Clustering cortical searchlights based on shared representational geometry

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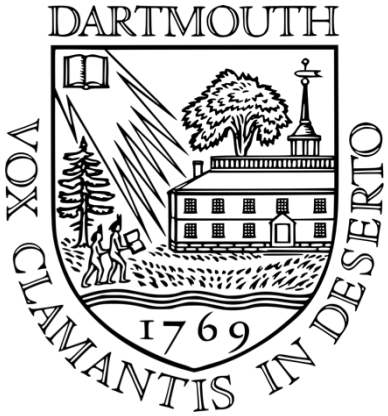

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Poster ID: 3983
Today 12:45-2:45 pm
Category: Modeling and analysis methods

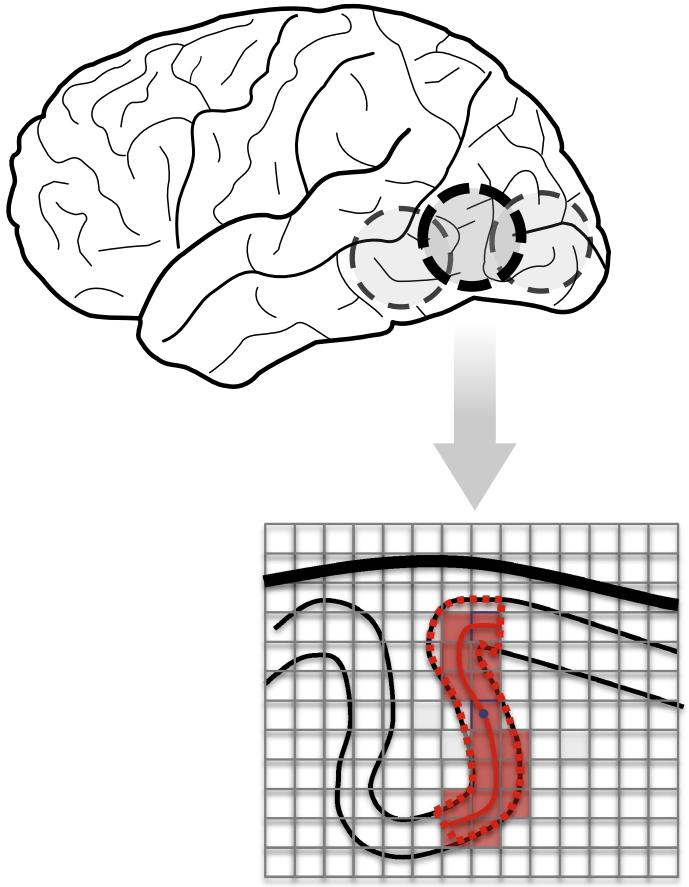
Matteo Visconti di Oleggio Castello
Gobbini Lab
(co-first author)

Yaroslav O. Halchenko

Clustering **cortical searchlights** based on shared representational geometry

Surface-based searchlight analysis

- Each searchlight references 100 nearest voxels according to geodesic distance on cortical surface



Kriegeskorte et al, 2006
Oosterhof et al, 2011

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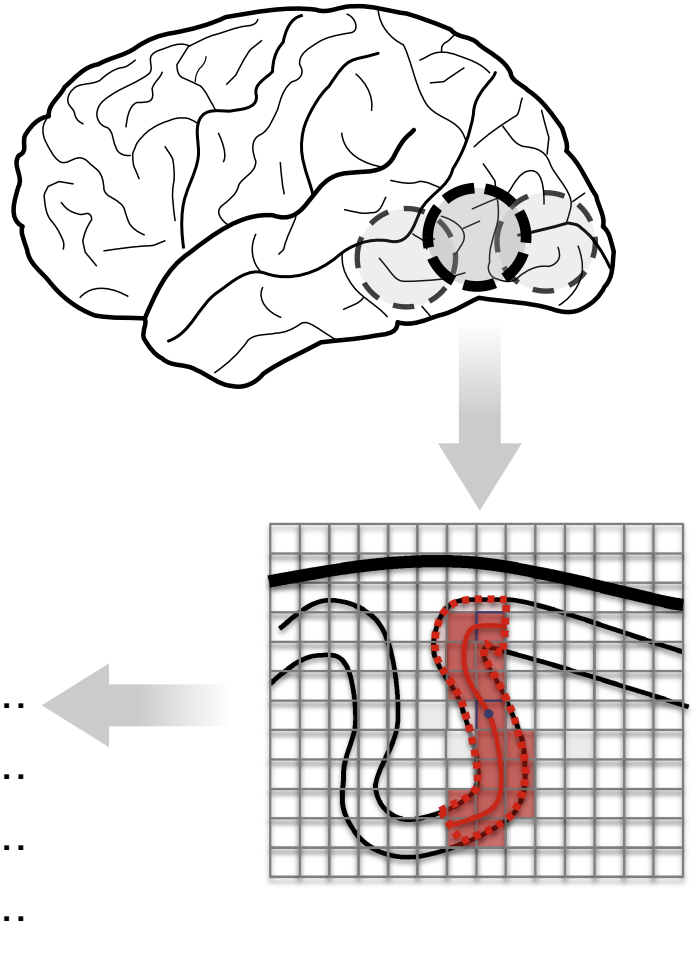

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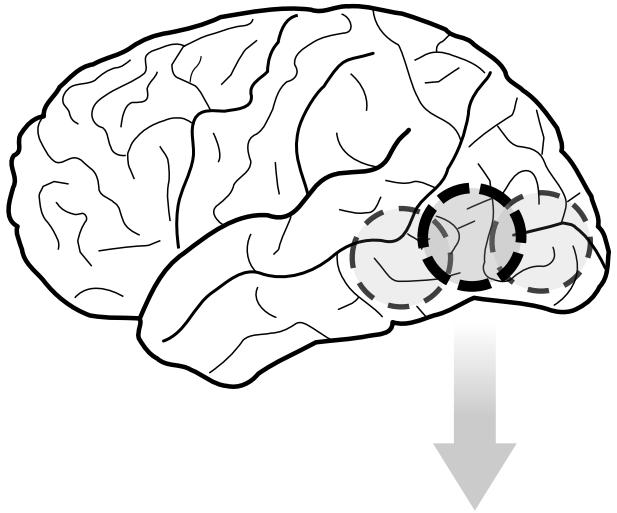

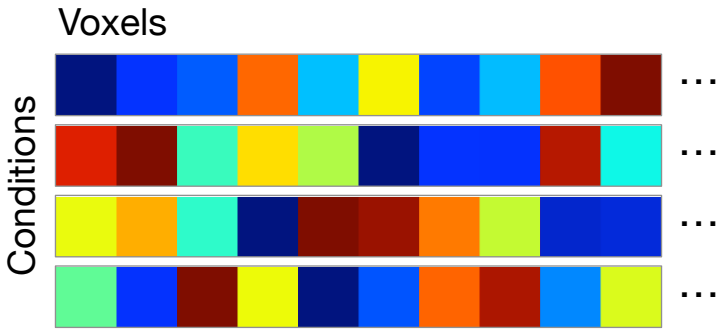

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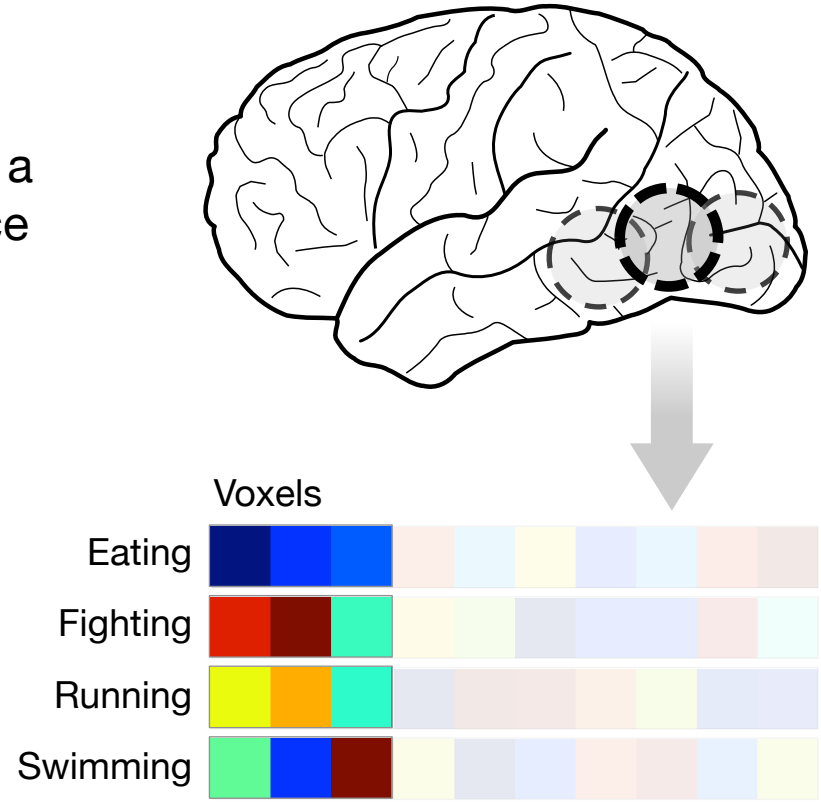
Clustering cortical searchlights based on shared **representational geometry**

Representational similarity analysis

- Response pattern for each condition is a location in neural representational space



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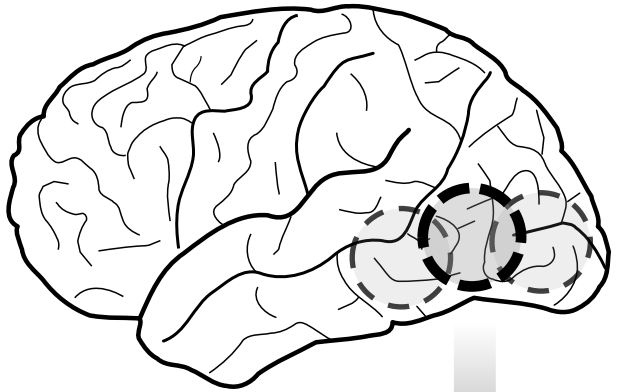
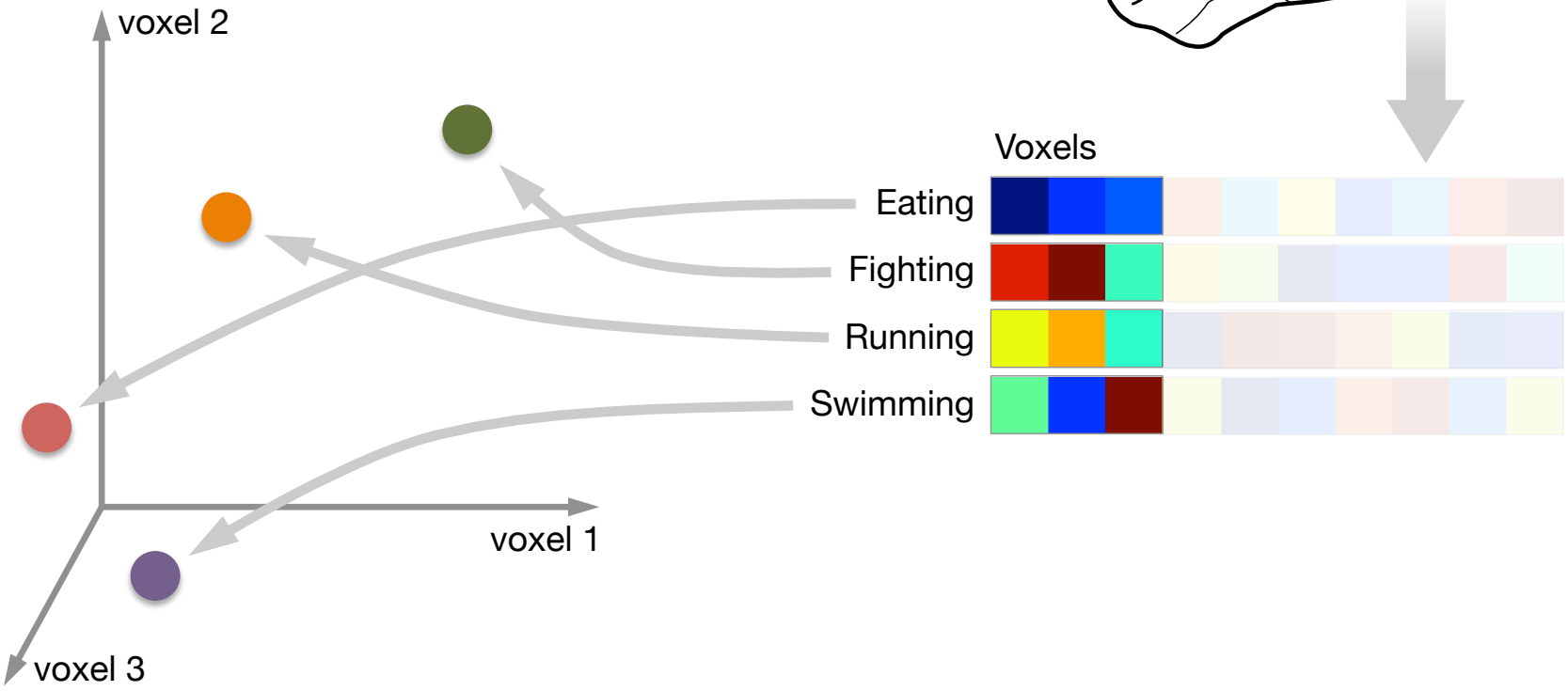


