

Experimental Design

Block design

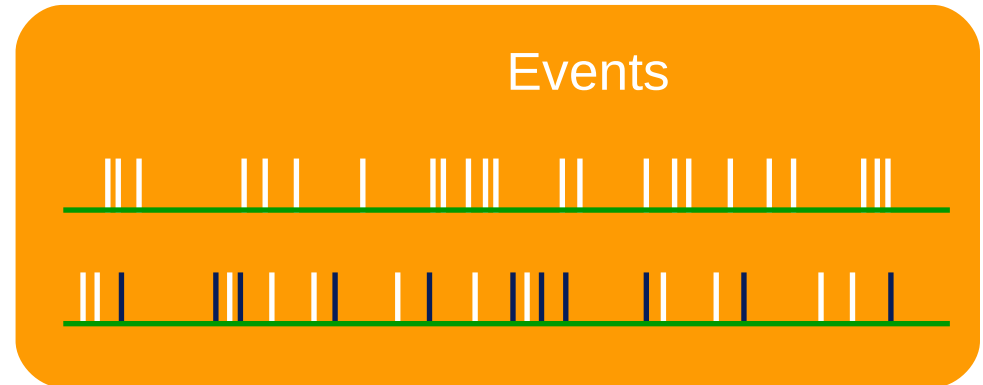
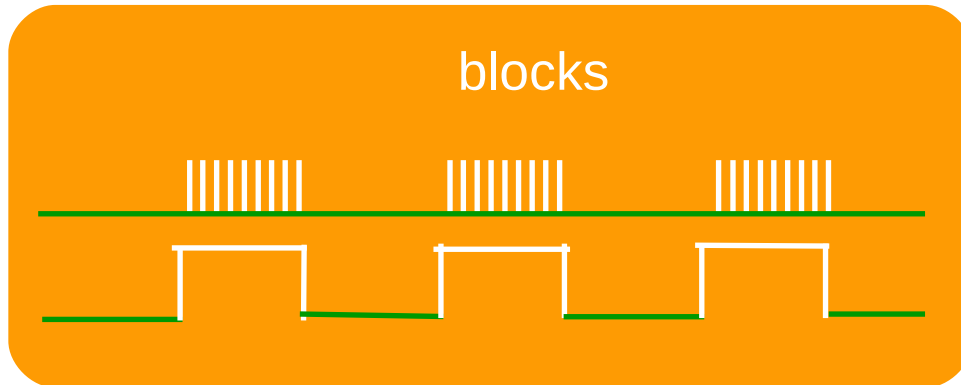
Comparing 2 or more conditions by alternating periods of 10s-30s where the condition is held “constant”.

Example: Speech vs. Music (vs. Silence)

Example: Reading rate: 1 word every 500, 1000, 2000 msec.

(Note: The optimal duration is 10-30 second because the raw fMRI signal contains low frequencies at above ~120s which are filtered as a first step in data analysis)

Another type of design : Event-related

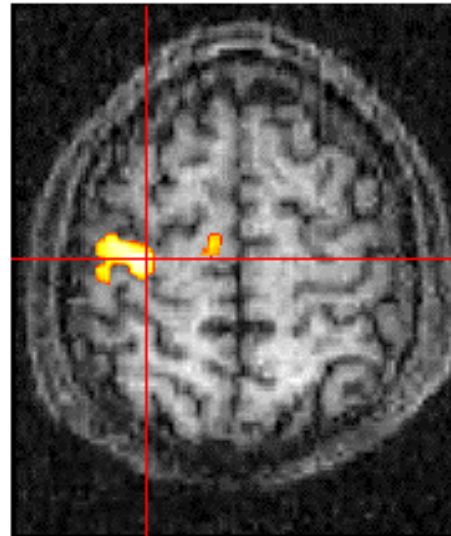


- Simple analysis
- Habituation issue
- Good signal to noise ratio thanks to the summation of responses to close events

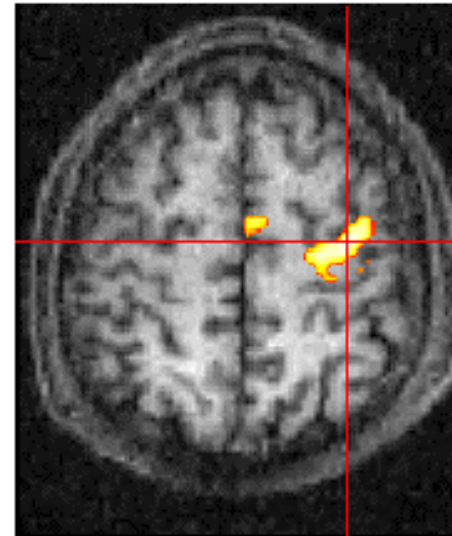
- More flexible from an experimental point of view
- Random presentation of condition, avoiding anticipation or habituation effects
- Allows to estimate the shape of the hemodynamic response
- But weak signal to noise ratio

Predicting manual responses

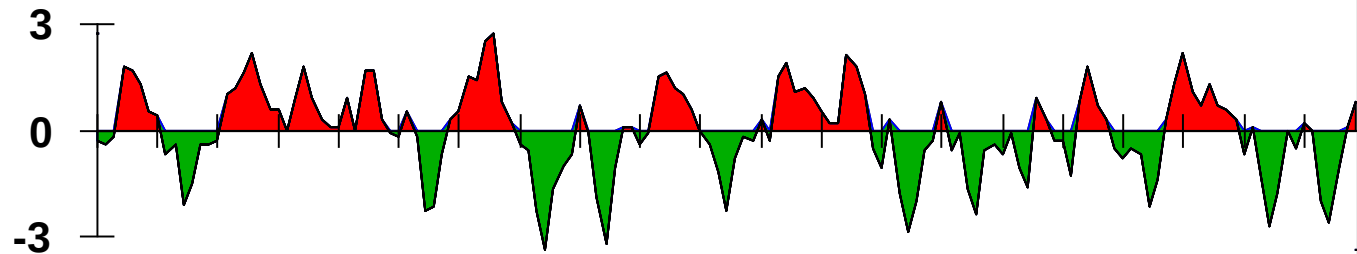
right hand > left hand



left hand > right hand



Lateralized
BOLD
Response

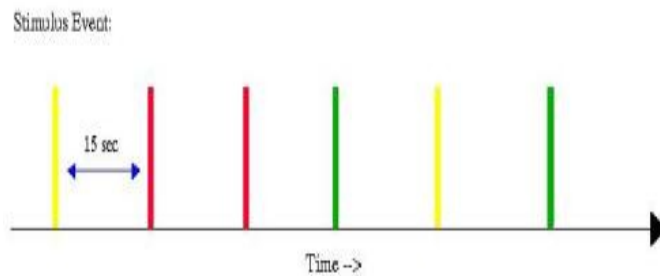


Response Side

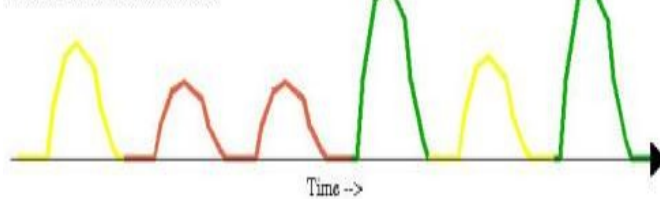
L R L L L R L R R L R L L R R R L R L R R

Slow vs. fast event related paradigms

Figure 2:
Slow Event-Related Design -
Fixed Inter-Stimulus Interval



Individual Hemodynamic Response
Function for each Stimulus Event:



The Sum of the above HRFs:

