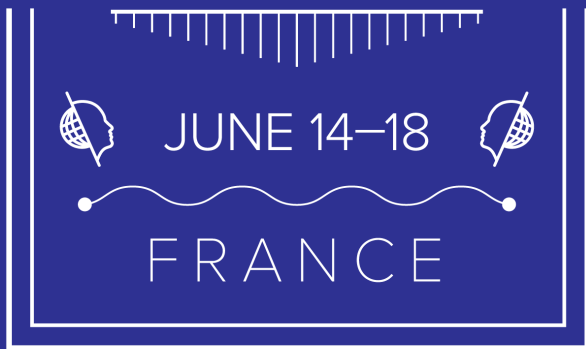




BORDEAUX



Spatial maps of similarity
across the cortex:

**EDGES in
SPACE**

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Section on Functional Imaging Methods

National Institute of Mental Health, Bethesda, MD

OHBM 2026 DISCLOSURES

I have no conflicts of interest in relation to this presentation to disclose.

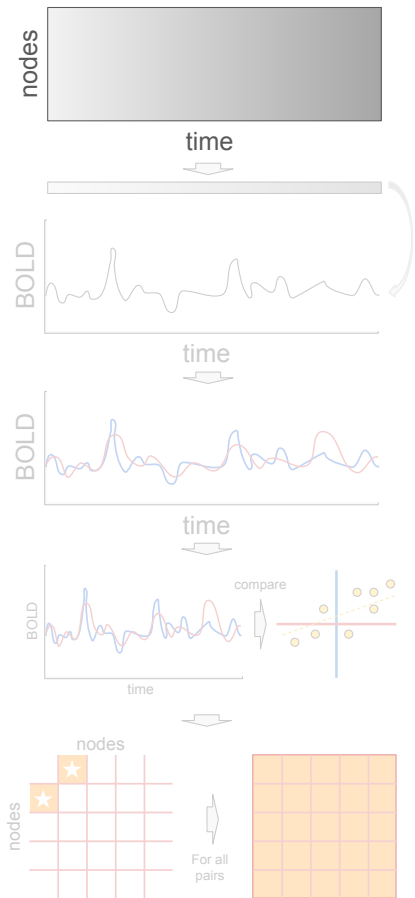


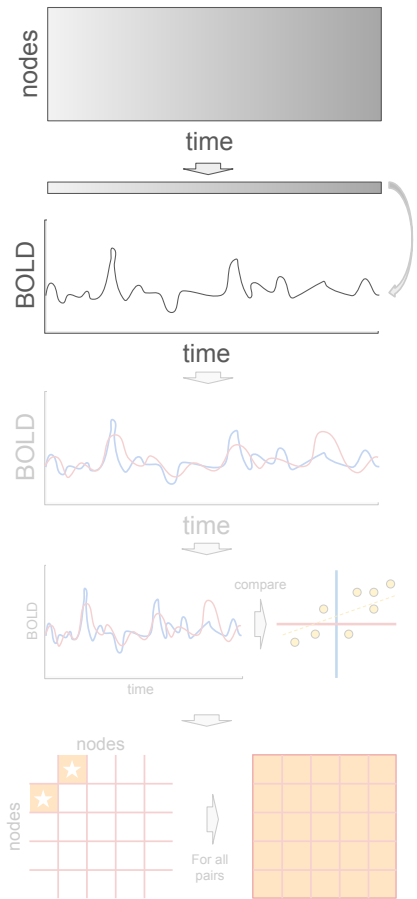
A journey from ***FC***, to ***edges***, to ***space***

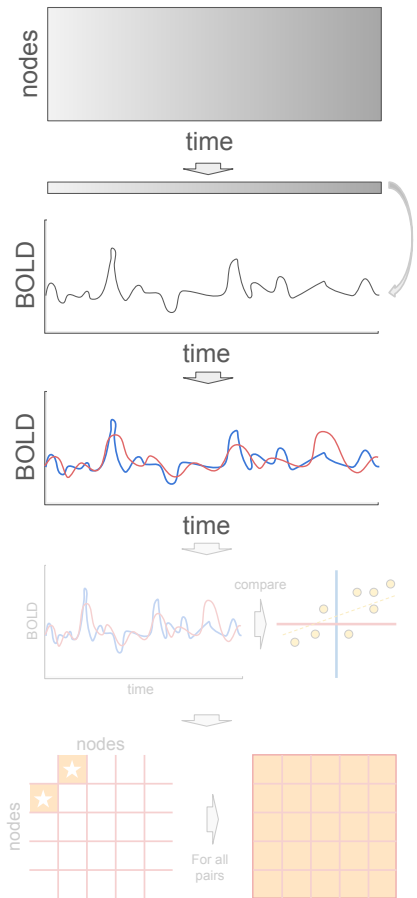


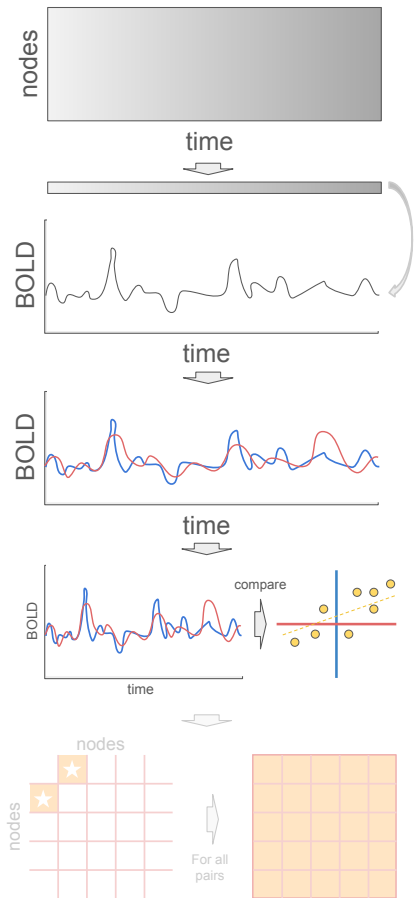
A journey from **FC**, to **edges**, to *spatial similarity*

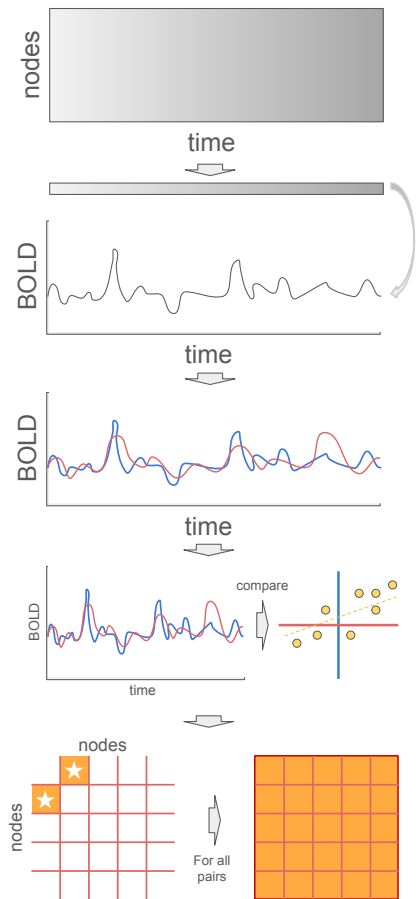


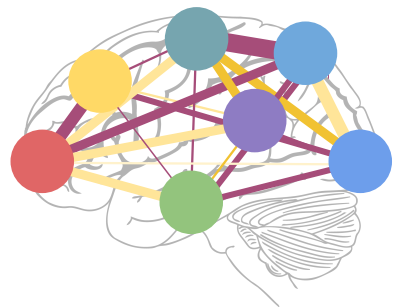
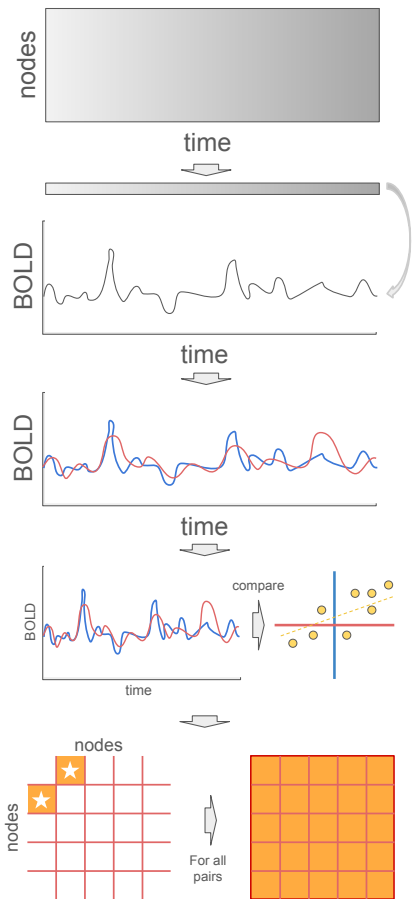


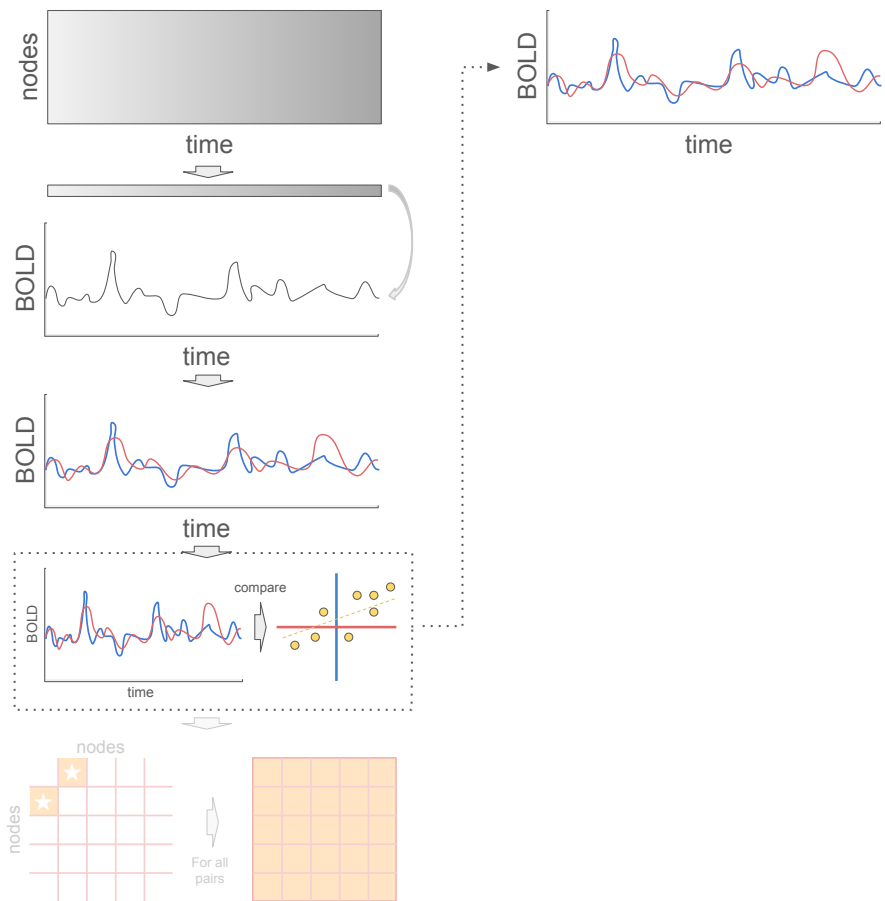


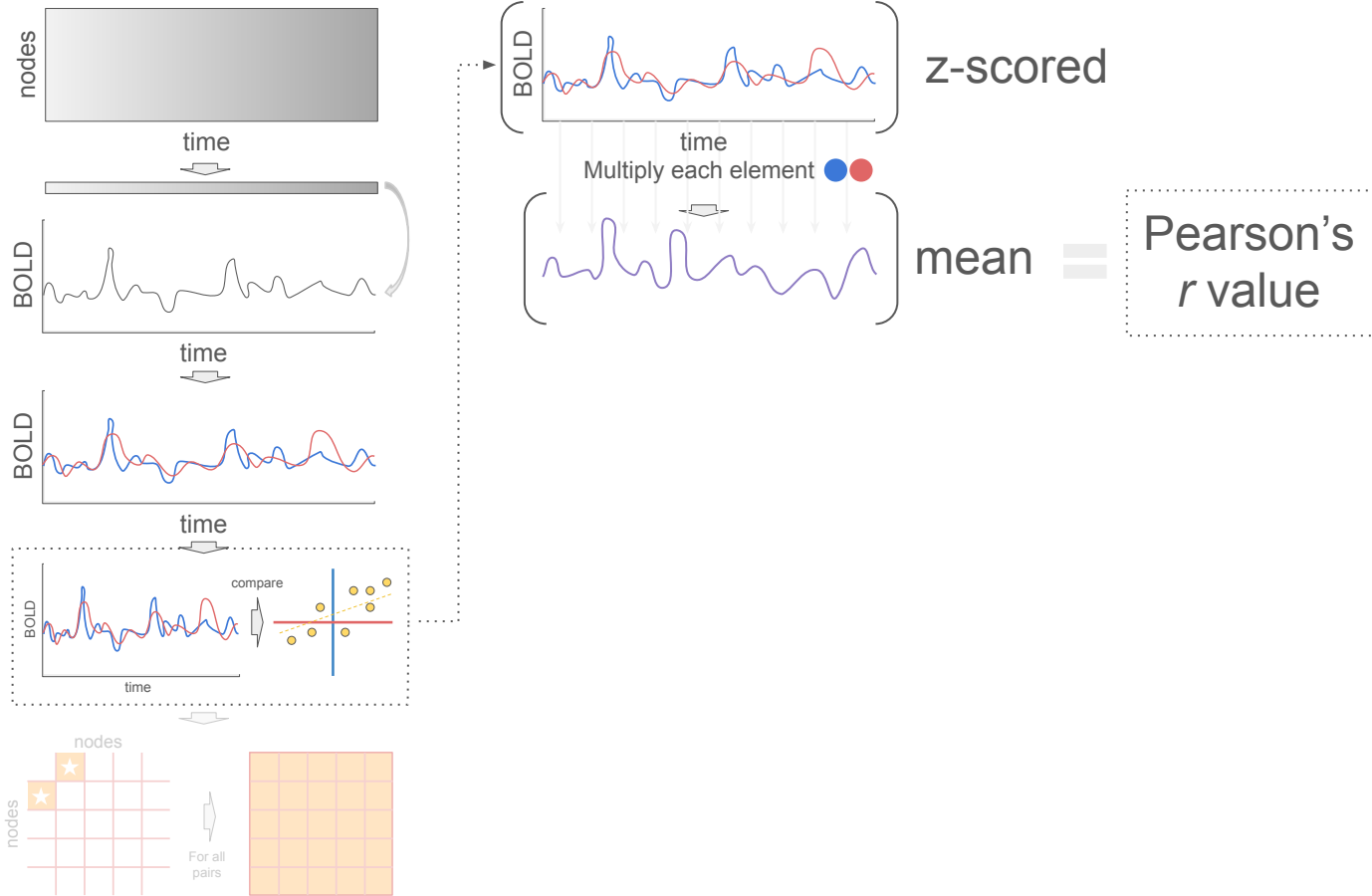


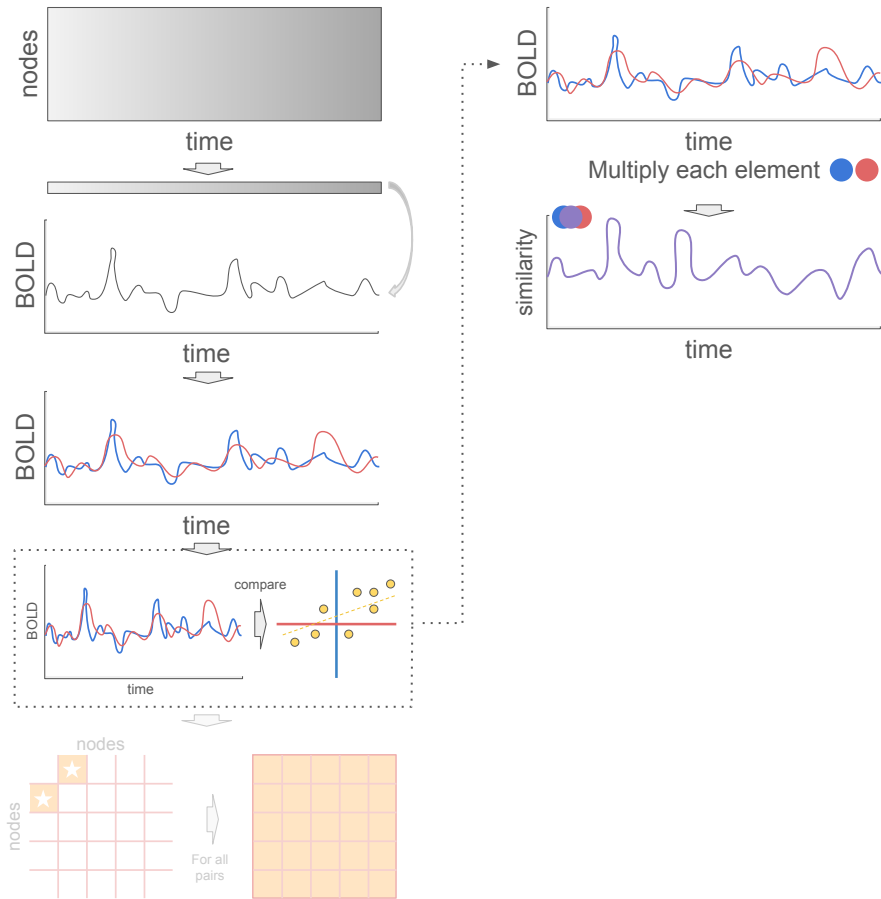




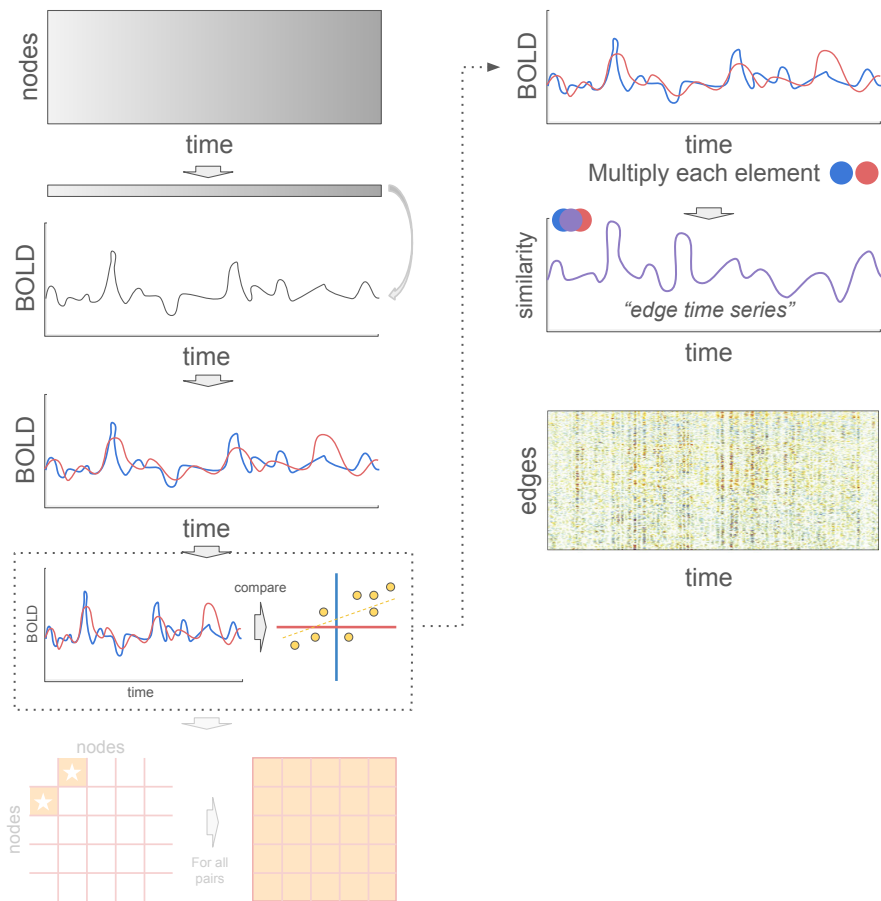




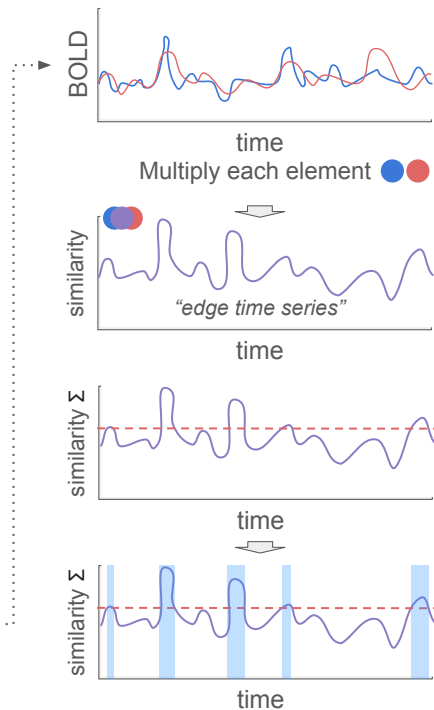
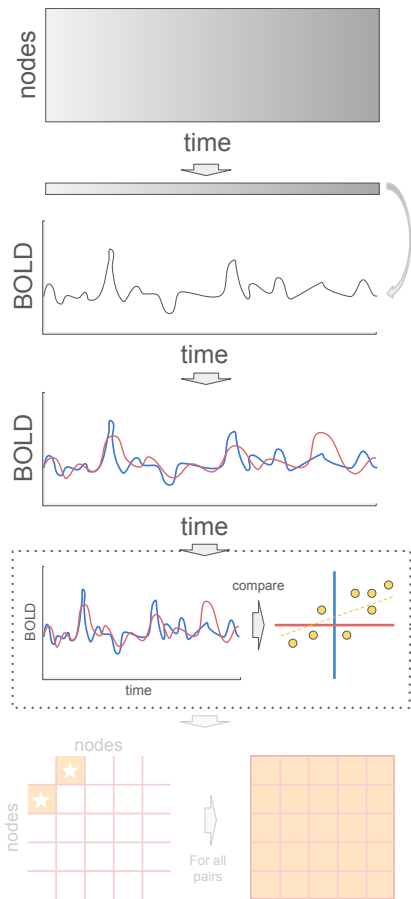