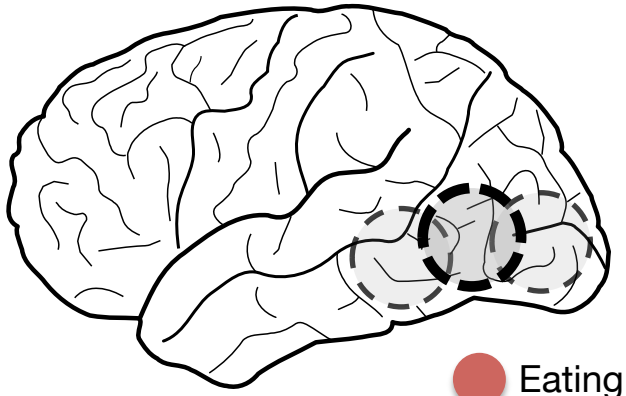


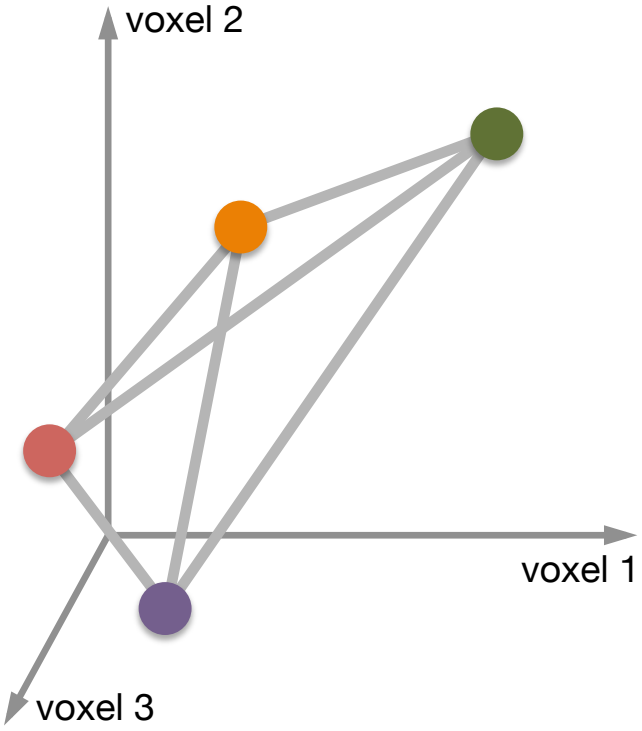
Kriegeskorte et al, 2008

Clustering cortical searchlights based on shared **representational geometry**

Representational similarity analysis

- Compute pairwise correlation distances between conditions





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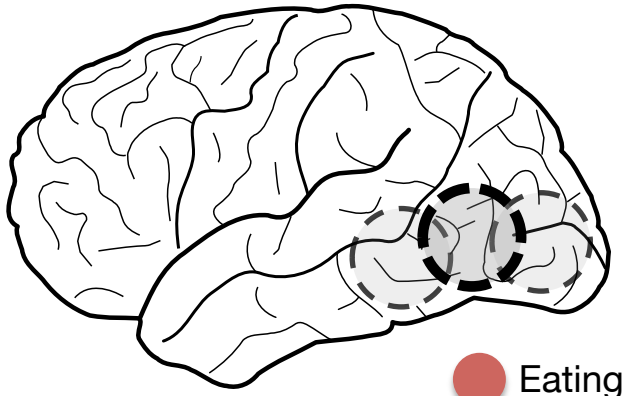

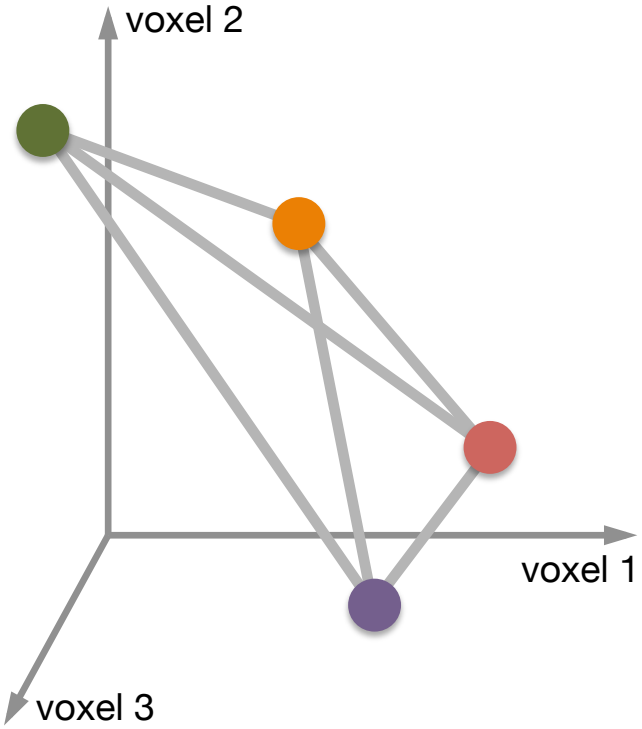

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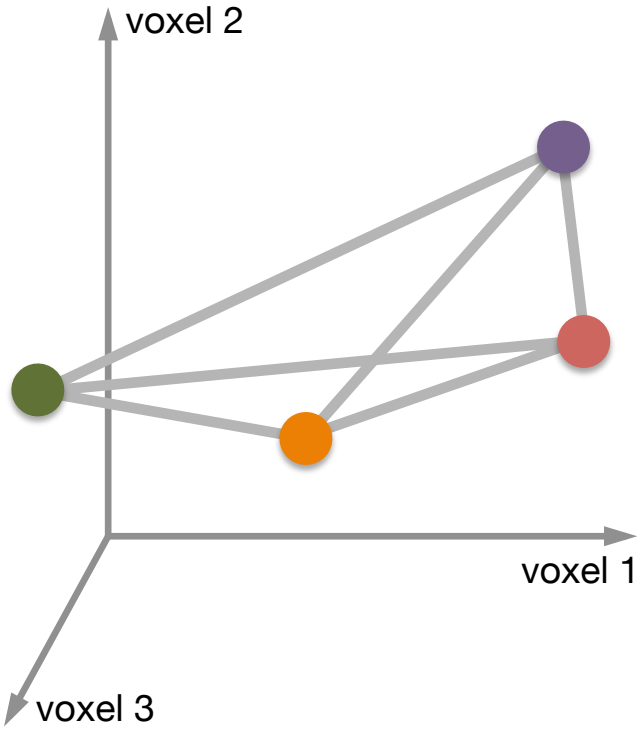

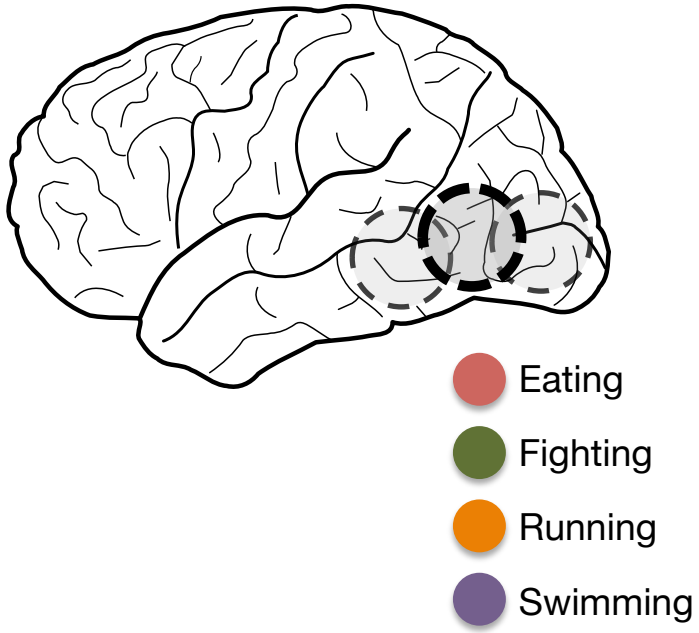

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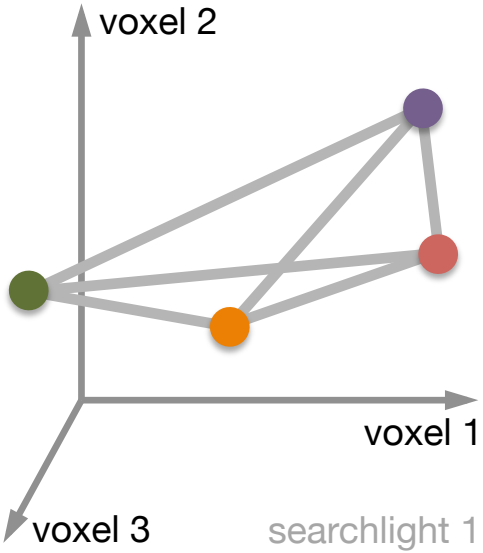

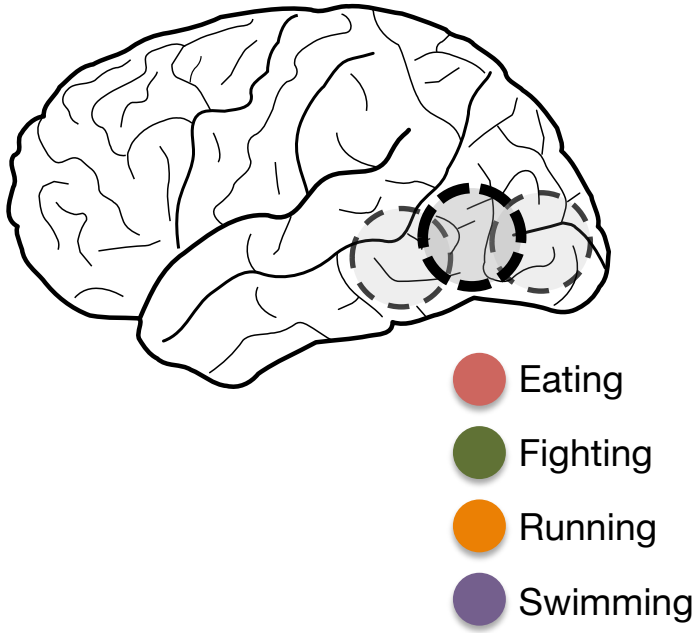

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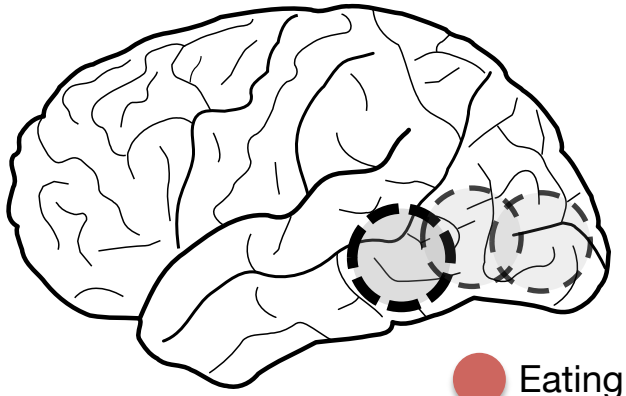

