OBJECTIVES

- The principles of representational similarity analysis (RSA)
- Applied contexts for RSA
- Application of RSA to brain data
- Relation between RSA and other alignment techniques
- Other approaches to multivariate analysis of brain data and difference from univariate analyses

KRIEGESKORTE 2008 - RSA

STUDYING REPRESENTATIONS VIA SIMILARITY SPACES

SIMPLE PREMISE

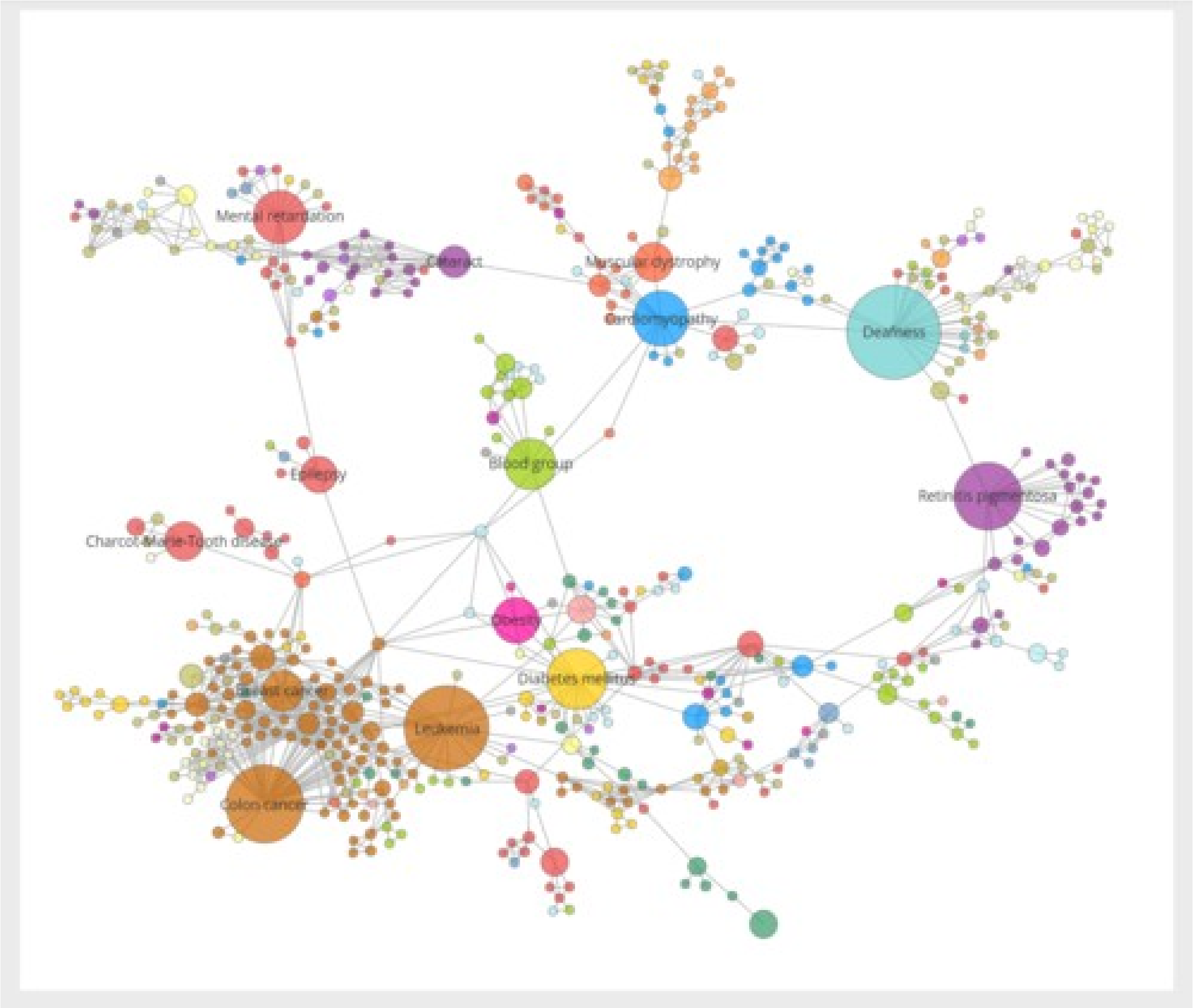
Relates modalities of human behavior (or brain-activity measurement) and information-processing models by comparing activity-pattern dissimilarity matrices

