Representational similarity analysis (RSA)

Marieke Mur
CBU, april 2016

Overview

- Why representational similarity analysis?
- Distance measures
- Inference
    - o Descriptive visualisations
    - o Goodness of model fit
    - o Model comparisons
- RSA applications in other areas of neuroscience
- Toolbox
- Literature

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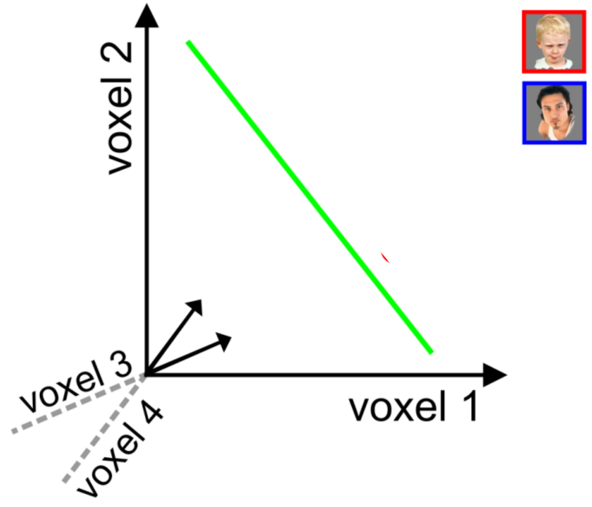
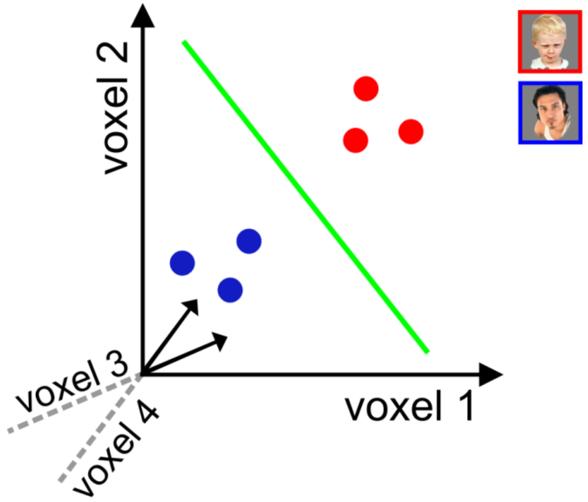
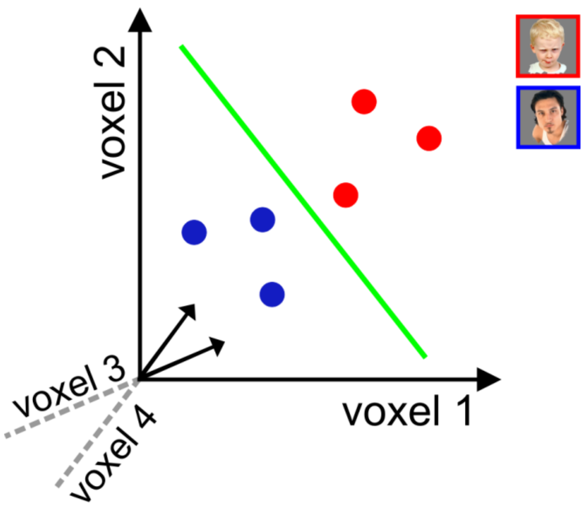
Linear classification: anything missing?



Linear classification: anything missing?

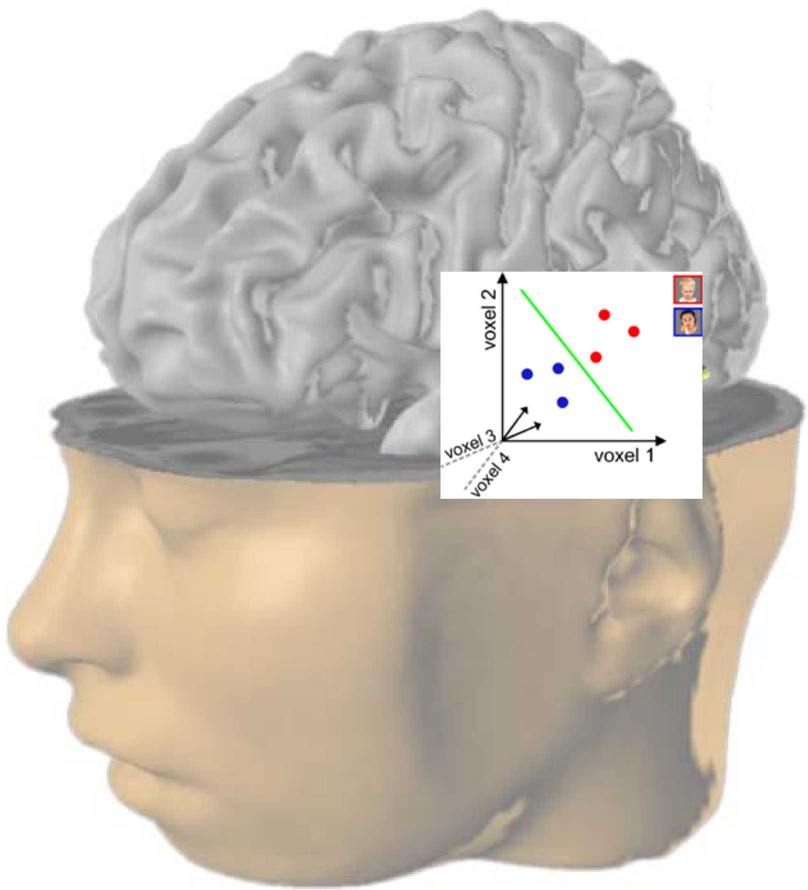


Linear classification: anything missing?

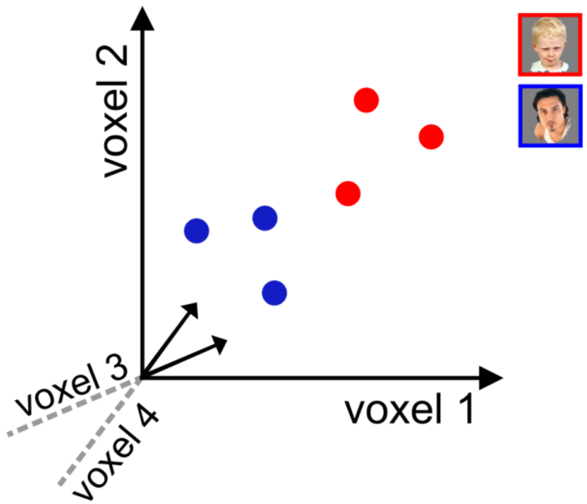


Need a richer characterisation of the stimulus representations.

One step further: how to relate brain representations to subjective experience?

