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Unraveling dynamic Brain Networks: A topological data analysis framework for state space estimation

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June 17, 2024 1:20 pm Ocean Way (Mezzanine Level)
S13: Novel statistical methods for imaging data analysis and beyond
Organizer Panpan Zhang

Abstract

We present a novel topological data analysis (TDA) framework for modeling state spaces in dynamic functional brain networks. Core principles of TDA are explored, particularly highlighting how topological distances can be harnessed to cluster time-evolving brain networks. The approach is centered on the use of Wasserstein metrics to measure distances between 0D and 1D topological features, which significantly enhances the ability to track the brain's connectivity patterns over time. Our approach outperforms traditional methods such as k-means and hierarchical clustering by capturing the hidden topological patterns in the data, which are ignored in existing methods. The analysis reveals that resting-state brain networks oscillate primarily between two major states, with an additional noisy intermediate state. These fluctuations are linked to the complex sulcal and gyral cortical patterns, where significant differences in functional and structural connectivity are observed. The variability in connectivity introduces a dynamic gradient across the network, influencing the overall dynamics of brain connectivity changes. The talk is partially based on arXiv:2201.00087 (PLOS Computational Biology).

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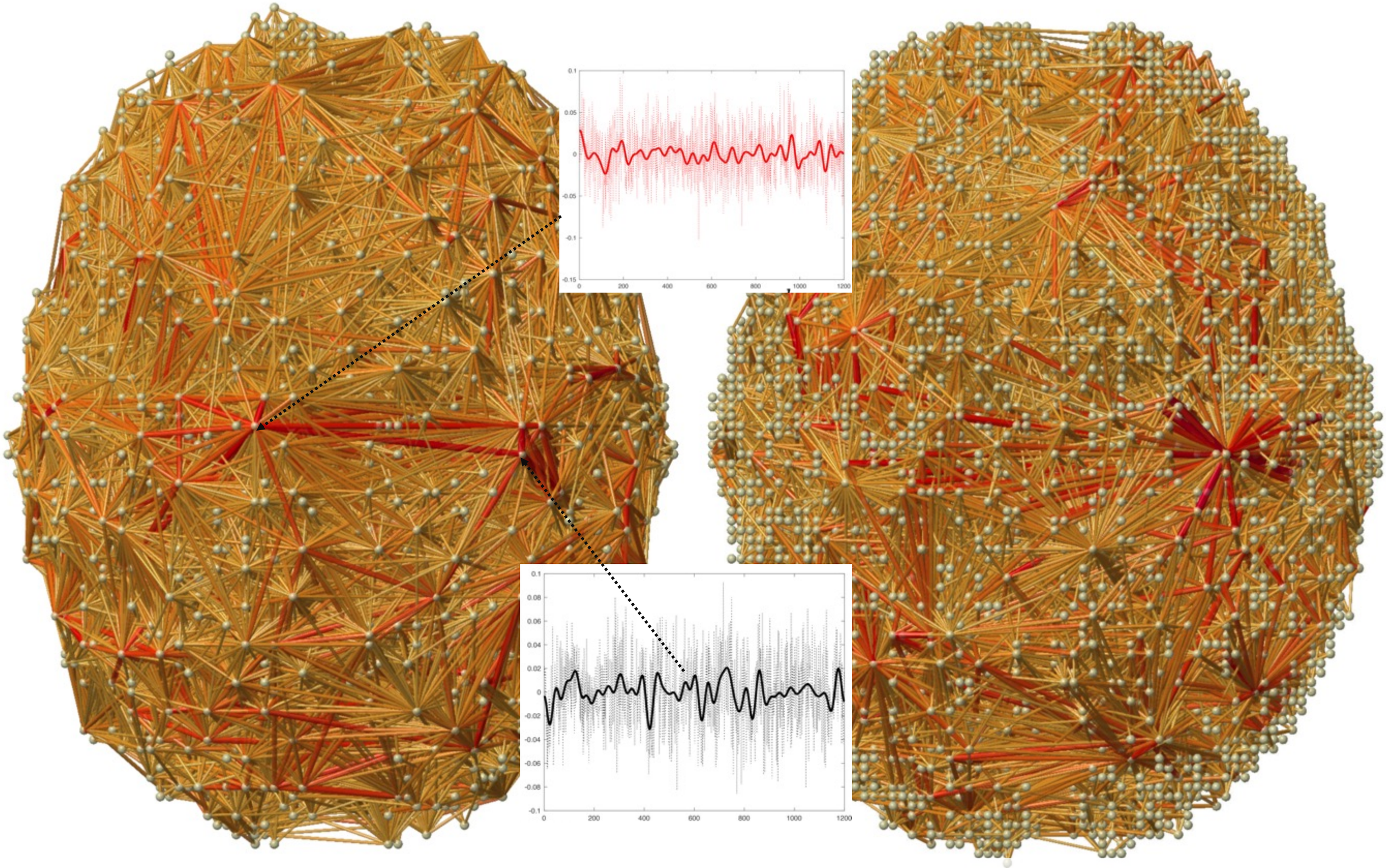
Magnetic resonance imaging (MRI)

3T GE Discovery X750
Waisman Brain Imaging Laboratory
University of Wisconsin-Madison

3T GE Discovery MR750
Center for Imaging Research
Medical College of Wisconsin, Milwaukee, WI

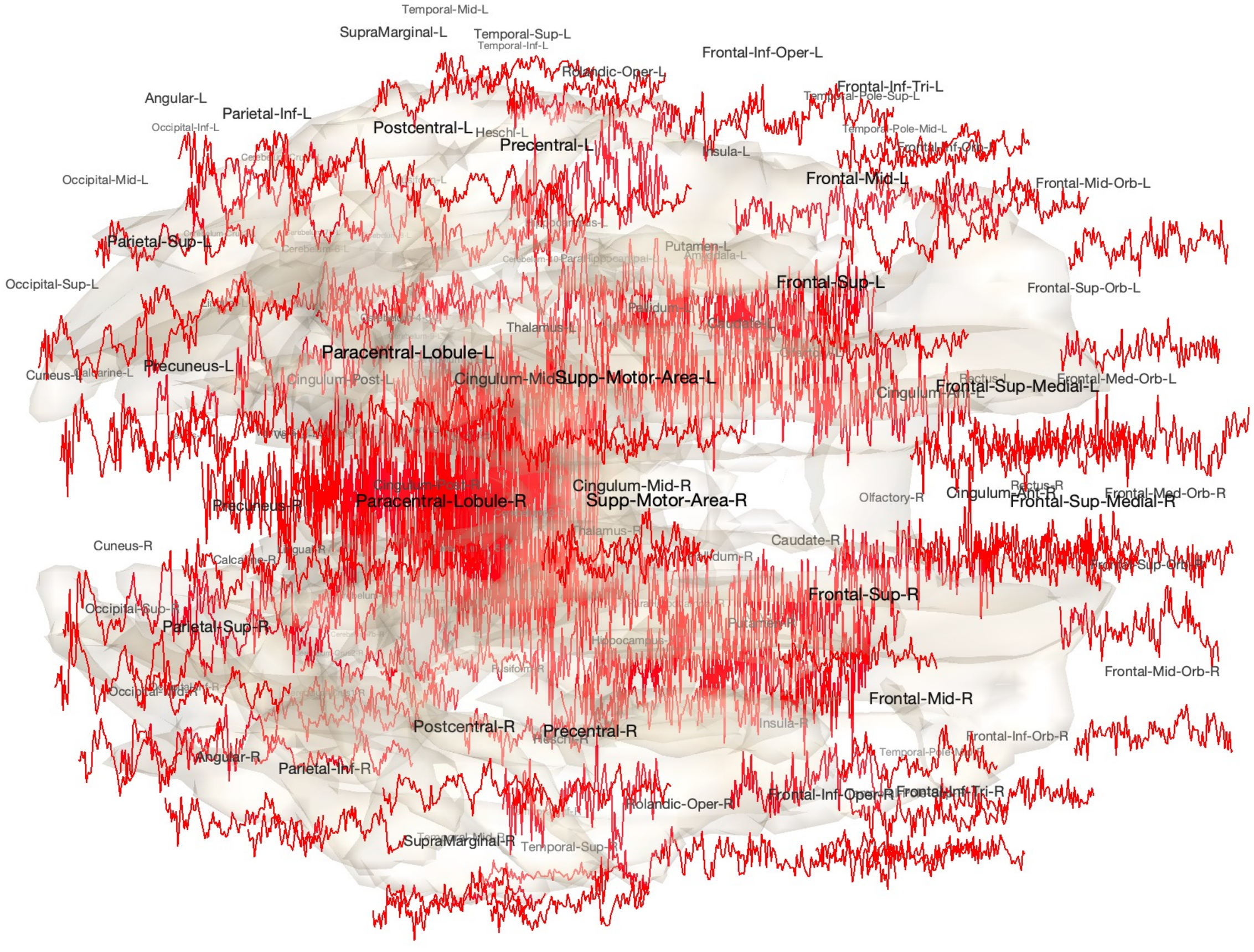
Dynamically changing correlation brain network