A singly similarity-matrix captures *first-order* similarity between stimuli (either similarity in brain response, or similarity as computed by a model)

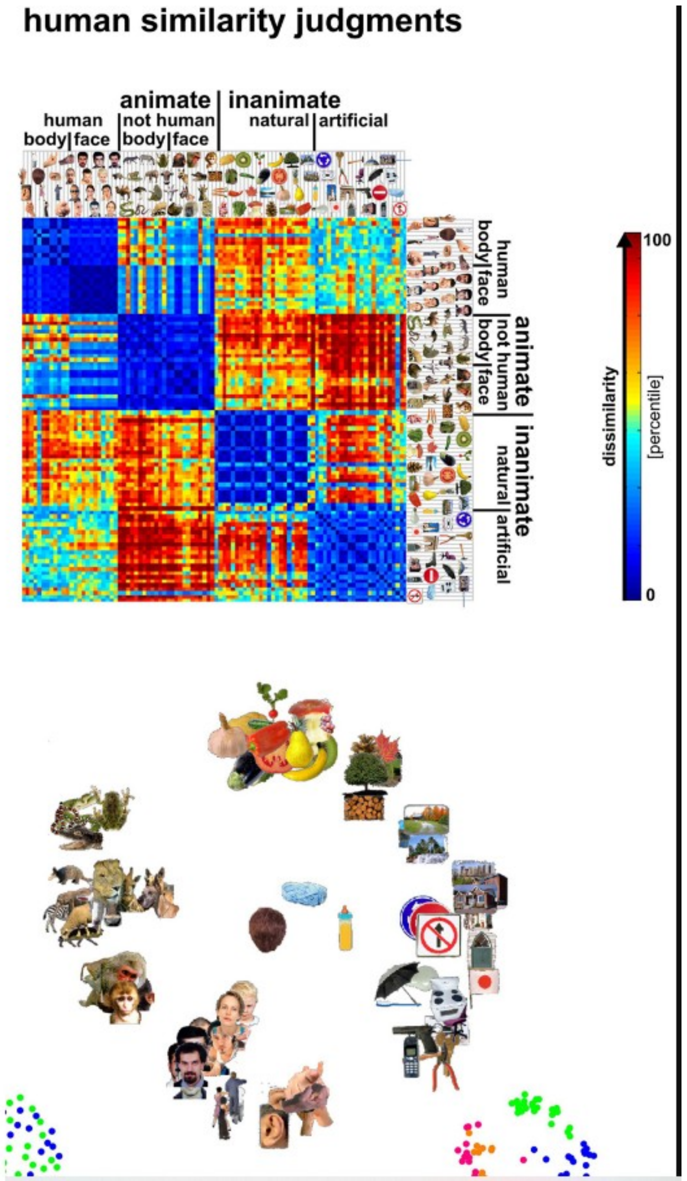
RSA is a 2-nd order similarity because it quantifies how alike two similarity-matrices are

RSA: FEATURES OF CHARACTERIZING

- Modality independent
- Could relate whatever modality of brain or behavioral measurement to information processing models
- Based on notion of similarity, or ‘distance’ between stimuli.