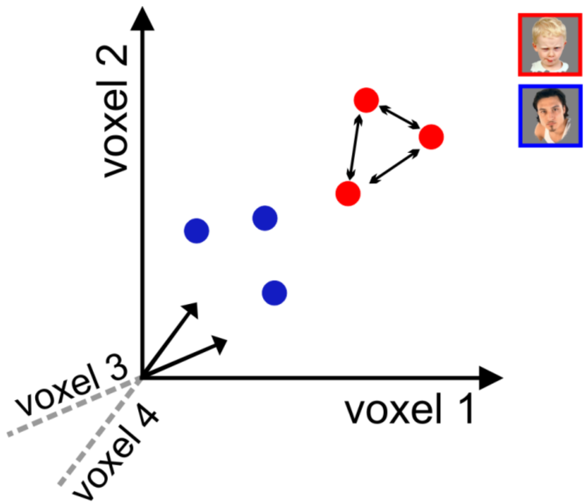


Relate brain and subjective experience

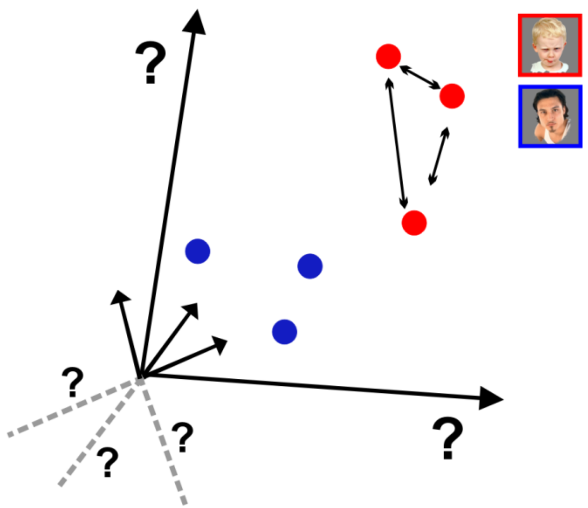


brain

Relate brain and subjective experience

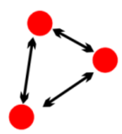


brain

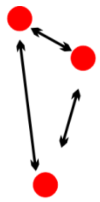


subjective
experience

Relate brain and subjective experience



brain



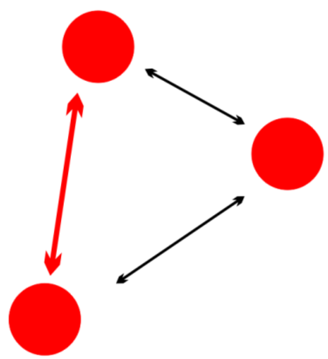
subjective
experience

Relate brain and subjective experience

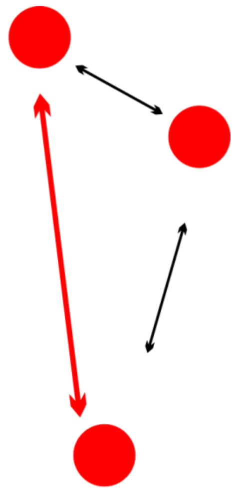
brain

subjective experience

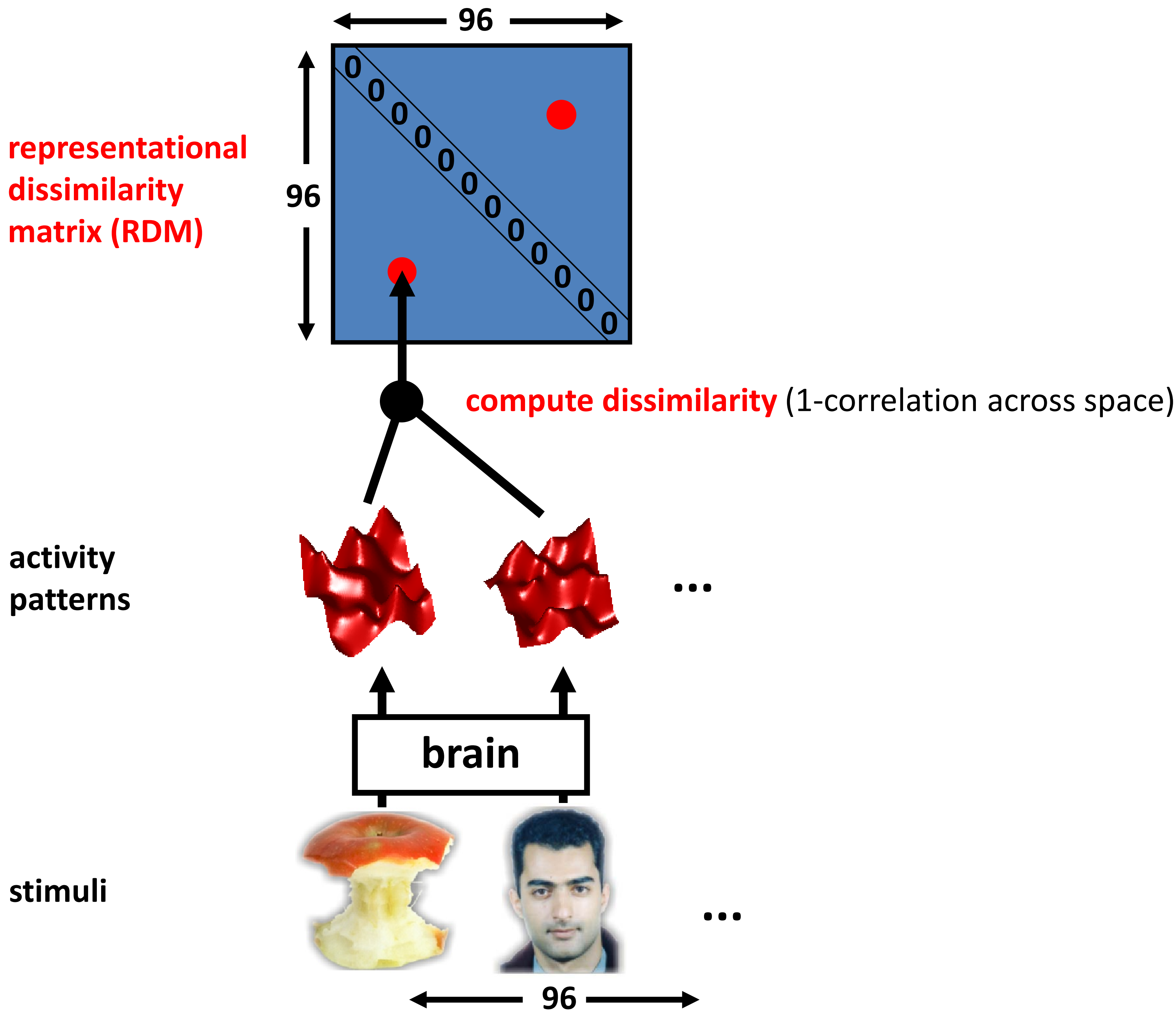
Relate brain and subjective experience



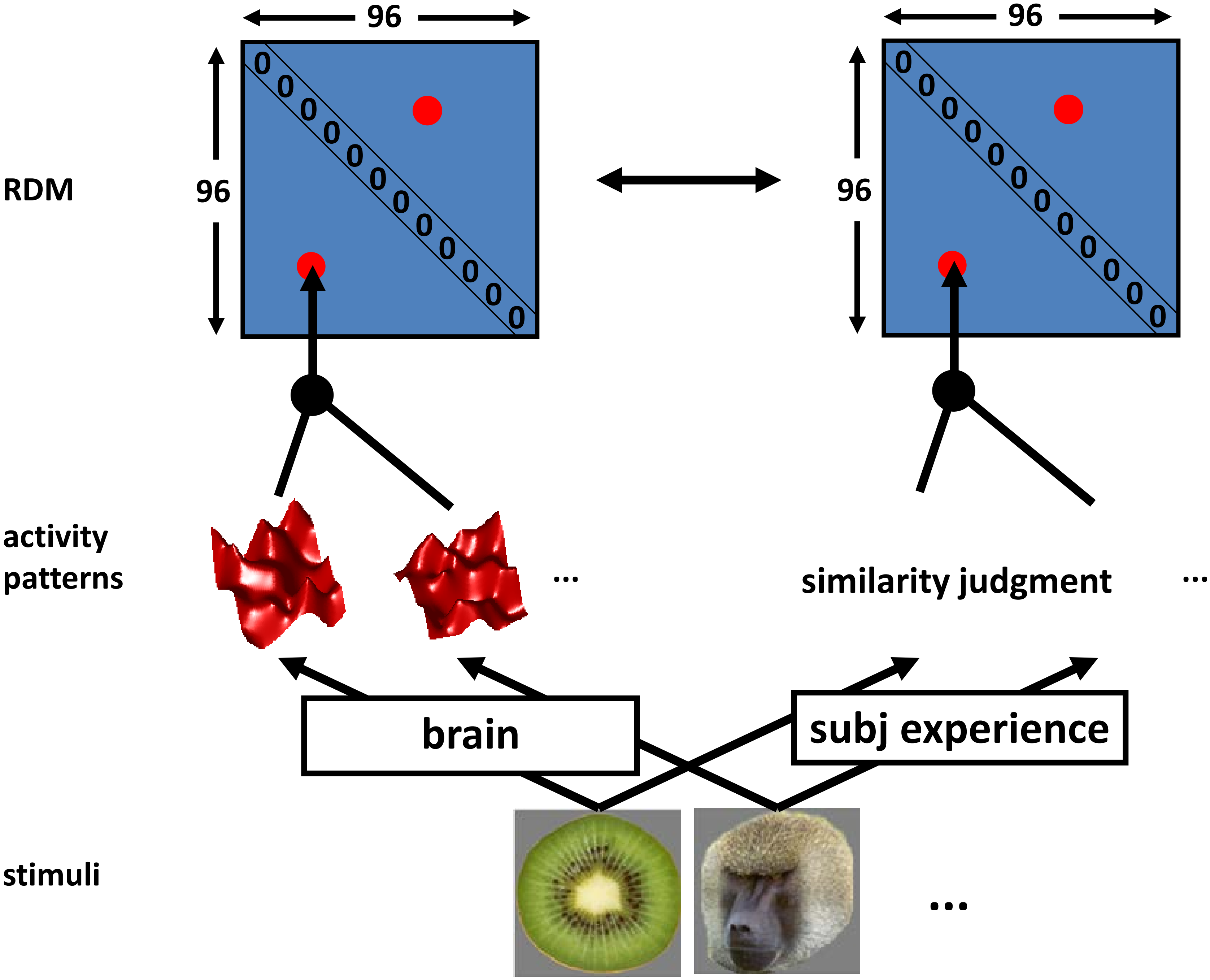
brain

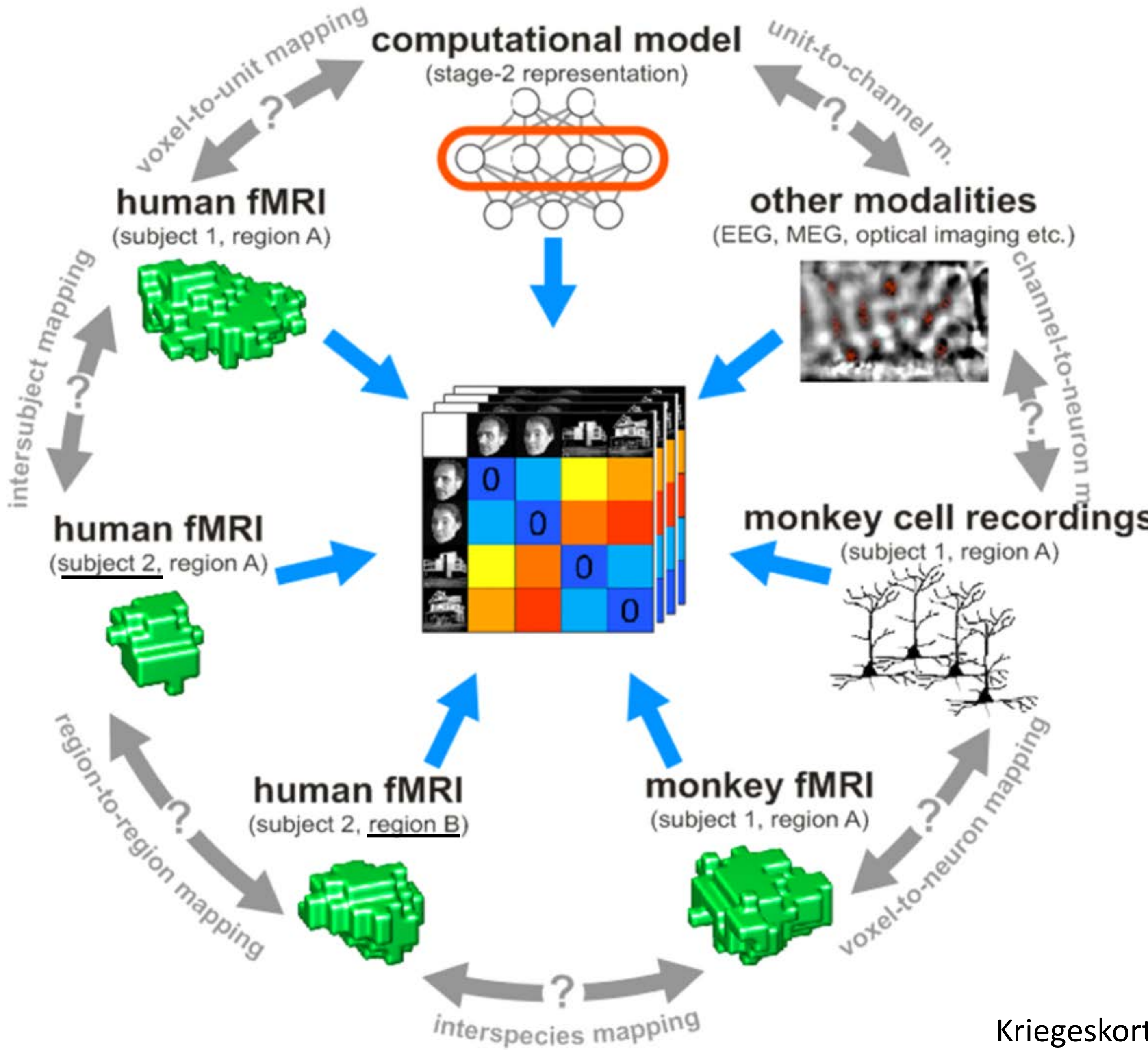


subjective
experience



96
0 0 0 0 0 0 0 0 0 0 0 0
representational dissimilarity matrix (RDM)
96
compute dissimilarity (1-correlation across space)
activity patterns
...
brain
stimuli
...
96


96
96
RDM
96
96
0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0
activity
patterns
...
similarity judgment
...
brain
subj experience
stimuli
...



Kriegeskorte et al. 2008

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Euclidean distance

Straight-line distance between two patterns in Euclidean space

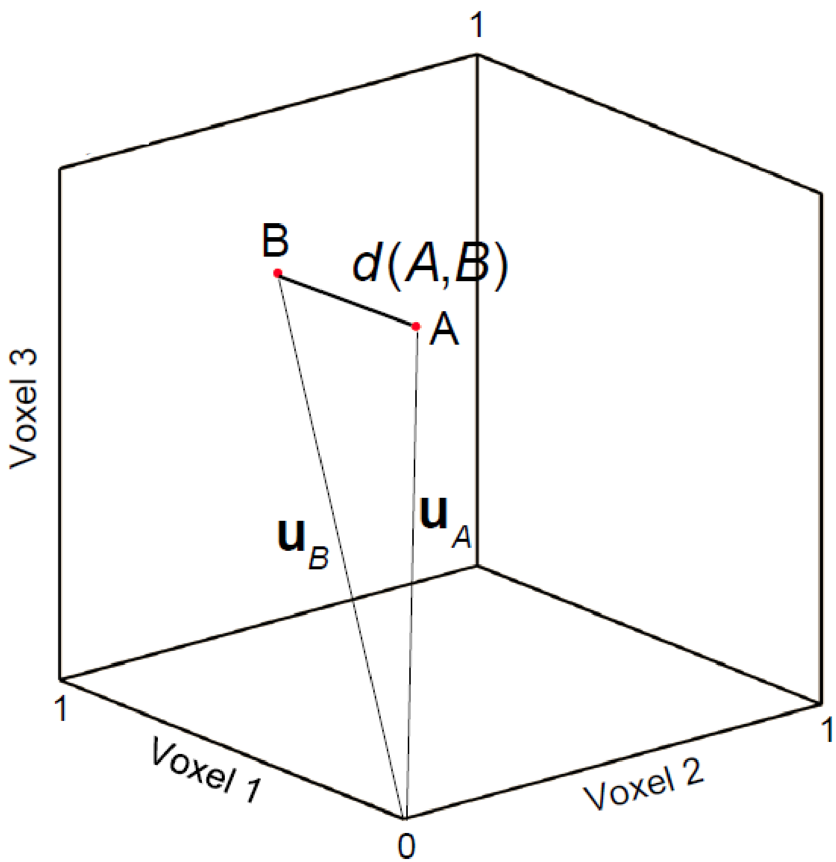


Image from Alex Walther
RSA workshop 2015

Correlation distance

1 – correlation

Correlation = cosine of the angle between normalised patterns

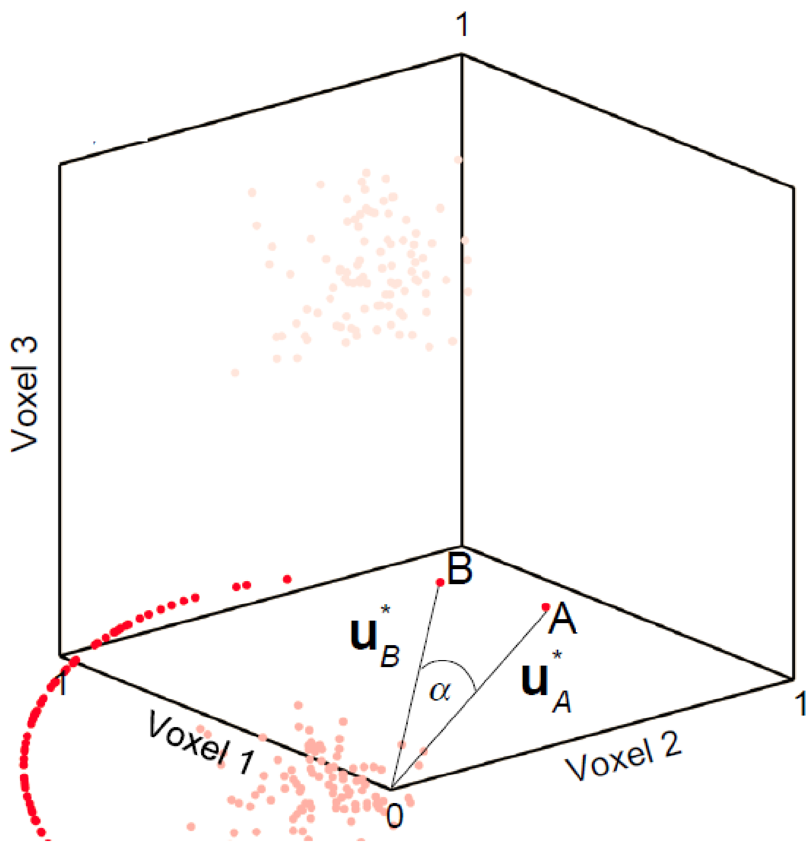


Image from Alex Walther
RSA workshop 2015

Linear discriminant t value (LDt)

The default distance measure used in the RSA toolbox.

It has two desired properties:

1. Multivariately noise normalised
2. Cross-validated

Noise normalisation

Noise normalisation of the fMRI response patterns increases the reliability of the estimated pattern distances.

Univariate:

Divide each voxel's beta weight by its standard deviation

→ t value

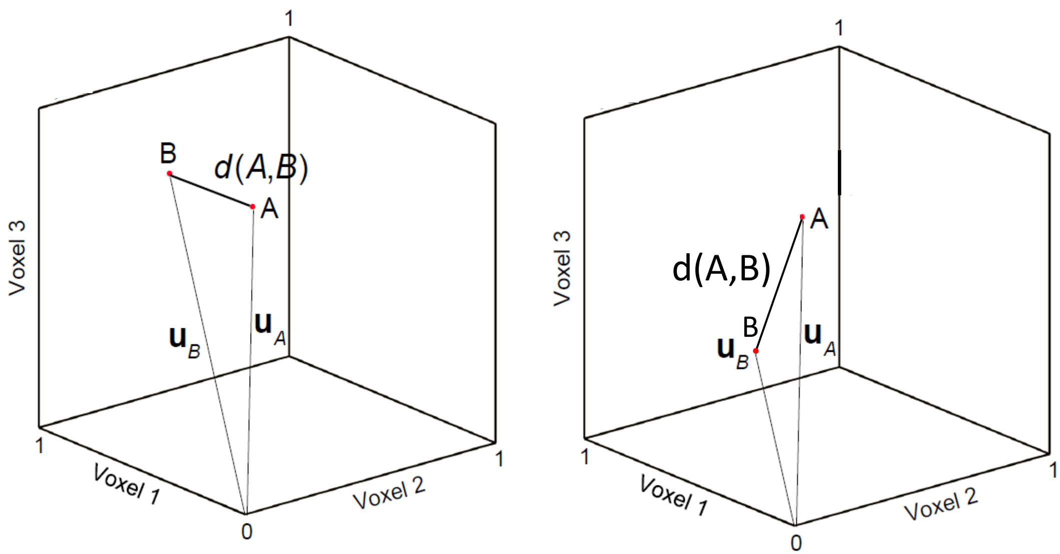
Multivariate:

Multiply each pattern with the inverse of the (square-rooted) covariance matrix → Mahalanobis distance

Cross-validated distance measures

Noise → distance measures are positively biased.