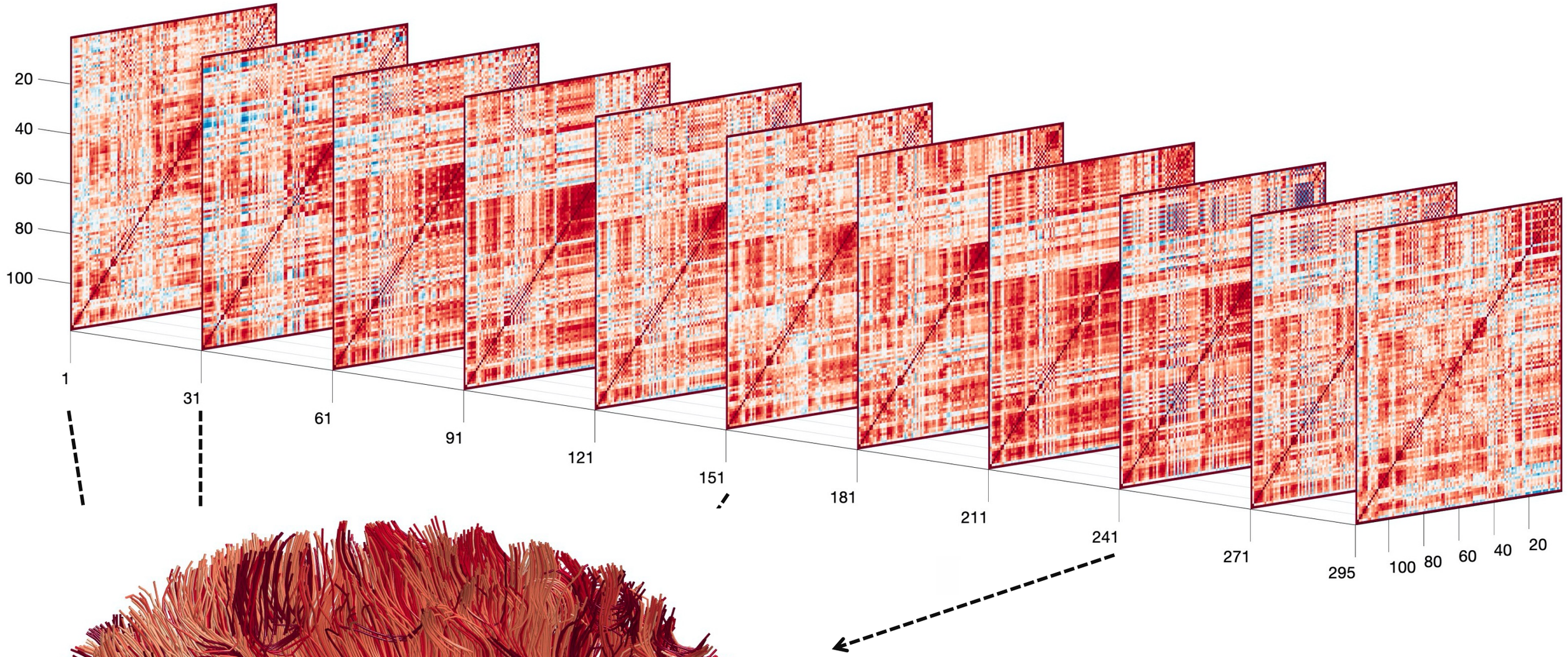


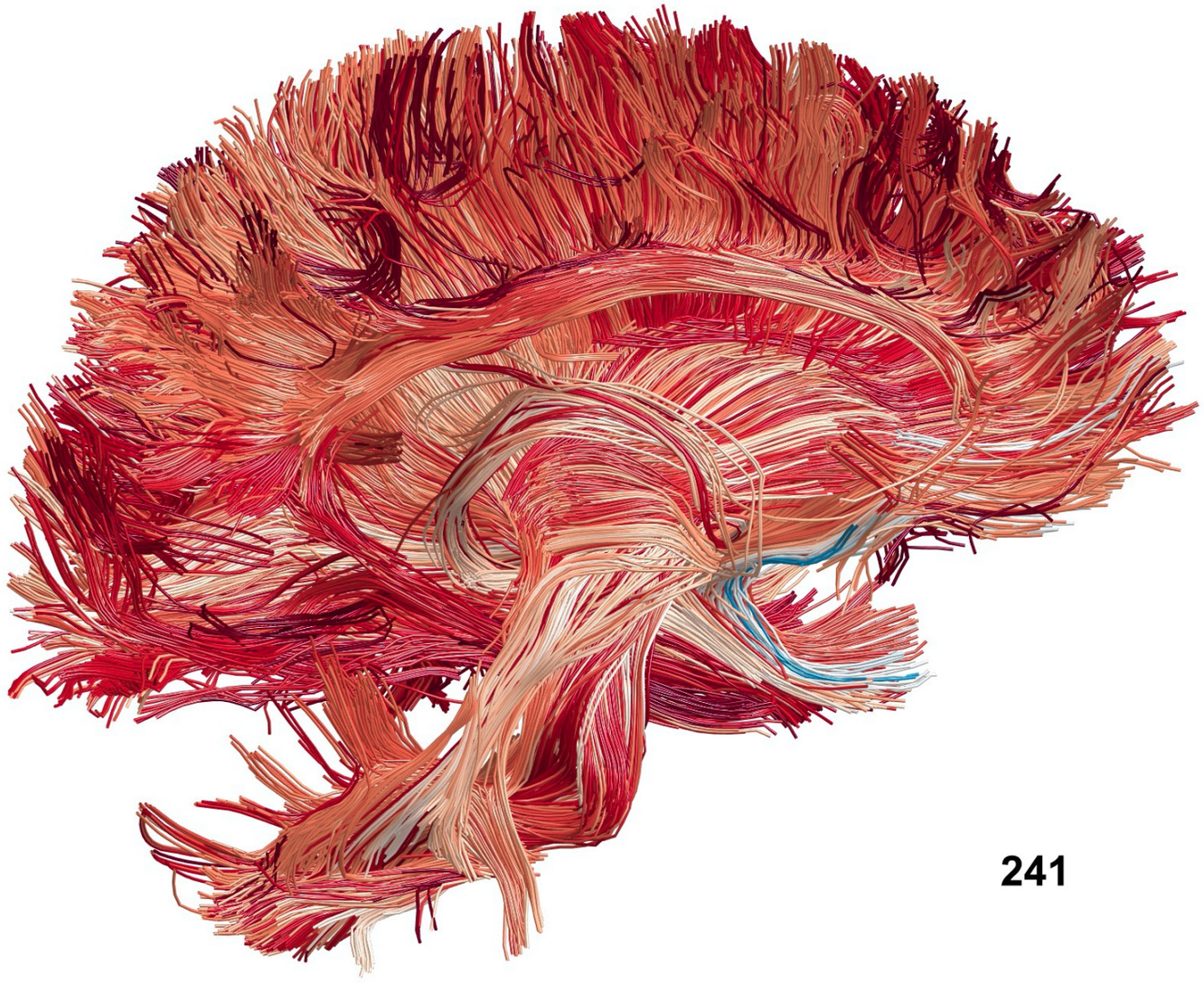
Correlation network of 300000 time series

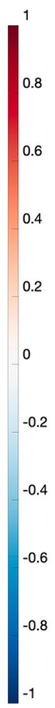
Dynamically changing complete graph with about $300000^2/2$ cycles.

Time series averaged into parcellations





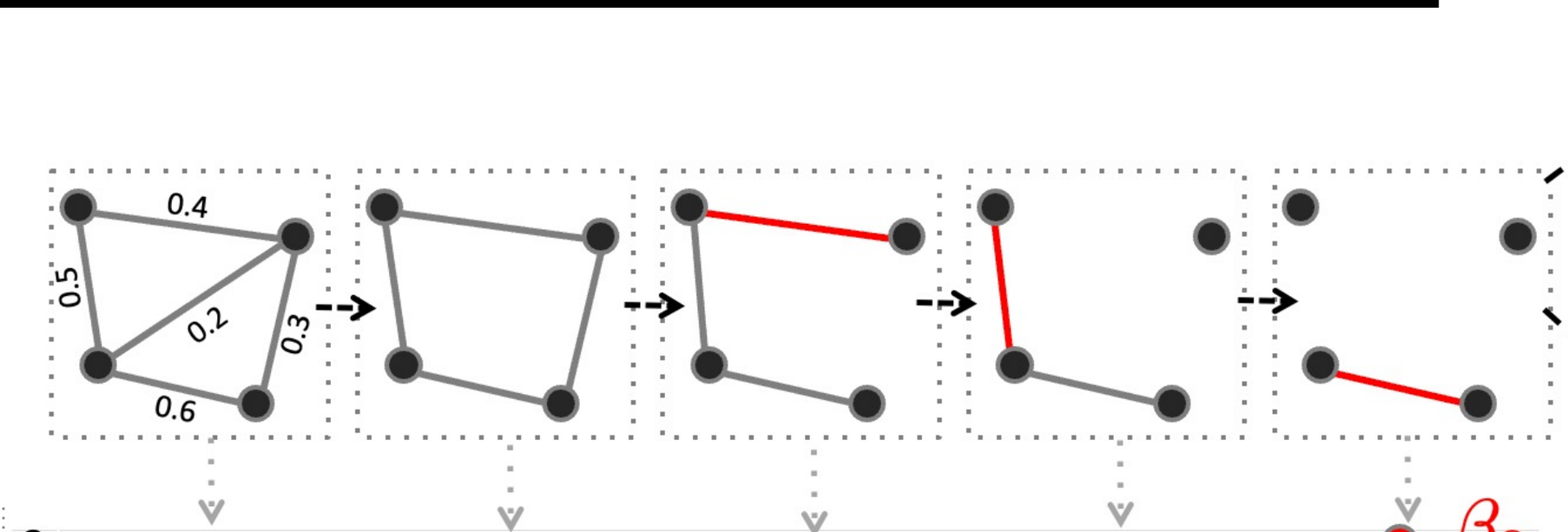


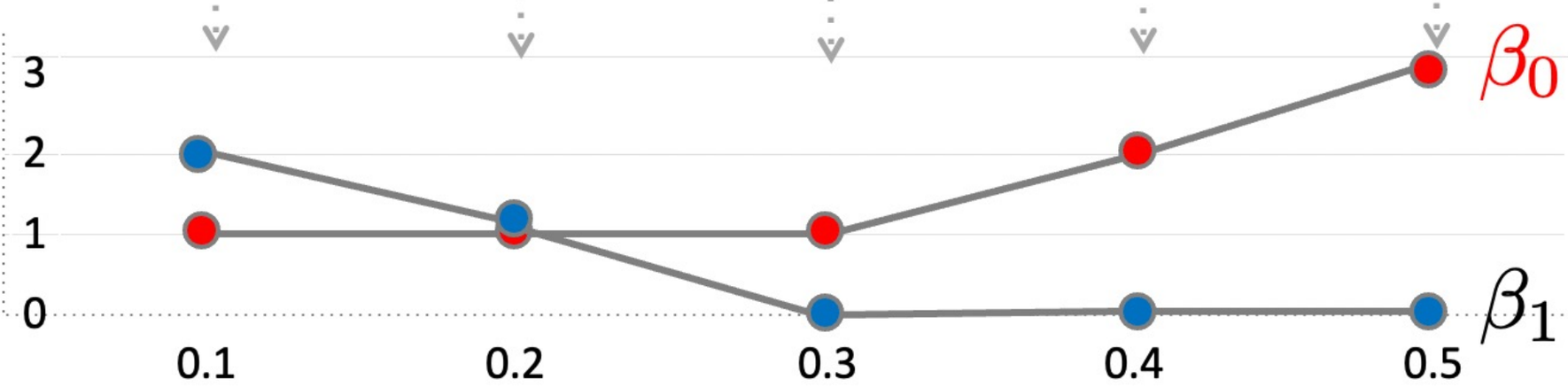


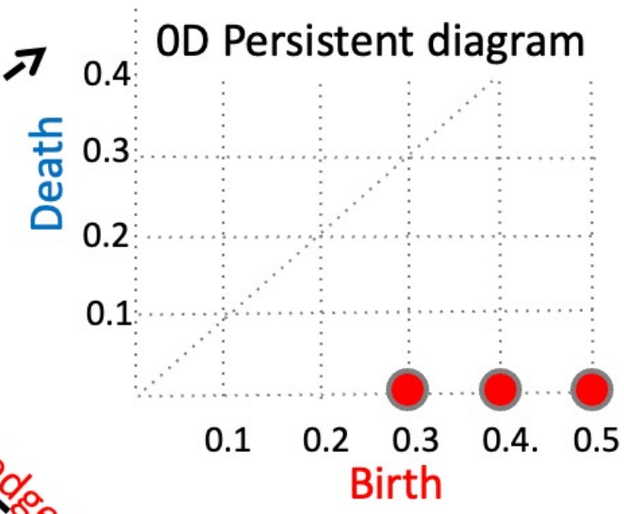
Dynamically changing functional connectivity superimposed on top of white matter tracts