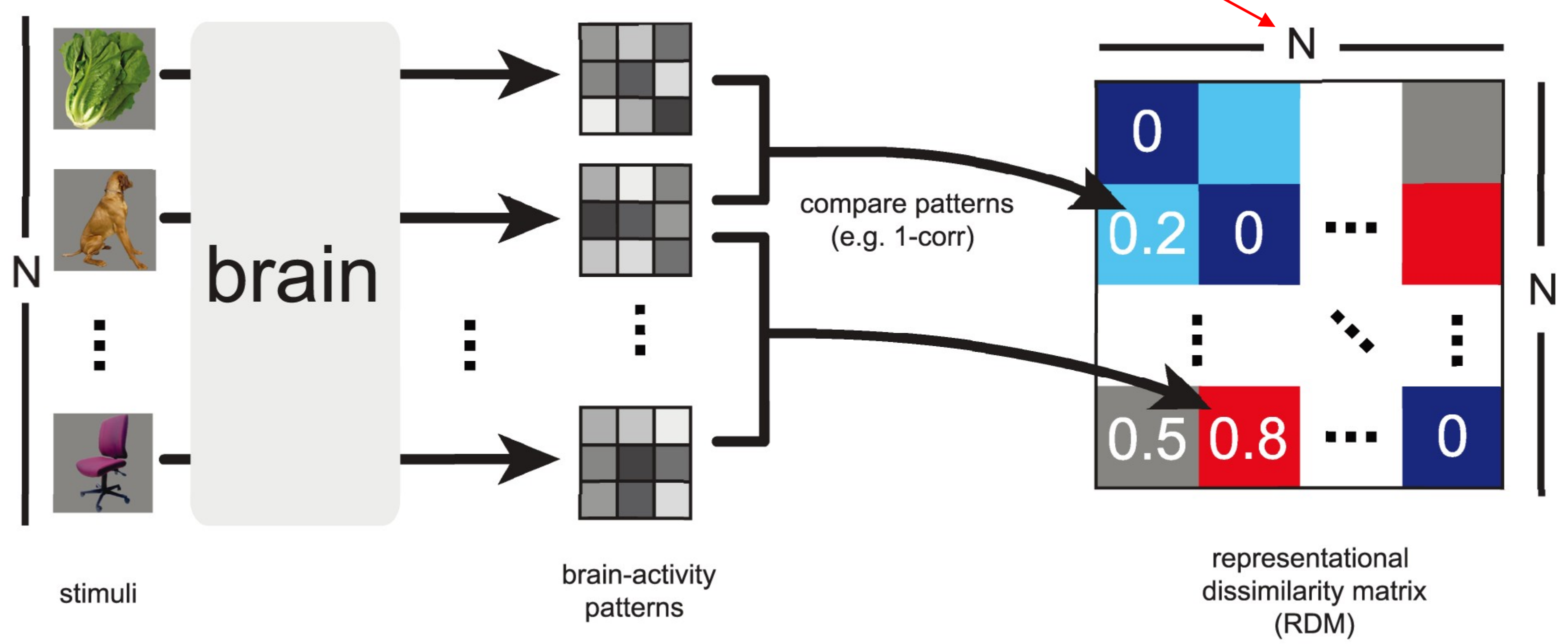


CONSTRUCTING A SINGLE SIMILARITY MATRIX: BEHAVIOR



