Representational similarity analysis of neuroimaging and electrophysiology data: Strengths, outstanding issues and potential

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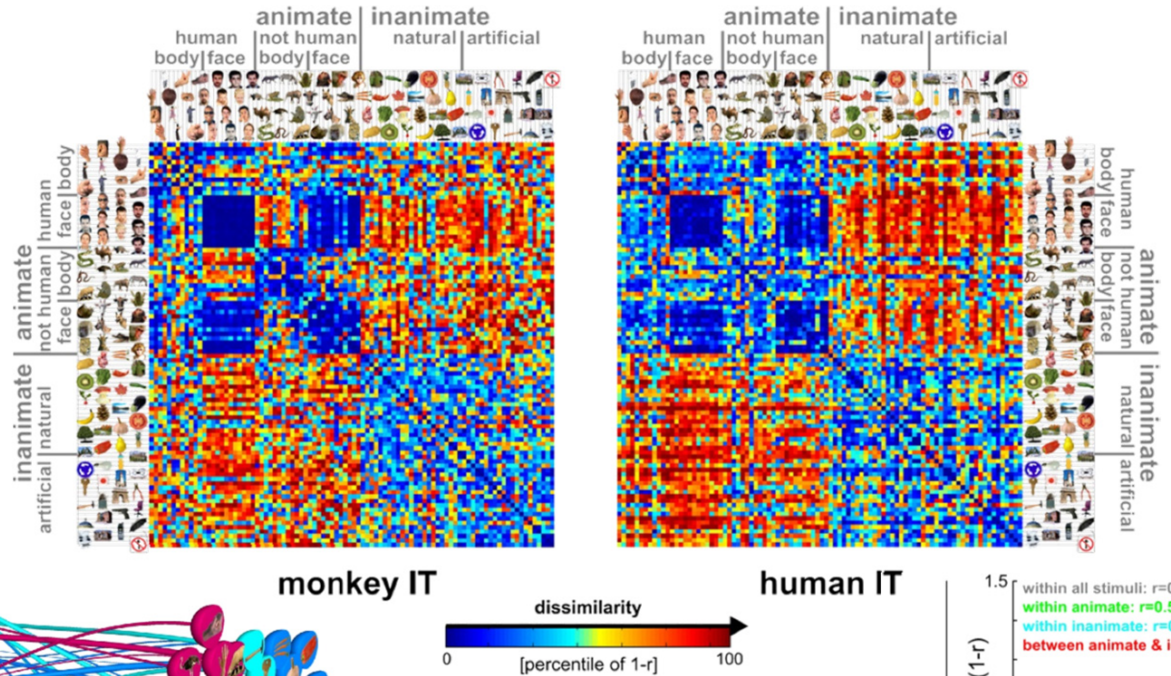
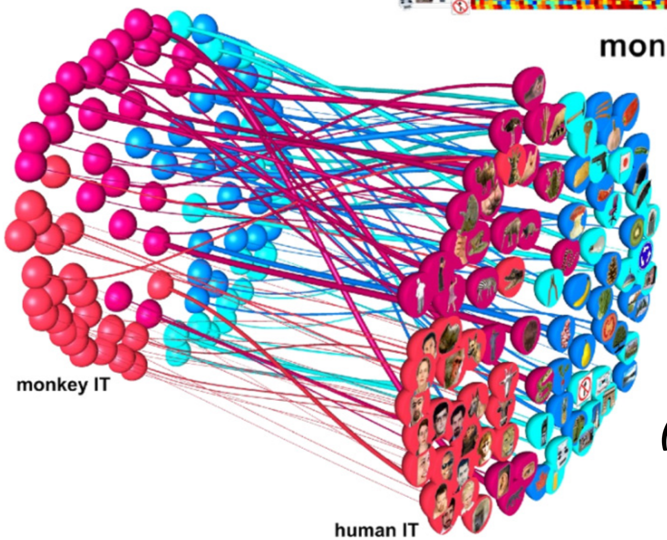
21/11/2019 – MVPA workshop @ CERIMED

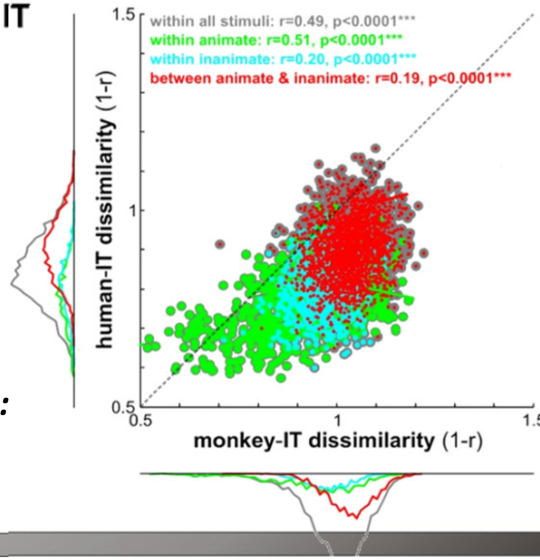
Neuron *60*, 1126–1141, December 26, 2008

Matching Categorical Object Representations in Inferior Temporal Cortex of Man and Monkey

Nikolaus Kriegeskorte,[1,*] Marieke Mur,[1,2] Douglas A. Ruff,[1] Roozbeh Kiani,[3] Jerzy Bodurka,[1,4] Hossein Esteky,[5,6] Keiji Tanaka,[7] and Peter A. Bandettini[1,4]