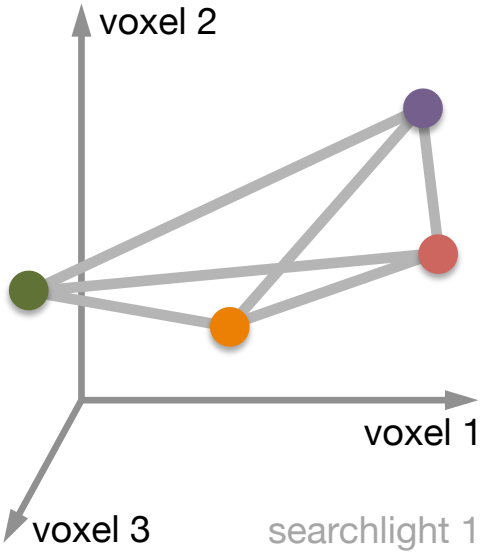

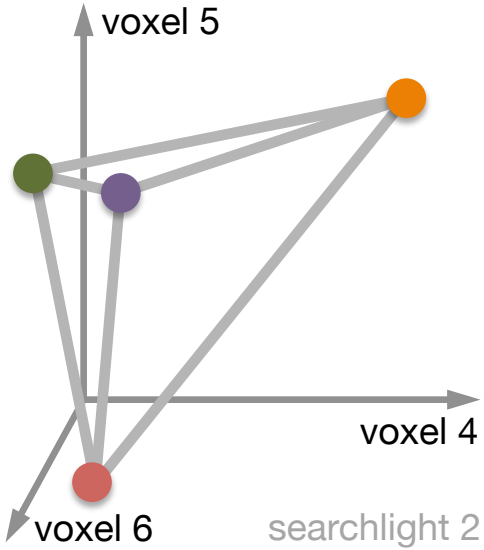

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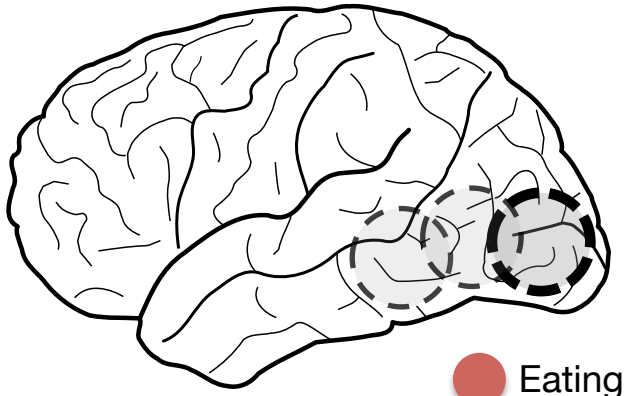
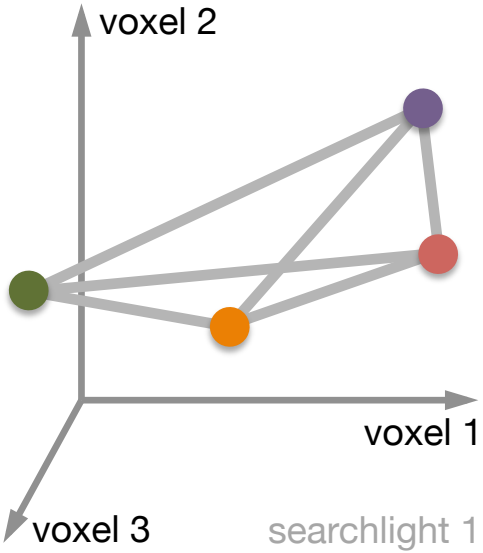
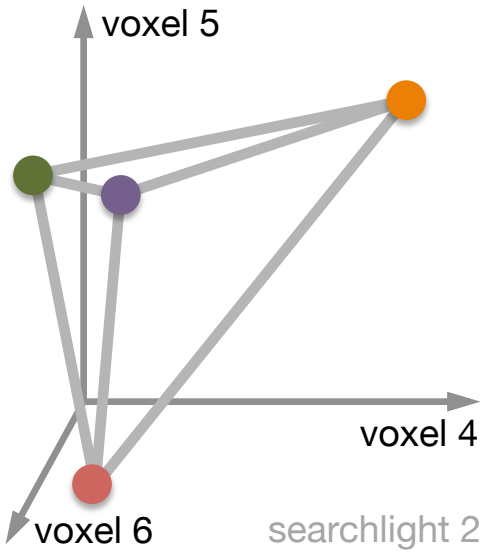
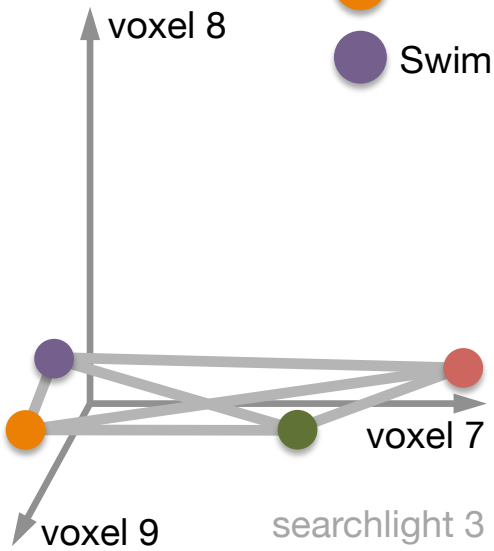




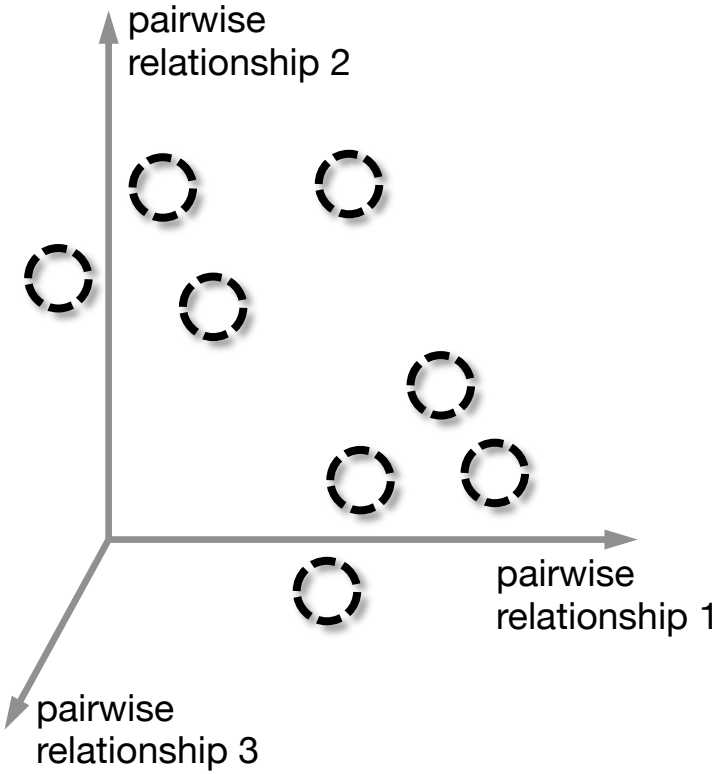




Clustering cortical searchlights based on shared representational geometry

Cluster analysis

- Cluster searchlights in feature space defined by pairwise relationships between conditions