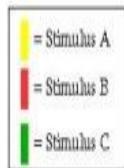
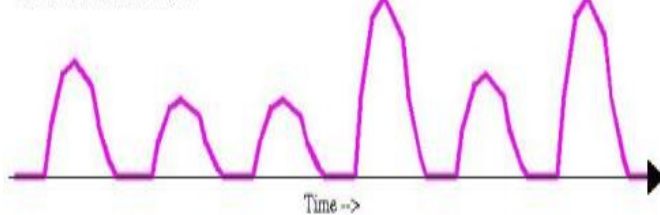
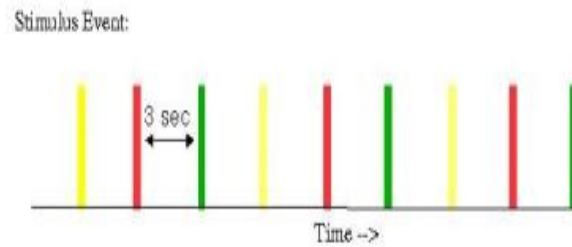
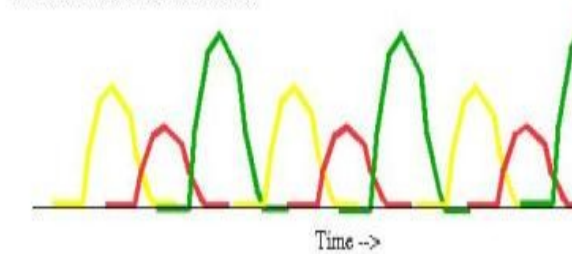


Figure 3:
Rapid Event-Related Design -
Fixed ISI and Nonrandom Stimulus Presentation



Individual Hemodynamic Response
Function for each Stimulus Event:



The Sum of the above HRFs:

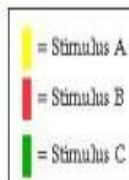
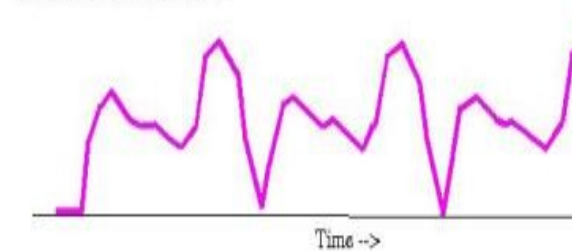
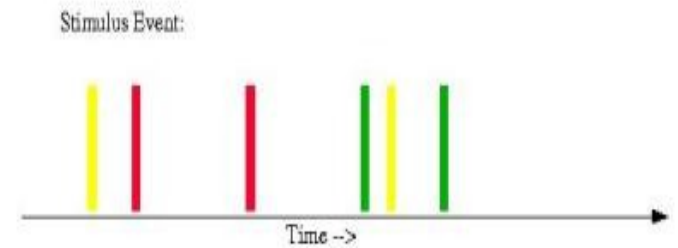
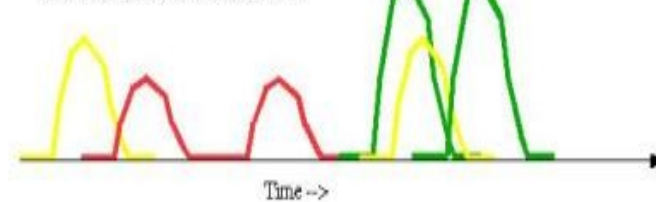


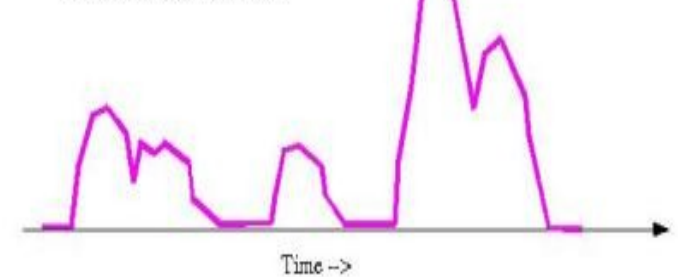
Figure 5:
Rapid Event-Related Design -
"Jittered" Inter-Stimulus Interval



Individual Hemodynamic Response
Function for each Stimulus Event:



The Sum of the above HRFs:



Experimental approaches

Subtraction method

comparing activations between different conditions.

- Fixed task/ varying stimuli (ex: listen to Speech or Music)
- Fixed stimuli/varying task (ex: detect speaker or detect word in the same speech stream)

Parametric manipulation

varying quantitatively some parameter(s). For example Speech rate.

Frequency tagging.

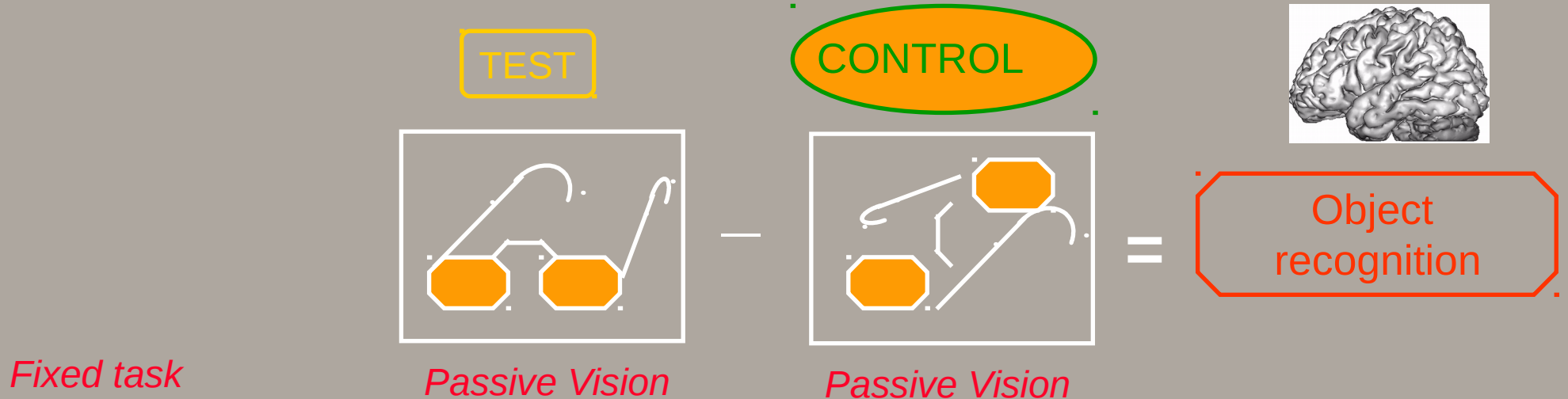
The stimuli has several characteristics that vary continuously at different frequencies. Then one can search these frequencies in the signal of different voxels

Priming method

- The repetition of a stimulus or a feature can lead to an habituation of the response