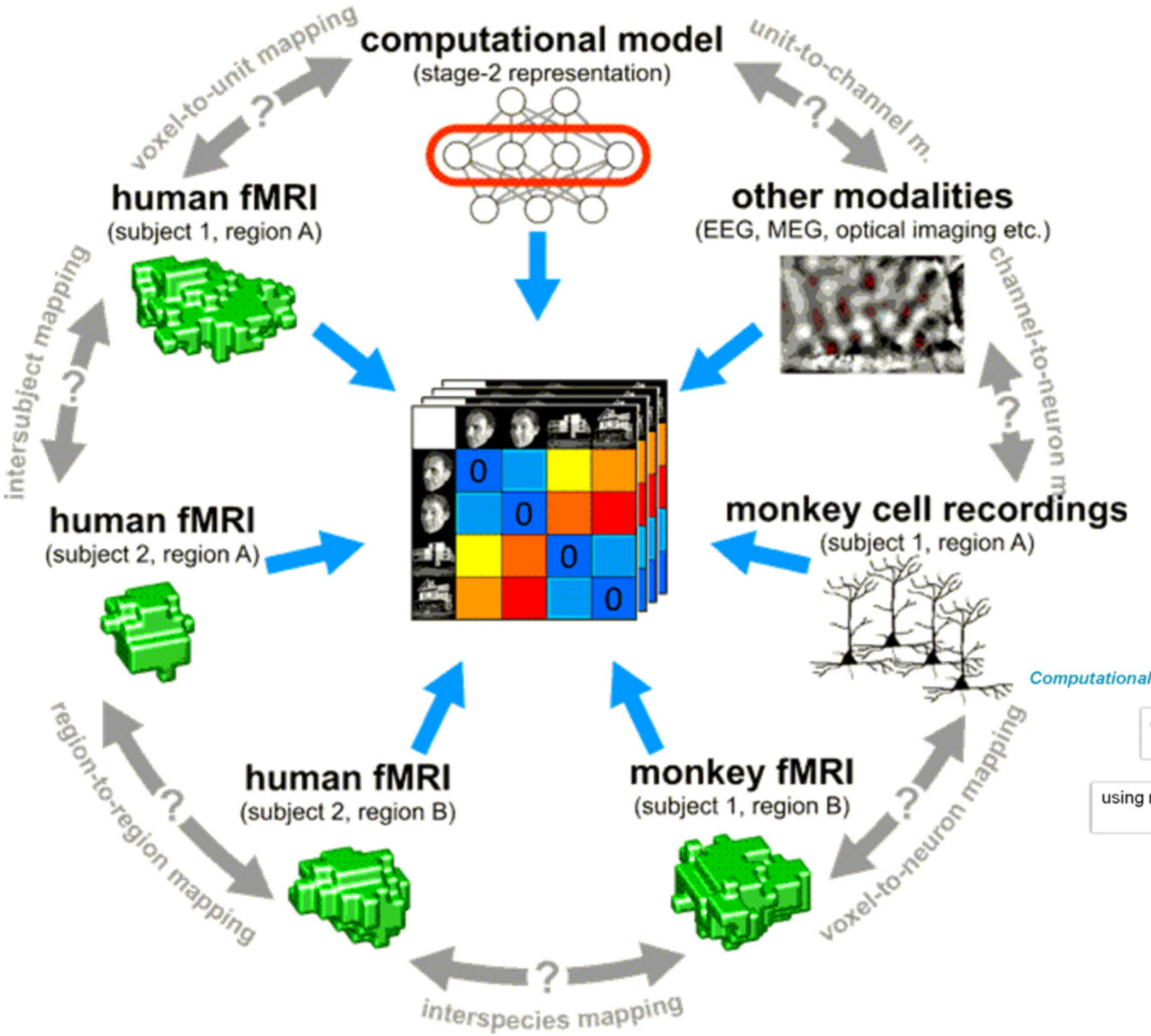


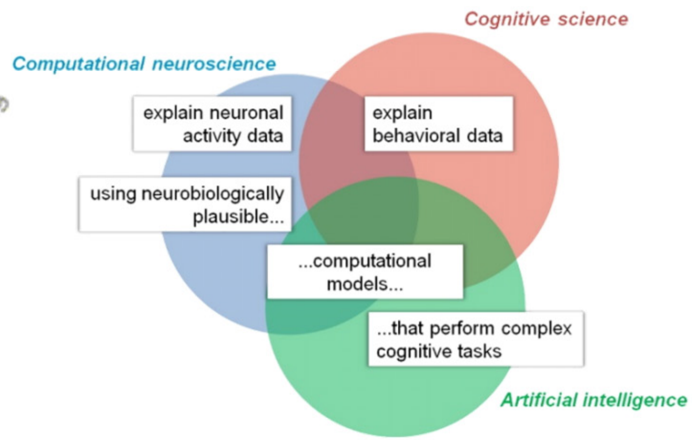


N citations for main RSA papers (2008, Neuron; Front Sys Neurosci): ~2300

Representational similarity analysis

Kriegeskorte et al. (2008, Front Sys Neurosci)

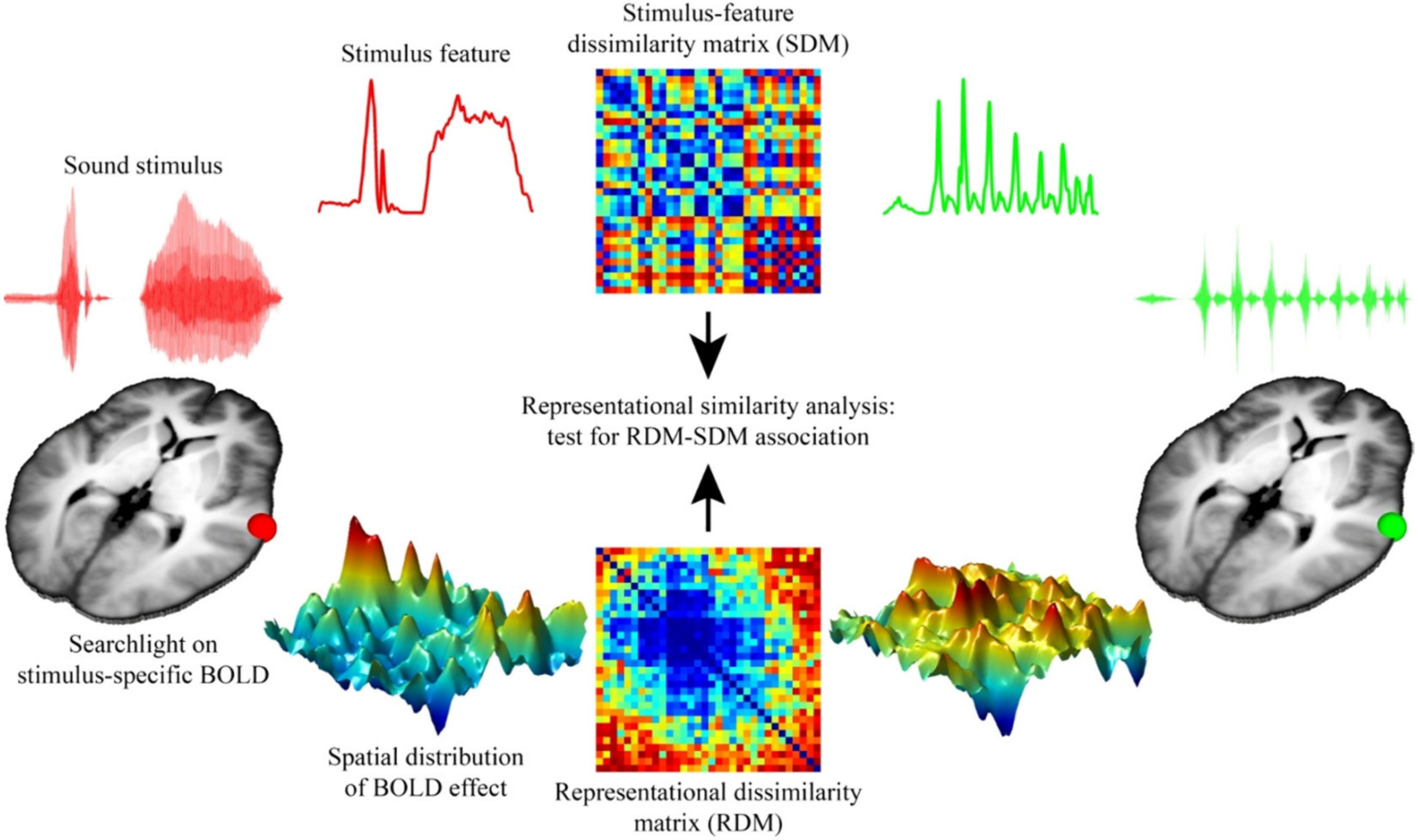




Douglas and Kriegeskorte (2018, Nat Neurosci)