Topological decomposition

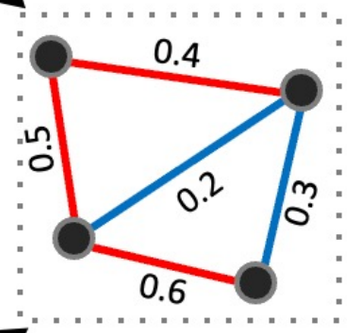
Theorem: Birth & death decomposition



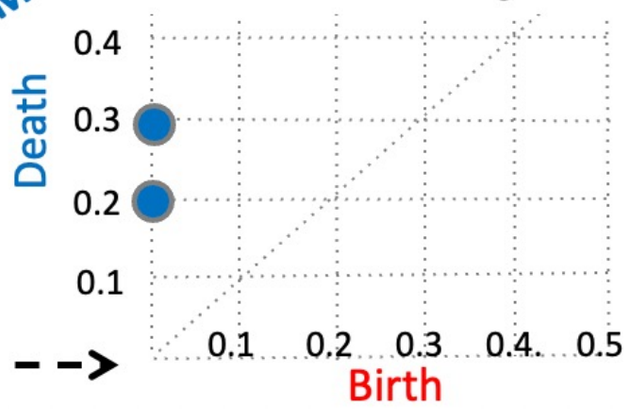




Birth edges (MST) E_0



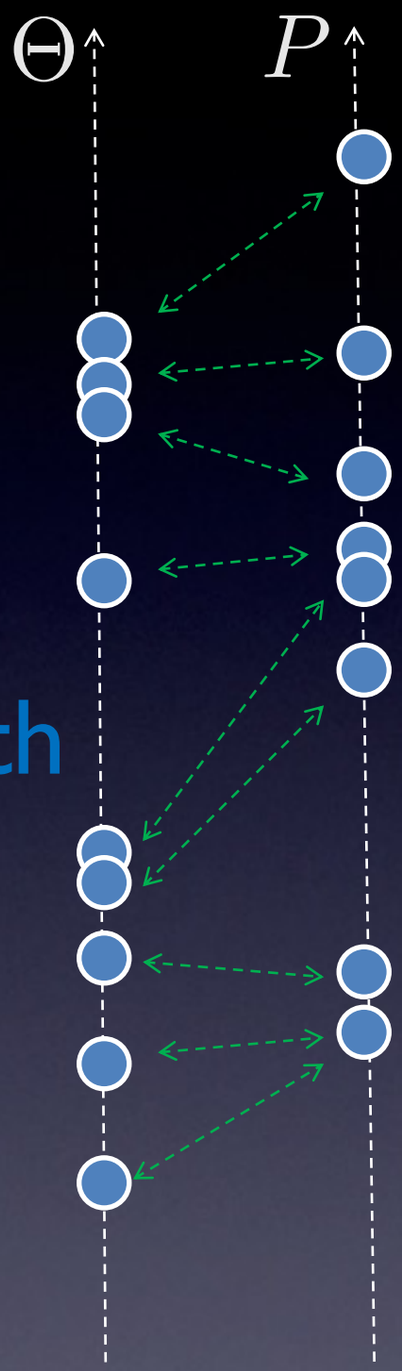
Death edges (none-MST) E_1



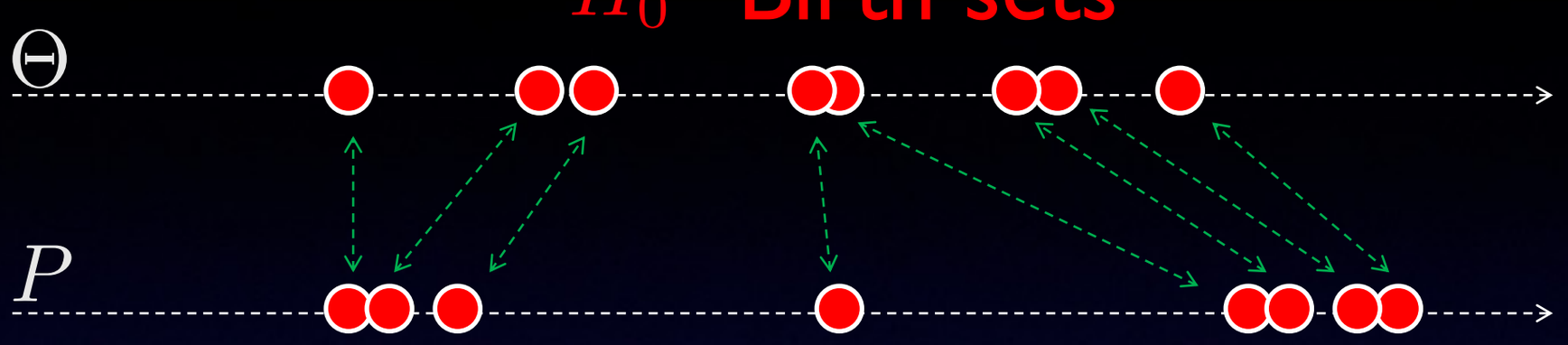
Edge set $E = E_0 + E_1$

Songdechakraiwut and Chung. 2023, Annals of Appled Statistics

Theorem: Minimization of the r-Wasserstein distance



$$\mathcal{L}_1(\Theta, P) = \min_{\tau} \sum_{d \in E_1} \left[d - \tau(d) \right]^r$$



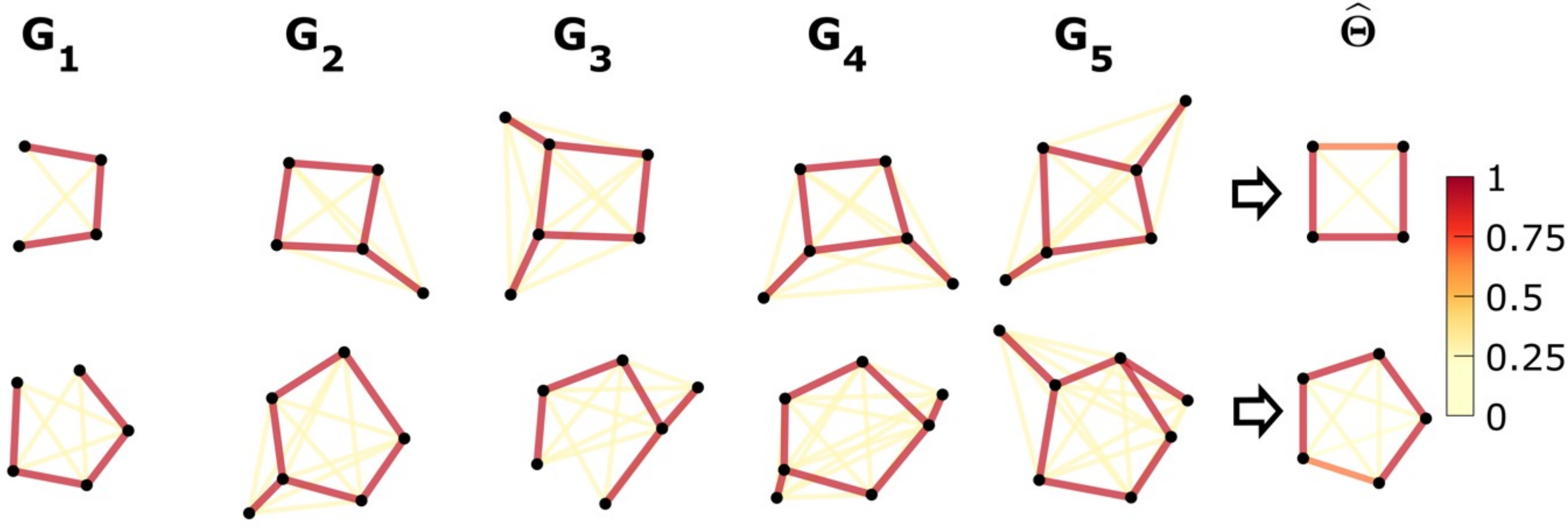
$$\mathcal{L}_0(\Theta, P) = \min_{\tau} \sum_{b \in E_0} \left[b - \tau(b) \right]^r$$

runtime $\mathcal{O}(q \log q)$

Proof in
Chung et al. 2024,
Foundations of Data Science

Nonlinear registration of topological objects

Topological mean
= minimizer of Wasserstein distance

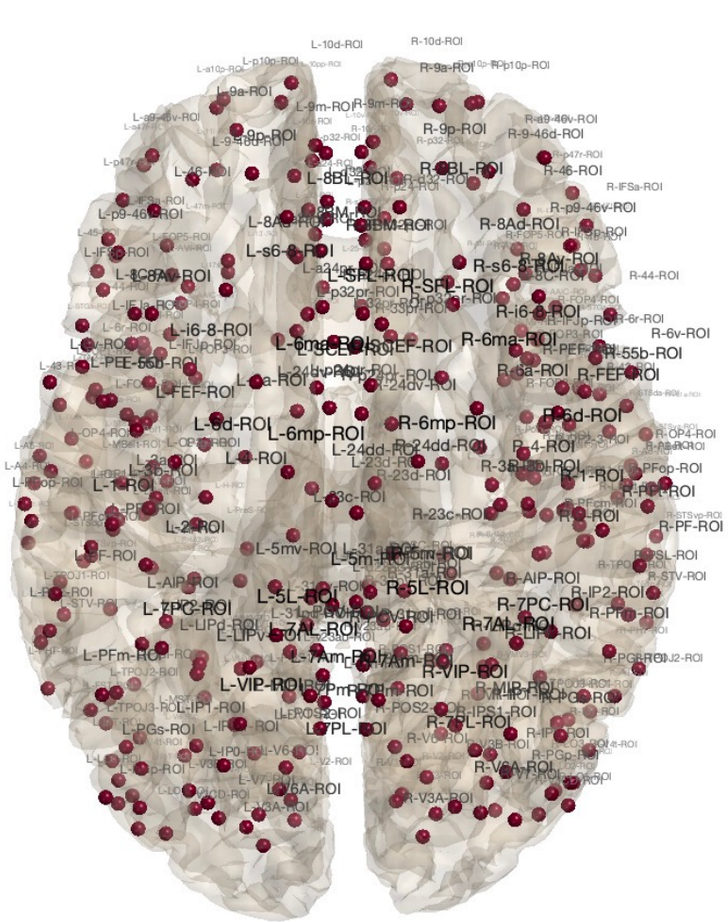


Average sorted edge weights over MST and none-MST separately and reconstruct → minimizer of topological distance

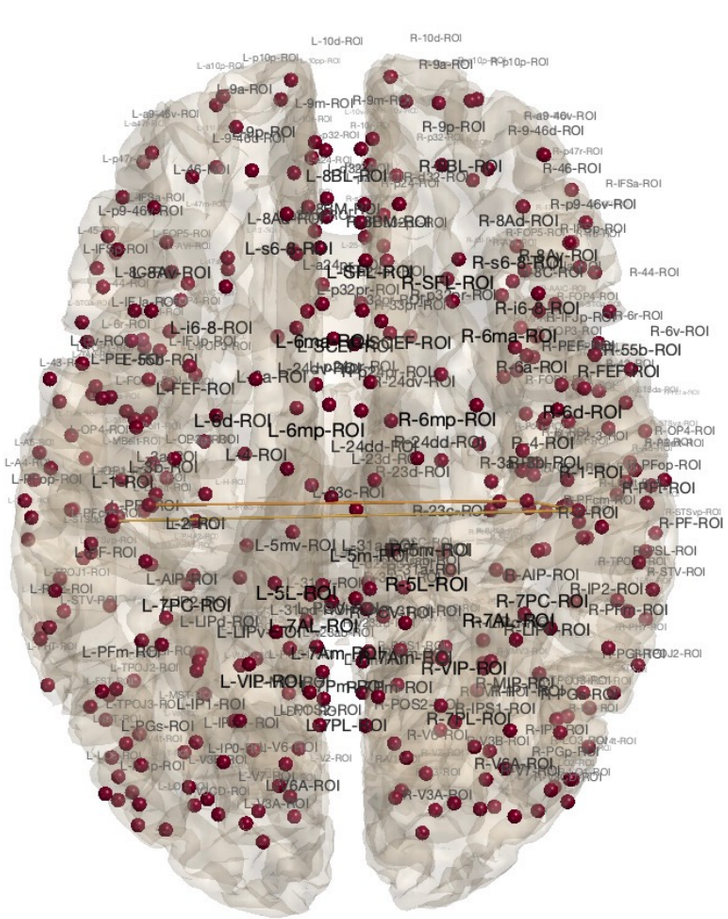
Songdechakraiwut and Chung. 2023, Annals of Appled Statistics