“unwrapped” correlation, or r , value to see its framewise ingredients

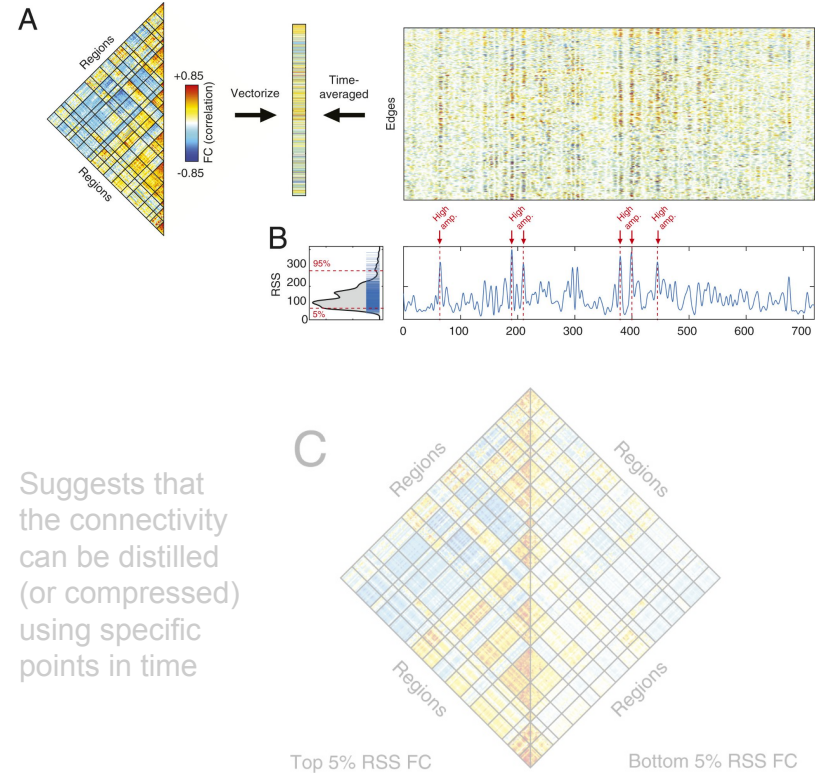


“unwrapped” correlation, or r , value to see its framewise ingredients





Finding where the “info” resides

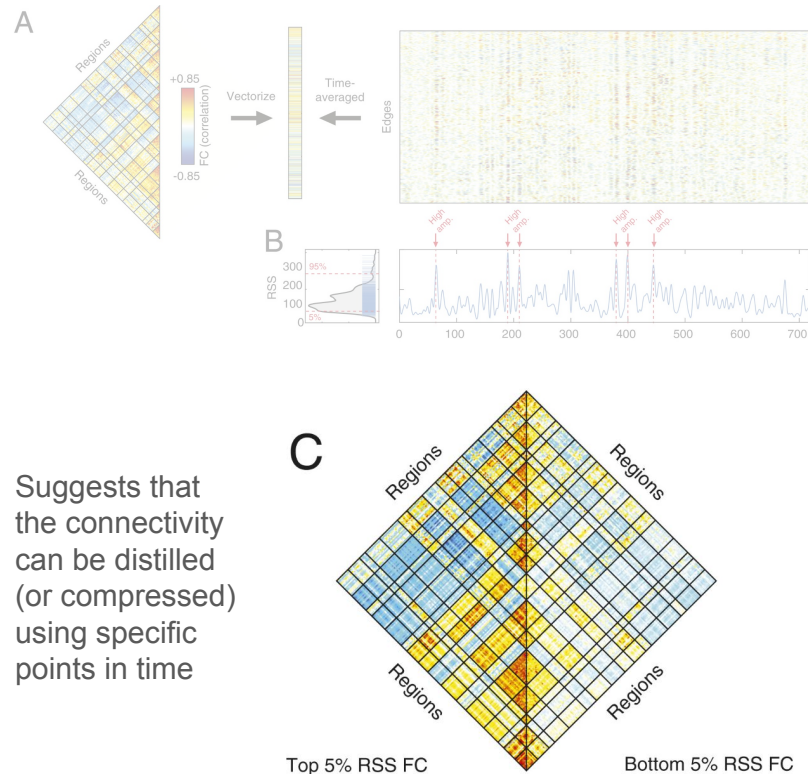


Suggests that the connectivity can be distilled (or compressed) using specific points in time

Esfahlani et al. (2020). *PNAS*

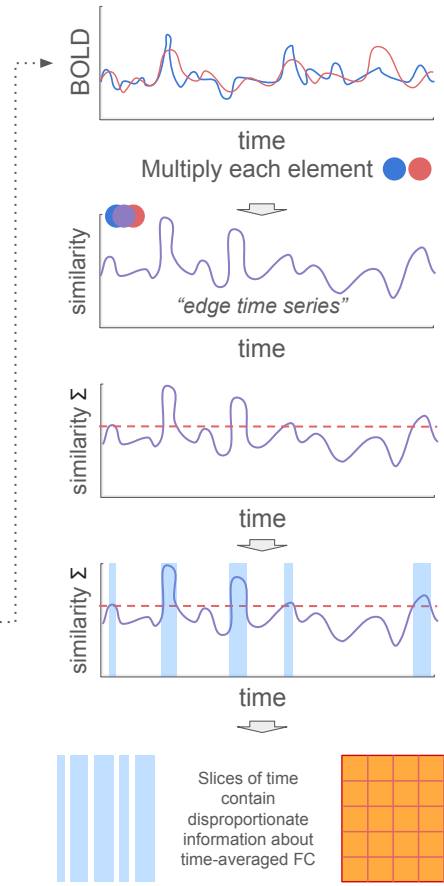
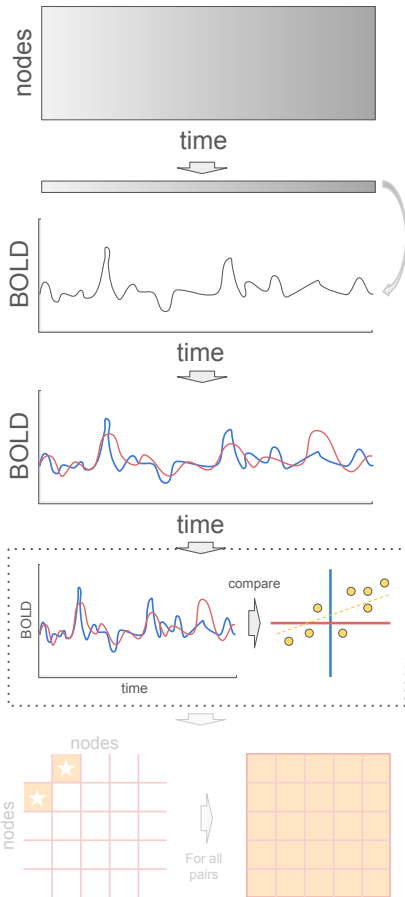


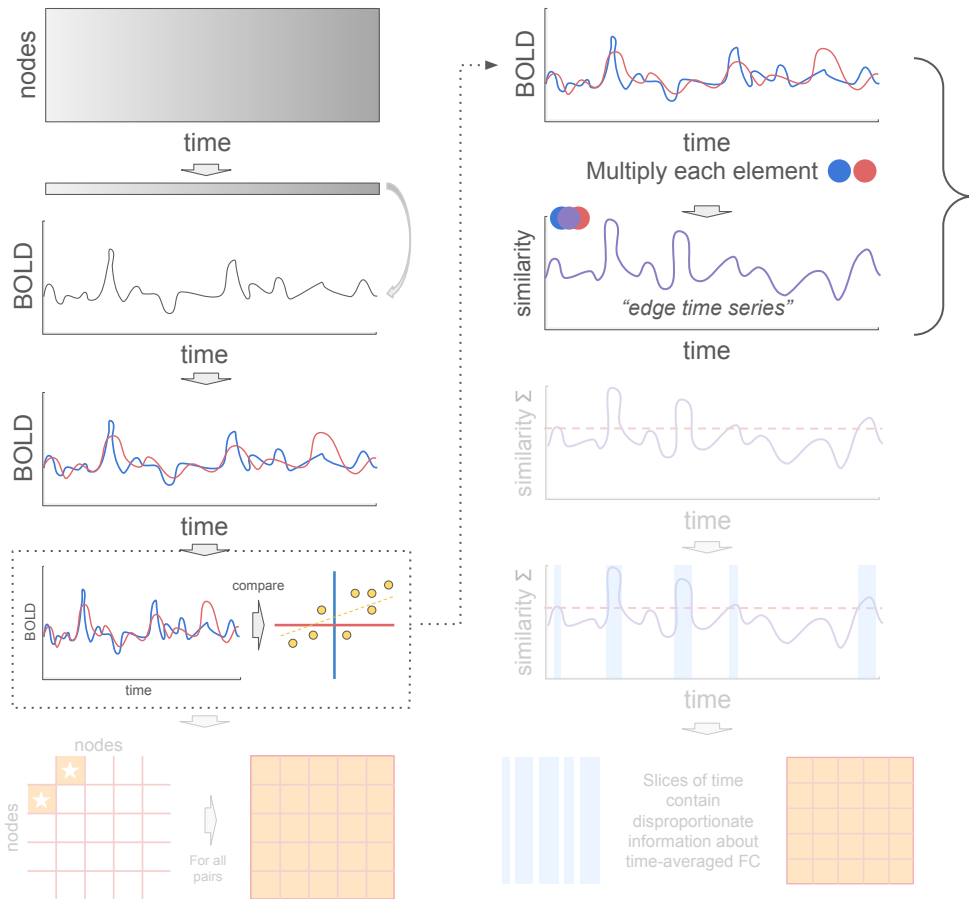
Finding where the “info” resides



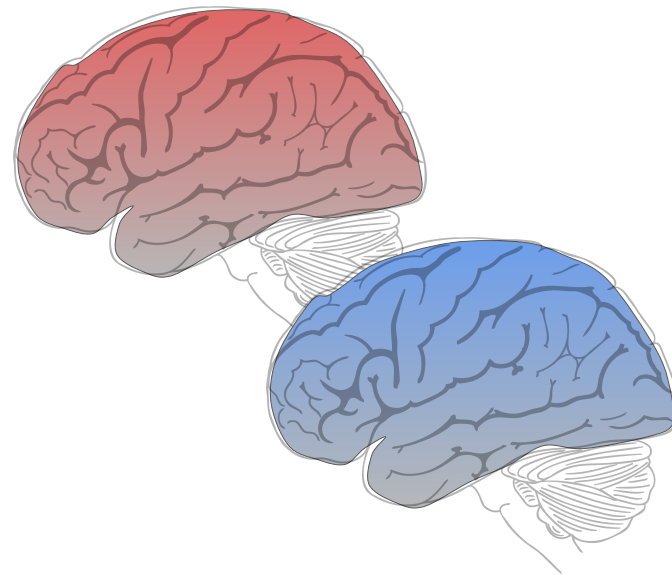
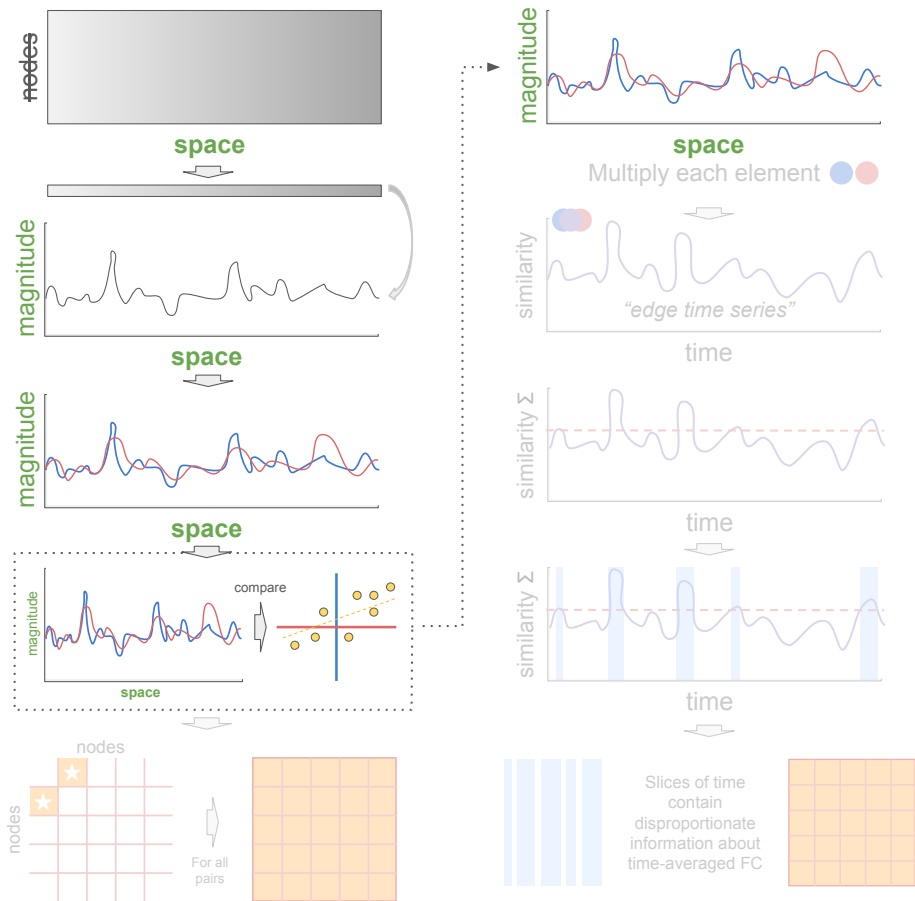
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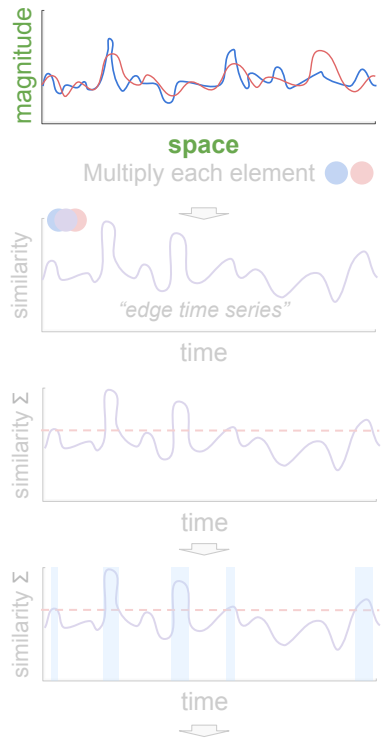
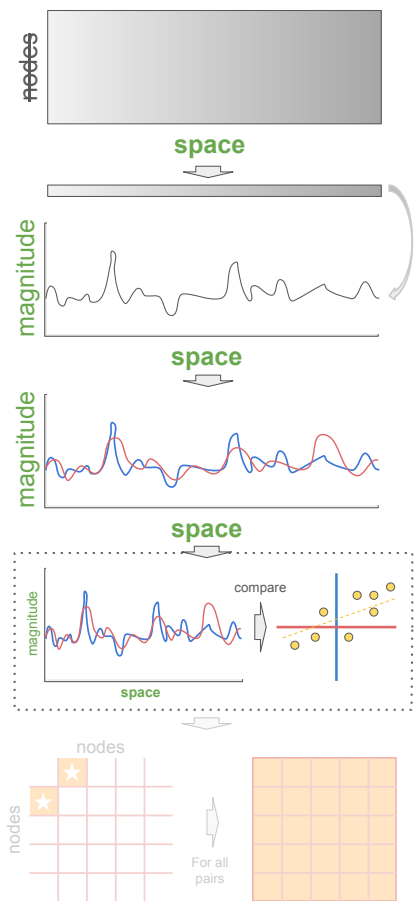




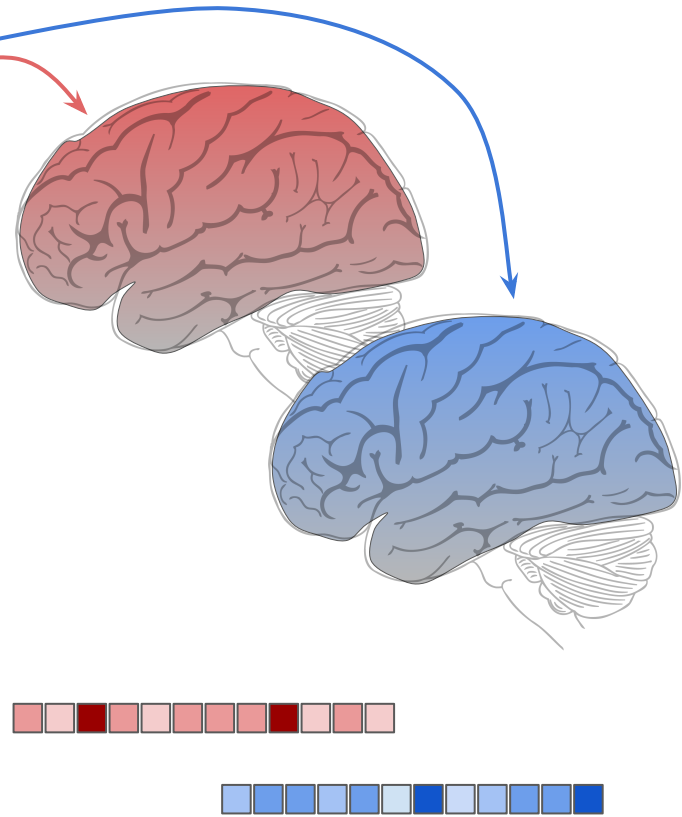
This “unwrapping” trick is not limited to time series correlations

