UNIVERSITY OF BIRMINGHAM | CHBH CENTRE FOR HUMAN BRAIN HEALTH

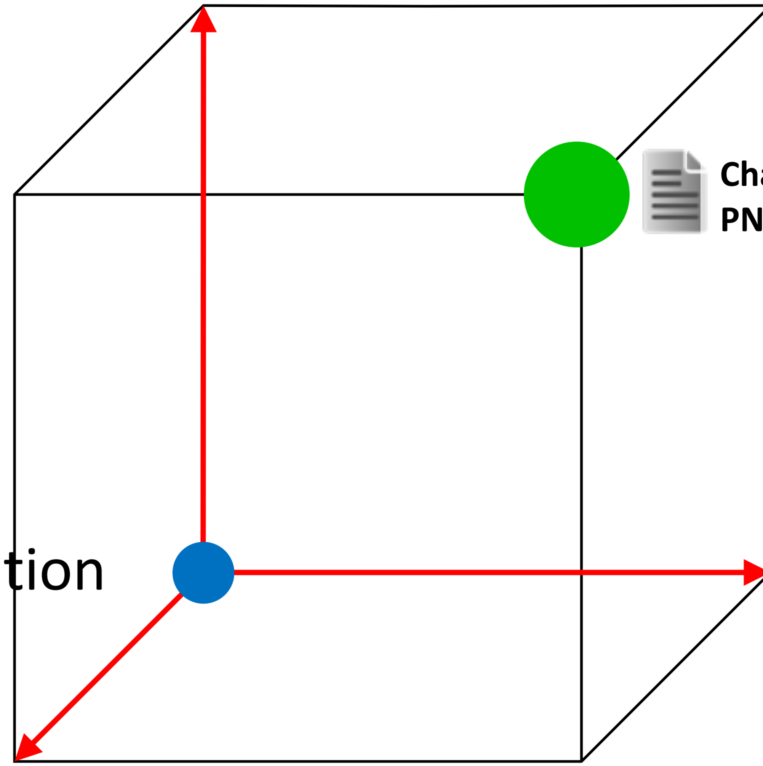
Tracking object representations in the brain

Ian Charest, Marseille 2018

European Research Council

Established by the European Commission

Honouring individual voxels, stimuli, and people



Charest & Kriegeskorte, 2015

Overview

Representational Similarity Analysis …

- … applied to fMRI

- … applied to M/EEG

Access to consciousness

Overview

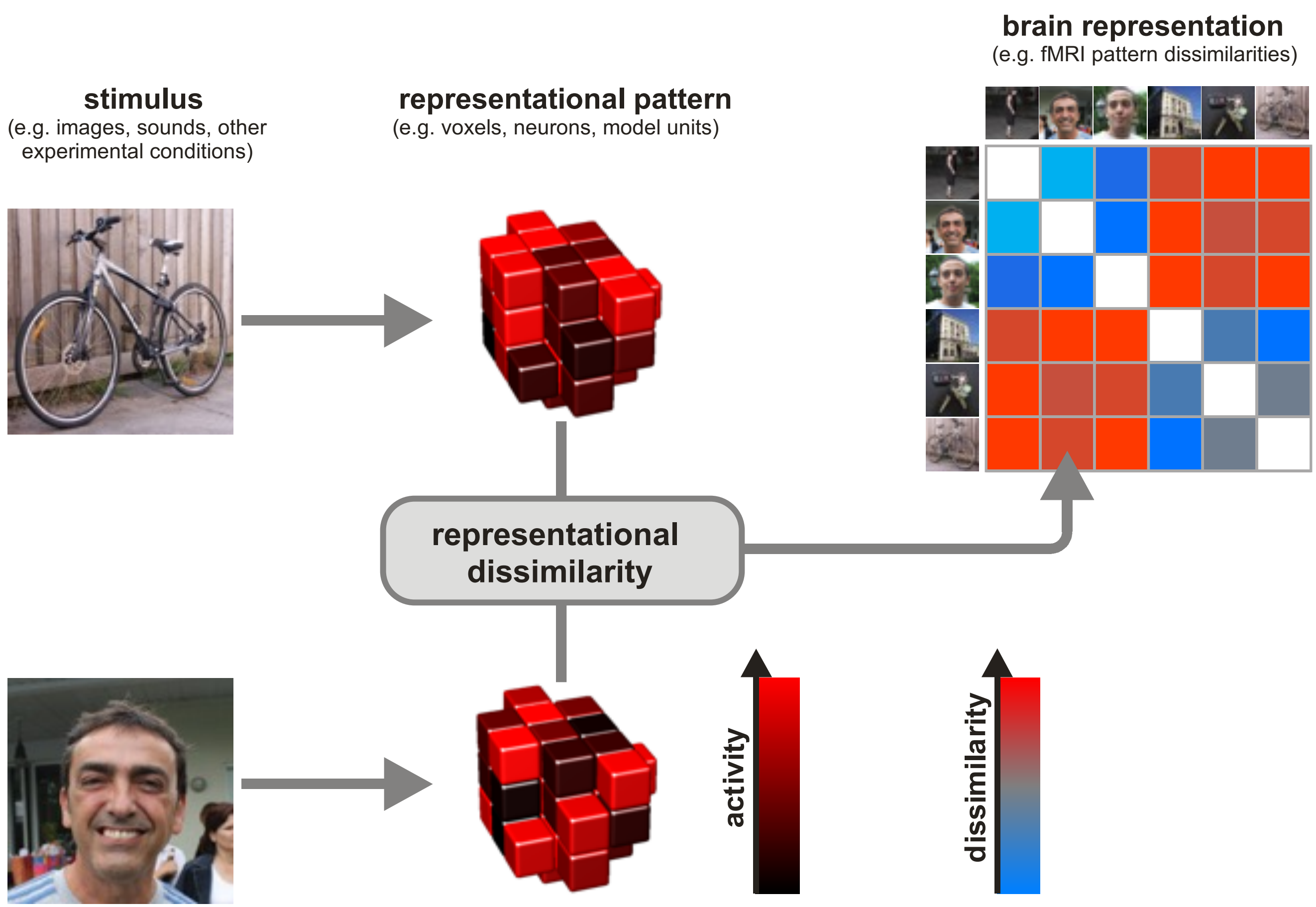
Representational Similarity Analysis …

- … applied to fMRI
- … applied to M/EEG

Access to consciousness

Representational similarity analysis

representational dissimilarity matrices
(RDMs)



Charest et al. 2014, 2015, Kriegeskorte & **Kievit** 2013, see also: **Edelman et al.** 1998,
Laakso & Cottrell 2000, **Op de Beeck** et al. 2001, **Haxby** et al. 2001, **Aguirre** 2007, **Kriegeskorte** et al. 2008

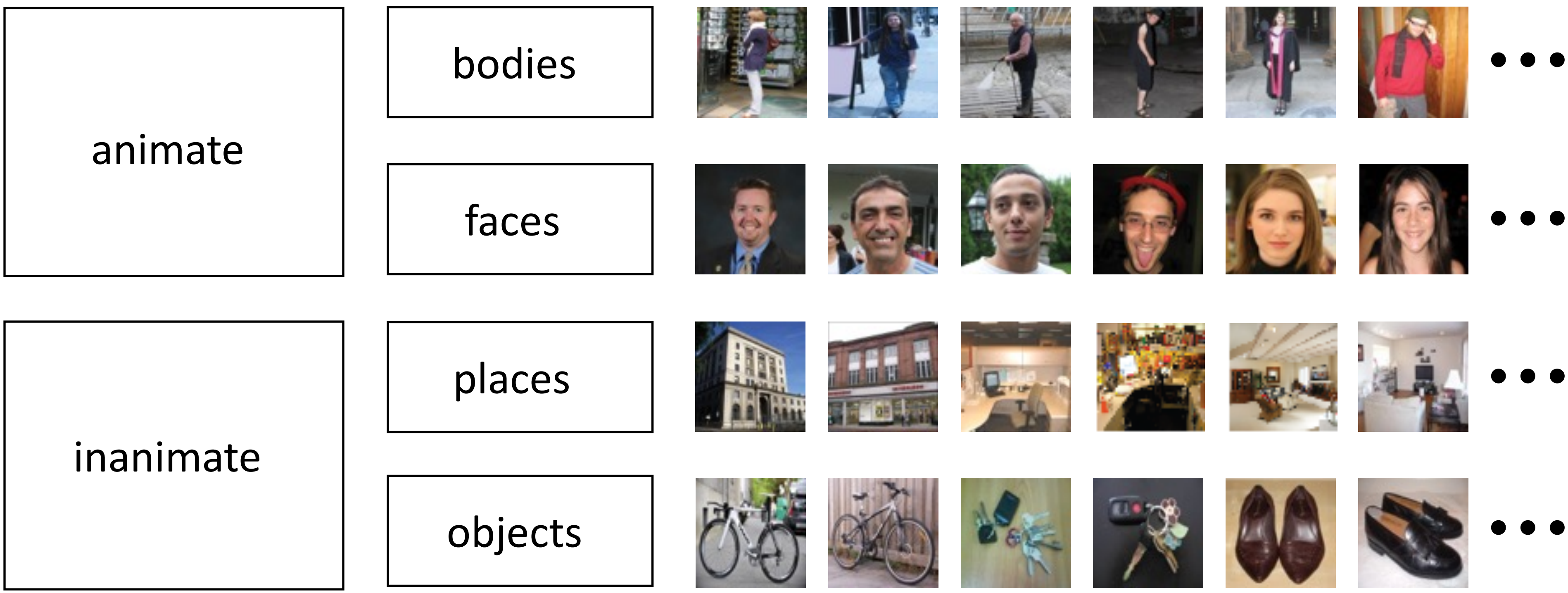
Overview

Representational Similarity Analysis …

- … applied to fMRI
- … applied to M/EEG

Access to consciousness

Stimuli



Charest et al. 2014 ***PNAS***

Stimuli

Objects from the subject's own photo-album

animate

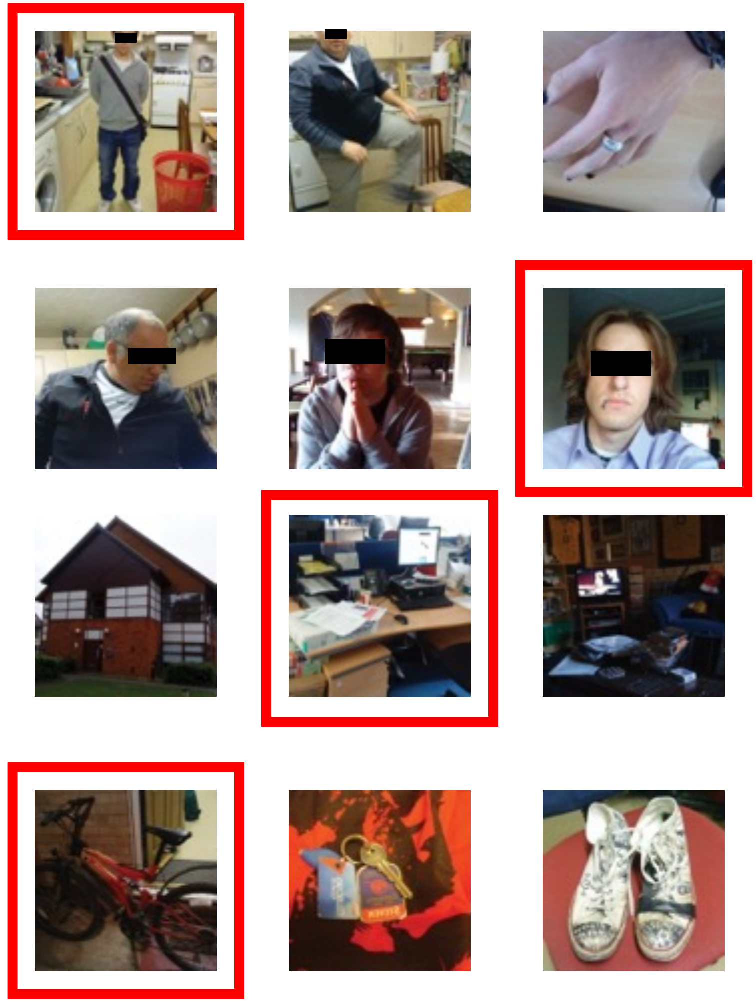
bodies

faces

inanimate

places

objects

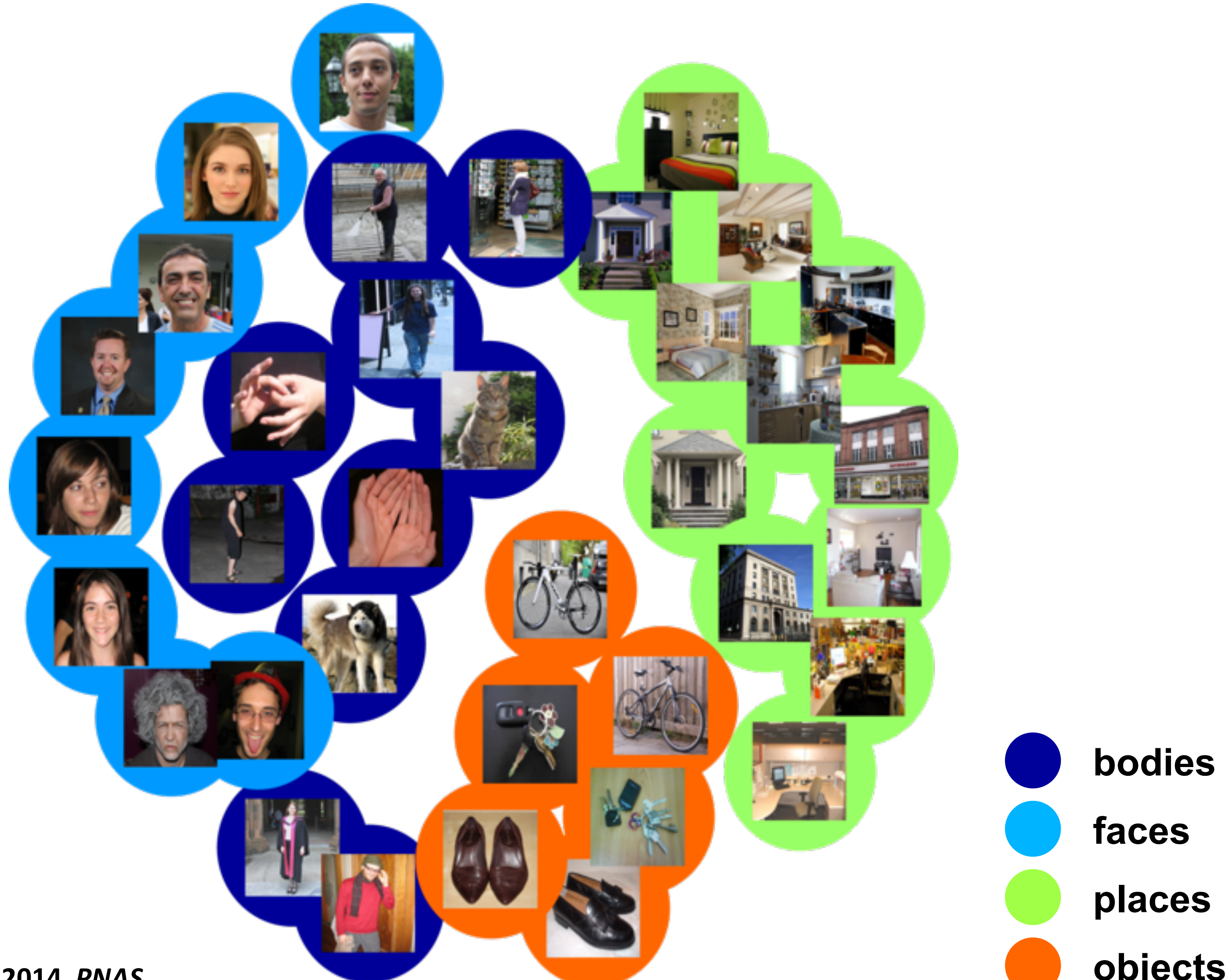


Charest et al. 2014 *PNAS*

Representational Dissimilarity Matrix (RDM)

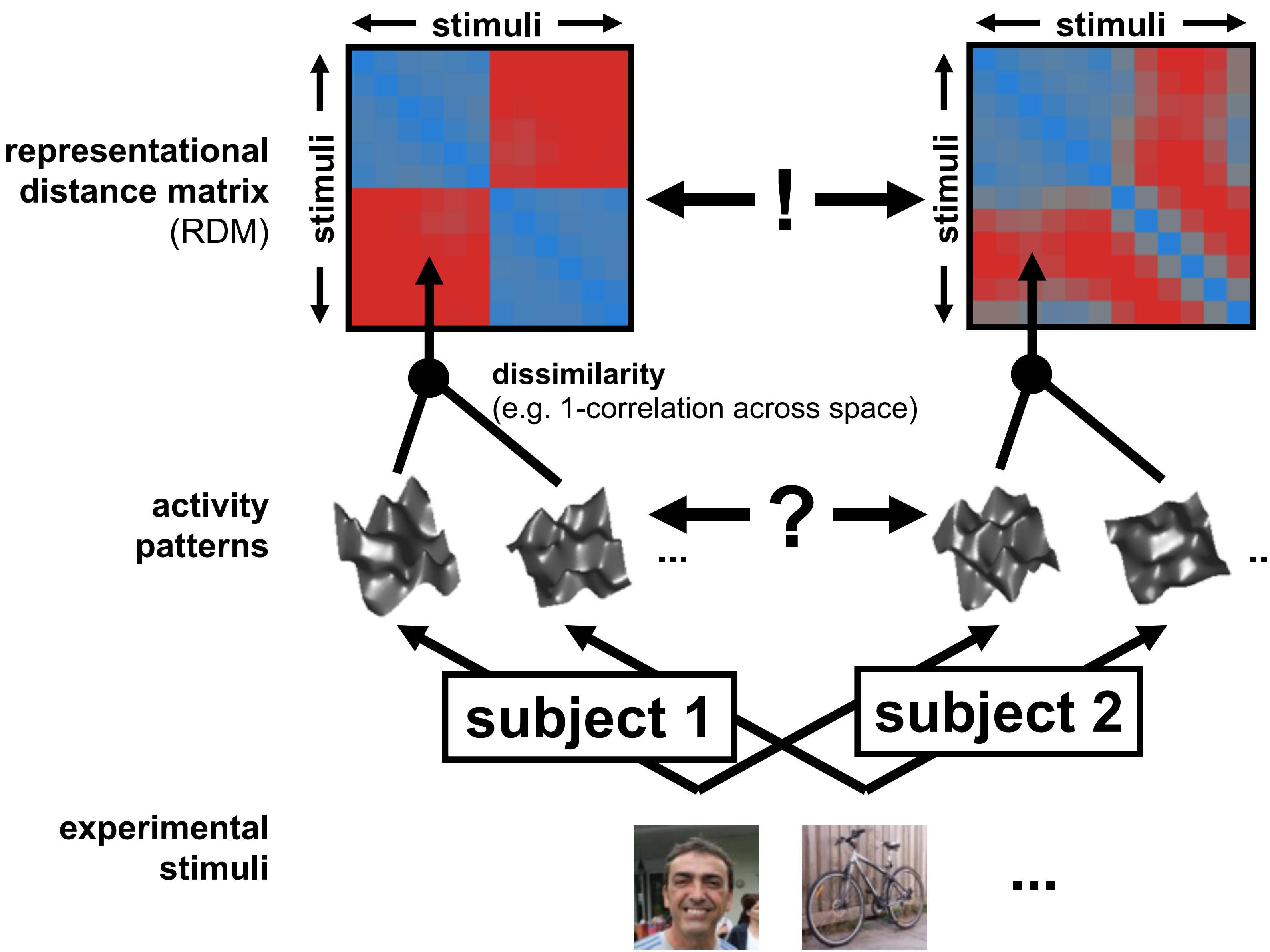
Charest et al. 2014 *PNAS*

Multi-dimensional scaling

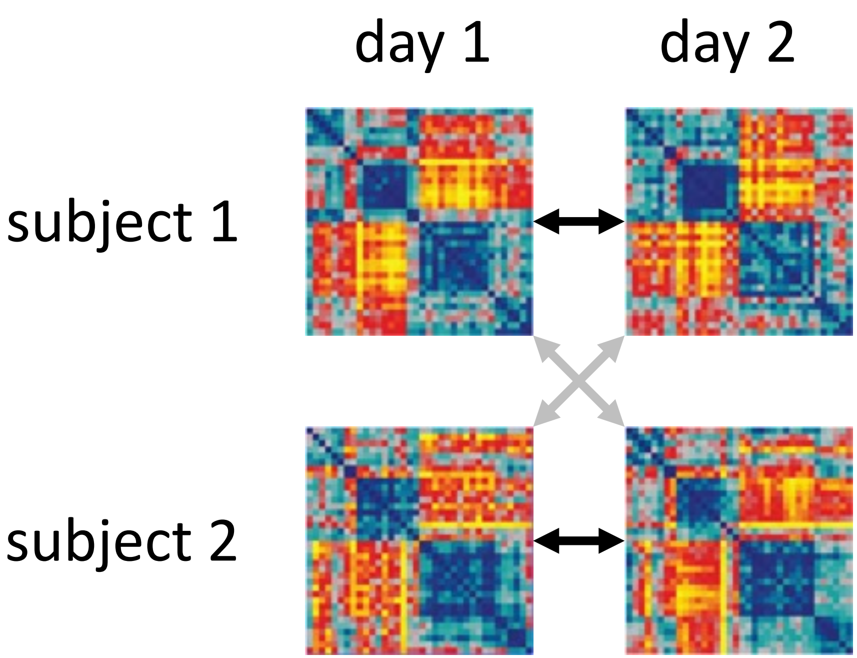


Charest et al. 2014 *PNAS*

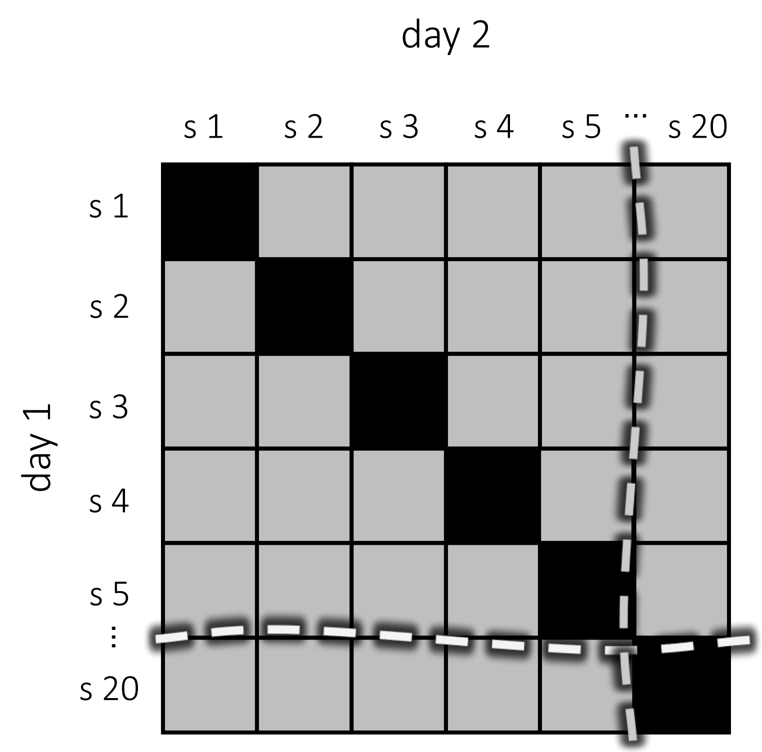
The representational similarity trick



Comparing brain RDMs between people



subject similarity matrix



correlation

within-subject (ws)