Unequivocal demonstration

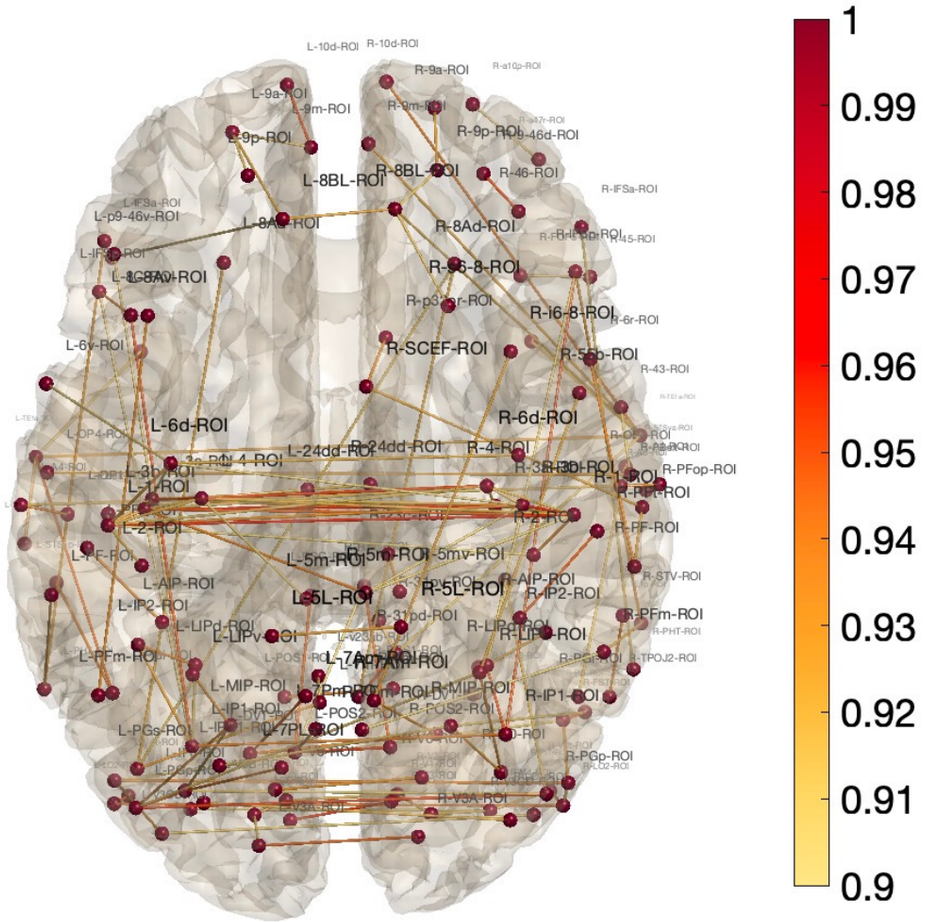
Superiority of topological averaging in rs-fMRI connectivity



Averging over time



Correlation over time



Topological averaging over time

Chung et al. 2024, arXiv:2405.07835

Topological clustering = topological inference

Within-group distance $$l_W \propto \sum_k \sum_{i,j \in C_k} \mathcal{L}(\mathcal{X}_i, \mathcal{X}_j)$$