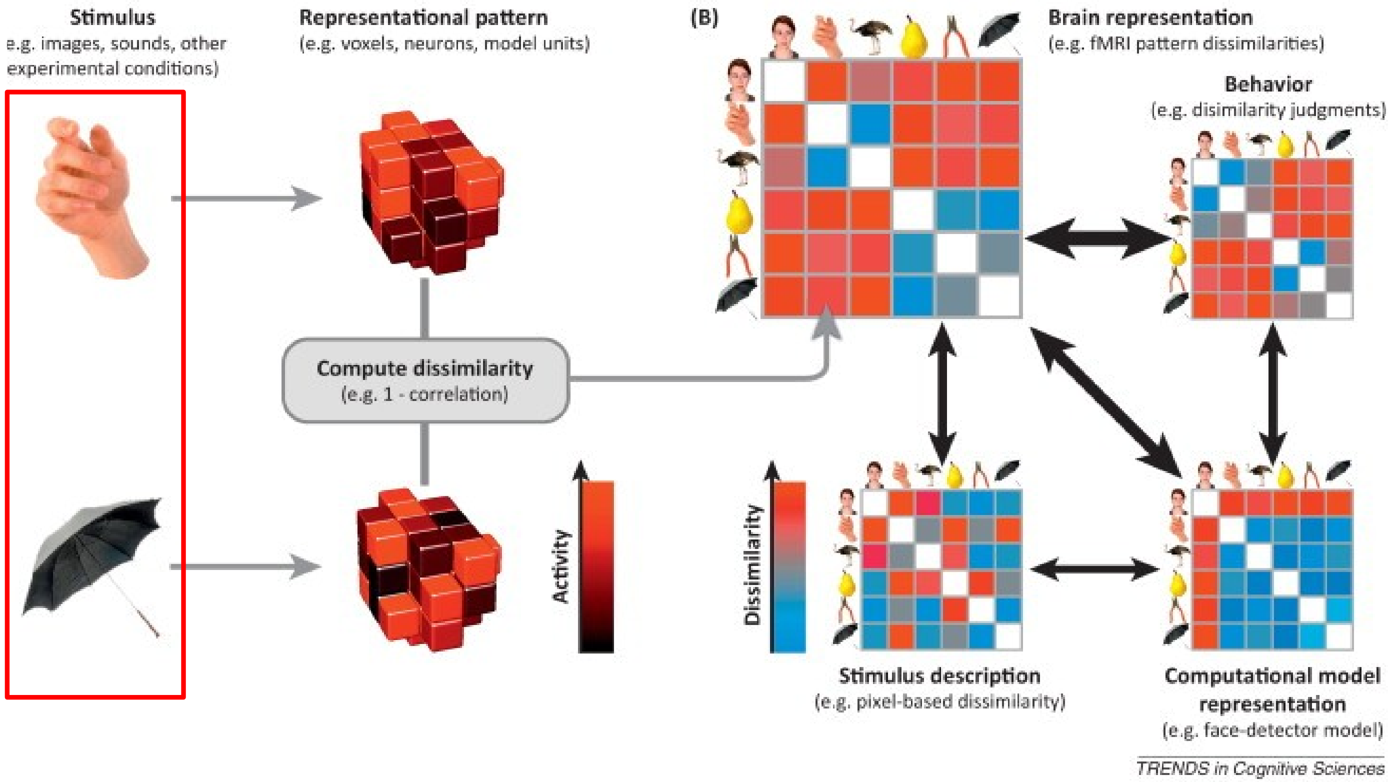
CONSTRUCTING A SINGLE SIMILARITY MATRIX: BRAIN

Representational Dissimilarity Matrix (RDM)