The mechanics of RSA

Giordano et al. (2013, Cereb Cortex)
Steps 1.-4.: I Charest



1. Estimate the patterns (e.g., BOLD response)

2. Select the voxels (or sensors or time points)

3. Estimate the distance

4. Test the representational model

RSA vs. decoding vs. encoding

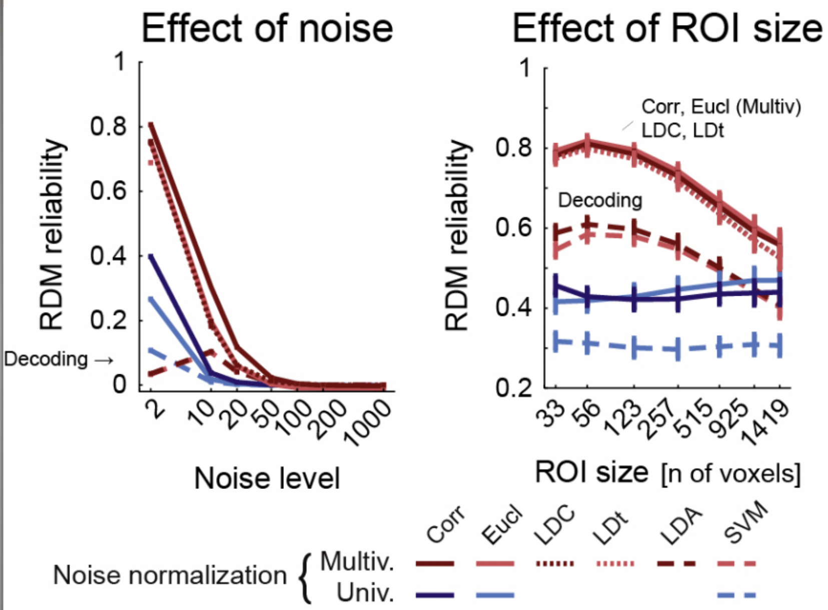
1. More reliable than decoding: confusions are quantized and range-constrained (next slide);

2. More computationally efficient than encoding

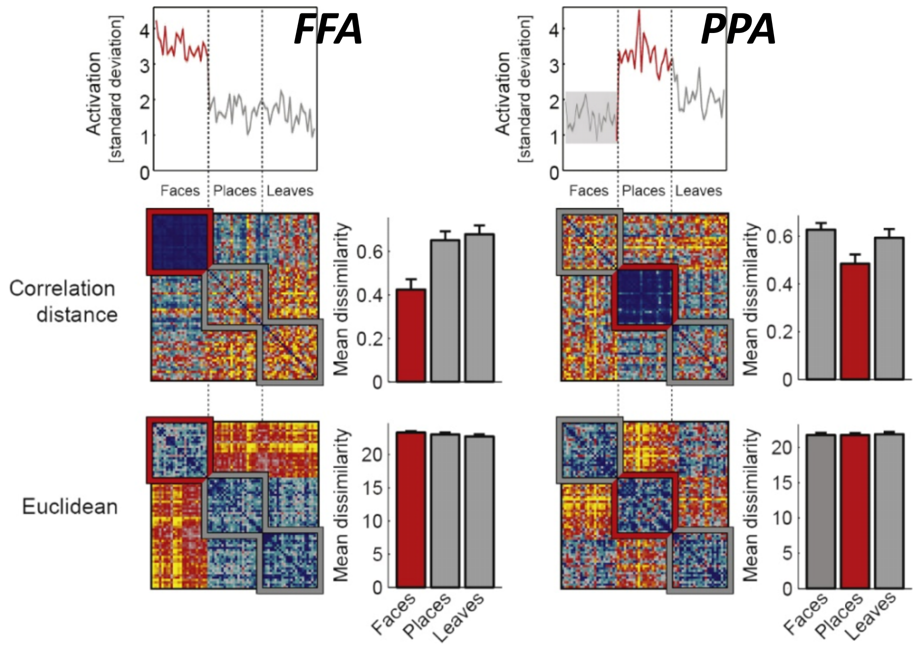
(regularization; Diedrichsen and Kriegeskorte, 2017, Plos Comp Bio);

Which distance?

Walther et al. (2016, NeuroImage)



Decoding confusions are less reliable and more vulnerable to noise



Correlation distance can be misleading with strong regional activation differences!

Current recommendations:

*1. **Crossnobis**: cross-validated Euclidean with **multivariate noise normalization** (Walther et al., 2016, NeuroImage)*

*2. **Correlation with clean data** (GLMdenoise) and **univariate noise normalization** (Charest, Kay and Kriegeskorte, 2018, NeuroImage).*

Remainder of talk

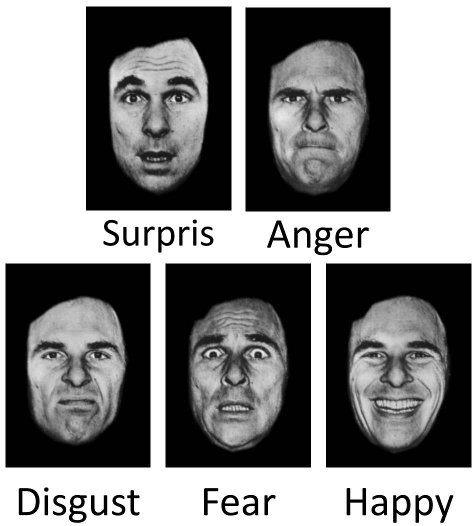
1. *Testing otherwise complex hypotheses (high-dimensional models);*
2. *Handling correlated models with variance partitioning;*
3. *Fusion of multimodal data;*
4. *RSA for interindividual differences;*
5. *RSA for directed connectivity;*
6. *Which distance?*
7. *Visualization tips and tricks;*
8. *Python packages.*

Representational dynamics of perceived voice emotions unfolds categories into dimensions

BL Giordano, C Whiting , N Kriegeskorte, SA Kotz, J Gross, P Belin*   *co-senior*

BiorXiv (2018): https://goo.gl/ChbTdN

Categories



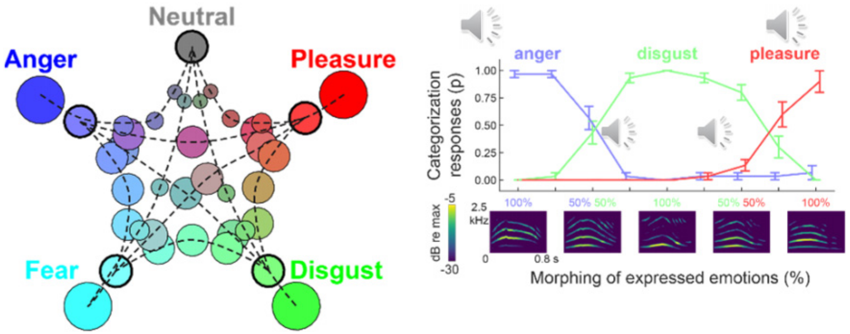
Ekman & Friesen (1978)

Dimensions

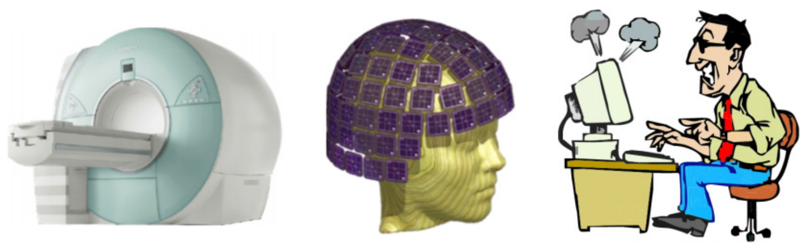
Russell (1980)