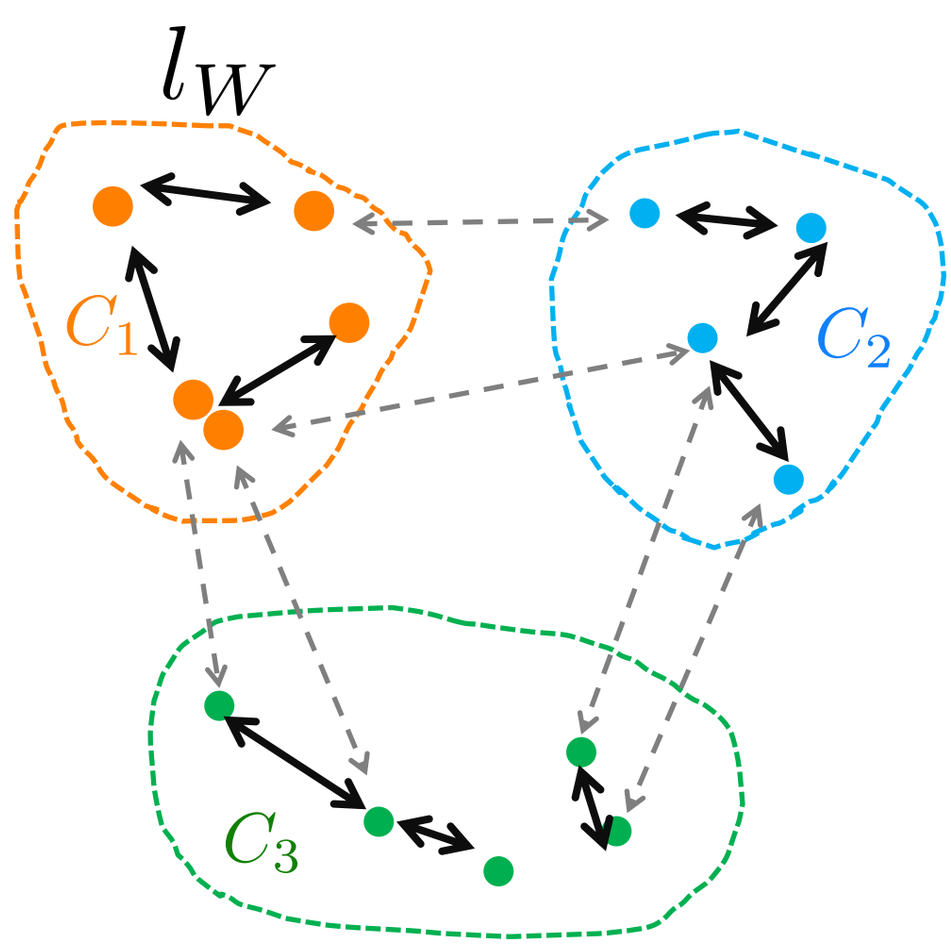
0D and 1D combined distances

Clustering accuracy

$$\frac{dA}{dp} = \frac{dA}{d\phi} \cdot \frac{d\phi}{dp} \leq 0$$

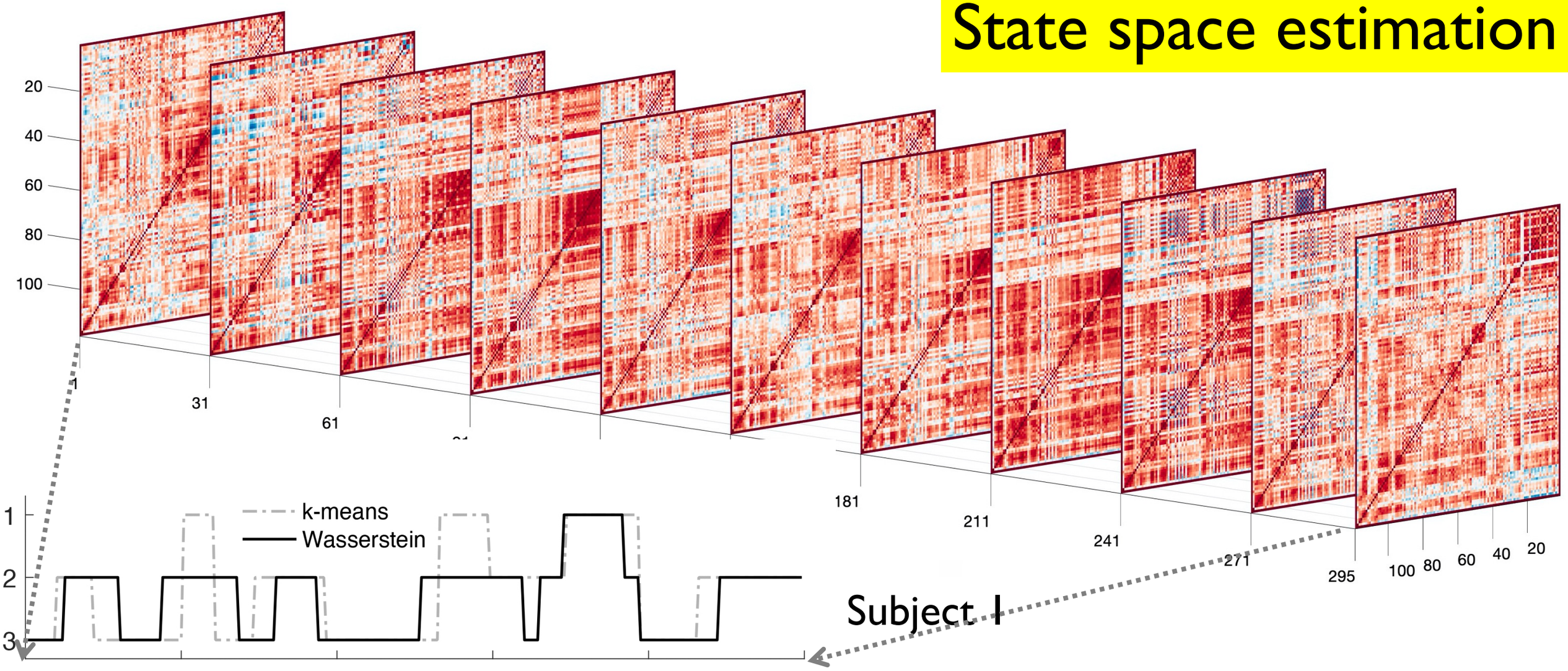
p-value

There exists a monotone function f satisfying $p = f(A)$

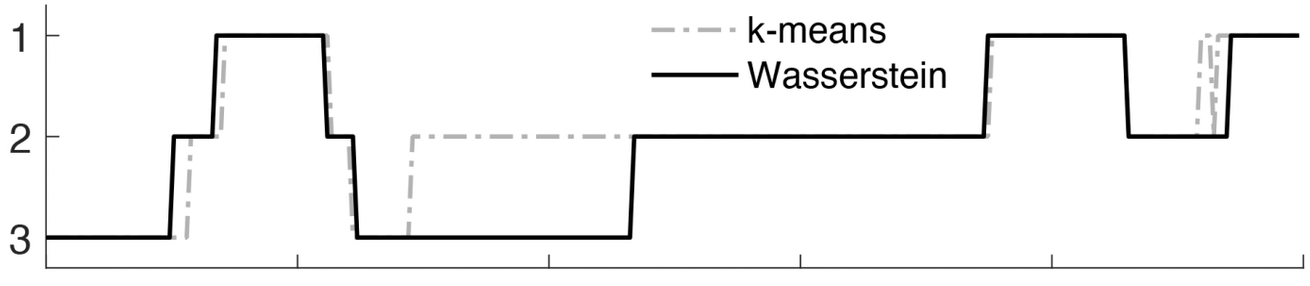


Proof in Chung et al. 2023 NeuroImage

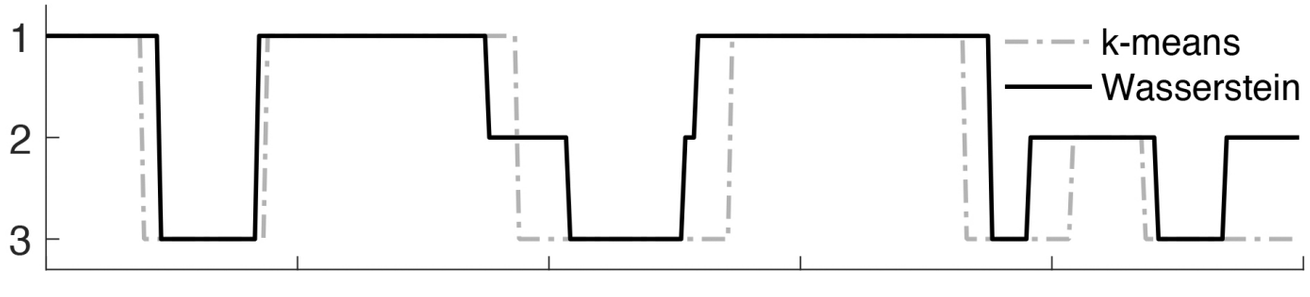
State space estimation



Subject 1



Subject 2

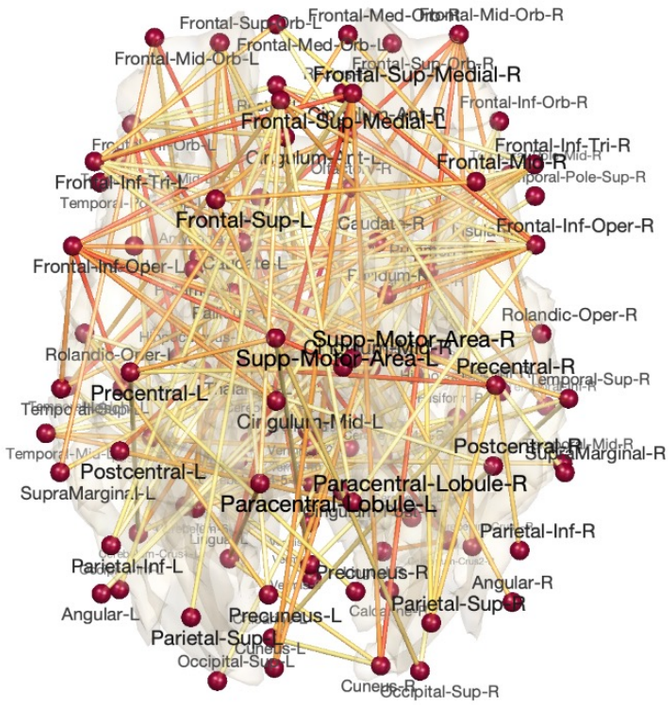


Subject 3

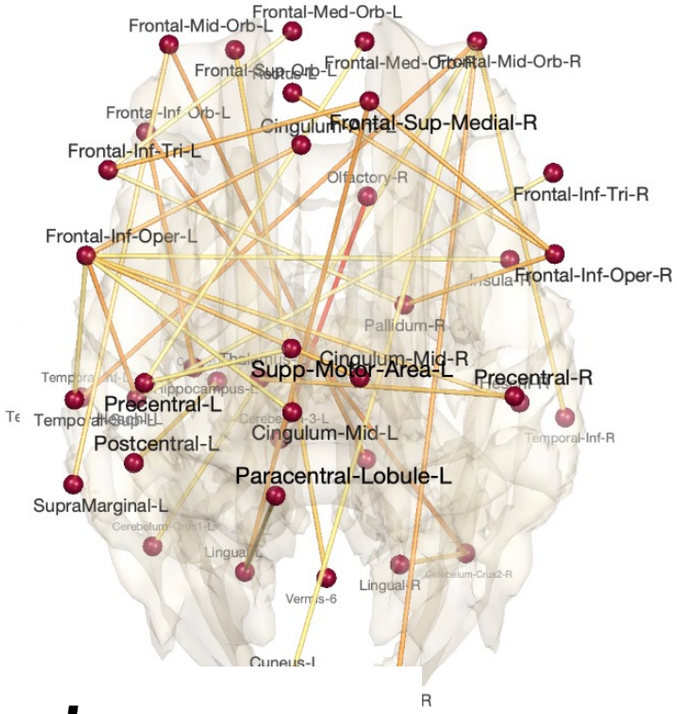
How many states?

Any clinical relevance?

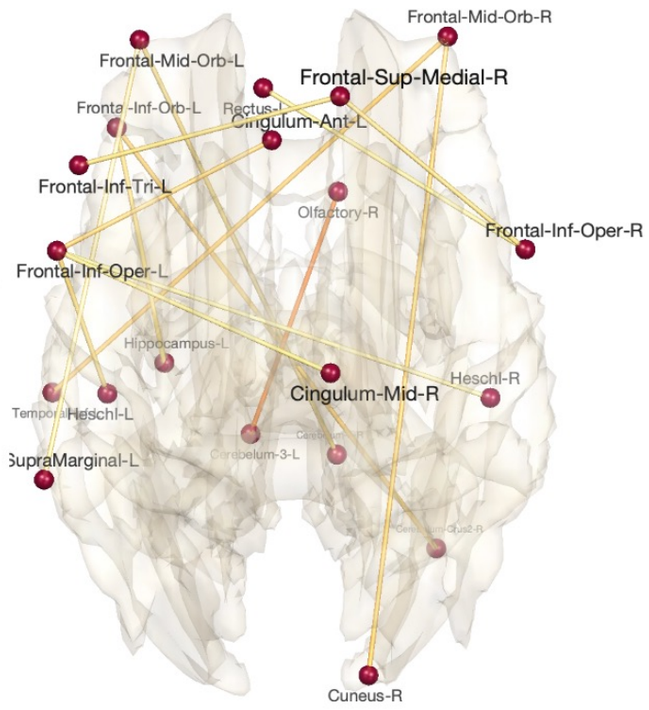
State 1



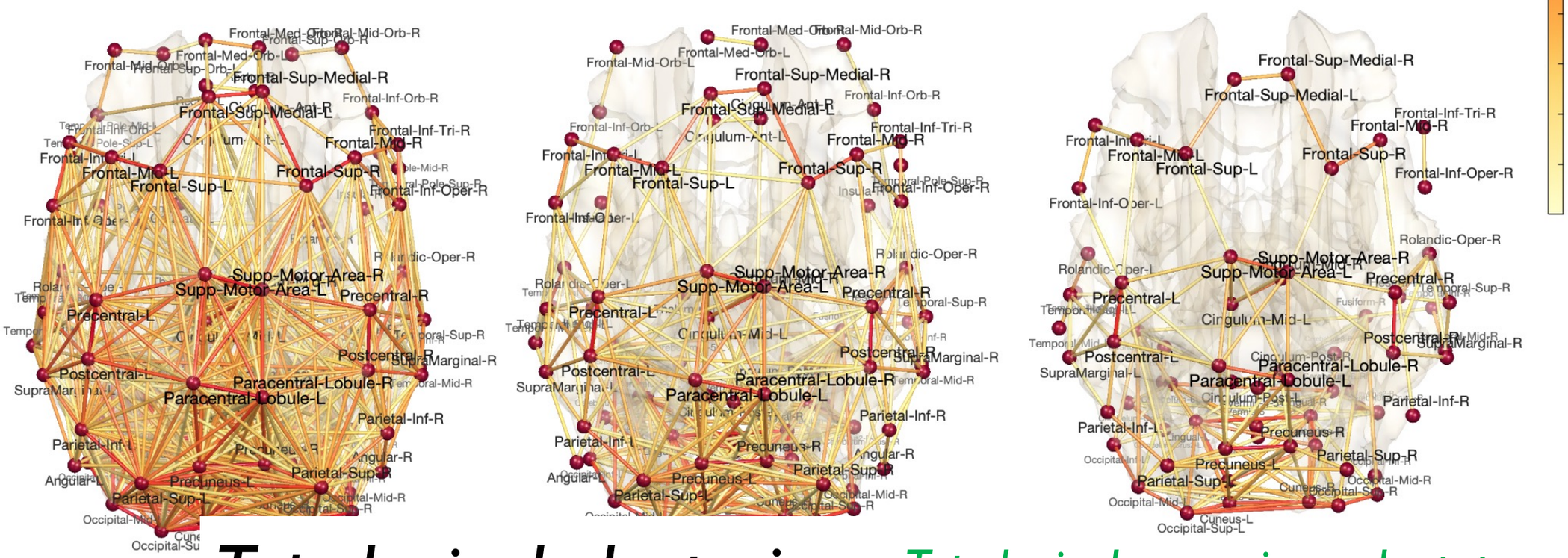
State 2



State 3



k-means *Sample mean in each state*



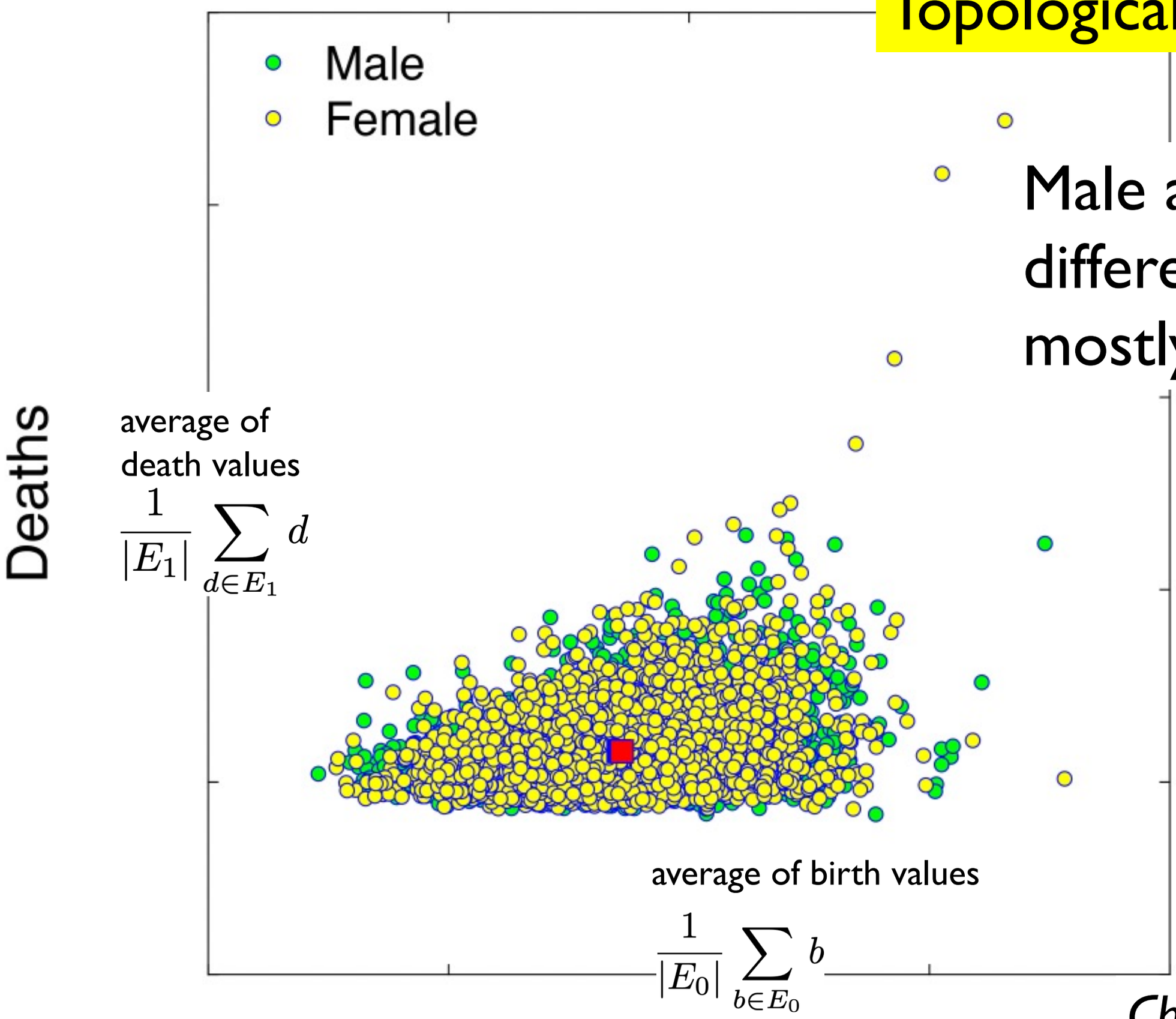
Topological clustering *Topological mean in each state*