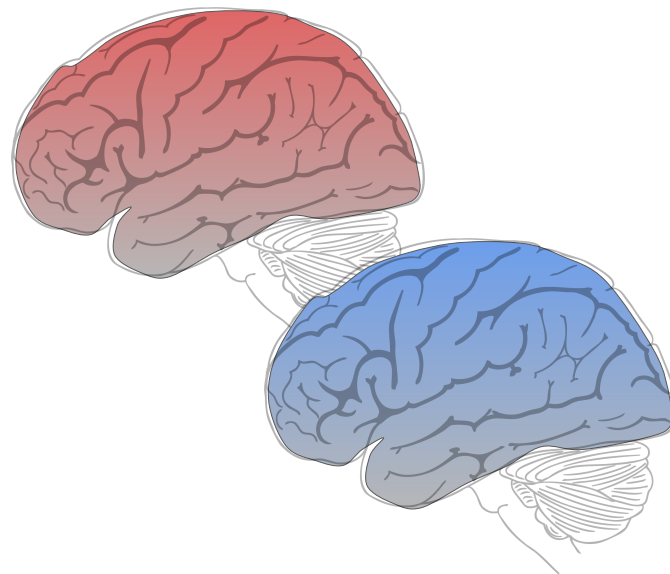
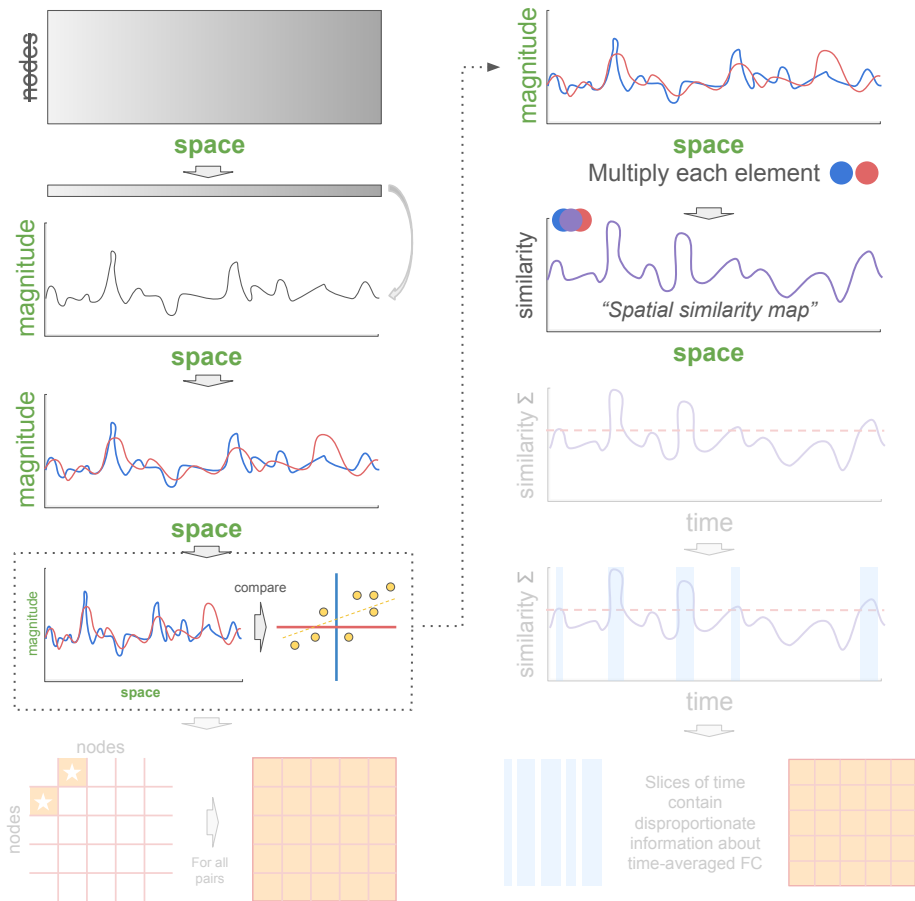


Replace *time* with *space*

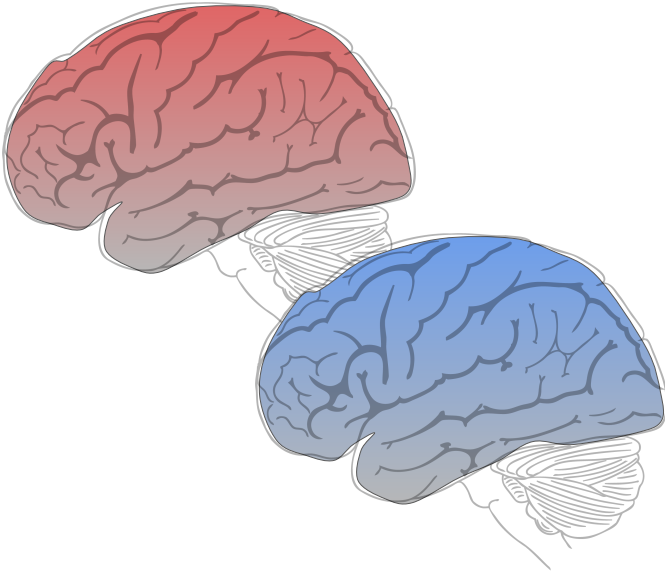


Slices of time contain disproportionate information about time-averaged FC

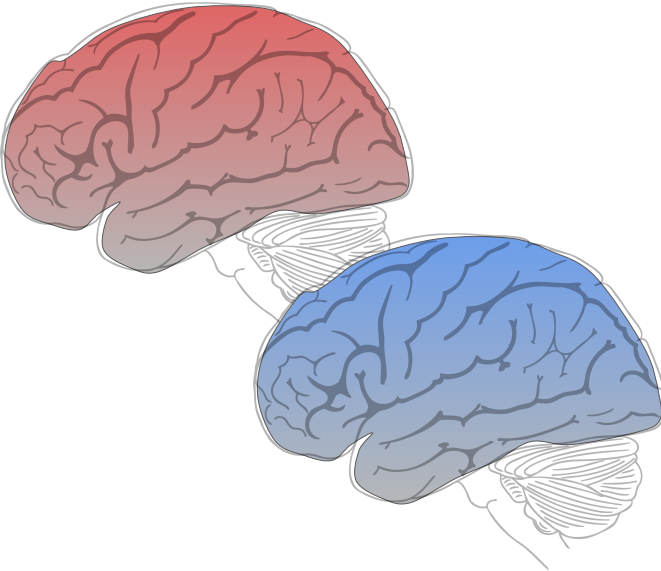




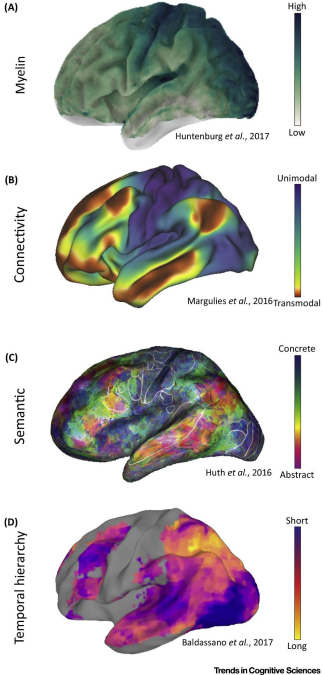
Why space?



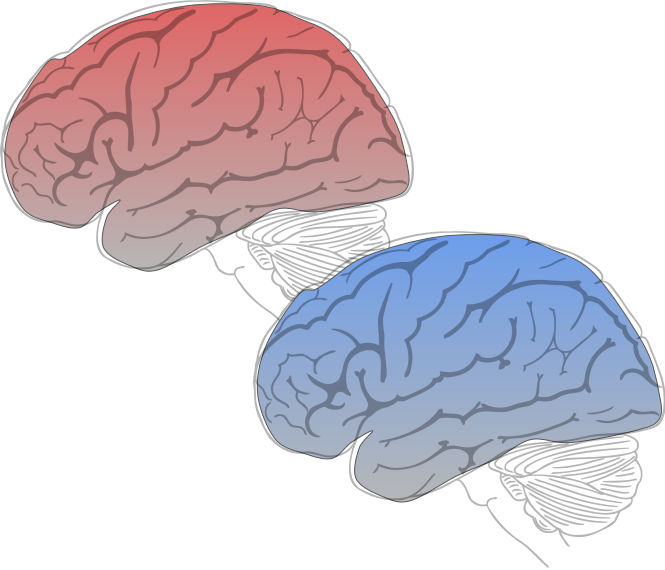
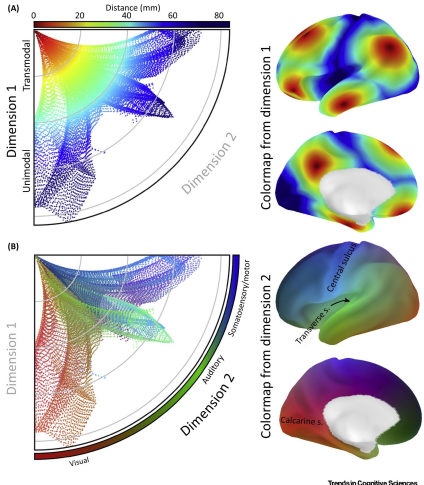
When do we spatially **correlate** brain maps?



When do we spatially correlate brain maps?



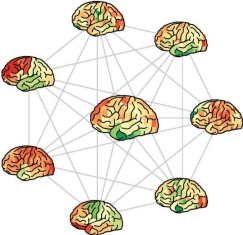
Validate the shared spatial patterning of your results / data



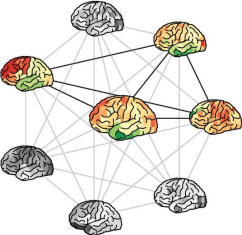
Huntenburg et al. (2018). *TICS*

When do we spatially correlate brain maps?

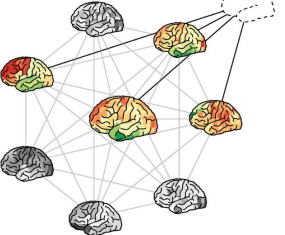
(A) Situating one brain map among others



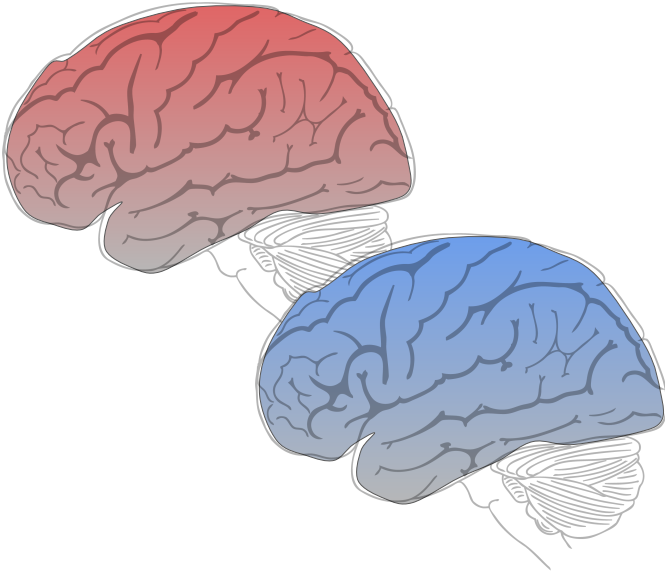
(B) Narrowing options



(C) Underlying latent effects



Trends in Neurosciences

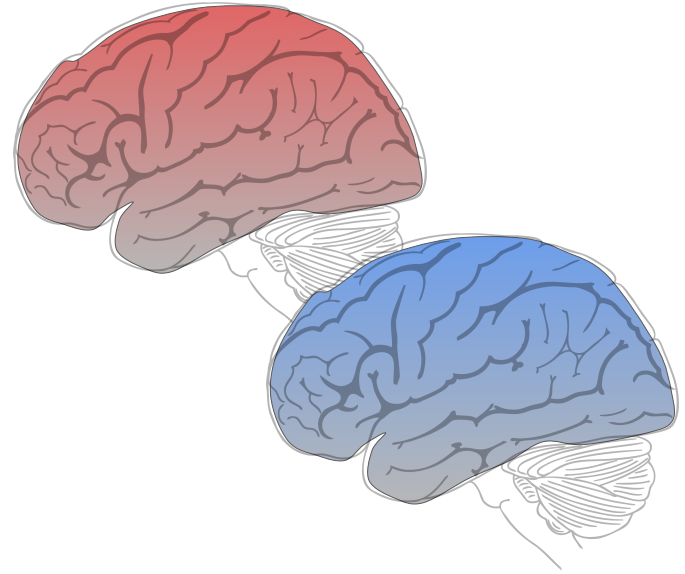


Situate patterns with respect to others,
to uncover additional info.

Hansen & Masic (2025). *TiN*

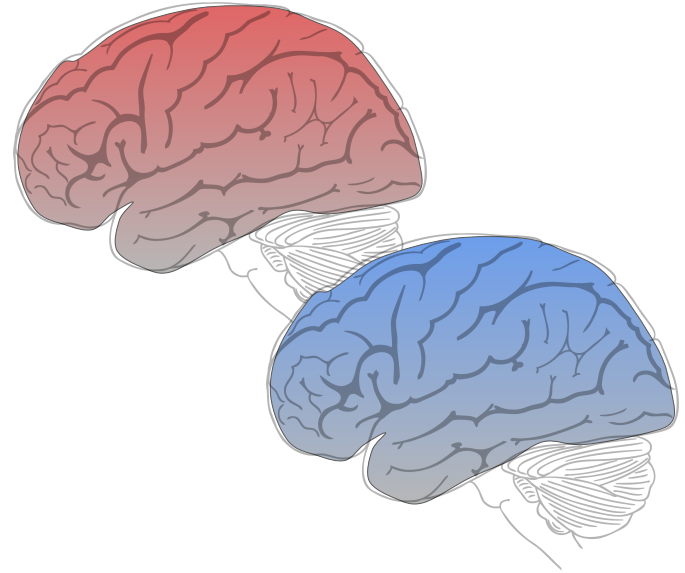
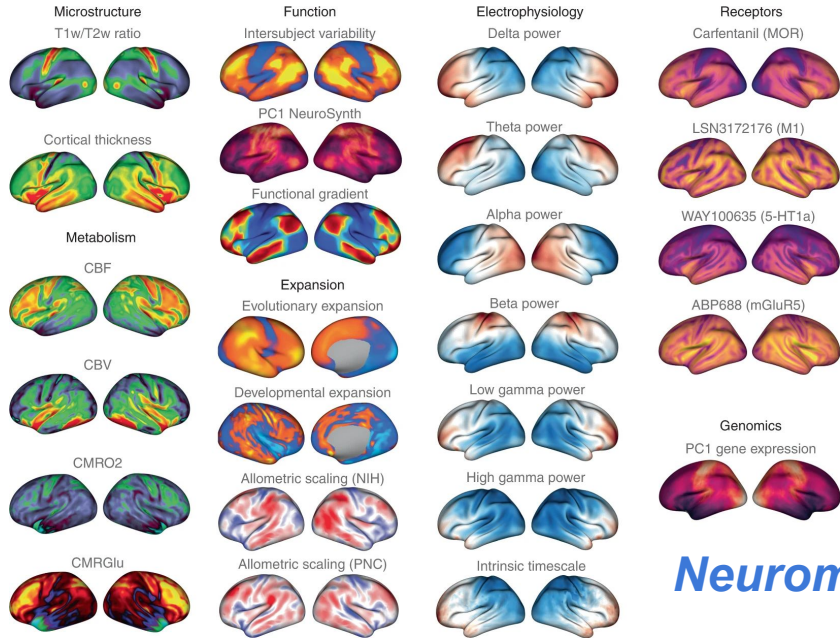
When do we spatially **correlate** brain maps?

All the time!

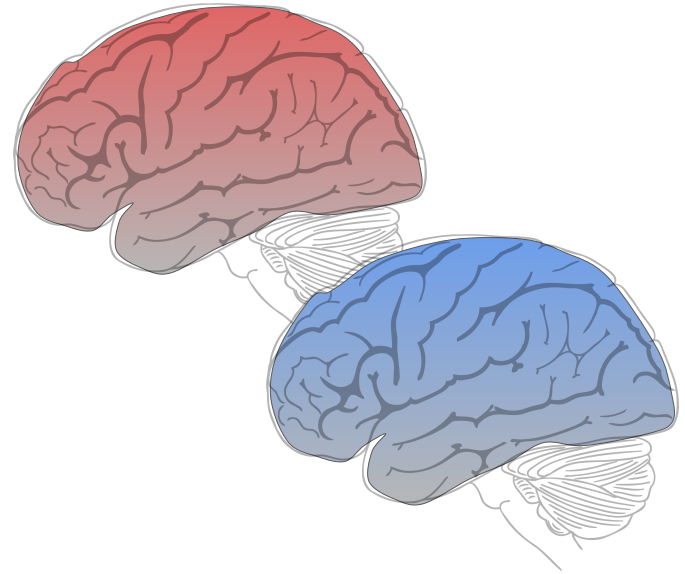


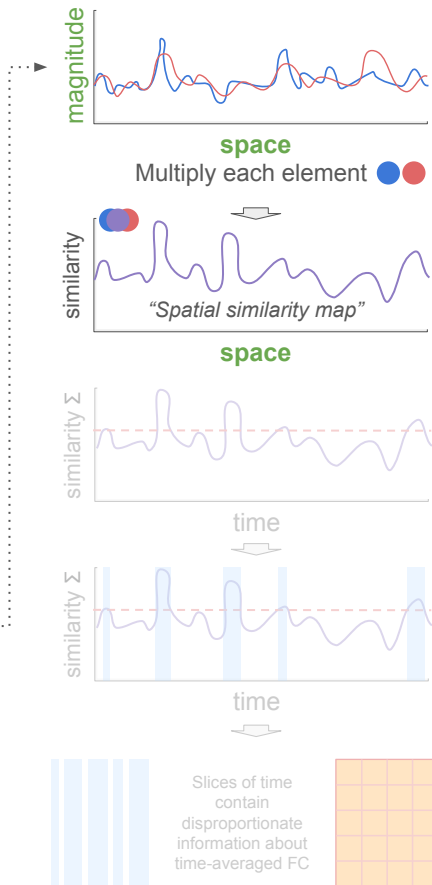
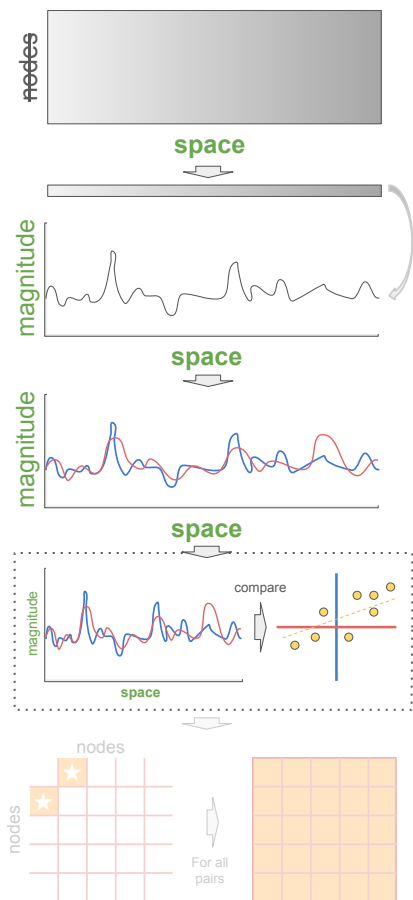
When do we spatially correlate brain maps?

All the time!