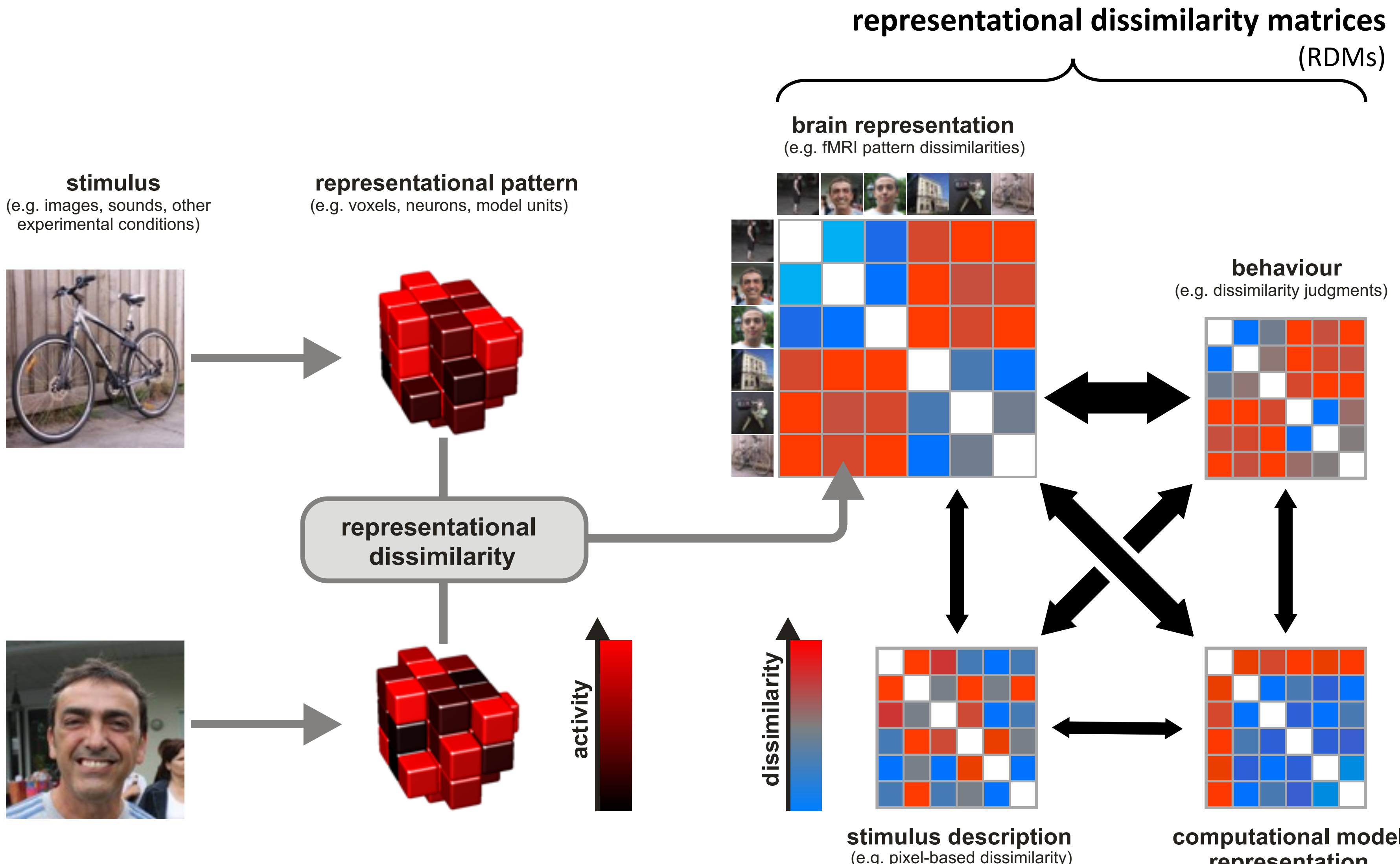
between-subject (bs)

individuation index (ws - bs) ?

Charest et al. 2014 *PNAS*

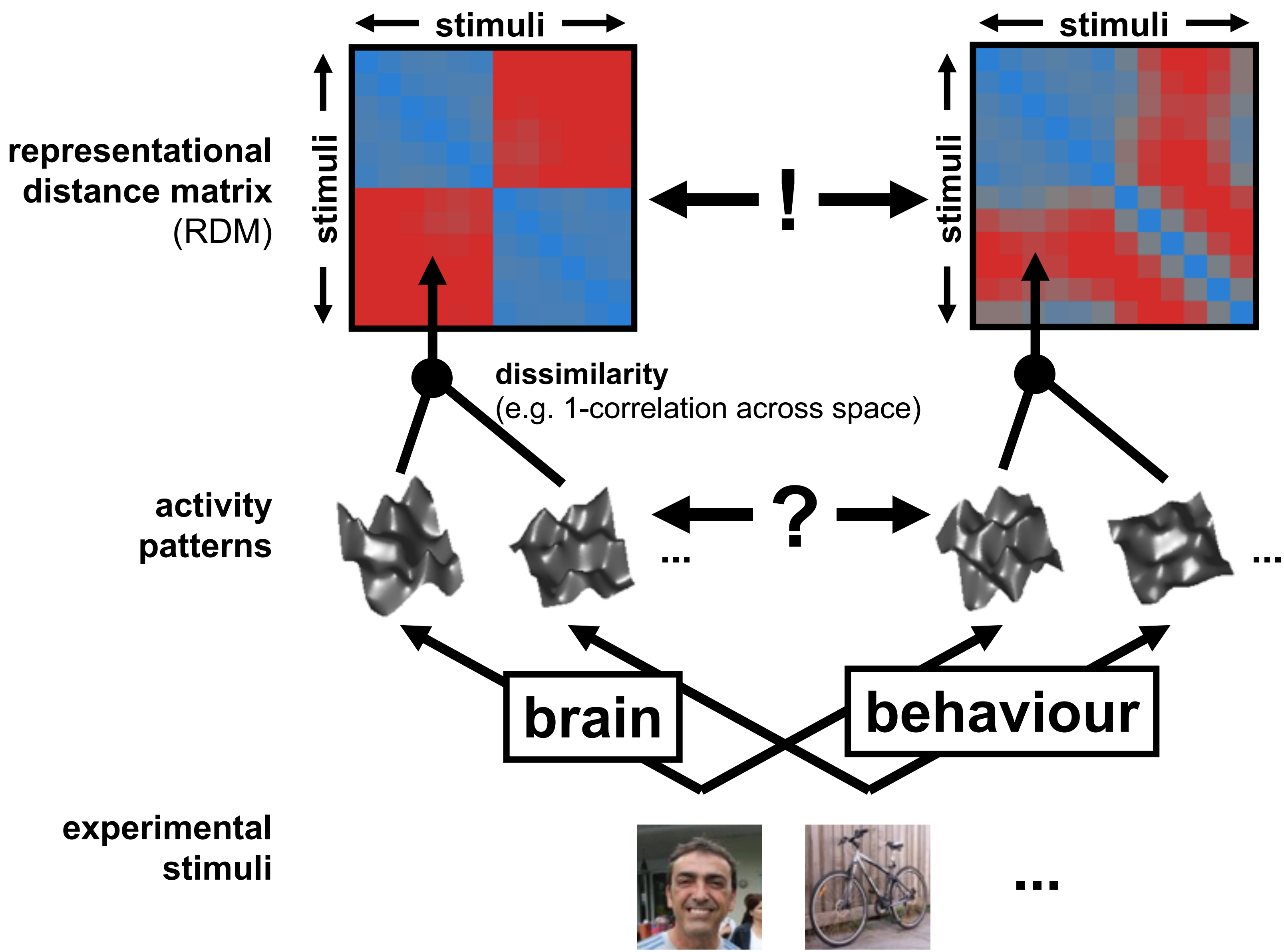
Brain representations unique?

Representational similarity analysis

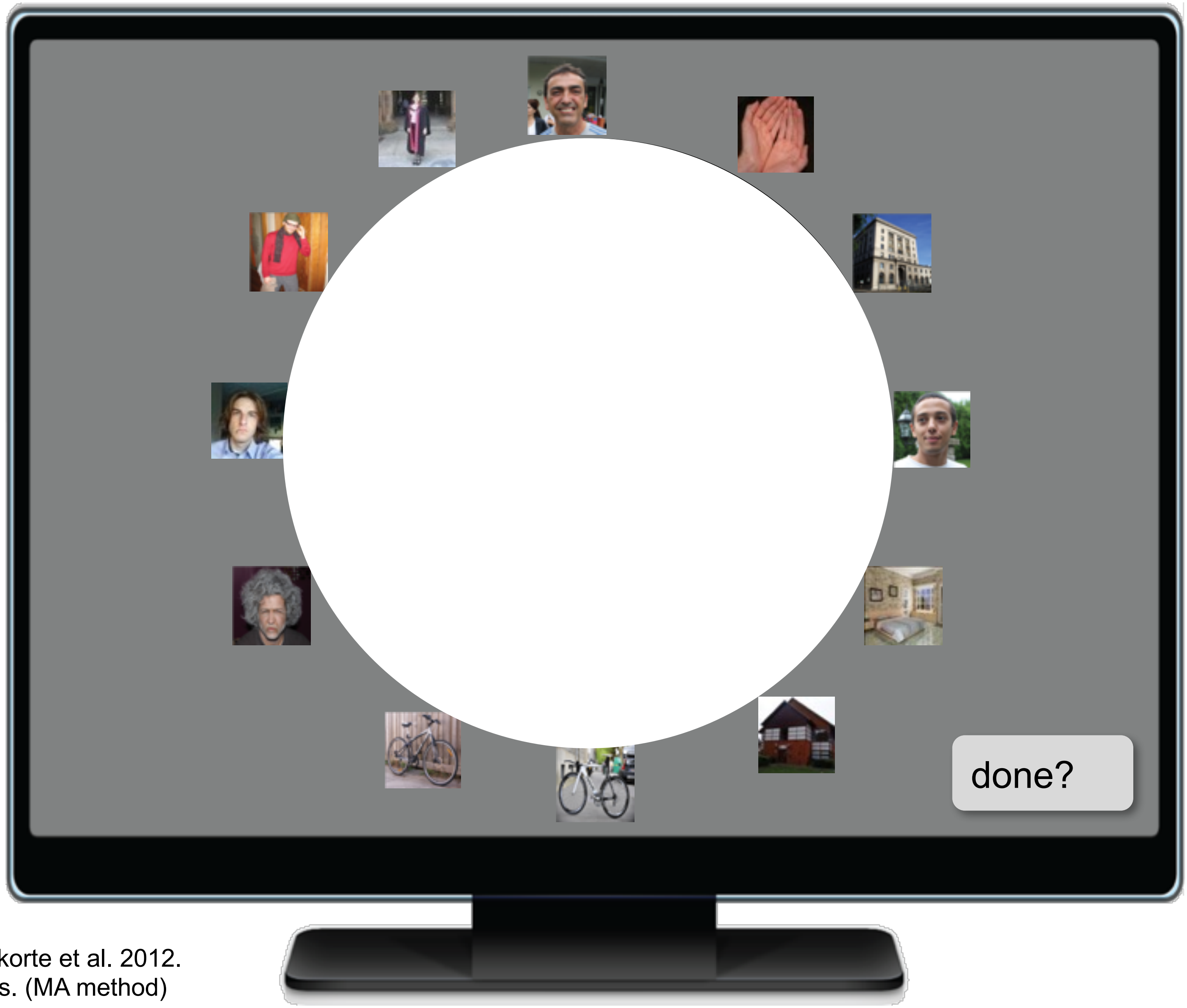


Charest et al. 2014, 2015, Kriegeskorte & **Kievit** 2013, see also: **Edelman et al.** 1998, **Laakso & Cottrell** 2000, **Op de Beeck** et al. 2001, **Haxby** et al. 2001, **Aguirre** 2007, **Kriegeskorte** et al. 2008

The representational similarity trick

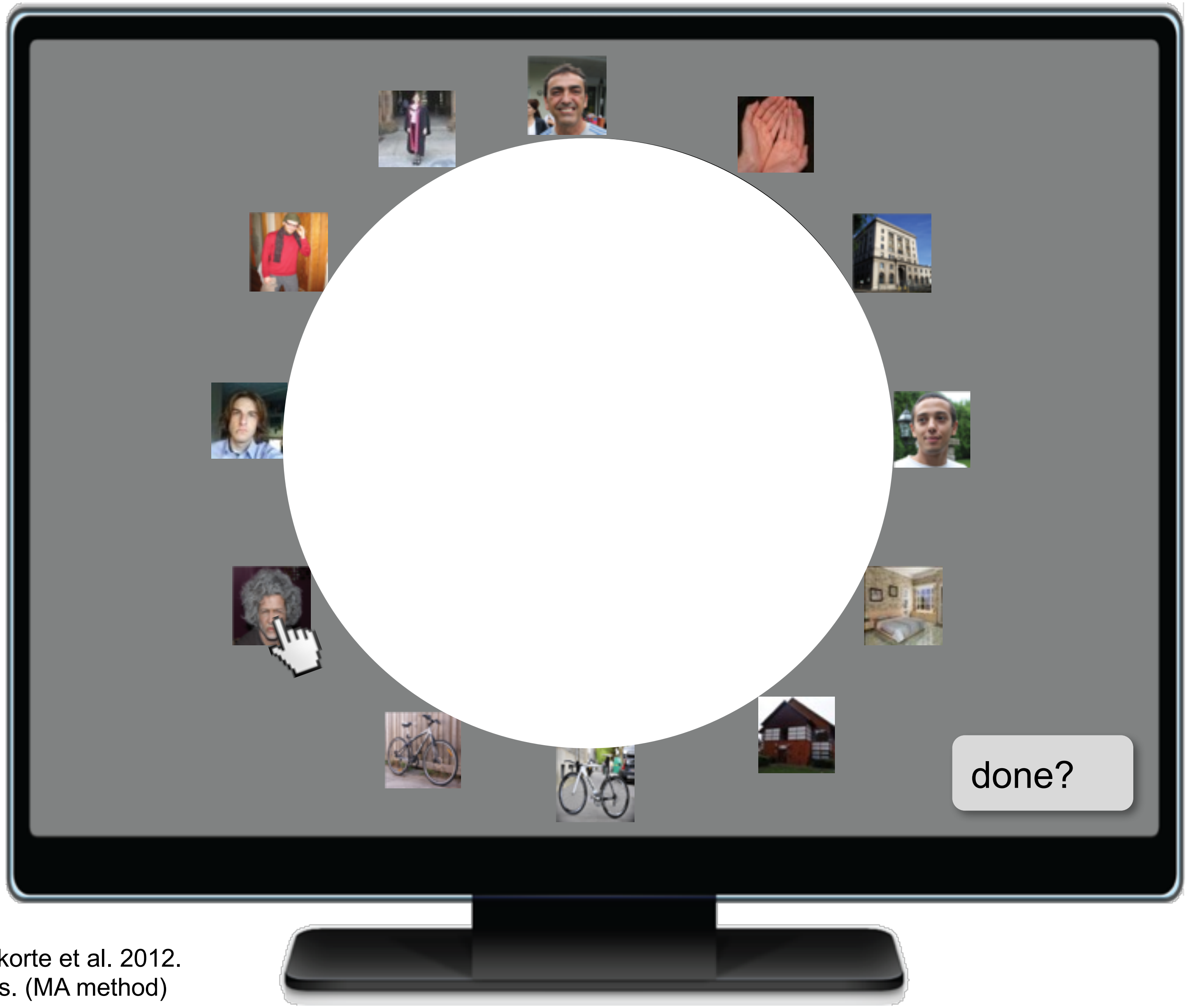


Please arrange the objects according to how similar they are to each other



Kriegeskorte et al. 2012.
Frontiers. (MA method)

Please arrange the objects according to how similar they are to each other



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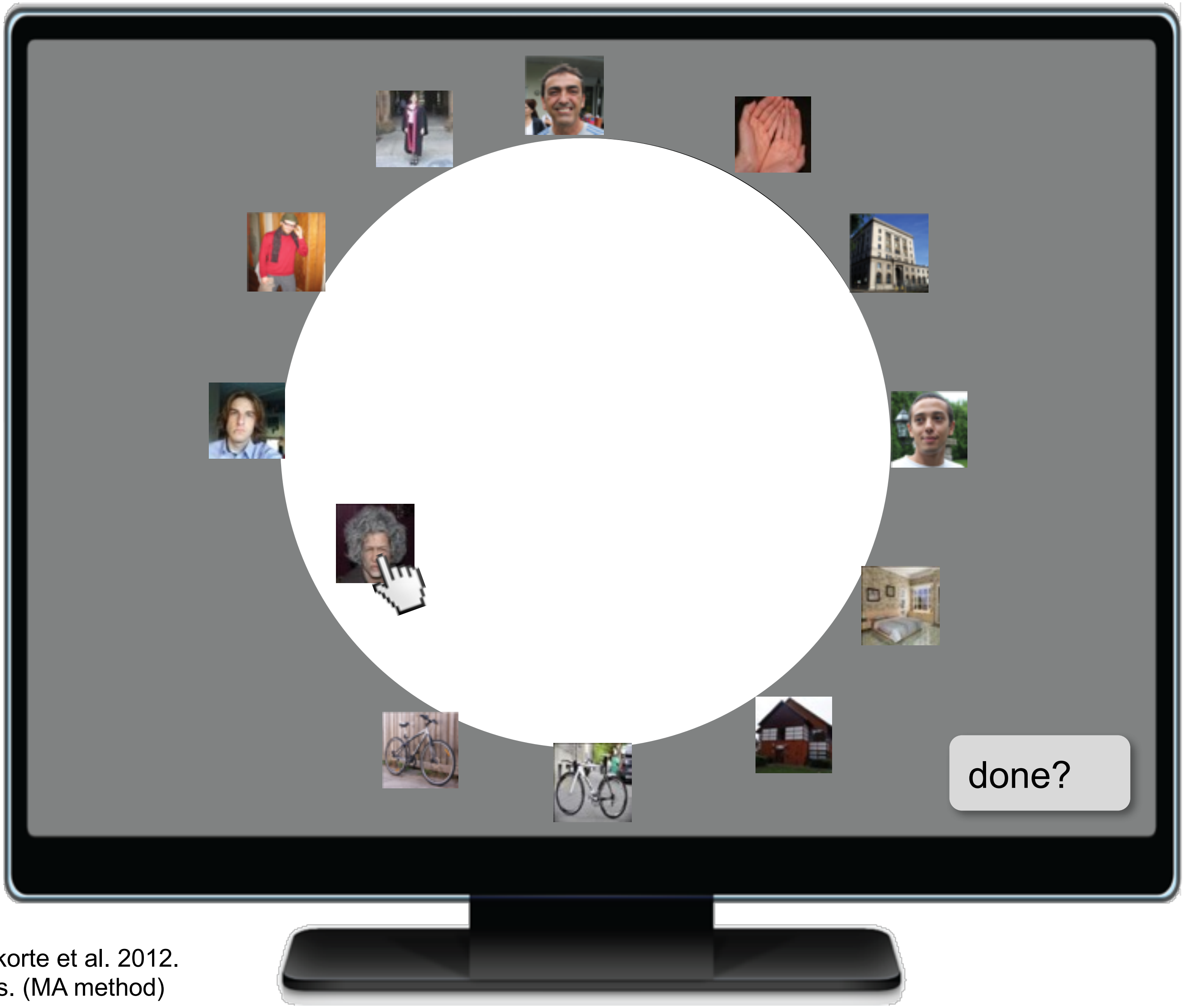