479 subjects

Chung at al. 2024 PLOS Computational Biology

Topological embedding

Topological Embedding



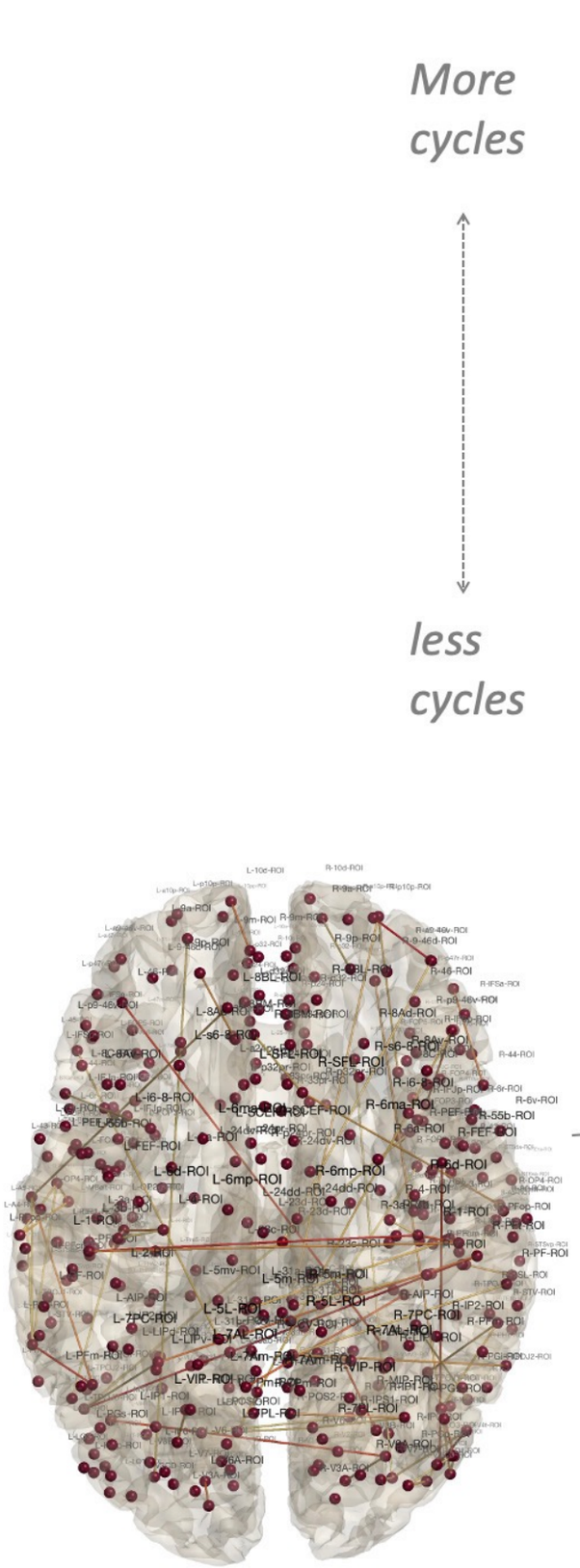
Male and female differences are mostly geometric

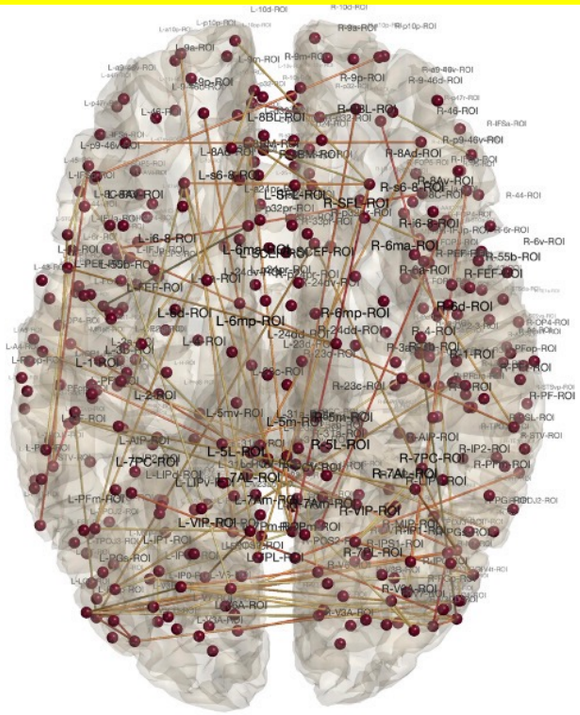
Chung et al. 2023 NeuroImage

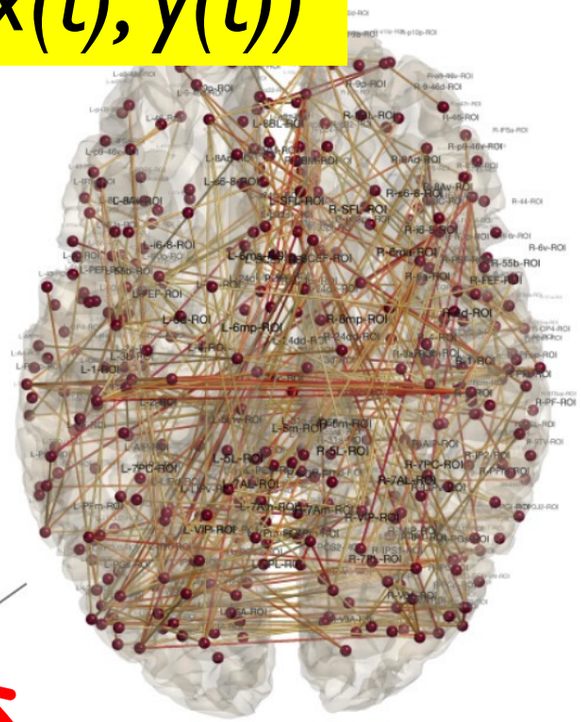
Topological Phase Diagram: parametrized by curve (x(t), y(t))