Methods

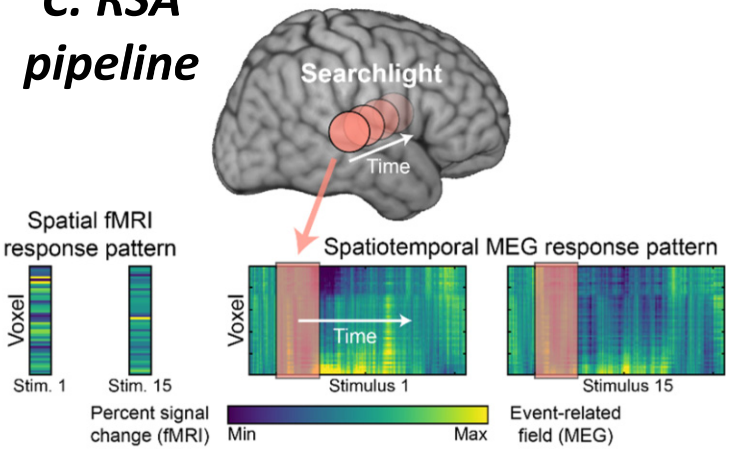
A. Stimuli



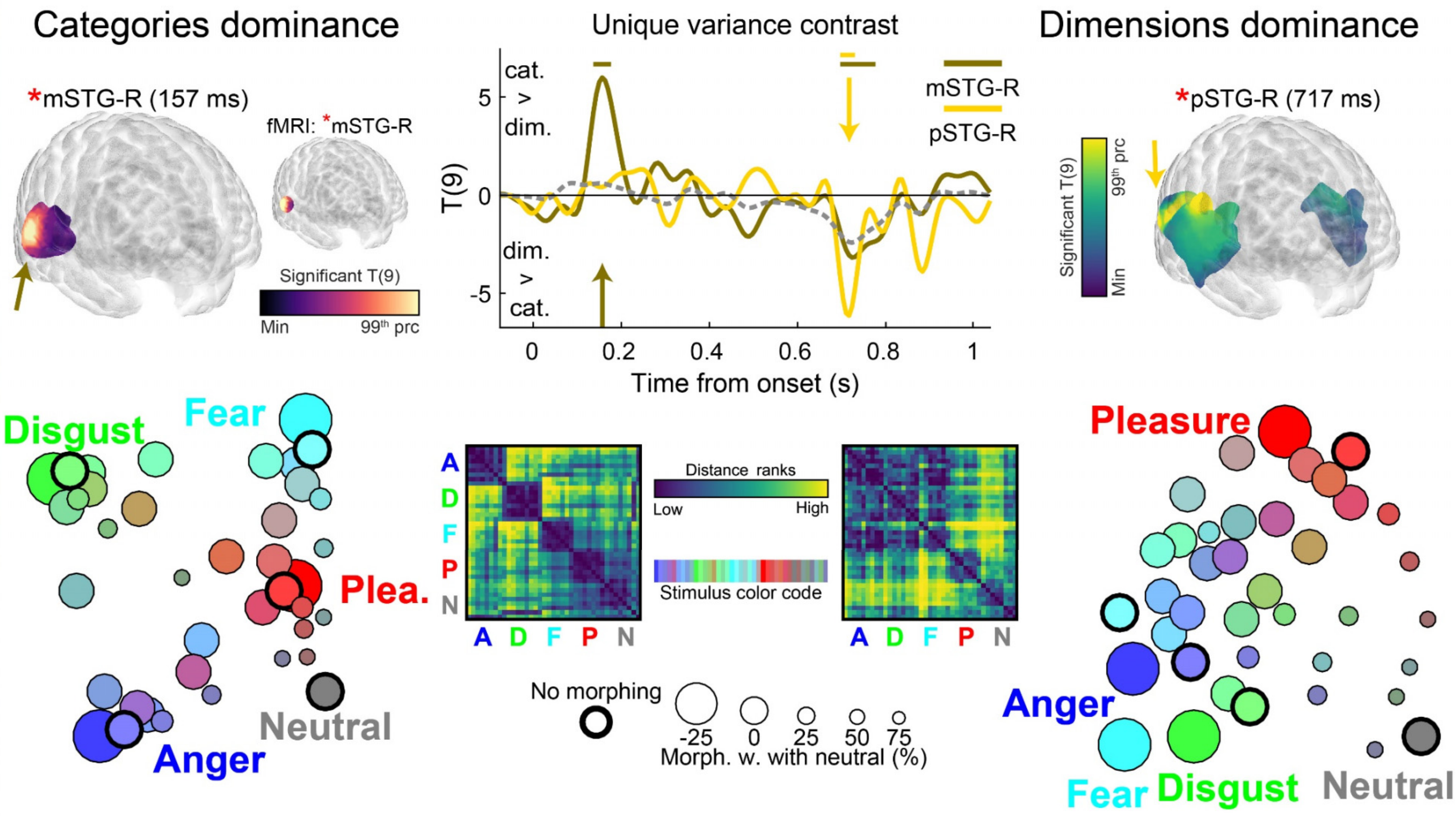
B. Data: fMRI, MEG, behavior



C. RSA pipeline

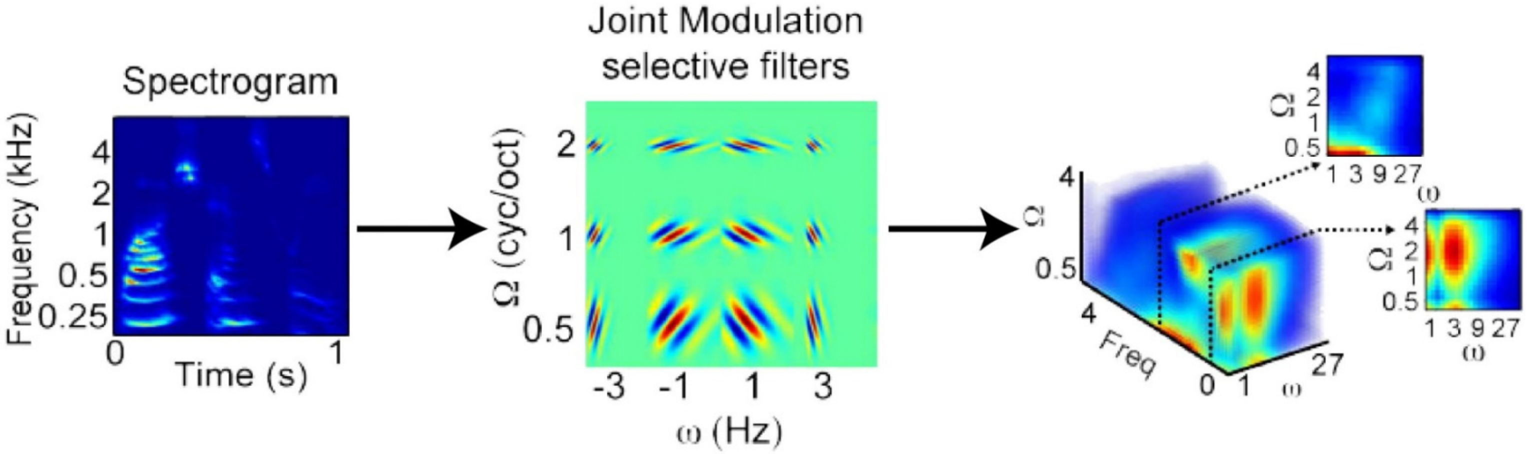


Main results

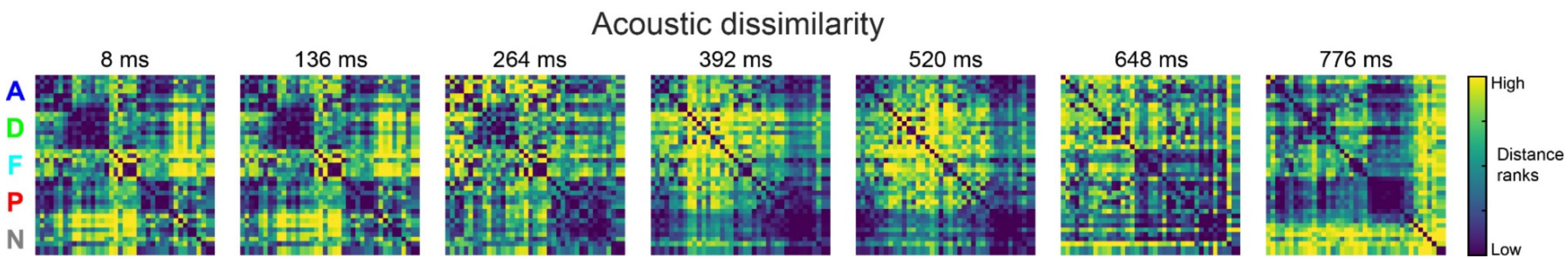


Acoustics ✌️confound✌️