Cross-validated distance measures are unbiased and have an interpretable zero point.



data set 1

data set 2

LDt
The cross-validated Mahalanobis distance divided by its standard error

Images (adopted) from Alex Walther RSA workshop 2015

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96 object images

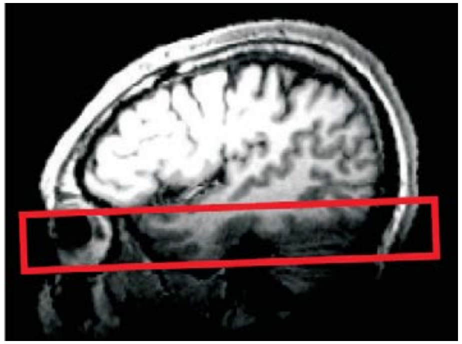
Stimuli from Kiani et al. 2007, Kriegeskorte et al. 2008

96-object-image fMRI experiment

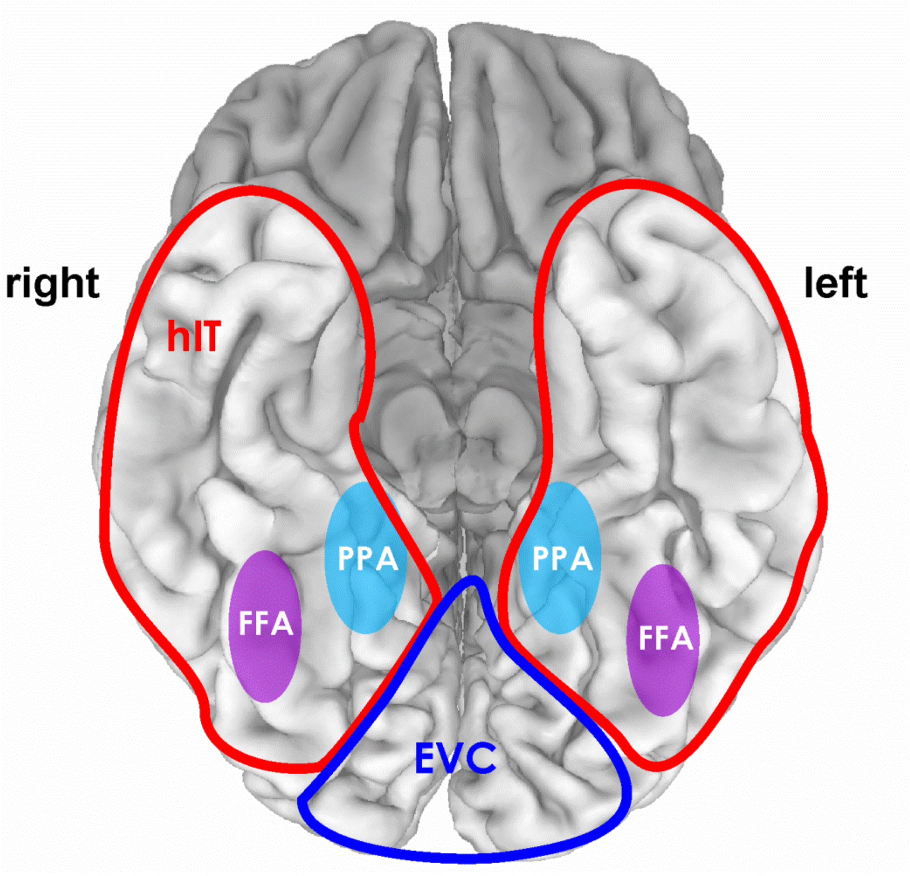
- 4 healthy human subjects
- rapid event-related design (minimum SOA: 4 s)
- stimulus duration: 300 ms
- object images spanned a visual angle of 2.9°
- fixation-cross color-discrimination task
- 12 runs/subject, each object image presented once per run

96-object-image fMRI experiment

- 25 axial slices covering ventral occipital and inferior temporal cortex (no gap)
- voxel size: $1.95*1.95*2\ mm^3$
- TR: 2 s



Region of interest: hIT



- independent data
- bilateral
- most visually-responsive voxels within "red" region
- results same if FFA and PPA excluded from hIT

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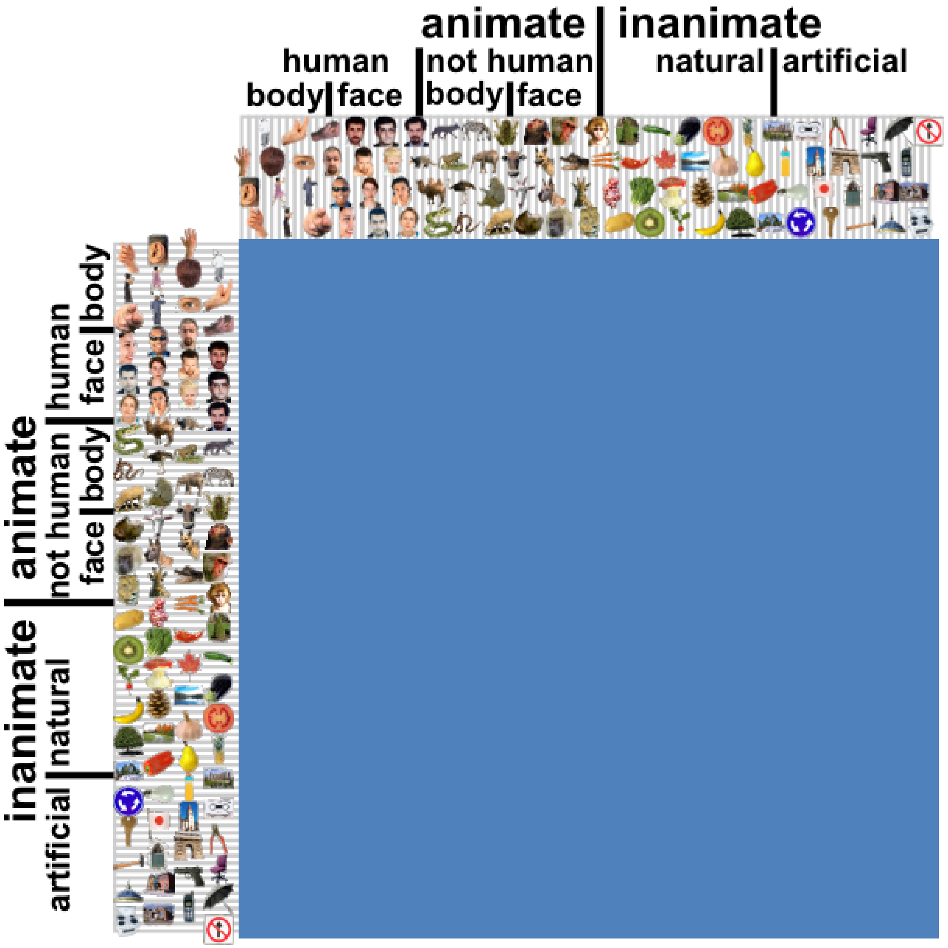
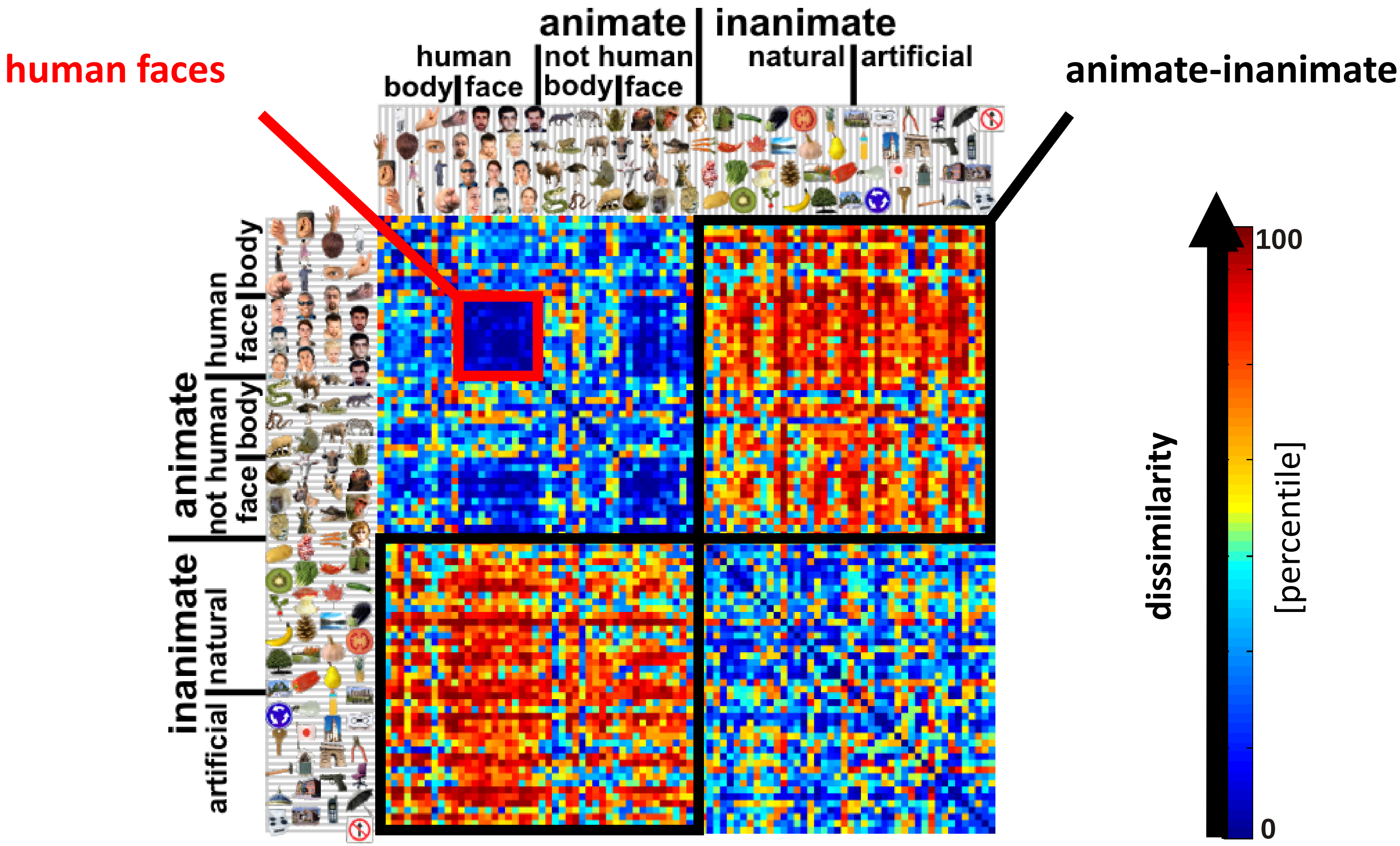
RDM of IT activity patterns



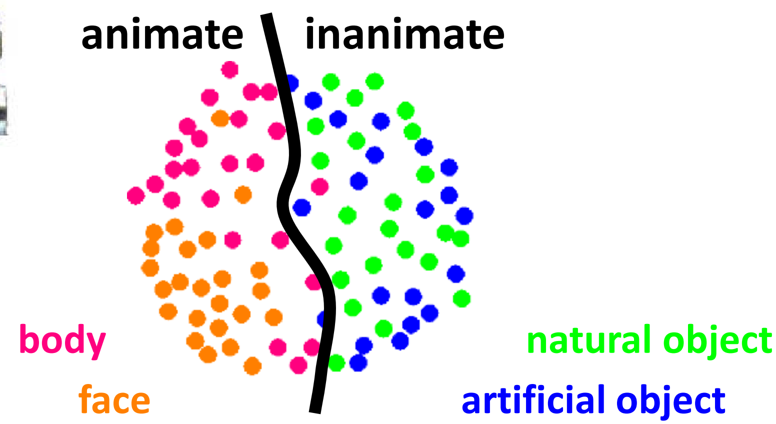
RDM of IT activity patterns



4 subjects' average

Kriegeskorte et al. 2008

Multidimensional scaling of IT dissimilarities



Kriegeskorte et al. 2008

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How well do brain representations and subjective experience match?

Conventional method:
Pairwise similarity ratings

How similar are these objects?

