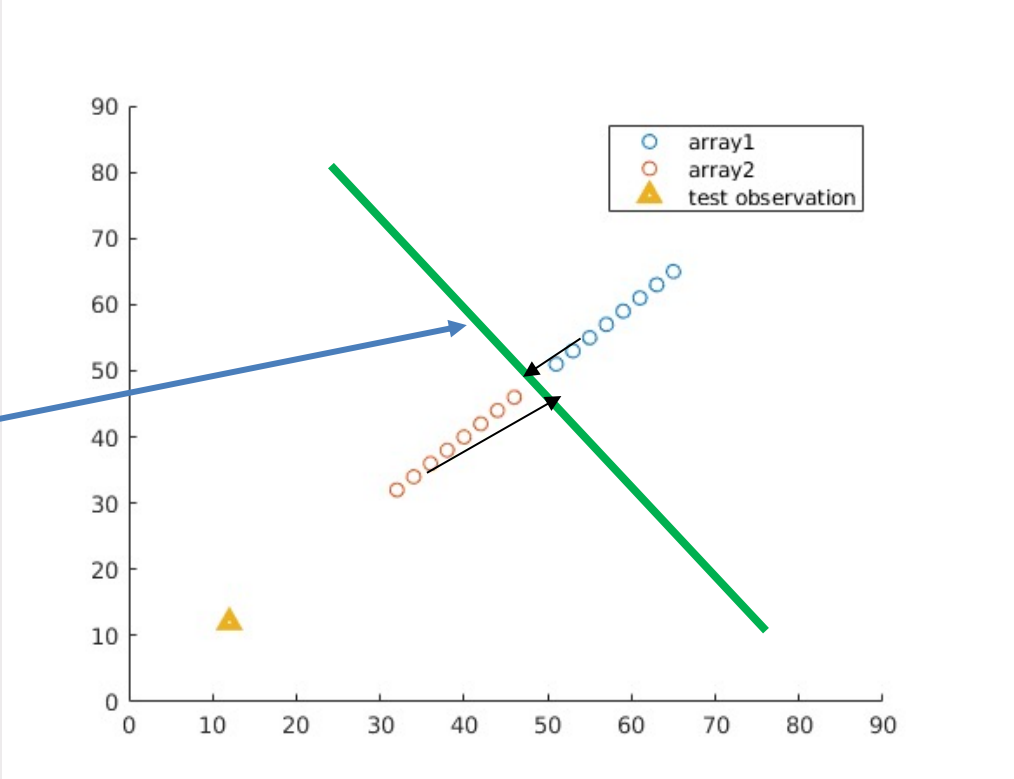
Introduction to machine learning classifiers.

Decision boundary



Introduction to machine learning classifiers.

Decision boundary

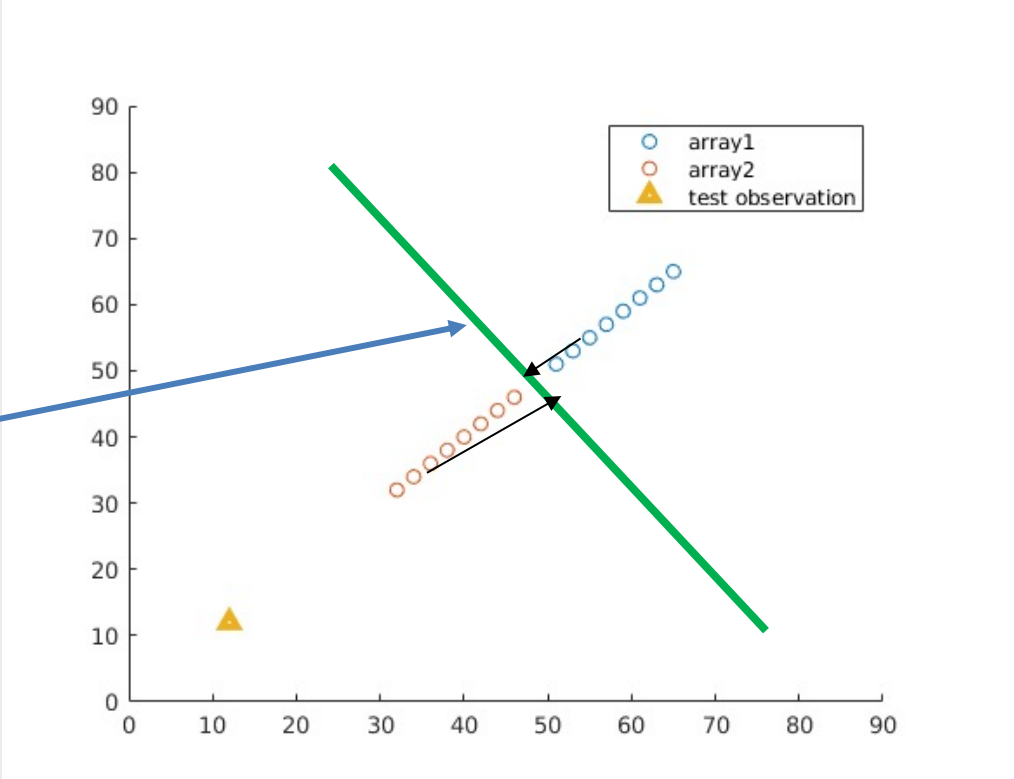


Why is independent validation necessary?

- Shows generalizability (avoids overfittings)
- Avoids overfitting

Introduction to machine learning classifiers.

Decision boundary



Problems:

- We need to collect more data to have independent observations?
- The information on the testing data is not used to learn.