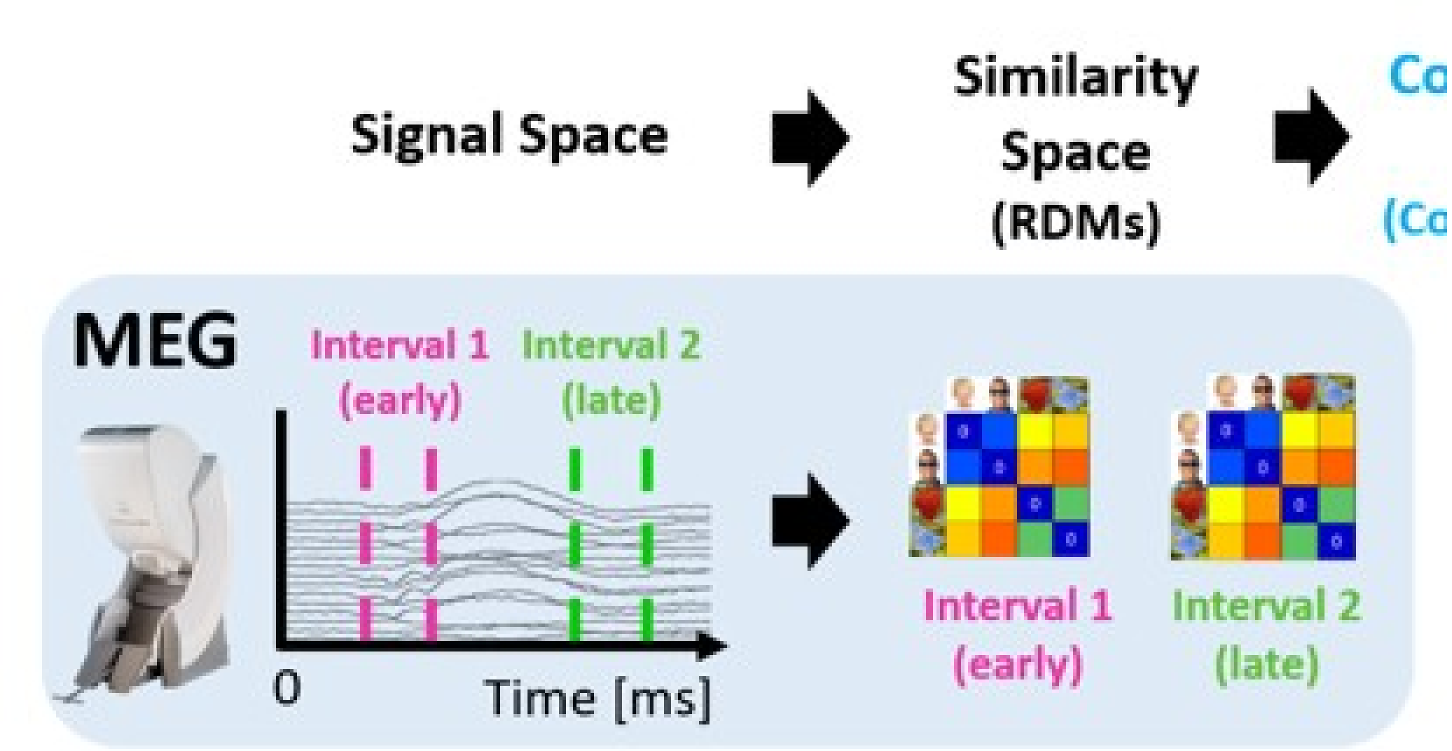


COMPARING SIMILARITY MATRICES I

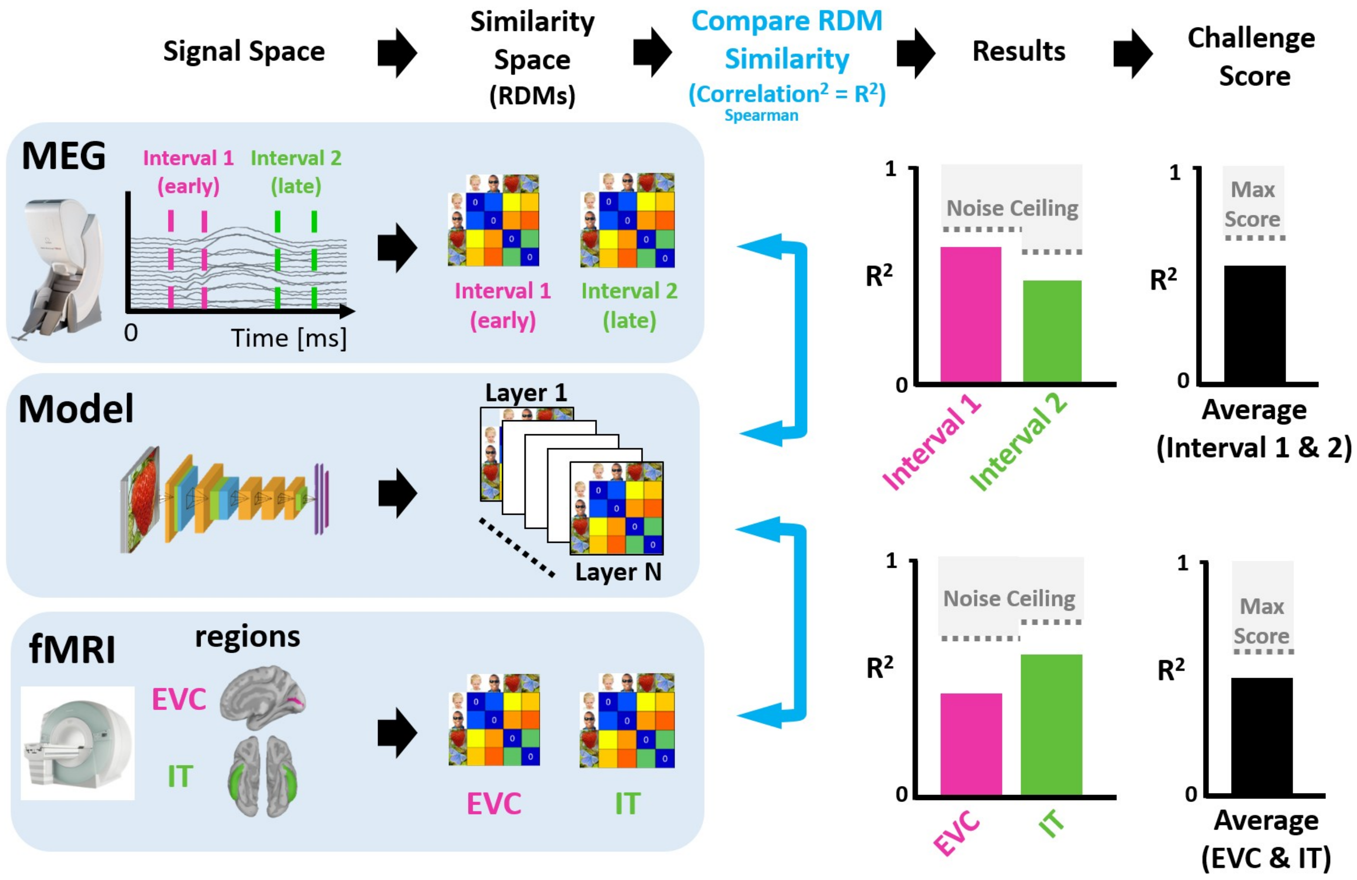
Example of 2 stimuli and brain response



APPLICABLE TO SENSOR X TIME REPRESENTATIONS



COMPARING SIMILARITY MATRICES II



Extrastriate and Inferior temporal fit with DNN

CLARIFICATION POINTS

- The Noise ceiling is the maximal (ceiling) value expected given the noise in the data.
- Oftentimes the noise ceiling is estimated as the correlation between the estimates of the responses in two independent repetitions of the same experimental procedure.
- The idea that the ability of X to predict Y cannot exceed the noise ceiling, defined as the correlation between Ys (Y1 and Y2) obtained for the same stimuli on 2 different test data.

APPLICATIONS

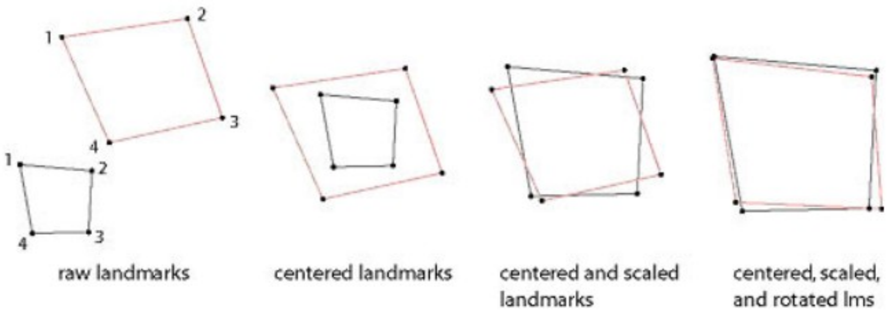
- Probe for 2-nd order similarity across brain regions (no model): **what does this answer**?
- Relate brain and behavior
- Find areas that code similarly for different stimuli across participants or even species.
- Allows to code a single set of stimulus across multiple dimensions and code RDMs at each feature level. (Figure5 p. 8 for model, Figure 6 p.9 for RDM)

A NOTE: RSA AND LOSS OF DIMENSIONS (I)

- When using Human Similarity Judgments, we create an RDM directly from those judgments.
- When using **NeuroBio** data to produce RDMs we use an S (stimuli/observation) x V (voxels/sensors/regions) matrix
- When using **Computational Models** to produce RDMs we use an S (stimuli/observation) x F (features >0; can be 1) matrix.
- When relating NeuroBio and Computational models the [S x V] and [S x F] matrices are first converted to RDMs.
  - Consider you can get the exact same RDM from different SxF matrices that differ massively on the number of F. This means that when we convert to RDMs we don't have specific information on dimensions that produce the alignment.