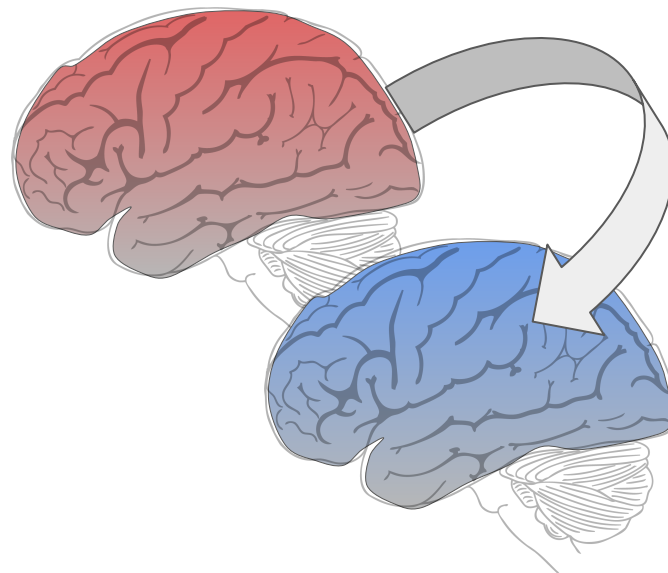


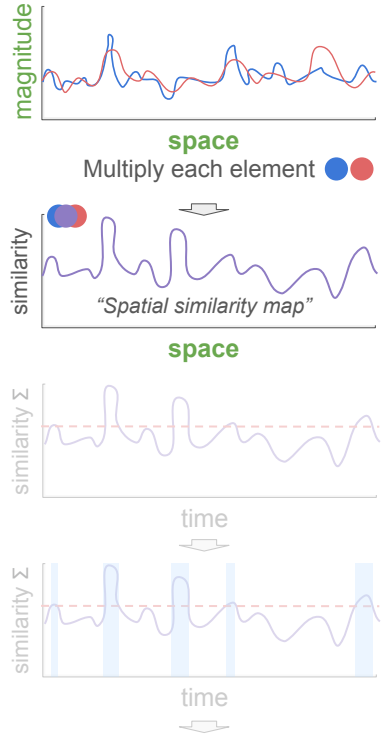
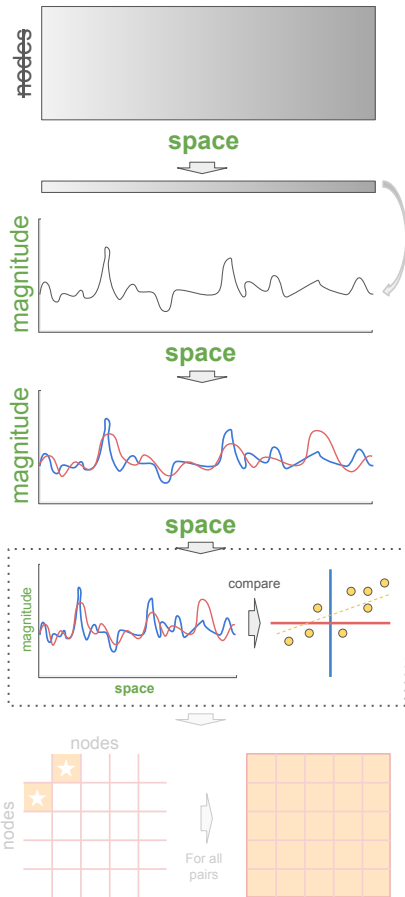
Markello et al. (2022). *Nat. Methods*



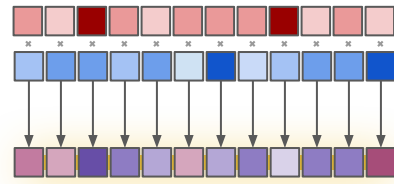
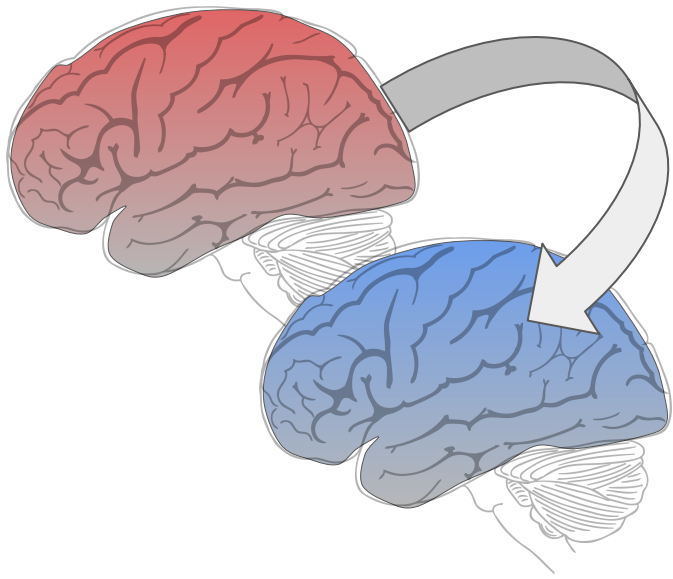


Instead of one r value

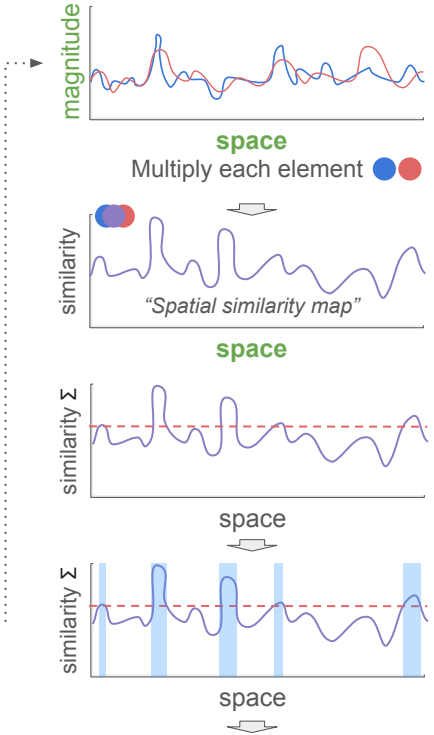
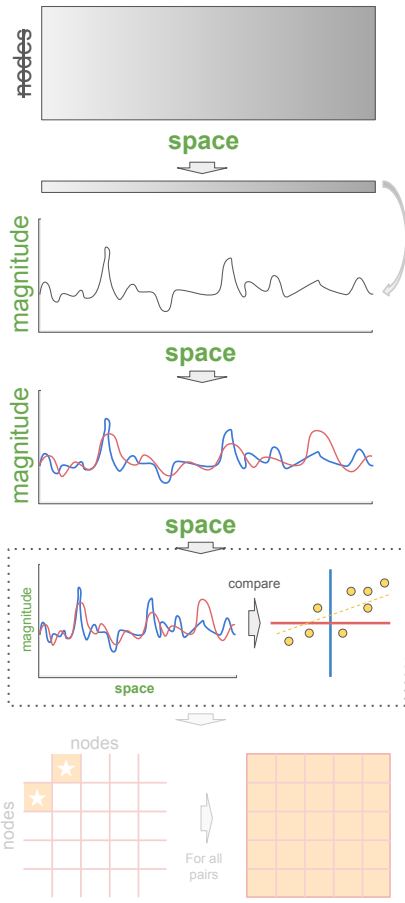




Instead of one r value

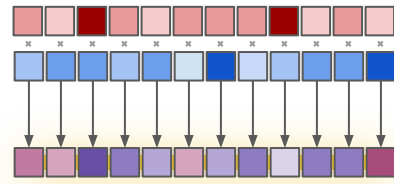
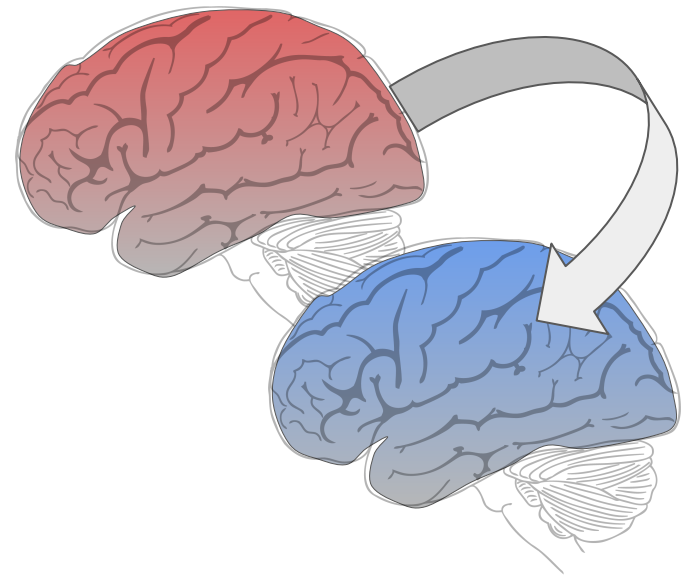


We can get a map of **similarity**



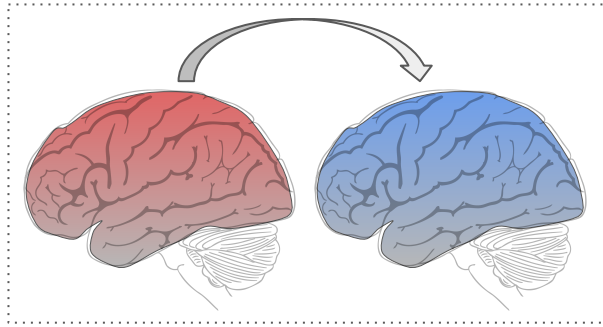
Look for information in the unwrapped correlation that we would not have observed before with Pearson's r

Instead of one r value

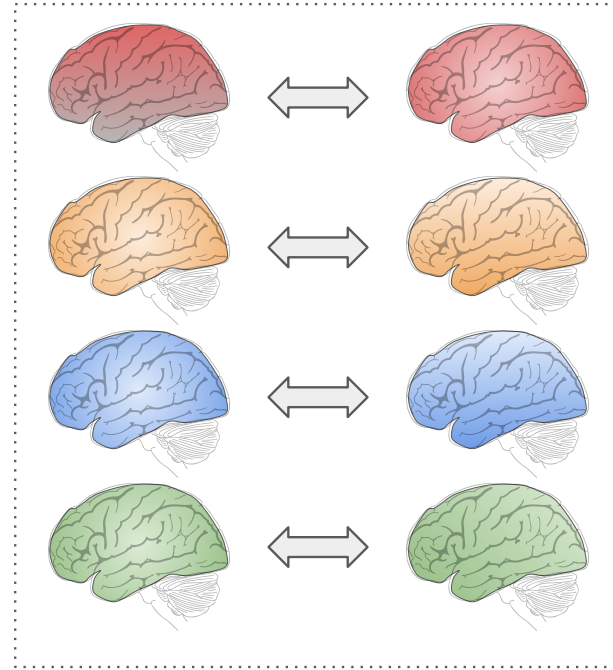


We can get a map of **similarity**

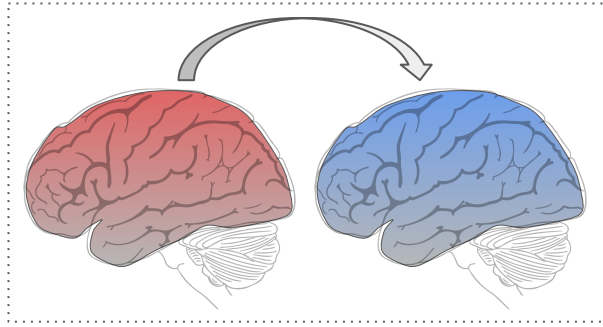
Demonstrations



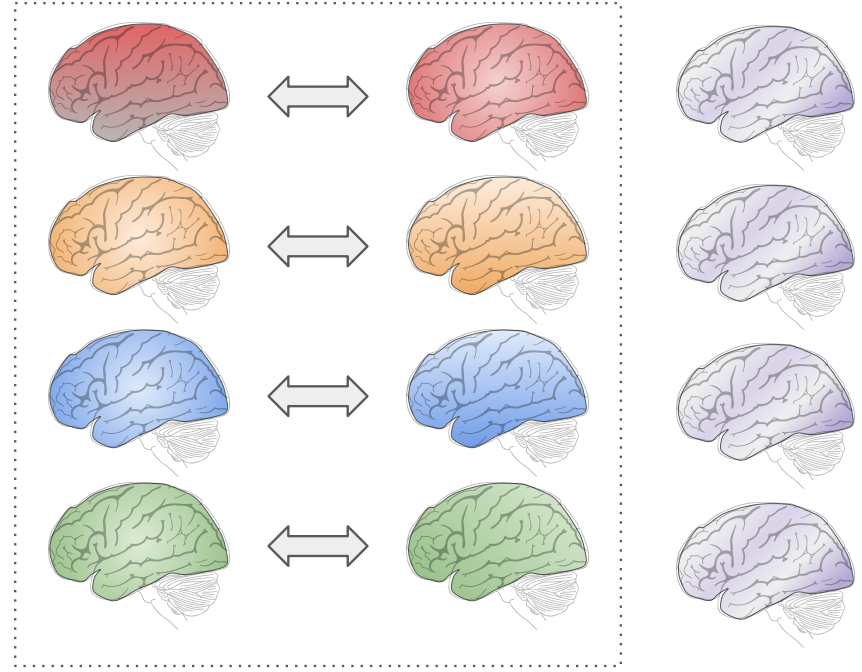
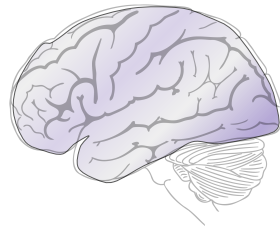
Map to map