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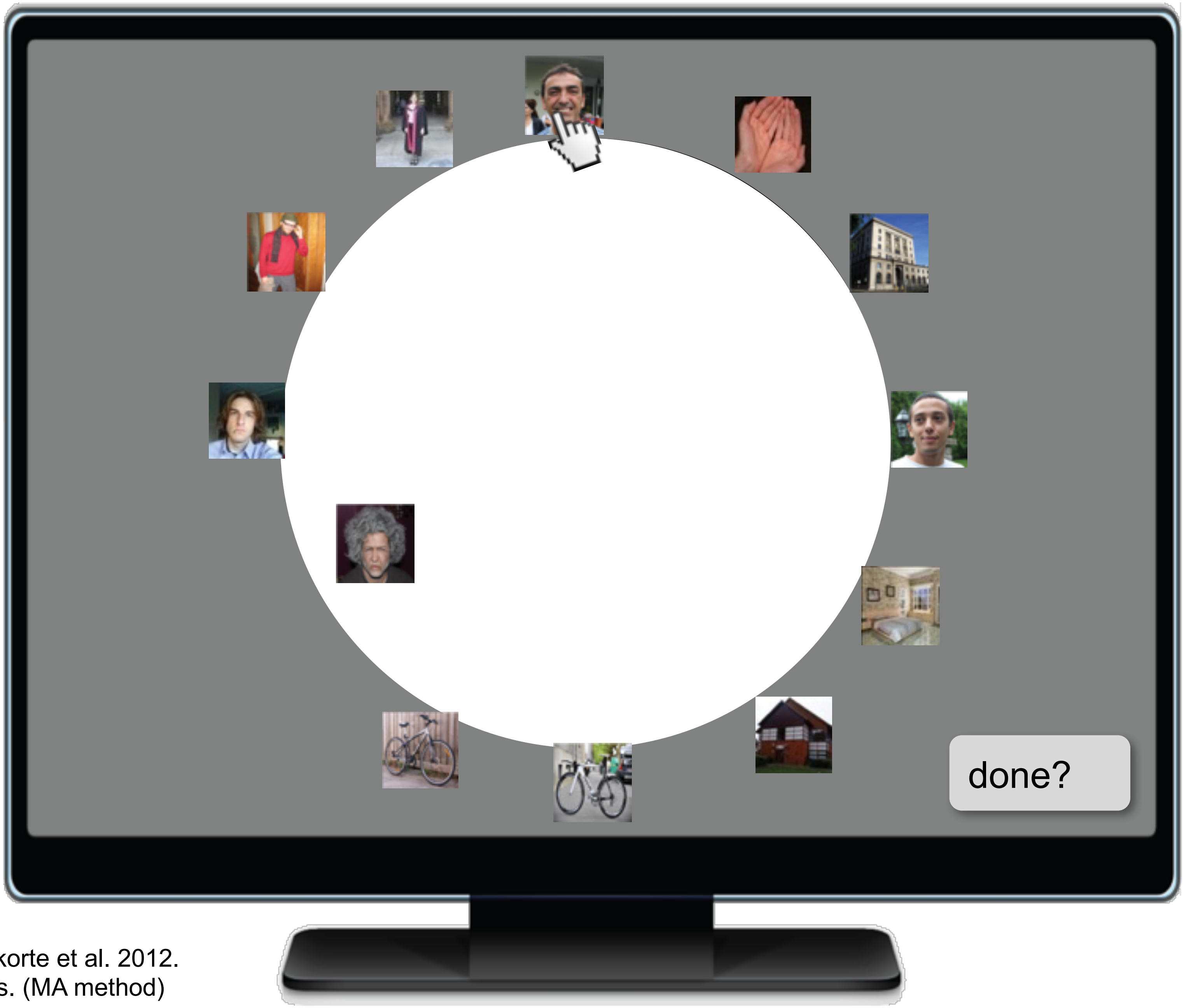

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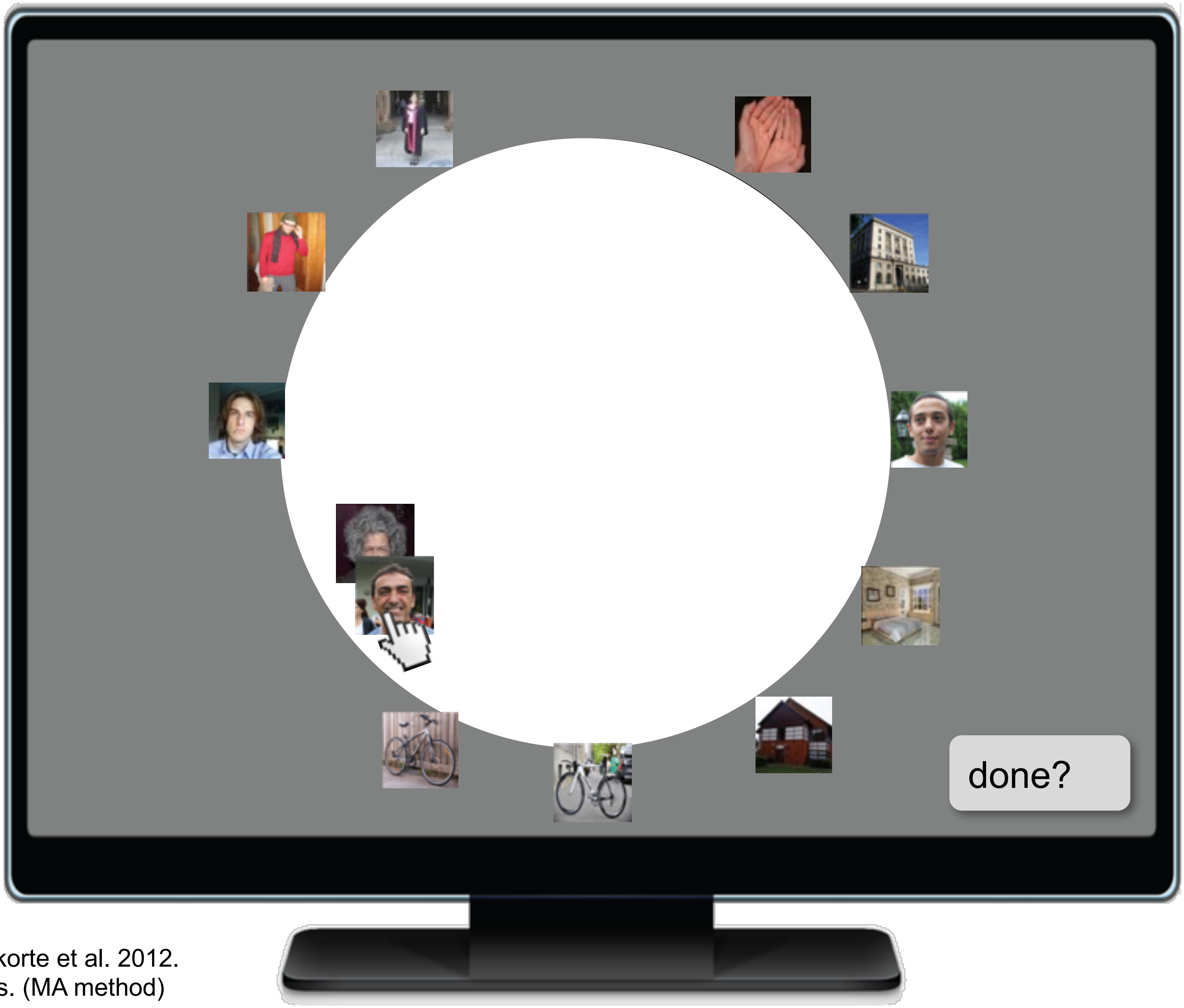

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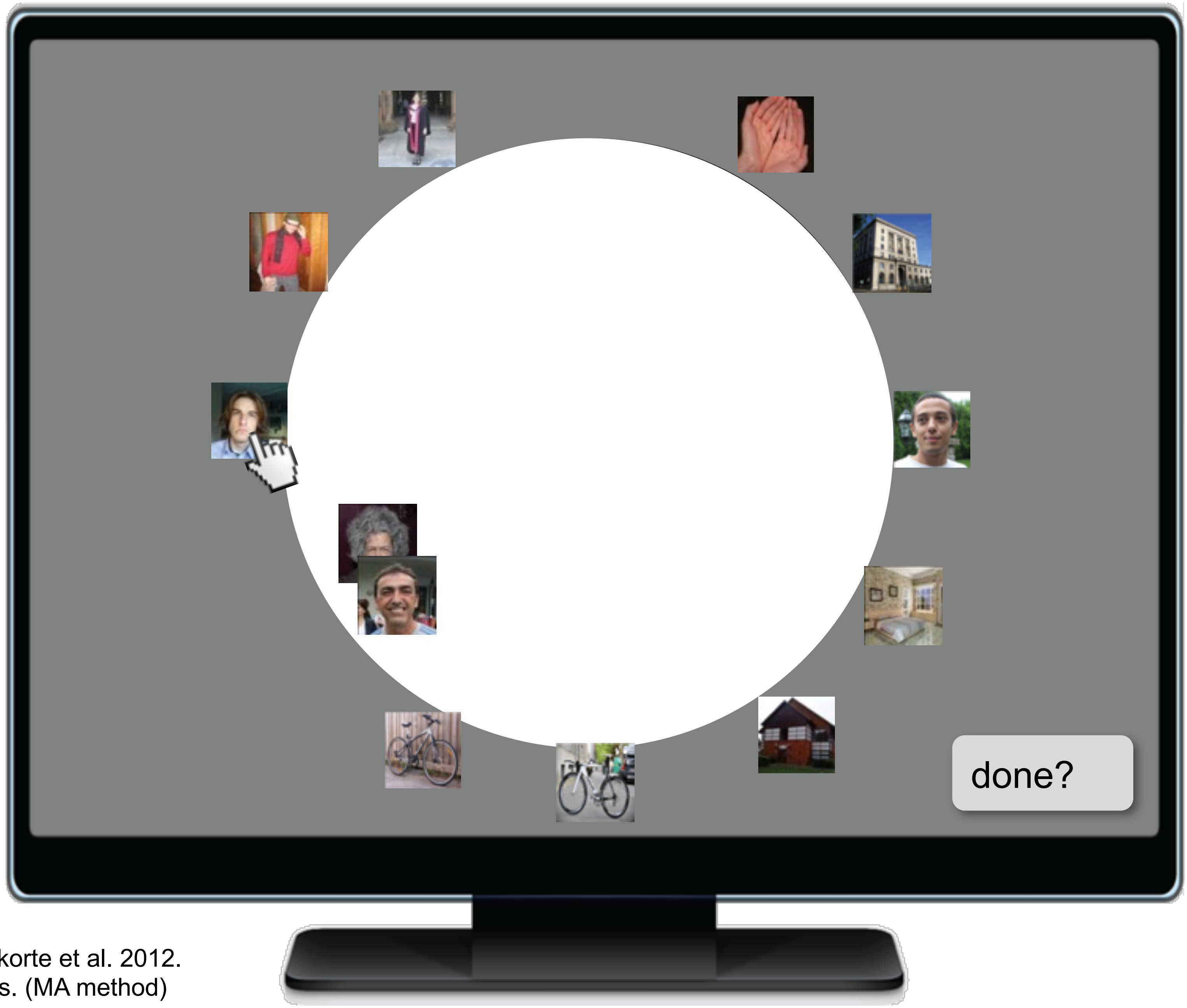

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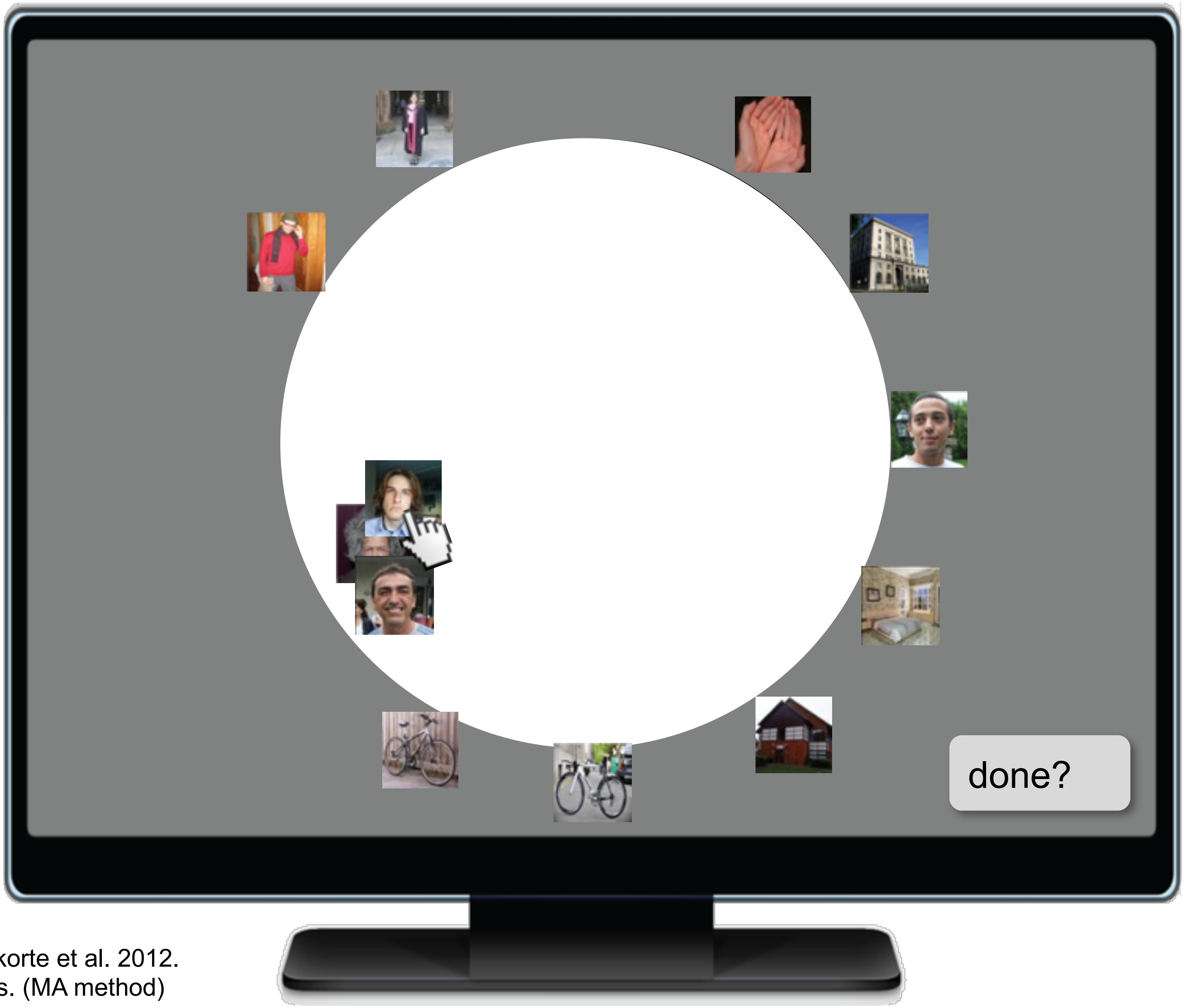

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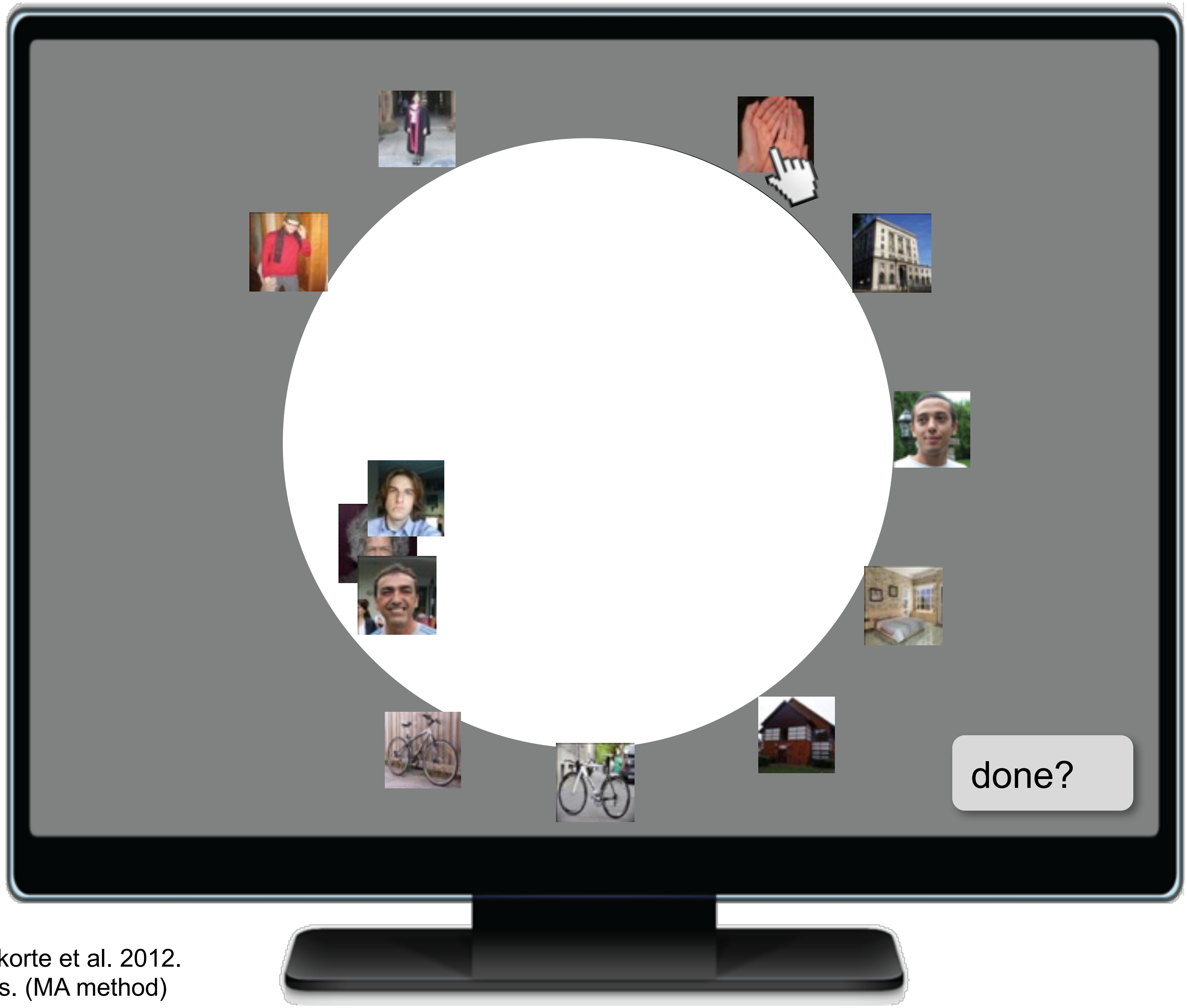