The most common approach is to vary the stimuli. It is not without problem

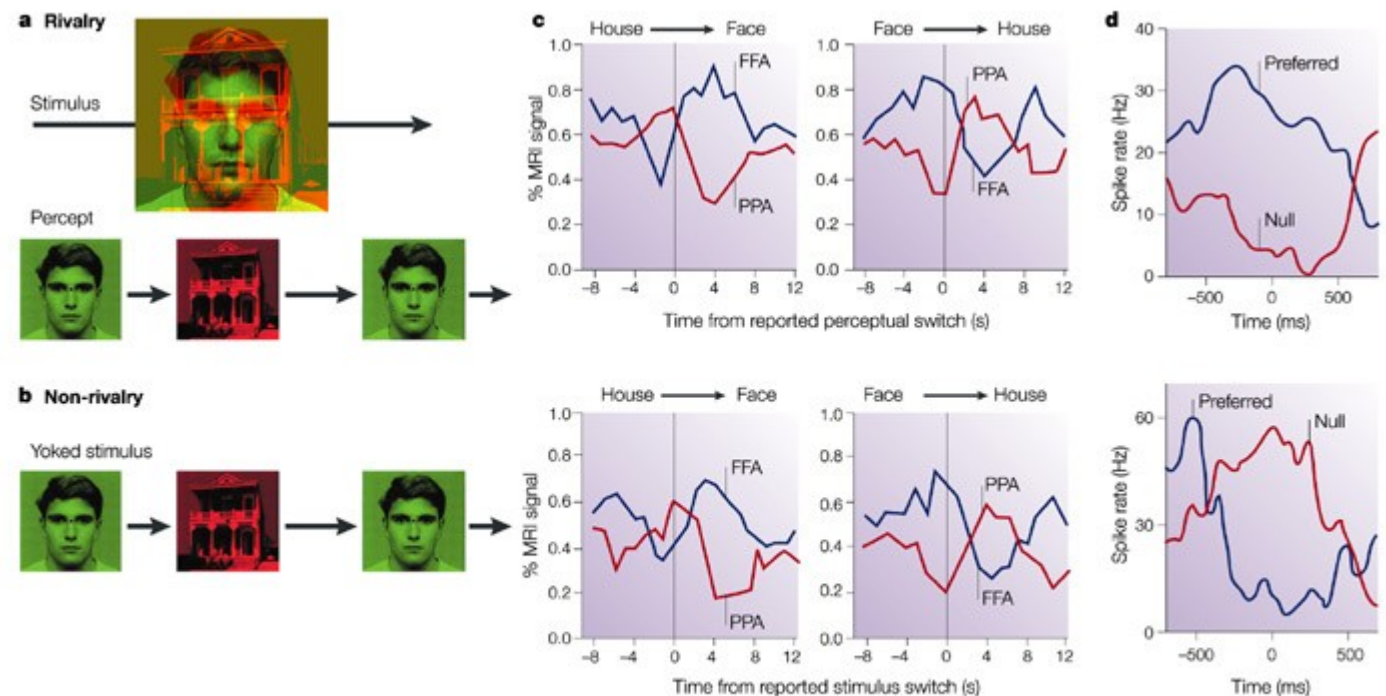
To uncover the region which do object recognition, one may devise the following experiment :



Problem : It is unlikely that the participant is really 'passive' : for example, it probable that he will covertly name the word 'glasses' in the test condition, or try to reconstruct the object in the Control condition...

Example of Fixed stimuli/Change Task

- Pay attention to speed or shape
- Bistable stimuli
 - Binocular rivalry (Rees, Kreiman & Koch, 2002)



Nature Reviews | Neuroscience

- Sine wave speech (Dehane-Lambertz & Pallier, 2005)

Frequency tagging. Application to retinotopy

“Traveling wave” or “phase-encoded” mapping method:

Engel et al. Nature 1994, Sereno et al. Science 1995

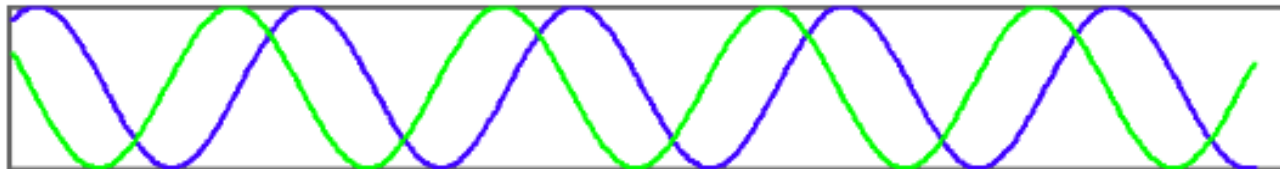
polar angle:



eccentricity:



idealized response of visual cortex voxels with blue and green receptive fields:



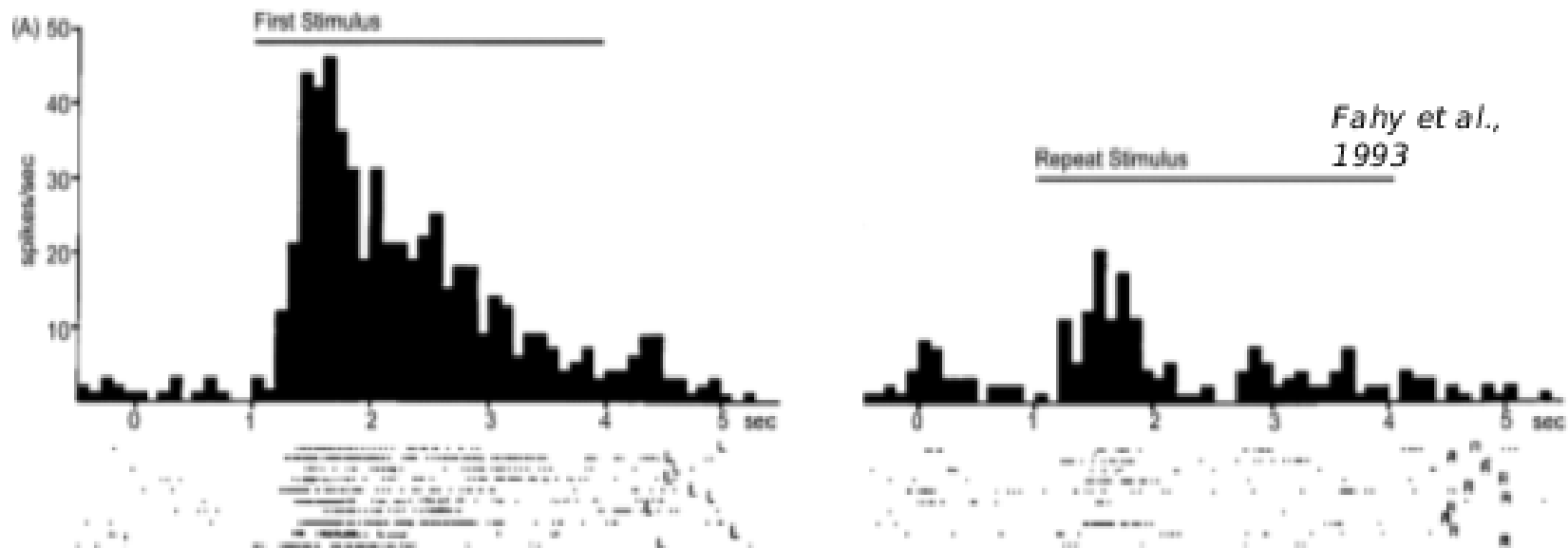
- Periodic stimuli map out visual space in polar angle in eccentricity
- Voxel responses are periodic, having the same frequency but different phases
- So, parameter of interest is response **phase** because it tags visual field location

The priming method in fMRI (fMRI-A)

Priming: in cognitive psychology, repeating a stimulus (“*repetition priming*”), or some features of a stimulus, typically accelerates its processing.

At the neuronal level, repetition can lead to *neural suppression*:

- Adaptation in a perirhinal neuron of monkey:



May 16, 2014
In fMRI, if enough neurons show habituation, the signal will decrease.