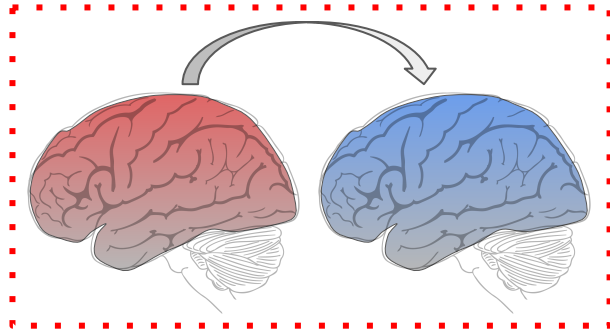
Test-retest



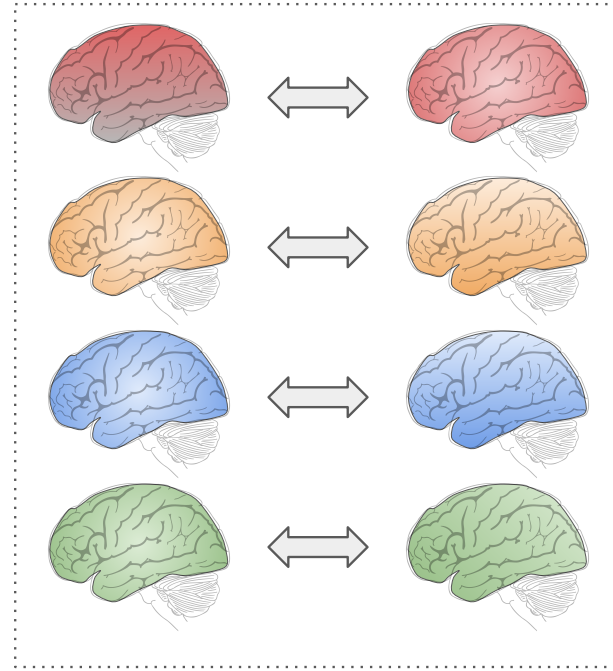
Map to map



Test-retest

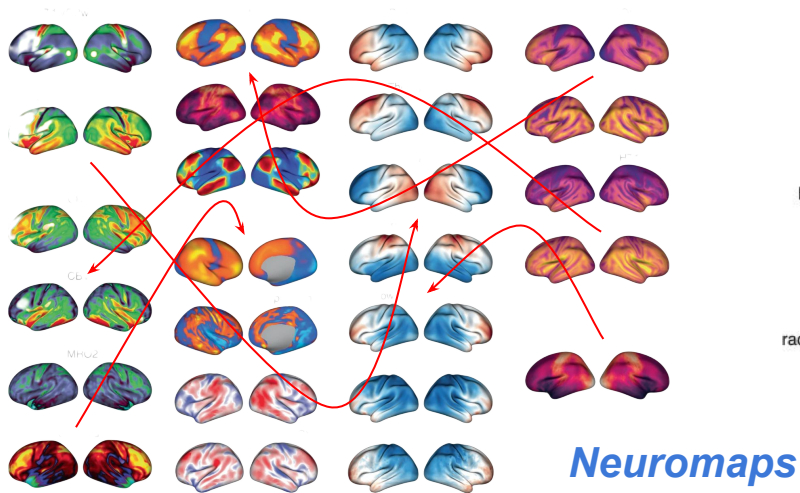


Map to map

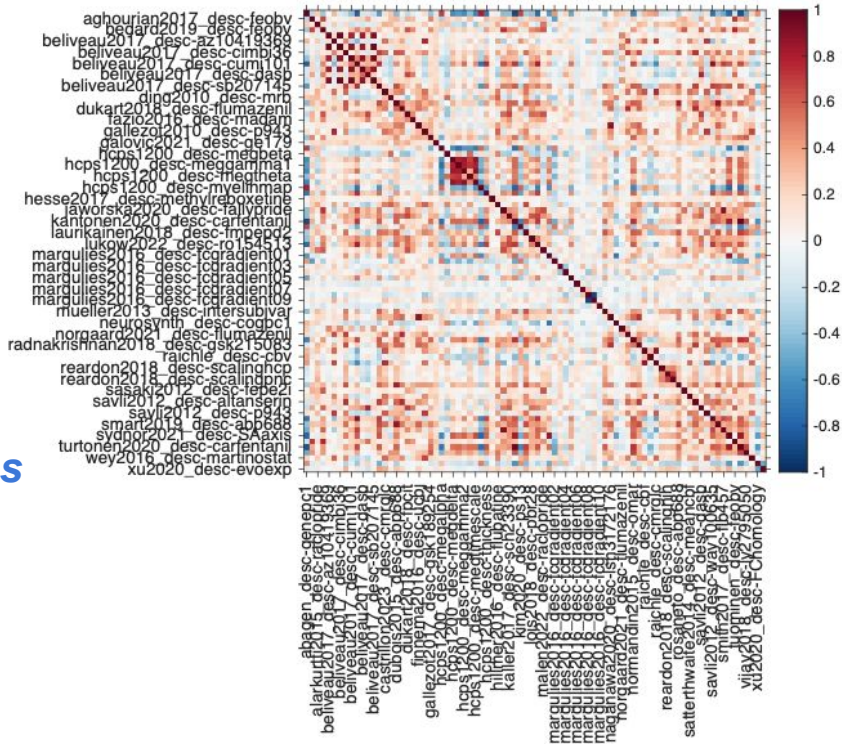


Test-retest

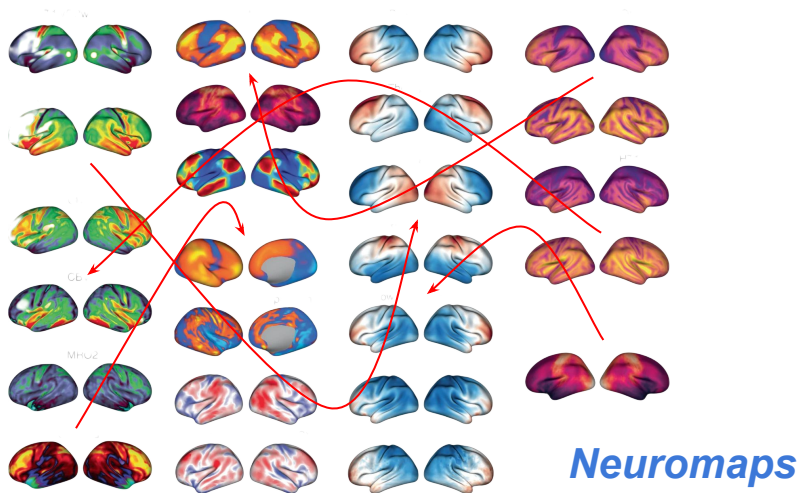
One map to another



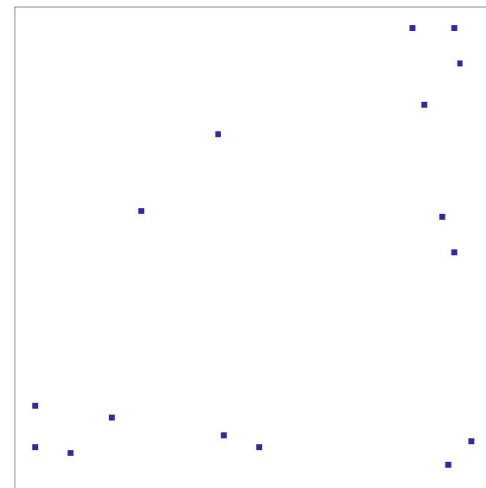
Markello et al. (2022). *Nat. Methods*



One map to another

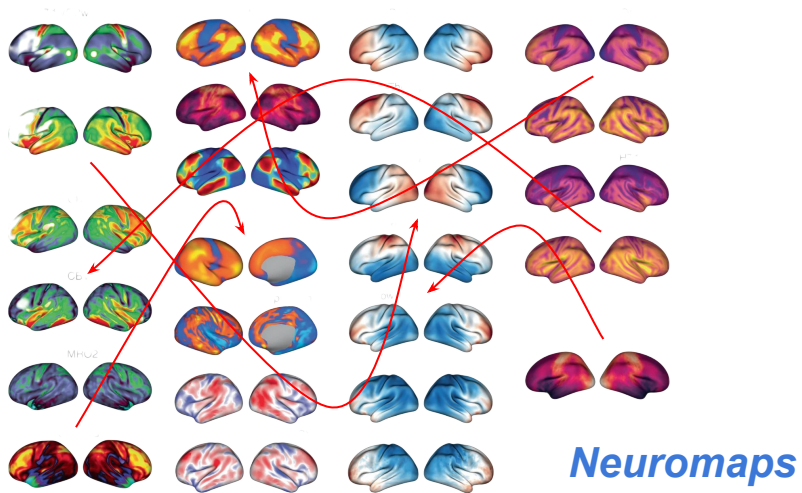


Markello et al. (2022). *Nat. Methods*

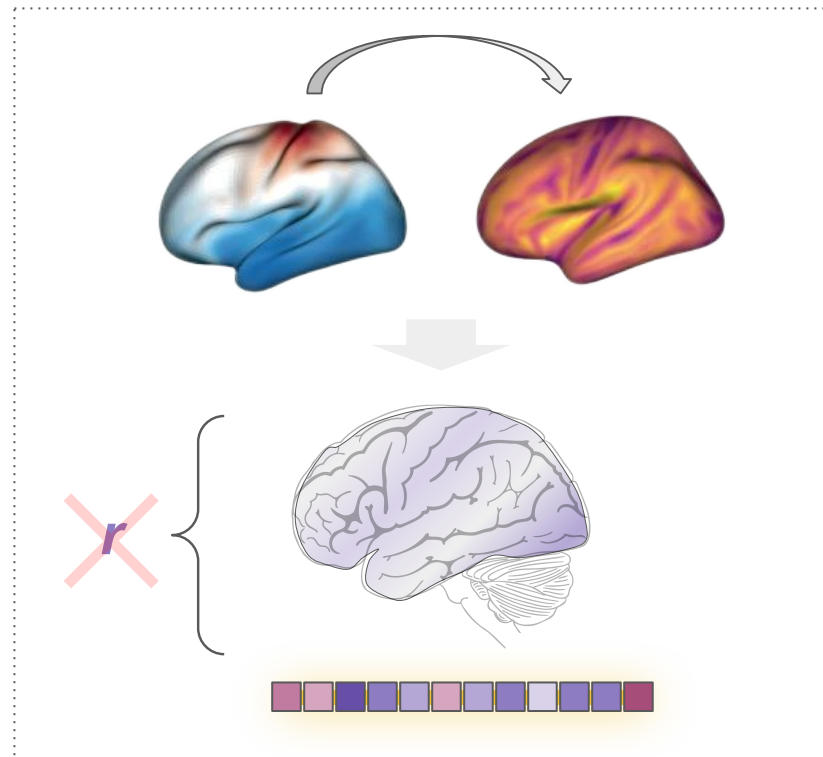


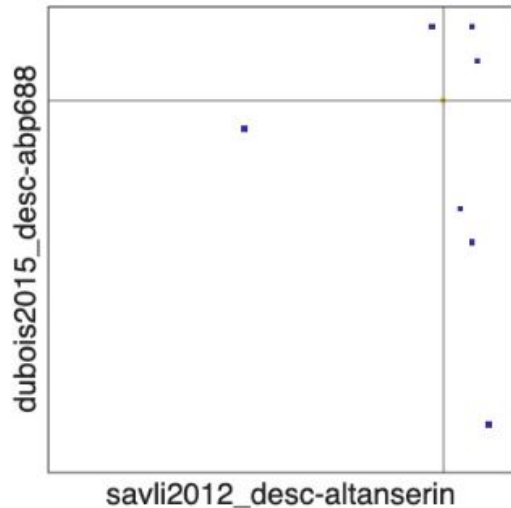
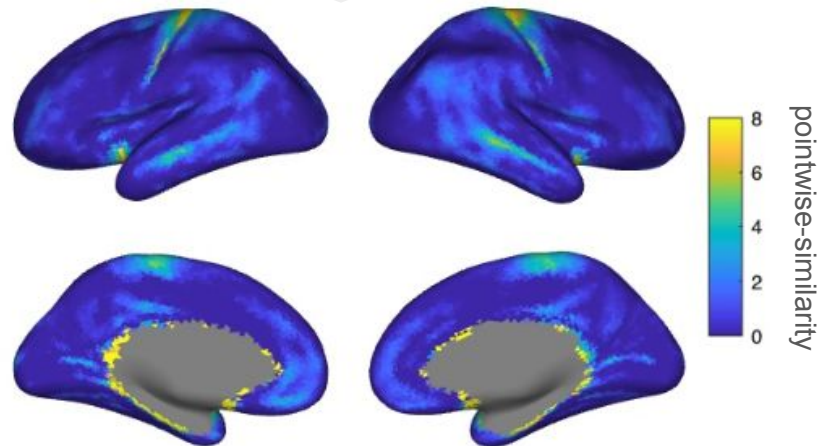
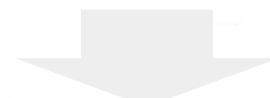
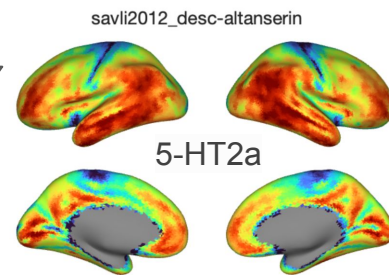
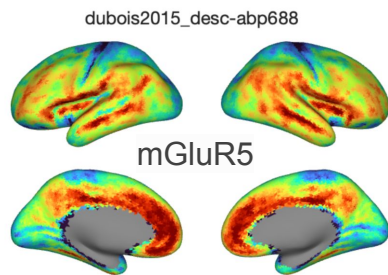
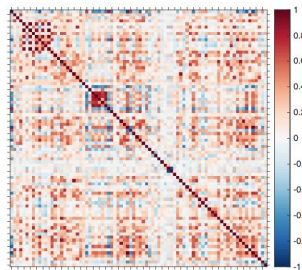
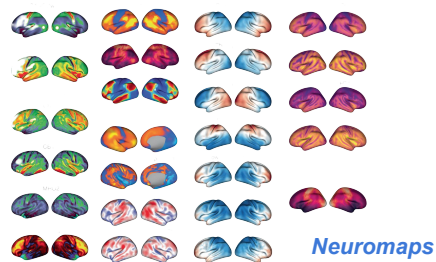
Let's pick out the correlations
within 0.002 of $r=0.6$

One map to another

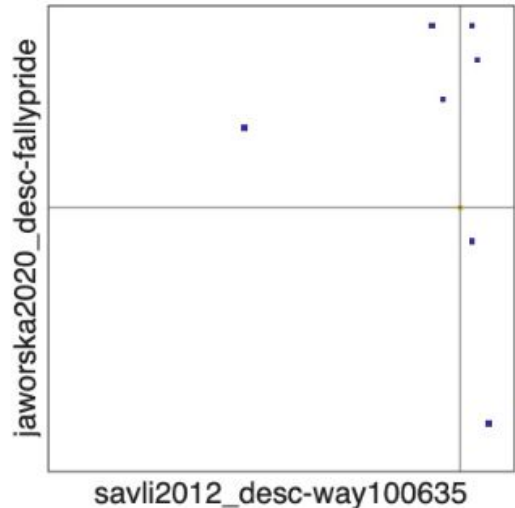
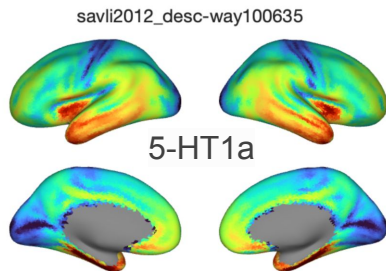
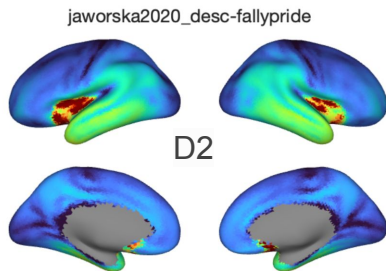
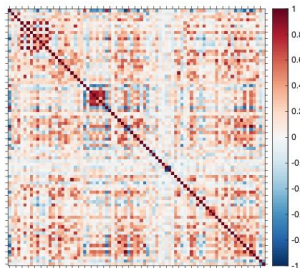
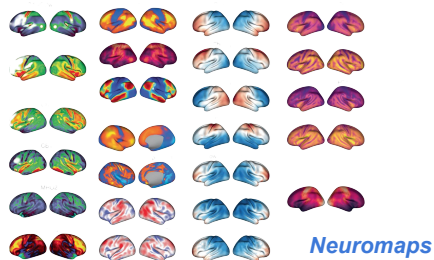


Markello et al. (2022). *Nat. Methods*

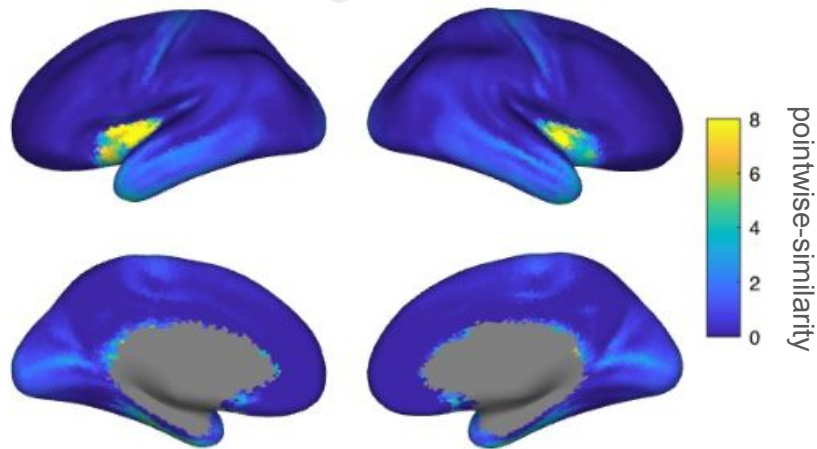


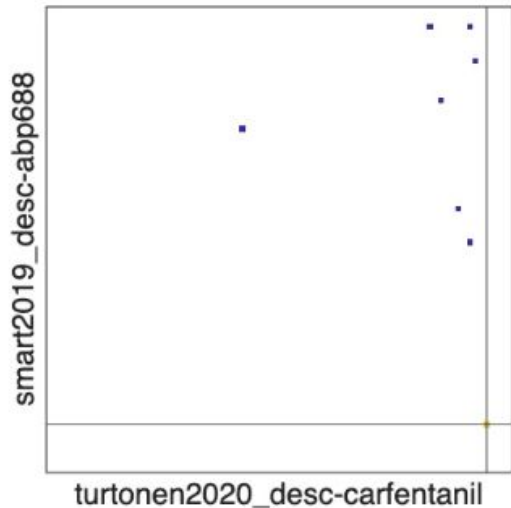
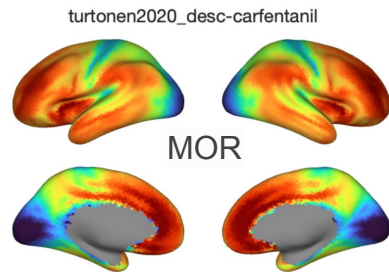
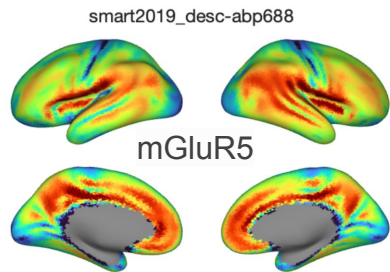
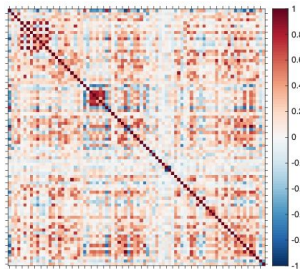
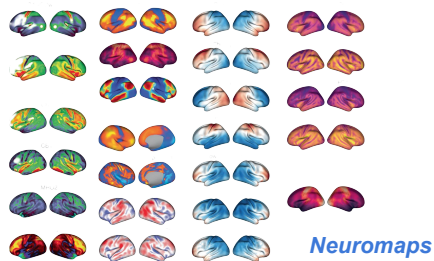