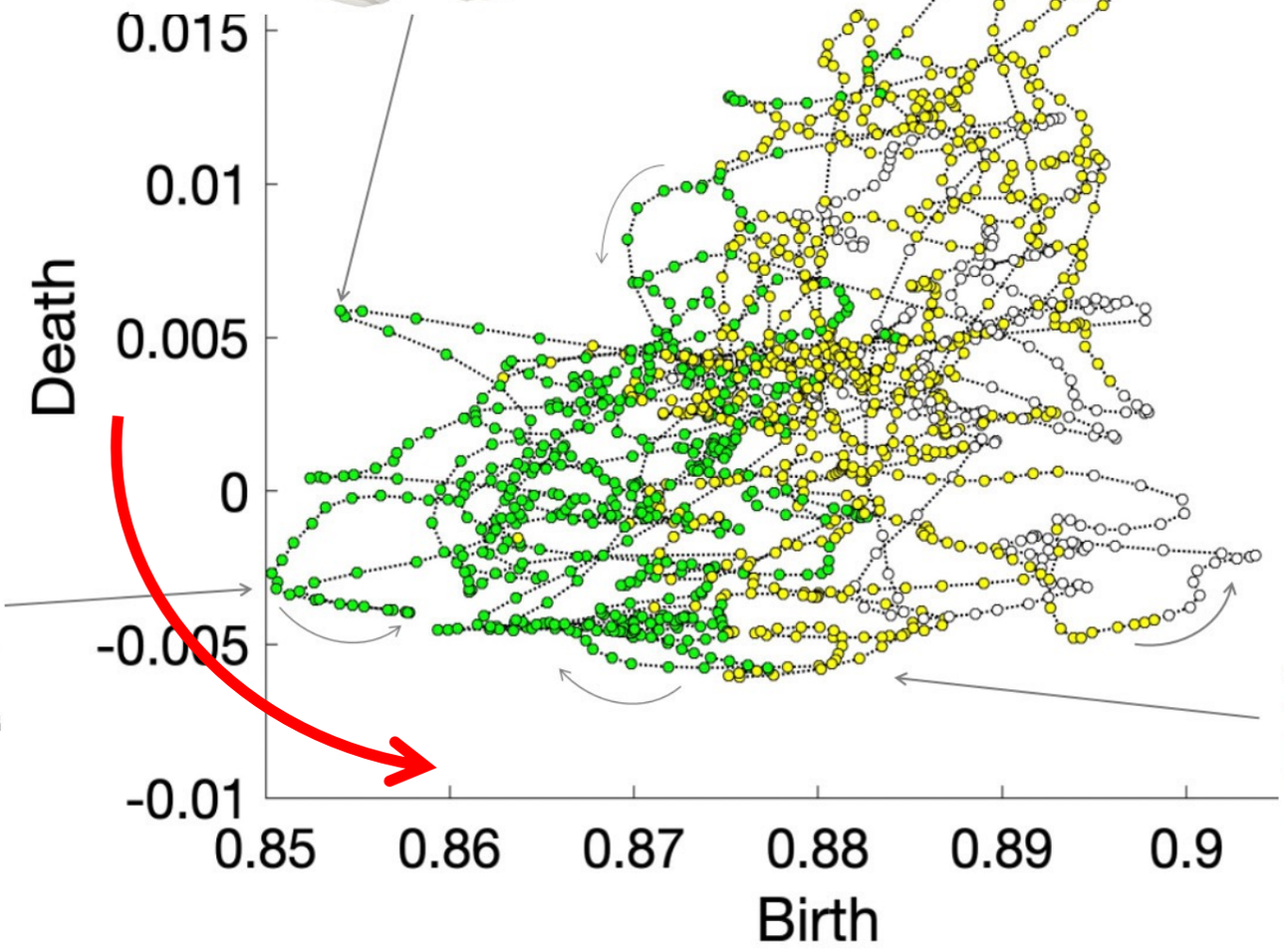
More cycles

less cycles

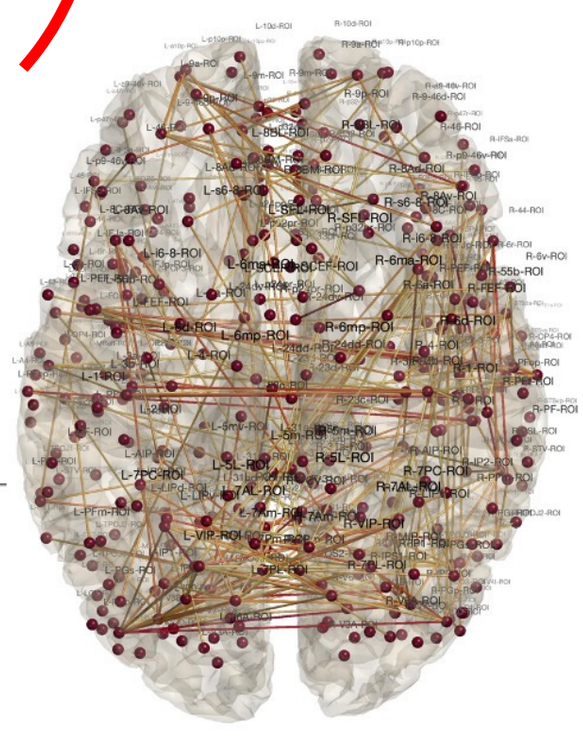








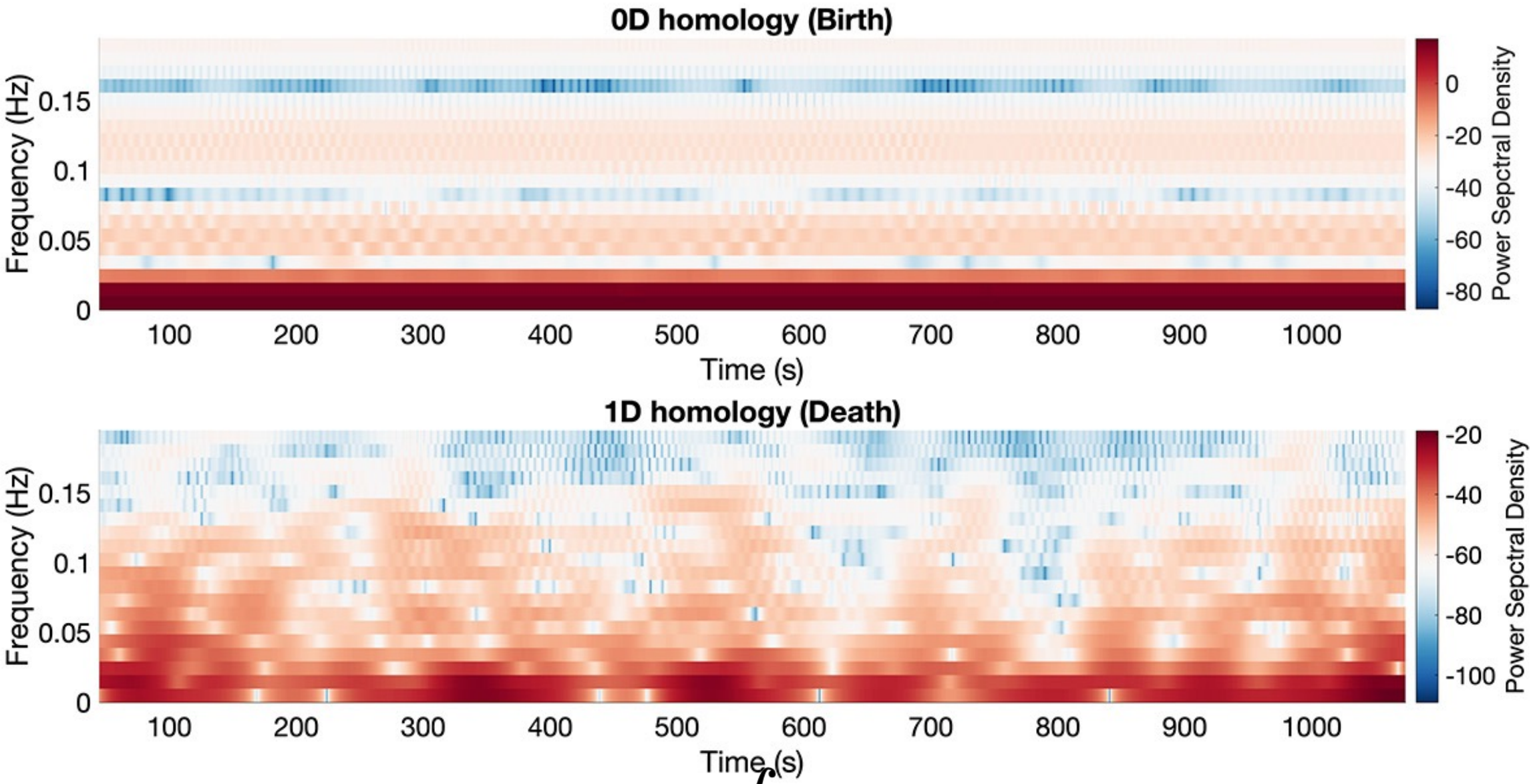
Mostly counter clockwise



More disjoint subnetworks ⟷ *Less disjoint subnetworks*

Topological Time frequency analysis: Topological spectrogram

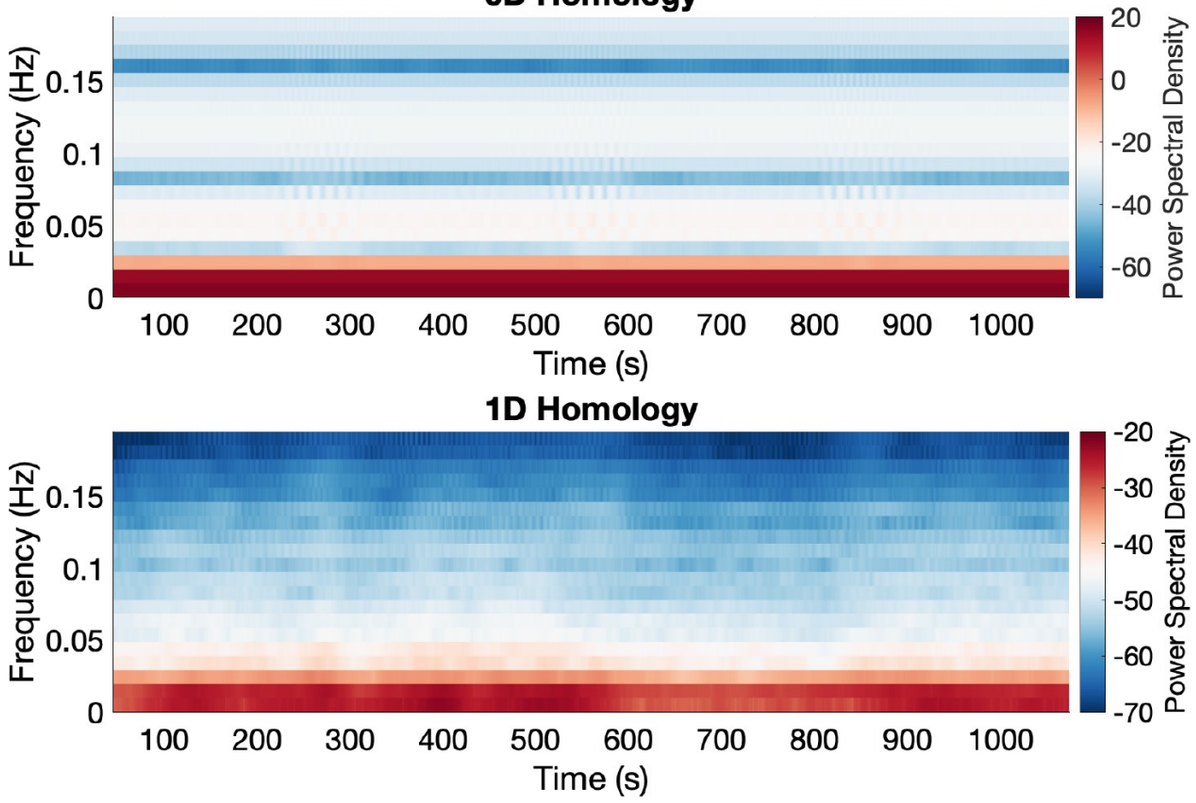
$$X(\tau,\omega) = \int x(t)w(t-\tau)e^{-j\omega t}dt$$



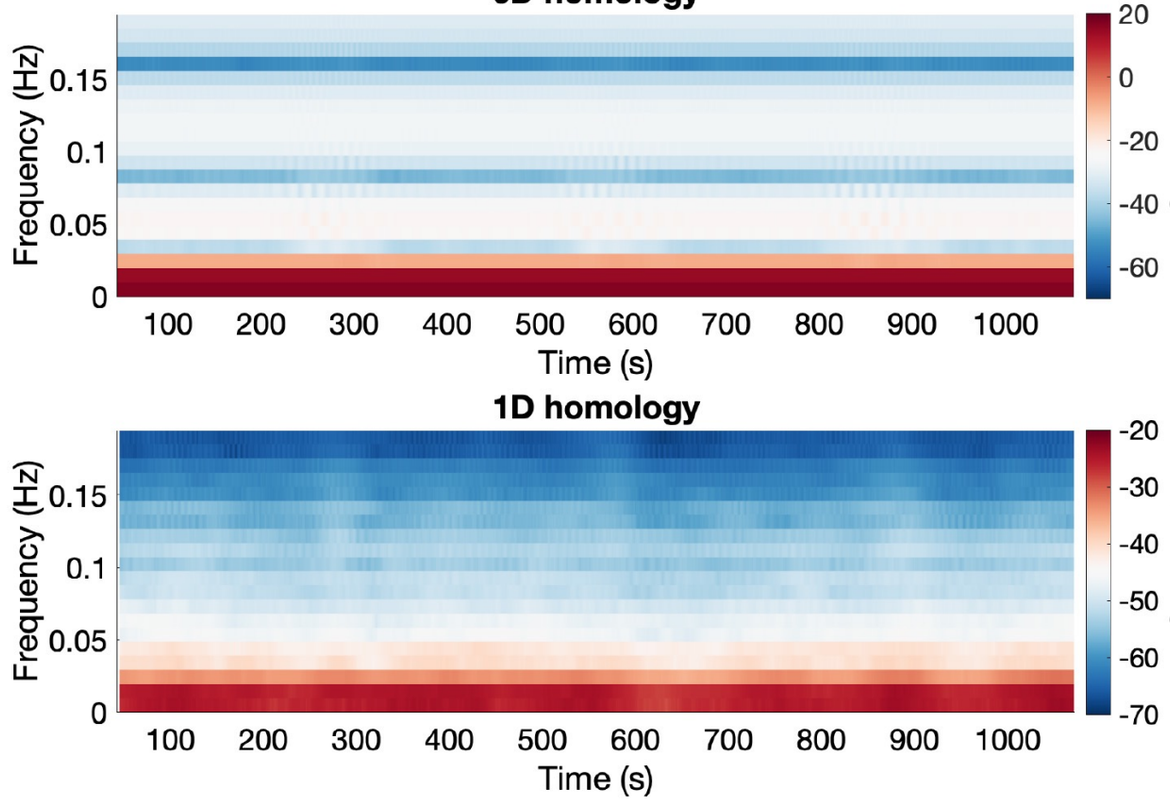
$$Y(\tau,\omega) = \int y(t)w(t-\tau)e^{-j\omega t}dt$$