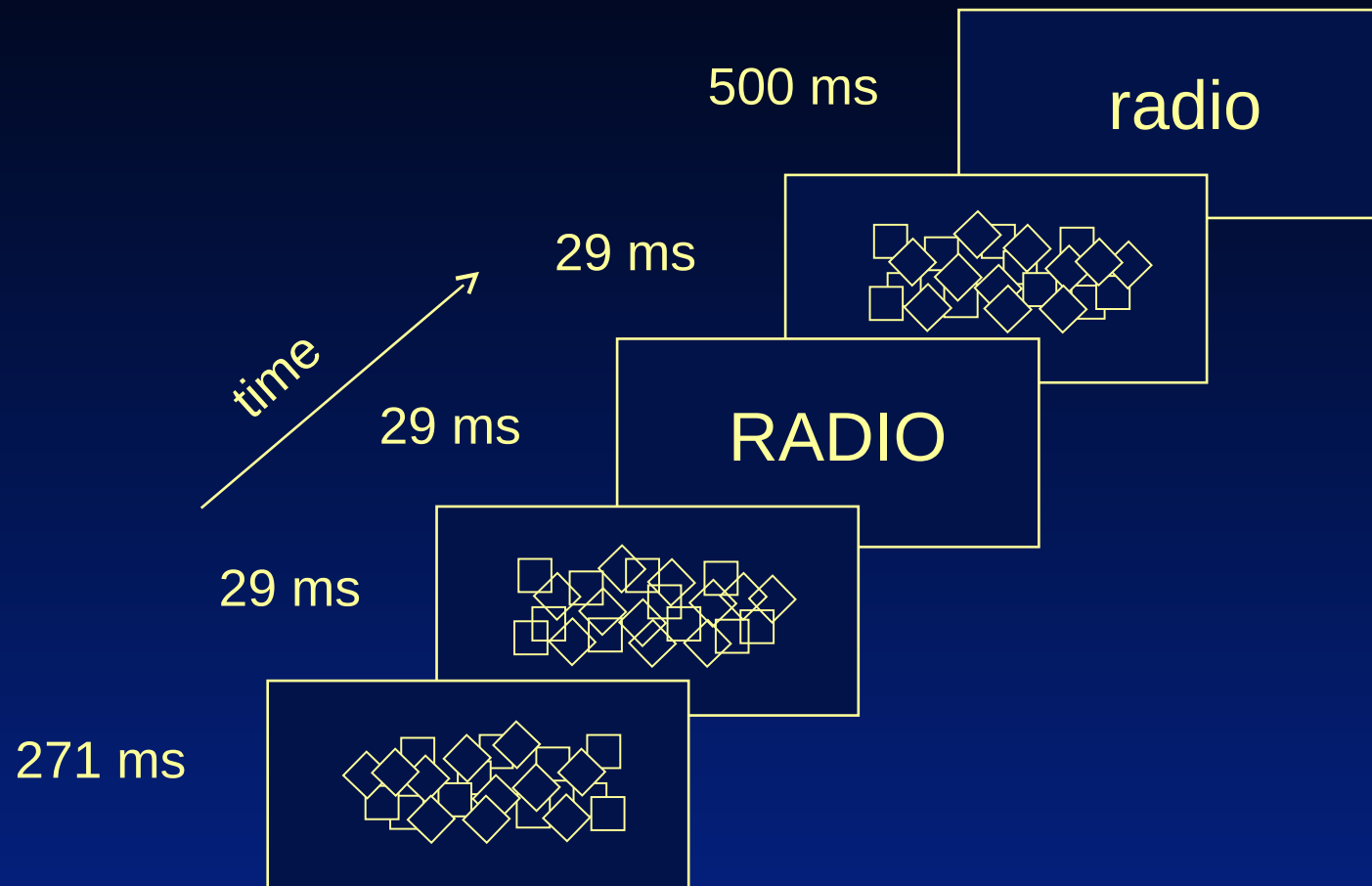
Using priming to read the “neural code”

Different neurons are characterized by their responsiveness or lack of responsiveness to variations in stimulus parameters

For instance, face-specific neurons may respond to a specific face, independently of its size or location in the visual field

Using repetition priming combining imaging allows you to ask what counts as a repetition for a given brain area.

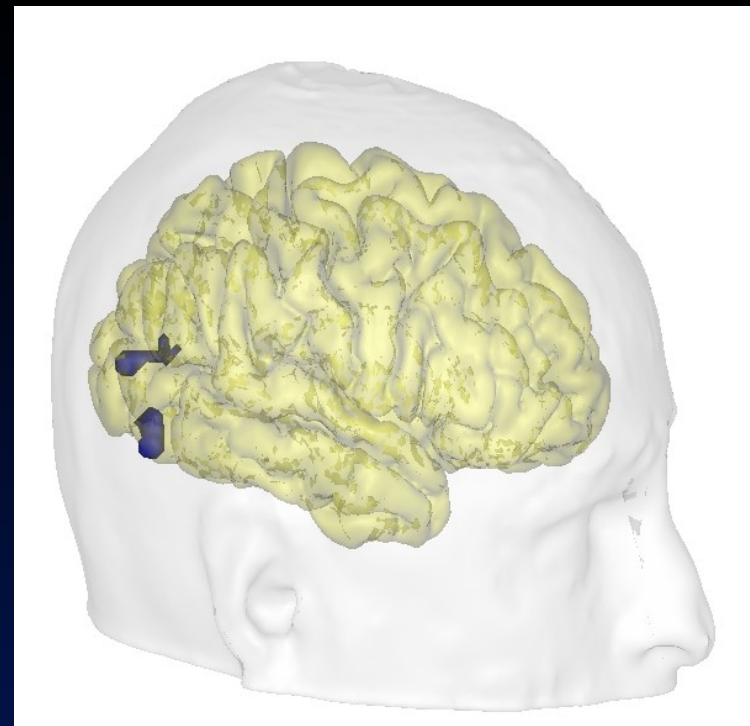
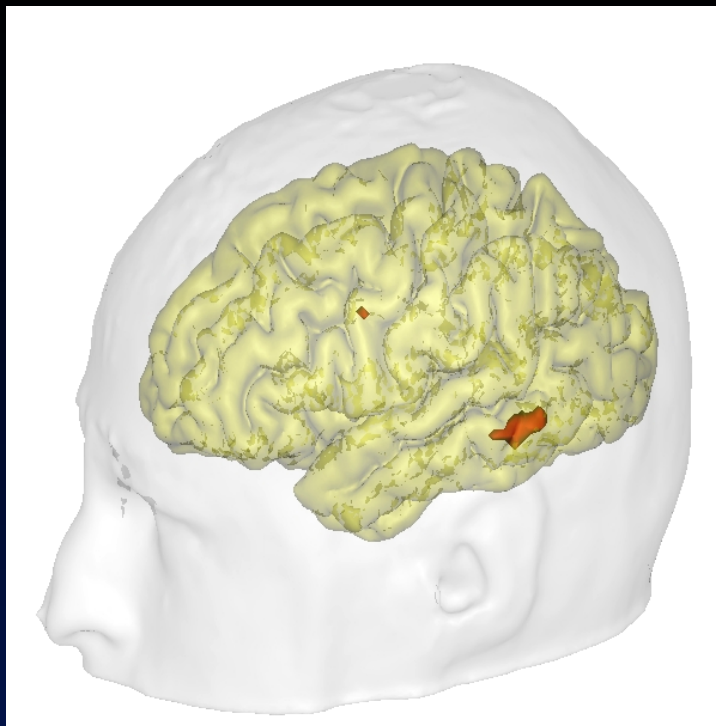
“Cerebral Mechanisms of Word Masking and Unconscious Repetition Priming” (Dehaene et al. 2001; *Nature Neuroscience*)



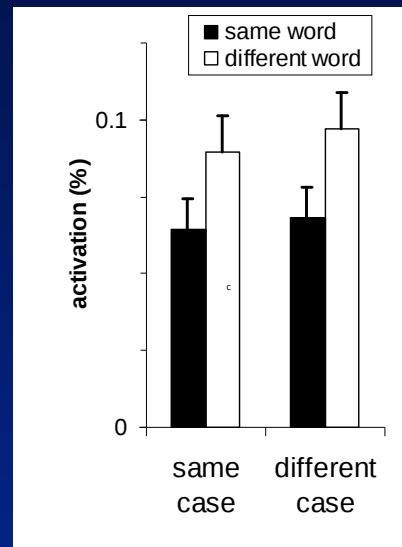
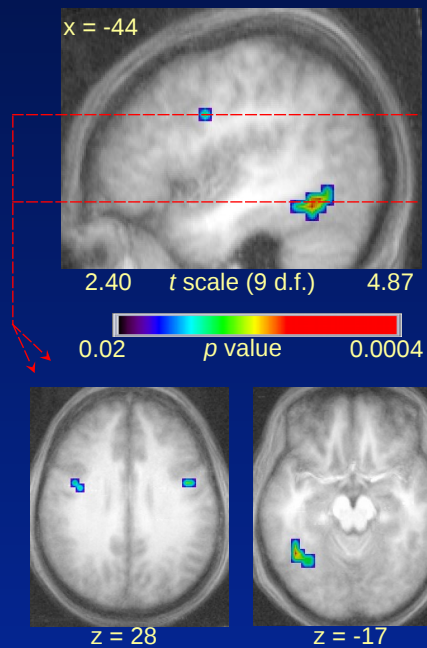
Unconscious repetition priming paradigm