Introduction. Validation on independent dataset .

What can we do when we have limited data? Cross-validation.

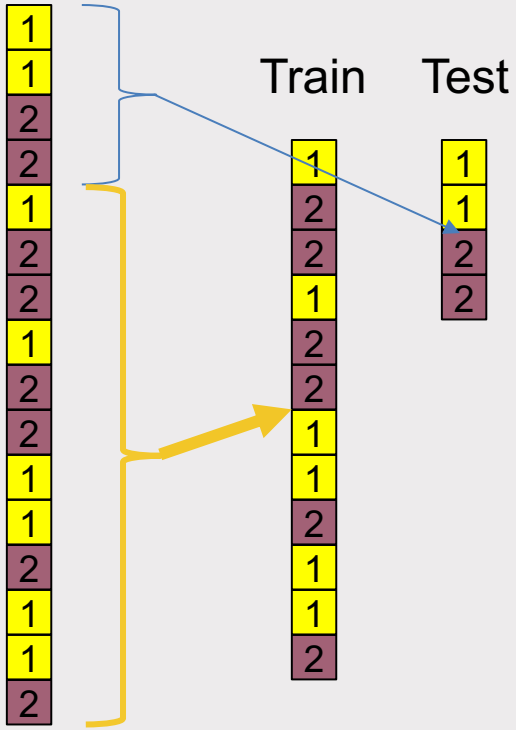
Different cross-validation schemes allow for different (levels of) control or put more or less weight on the number of observations. Most common approaches:

- Even/Odd observations (2 folds).
- Leave one (observation/chunk) out.

Let's do a practical exercise on *even/odd* cross-validation.

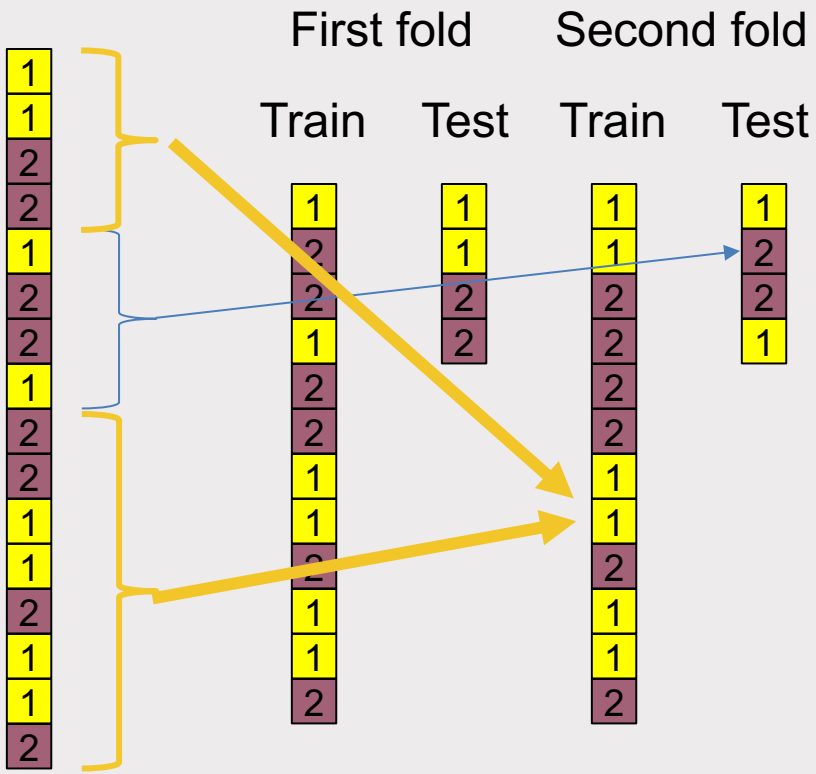
Introduction. Validation: Leave one (chunk) out .

Original data set



Introduction. Validation: Leave one (chunk) out .

Original data set



Introduction. Validation: Leave one (chunk) out .