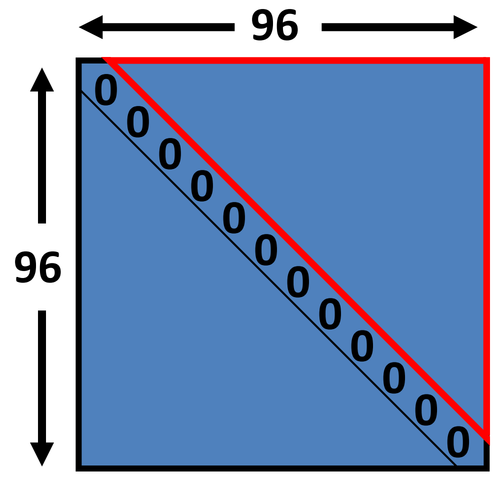
very similar very dissimilar

0 **5**

Many pairwise dissimilarities

96 x 95 / 2 = 4560 pairs

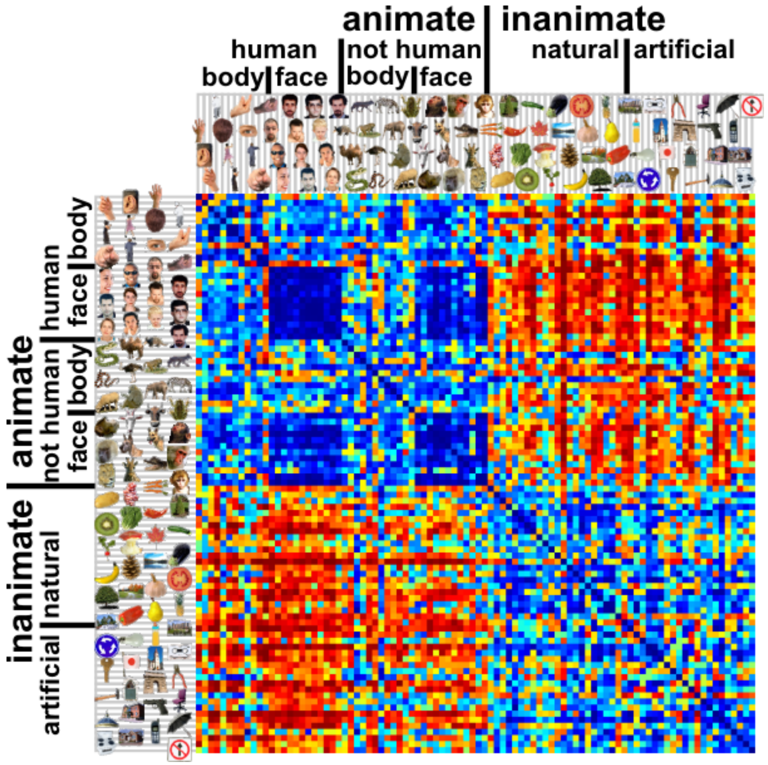
4560 * 4 s = 5 hours per subject



similarity-judgment RDM

RDM

2D arrangement by dissimilarity



multidimensional scaling

inverse multidimensional scaling

Goldstone, 1994; Risvik et al., 1994

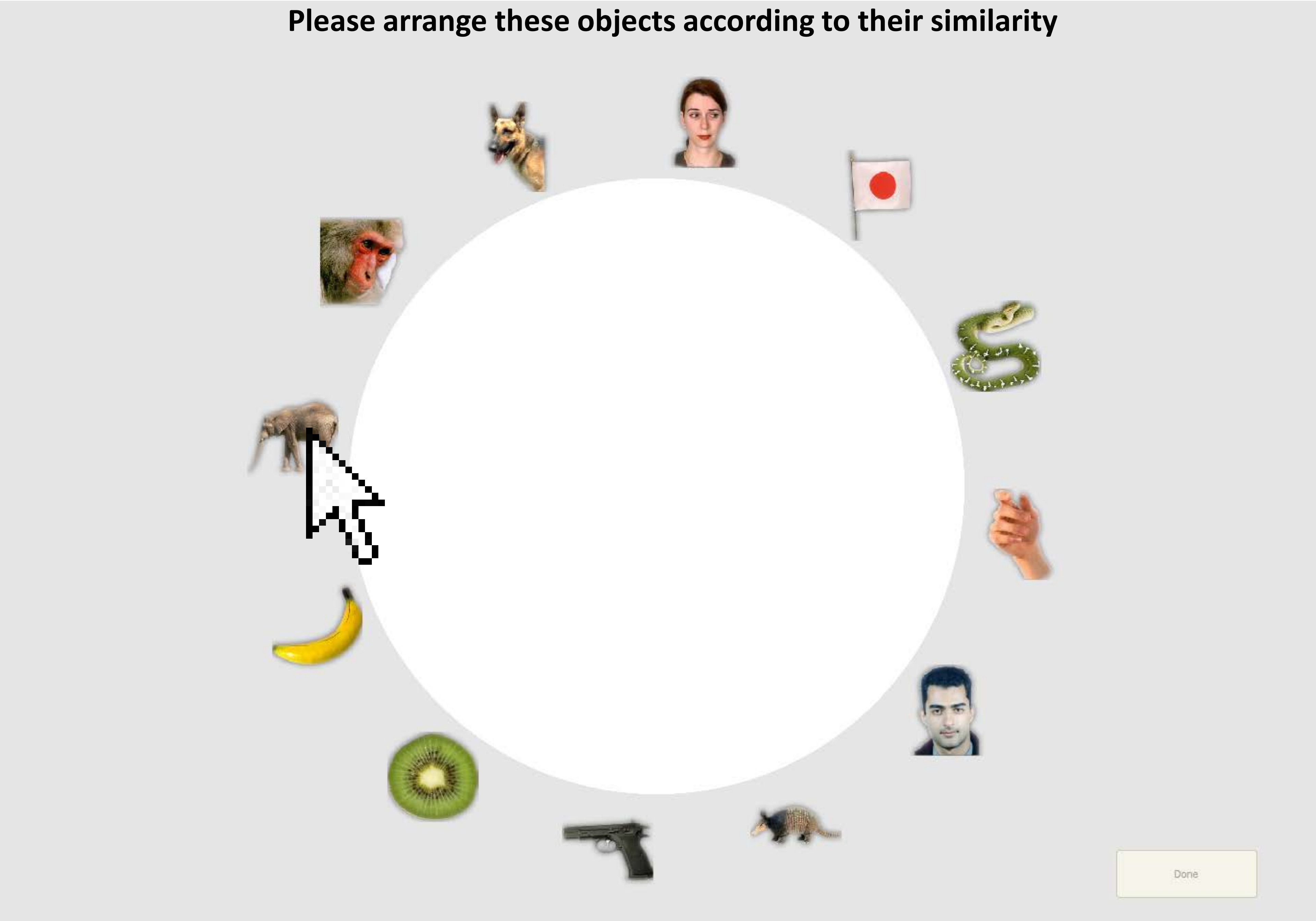
Multi-object arrangement (MA) method

- Subjects arrange objects in 2D by mouse drag-and-drop.

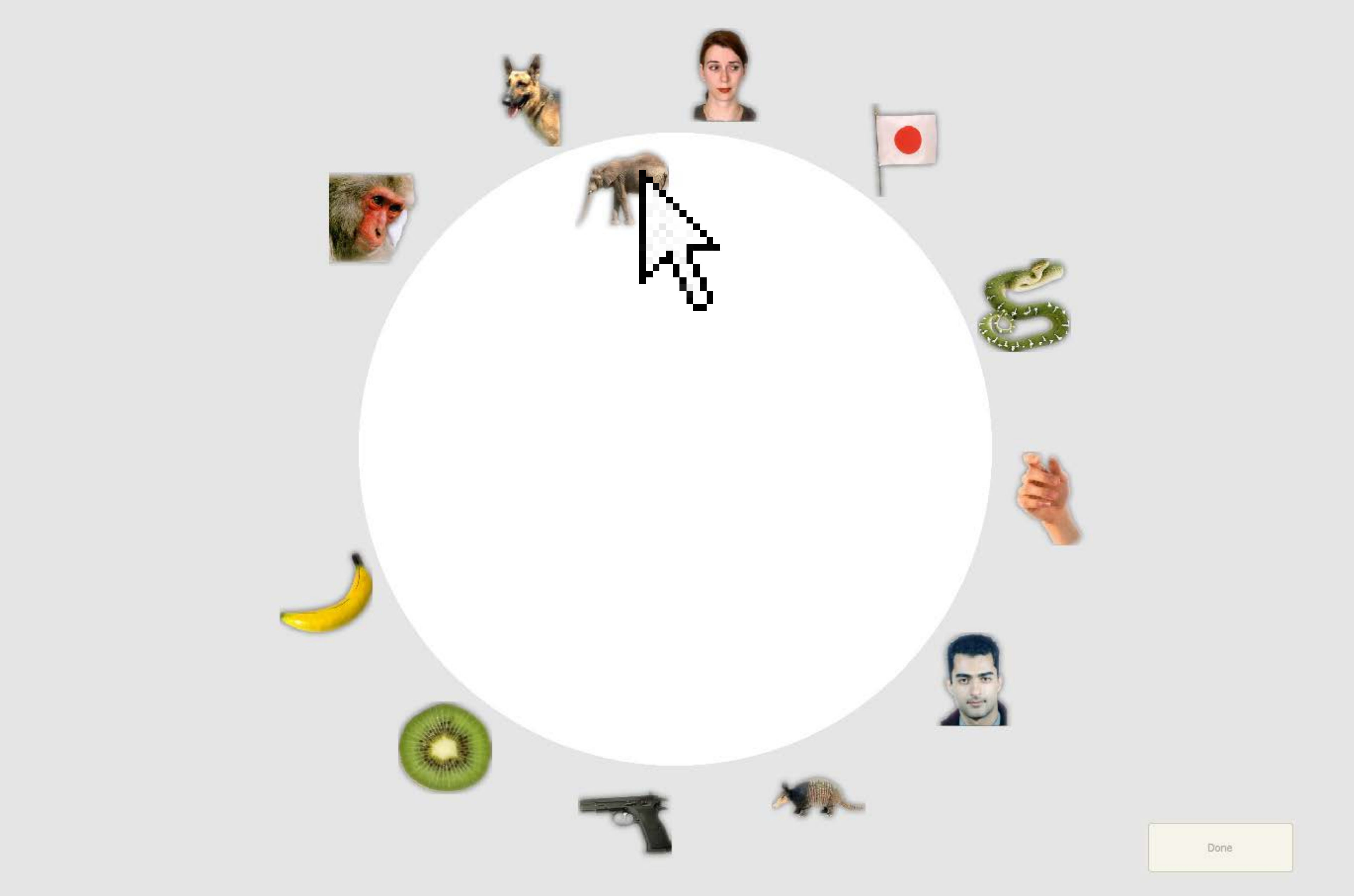
- More efficient than pairwise similarity ratings.

- Subjects arrange objects in the context of the other objects in the set.

Kriegeskorte & Mur 2012


Please arrange these objects according to their similarity
Done

Please arrange these objects according to their similarity



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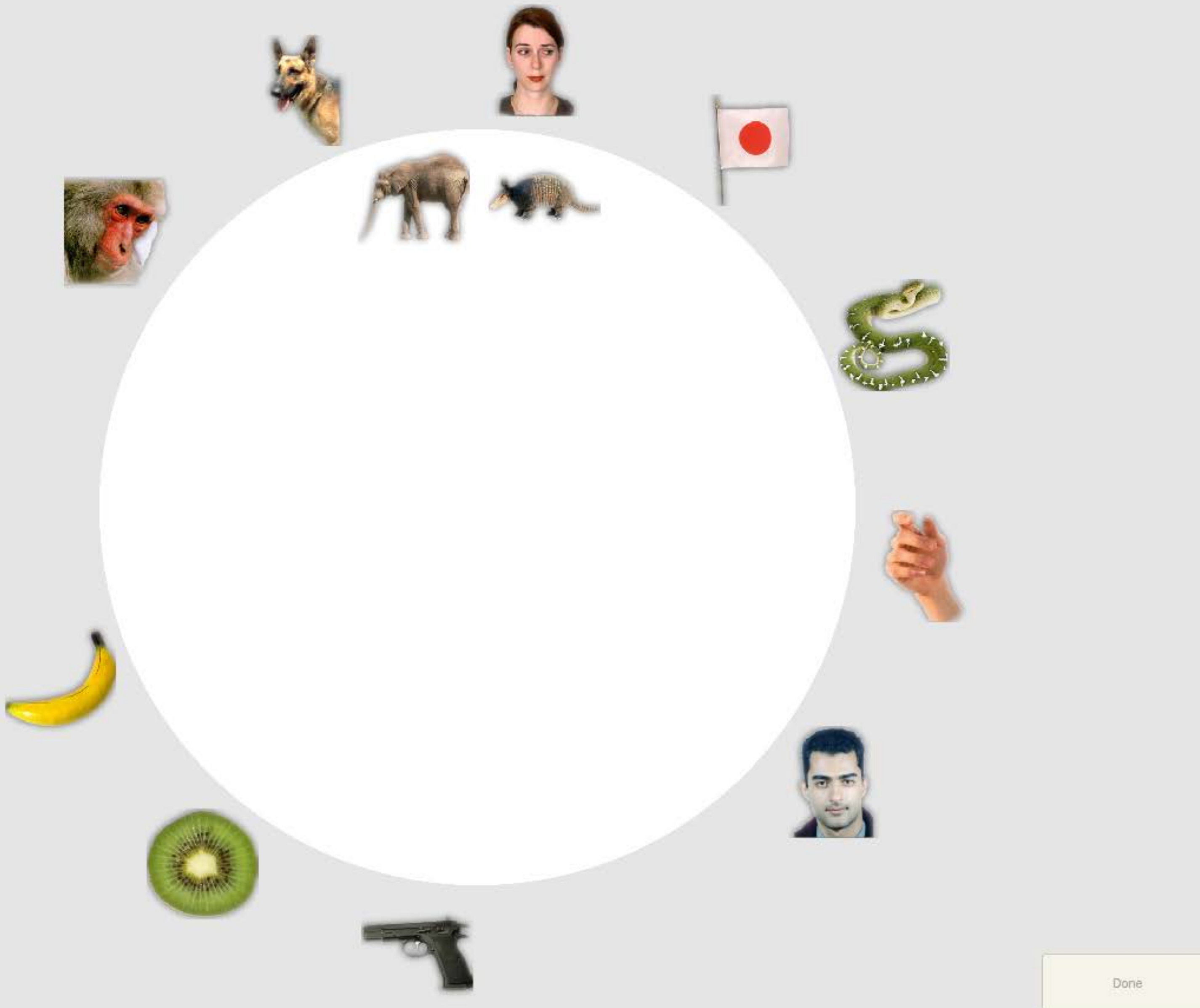