	Same case	Different case
Same word	RADIO-RADIO radio-radio	RADIO-radio radio-RADIO
Different word	RADIO-FRUIT radio-fruit	RADIO-fruit radio-FRUIT

Task = Bimanual classification into man-made versus natural

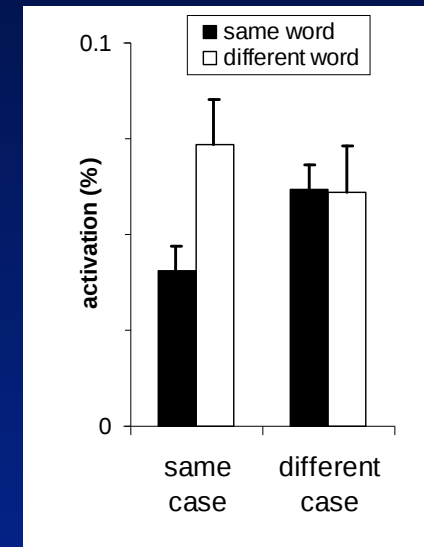
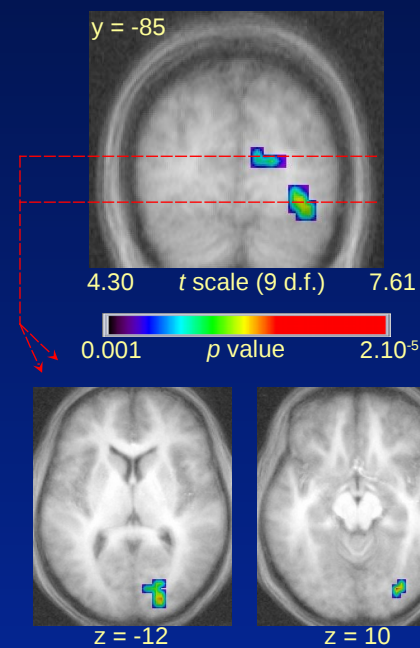


case-independent priming



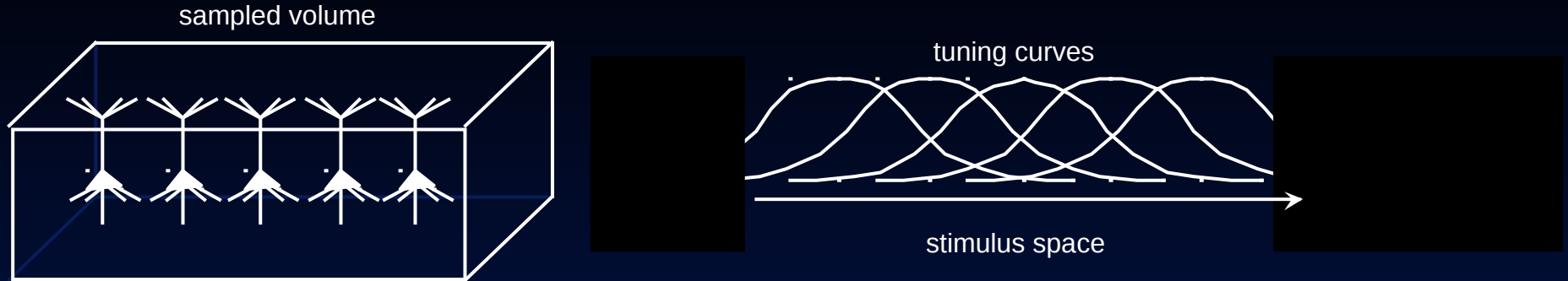
left fusiform
(-44, -52, -20)

case-specific priming

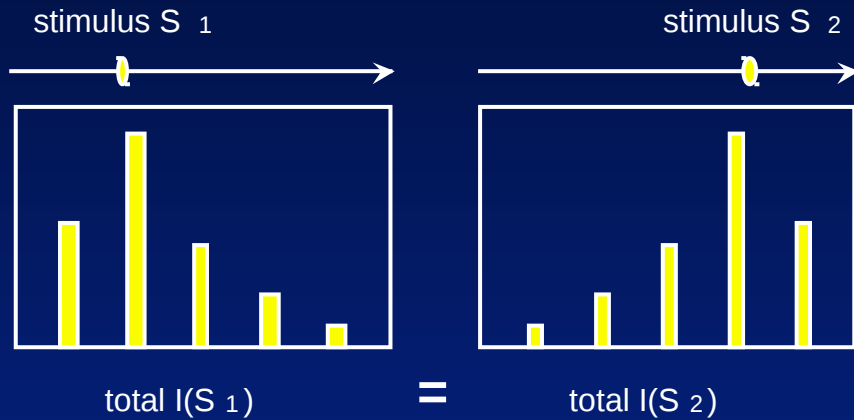


right extrastriate
(32, -80, -16)

Using priming to obtain “hyper-resolution”