$$r = 0.59838$$

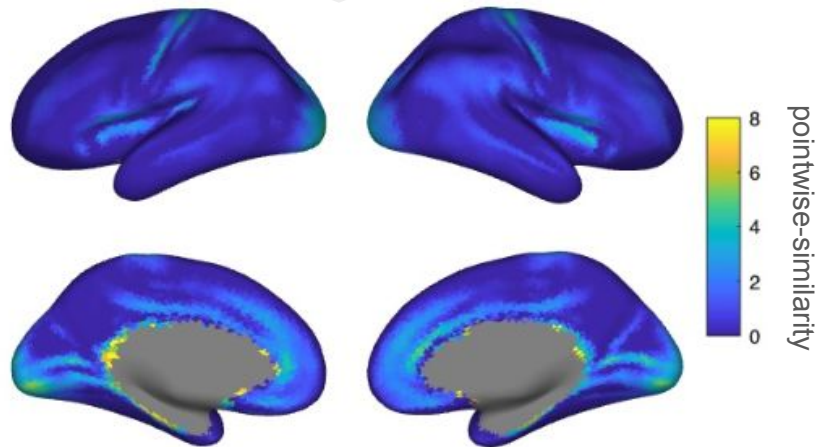


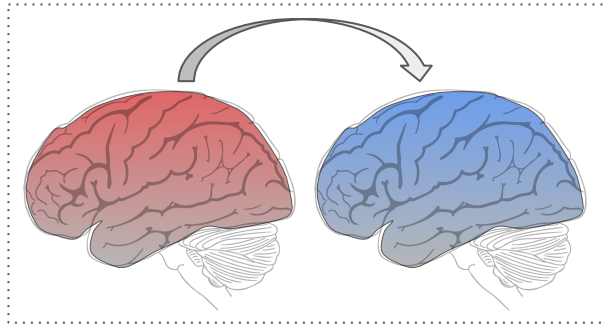
$$r = 0.60022$$



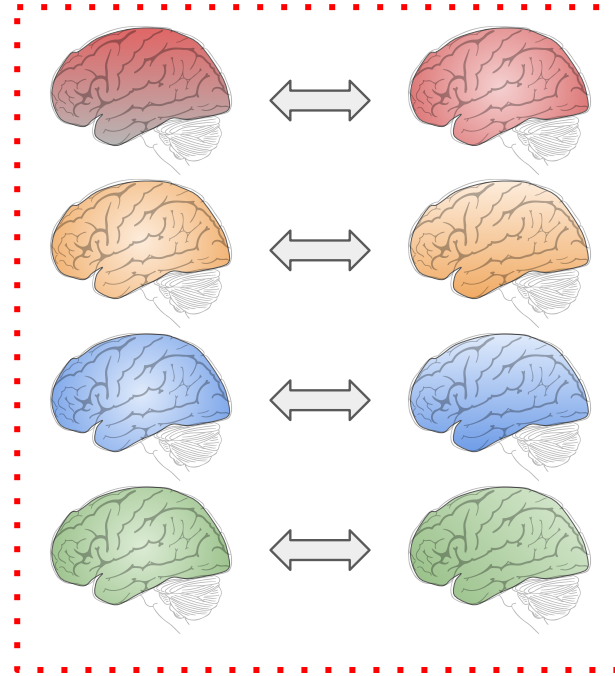


$$r = 0.59879$$



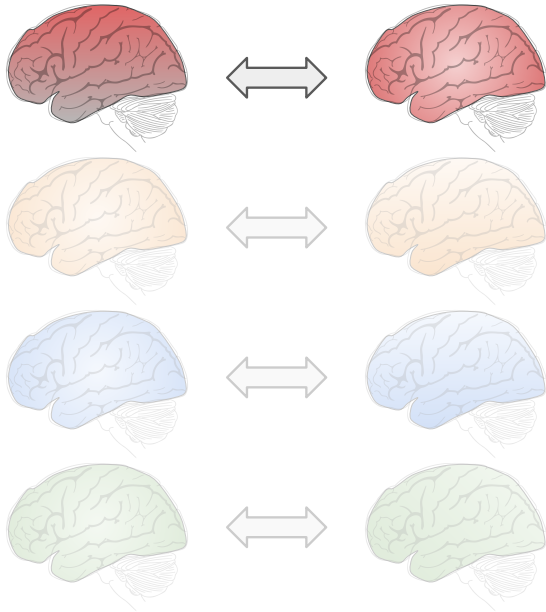


Map to map

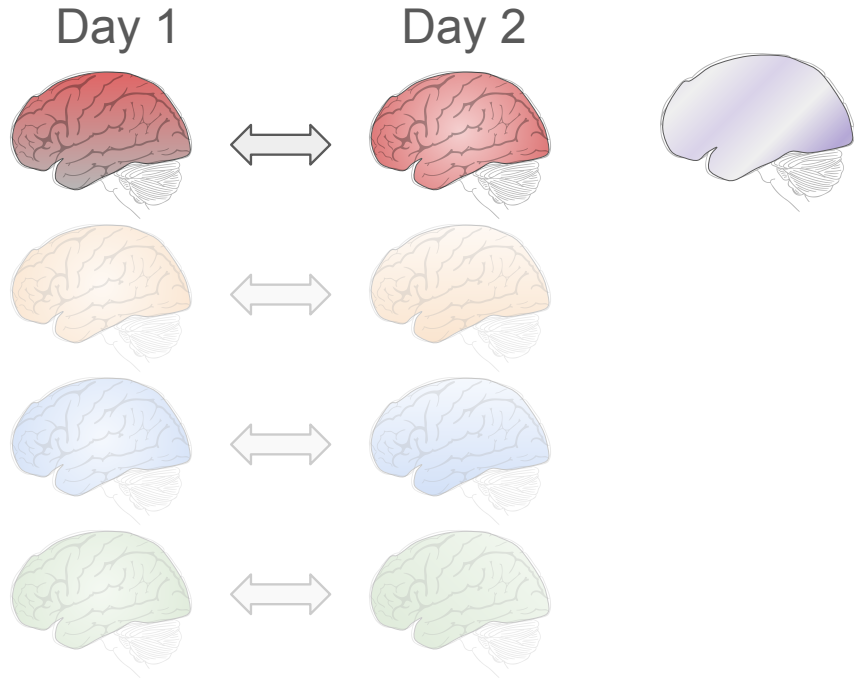


Test-retest

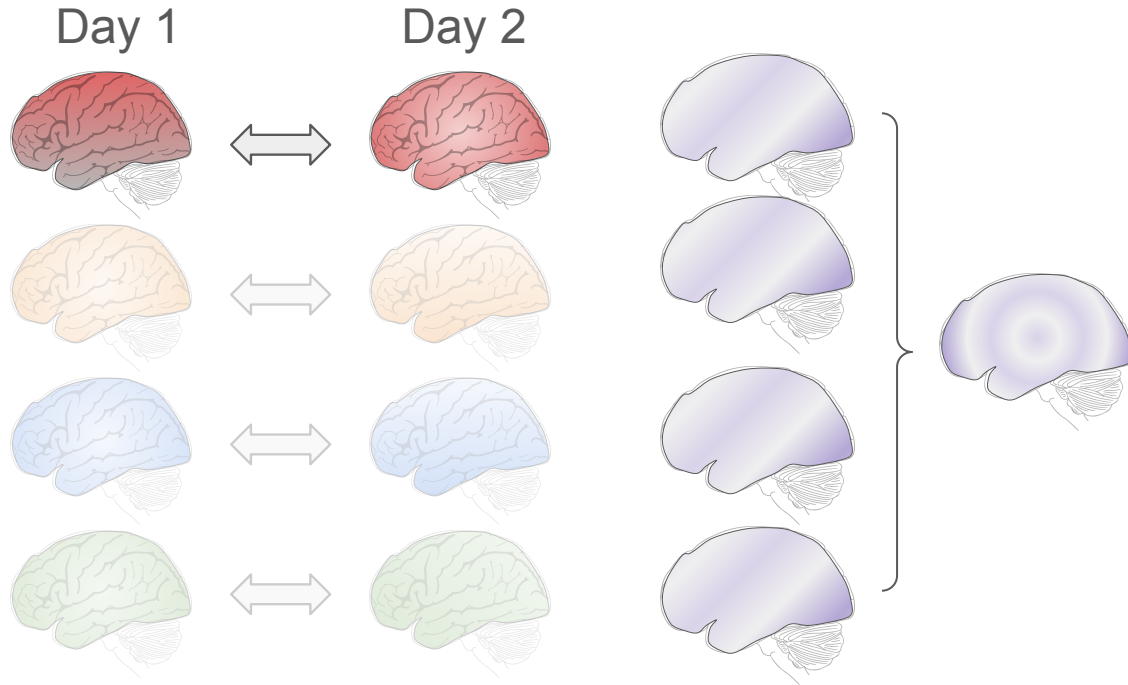
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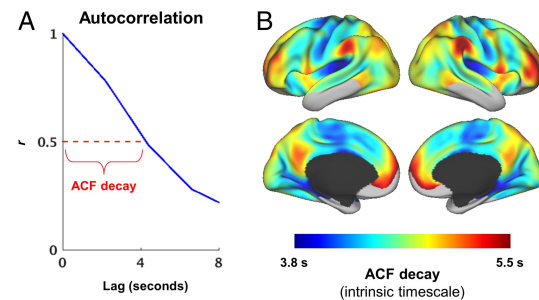
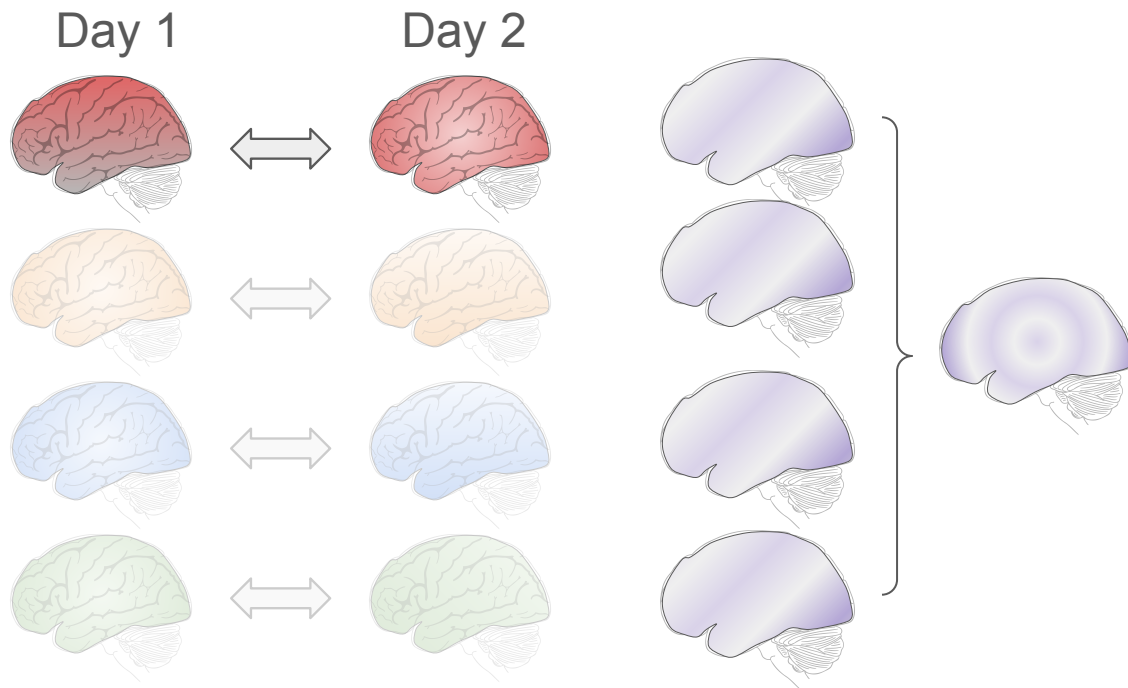
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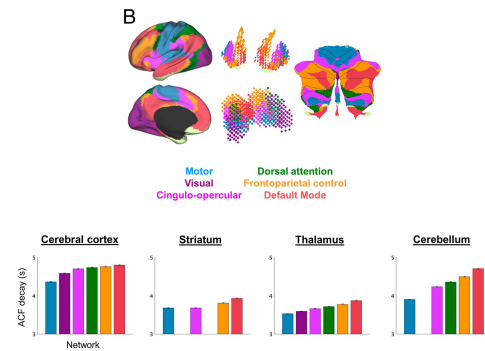
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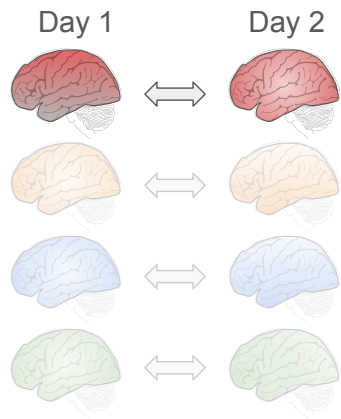
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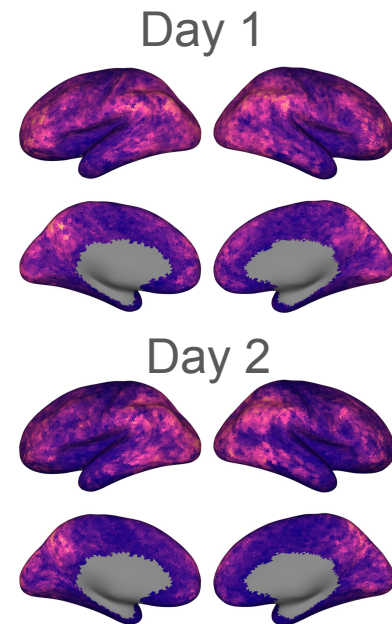
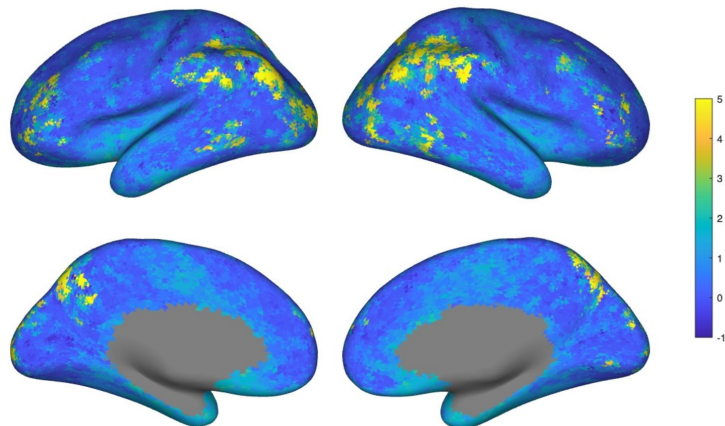
Raut et al. (2020). *PNAS*



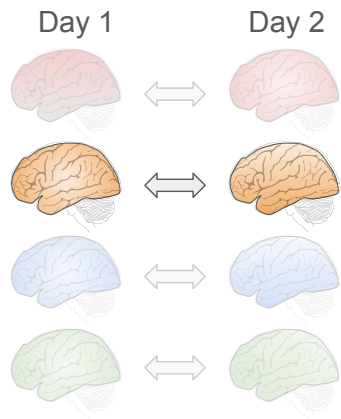
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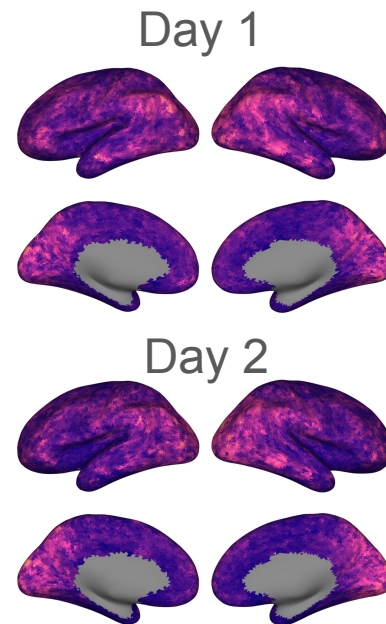
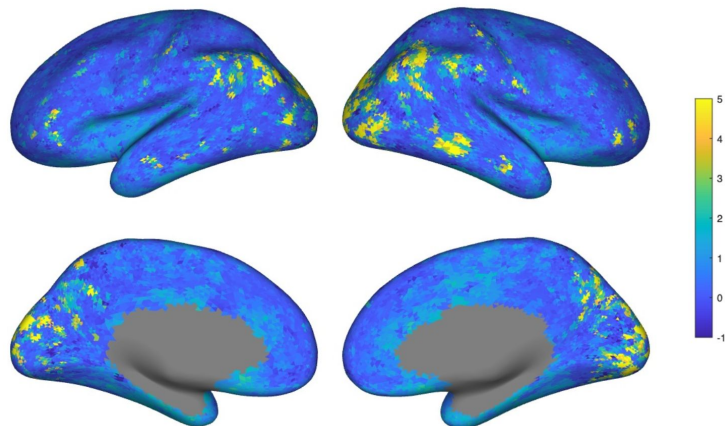
Spatial similarity map of autocorrelation for subject A



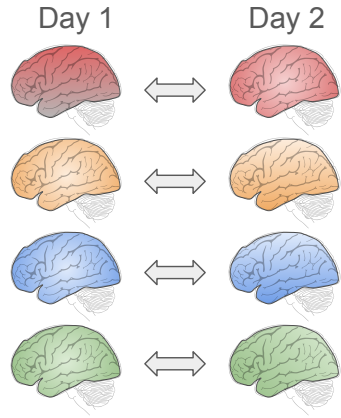
Test-retest



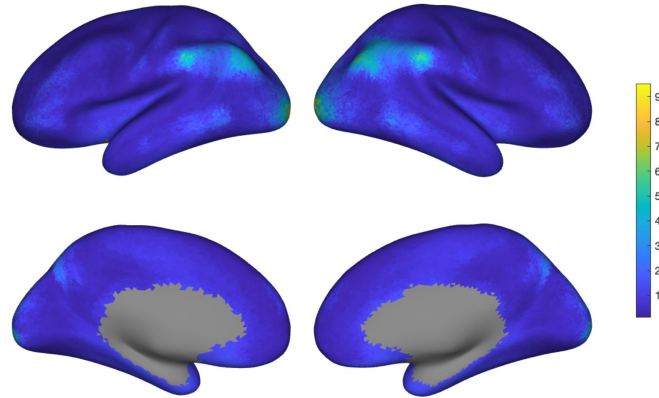
Spatial similarity map of autocorrelation for subject B



Test-retest

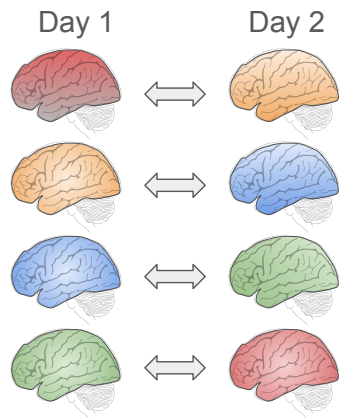


Spatial similarity map of autocorrelation averaged (N=352)

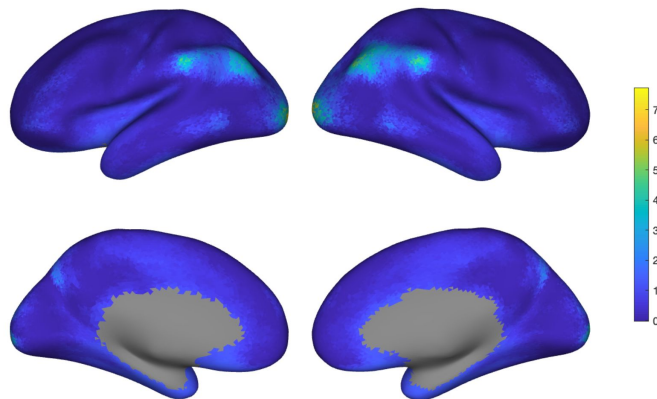


Within-subject similarity

Test-retest

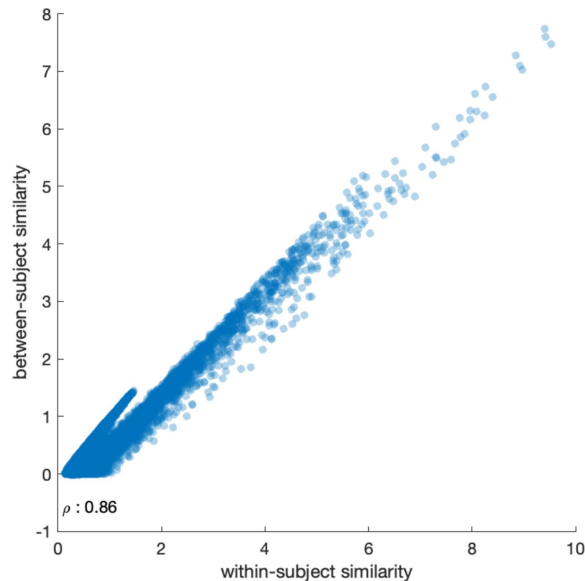
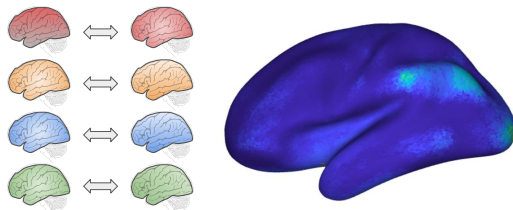


Spatial similarity map of autocorrelation averaged (N=352)

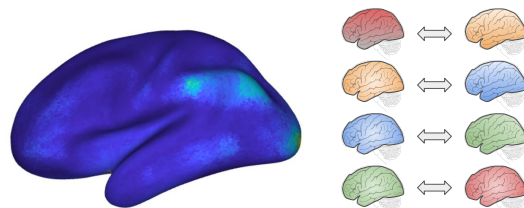


Between-subject similarity

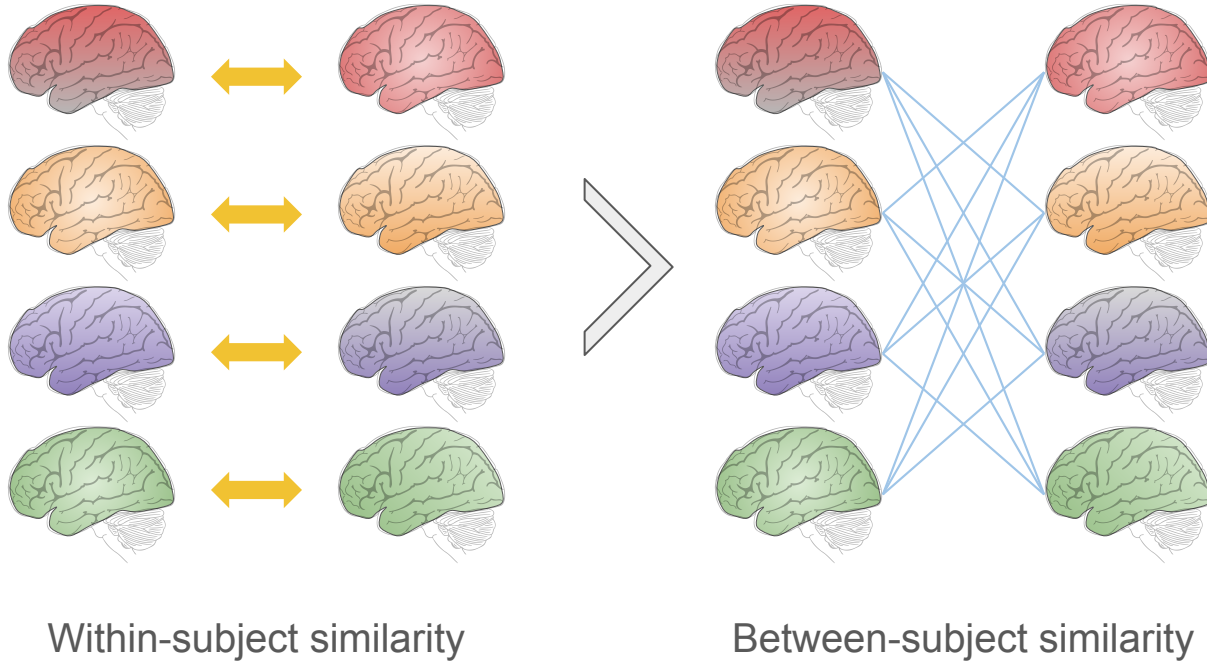
Within vs. between-subject similarity?



Within- and between-subject similarity “driven” by data at the same locations?



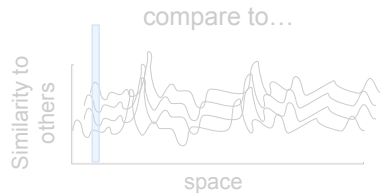
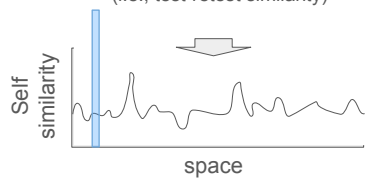
Individual specific information



Individual specific information



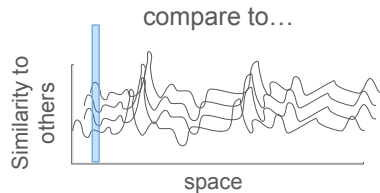
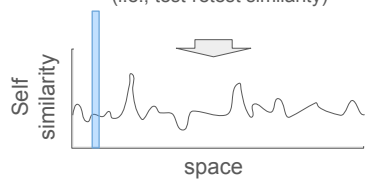
Where each row is a subject's self spatial similarity map (i.e., test-retest similarity)



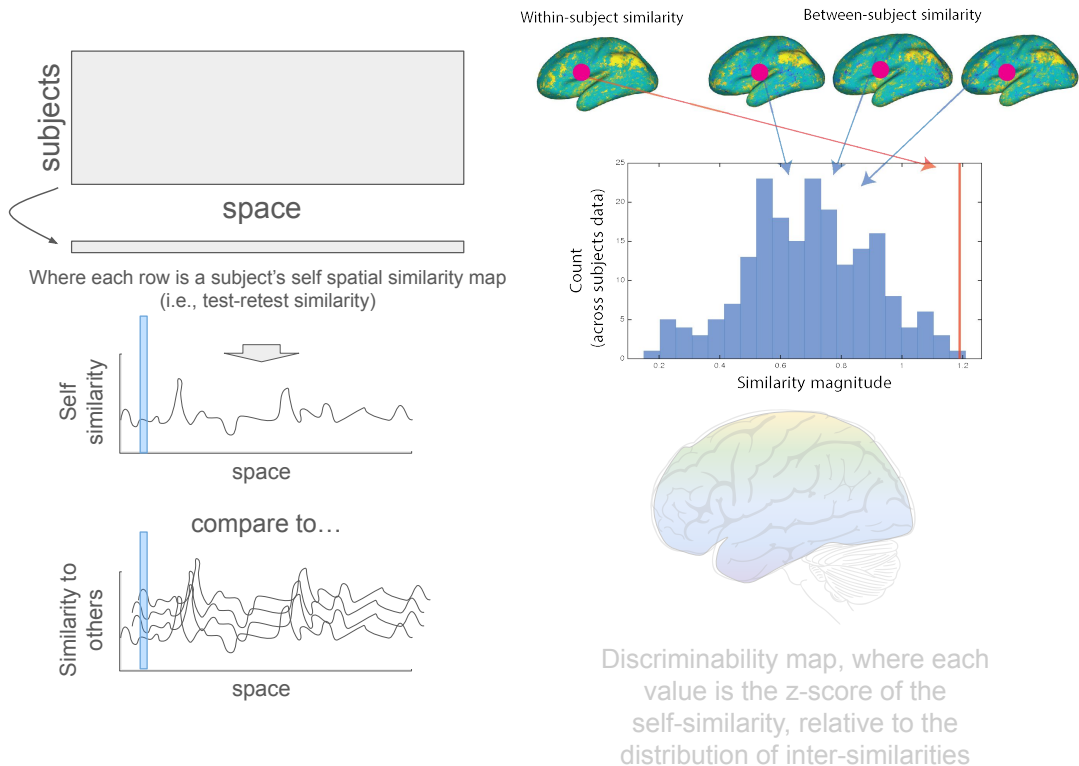
Individual specific information



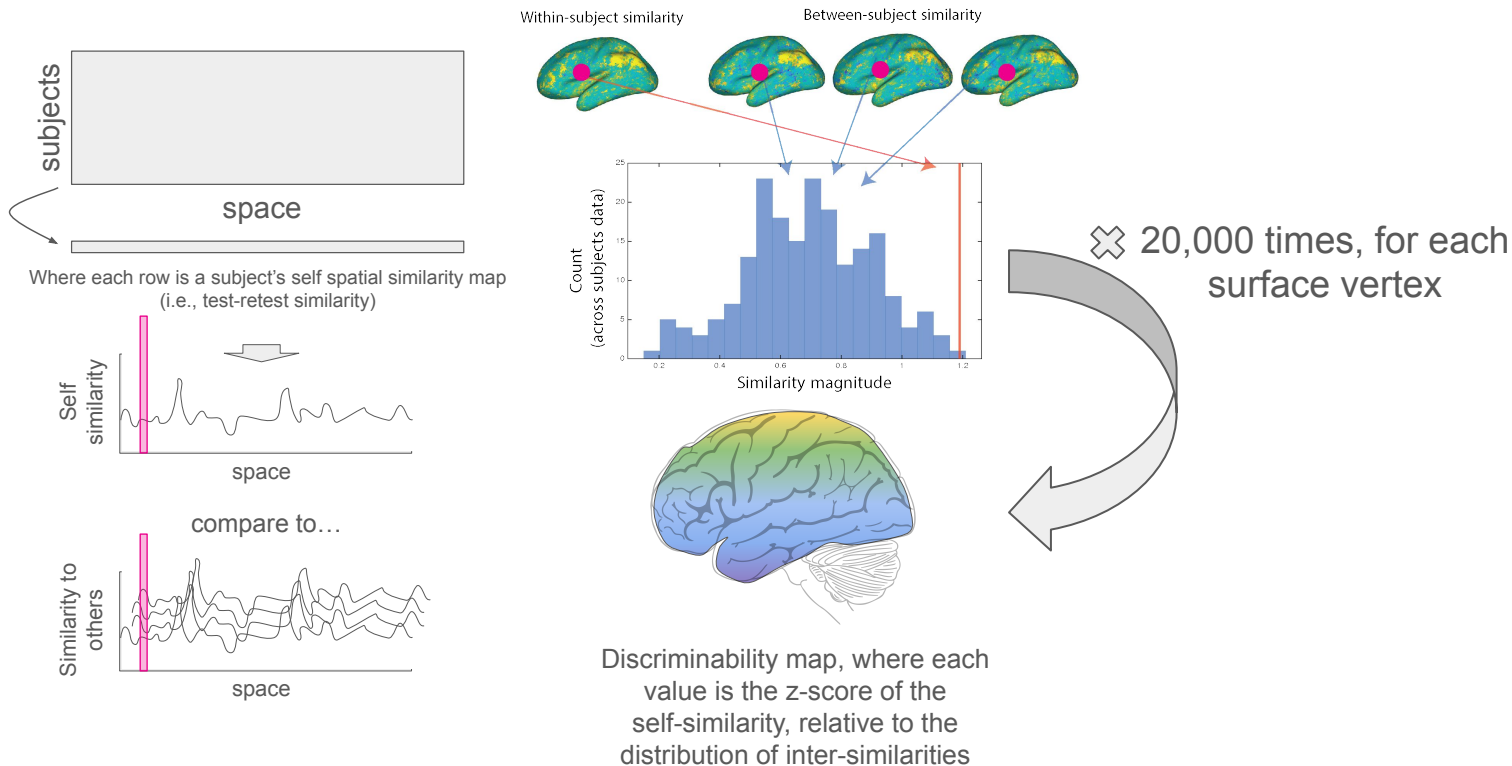
Where each row is a subject's self spatial similarity map (i.e., test-retest similarity)