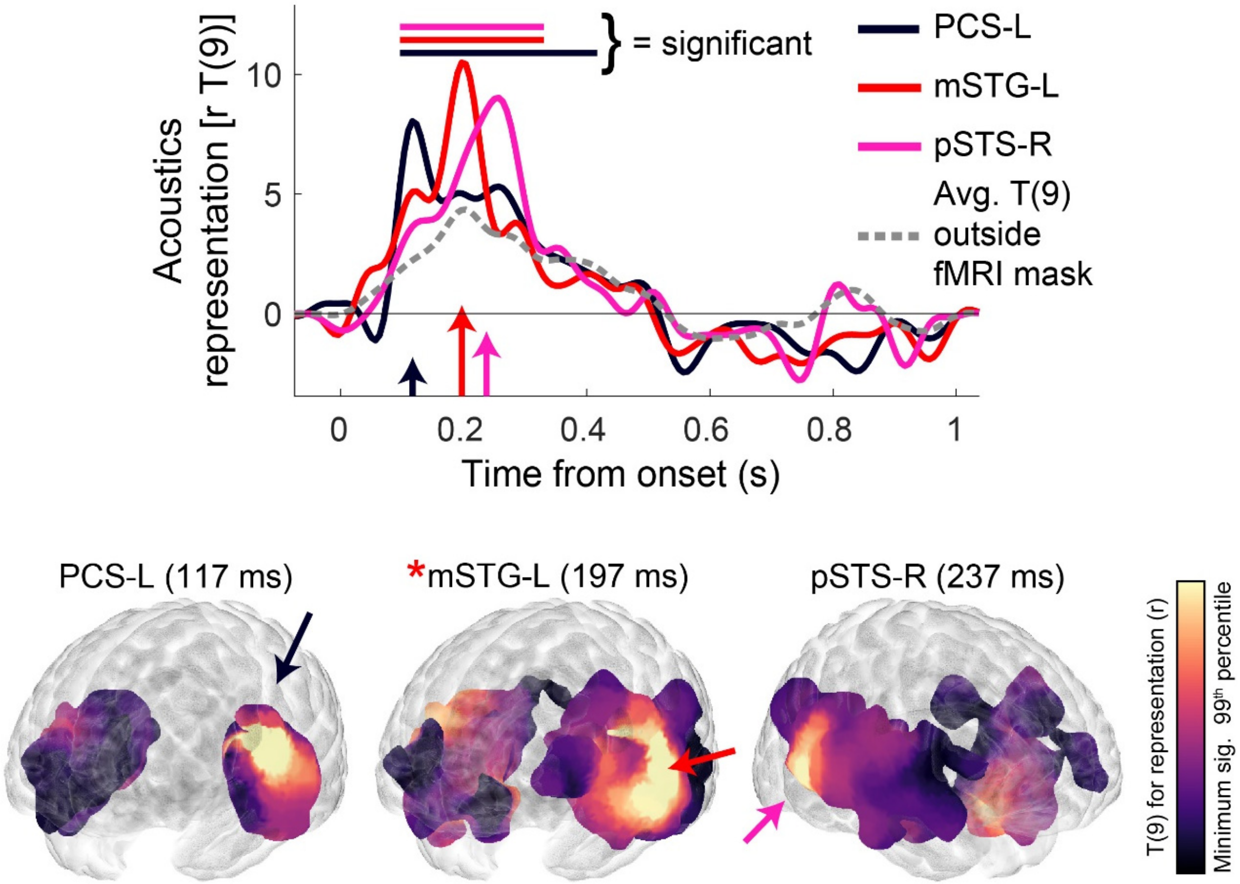
Modulation Transfer Function
Chi et al. (2005; Jasa; Santoro et al. 2014)



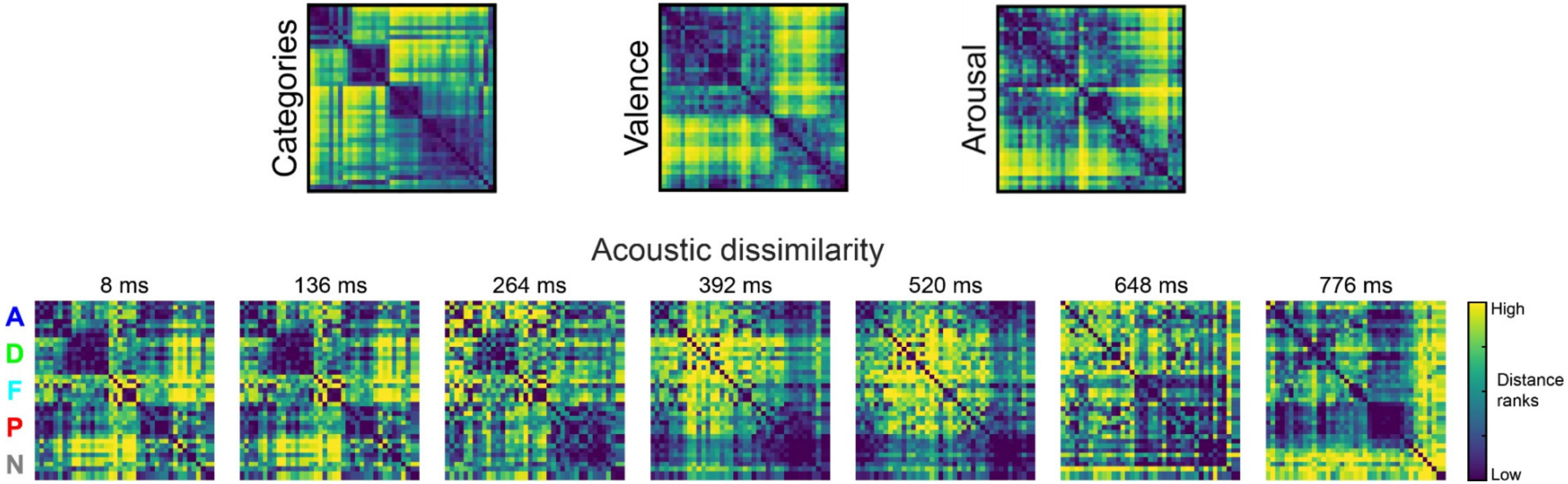
Highly dimensional complex-number representation:
1. frequency; 2. rate (temp. mod.); 3. scale (spectr. mod.); 4. direction (up/down); 5. time.