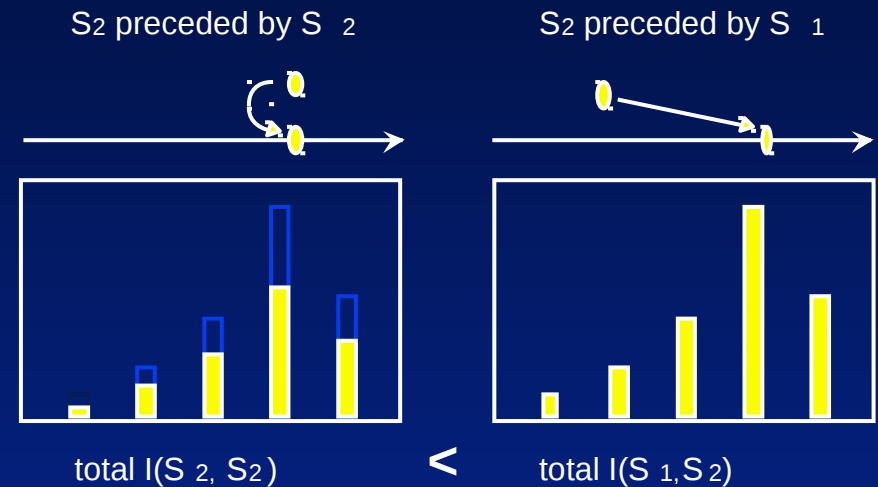


Classical Subtraction Method



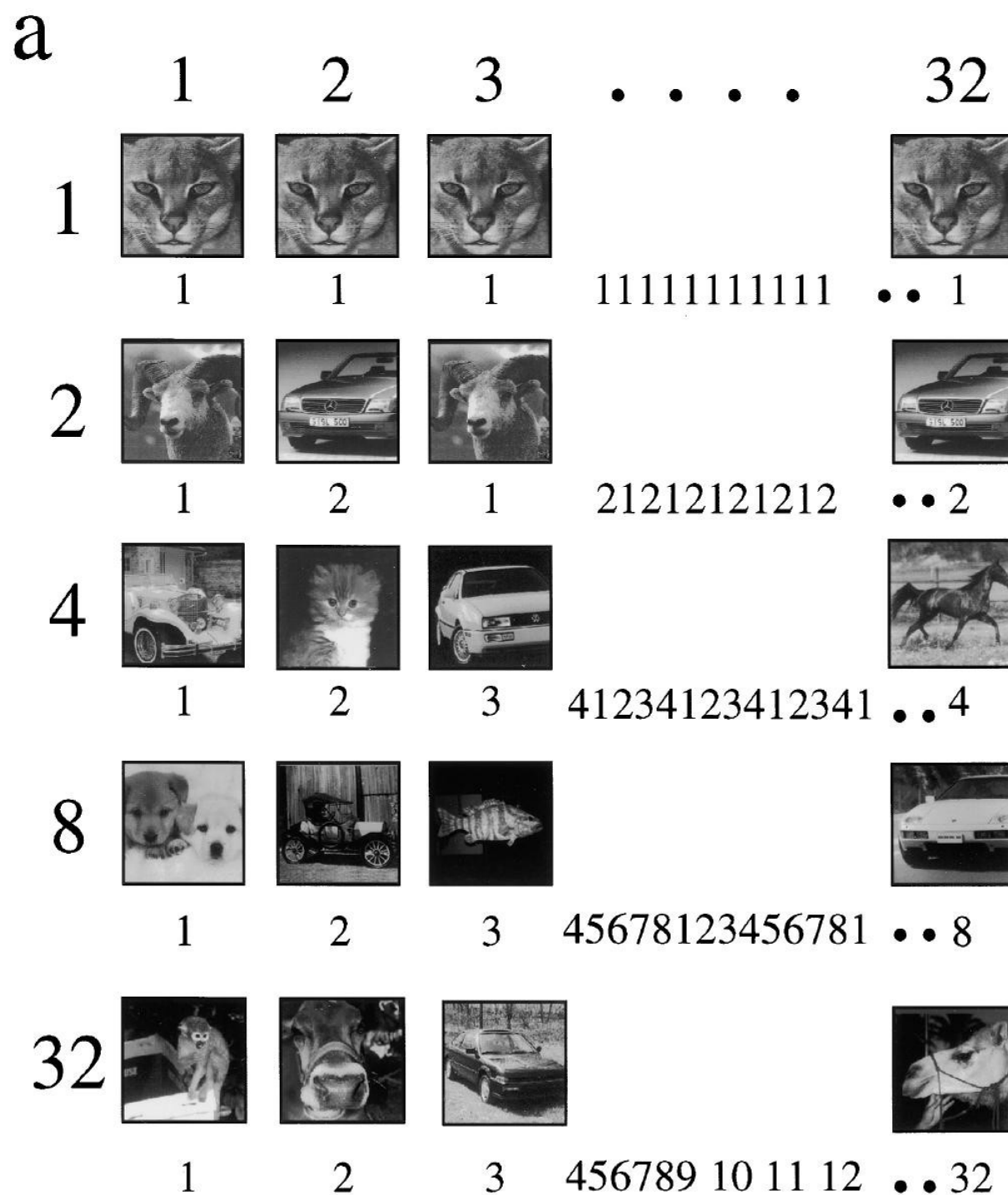
Different population codes,
but same activation

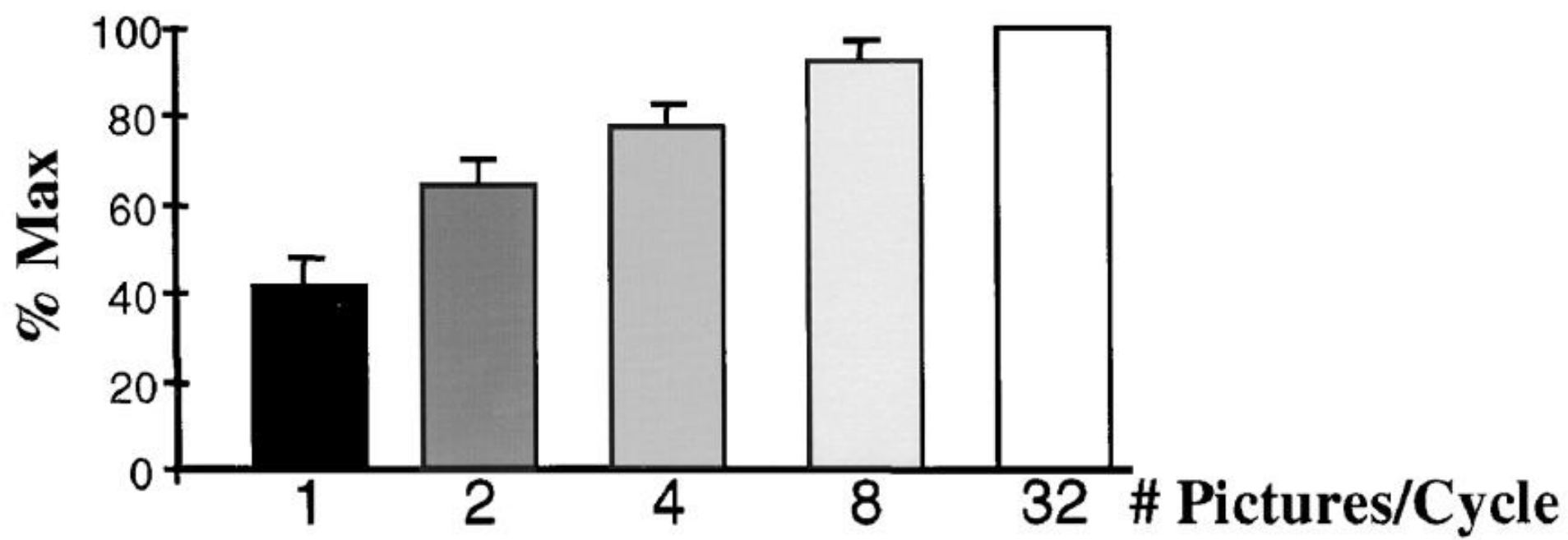
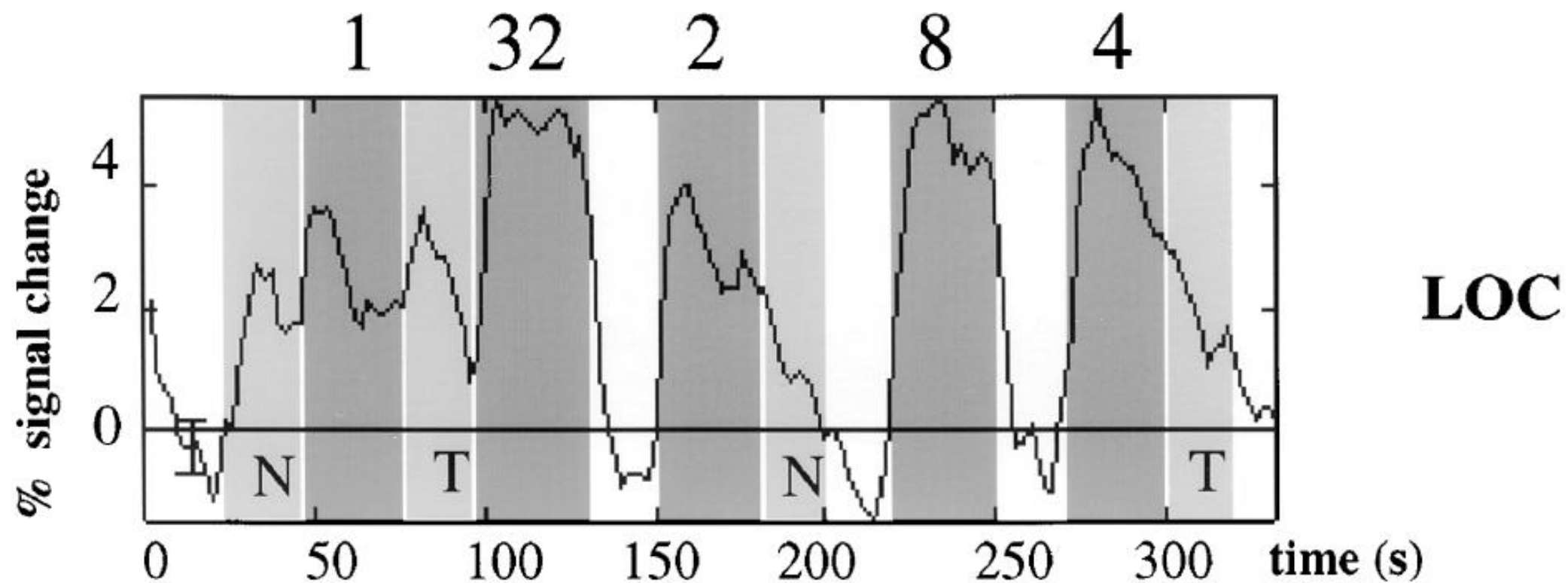
Priming Method



Measurable difference in activation
indicates that S_1 and S_2 activate
different neural populations

Grill-Spector et al.
(1999). Differential
processing of
objects under
various viewing
conditions in the
human lateral
occipital complex.
Neuron, 24(1),
187-203.



