Representational similarity analysis

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A space for neuroimaging studies

Pattern across subjects

Cross-subject correlation studies (e.g. social neuroscience)

Pattern across stimuli

Univariate regional-mean activation studies

Kanwisher et al. 1997 (face area)

Pattern across voxels

Haxby et al. 2001.
(distinct category-average patterns)

Raizada et al. 2010

Kriegeskorte et al. 2008
(single-image patterns cluster by category)

Mur et al. 2012.
(single-image regional average activation)

Charest & Kriegeskorte, 2015
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Pattern across subjects

Pattern across voxels

univariate regional-mean activation studies

Pattern across stimuli
A space for neuroimaging studies

Pattern across subjects

Pattern across stimuli

Pattern across voxels

univariate regional-mean activation studies

Classical MVPA
A space for neuroimaging studies

Pattern across subjects

Pattern across stimuli

Pattern across voxels

univariate regional-mean activation studies

Classical MVPA

RSA
Representational similarity analysis

stimulus
(e.g. images, sounds, other experimental conditions)

representational pattern
(e.g. voxels, neurons, model units)

representational dissimilarity

brain representation
(e.g. fMRI pattern dissimilarities)

behaviour
(e.g. dissimilarity judgments)

stimulus description
(e.g. pixel-based dissimilarity)

computational model representation
(e.g. face-detector model)

representational dissimilarity matrices
(RDMs)

Why investigate representational geometries?
Representational geometry

The geometry of the points in a high-dimensional response pattern space, which are thought to represent particular stimuli.

downstream neurons can read out the same information from these codes

same geometry → same information
→ same format

slide kindly provided by N. Kriegeskorte
category information
...for linear readout
...for nonlinear readout
...inherently categorical
How can we best measure representational distances?
Distance estimates are positively biased
Distances are positively biased – just like training-set decoding accuracies!
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
Linear discriminant contrast (LDc)

The default distance measure used in the RSA toolbox (based on the Euclidean distance).

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 $\rightarrow$ distance measures are positively biased.
Cross-validated distance measures are unbiased and have an interpretable zero point.

LDc
The cross-validated Mahalanobis distance

Images (adopted) from Alex Walther RSA workshop 2015
The representational similarity trick

representational distance matrix (RDM)

activity patterns

brain

model

dissimilarity (e.g. 1-correlation across space)
The representational similarity trick

representational distance matrix (RDM)

activity patterns

experimental stimuli

stimuli

subject 1

subject 2

dissimilarity (e.g. 1-correlation across space)
The representational similarity trick

representational distance matrix (RDM)

stimuli

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behaviour

stimuli

dissimilarity (e.g. 1-correlation across space)

experimental stimuli
The representational similarity trick

representational distance matrix (RDM)

stimuli

activity patterns

experimental stimuli

region 1

region 2

dissimilarity (e.g. 1-correlation across space)
The representational similarity trick

representational distance matrix (RDM)

activity patterns

eXperimental stimuli

fMRI

cell recording

dissimilarity (e.g. 1-correlation across space)
The representational similarity trick

representational distance matrix (RDM)

stimuli

activity patterns

fMRI

MEG

experimeental stimuli

dissimilarity (e.g. 1-correlation across space)
The RSA trick
Comparing brain RDMs between people

representational distance matrix (RDM)

activity patterns

experimental stimuli

stimuli

stimuli

stimuli

stimuli

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stimuli

stimuli

stimuli

stimuli

stimuli
Stimuli

animate

bodies

faces

inanimate

places

objects

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
Multi-dimensional scaling
Comparing brain RDMs between people

subject 1

subject 2

correlation

within-subject (ws) ✔

between-subject (bs) ✔

individuation index (ws - bs) 

Charest et al. 2014 PNAS
Brain representations unique?
Representational geometries in human inferior temporal cortex

Neurotypicals

ASC
GLMdenoise improves MVPA analyses
GLMdenoise improves MVPA analyses

Within-participant consistency is improved when using GLMdenoise
GLMdenoise improves MVPA analyses