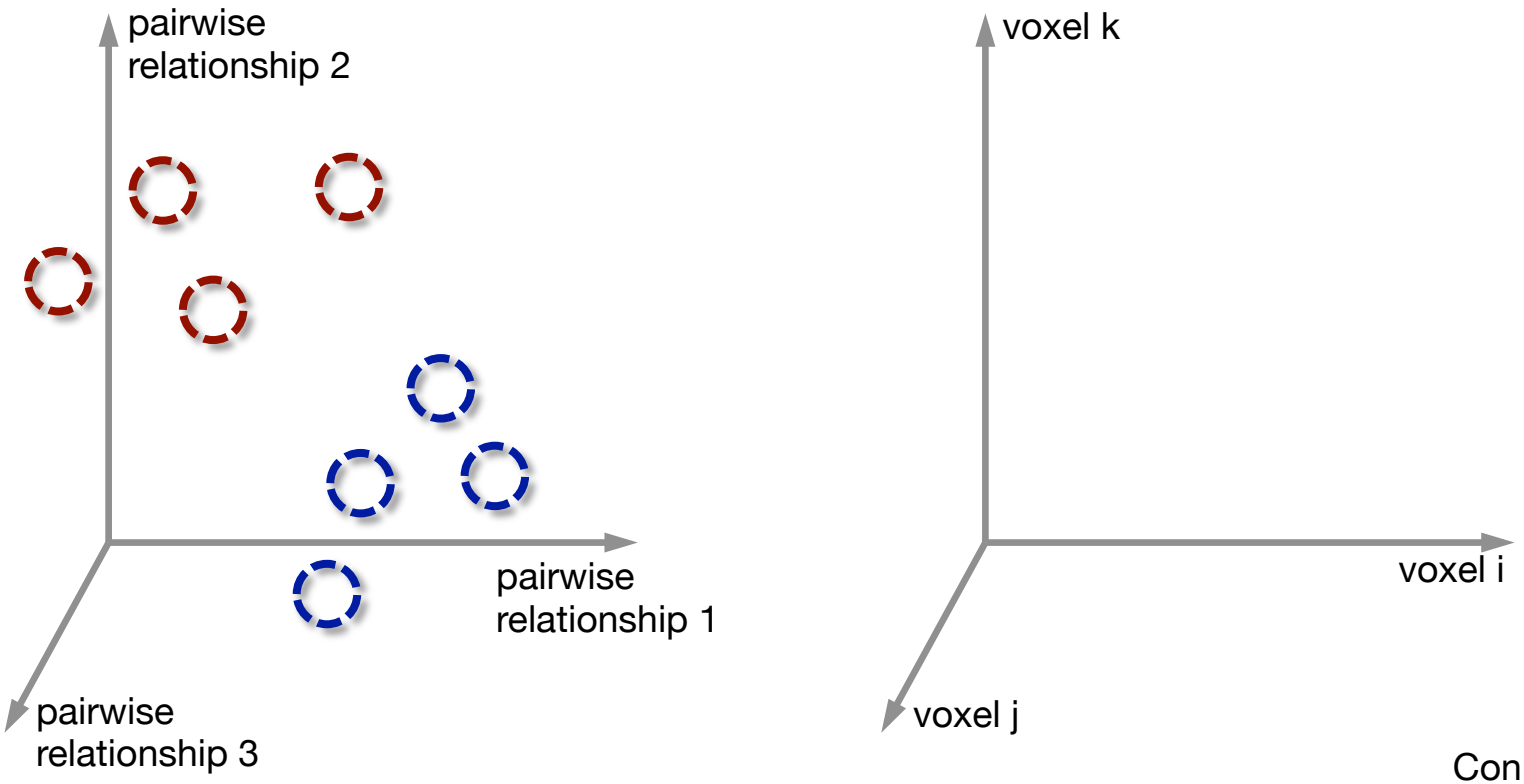


Connolly et al, 2012

Clustering cortical searchlights based on shared representational geometry

Cluster analysis

- Each searchlight is clustered according to its representational geometry



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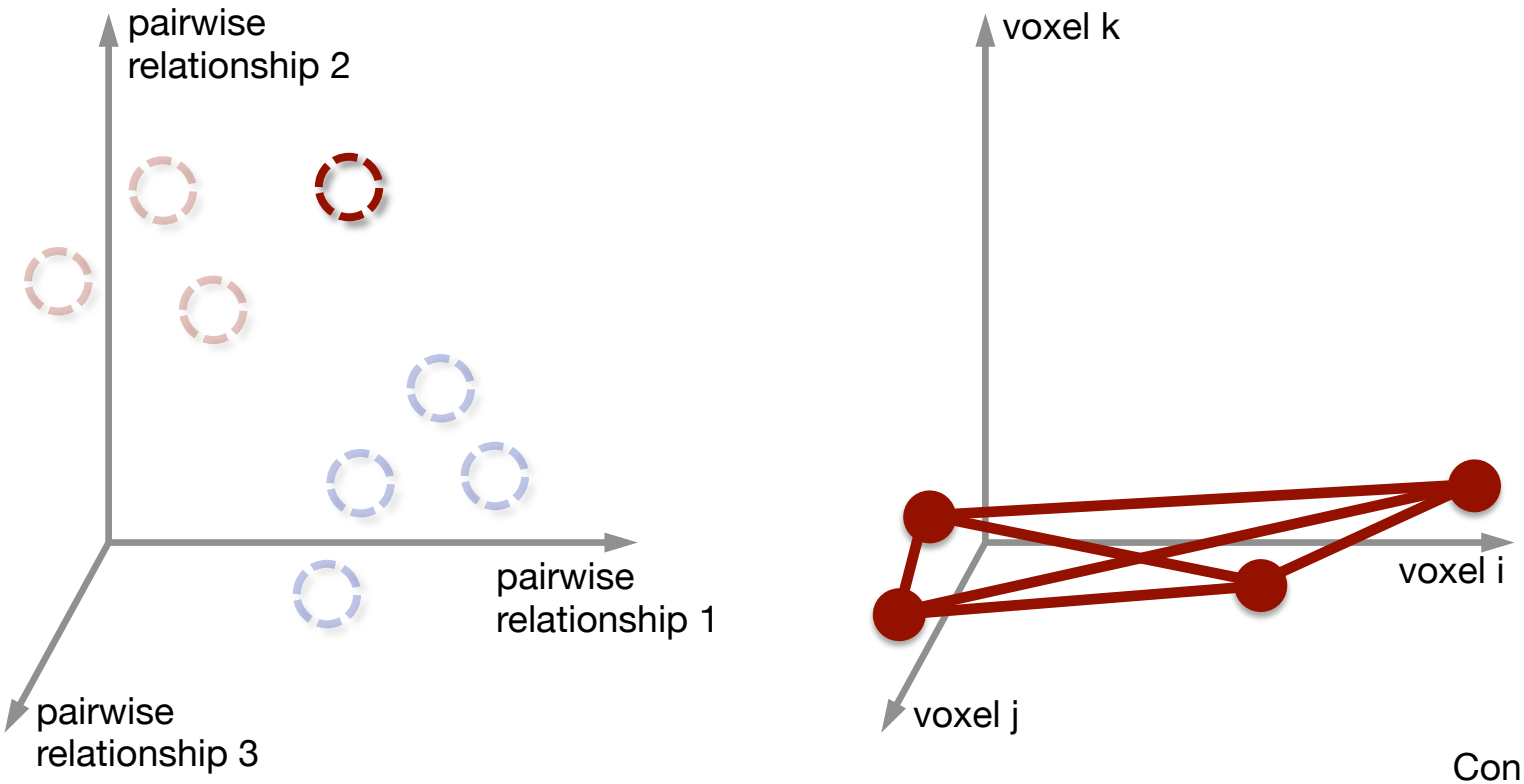

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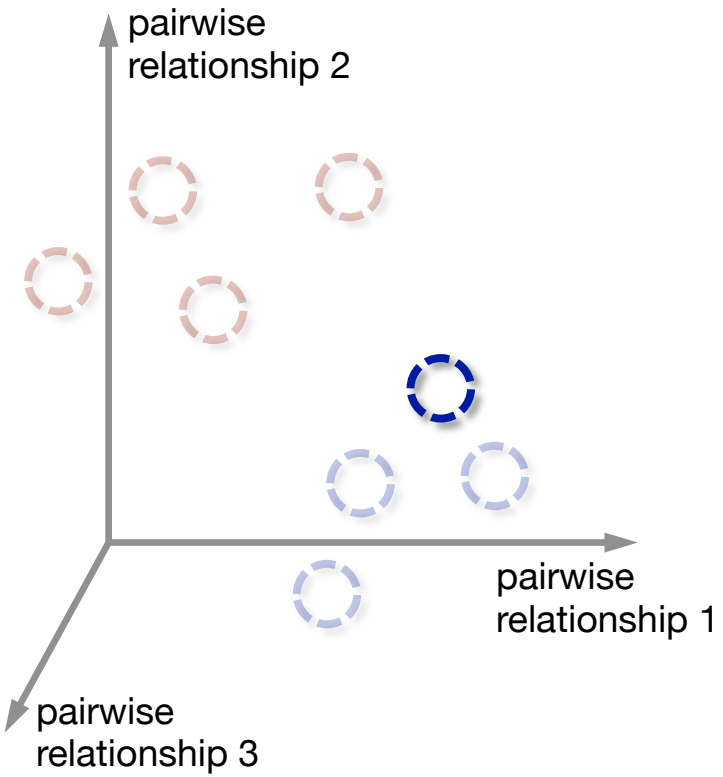

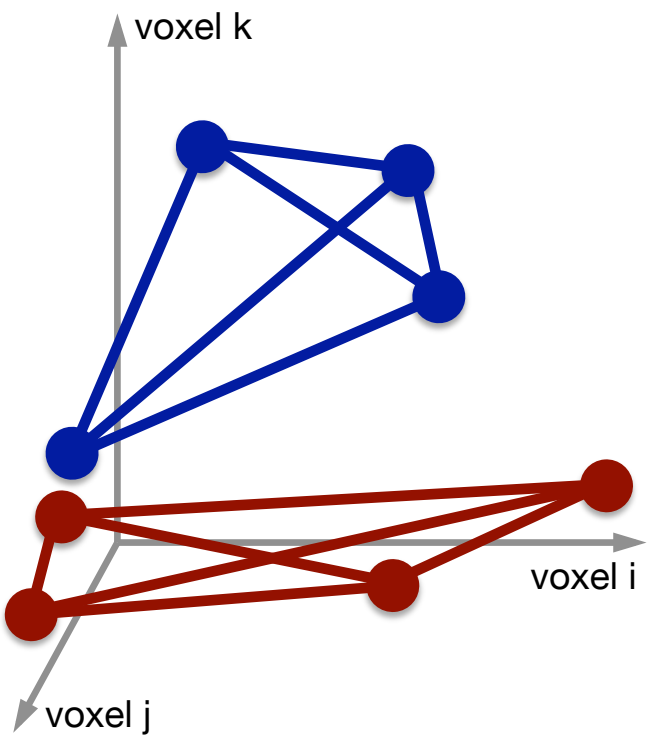

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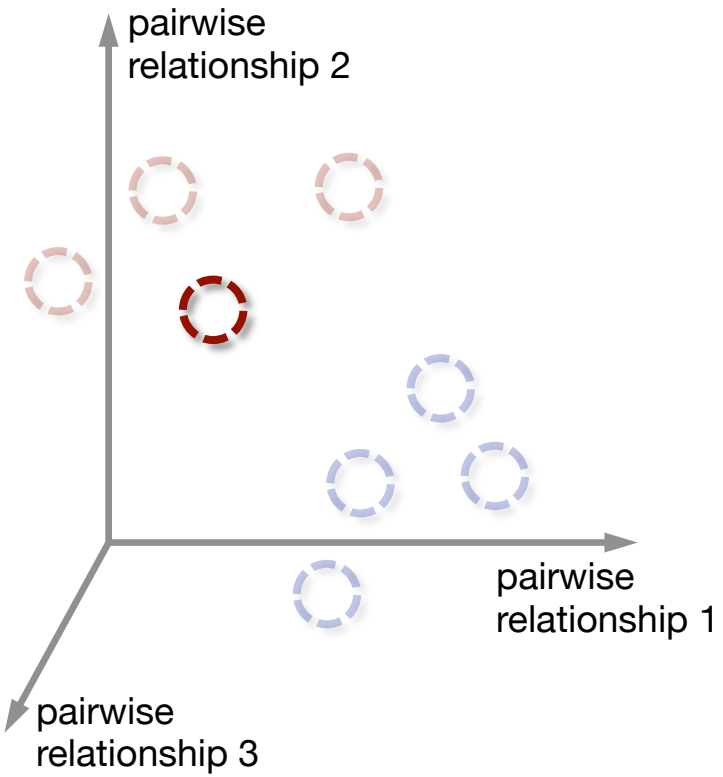

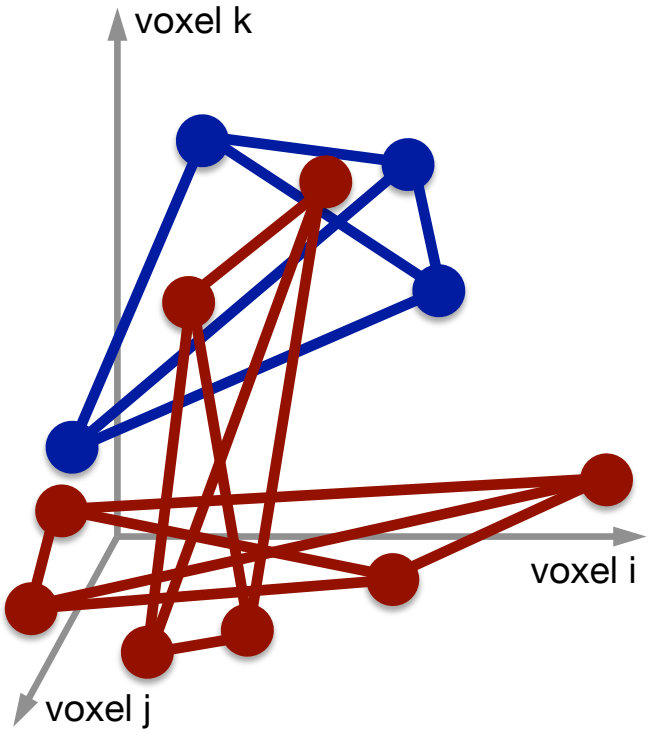

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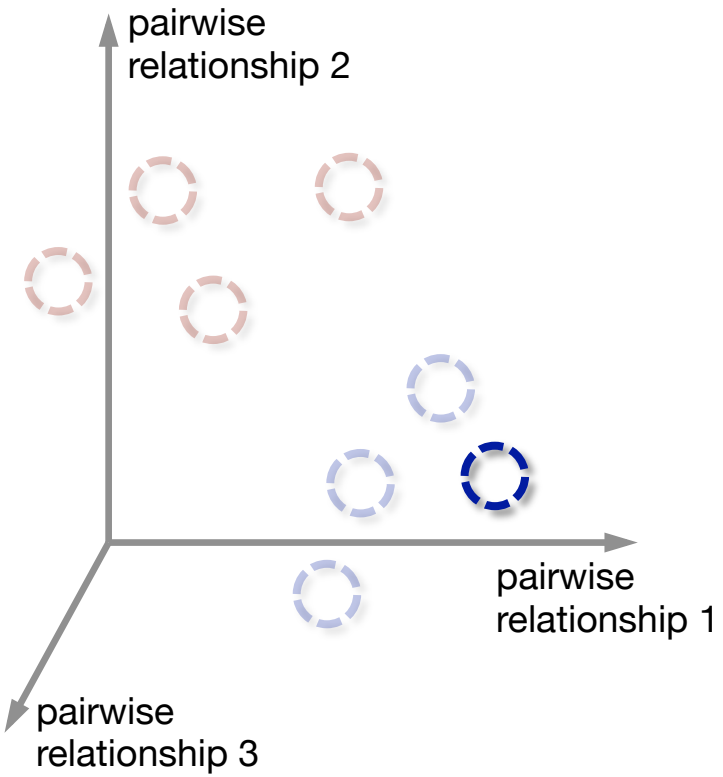