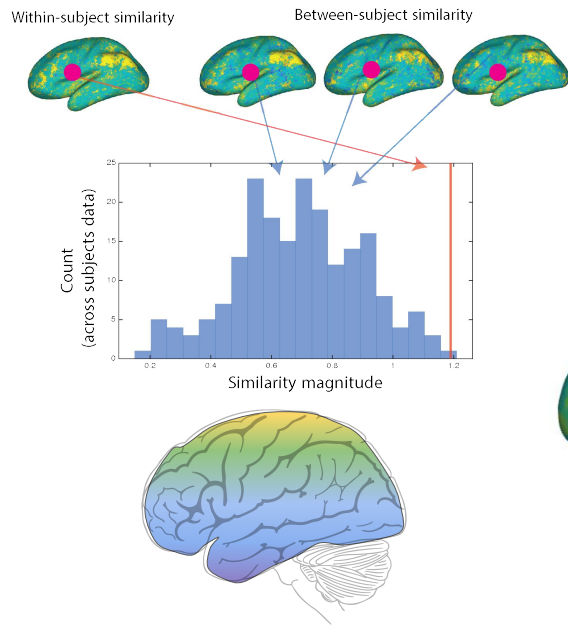
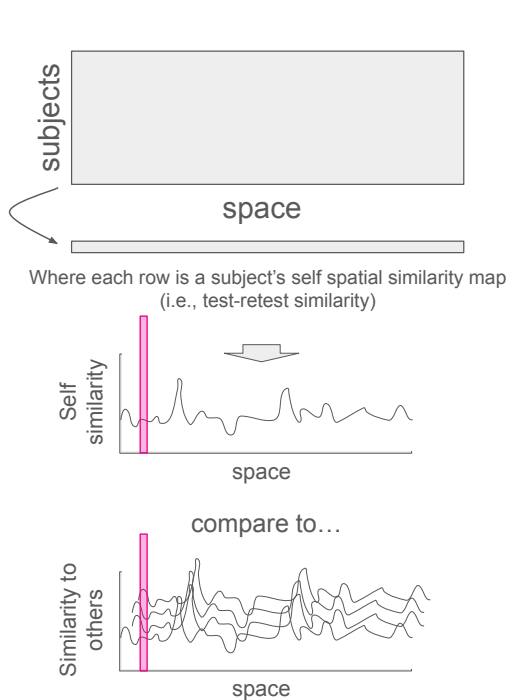
Individual specific information



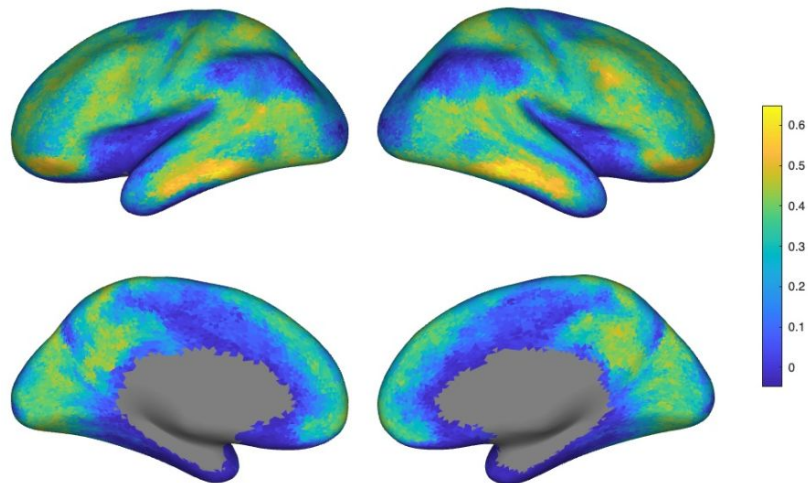
Individual specific information



Individual specific information



Average spatial distribution of subject discriminability

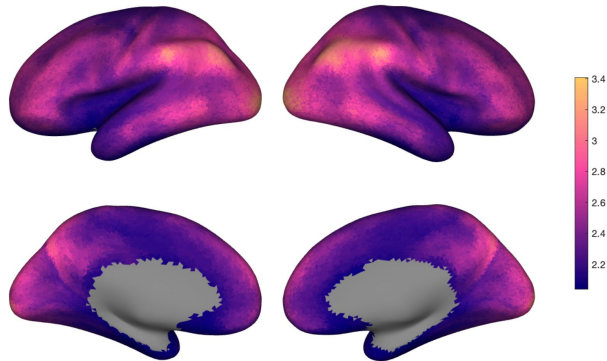


Discriminability map, where each value is the z-score of the self-similarity, relative to the distribution of inter-similarities

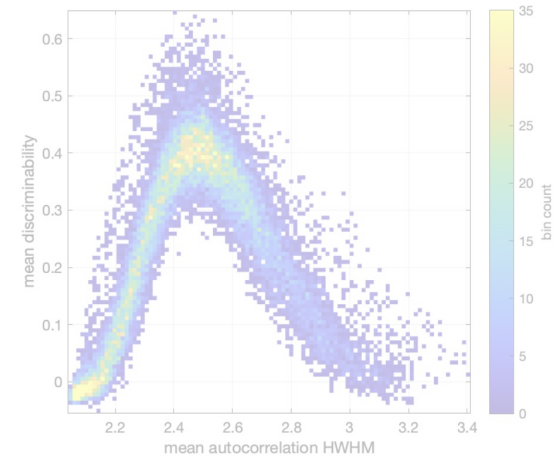
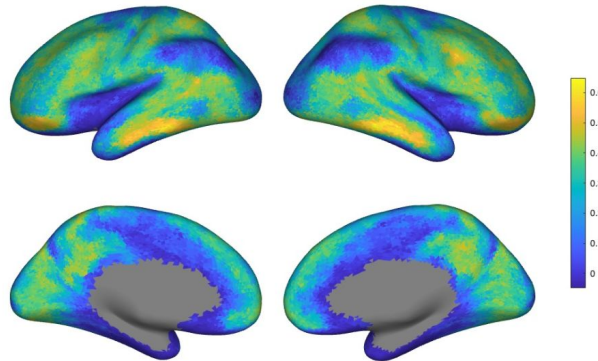


Individual specific information

Average HWHM autocorrelation

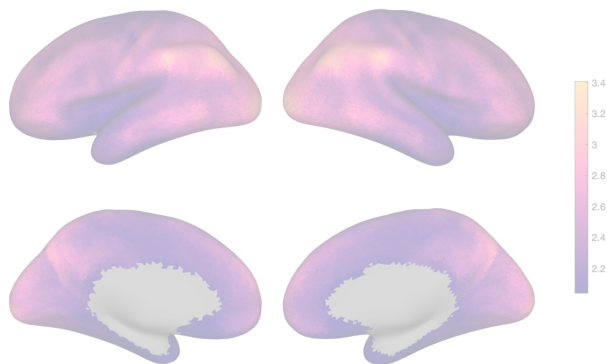


Average spatial distribution of subject discriminability

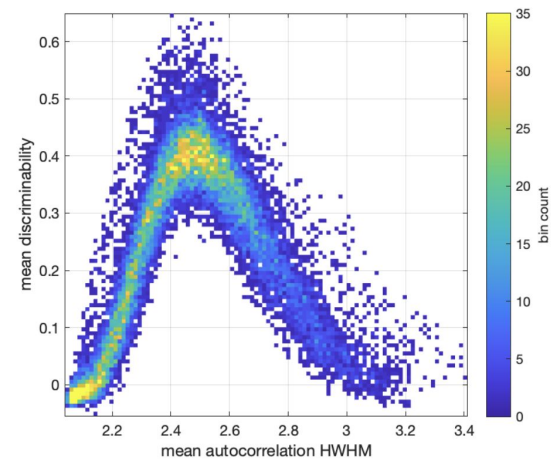
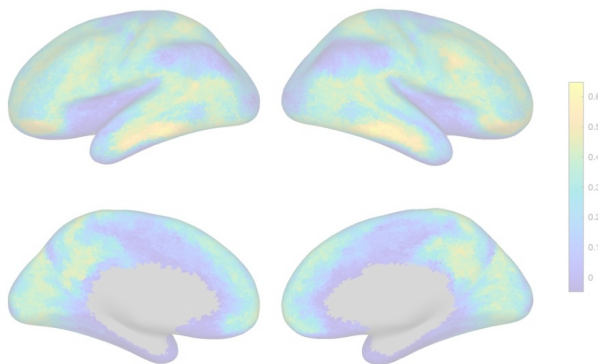


Individual specific information

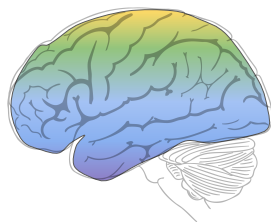
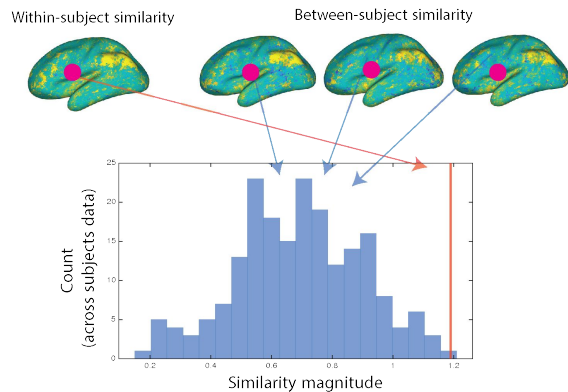
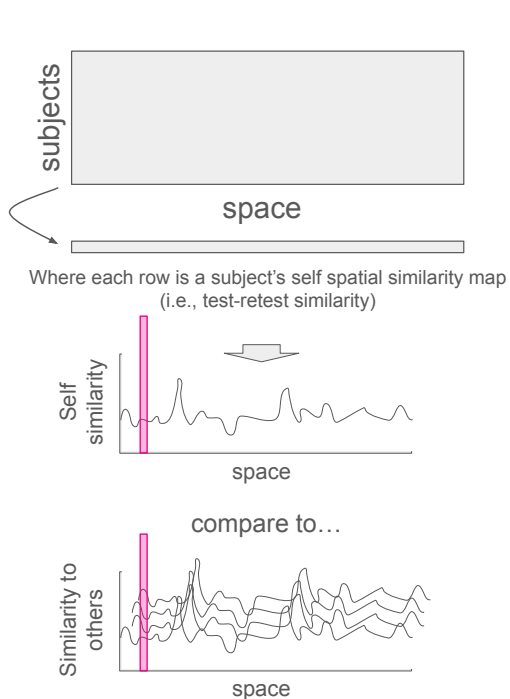
Average HWHM autocorrelation



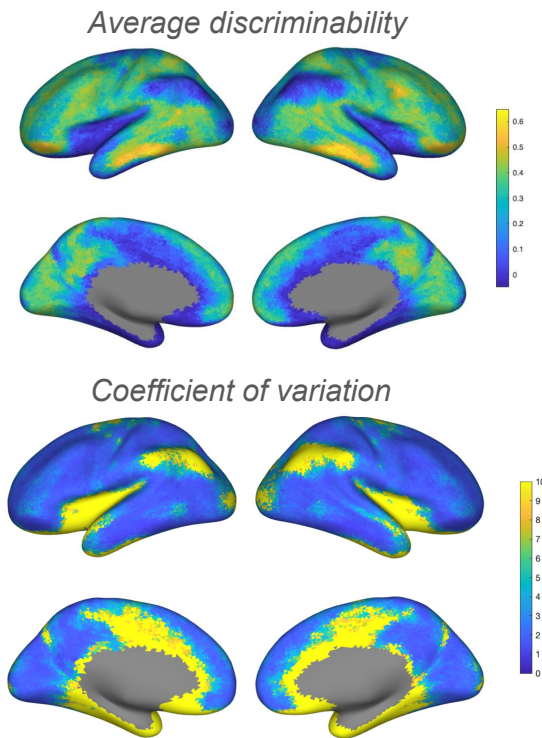
Average spatial distribution of subject discriminability



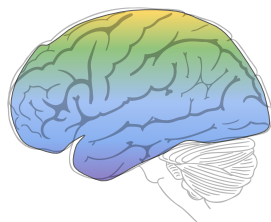
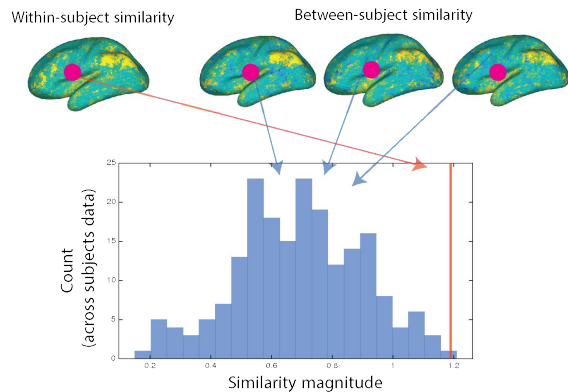
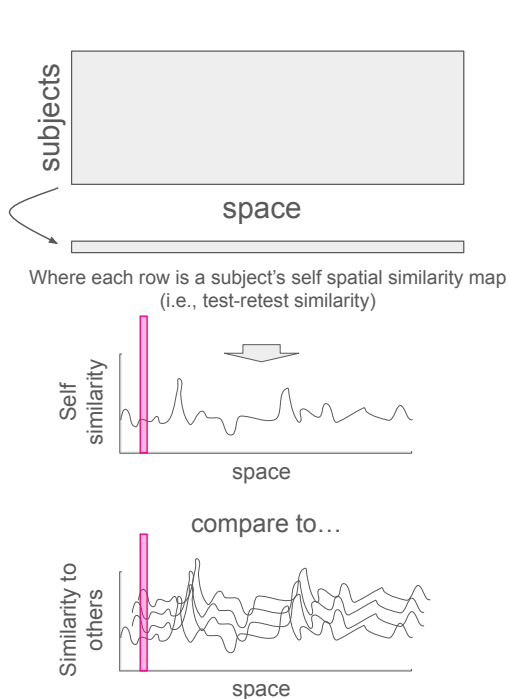
Individual specific information



Discriminability map, where each value is the z-score of the self-similarity, relative to the distribution of inter-similarities

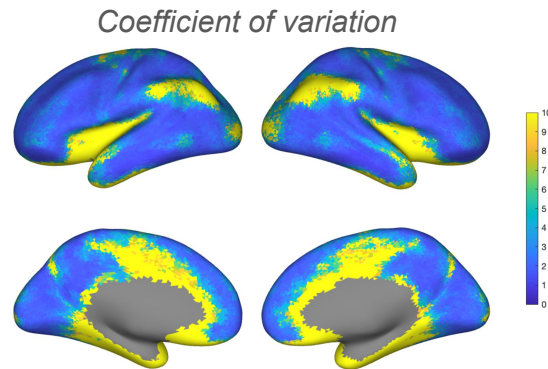


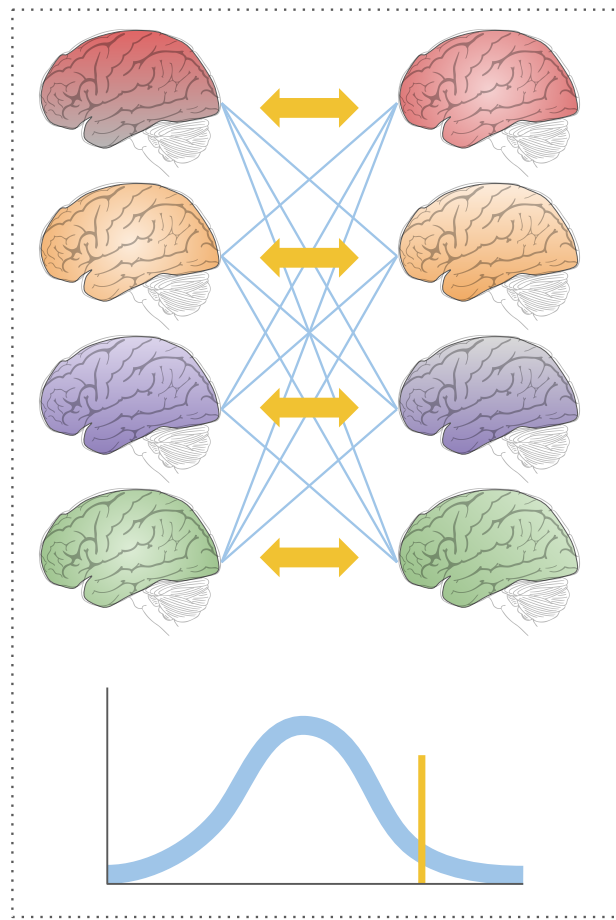
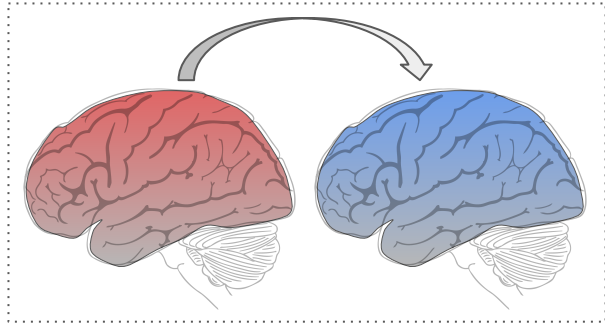
Individual specific information



Discriminability map, where each value is the z-score of the self-similarity, relative to the distribution of inter-similarities

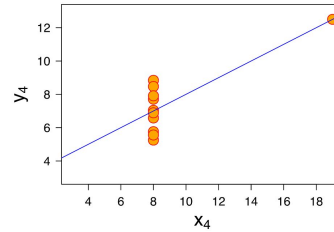
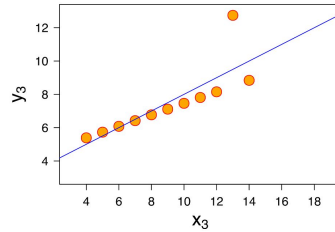
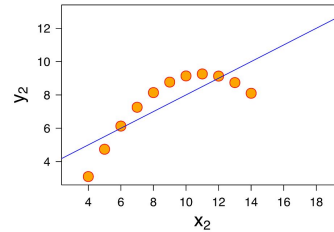
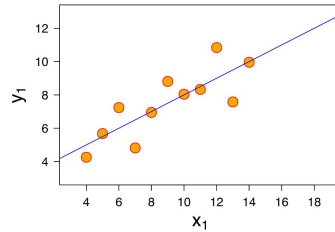
Future work: to use individual feature maps in tandem with phenotypic clustering/dimension reduction to see if location-specific & relevant areas appear



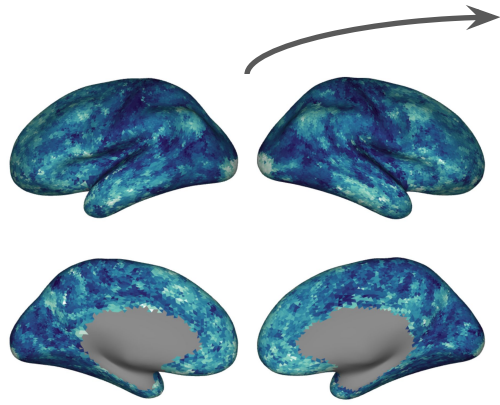


How do associations look?