Between-participants consistency is improved when using GLMdenoise
Relating brain and model RDMs

representational distance matrix (RDM)

activity patterns

experimental stimuli

stimuli

dissimilarity (e.g. 1-correlation across space)

brain

model

...
Deep convolutional neural network

- state of the art in computer vision
- trained with stochastic gradient descent
- supervised with 1.2 million category-labeled images
- 60 million parameters and 650,000 neurons

Is this network functionally similar to the brain?
accuracy of human IT dissimilarity matrix prediction
[group-average of Kendall’s $\tau_a$]

* accuracy above chance
p<0.001
(subjects and stimuli as fixed effects)

highest accuracy any model can achieve
other subjects’ average as model

Khaligh-Razavi & Kriegeskorte (2014), Nili et al. 2014 (RSA Toolbox)
Accuracy of human IT dissimilarity matrix prediction
[group-average of Kendall’s $\tau_a$]

* accuracy above chance
p<0.001
(subjects and stimuli as fixed effects)

Model comparison (stimulus bootstrap)

Highest accuracy any model can achieve

Other subjects’ average as model

Khaligh-Razavi & Kriegeskorte (2014), Nili et al. 2014 (RSA Toolbox)
Comparing brain RDMs and behavioural RDMs

Representational distance matrix (RDM)

Activity patterns

Experimental stimuli

Brain

Behaviour

Dissimilarity (e.g. 1-correlation across space)
Please arrange objects according to their similarity
unfamiliar
Similarity Judgements
Comparing brain RDMs and behavioural RDMs

subject 1

subject 2

correlation

within-subject (ws) ✔

between-subject (bs) ✔

individuation index (ws - bs) ?

Charest et al. 2014 PNAS

subject similarity matrix

day 2

s 1 s 2 s 3 s 4 s 5 ⋯ s 20

s 1 s 2 s 3 s 4 s 5 ⋯ s 20

s 1 s 2 s 3 s 4 s 5 ⋯ s 20

s 1 s 2 s 3 s 4 s 5 ⋯ s 20

s 1 s 2 s 3 s 4 s 5 ⋯ s 20
Brain-behavior relationship unique?
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)

compute the dissimilarity (e.g. 1 – correlation) linear discriminant analysis

representational pattern (population code representation)

... experimental stimuli

EEG activity-pattern at time $t$

EEG Channel amplitudes

RSA
RSA

EEG Sensor Activation Patterns

decode pair-wise activation patterns for objects 1:n

representational dissimilarity matrix at time $t$
EEG contains rich topographic information from which you can distinguish mental states.
EEG contains rich topographic information from which you can distinguish mental states.
Object familiarity decoding from EEG activity patterns

![Graph showing classification accuracy over time for unfamiliar and familiar objects. The graph indicates significant above-chance decoding for familiar objects.](image)
Object familiarity decoding from EEG activity patterns
Object familiarity decoding from EEG activity patterns
Comparing RDMs between measurement modalities

representational
distance matrix
(RDM)

stimuli

activity
patterns

fMRI

MEG

stimuli

stimuli

stimuli

dissimilarity
(e.g. 1-correlation across space)

experimental
stimuli
Similarity based fusion of M/EEG and fMRI

Cichy et al. 2014, 2016
Similarity based fusion of M/EEG and fMRI

Cichy et al. 2014, 2016
The spatio-temporal dynamics of personally meaningful objects
The spatio-temporal dynamics of personally meaningful objects
Key insights

Representational geometries encapsulate the *content* and *format* of brain representations.

Representational geometries can be characterised by representational dissimilarity matrices (RDMs).

RDMs can easily be compared between brains and models, individuals and species, different brain regions, different measurement modalities, and brain and behaviour.

We can statistically compare multiple computational/theoretical models and assess whether they fully explain the measured brain response patterns.
A Matlab toolbox for representational similarity analysis

A Matlab toolbox for representational similarity analysis