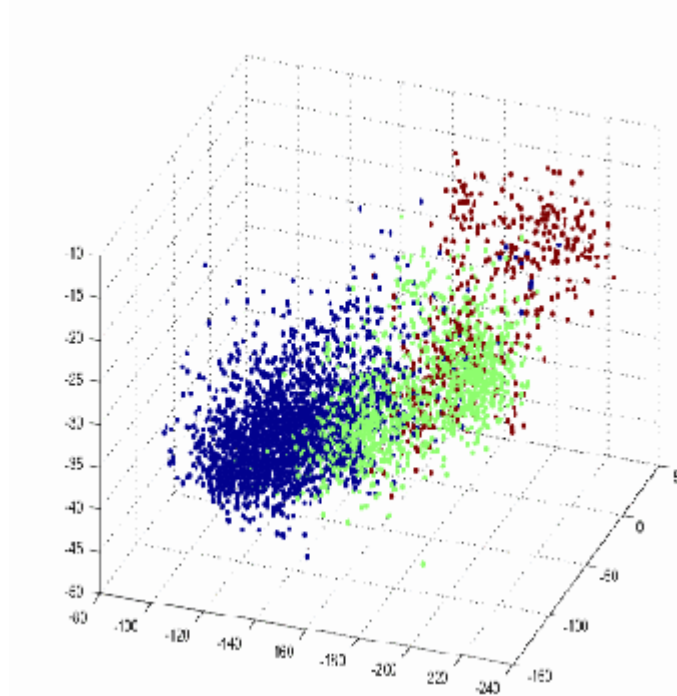


Multivariate analyses

The massive **univariate** approach to analyse fMRI data described earlier compare activity independently at each voxel.

Multivariate analyses rely on activity patterns from several voxels (the whole brain or, more typically, Regions of Interest).

Pattern-classification algorithms are trained (supervised learning) on these vectors, and their performance is tested on new patterns (how well do they predict the condition given the activity pattern).



Algorithms:

Linear Discriminant Analysis (LDA),

neural networks

support vector machine (SVM)

Penalized Logistic Regression

Localizing the information

If patterns consist of activations over the whole brain, it is only possible to say that brain activity contains some information about the conditions (e.g. Bachrach & Pallier, decoding of syntactic trees)

Localizing *where* the information is is a difficult problem.

One approach is the **search-light method**:

For all voxels, use a sphere centered on it and containing ~several hundred voxels, and use it as a ROI, that is, for each participant, obtain the decoding accuracy from the patterns extracted in this ROI.

Enter individual subjects accuracy maps in a group analysis to test if accuracy is better than chance.

Reference:

Haxby, James V., Andrew C. Connolly, and J. Swaroop Guntupalli (2014). “Decoding Neural Representational Spaces Using Multivariate Pattern Analysis.” *Annual Review of Neuroscience* (July 8, 2014): 435–456.

Haxby, James V. “Multivariate Pattern Analysis of fMRI: The Early Beginnings.”
May 16, 2014
NeuroImage 62, no. 2 (August 2012)

Representational Similarity Analysis

Kriegeskorte and Kievit.
(2013)

“Representational
Geometry: Integrating
Cognition,
Computation, and the
Brain.” *Trends in
Cognitive Sciences*

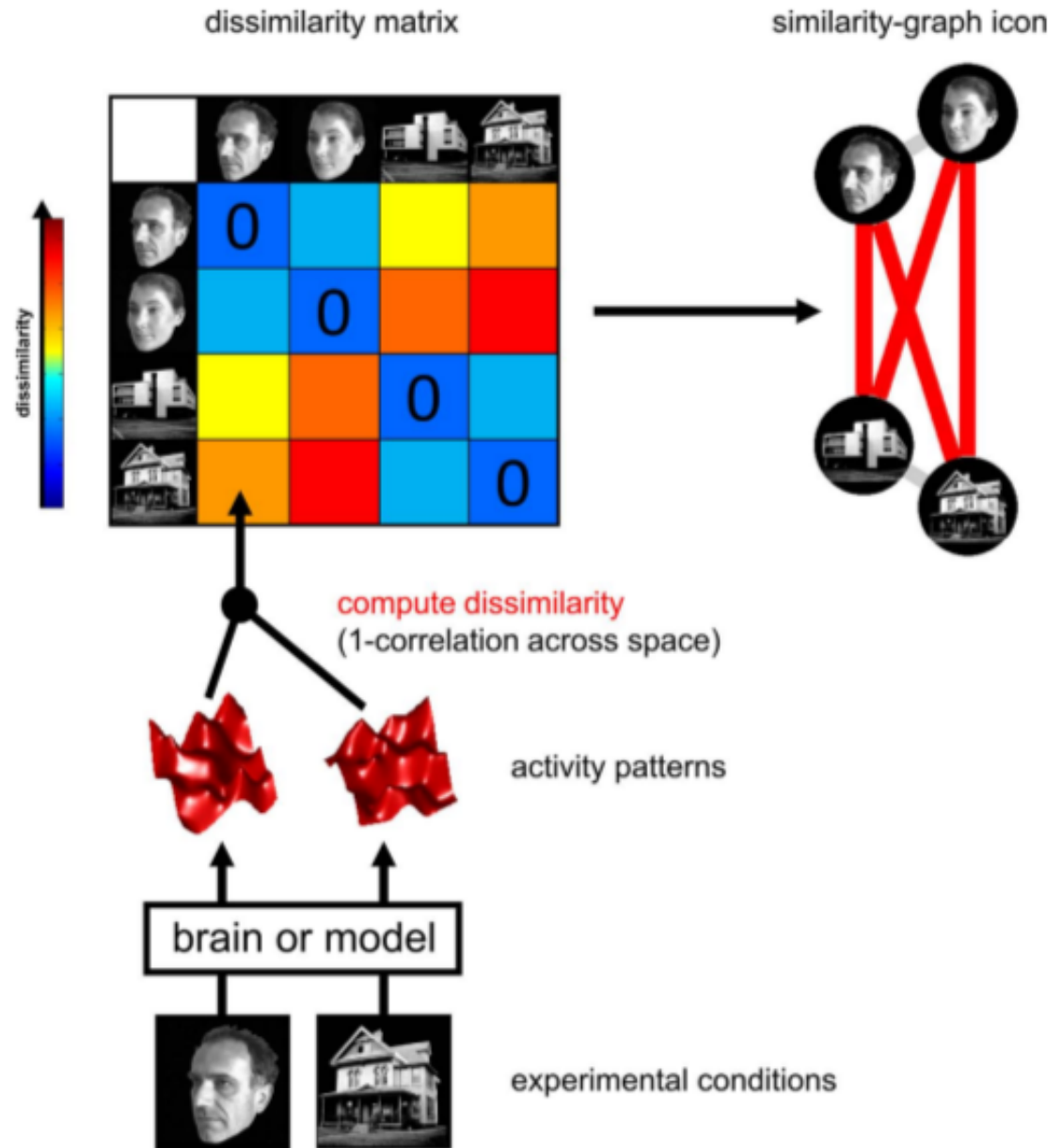
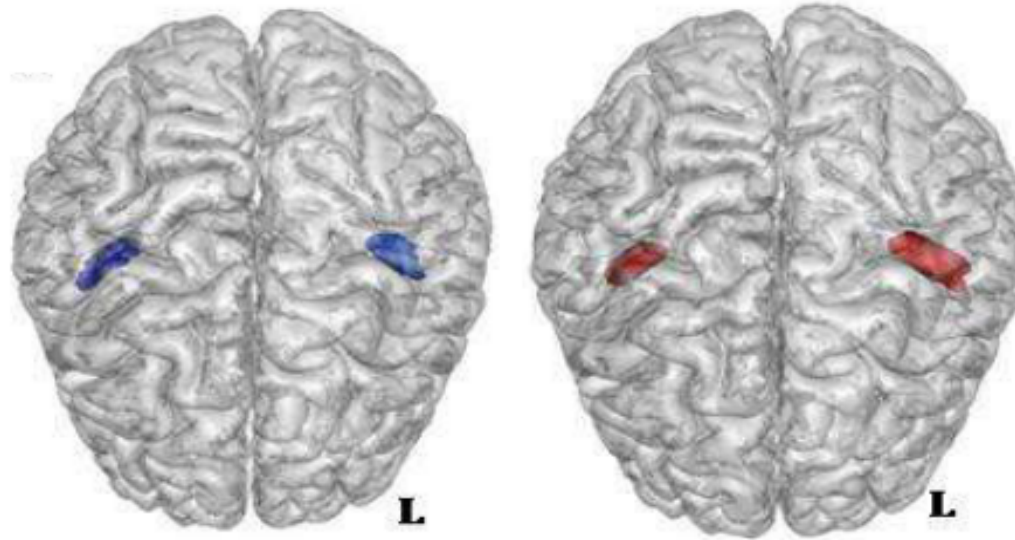