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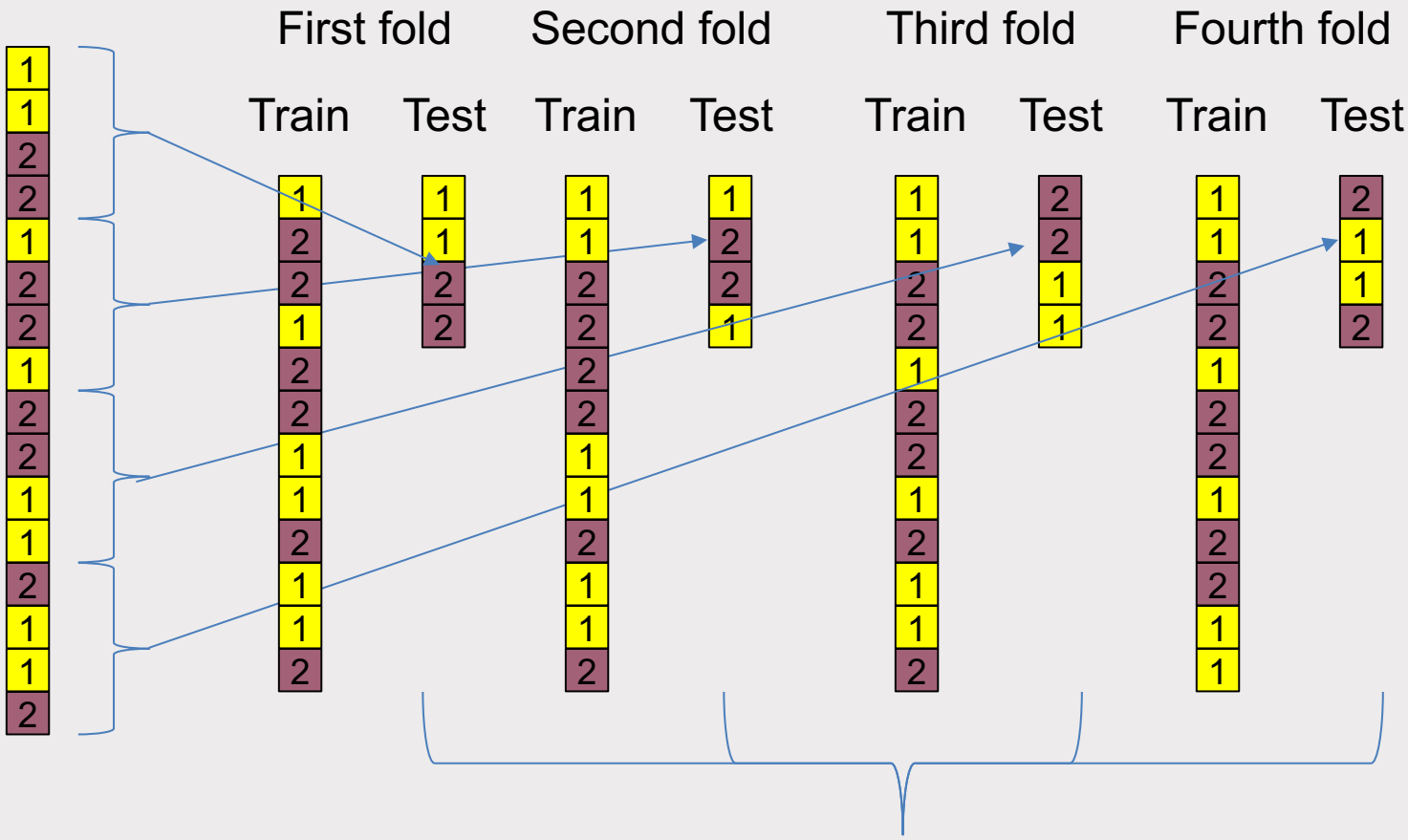


Bonus task: Try to set up a leave-one-out cross-validation scheme in the tutorial script.

Time for a break.

Questions?

Second part:

Classification in fMRI.

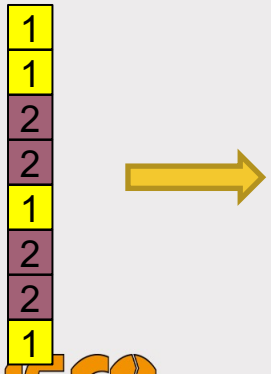
Classification in fMRI. Refining the jargon

Class: *Each "pattern" that we want find (we need at least two)*. In cognitive neuroscience classes are usually cognitive states (e.g., memory traces, task sets, representations).

Observations: *Each one of the items inside a class that we will use in our analysis*. Beta values (regressors in our GLM) of each condition.

Features: *Each element inside an observation*. Individual voxels (either in our ROI or in the entire brain).

8 observations x
1 feature



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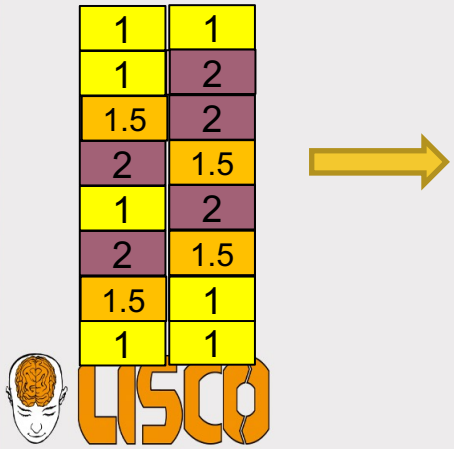
8 observations x
2 feature



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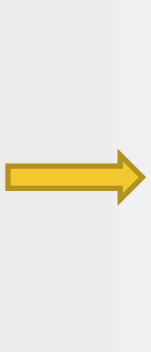
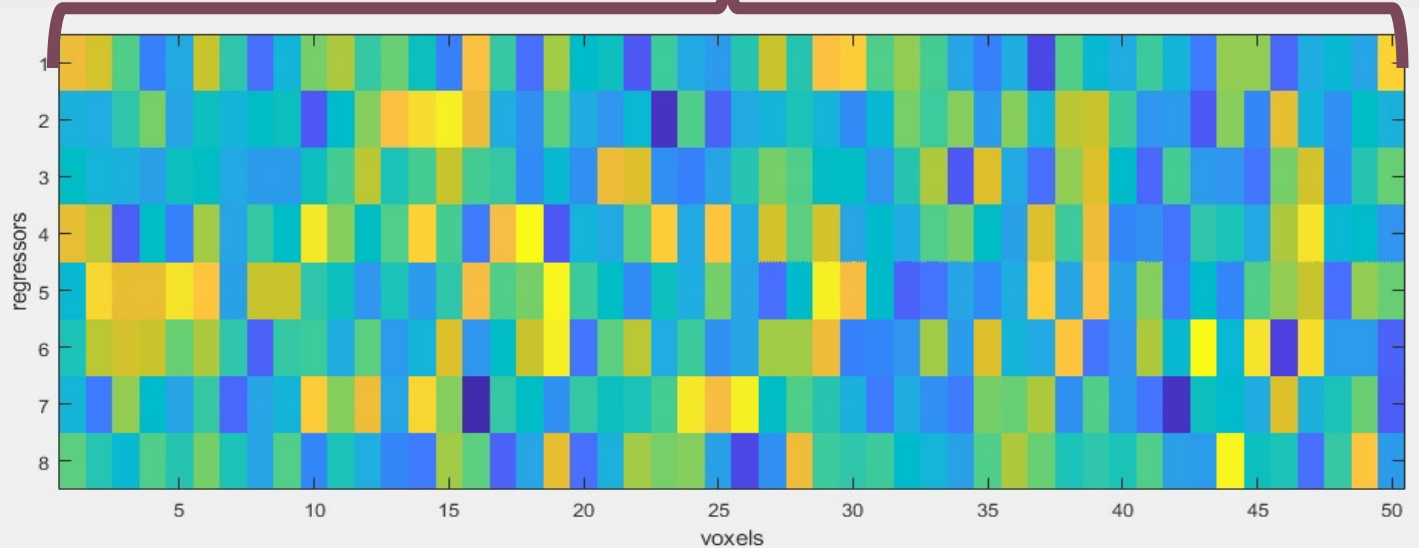
8 observations x 50 features