A NOTE: RSA AND LOSS OF DIMENSIONS (II)

- When dealing with 2 domains (brain, model) represented as observation x feature matrices, and when the two matrices reflect the same feature, we could evaluate the fit directly at the matrix level.
- The following techniques all probe for strength of common dimensions between two matrices.
  - Procrustes rotation:
  - Principal component regression
  - Partial least squares correlation
  - Canonical correlation analysis

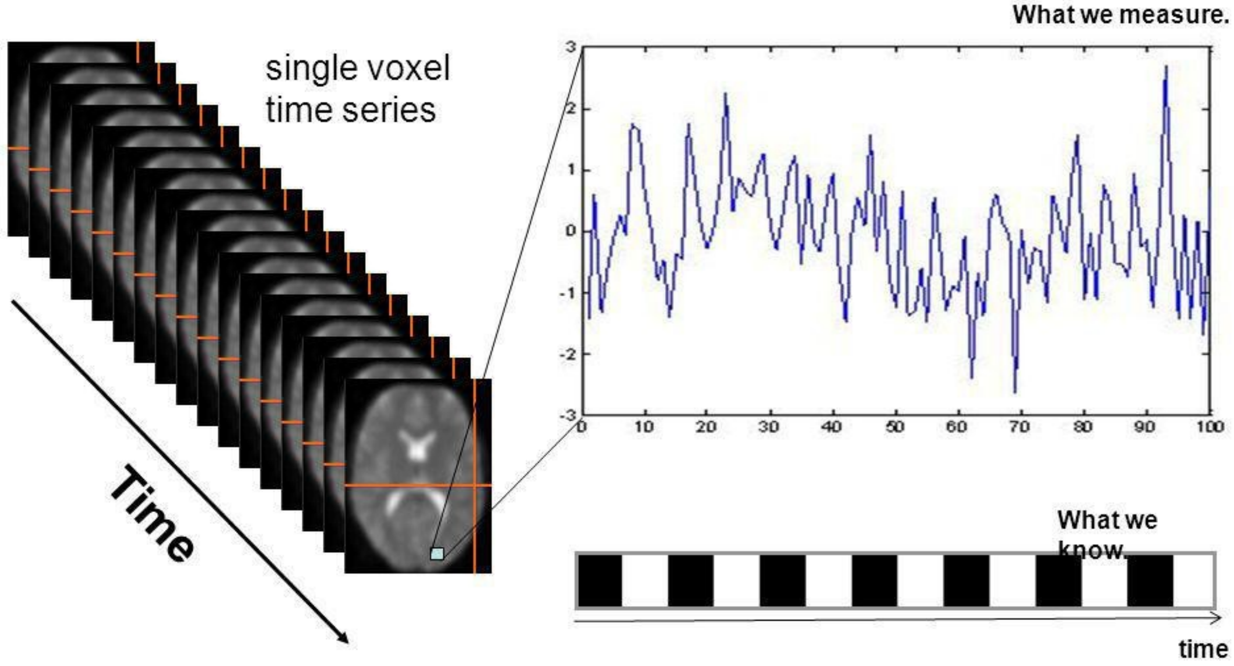


The three steps in Procrustes superimposition: Translation to a common centroid, scaling to the same centroid size, and rotation to minimize summed squared distances between the corresponding landmarks.

CONTEXT

UNIVARIATE AND MULTIVARIATE APPROACHES

Image a very simple experiment…



Question: Is there a change in the BOLD response between listening and rest?

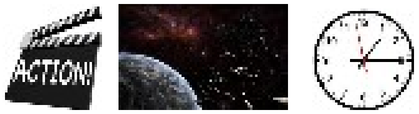
INFORMATION CONTAINED IN MULTIPLE VOXELS: MULTIVARIATE ANALYSES

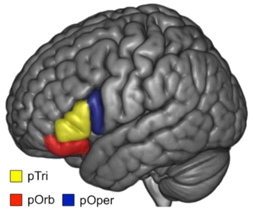
Studied brain responses during narrative comprehension as participants focused on spatial, temporal, or action-related dimensions of a narrative.