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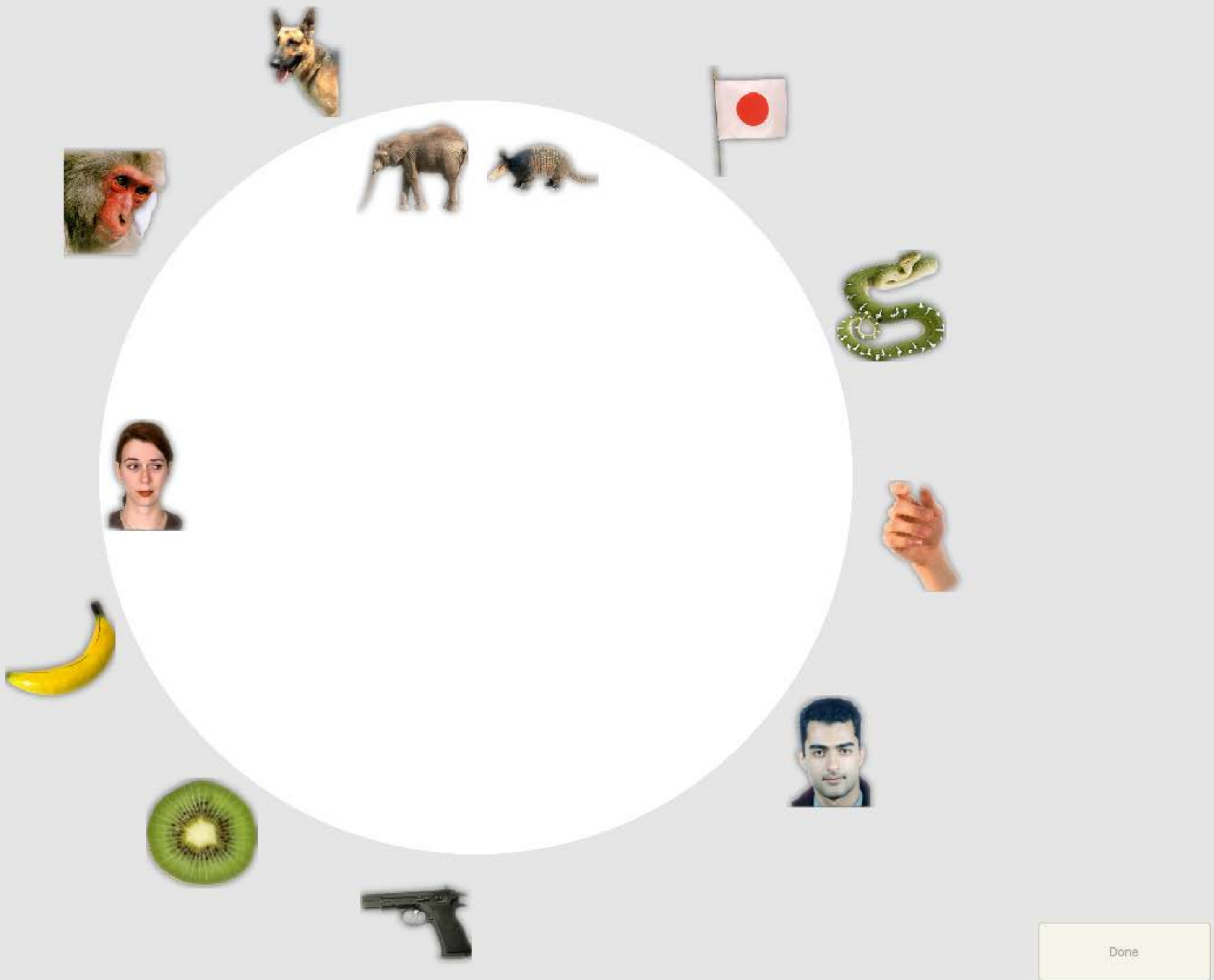

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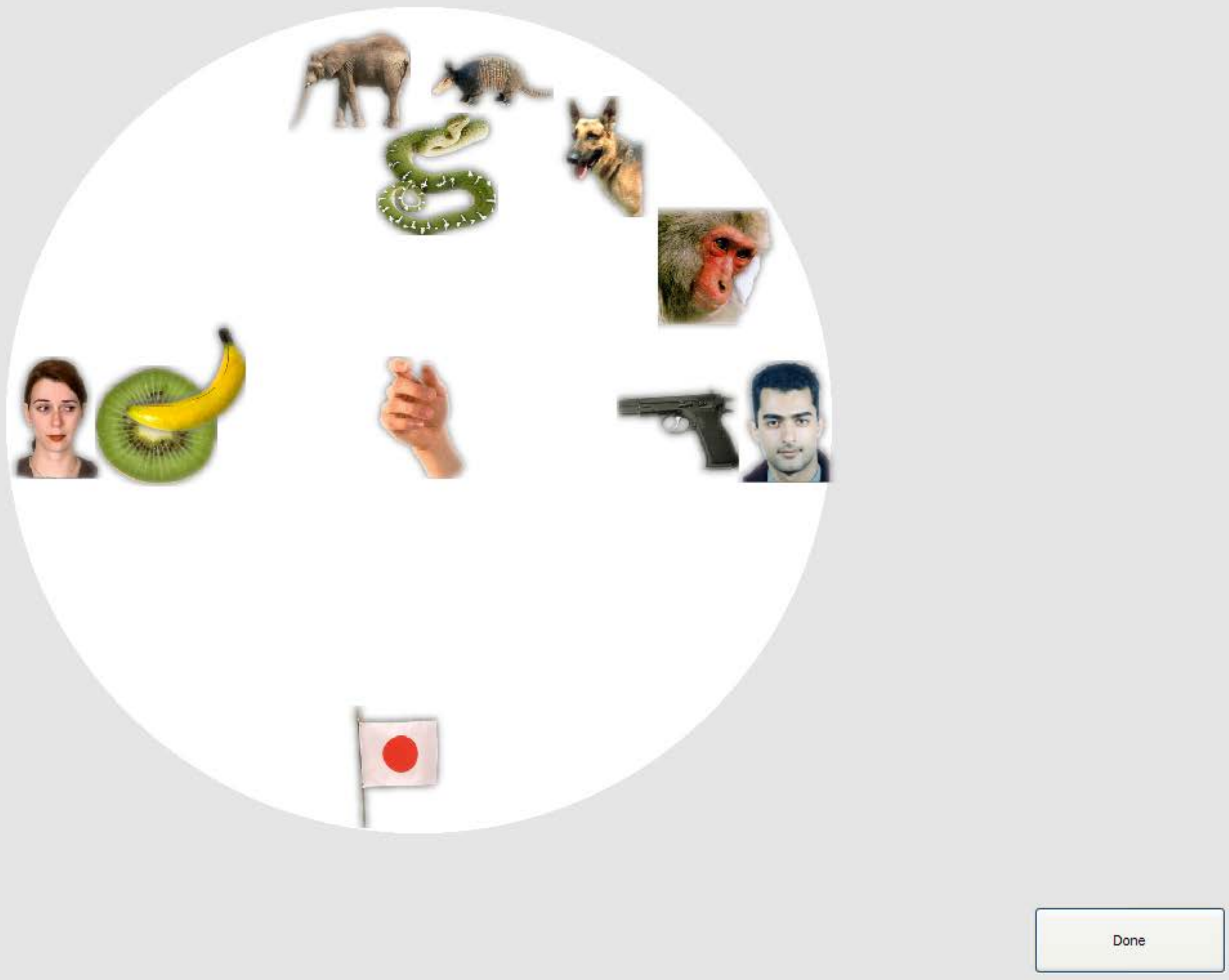

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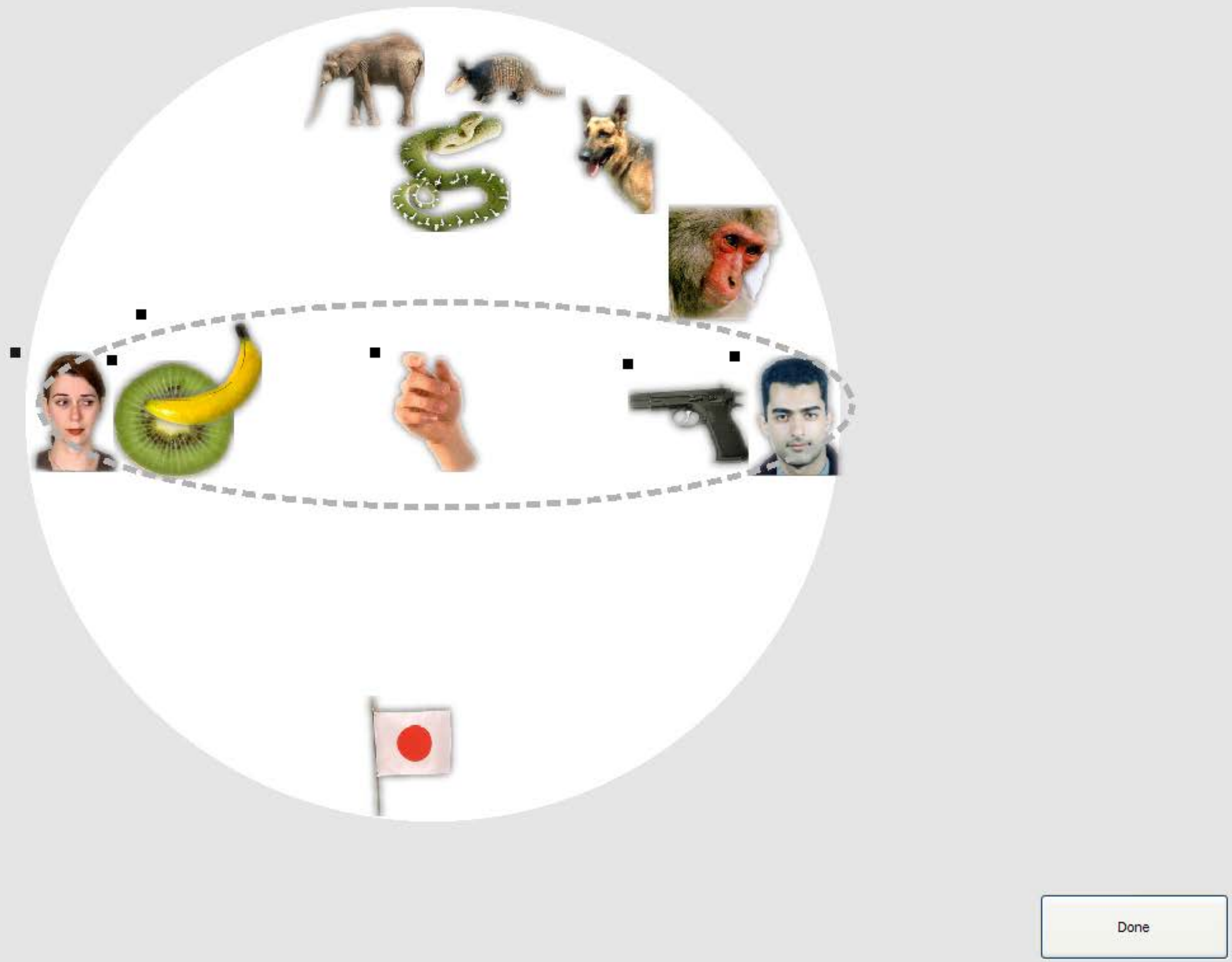

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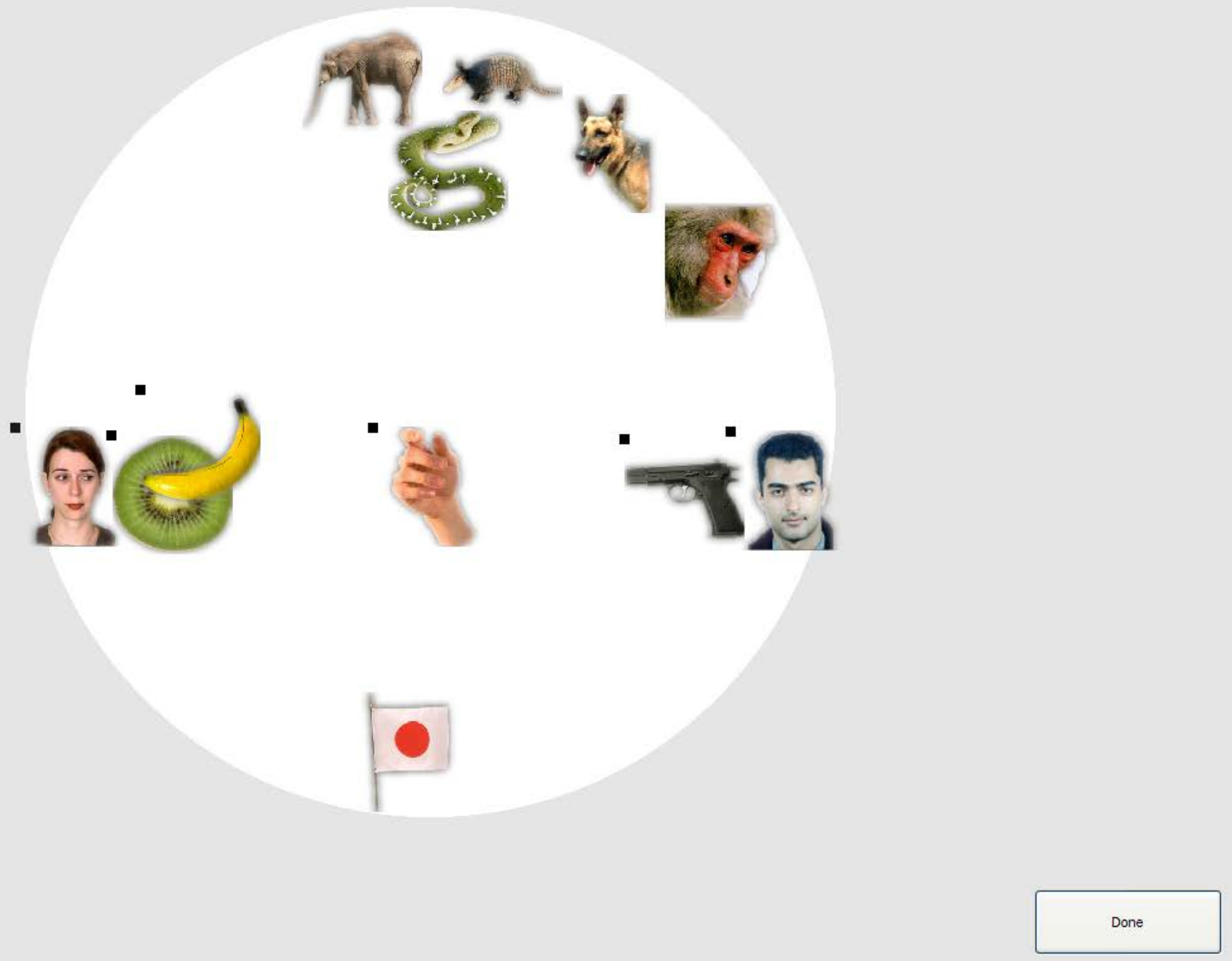