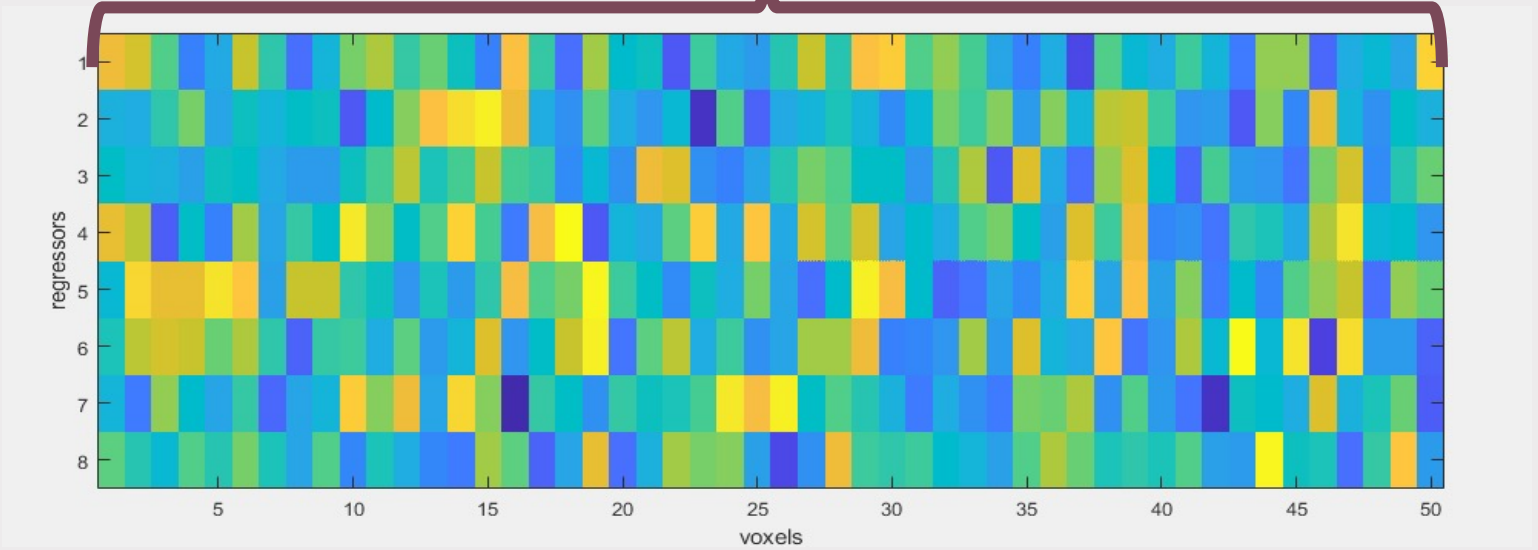
8 observations x
1 feature



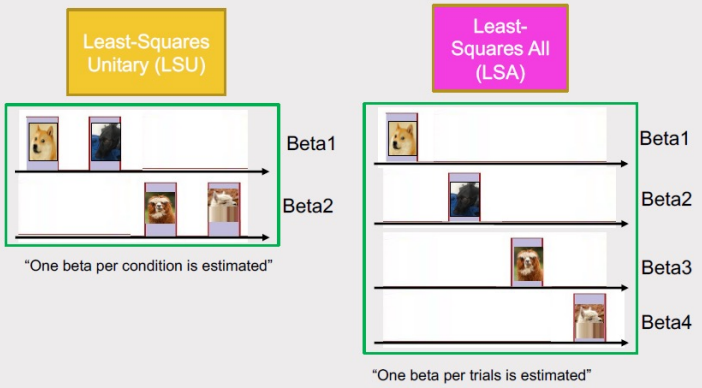


Classification in fMRI.

8 observations x 50 features



Rule of thumb:
"*The number of observations must be bigger than the number of features*"



Single-trial estimates (with appropriate methods) render better performance for multivariate analysis than condition-level estimates.