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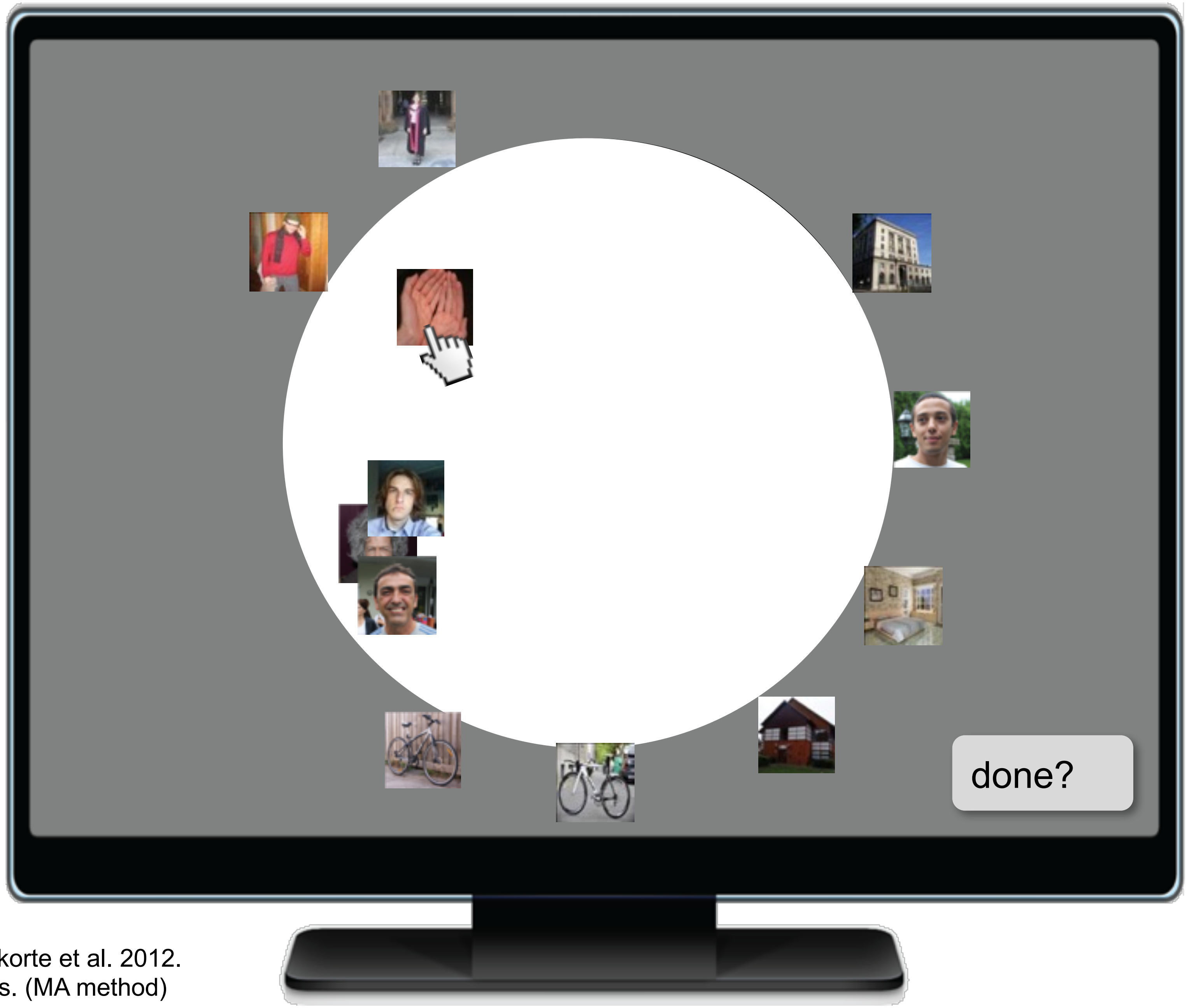

Kriegeskorte et al. 2012.
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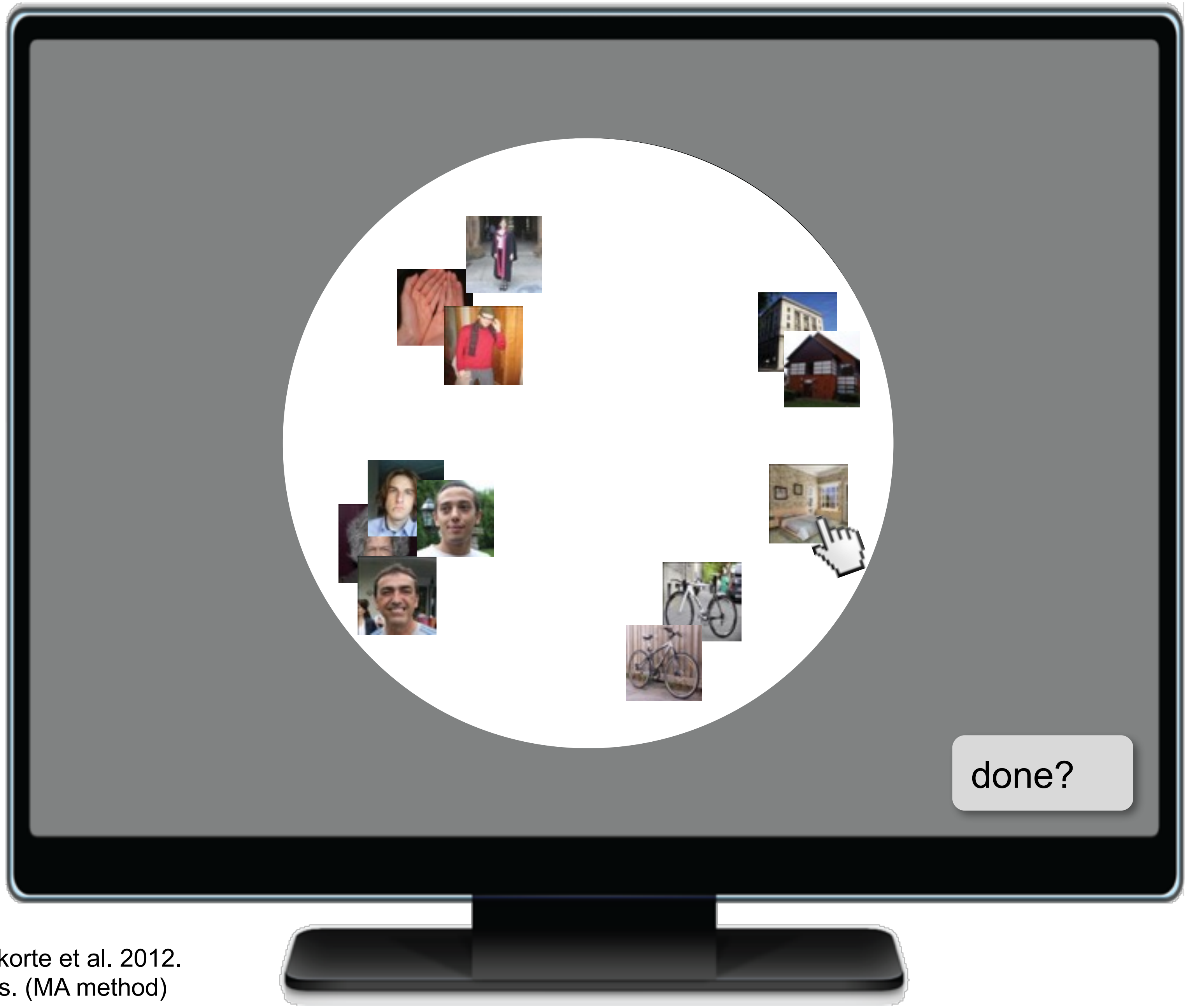

Kriegeskorte et al. 2012.
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Kriegeskorte et al. 2012.
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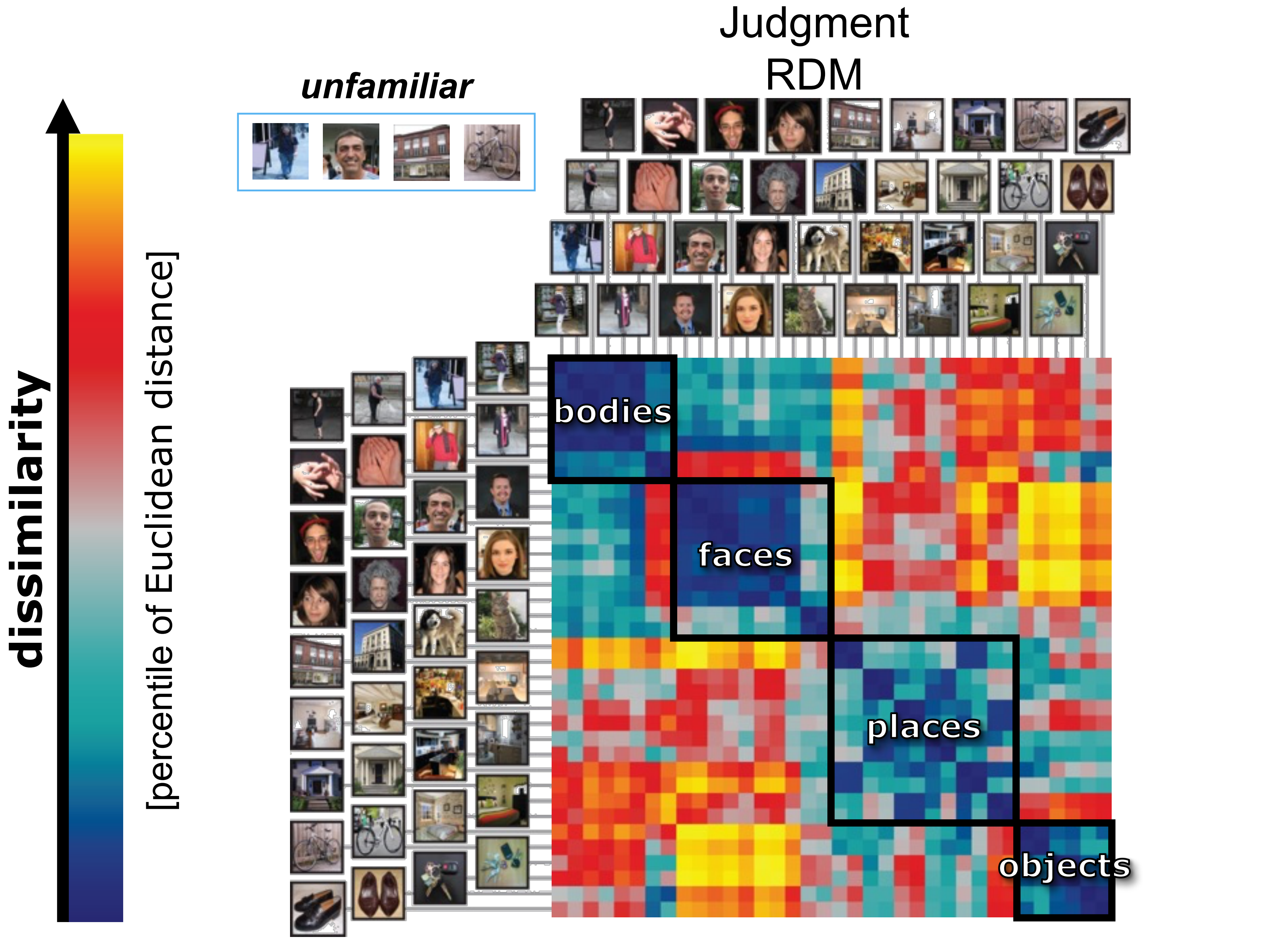
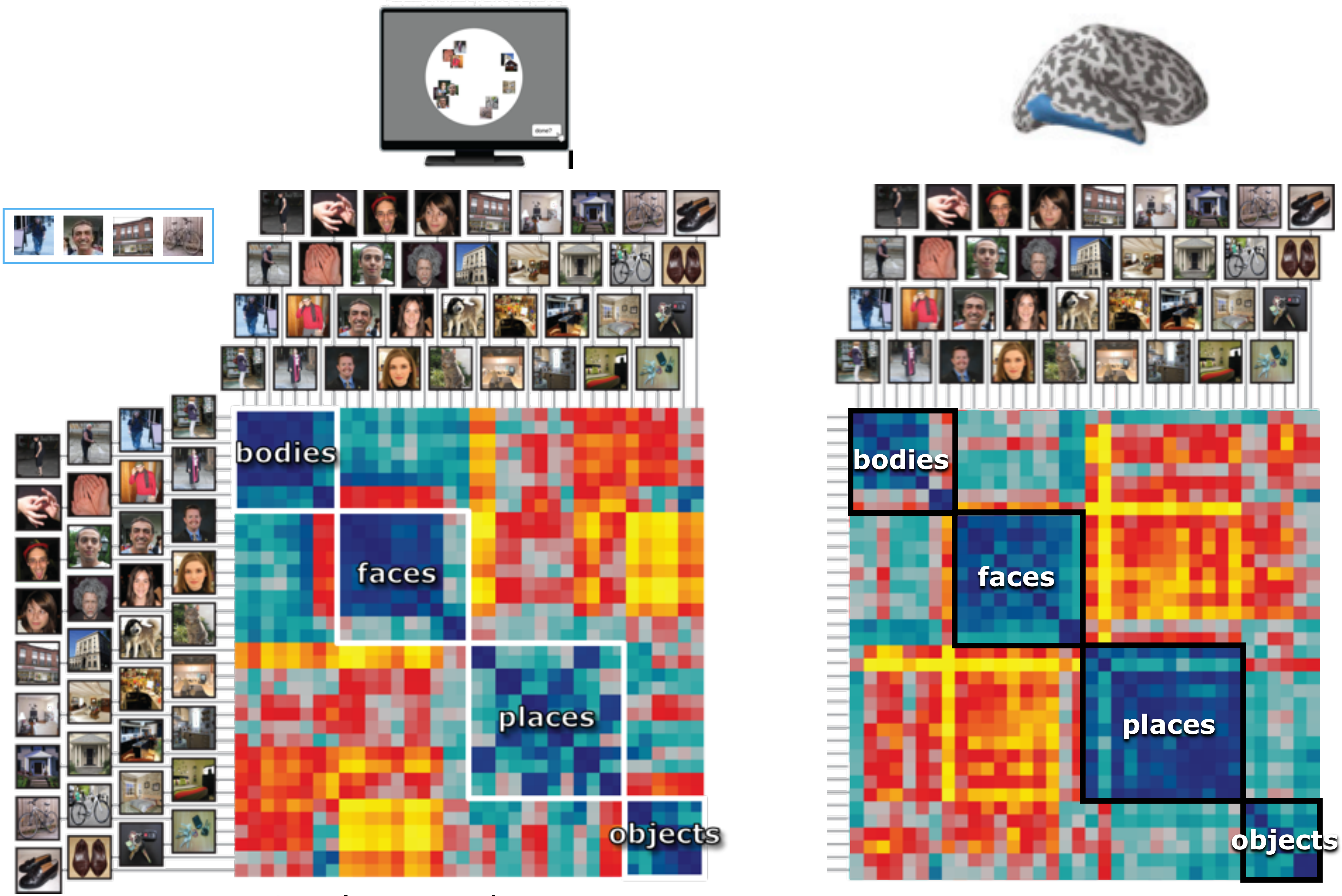
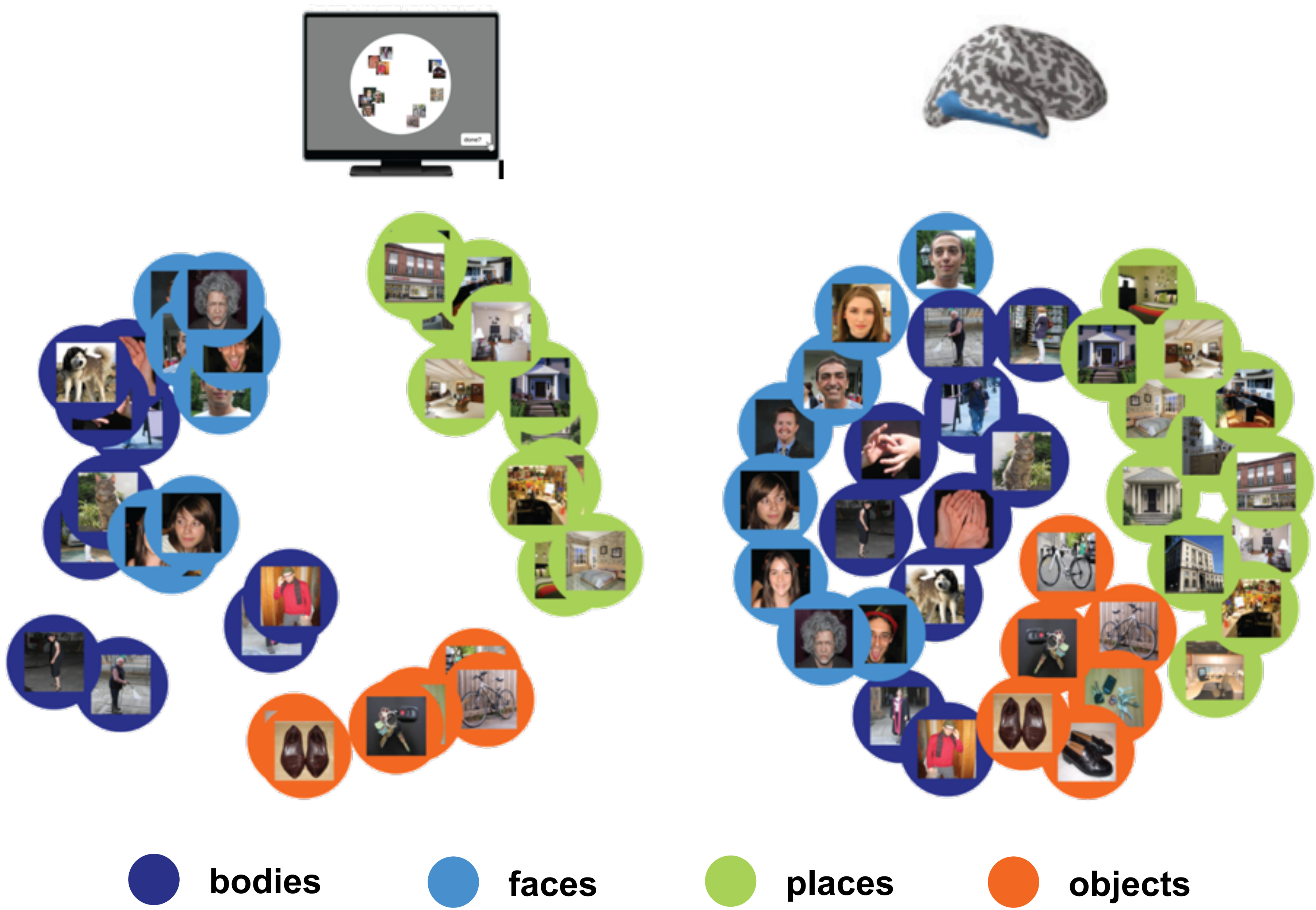
meadows-research.com


Judgment
RDM
unfamiliar
dissimilarity
[percentile of Euclidean distance]
bodies
faces
places
objects

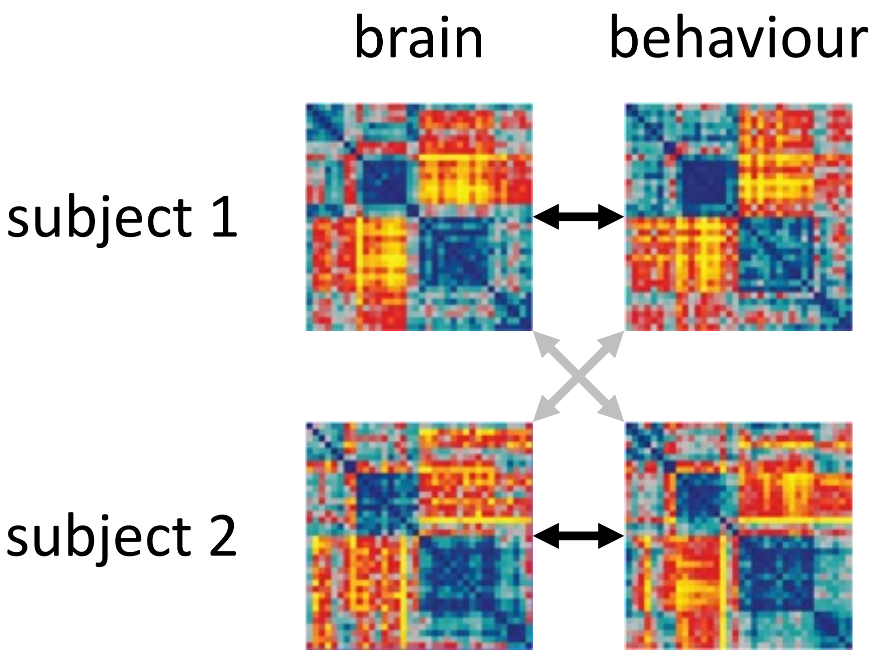


Similarity Judgements



done?
bodies
faces
places
objects

Comparing brain RDMs and behavioural RDMs



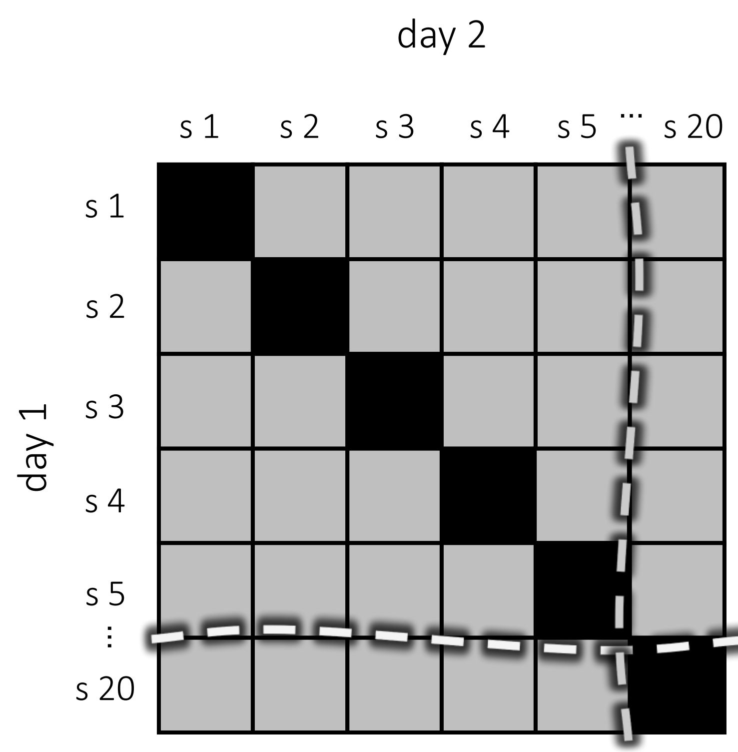
correlation

within-subject (ws) ✔

between-subject (bs) ✔

individuation index (ws - bs) ?