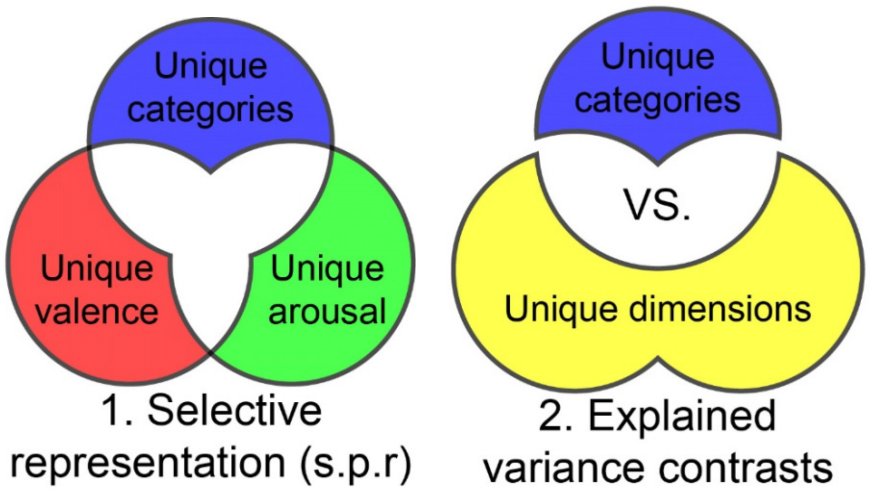


Acoustics representation



Variance partitioning





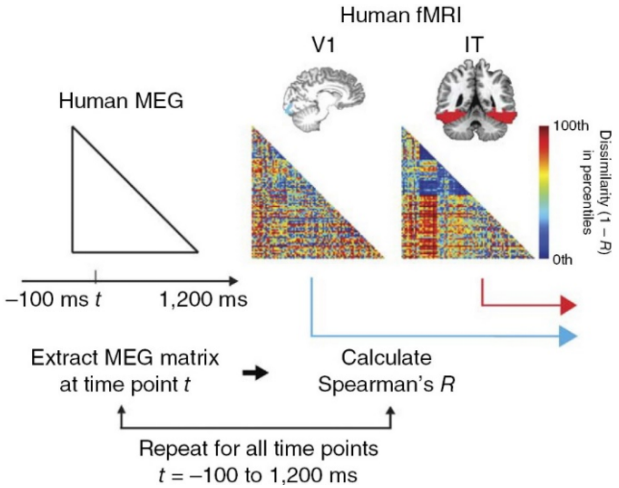
Equivalent (quick) methods:

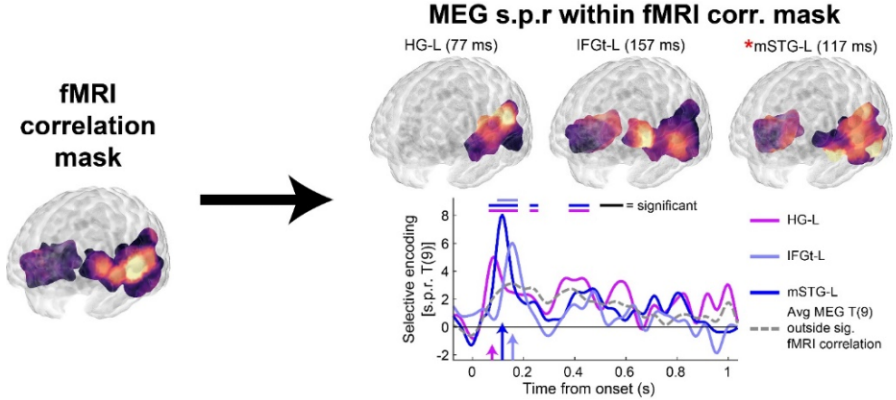
closed form solutions

or

regression residuals.

RSA fusion of multimodal imaging data



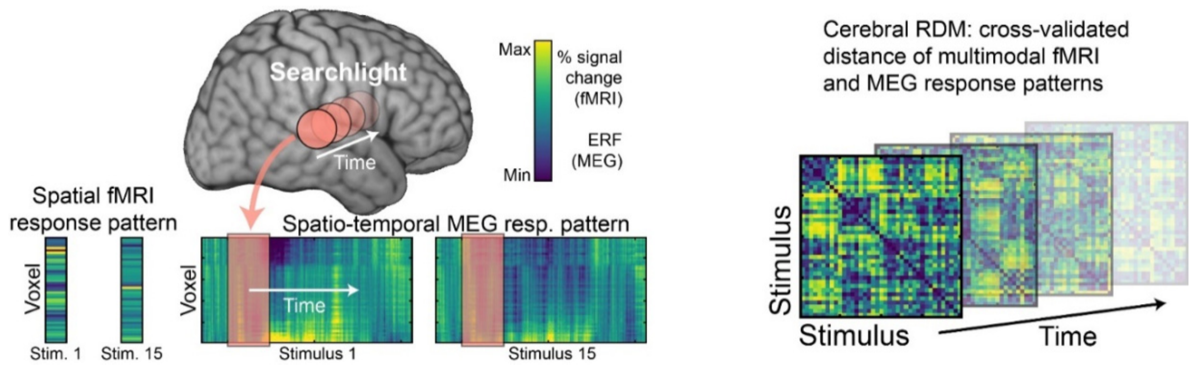


- ✓ ***MEG in sensor space (suboptimal)***
- ✓ ***No MEG tests of representation***

Cichy et al. (2014, Nat Neurosci)

- ✓ ***Uses spatial information in MEG***
- ✓ ***Tests for MEG representation***

Giordano et al. (2018, BiorXiv)