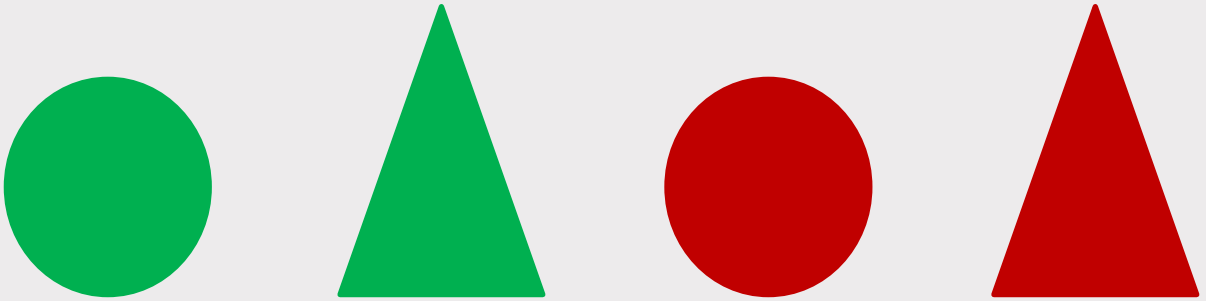
Mumford, et al. (2012). *Neuroimage;* Turner, et al. (2012). *NeuroImage*

Classification in fMRI. Hands-on.

Simulated experiment.

Participants are exposed to circles and triangles in two different colors. They need to indicate the color of the shape by pressing one of two buttons.

Shapes are shown sequentially for 2 seconds and there's a variable interval between shapes that ranges between 3s-15s.



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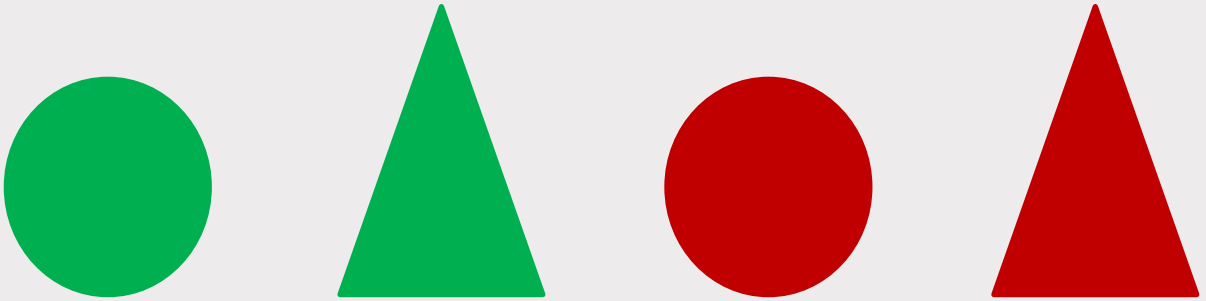
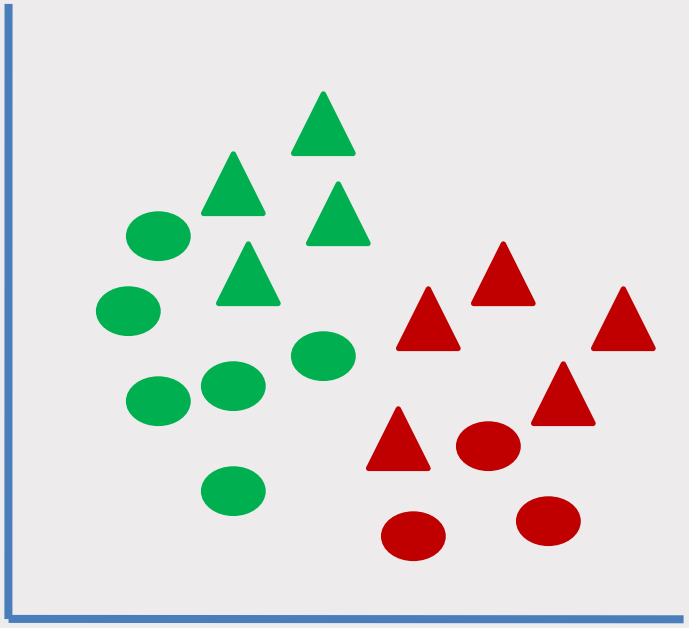


We have already estimated one beta per trial for a total of 16 trials on a full brain LSA GLM.

Classification in fMRI. Hands-on.

Once we have our beta values. What do we do with them?

First decision: what do I want to classify?
Depending on the classes you select (i.e., the question that you ask the classifier), you can get different types of information.



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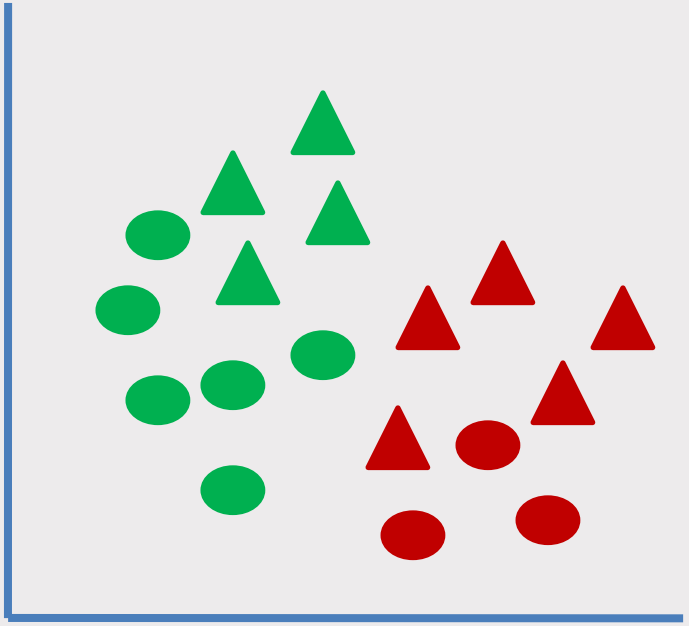

Red vs. green?