subject similarity matrix

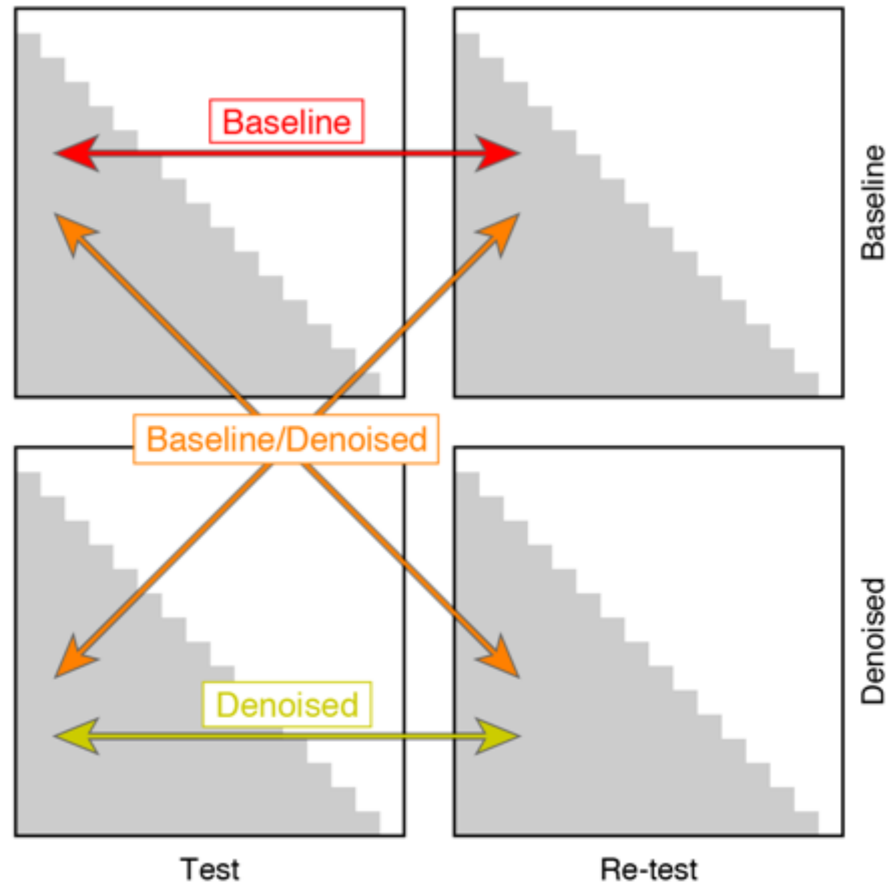


Charest et al. 2014 *PNAS*

Brain-behavior relationship unique?

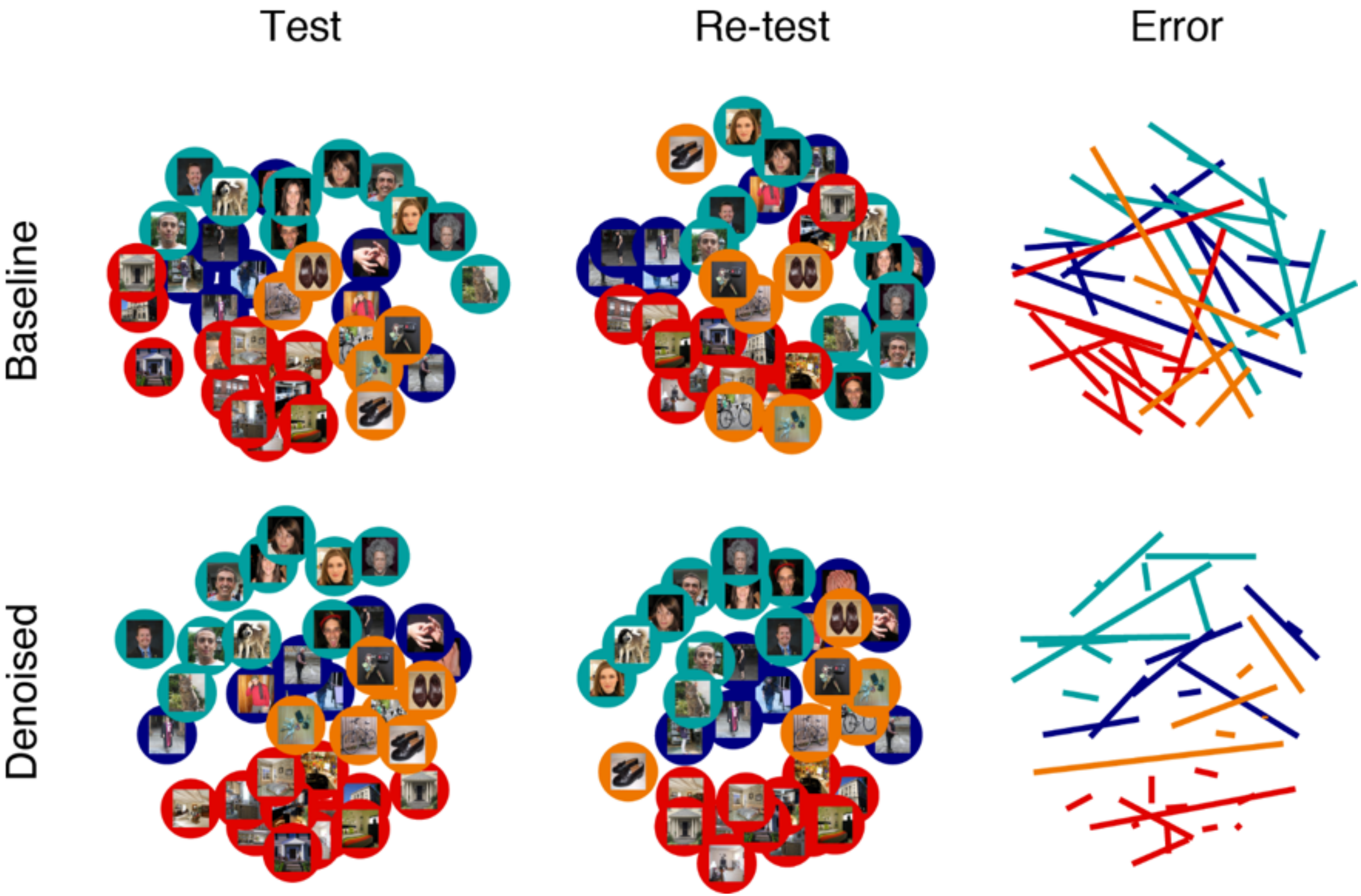
GLMdenoise improves multivariate pattern analysis (MVPA)

- 31 datasets
- 4 experiments
- Compare RSA and MVPA with and without GLMdenoise.



Charest, Kriegeskorte, Kay (in prep)

GLMdenoise improves multivariate pattern analysis (MVPA)



GLMdenoise improves multivariate pattern analysis (MVPA)

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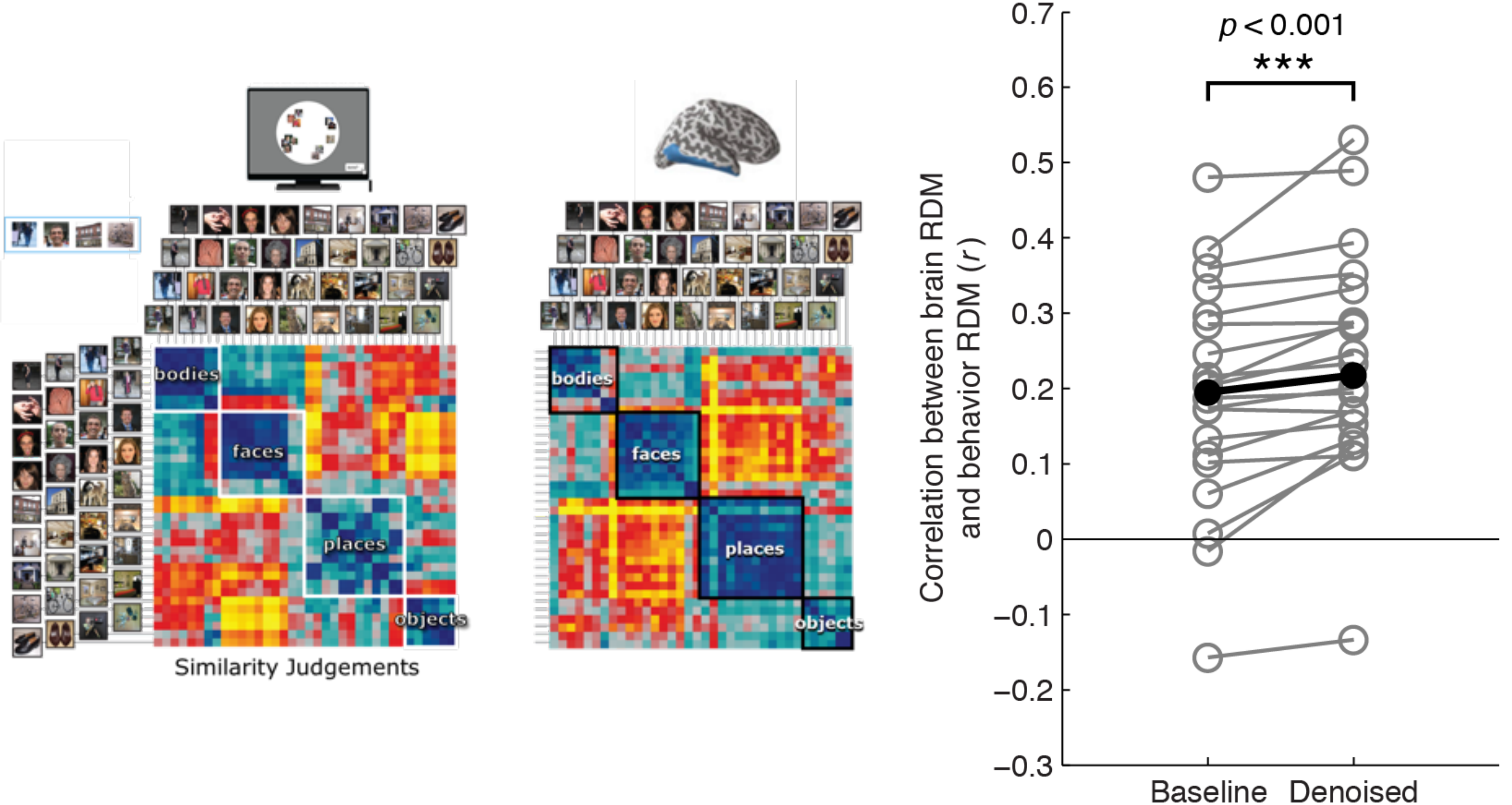


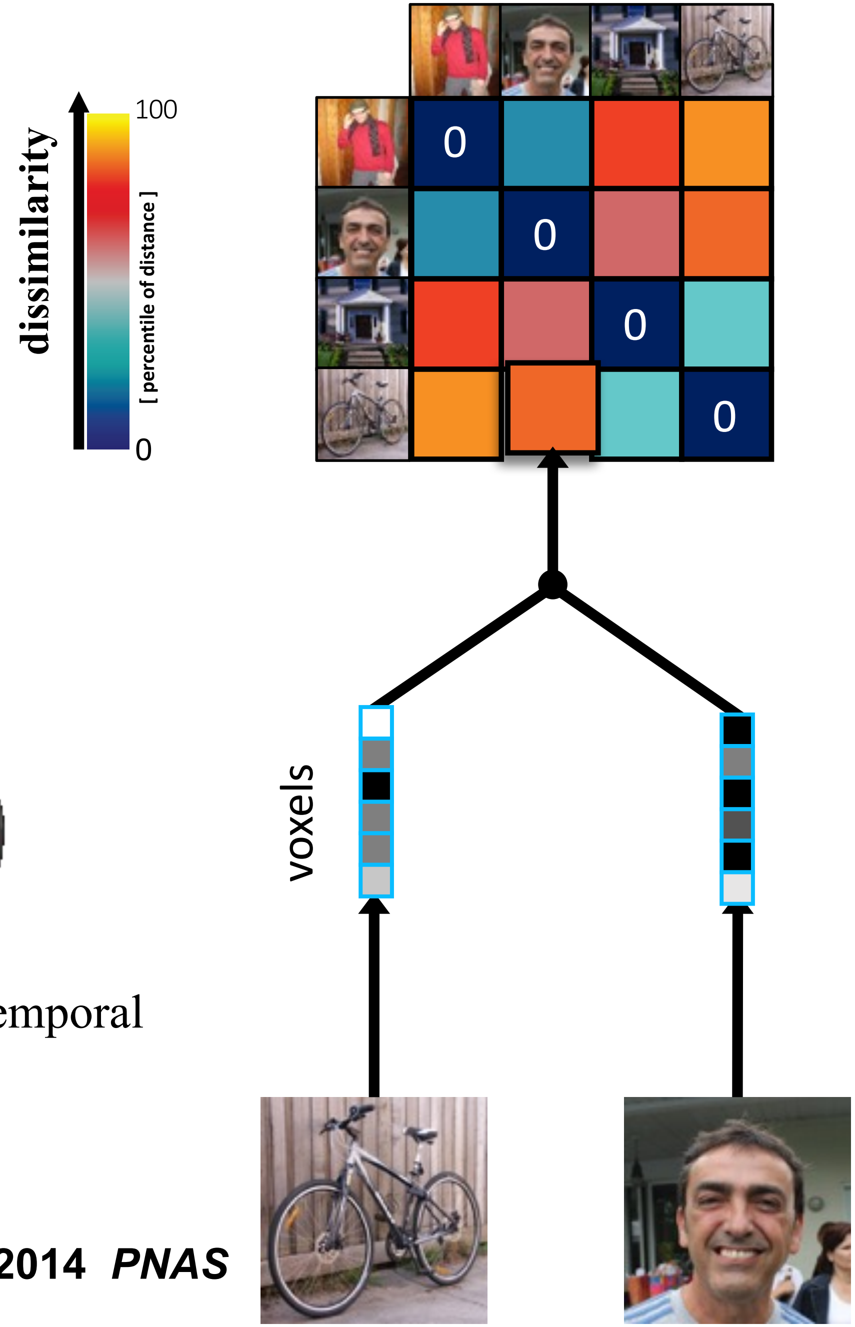
Overview

Representational Similarity Analysis …

- … applied to fMRI
- … applied to M/EEG

Access to consciousness

Representational Dissimilarity Matrix (RDM)



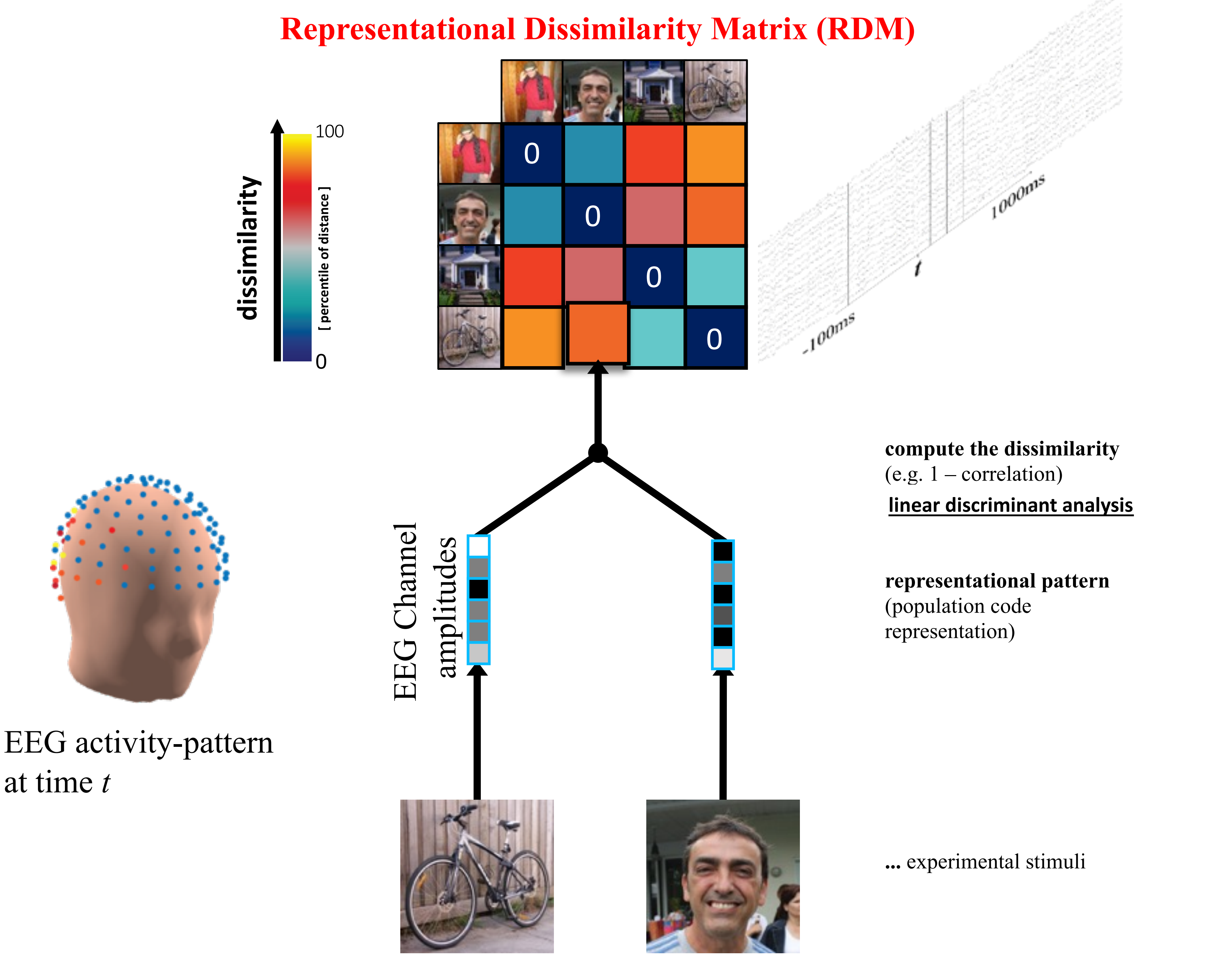
compute the dissimilarity
(e.g. 1 – correlation)

representational pattern
(population code representation)

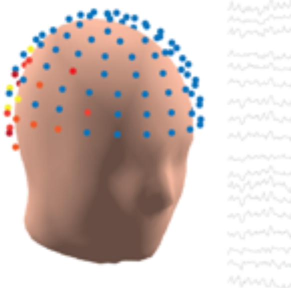
... experimental stimuli

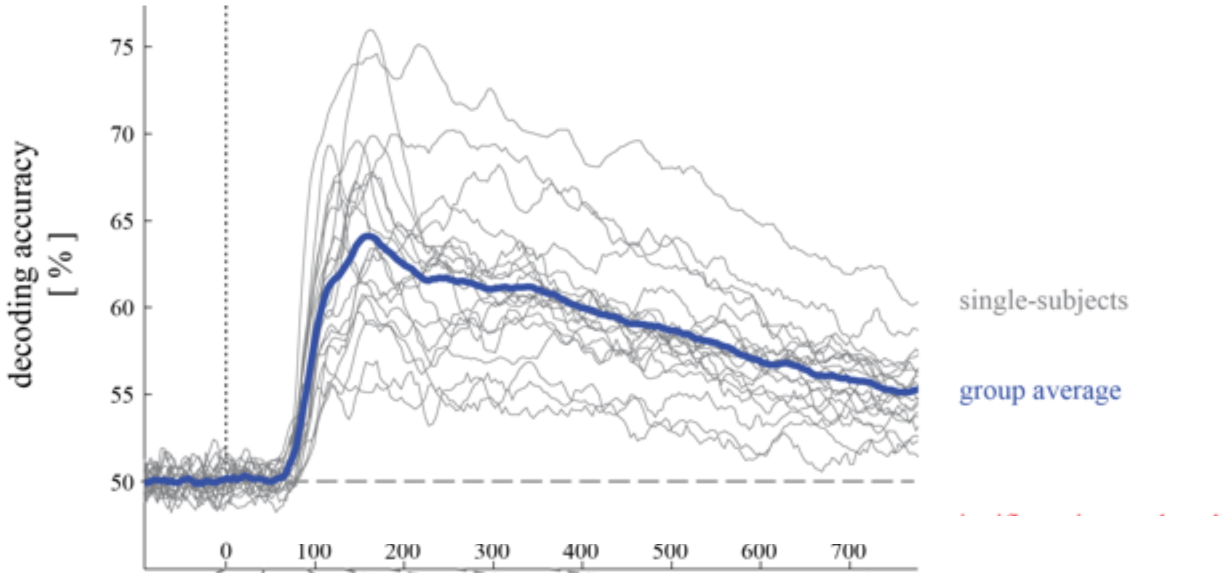
human inferior temporal (hIT)