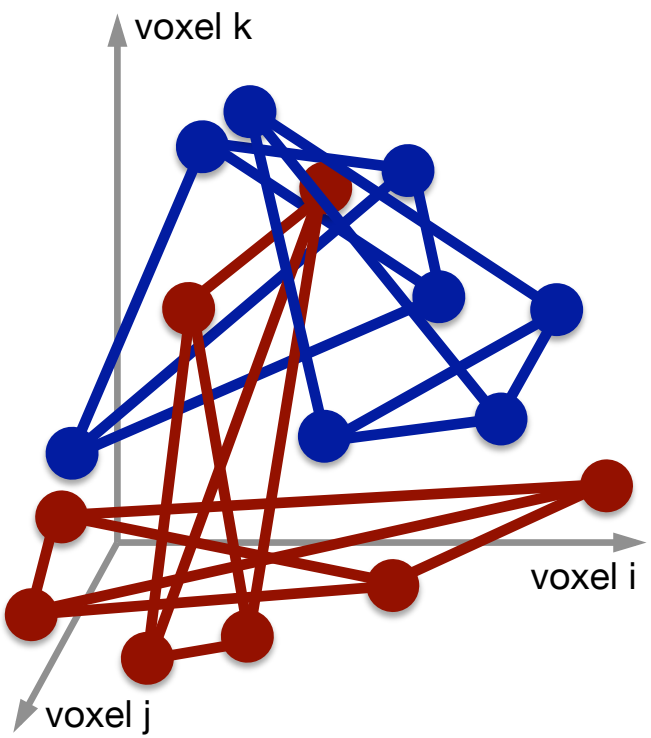

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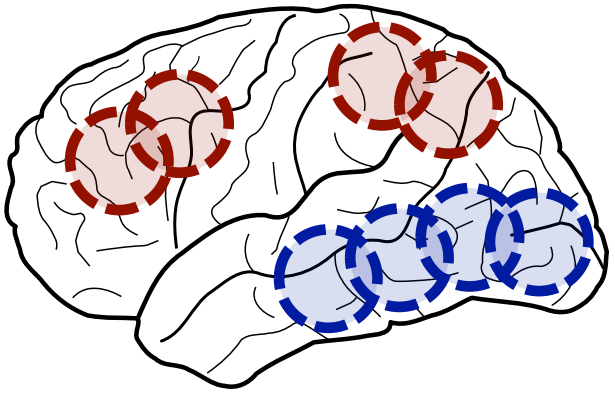
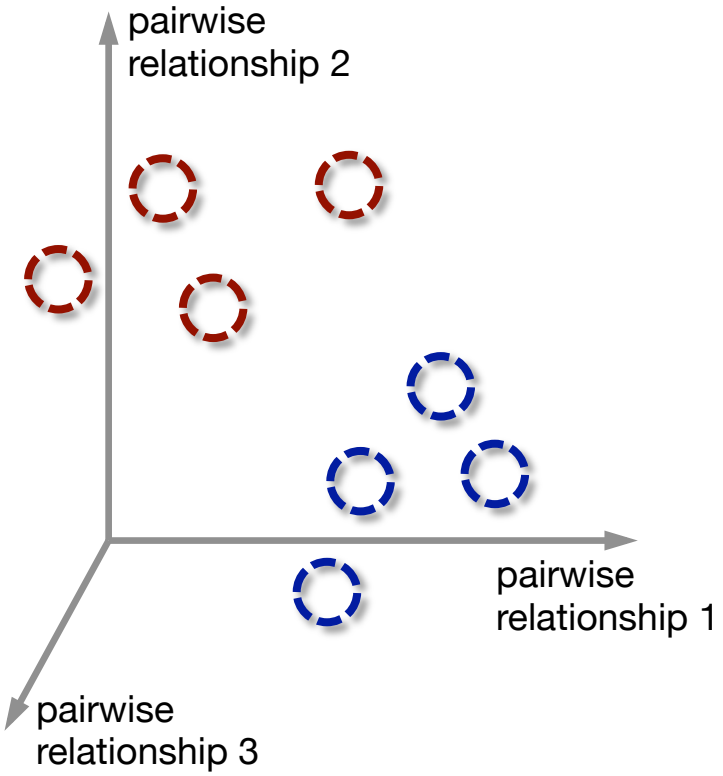
Cluster analysis

- Labeled clusters can then be projected back to cortical surface





Connolly et al, 2012

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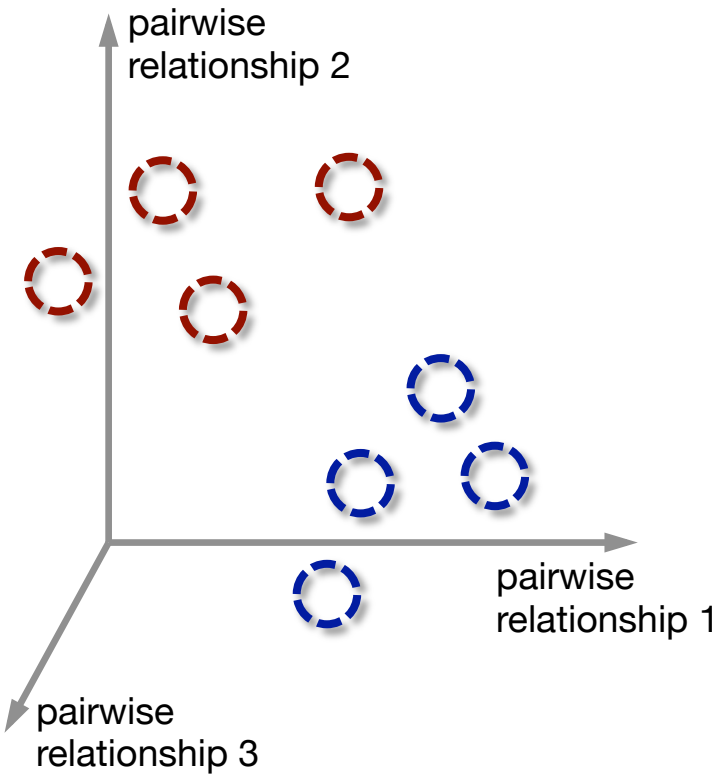
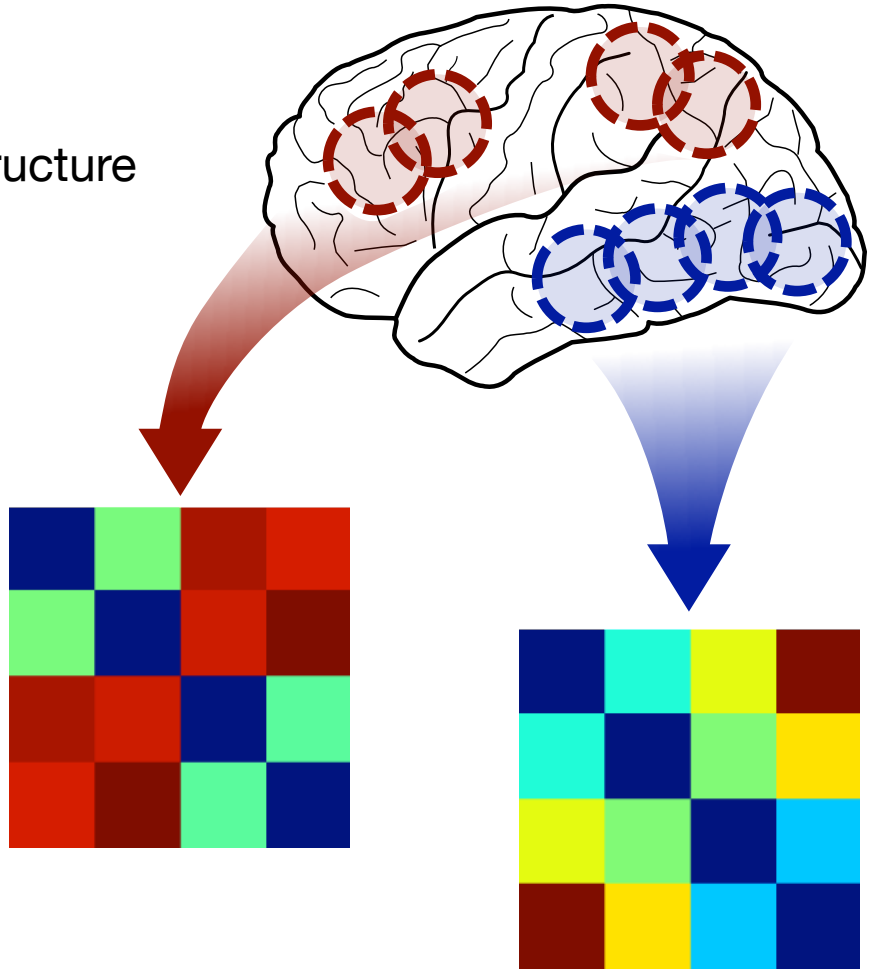
Cluster analysis

- Extract representational similarity structure for each cluster





An example

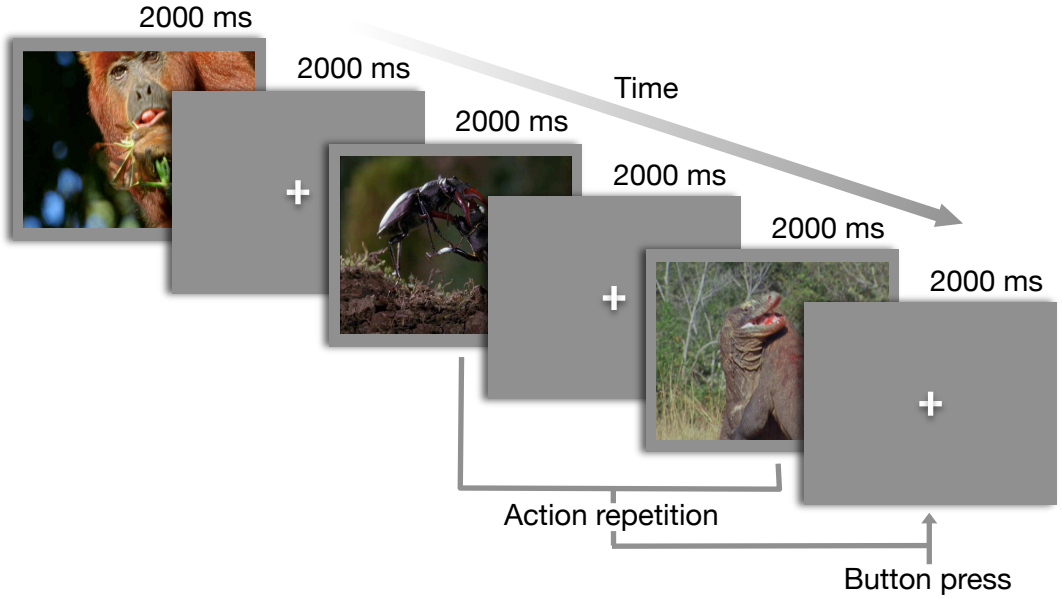
12 participants viewed 2 s video clips of behaving animals

5 types of animals performing 4 different behaviors for 20 total conditions

20,484 surface-based searchlights each referencing 100 voxels

Response patterns for 20 conditions estimated via GLM used to construct RDM (190 pairwise distances)

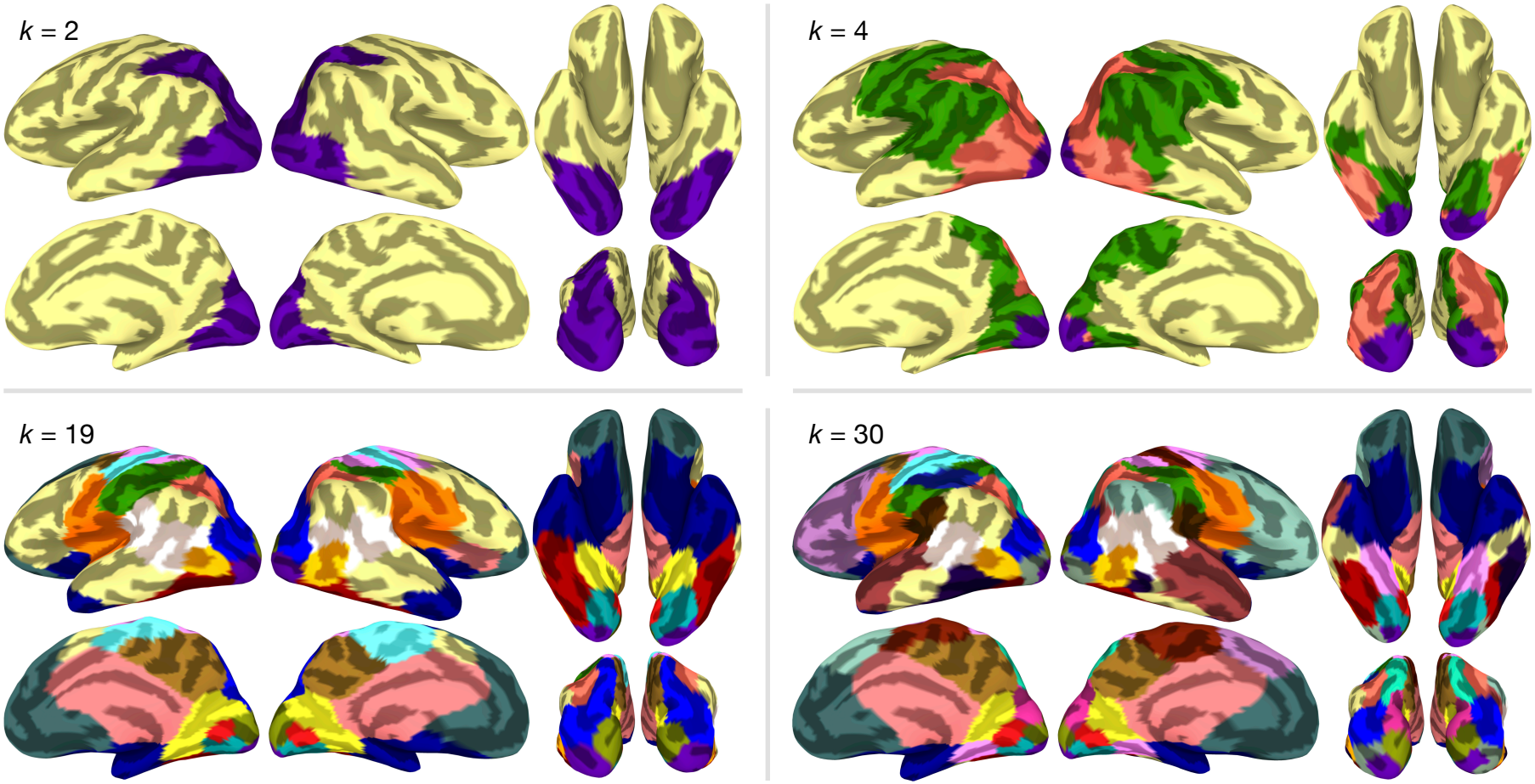
Whole-brain hyperaligned based on responses to *Life* nature documentary