Classification in fMRI. Hands-on.

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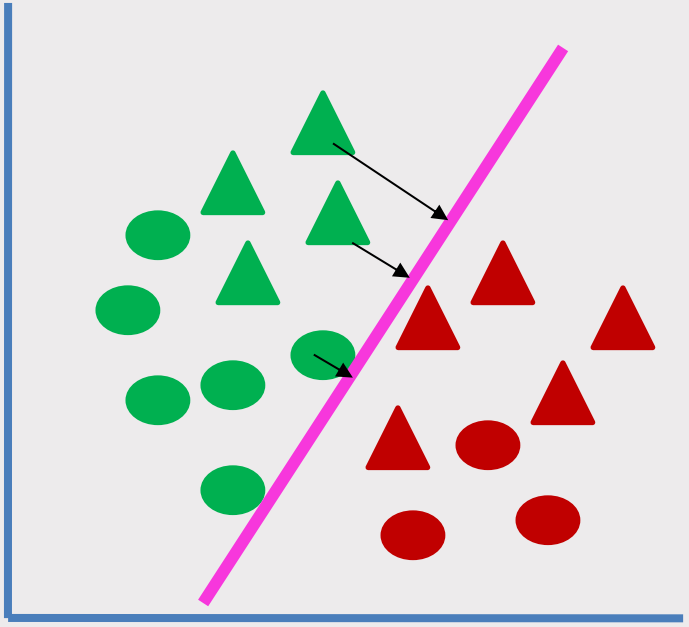

Red vs. green?

100%

Classification in fMRI. Hands-on.

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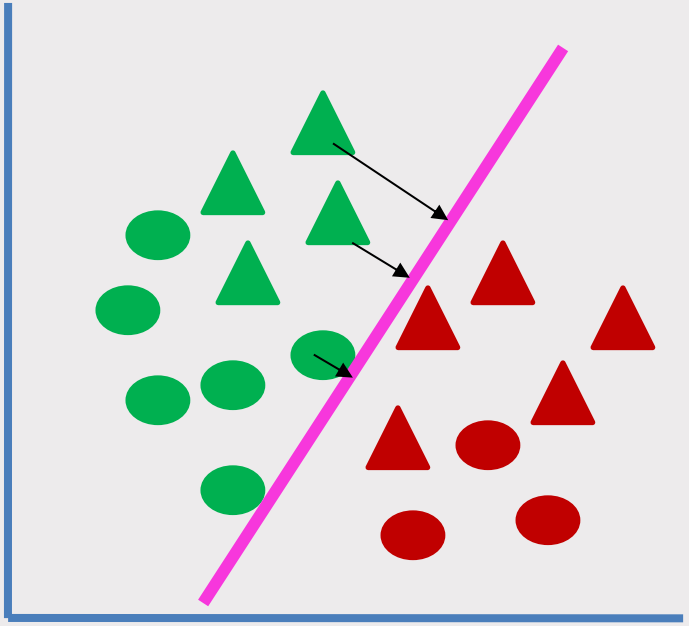
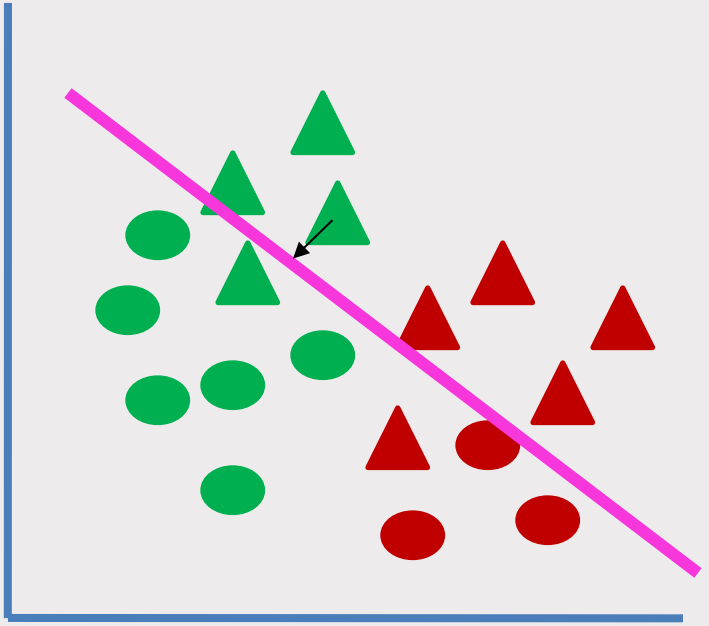


100%

Red vs. green?