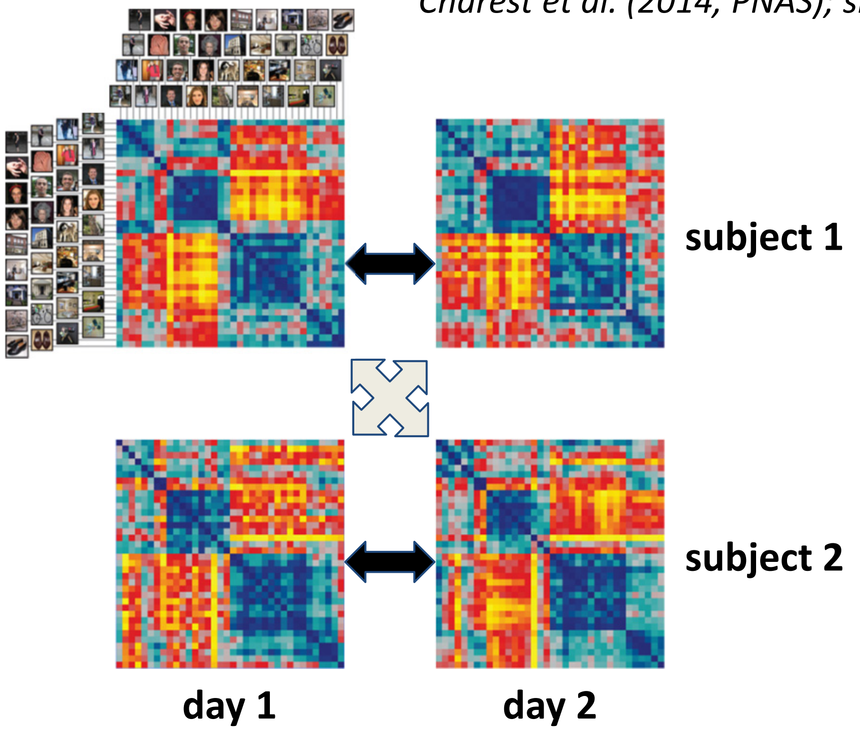


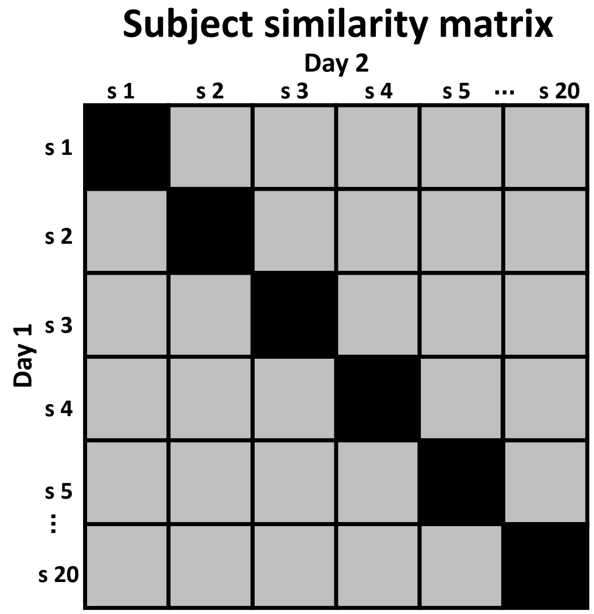
RDM at simultaneous high spatial and temporal resolution (Holy Grail)

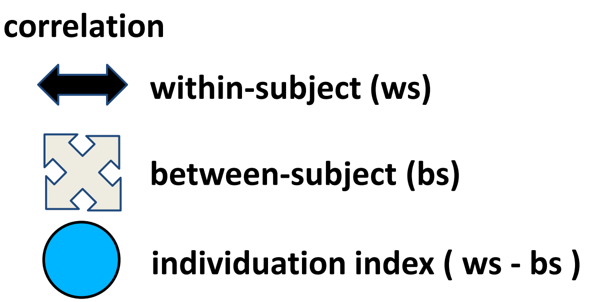
Giordano et al. (work in progress)

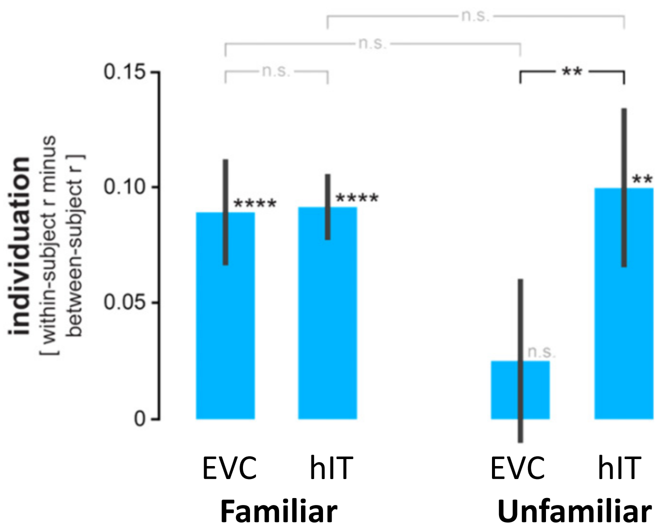
Interindividual representational differences