FIGURE 2 | Computation of the representational dissimilarity matrix. For each pair of experimental conditions, the associated activity patterns (in a brain region or model) are compared by spatial correlation. The dissimilarity between them is measured as 1 minus the correlation (0 for perfect correlation, 1 for no correlation, 2 for perfect anticorrelation). These dissimilarities for all pairs of

conditions are assembled in the RDM. Each cell of the RDM, thus, compares the response patterns elicited by two images. As a consequence, an RDM is symmetric about a diagonal of zeros. To visualize the representation for a small number of conditions, we suggest the similarity-graph icon (top right, cf. **Figure 1**).

Beyond fMRI. Morphometry

Drawing (manual or automatic)



Voxel-based (VBM)

To compare two groups of participants, the basic idea is to compare the probability that there is grey matter (or white matter) in a given location in the normalised space. So all anatomies are normalized on the same template, then thresholded to obtain binary maps of gray matter, and the percentages of participants having grey matter in a given voxel are compared. (actually, to detect volumetric differences, it is not binary maps that are compared)

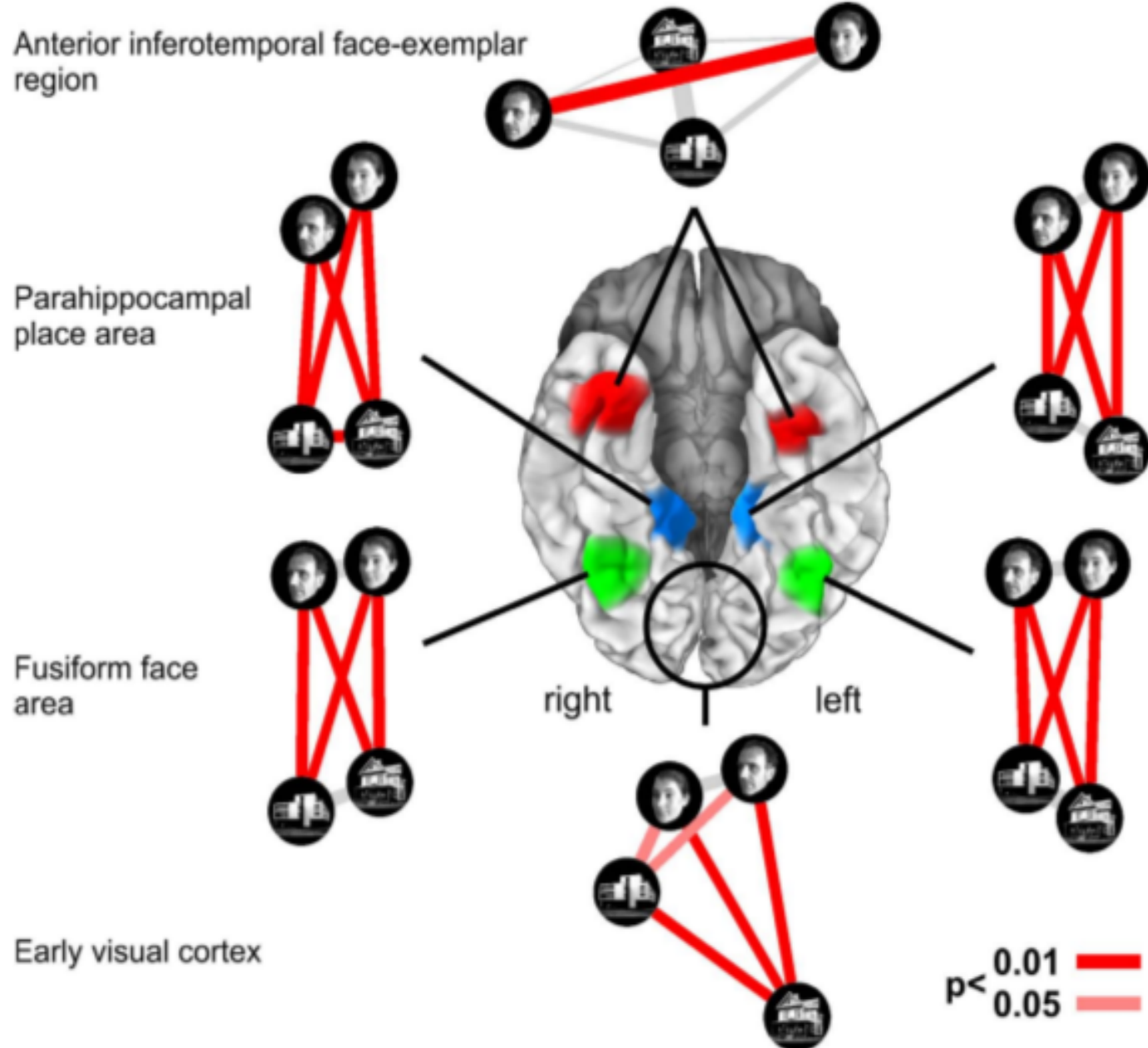


FIGURE 1 | Characterizing brain regions by representational similarity structure. For each region, a similarity-graph icon shows the similarities between the activity patterns elicited by four stimulus images. Images placed close together in the icon elicited similar response patterns. Images placed far apart elicited dissimilar response patterns. The color of each connection line indicates whether the response-pattern difference was significant for the group (red: $p < 0.01$; light gray: $p \geq 0.05$, not significant). A connection line, like a rubberband, becomes thinner when stretched beyond the length that would exactly reflect the dissimilarity it represents. Connections also become thicker

thickness of the connection lines is chosen such that the area of each connection (length times thickness) precisely reflects the dissimilarity measure. This novel visualization of fMRI response-pattern information combines (A) a multidimensional-scaling arrangement of activity-pattern similarity (as introduced to fMRI by Edelman et al., 1998), (B) a novel rubberband-graph depiction of inevitable distortions, and (C) the results of statistical tests of a pattern-information analysis (for details on the test, see Kriegeskorte et al., 2007). The icons show fixed-effects group analyses for regions of interest individually defined in 11 subjects. Early visual cortex was anatomically defined; all other