or

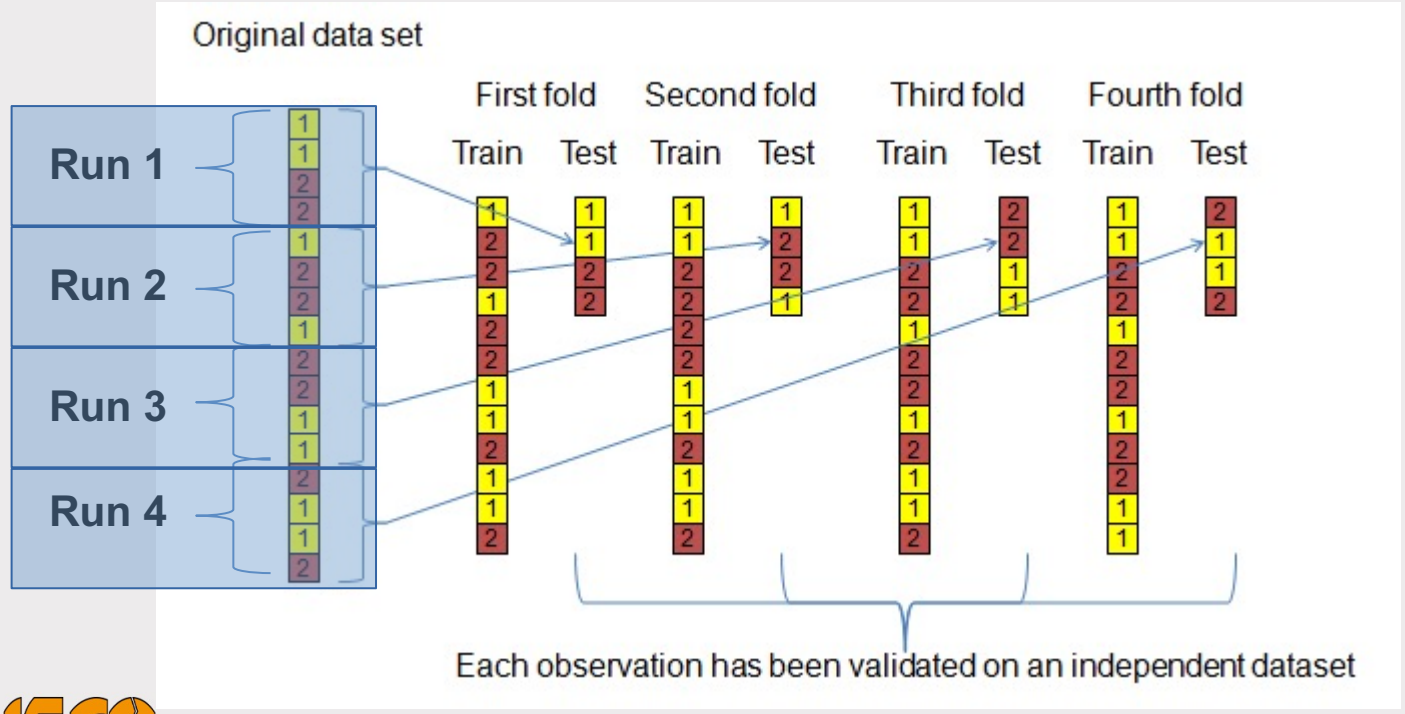
Circles vs. triangles?



?%

Classification in fMRI. Hands-on.

Second decision: how will I validate my classifier?
The validation method can also add information (on top of controlling for biases; e.g., cross classification). In fMRI the standard method is **leave-one-run-out**: one scanning run is held for testing and training is performed with the remaining ones.

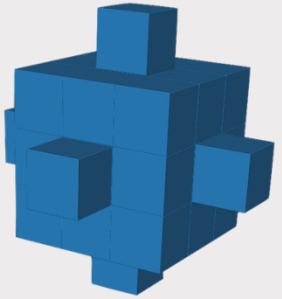


Classification in fMRI. Hands-on.

Third decision: which voxels will I use (i.e., feature selection)? Two main approaches to consider:

- **Region of interest (ROI):** Only voxels within a given ROI are used in the analysis. ROIs can be defined either anatomically (e.g., right TPJ, left CA1) or functionally (e.g., only voxels that response more to faces than to houses). Functional localizers can be set up as an independent task (e.g., FFA localizer, retinotopy).

- **Searchlight**: a small cluster of voxels is selected for classification; the classification accuracy of that cluster is assigned to the central voxel in the cluster; then, an adjacent cluster is selected, and the process is repeated until the entire brain (or ROI) is covered.



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Classification in fMRI. Hands-on.

Fourth decision: how do I want to do it?

CoSMoMVPA. Oosterhof, Connolly, & Haxby, (2016). *Frontiers in neuroinformatics.*
Multimodal environment. Works with matrices of data; requires the user to arrange datsets.
Matlab-based.

The Decoding Toolbox (TDT). Hebart, Görgen, & Haynes. (2015). *Frontiers in neuroinformatics.*
SPM-based. Works with beta maps (.nii) and SPM.mat from SPM; minimal user intervention for standard analysis.
Matlab-based.

PyMVPA. Hanke, Halchenko, Sederberg, Hanson, Haxby, & Pollmann, (2009). *Neuroinformatics*.
Python-based.

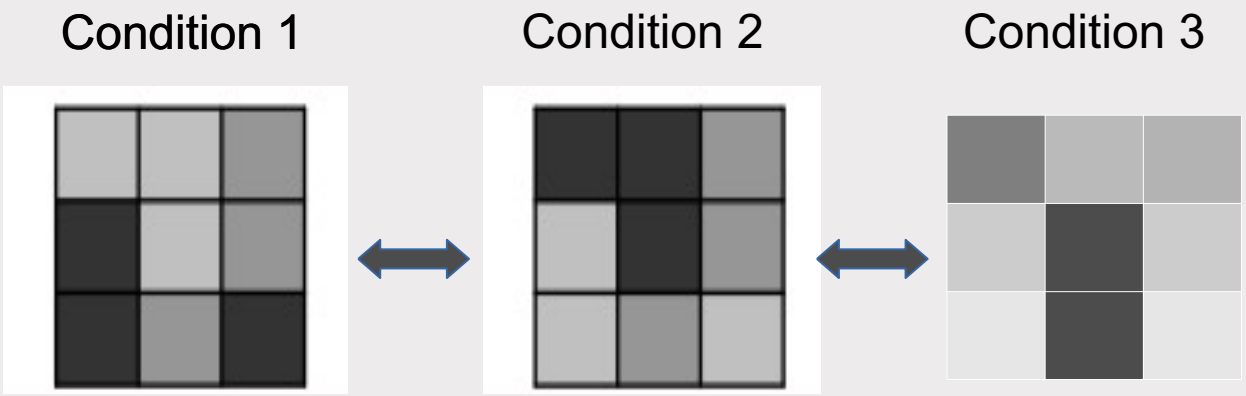
Classification in fMRI. Hands-on.