Charest et al. (2014, PNAS); slide courtesy of I Charest



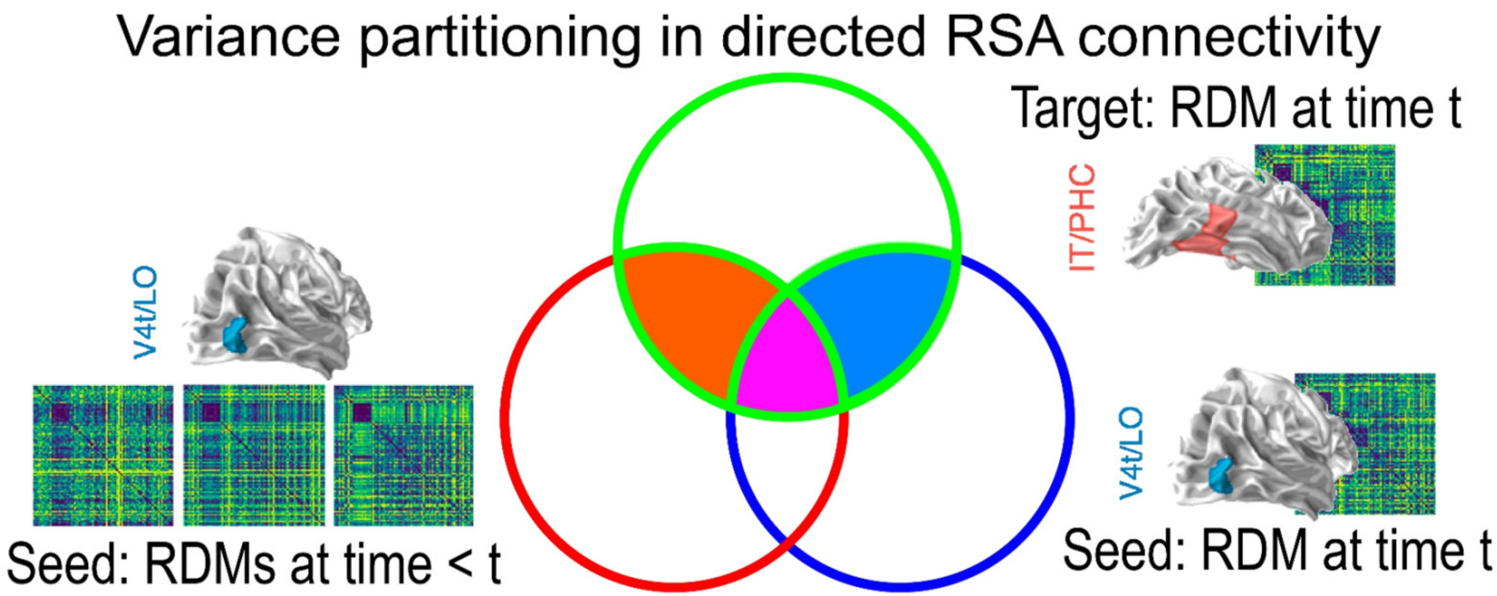


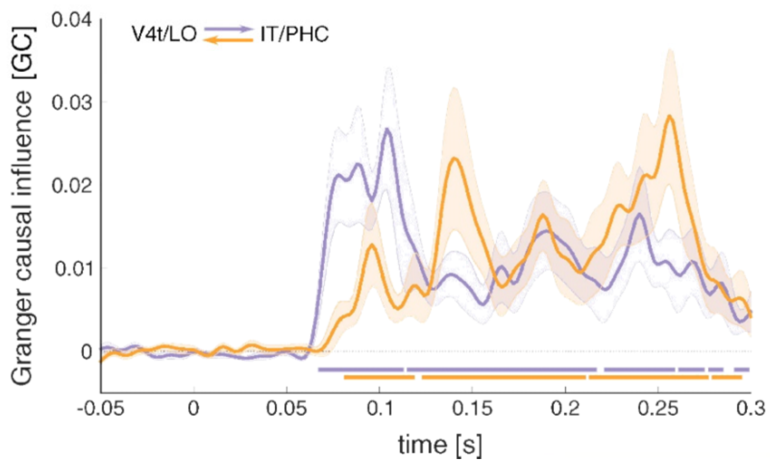




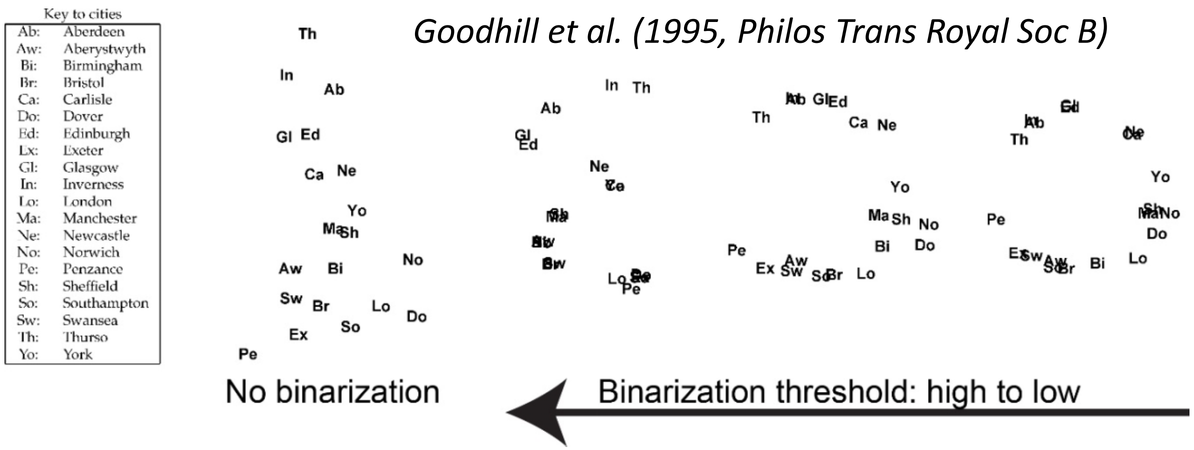
Directed RSA connectivity (“Granger”)

Kietzmann et al. (2019, PNAS)





Visualization: the annular bias et al.

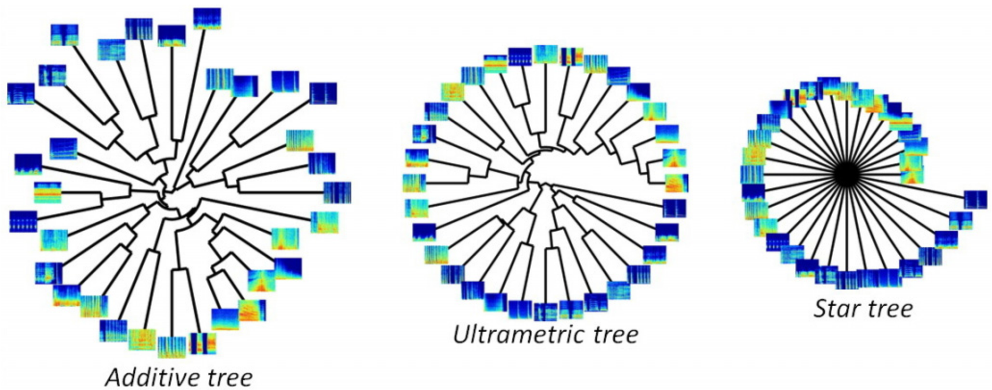


Goodhill et al. (1995, Philos Trans Royal Soc B)

1. Be wary of circular solutions;

2. Don't average distances: Euclidean bias (Ashby et al., 1994, Psychol Sci)…

… use INDSCAL instead (e.g., SMACOF, de Leeuw and Mair, 2009, Stat Softw);

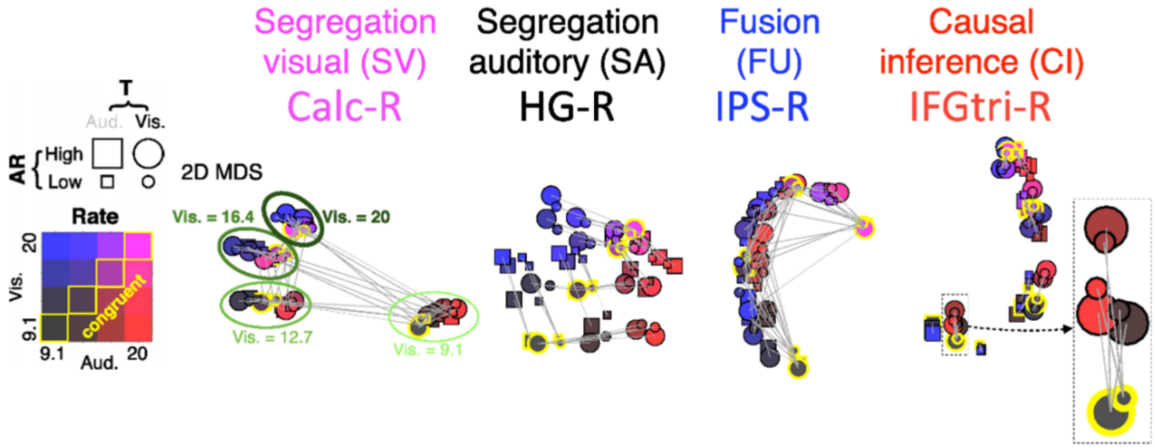


3. Consider other distance models: trees fit clustered data better
(Giordano et al., 2011, Multivariate Behav Res; appendix: taxonomy of models).

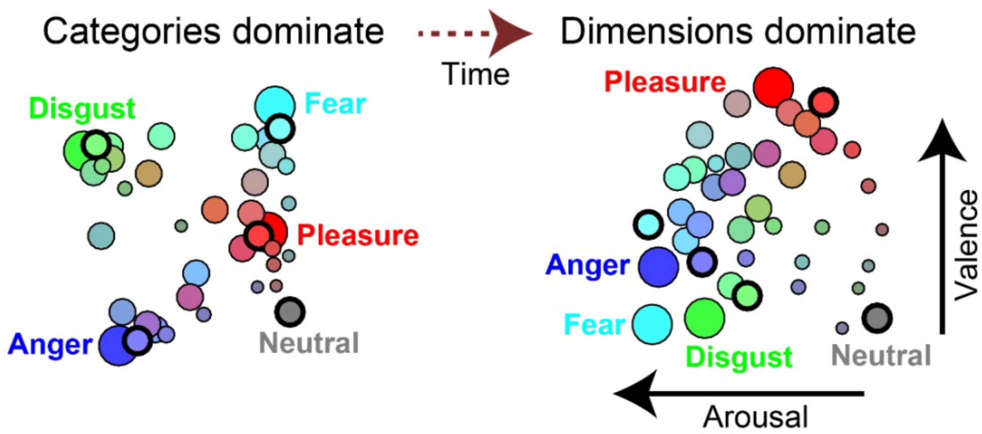
Visualizing model-diagnostic representations

- ✓ *Brain distances can be noisy → MDS suffers.*
- ✓ *Solution: cross-validated extraction of model-RDM variance in brain RDM → MDS.*

Computational models of audiovisual integration
Cao et al. & Giordano, Kayser* (2019, Neuron)*



Behavioral measures of perceived emotions and dissimilarity
Giordano et al. (2018, BioRxiv)



Python tools (under development)

Charestlab / **pySearchlight**

Code | Issues 1 | Pull requests 1

python tool for searchlight mapping

rsagroup / **pyrsa**

Code | Issues 13 | Pull requests 4 | Actions

Python library for Representational Similarity Analysis

Merci!