Haxby et al, 2011
Guntupalli et al, under review
Nastase et al, in preparation

An example

Cluster solutions using Gaussian mixture models (GMMs) at k = 2, 4, 19, and 30



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Parcellation evaluation

How do we choose a particular cluster solution?

Is there any single “correct” parcellation of the brain?

Given a parcellation, how do we determine which parcels are meaningful?

Quantitative benchmarks for parcellation quality:

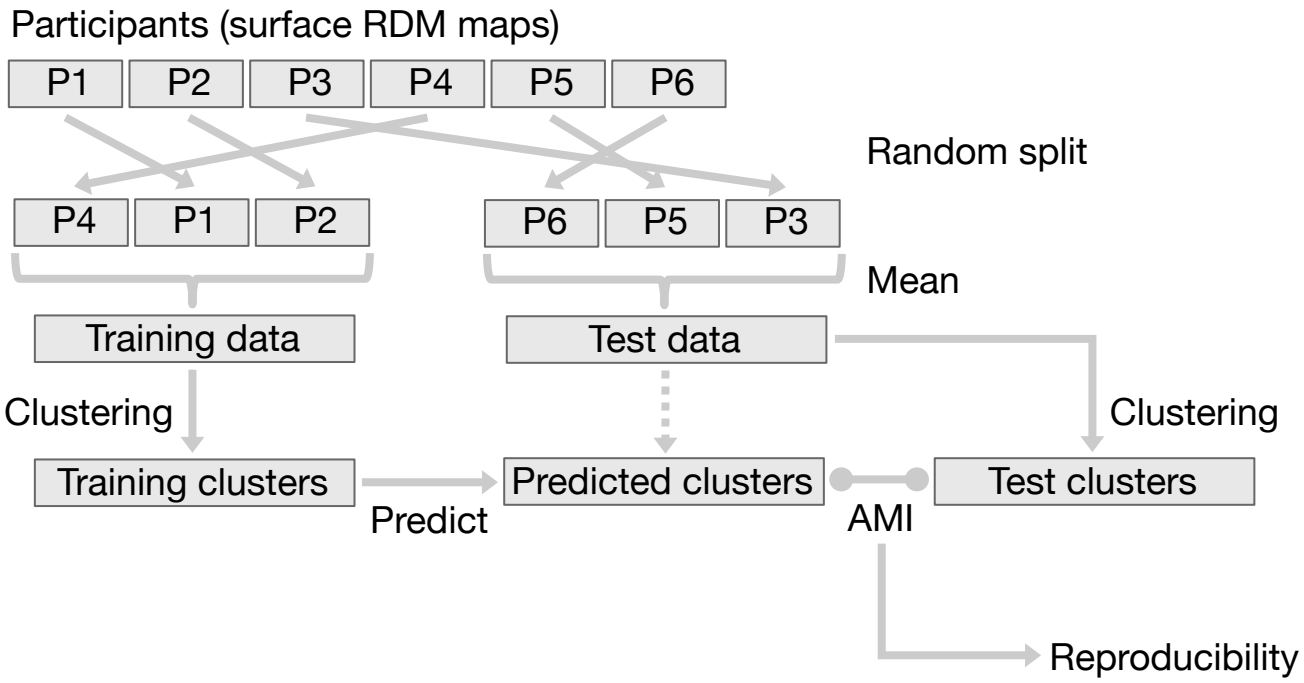
- Reproducibility
- Homogeneity

Thirion et al, 2014

Parcellation evaluation: Reproducibility

Split-half cross-validation at the participant level to evaluate parcellation reproducibility

Compare clustering algorithms and different values of *k*



Lange et al, 2004
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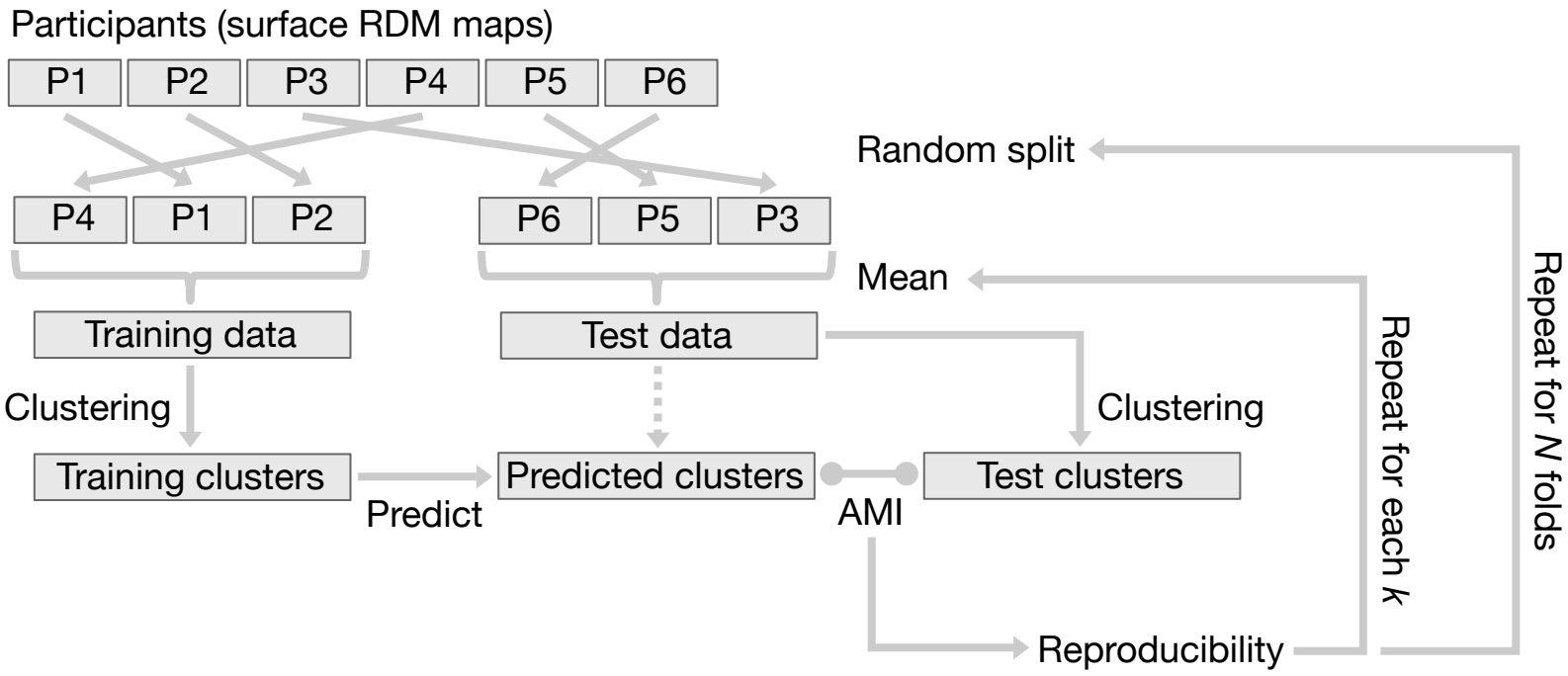

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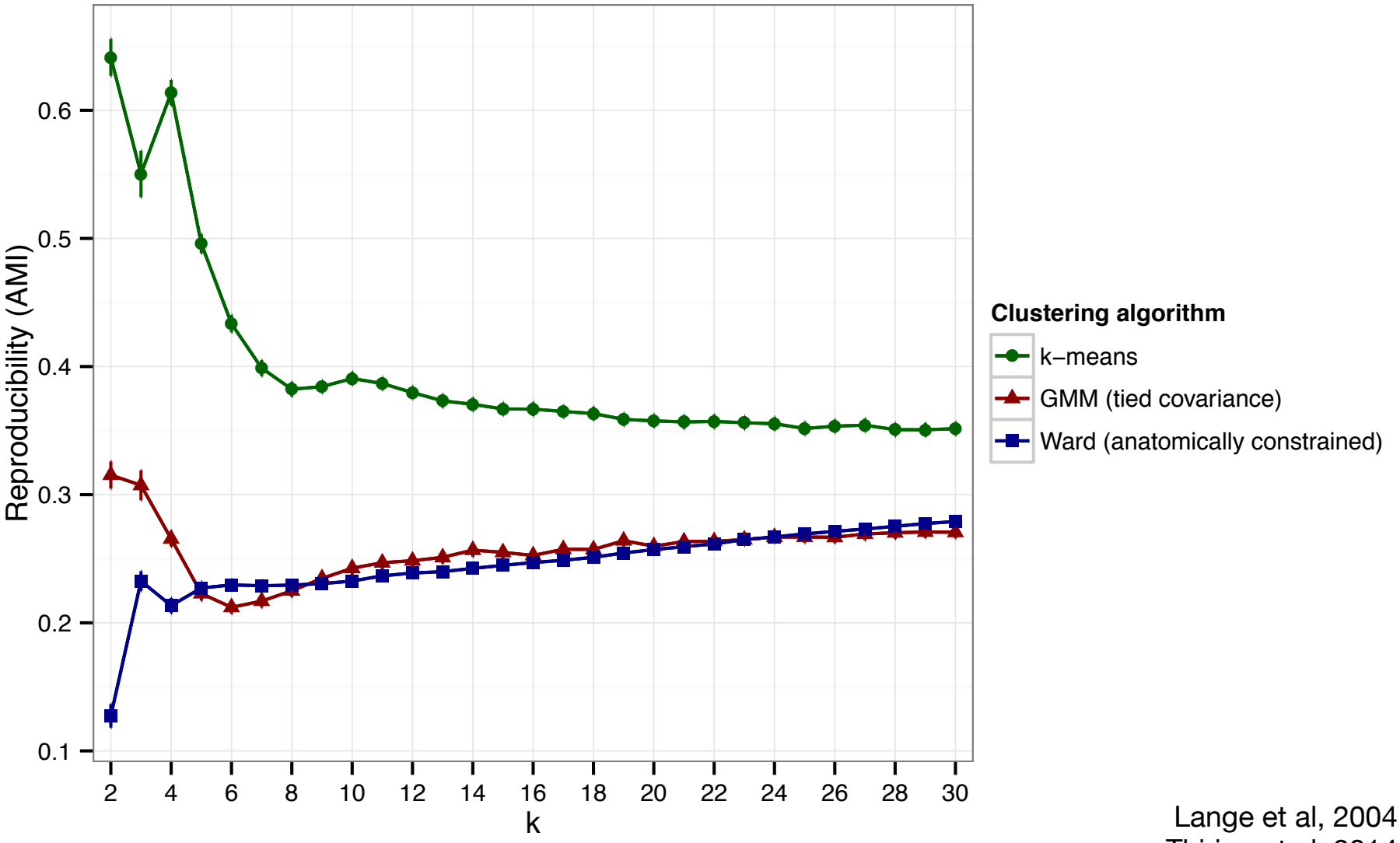
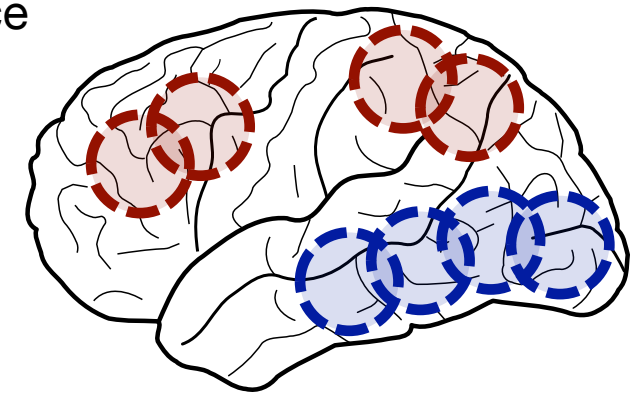