Charest et al. 2014 *PNAS*

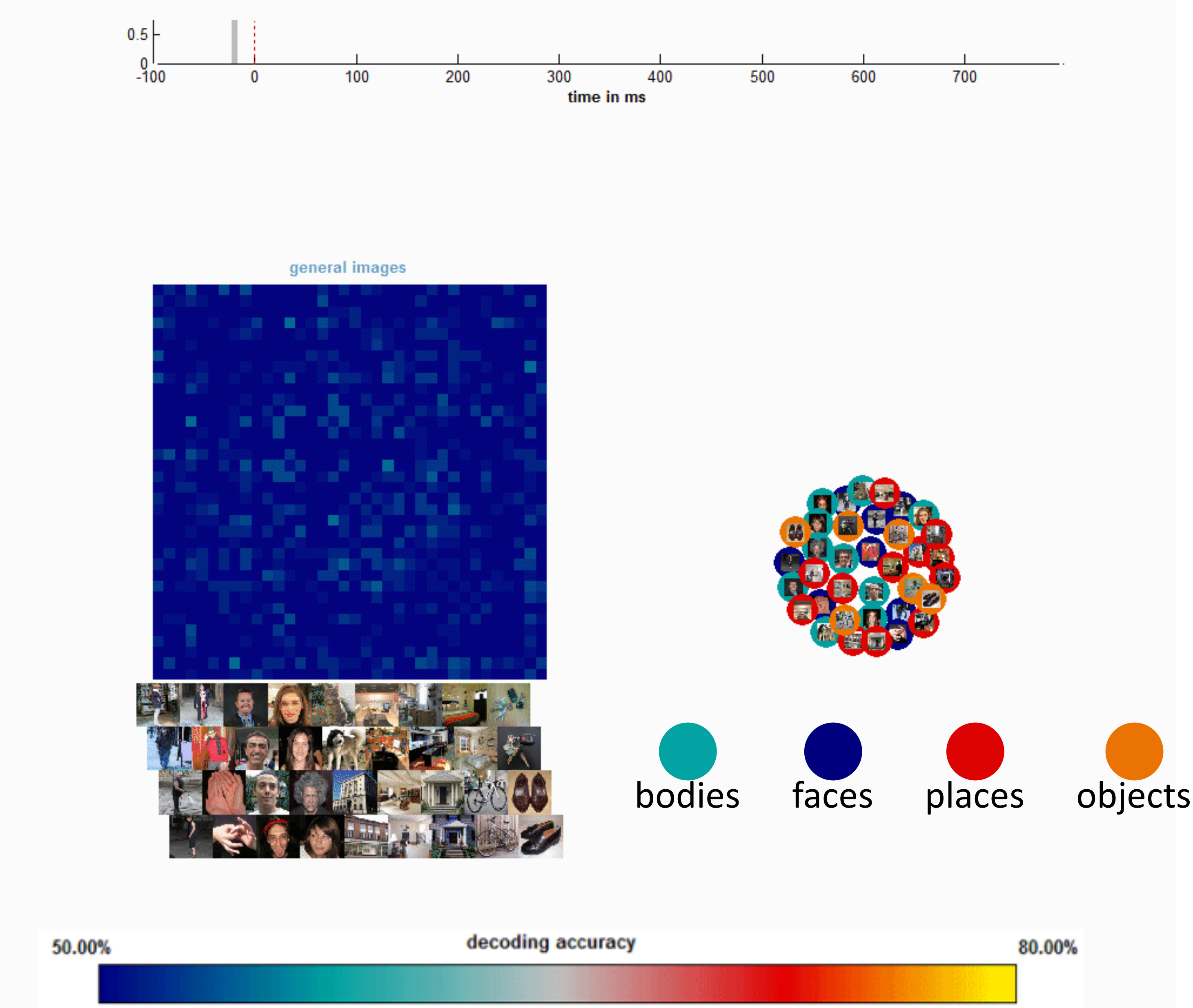

Representational Dissimilarity Matrix (RDM)
dissimilarity
[percentile of distance]
100
0
0
0
0
0
-100ms
t
1000ms
compute the dissimilarity
(e.g. 1 – correlation)
linear discriminant analysis
EEG Channel amplitudes
representational pattern
(population code representation)
EEG activity-pattern at time t
... experimental stimuli

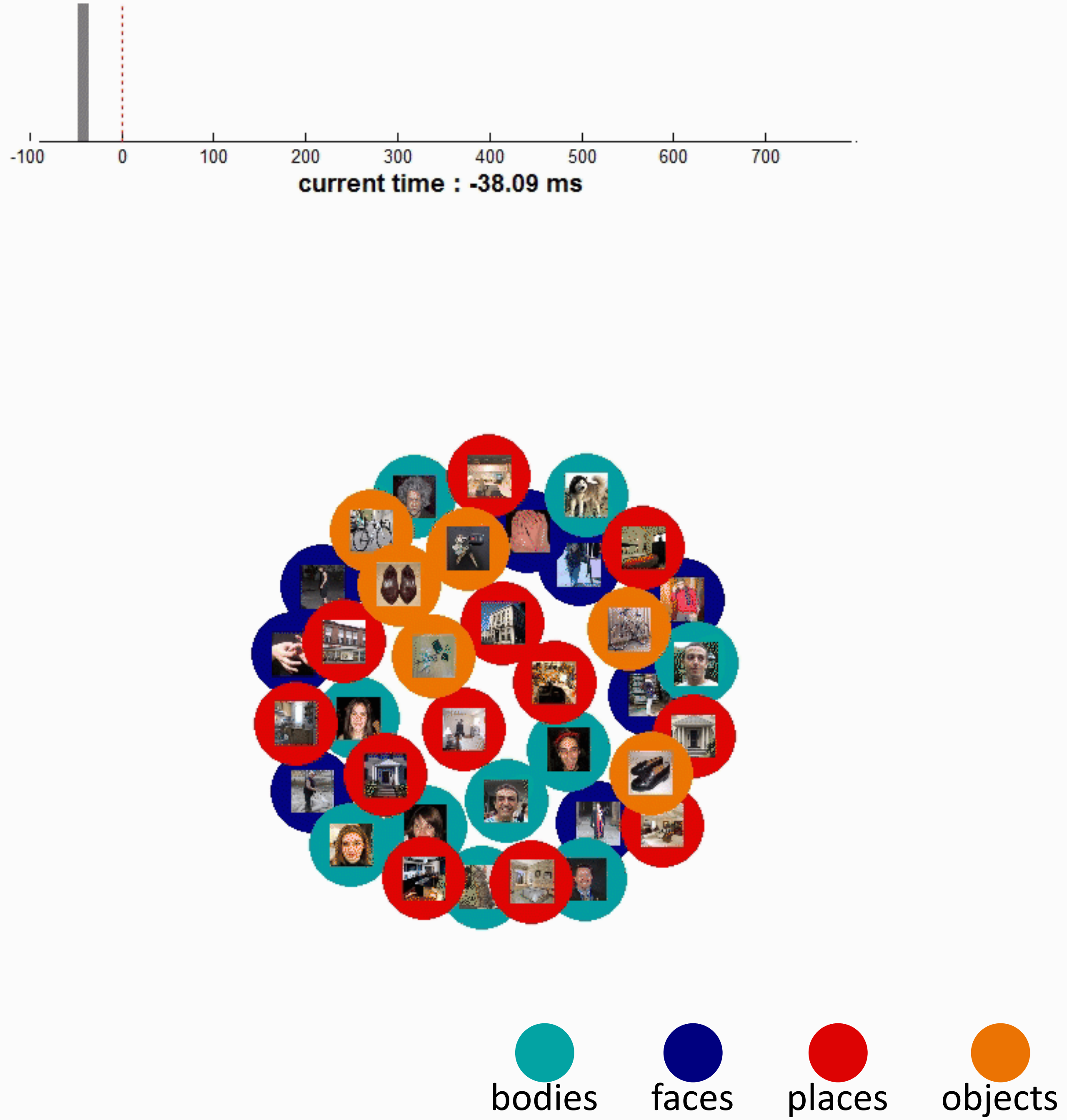
EEG contains rich topographic information from which you can distinguish mental states



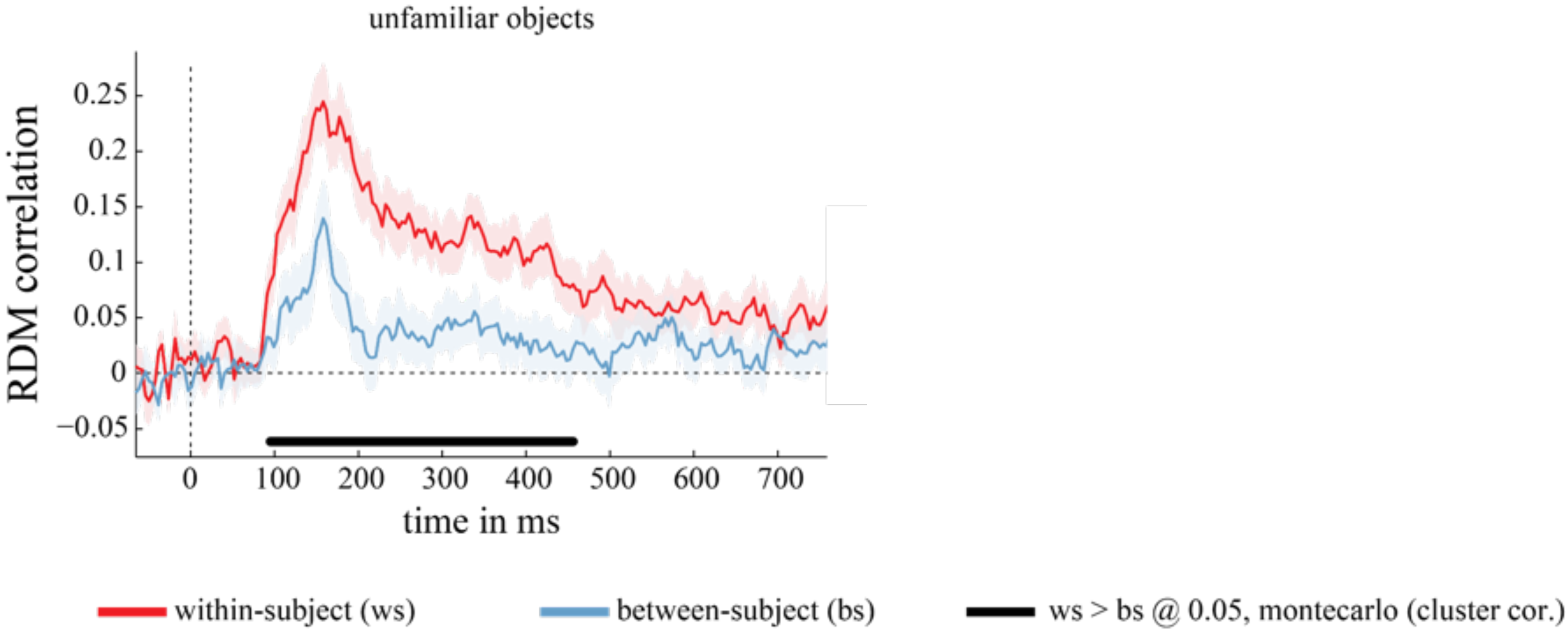


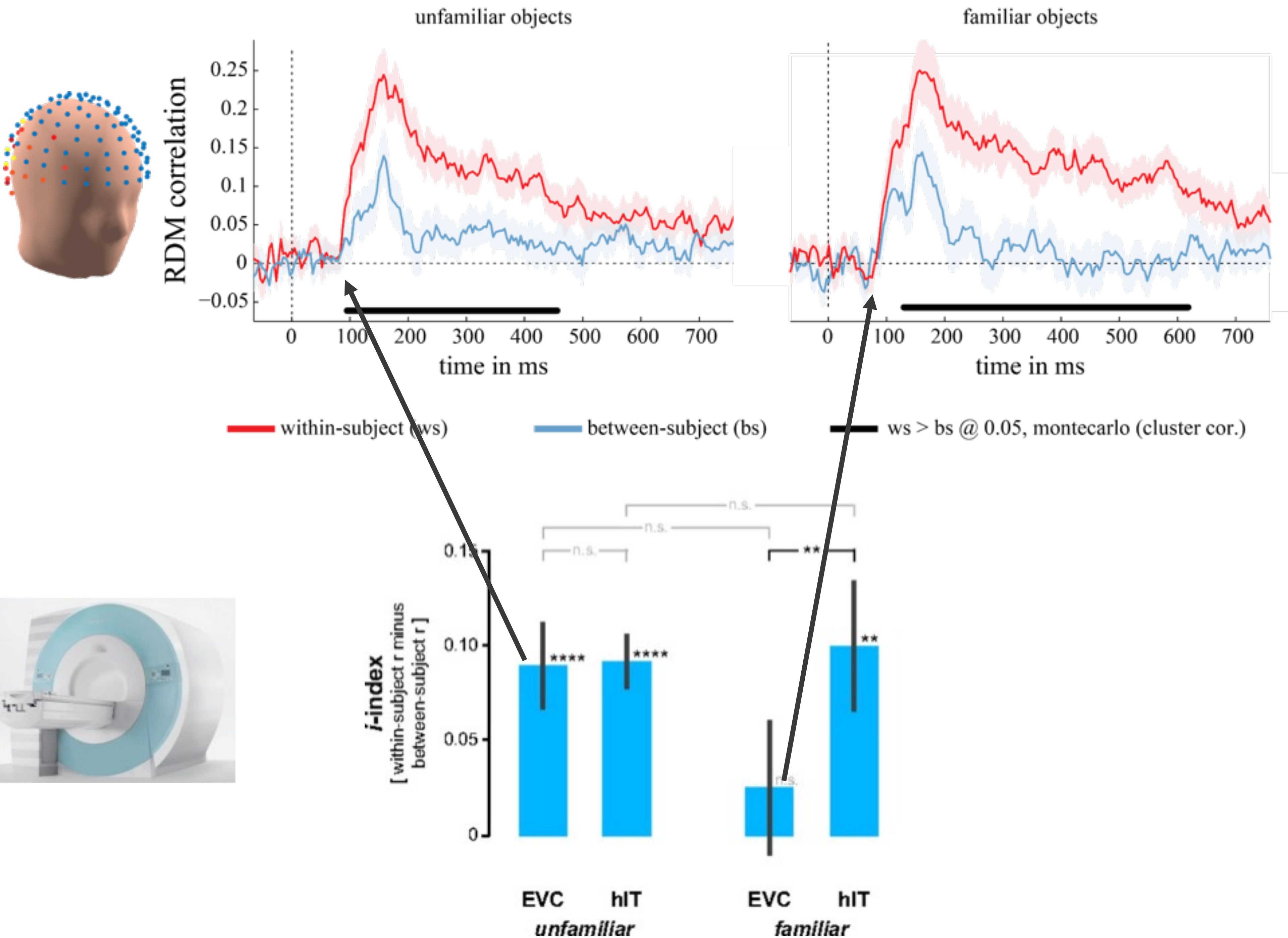
EEG contains rich topographic information from which you can distinguish mental states




-100
0
100
200
300
400
500
600
700
current time : -38.09 ms
bodies
faces
places
objects

Comparing individuals' representations





unfamiliar objects
familiar objects
RDM correlation
0.25
0.2
0.15
0.1
0.05
0
−0.05
0
100
200
300
400
500
600
700
time in ms
within-subject (ws)
between-subject (bs)
ws > bs @ 0.05, montecarlo (cluster cor.)
n.s.
n.s.
n.s.
**
****
****
**
n.s.
0.15
0.10
0.05
0
i-index
[within-subject r minus between-subject r]
EVC
hIT
EVC
hIT
unfamiliar
familiar

Overview

Representational Similarity Analysis …

- … applied to fMRI
- … applied to M/EEG

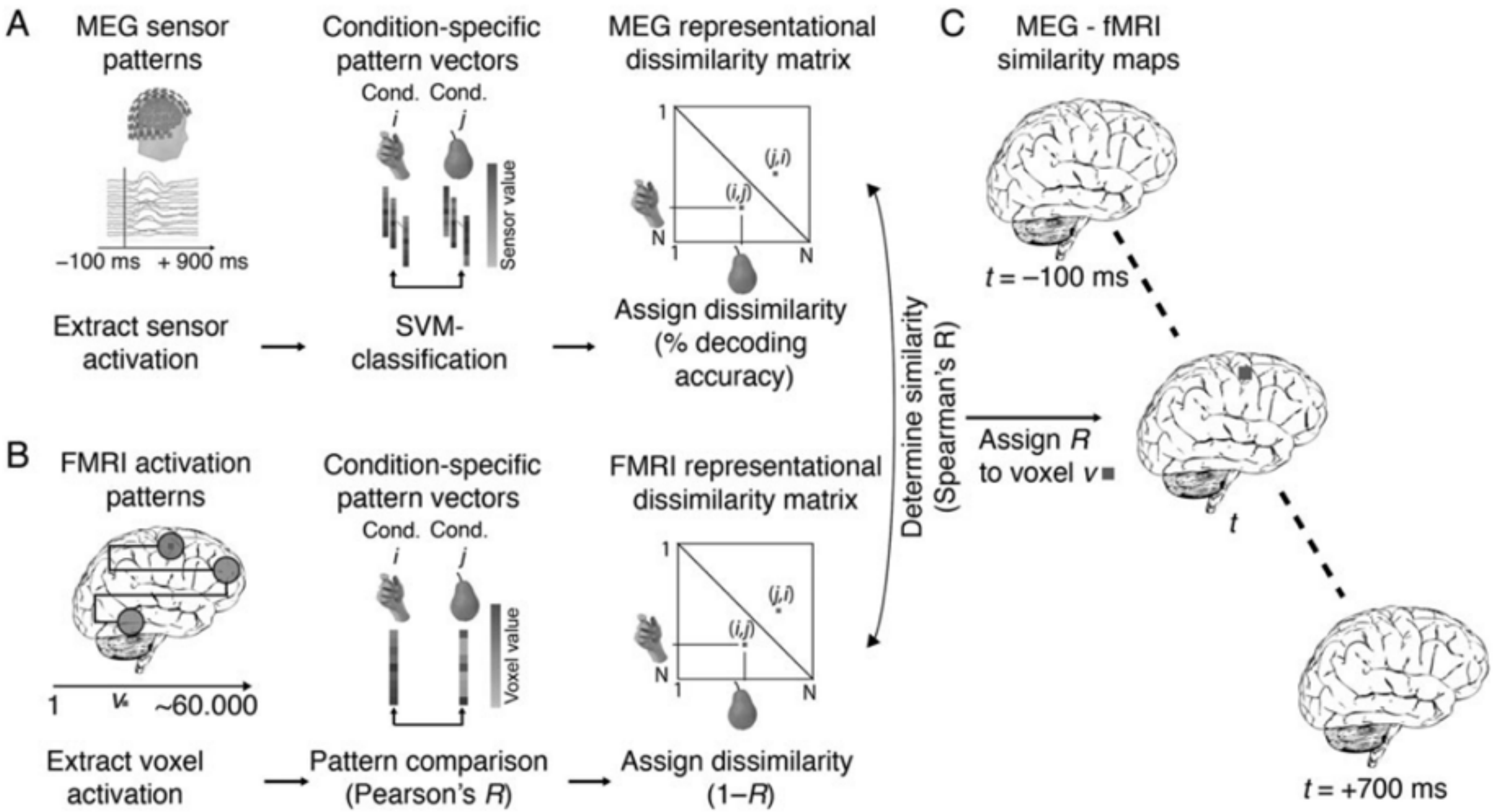
Access to consciousness

RSA fusion of M/EEEg + fMRI

https://www.youtube.com/watch?v=YBv_Bju4_aM

Cichy et al. 2014, 2016

RSA fusion of M/EEG and fMRI



Cichy et al. 2014, 2016

First interim conclusion

- Using RSA, cognitive neuroscience can combine strengths of measurement modalities.
- Individually unique object representations in space, and time.
- Combining M/EEG and fMRI data using RSA has enabled mapping the first few hundred milliseconds of object recognition in the brain.