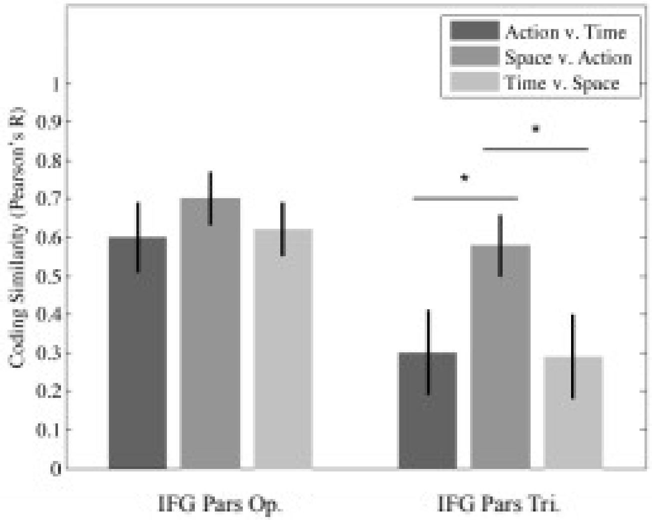
We considered each IFG sub-region as a 'voxel'

Univariate: regional activity in pOper higher for some conditions but null effect for Pars Triangularis.

Multivariate: Considered the entire set of values in each region, and quantified how similar those activity patterns were for the 3 conditions.







Cooper et al., 2011

Multivariate pair-wise similarity of 3 conditions in two IFG sub-regions

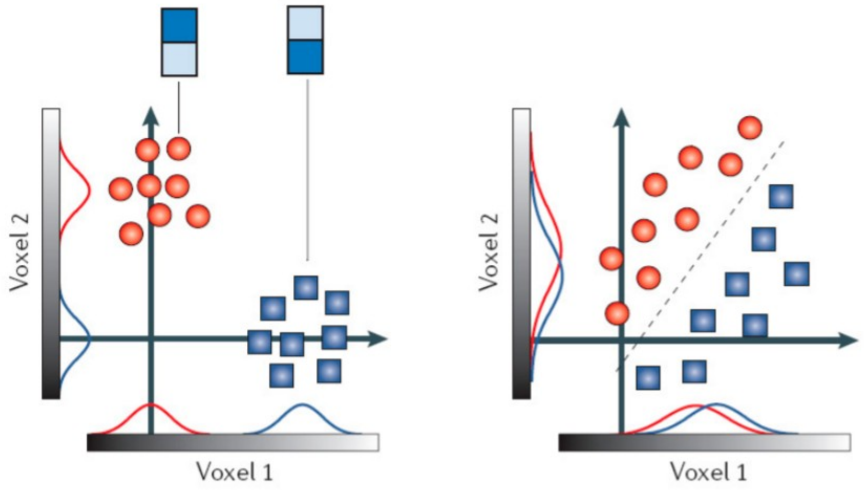
MULTIVARIATE VS. UNIVARIATE VALUES

Vector1	0.392938	-0.42772	-0.3231	-0.86442	0.096557		-0.22515		0.998319	cor(vec1, vec2)	
Vector	0.398872	-0.37425	-0.28038	-0.87645	0.098465		-0.20675		0.752491	cor(vec1, vec3)	
Vector	0.420993	-0.37238	-0.89733	-0.45174	0.161454		-0.2278				

DECODING CATEGORY (BINARY CASE) FROM BRAIN

MULTI VARIATE PATTERNS: MULTI VOXEL PATTERN ANALYSIS (MVPA)

- Two conditions are presented, which produce different distributions of activity across trials. **Each trial** is captured by circle/square.
- In Case1, each condition produces different activity levels, in both voxel1 and voxel2. Clearly, the region discriminates the classes.
- In Case2, each condition produces highly similar mean activity levels in both Voxel1 and Voxel2. So you would conclude that the region does not discriminate if aggregating across univariate analysis.
    - BUT: the 'region' containing Voxels1,2 contains information about conditions in the Joint Distribution of voxel1,voxel2



Case 1 Case 2

http://imaging.mrc-cbu.cam.ac.uk/imaging/Introduction_to_fMRI_2010?action=AttachFile&do=get&target=Intro_fMRI_2010_03_MVPA.pdf

CLARIFICATION POINTS

- In classifying to classes given data in N voxels (of a single brain region), voxels are treated as features or column.
- Response to each stimulus trial is coded as an activity pattern across the N voxels.
- For each person, there are as many rows as total stimulus, and as many columns as voxels.
- In a ML workflow, 80% of the rows will be used for training, and 20% for testing.