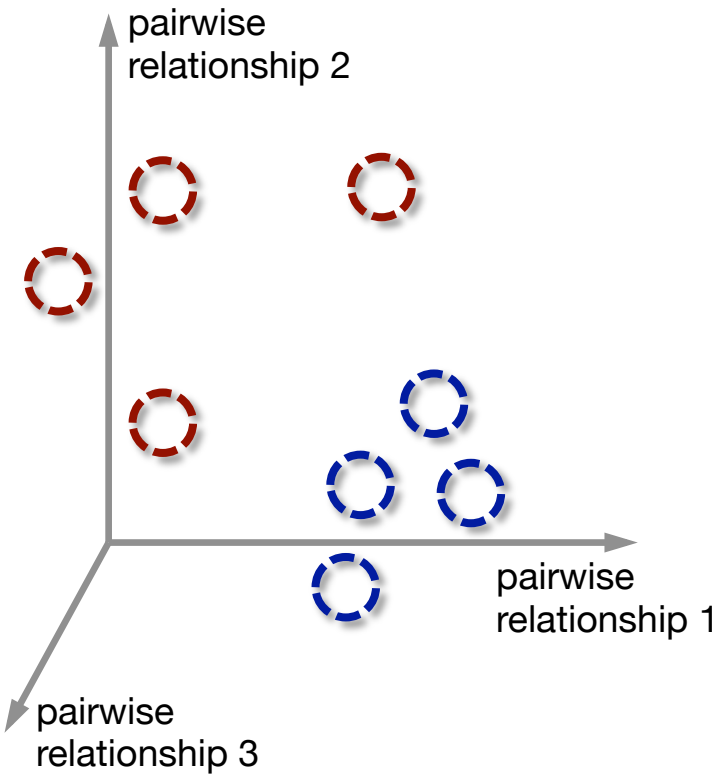
Lange et al, 2004
Thirion et al, 2014
Yeo et al, 2011

Parcellation evaluation: Homogeneity

Homogeneity measured by mean pairwise distance between all searchlight RDMs within a parcel

Estimated null distribution of homogeneities by applying random rotations to the spherical projection of the cortical surface





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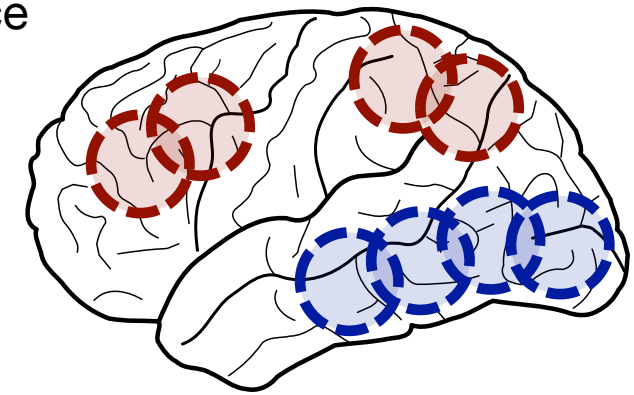

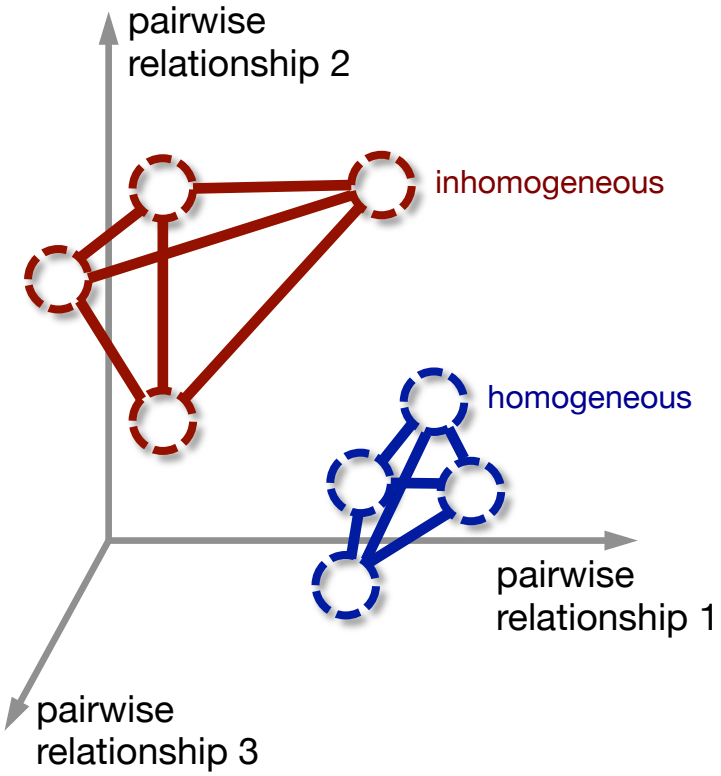

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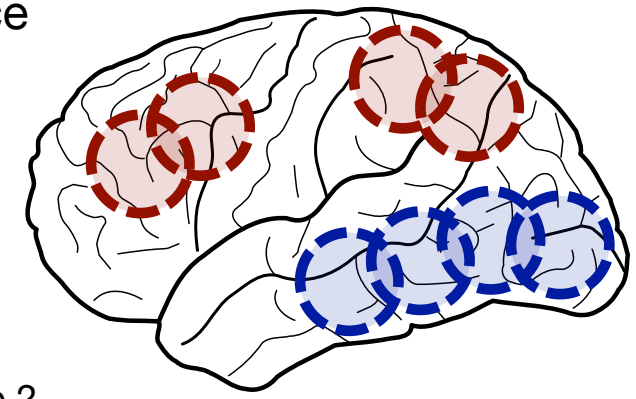

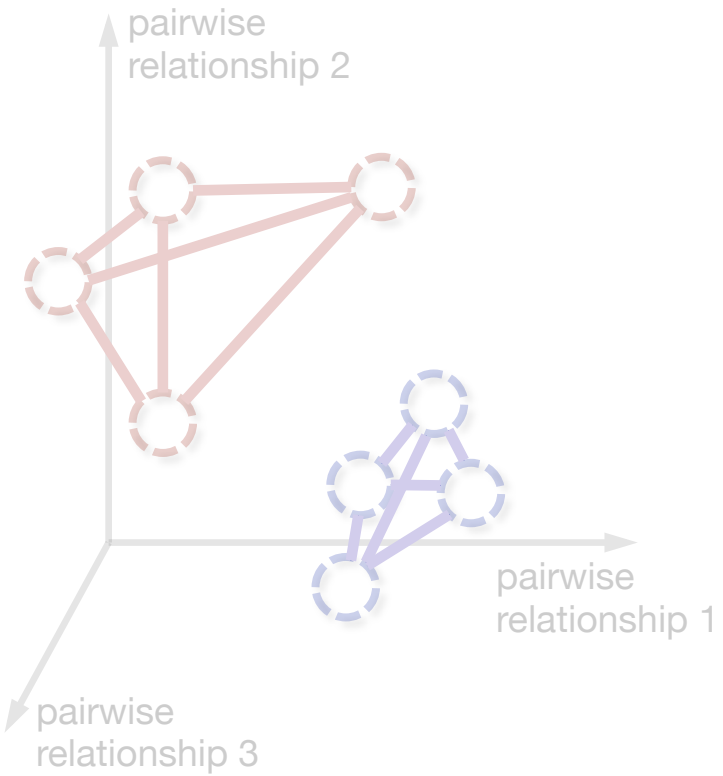

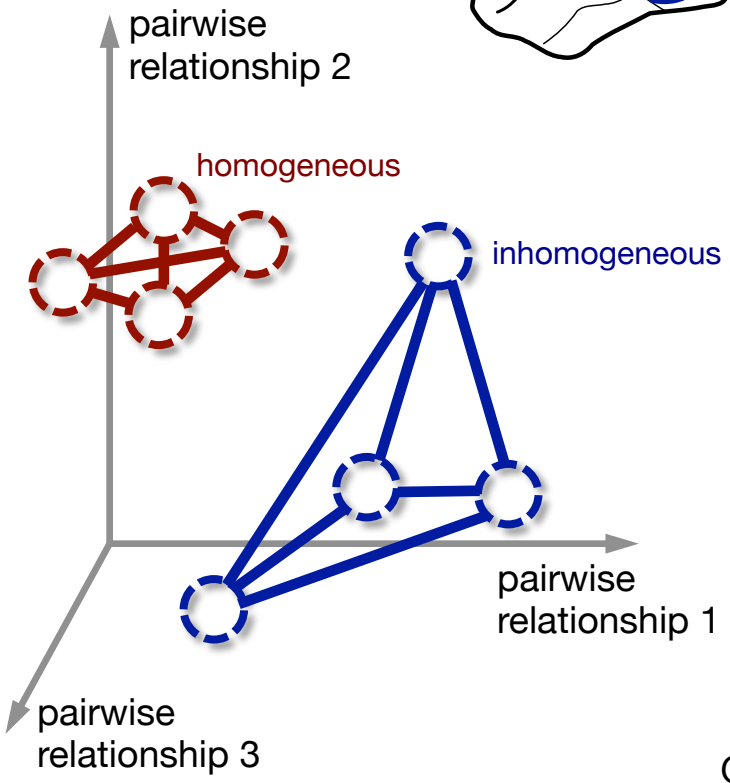

Gordon et al, 2014

Parcellation evaluation: Homogeneity

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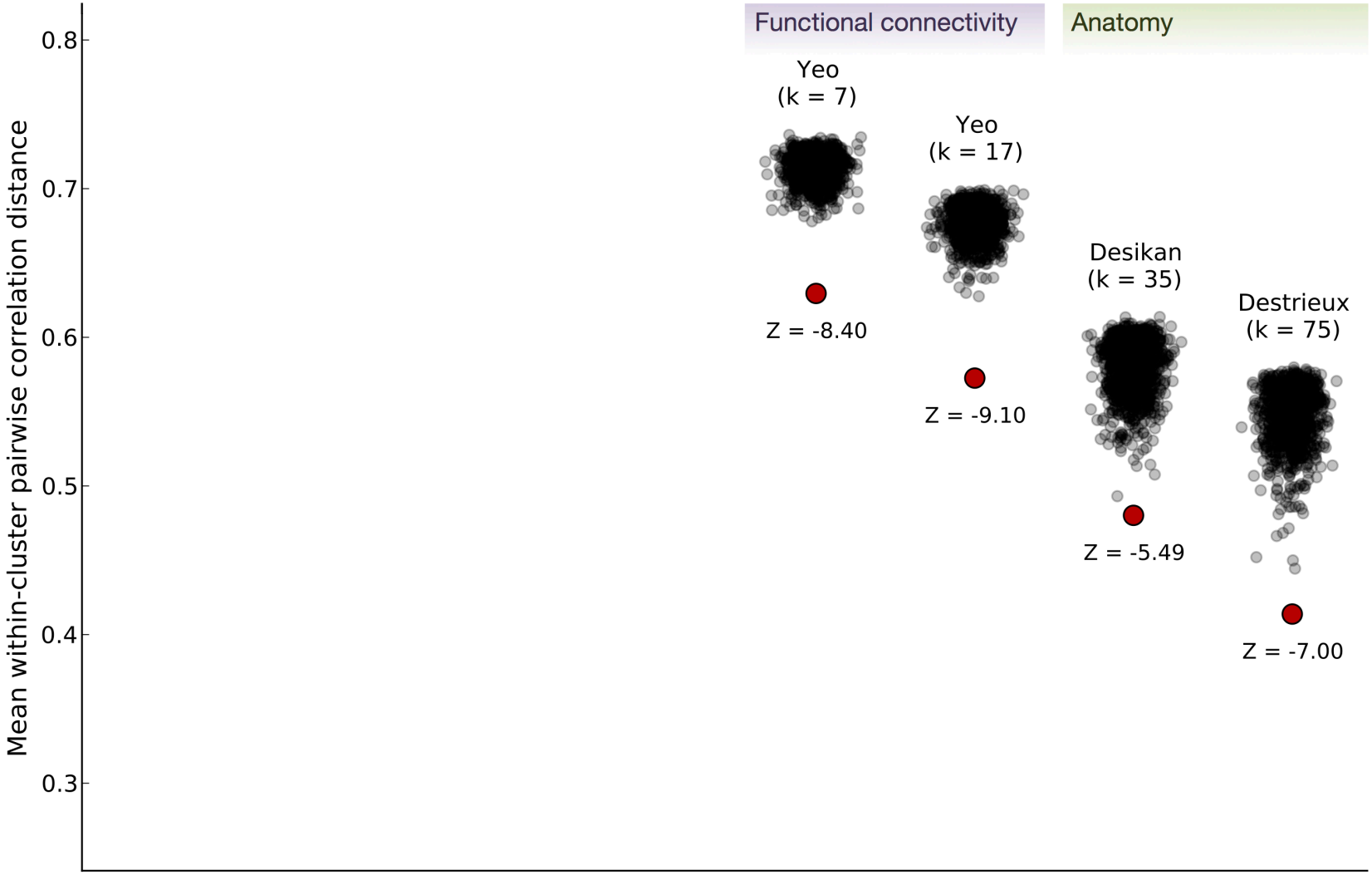