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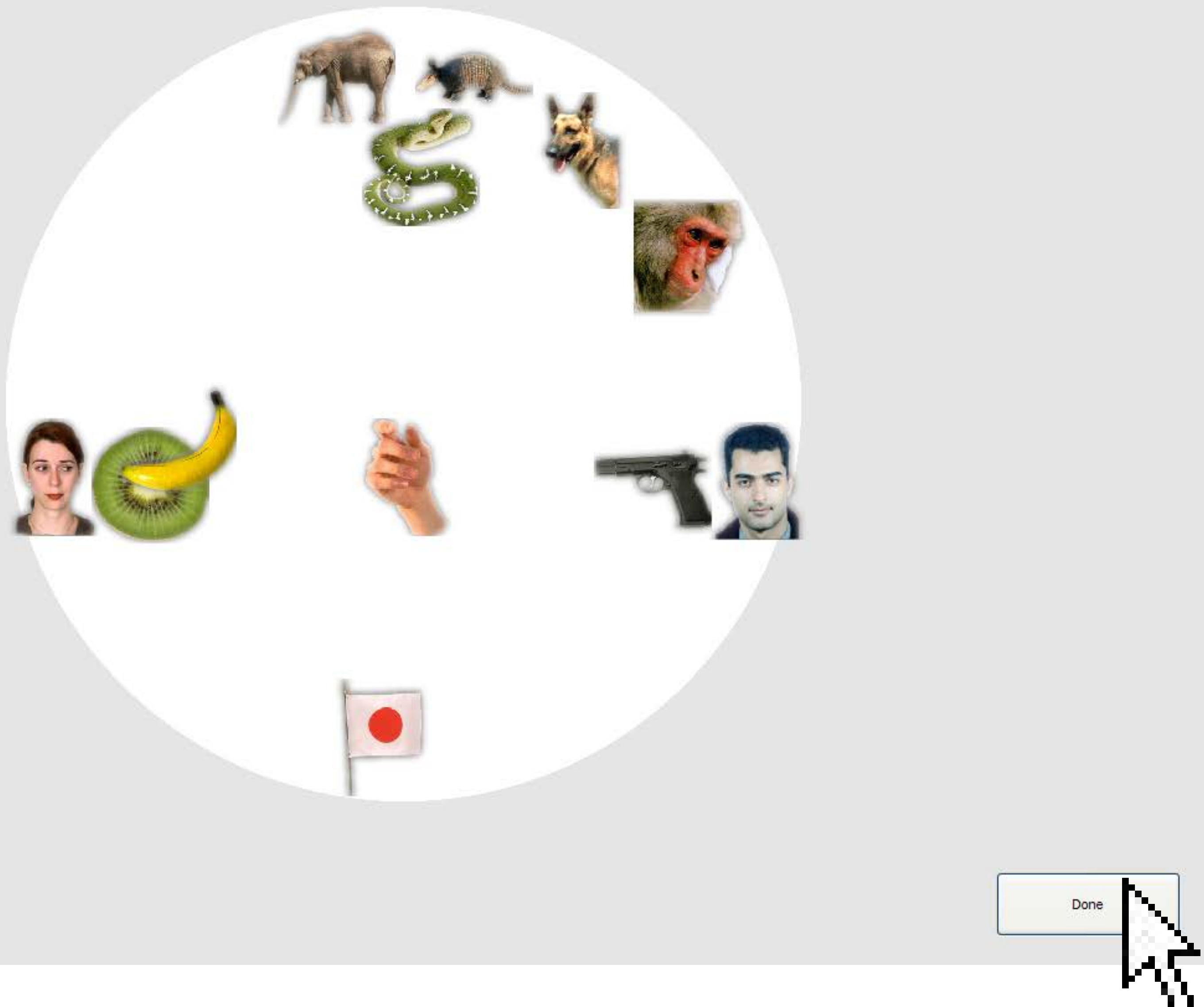

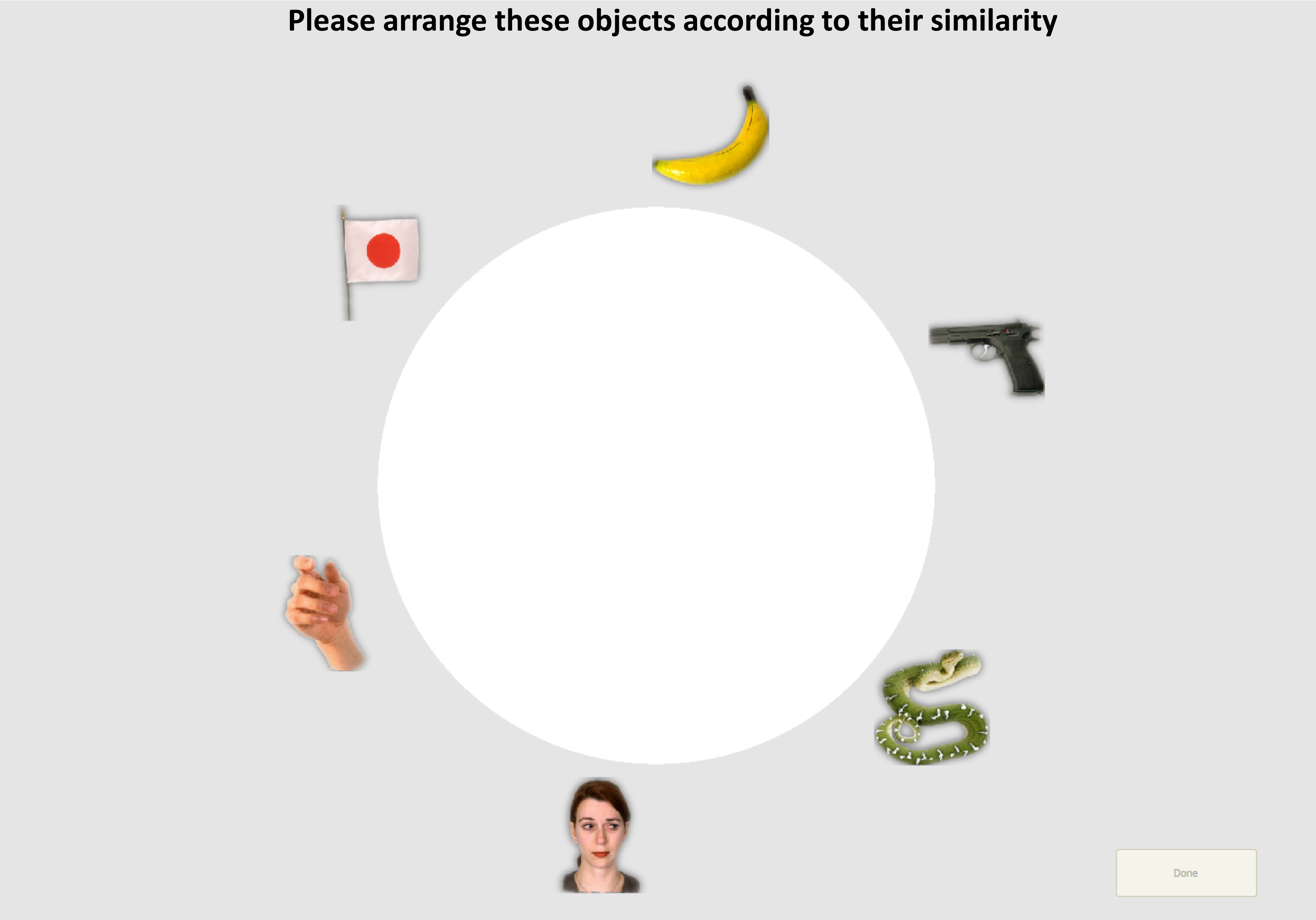
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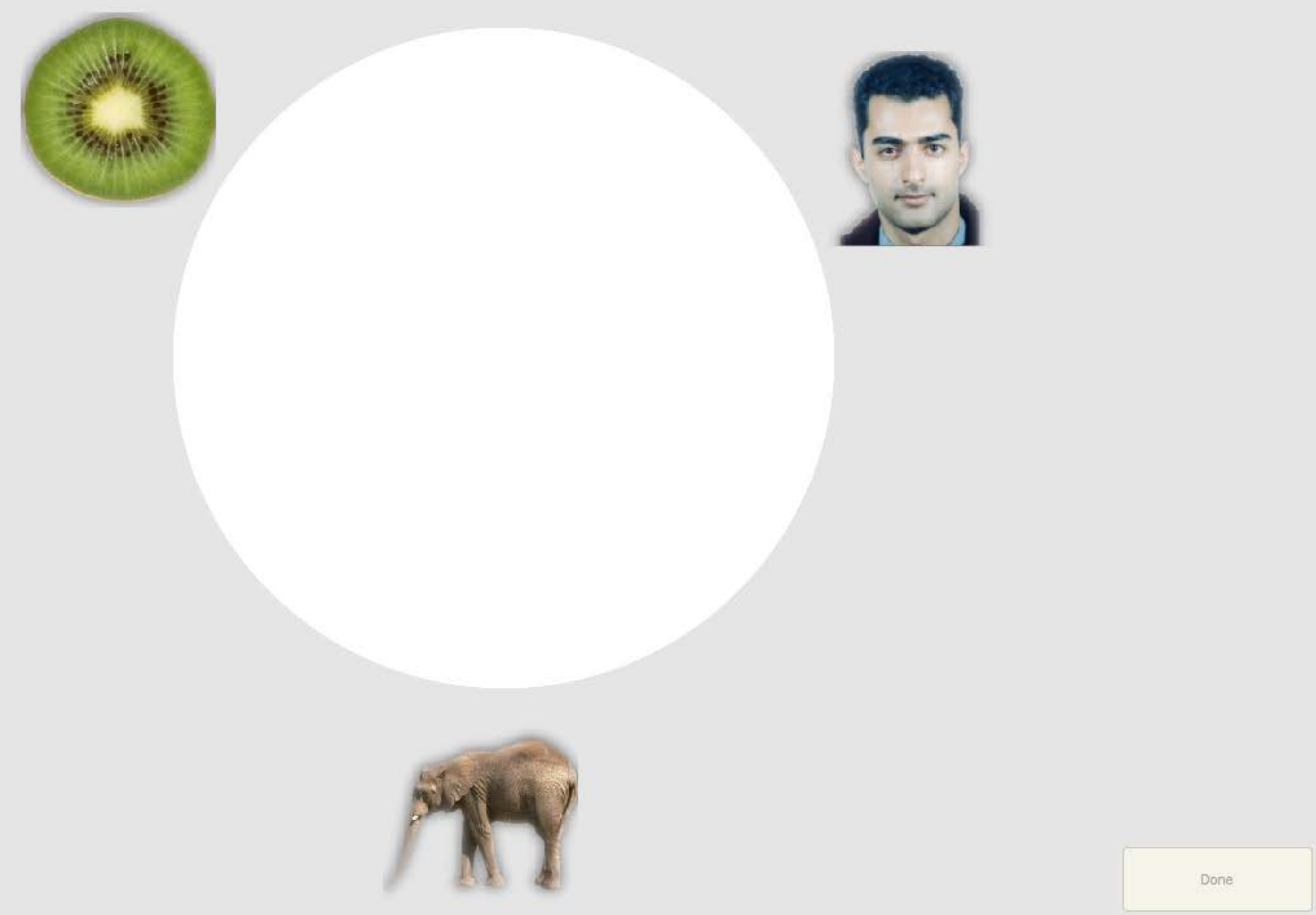
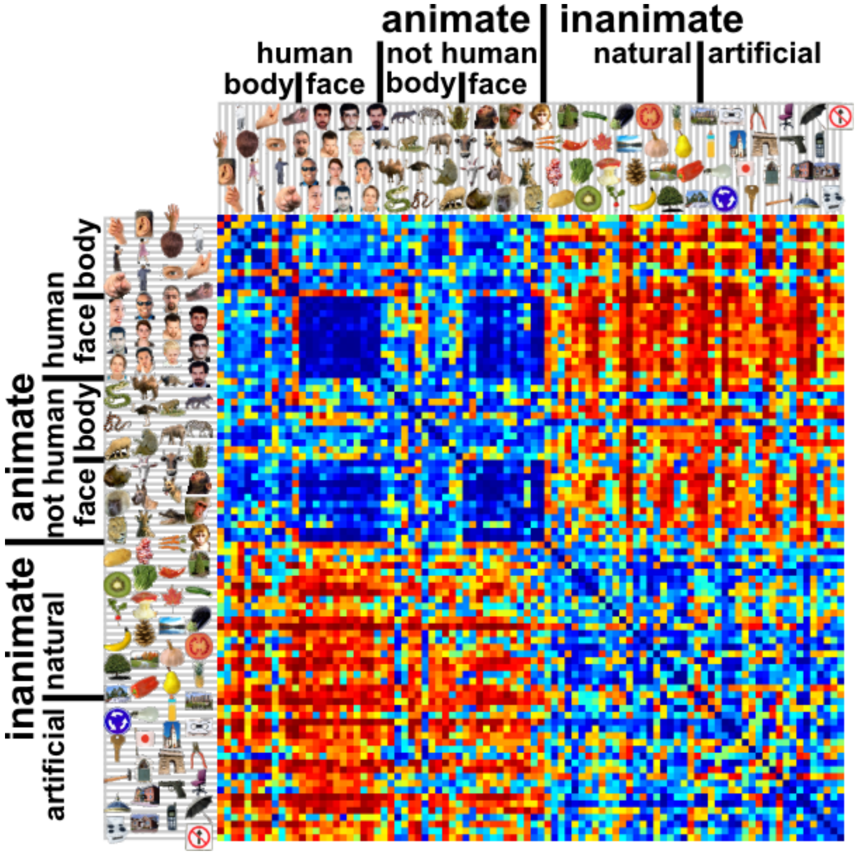