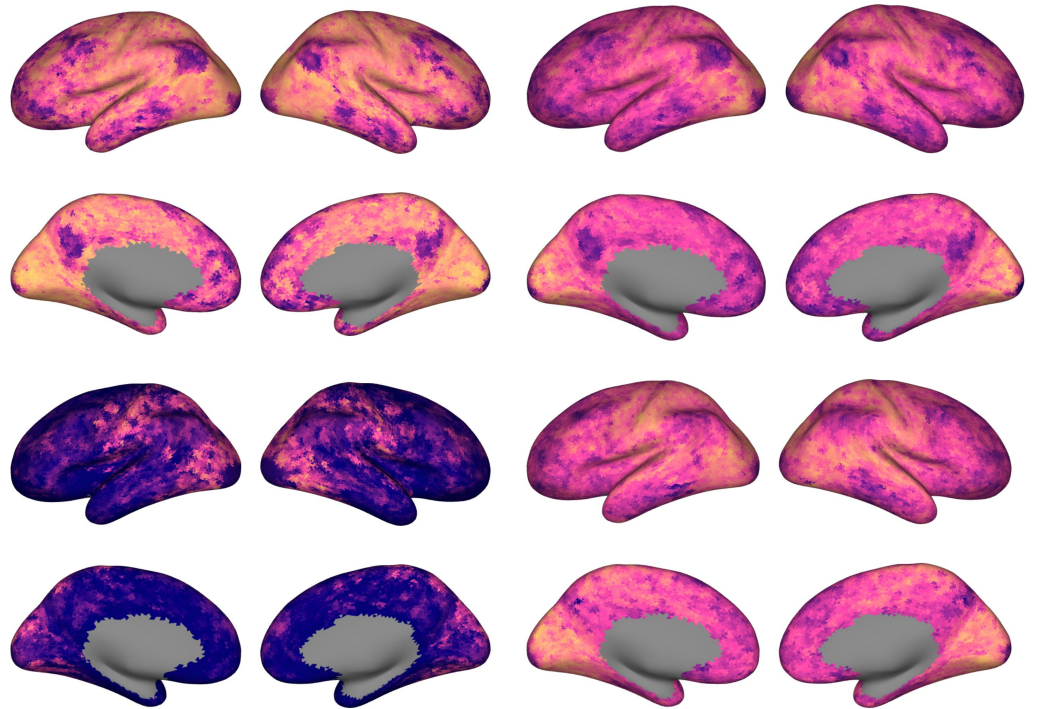
Anscombe's quartet emphasizes that correlation can be arrived upon in different manners

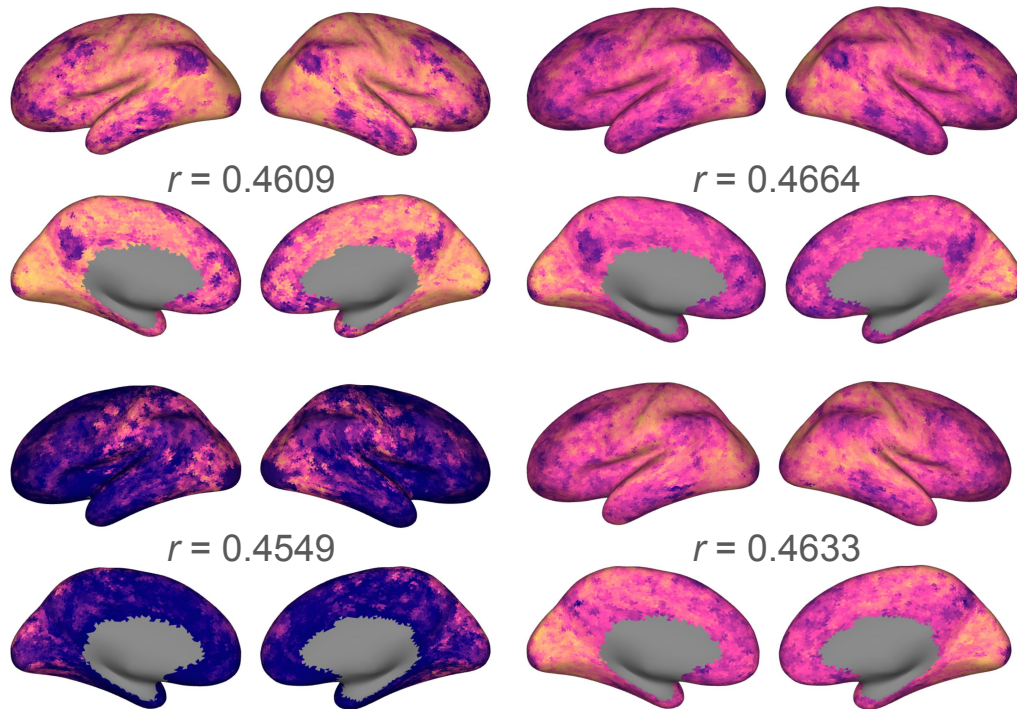
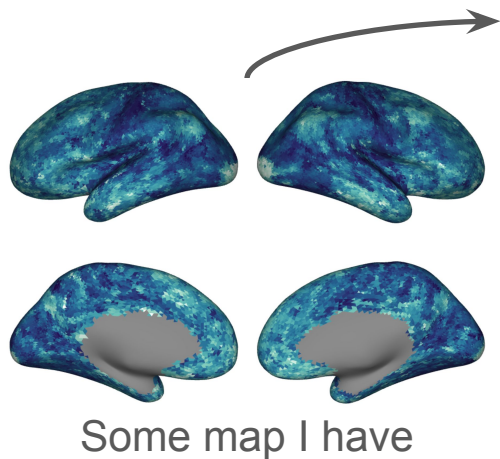


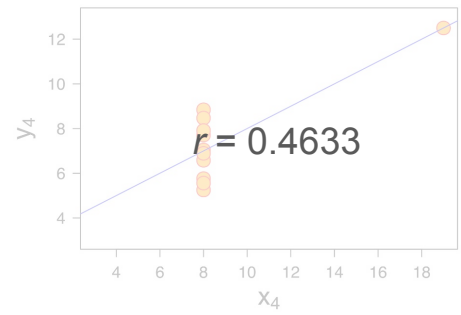
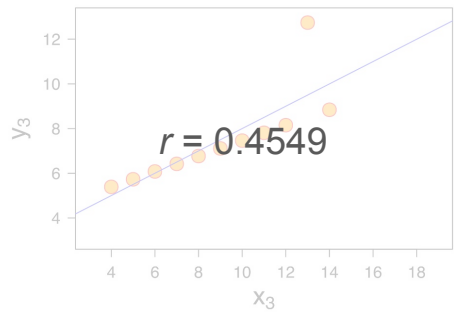
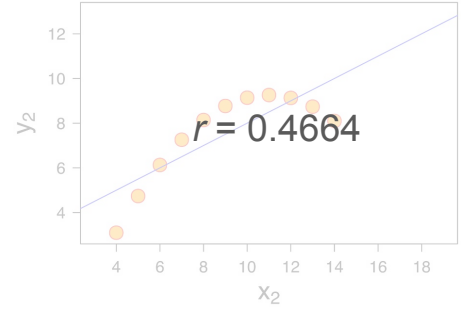
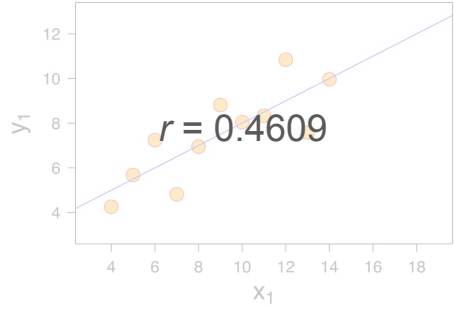
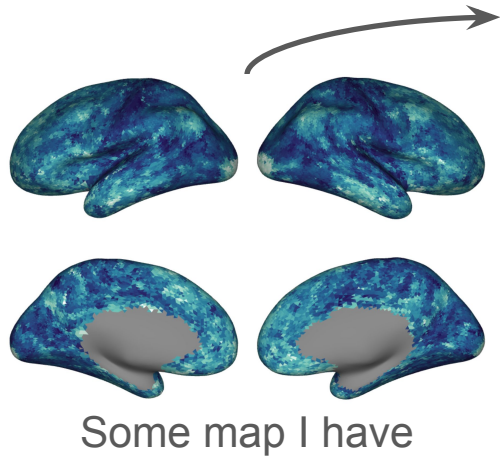
source: wikimedia commons



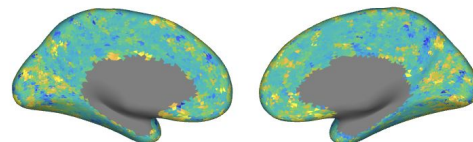
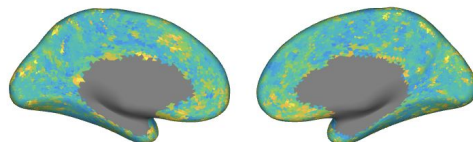
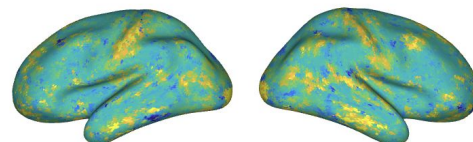
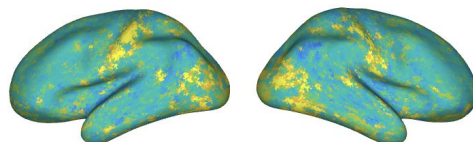
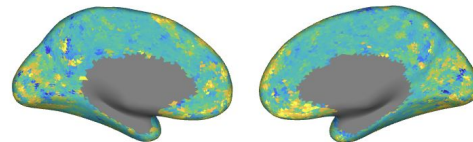
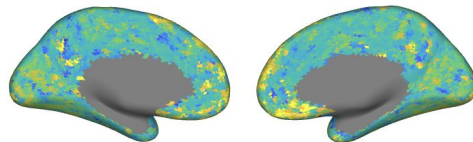
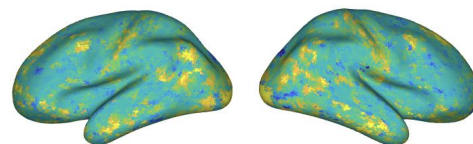
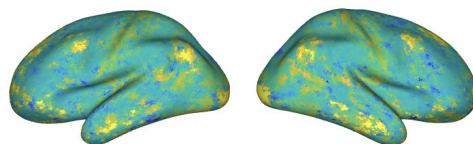
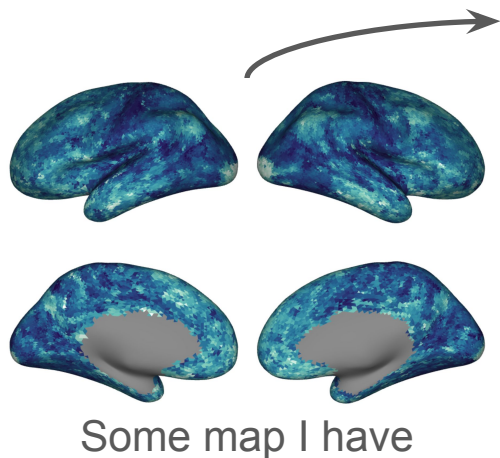
Some map I have



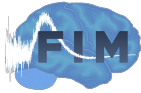




We visualize the “ingredients” that go into *spatial* correlation



Thanks for your attention!



Section on Functional Imaging Methods

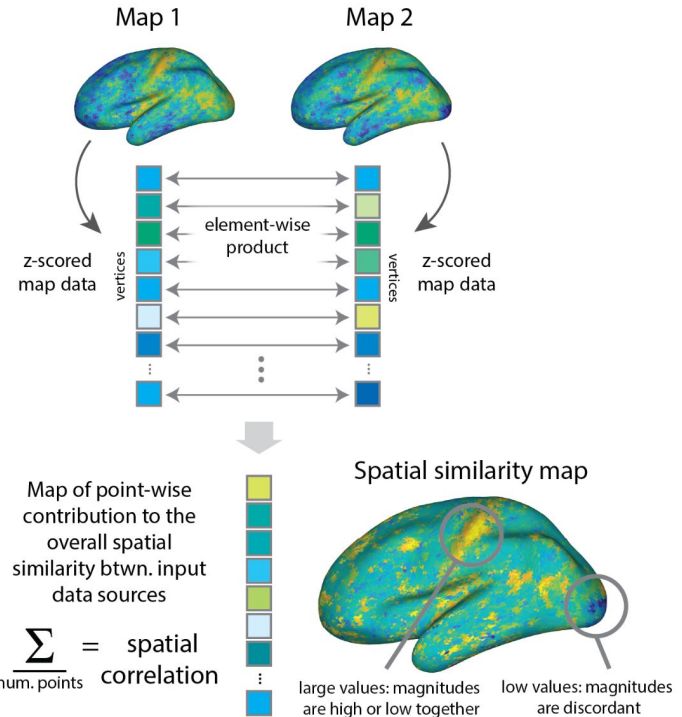


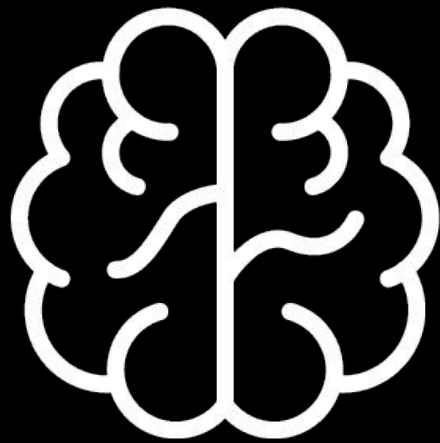
Javier Gonzalez-Castillo, Ph.D.



Peter Bandettini, Ph.D.

Burak Akin, Ph.D.
Catherine Walsh, Ph.D.
Daniel A Handwerker, Ph.D.
Dorian D. Van Tassel
Esther Lin
Marlene Smith
Marly Rubin
Plyfaa Suwanamalik-Murphy
Sharif Kronemer, Ph.D.
Stephanie Swegle

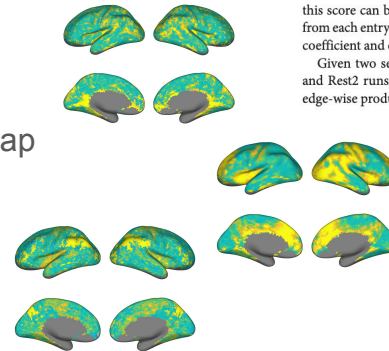
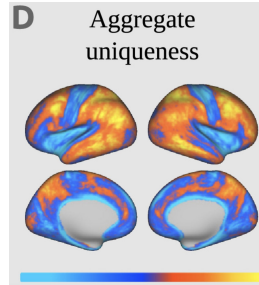




OHBM 2026

Closing remarks

- **Spatial similarity maps** can be used to highlight areas which disproportionately influence *spatial similarity*
 - Between maps comparison
 - Test-retest
 - Discriminability
- Relevant previous work
 - Spatial image registration
 - Finn & Shen et al. (2015). *Nature Neuro.*
 - Mansour et al. (2020). *NeuroImage*
- Future directions
 - Because this method uniquely renders a map per subject, there is more to explore:
 - Behavioral/phenotype relationship
 - Quantifying individual maps
 - Permutation statistical validations



ARTICLES

nature
neuroscience

Functional connectome fingerprinting: identifying individuals using patterns of brain connectivity

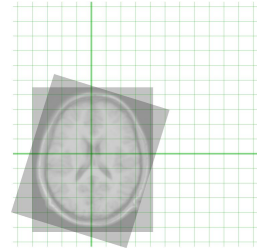
Emily S Finn^{1,2}, Xilin Shen^{2,3}, Dustin Scheinost¹, Monica D Rosenberg¹, Jessica Huang², Marvin M Chun^{1,4,5}, Xenophon Papademetris^{2,3} & R Todd Constable^{1,2,6}

Functional magnetic resonance imaging (fMRI) studies typically collapse data from many subjects, but brain functional organization varies between individuals. Here we establish that this individual variability is both robust and reliable, using data from the Human Connectome Project to demonstrate that functional connectivity profiles act as a 'fingerprint' that can accurately identify subjects from a large group. Identification was successful across scan sessions and even between task and rest conditions, indicating that an individual's connectivity profile is intrinsic, and can be used to distinguish that individual regardless of how the brain is engaged during imaging. Characteristic connectivity patterns were distributed throughout the brain, but the frontoparietal network emerged as most distinctive. Furthermore, we show that connectivity profiles predict levels of fluid intelligence: the same networks that were most discriminating of individuals were also most predictive of cognitive behavior. Results indicate the potential to draw inferences about single subjects on the basis of functional connectivity MRI.

Quantifying edgewise contributions to identification. Edge-based analyses were performed to determine whether specific edges contribute more to individual identification than other edges. When performing subject identification, the Pearson correlation coefficients were computed between the target connectivity pattern and all connectivity patterns in the database, and the subject identity was chosen to be the one that had the largest correlation coefficient. Computationally, the Pearson correlation of two vectors is the sum of element-wise products, given that the two vectors are z-score normalized (0 mean with unit s.d.). Therefore, this score can be broken down to quantify the individual amount contributed from each entry in the vector, where some edges contribute positively to the total coefficient and others contribute negatively.

Given two sets of connectivity matrices $[X_i^{R1}], [X_i^{R2}]$ obtained from Rest1 and Rest2 runs after z-score normalization, we computed the corresponding edge-wise product vector (φ_i),

$$\varphi_i(e) = X_i^{R1}(e) \cdot X_i^{R2}(e), e = 1, \dots, M$$



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A new method for improving functional-to-structural MRI alignment using local Pearson correlation

Ziad S. Saad^a, Daniel R. Glen^a, Gang Chen^a, Michael S. Beauchamp^b, Rutvik Desai^c, Robert W. Cox^a & R

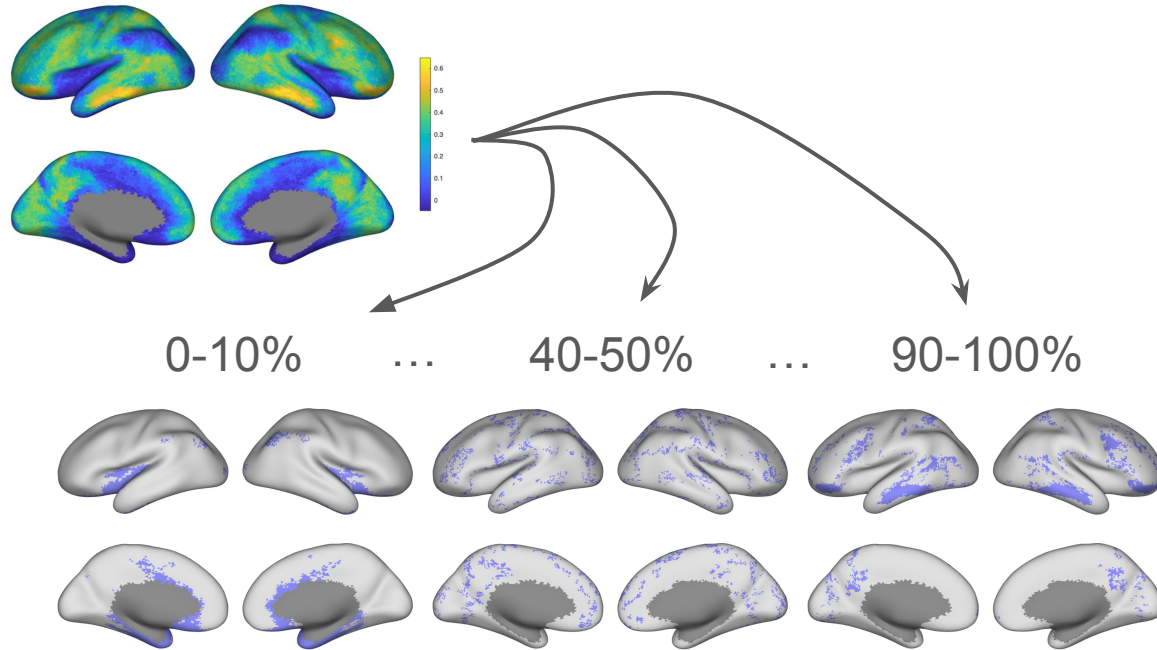
^a Scientific and Statistical Computing Core, National Institute of Mental Health, National Institutes of Health, Department of Health and Human Services, 10 Center Dr. Room 1D80 Bethesda, MD 20892-148 USA

^b Department of Neurobiology and Anatomy, University of Texas Health Science Center at Houston, Houston TX USA

^c Department of Neurology, Medical College of Wisconsin, Milwaukee WI USA

Individual specific information

Average spatial distribution of subject discriminability



Individual specific information

Average spatial distribution of subject discriminability