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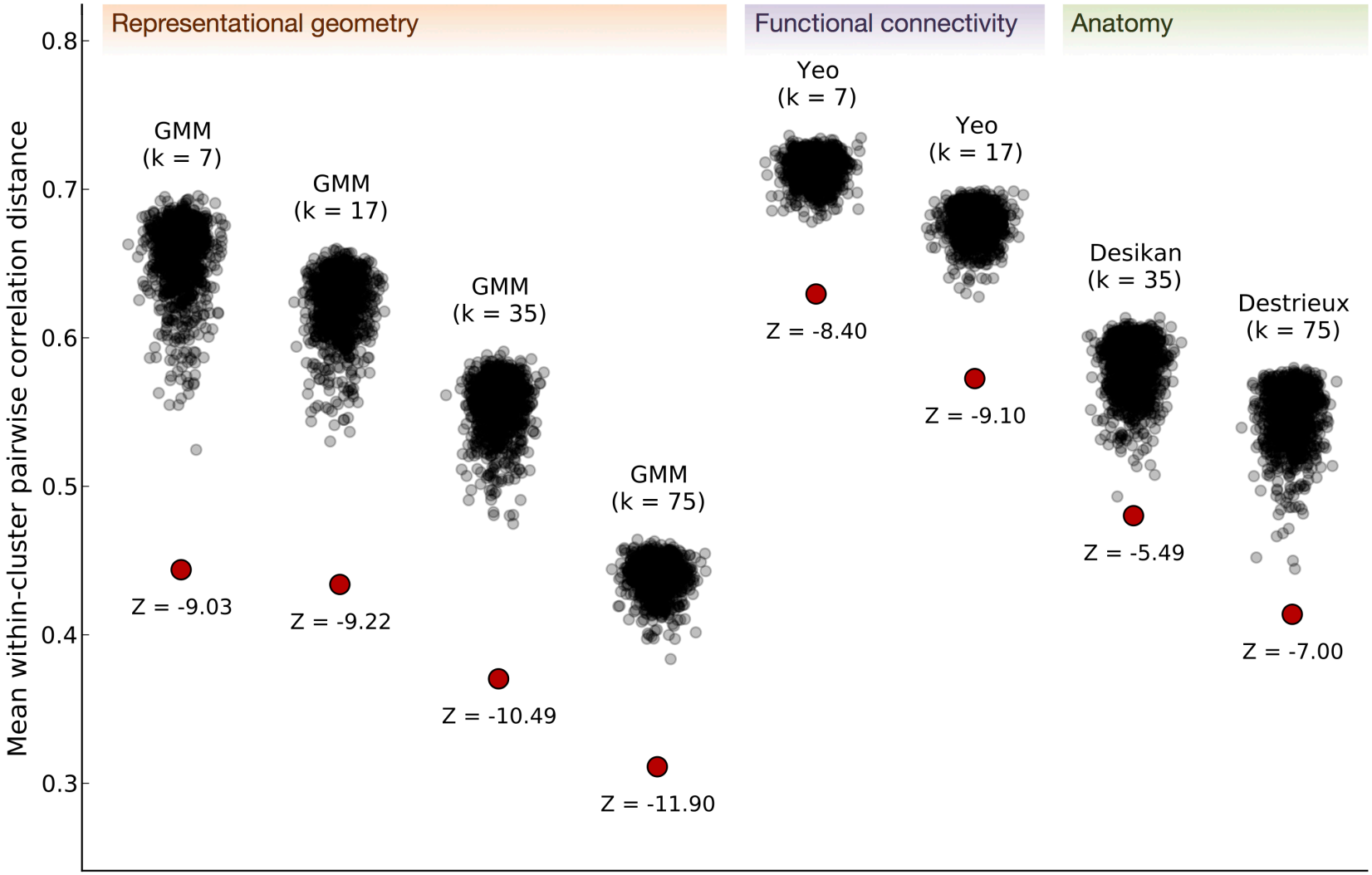

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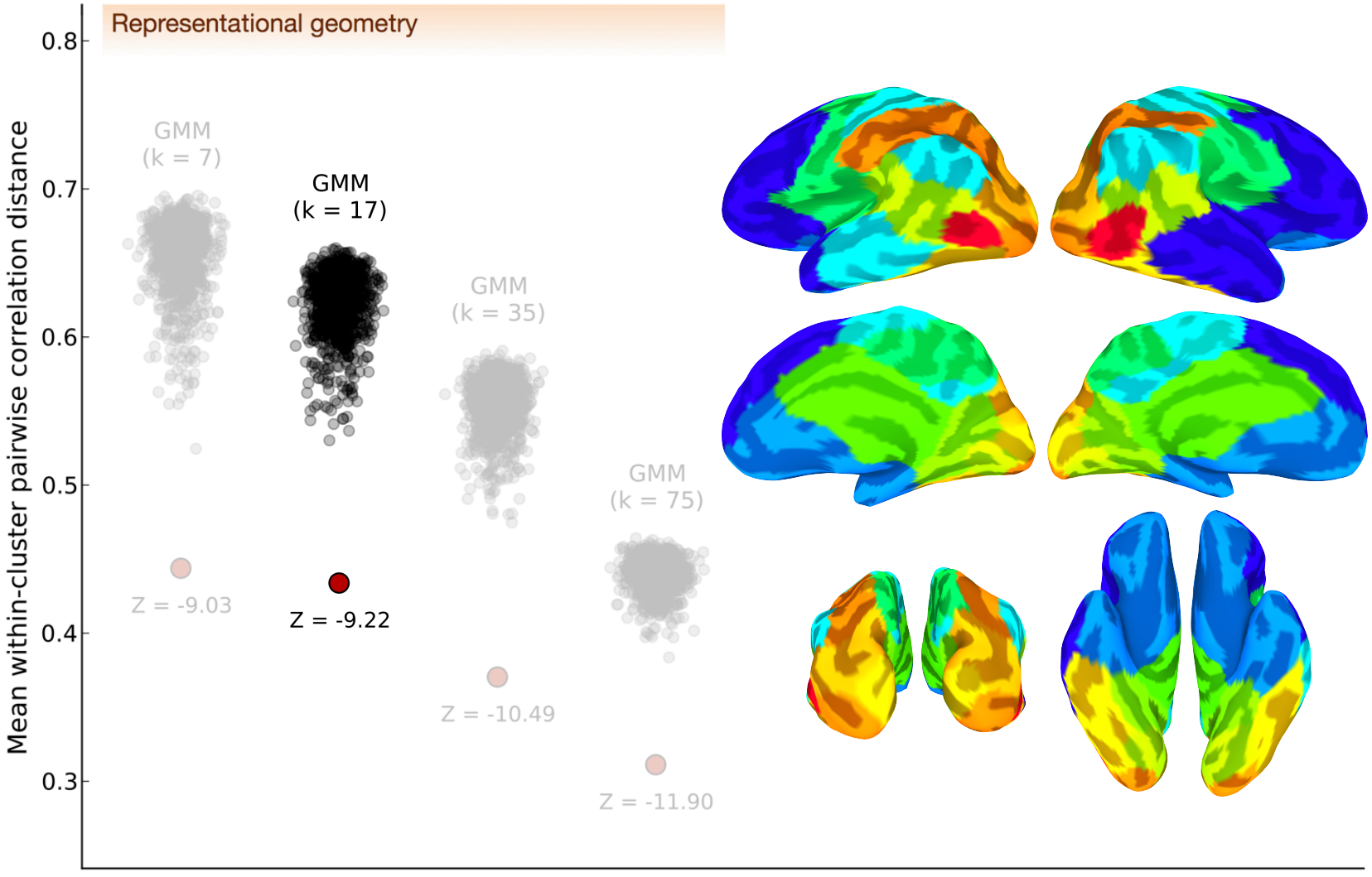

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Destrieux et al, 2010
Yeo et al, 2011

Summary

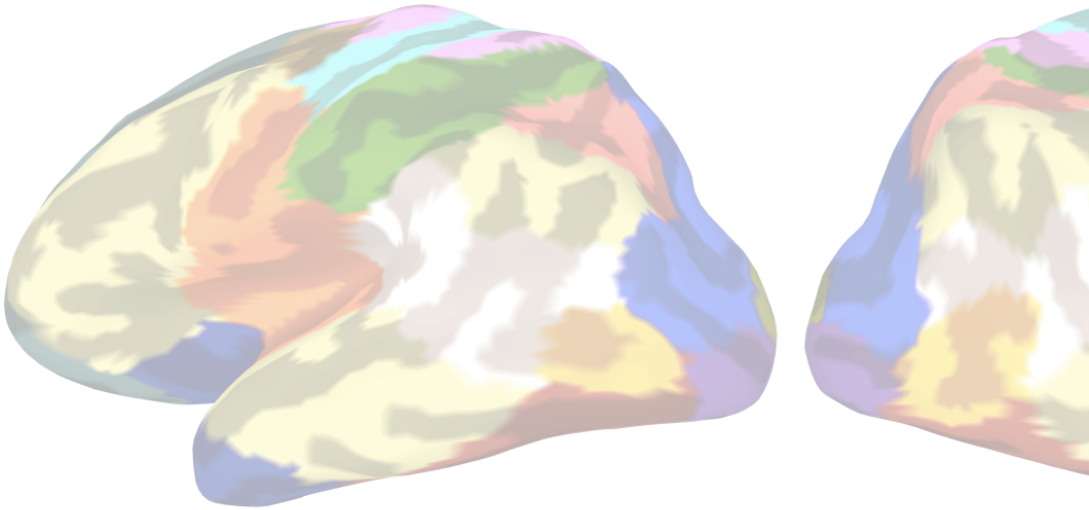
Functional parcellation of the cerebral cortex based on representational geometry

Reproducibility analysis quantifies how well parcellations generalize across participants

Homogeneity analysis identifies where representations are encoded most consistently

Future directions:

- Extend analyses to higher *k*
- Project group parcellations into individual participants' brains
- Quantify information content of parcels using classifiers



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http://www.pymvpa.org

http://NeuroDebian.net

INSTITUTE neukom

Free and open source software:
PyMVPA, NeuroDebian, scikit-learn, NumPy, SciPy,
AFNI, SUMA, R, RStudio, joblib…

Code available at `https://github.com/mvdoc/reprclust`
(and soon in PyMVPA)

Clustering cortical searchlights based on shared representational geometry
Poster ID: 3983
Today 12:45-2:45 pm
Category: Modeling and analysis methods