Overview

Representational Similarity Analysis …

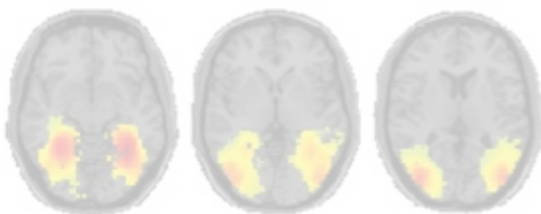
- … applied to fMRI
- … applied to M/EEG

Access to consciousness

START: Spatio-Temporal Attention and Representation Tracking

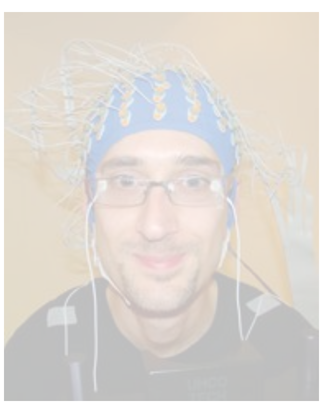
functional Magnetic Resonance Imaging (fMRI)

SPACE

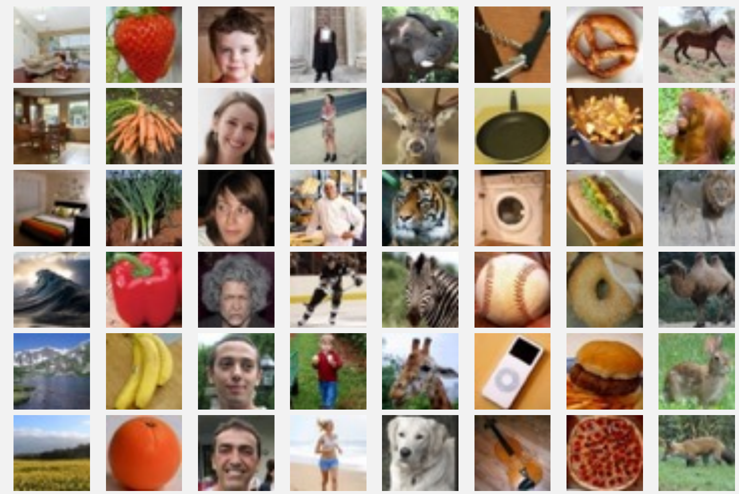


Electroencephalography (EEG)

TIME

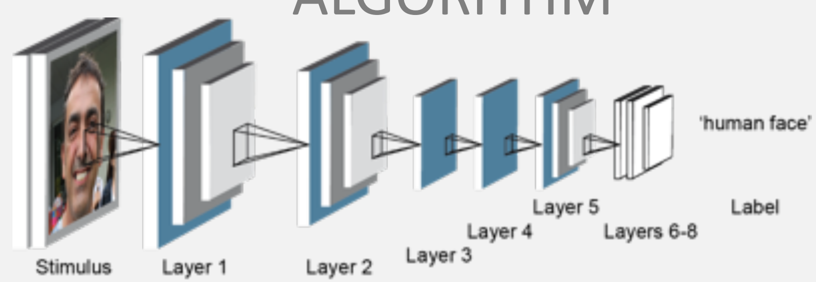


real-world object stimuli in the attentional blink

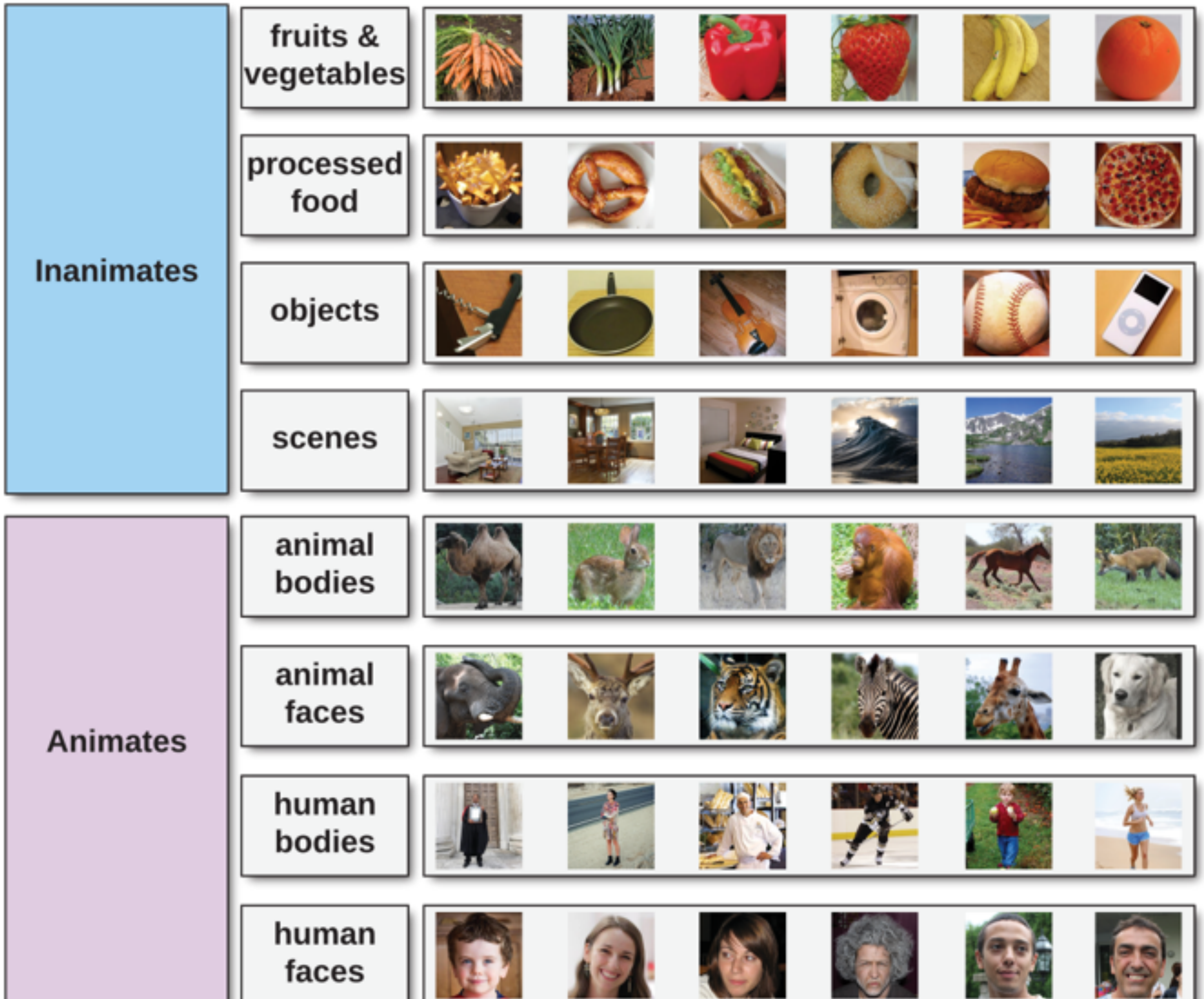


Deep convolutional neuronal networks (DCNN)

ALGORITHM

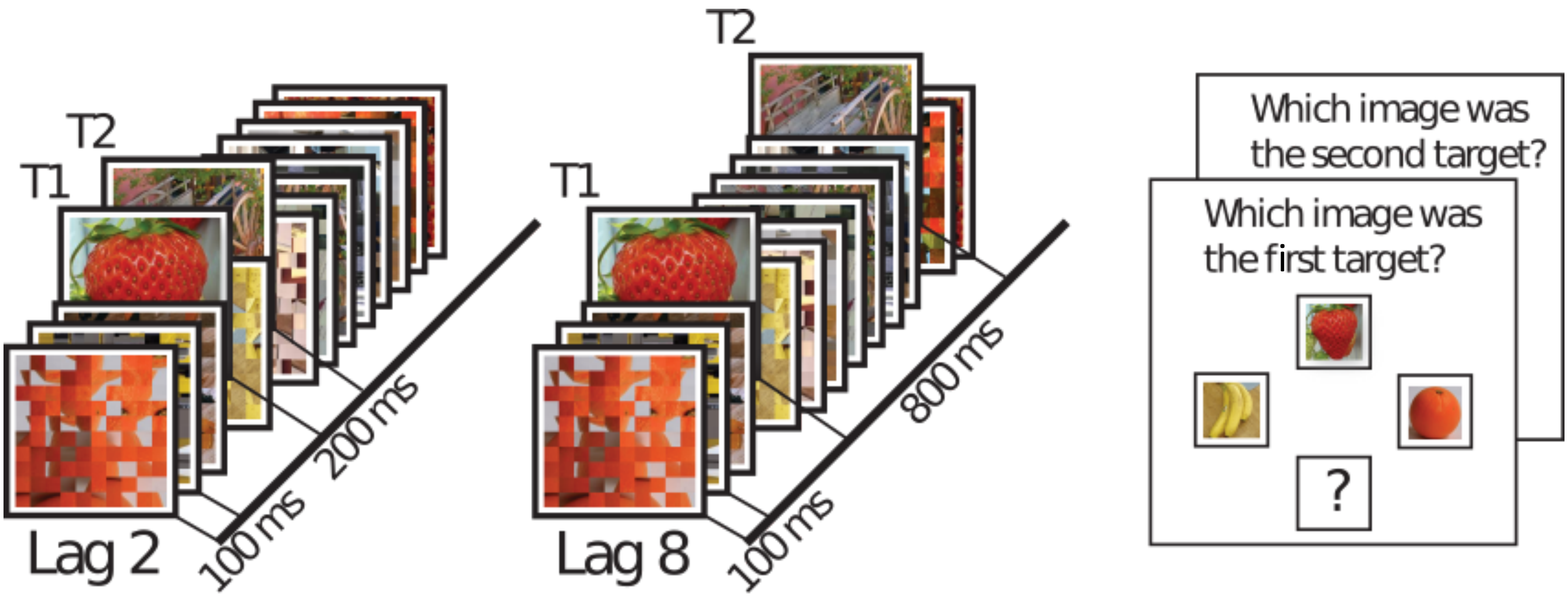


Stimuli



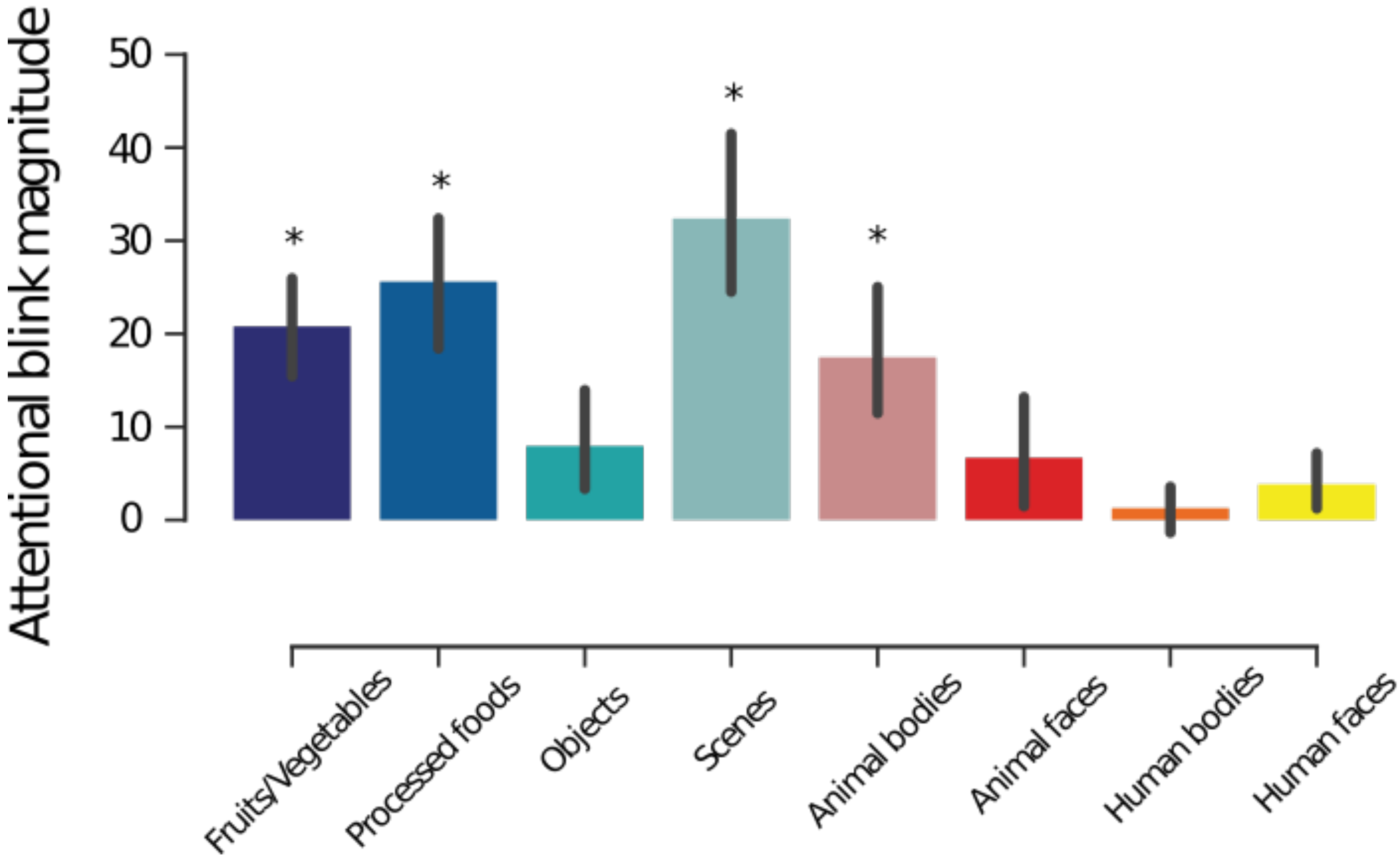
Lindh, Assecondi, Sligte, Shapiro, Charest. (in prep)

Task



Lindh, Assecondi, Sligte, Shapiro, Charest. (in prep)

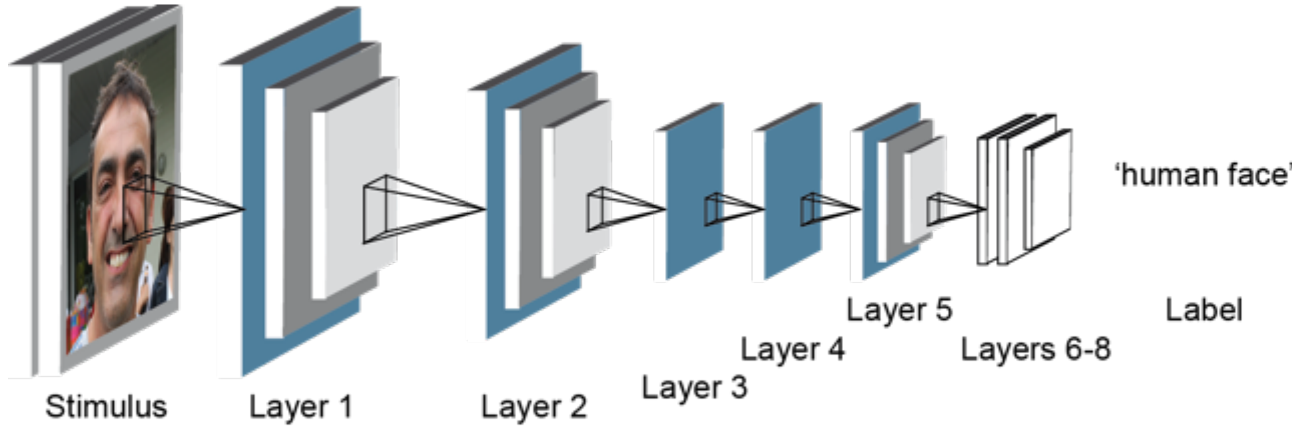
Categorical differences in attentional blink



Lindh, Assecondi, Sligte, Shapiro, Charest. (in prep)

Predicting conscious access using convolutional neuronal networks

Deep convolutional neuronal networks (DCNN)



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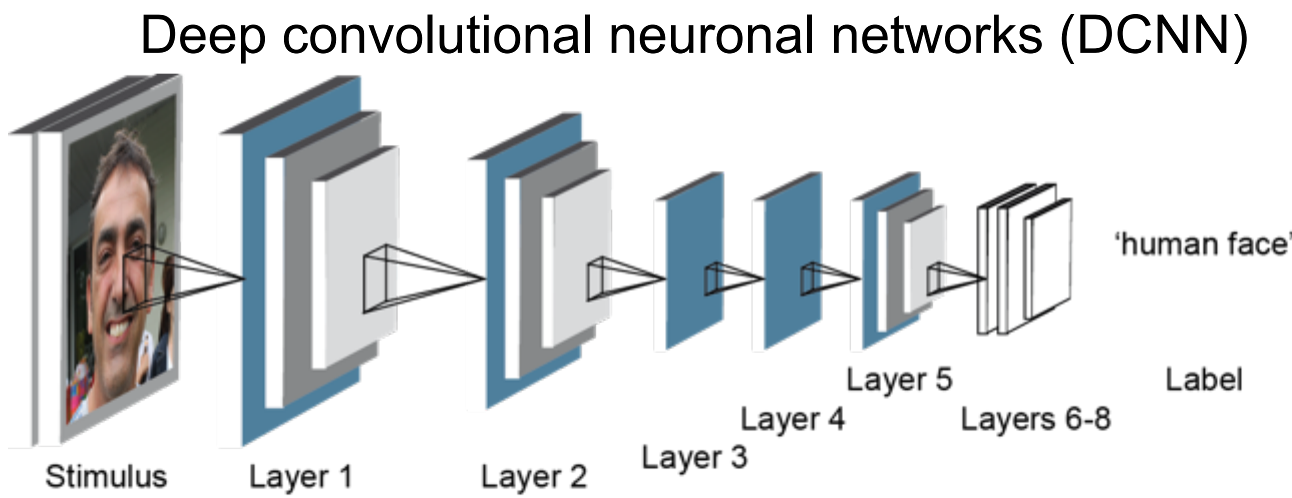
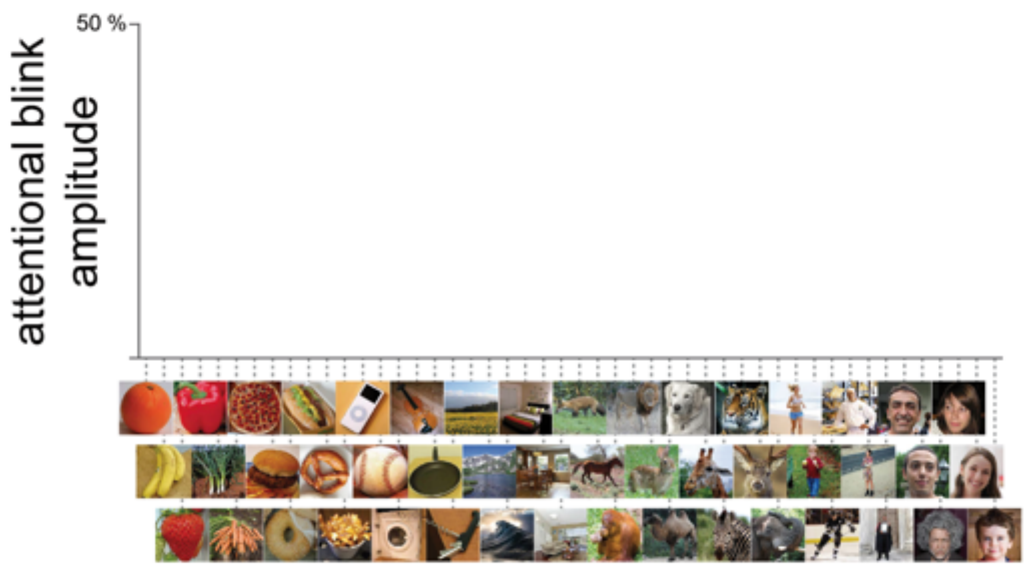
Predicting conscious access using convolutional neuronal networks