96-object-image MA experiment

- 16 healthy human subjects
- each subject performed one 1-hour session (outside the scanner)


animate
inanimate
human
not human
body
face
body
face
natural
artificial

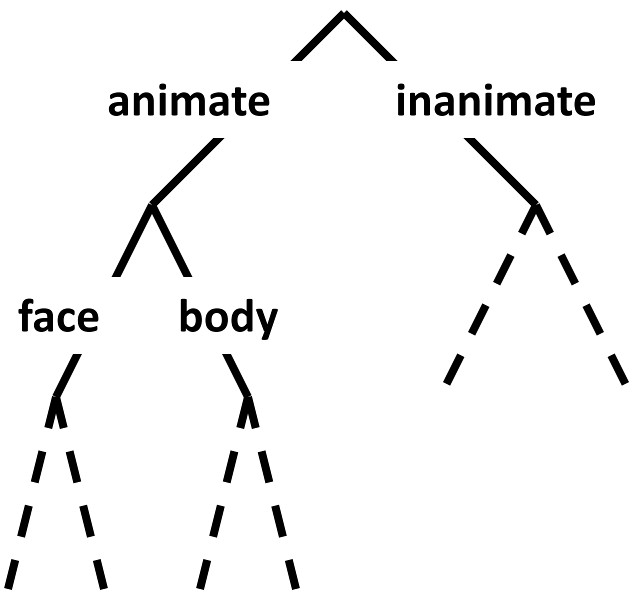
human IT

2D arrangements by dissimilarity

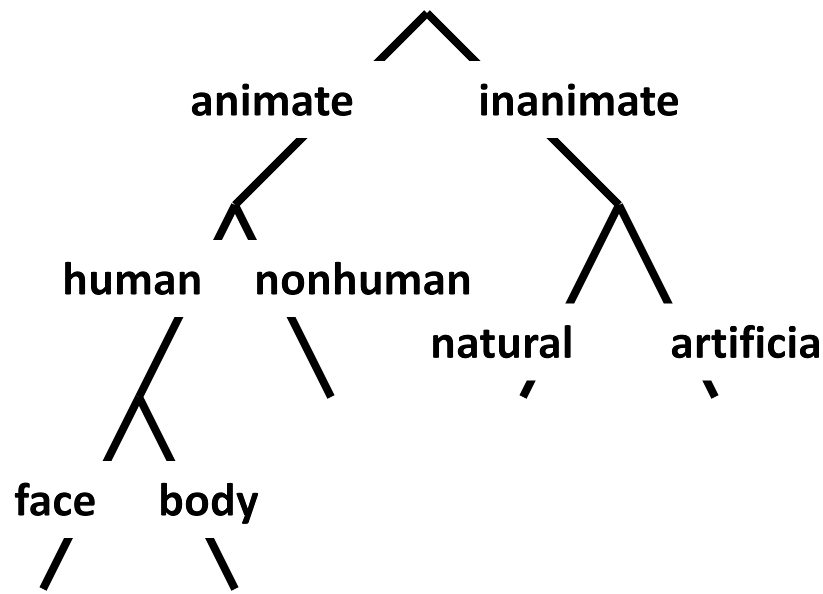
human IT

similarity judgments

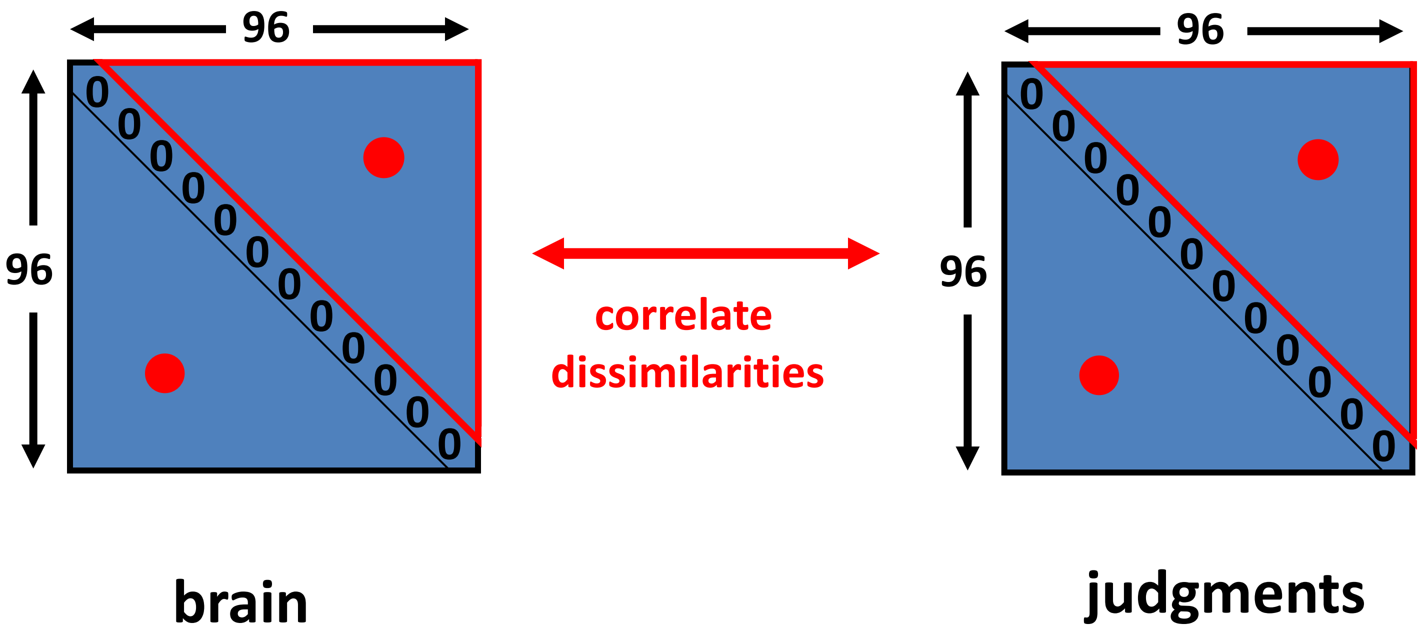
human IT



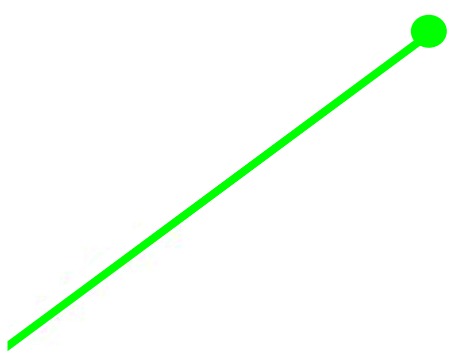
similarity judgments



Model fit: correlation



Are hIT and perceptual dissimilarities correlated?



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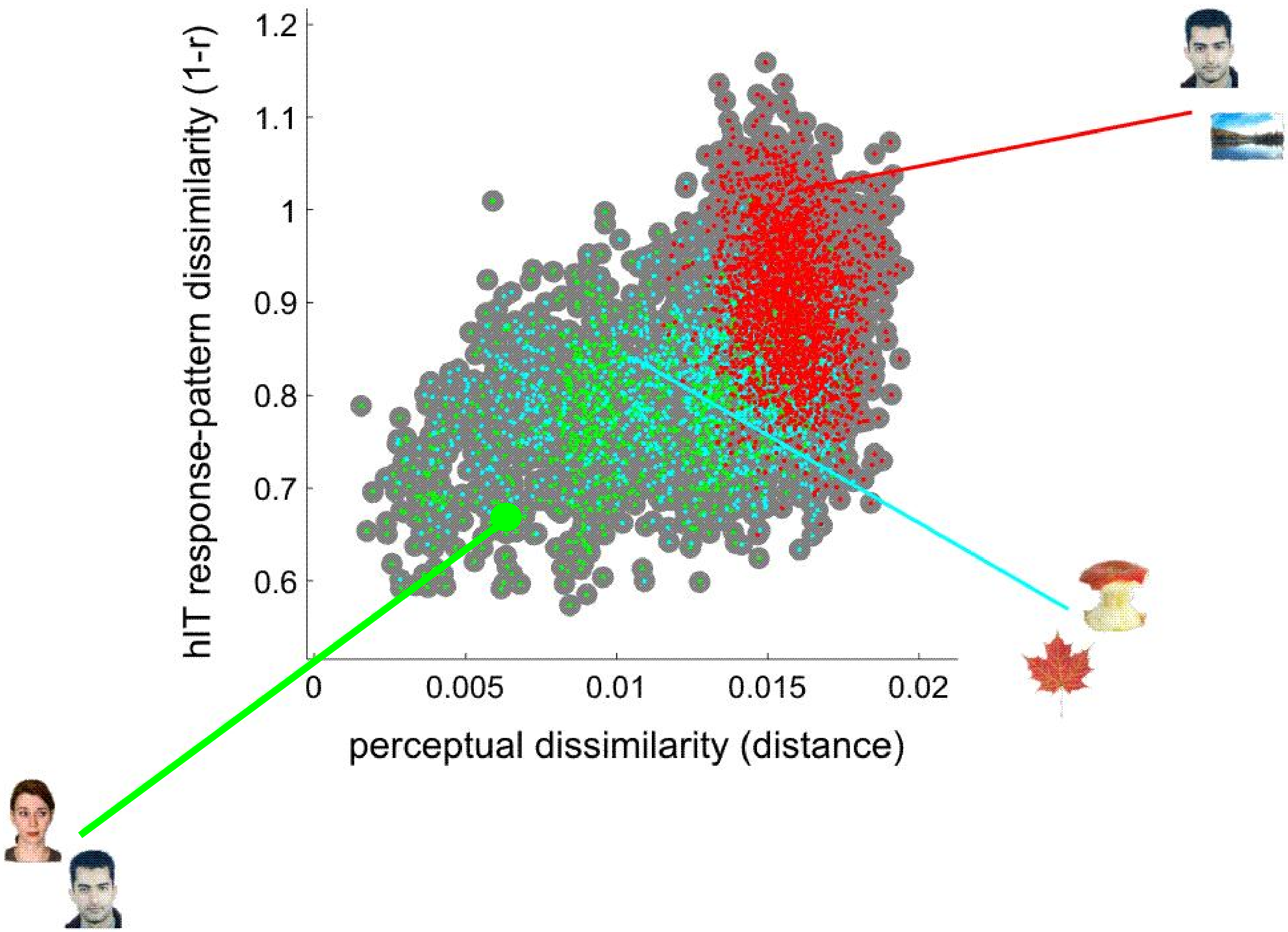


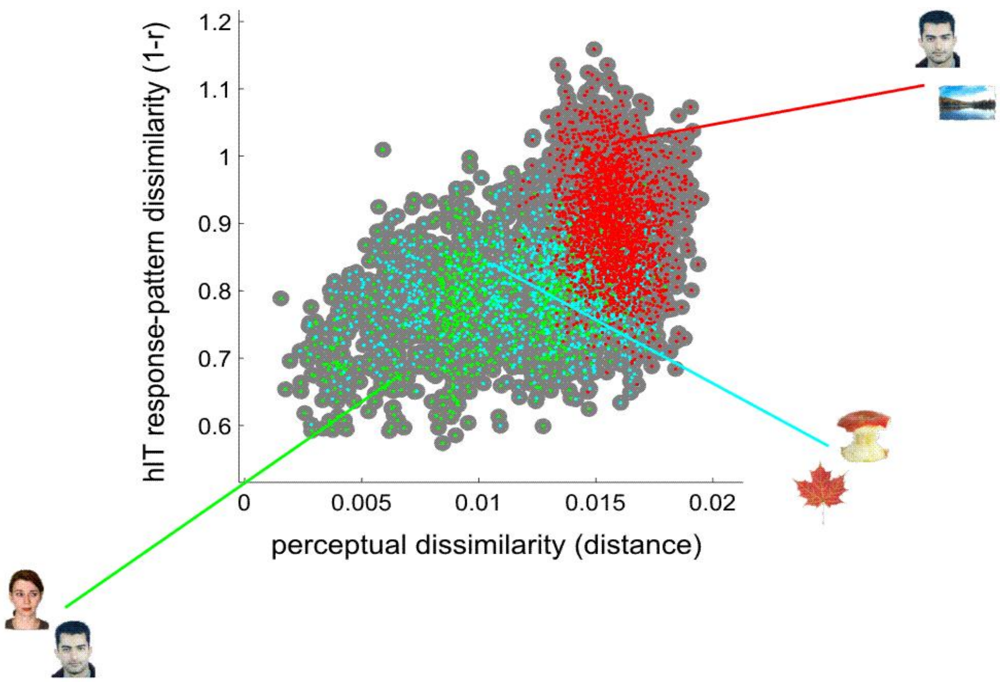
Are hIT and perceptual dissimilarities correlated?

within all images: r=0.39, p<0.0001***

within animates: r=0.34, p<0.0001***

within inanimates: r=0.19, p<0.0001***

between animates and inanimates: r=-0.16, ns



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Which model can best explain IT?