Practical exercise part 2.

Go into breakout rooms and follow the .mlx script. Discuss with your colleagues and try to understand every step.

Representational Similarity Analysis (RSA; Kriegeskorte, Mur and Bandettini, 2008)

Using similarity between activity patterns to infer representational structure.



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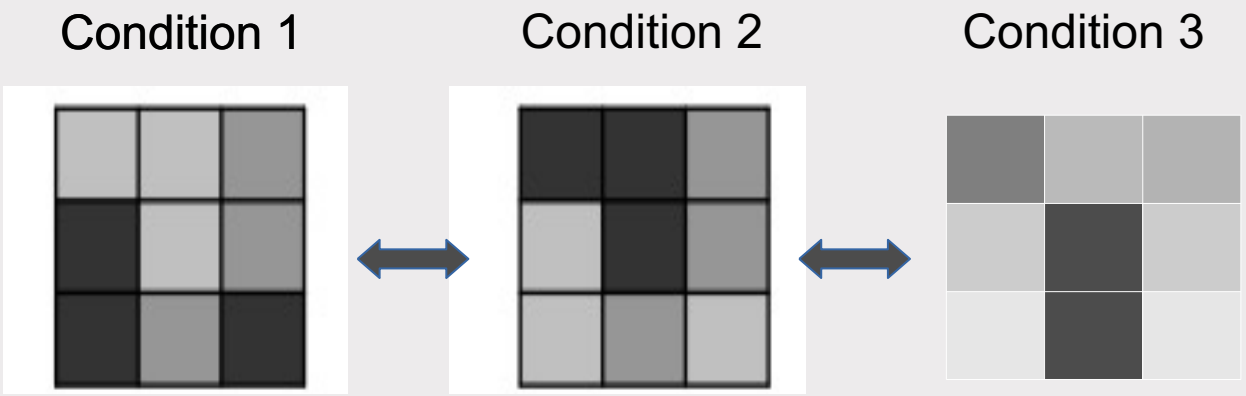


More similar *Less similar*

During condition 1 y 2, our ROI is representing the same *thing*; during condition 3 is representing *something else*.

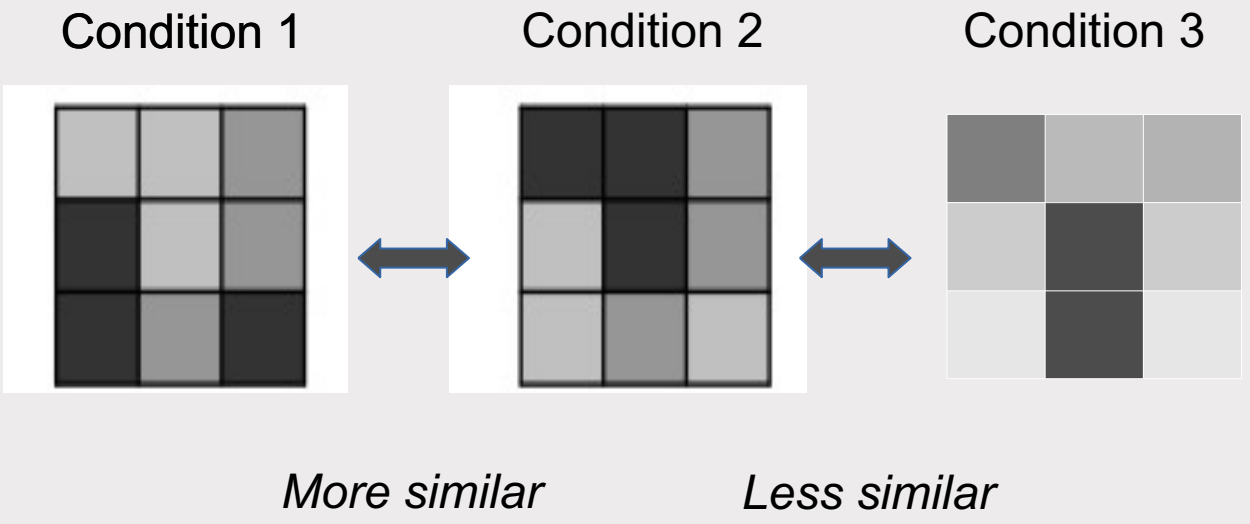
Representational Similarity Analysis (RSA; Kriegeskorte, Mur and Bandettini, 2008)

Glossary of RSA jargon:

- **Similarity** = correlation / degree of overlap in activity patterns of a given brain region.

- **Dissimilarity** (a.k.a., representational distance): Degree of non-overlap in activity patterns of a given brain region. Quite often is 1 – correlation.

- **RDM**: Representational Dissimilarity Matrix. Pair-wise matrix of dis(similarity) values.



Representational Similarity Analysis (RSA; Kriegeskorte, Mur and Bandettini, 2008)

Practical exercise RSA.

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