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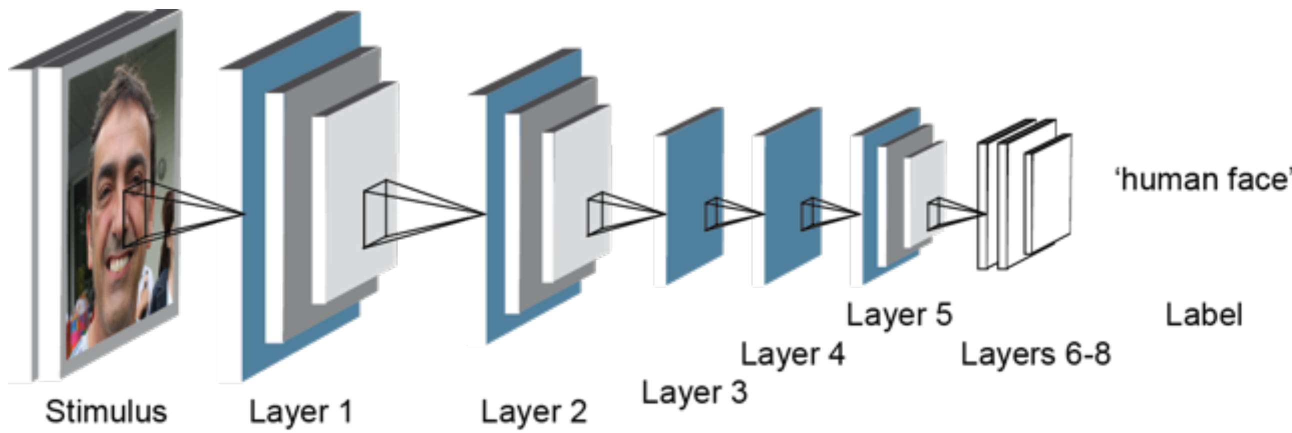
Predicting conscious access using convolutional neuronal networks

Deep convolutional neuronal networks (DCNN)



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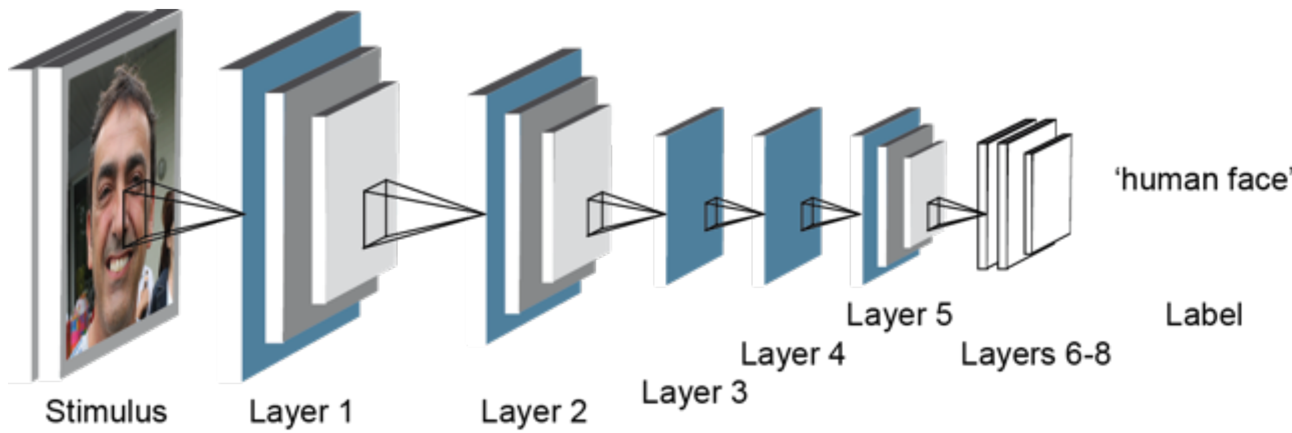
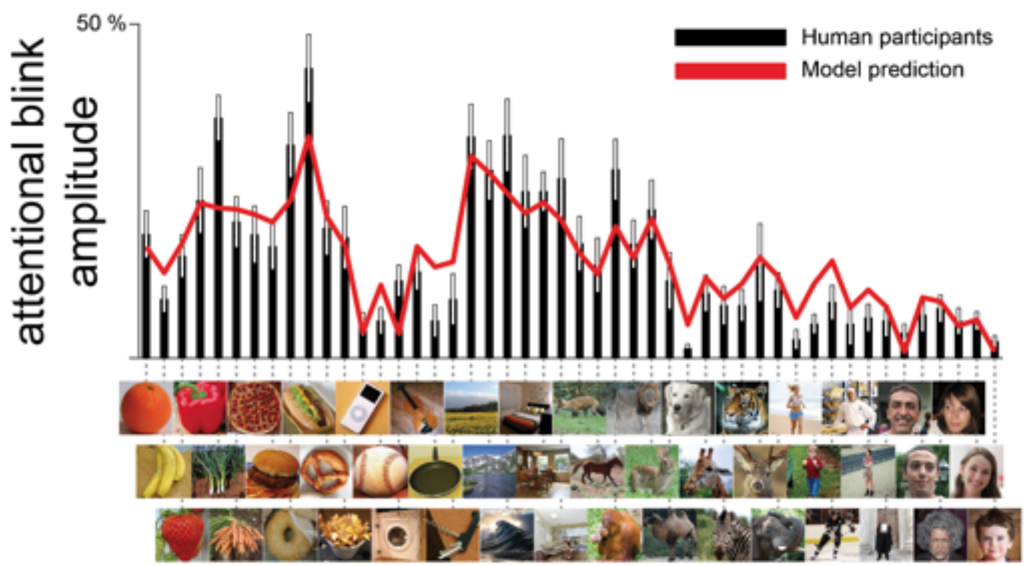
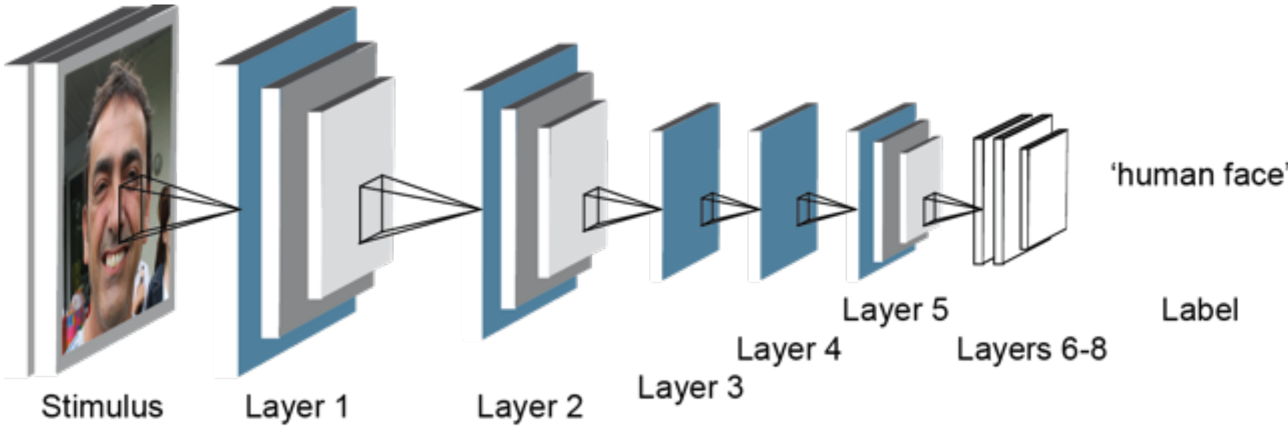




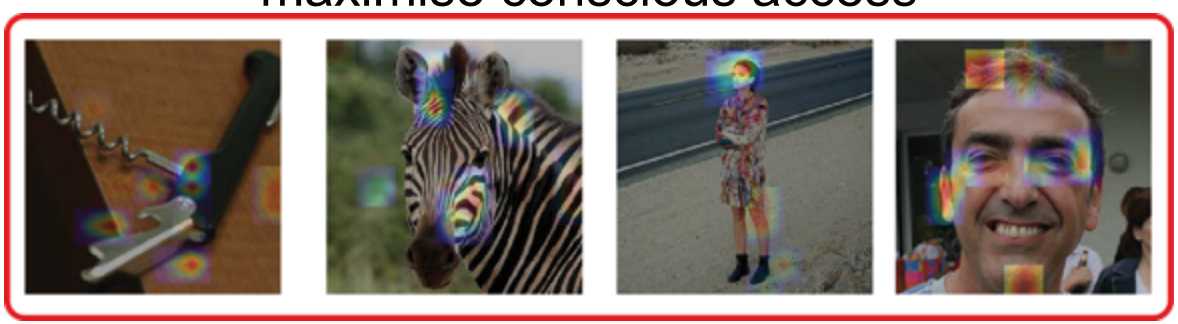
Lindh, Assecondi, Sligte, Shapiro, Charest. (in prep)

Predicting conscious access using convolutional neuronal networks

Deep convolutional neuronal networks (DCNN)



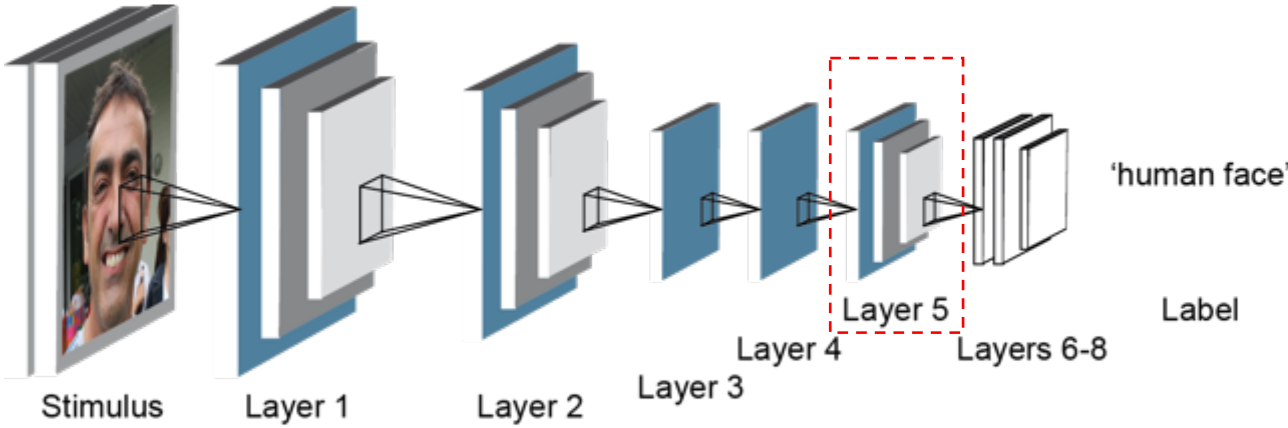
Reveal the features that maximise conscious access

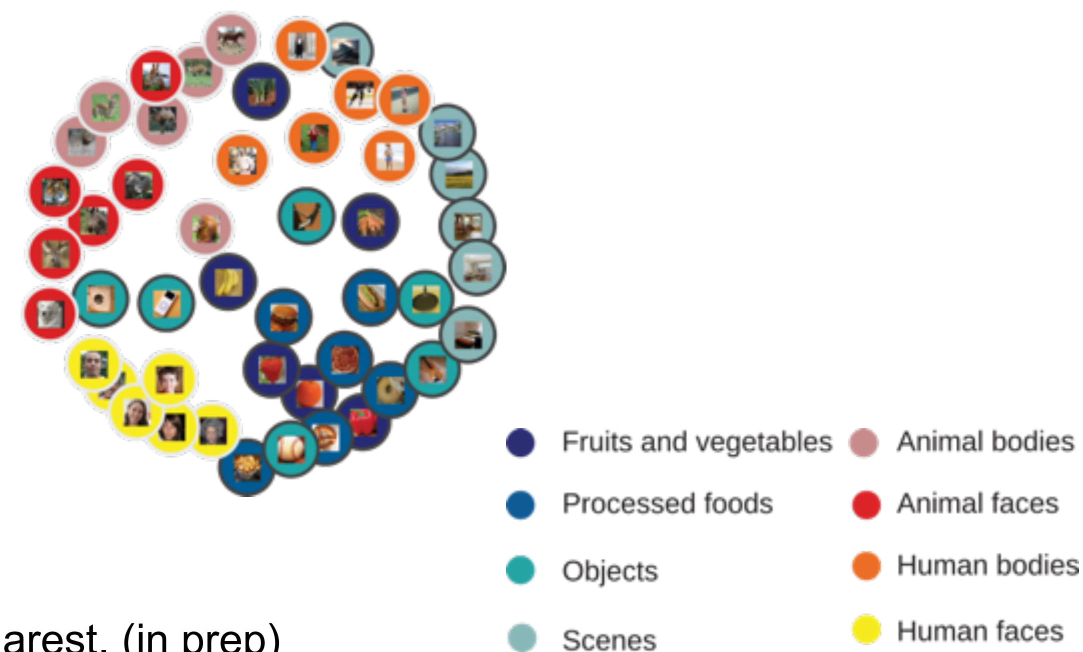


Lindh, Assecondi, Sligte, Shapiro, Charest. (in prep)

Similarity of AB targets

Deep convolutional neuronal networks (DCNN)





Lindh, Assecondi, Sligte, Shapiro, Charest. (in prep)

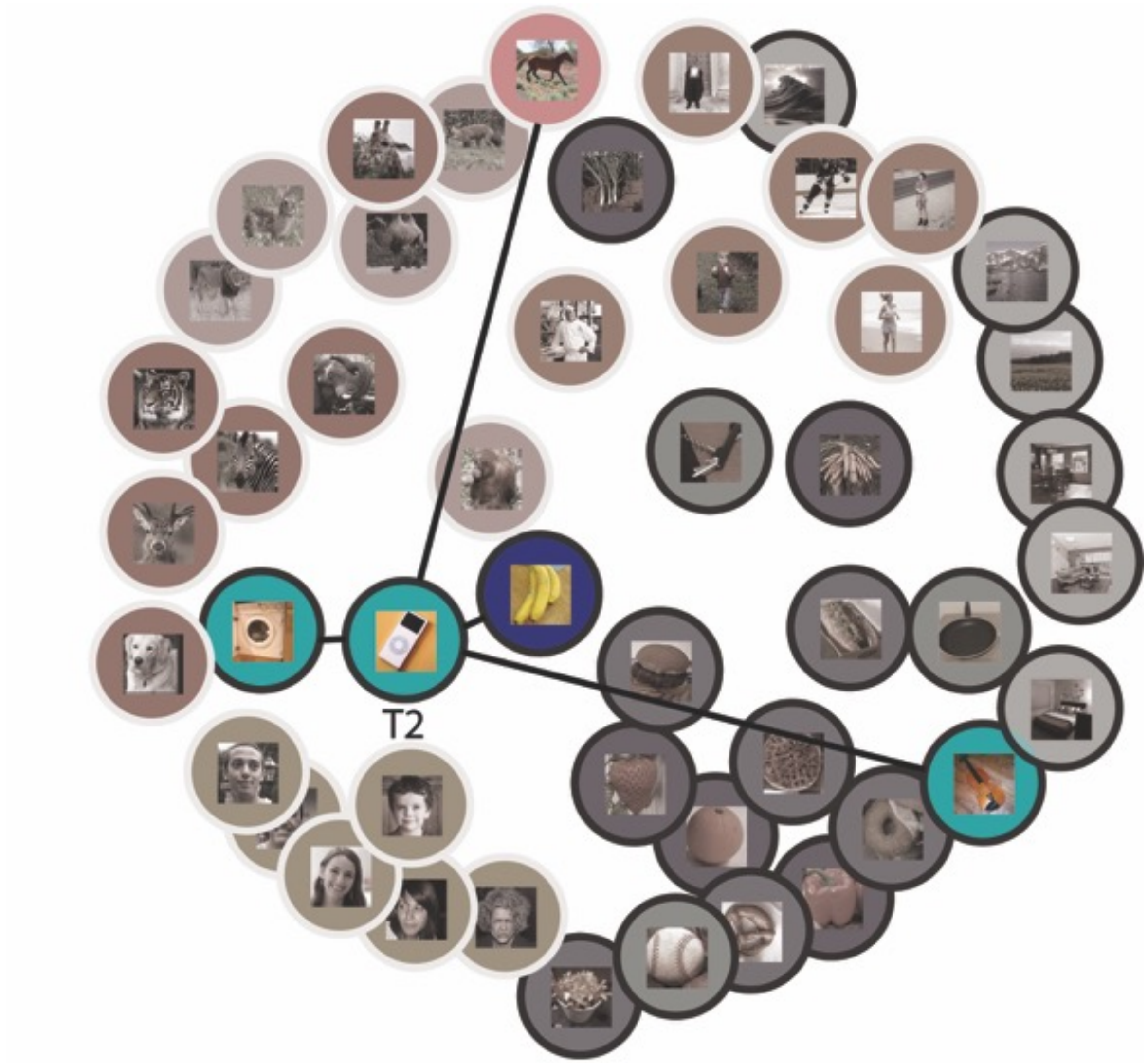
Similarity of AB targets

Lindh, Assecondi, Sligte, Shapiro, Charest. (in prep)

Similarity of AB targets

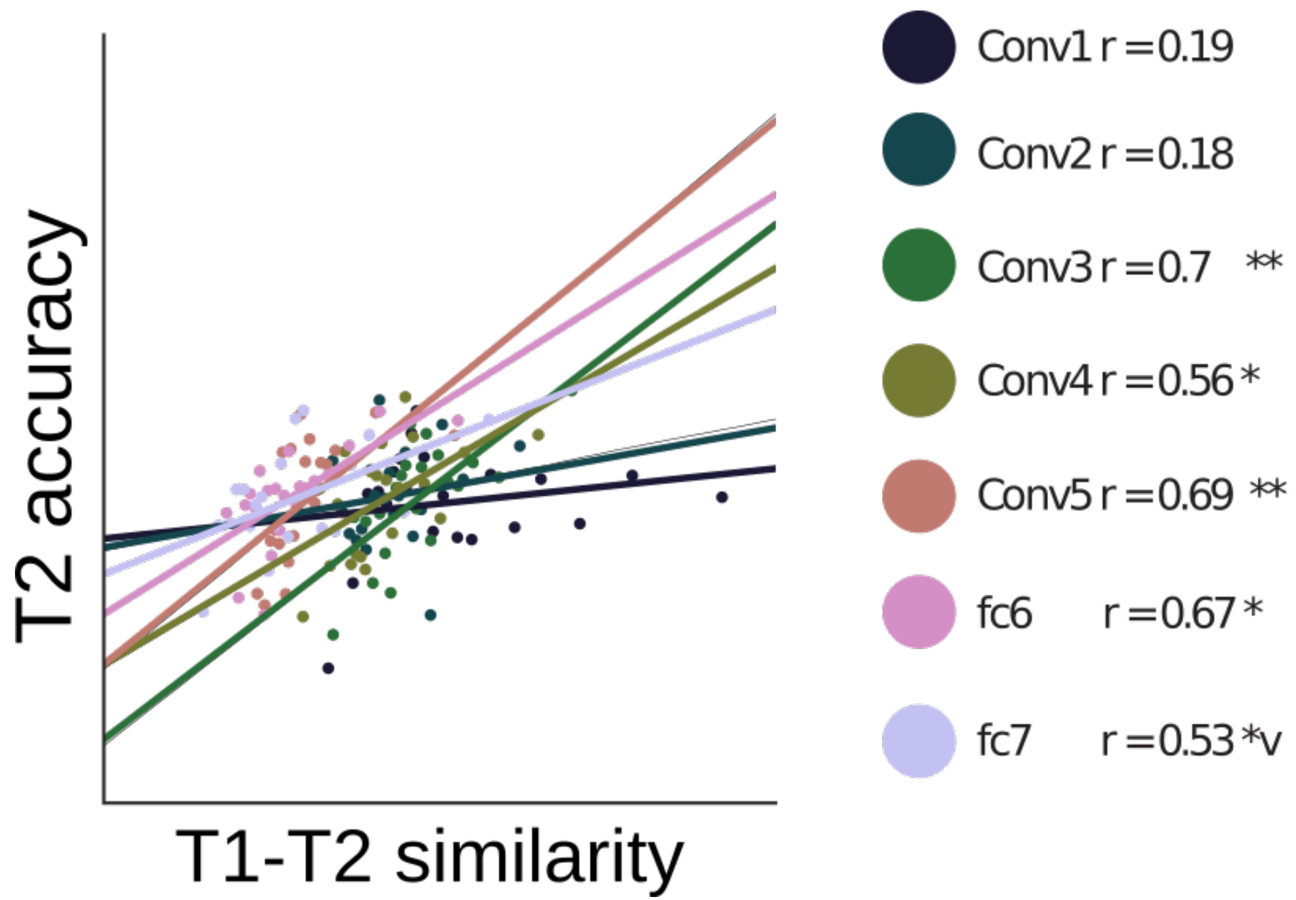
Lindh, Assecondi, Sligte, Shapiro, Charest. (in prep)

Similarity of AB targets



Lindh, Assecondi, Sligte, Shapiro, Charest. (in prep)

T1 – T2 similarity predicts AB



Lindh, Assecondi, Sligte, Shapiro, Charest. (in prep)

Second interim conclusion

- Categorical differences in Attentional Blink magnitude
- Computer vision models (DCNN) to predict AB in individual participants
- Similarity as a mechanism gating conscious access in the AB

Conclusions

- Representational Similarity Analysis:
  - Object representations are individually unique and reflect our subjective experience of the world.
- Conscious access
  - Categorical differences in the magnitude of the attentional blink
  - DCNN trained on object recognition predict likelihood of blinking and reveal the features that maximise conscious access
  - Similarity as a mechanism explaining inter-trial (and quite possibly inter-individual) differences in conscious access.

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On embauche!

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Merci!