To what extent do features and categories explain the **IT representation**?

visual features

parts, shape, color, and texture

"elongated"

"brown"

"tail"

"scales"

semantic categories

basic and superordinate levels

"reptile"

"lizard"

"living"

Jozwik et al. 2016

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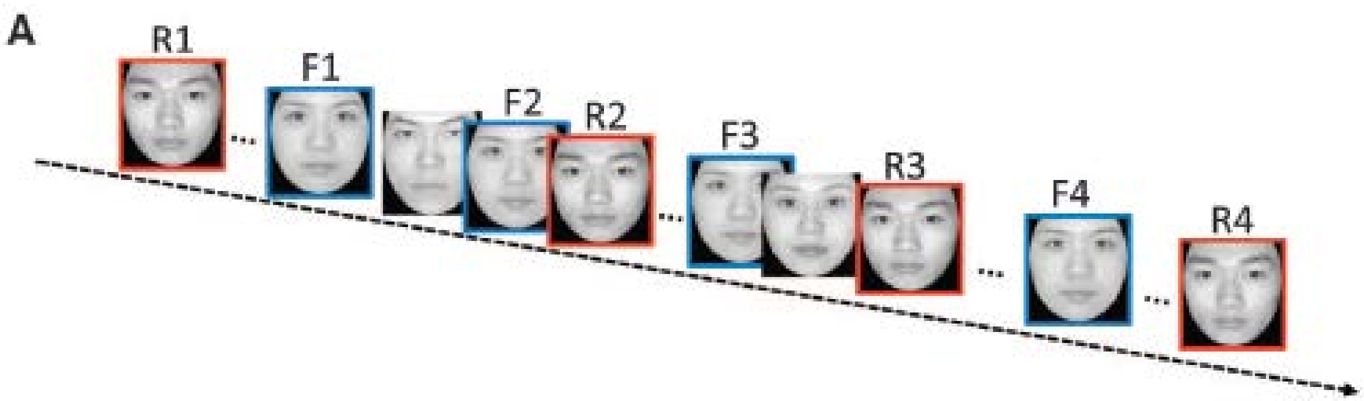
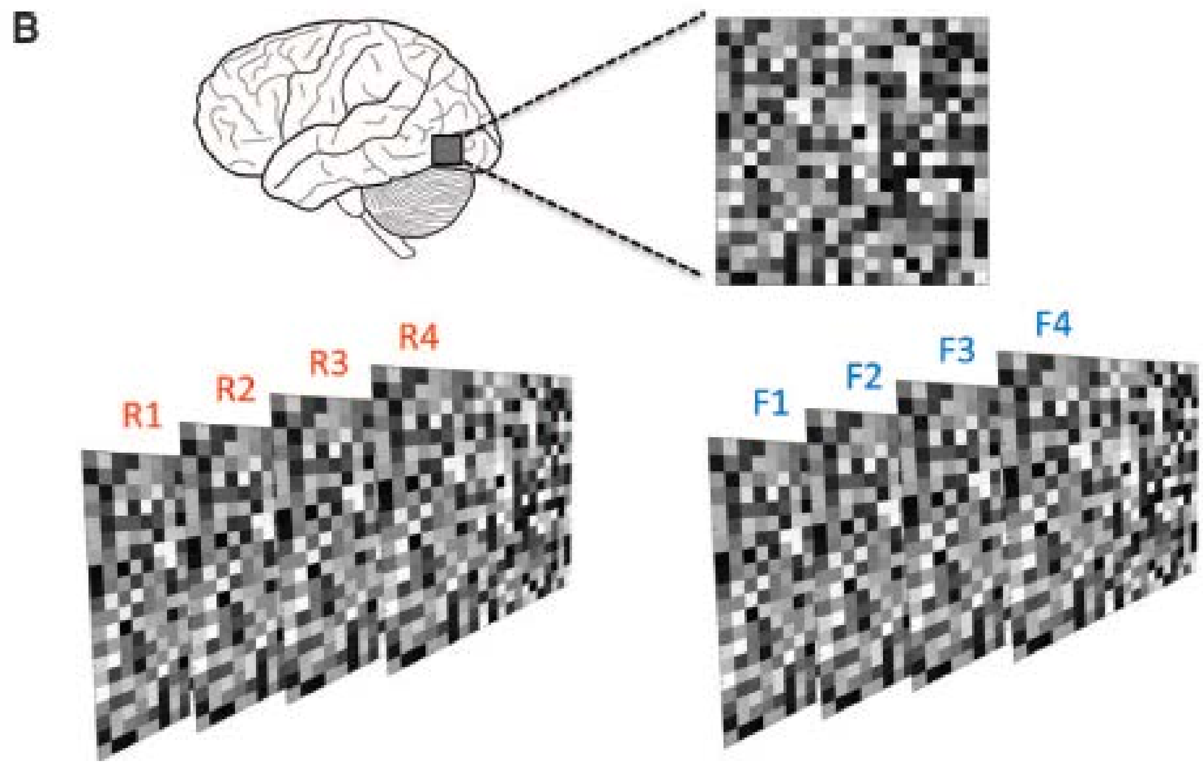
Applications: memory

Greater Neural Pattern Similarity Across Repetitions Is Associated with Better Memory

Gui Xue,[1,2] Qi Dong,[1*] Chuansheng Chen,[3] Zhonglin Lu,[2] Jeanette A. Mumford,[4] Russell A. Poldrack[5,4,6*]

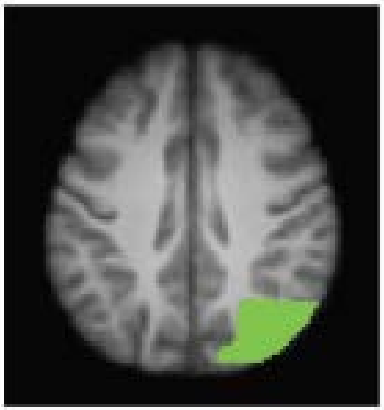


Applications: memory



Applications: memory

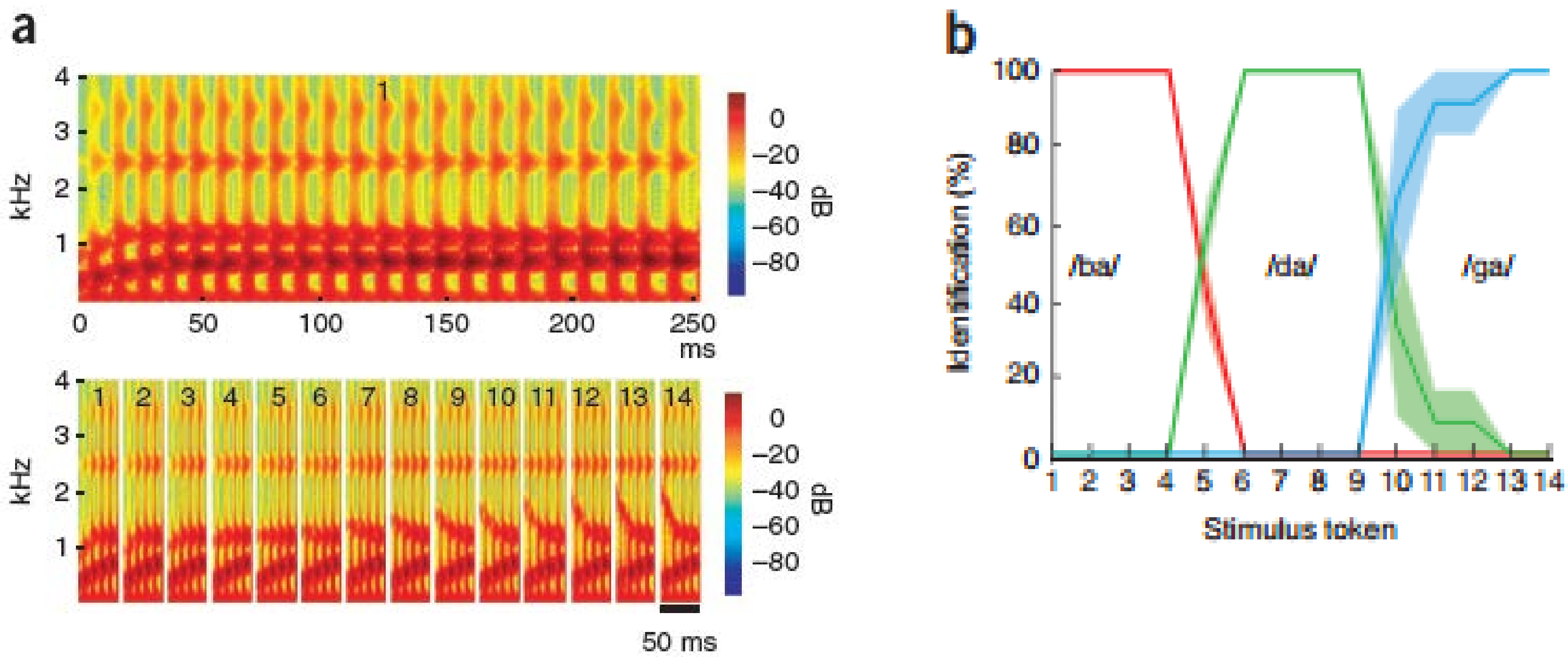
A



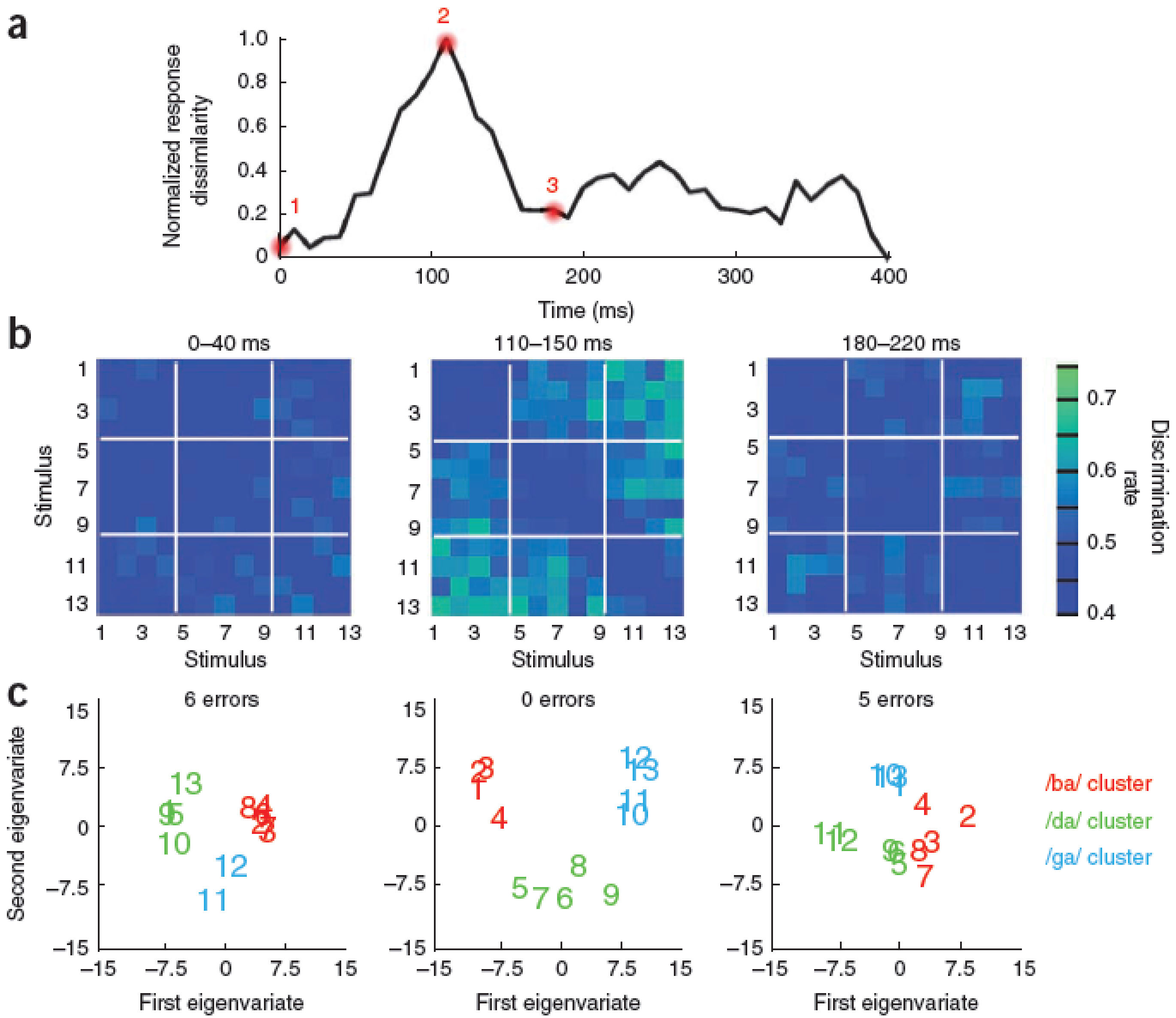
Applications: speech

Categorical speech representation in human superior temporal gyrus

Edward F Chang[1,2,6], Jochem W Rieger[2,3,6], Keith Johnson[4], Mitchel S Berger[1], Nicholas M Barbaro[1] &
Robert T Knight[1,2,5]



Applications: speech



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Toolbox

The RSA toolbox can be downloaded here:

http://www.mrc-cbu.cam.ac.uk/methods-and-resources/toolboxes/

The toolbox runs in Matlab and does not have a GUI, but contains good documentation and multiple demos to familiarise you with the analyses. You can use the demo scripts as a starting point for your own analyses.

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Literature

RSA

Kriegeskorte N et al. (2008) *Front Syst Neurosci 2*(4): 1-28. [original methods paper]

Kriegeskorte N, Kievit R (2013) *Trends Cogn Sci 17*(8): 401-412. [recent review]

RSA applications in neuroscience

Kriegeskorte N et al. (2008) *Neuron 60*: 1126-1141. [object vision: human - monkey]

Mur M et al. (2013) *Front Psychol 4*(128): 1-22. [object vision: brain - behaviour]

Xue G et al. (2010) *Science 330*: 97-101. [memory: forgotten vs remembered items]

Ward EJ et al. (2013) *J Neurosci 33*(37): 14749-14757. [memory: implicit vs explicit]

Ritchey M et al. (2013) *Cereb Cortex* doi:10.1093/cercor/bhs258. [memory]

RSA toolbox/workshop

Nili et al. 2014 (in press) *PLoS Comput Biol*

RSA workshop 2015: http://www.mrc-cbu.cam.ac.uk/rsa2015/rsa2015media/

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 tutorial.m