Window size = 16 or 40 seconds

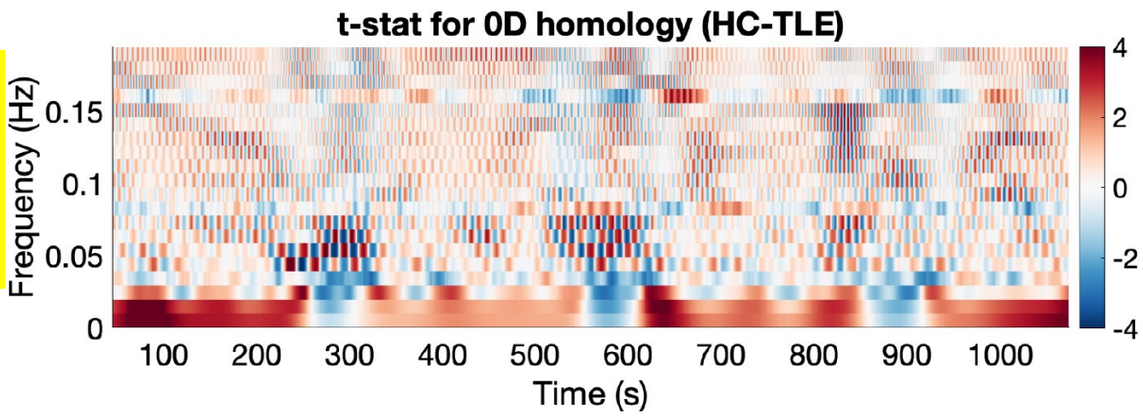
Mean power spectaral density: HC



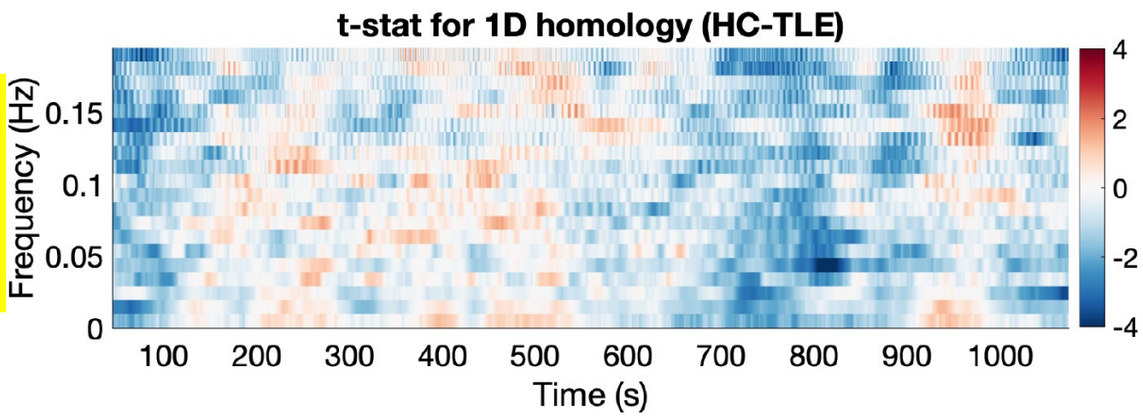
Mean power spectral density: TLE



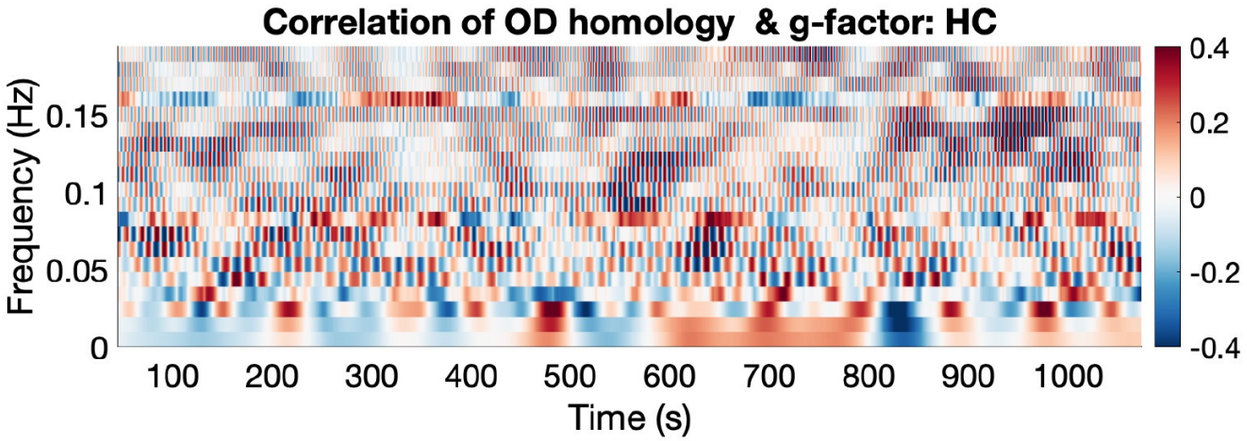
HC: 0D topology fluctuates faster.

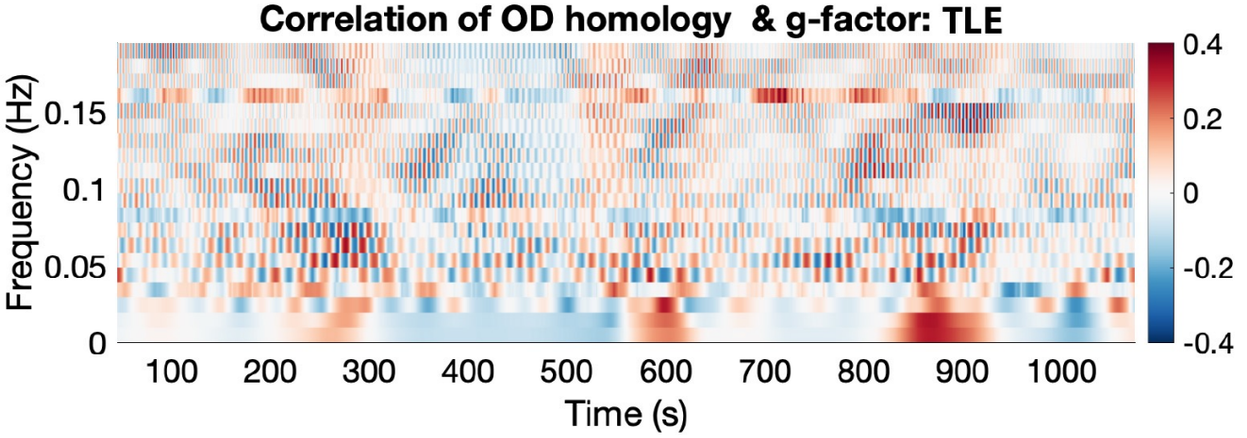


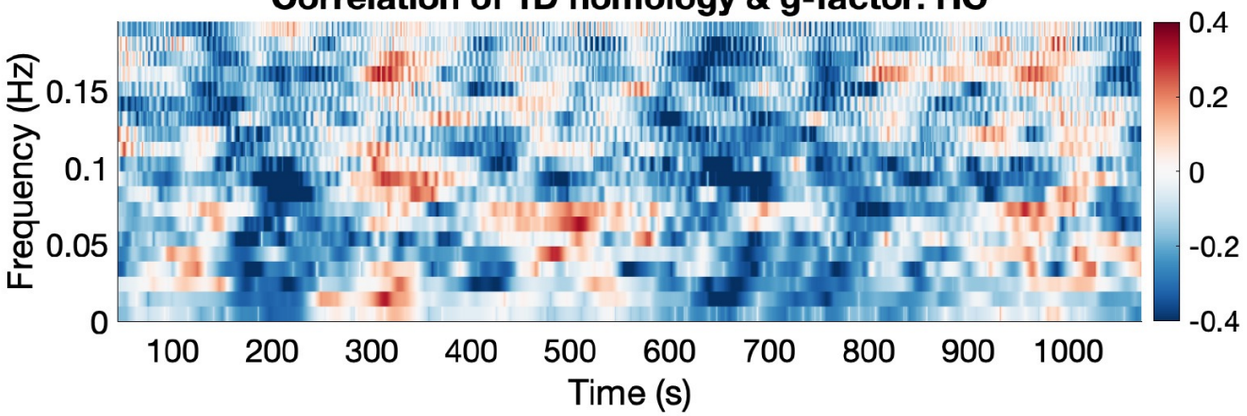
TLE: 1D topology fluctuates faster.

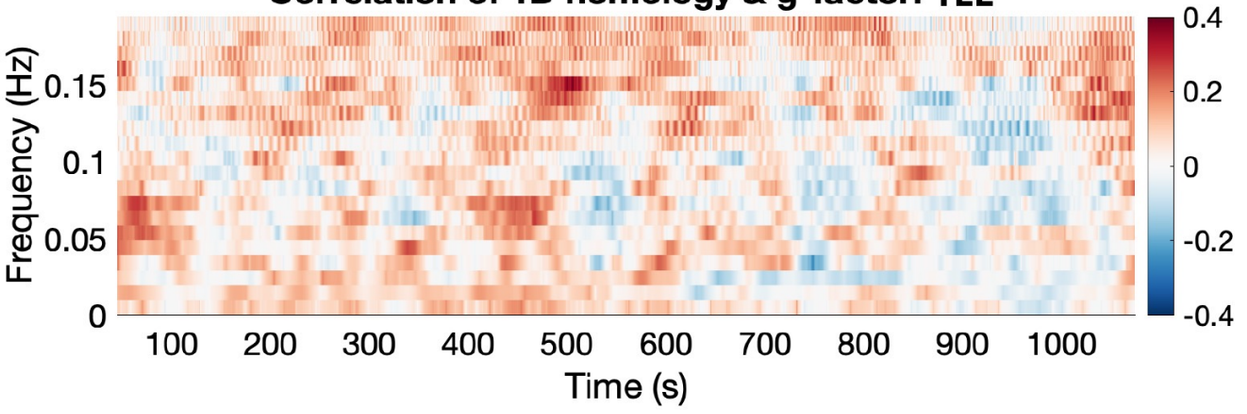


Smarter brain is a slow brain









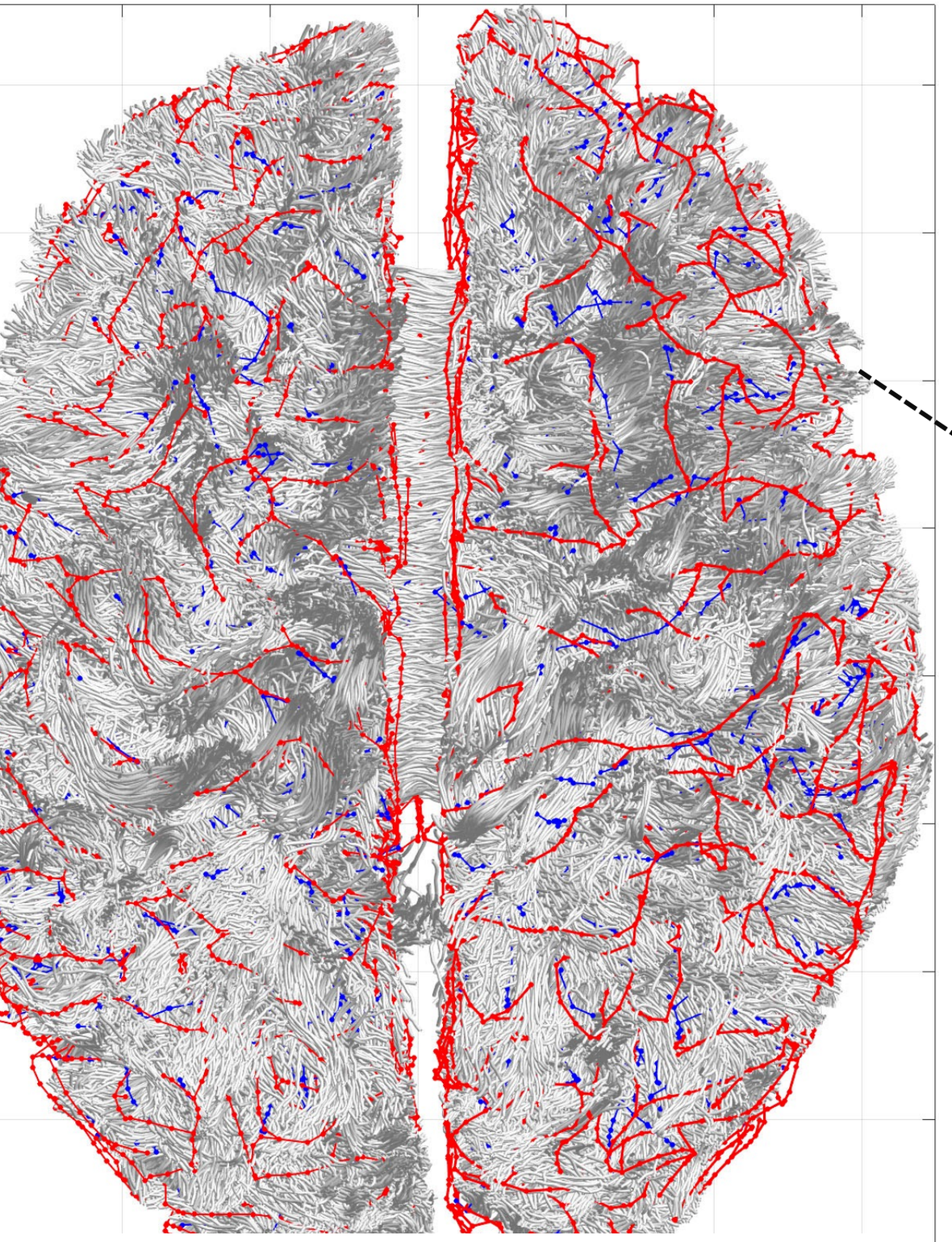
HC: Negative correlation of g-factor and 1D topology

TLE: Positive correlation of g-factor and 1D topology

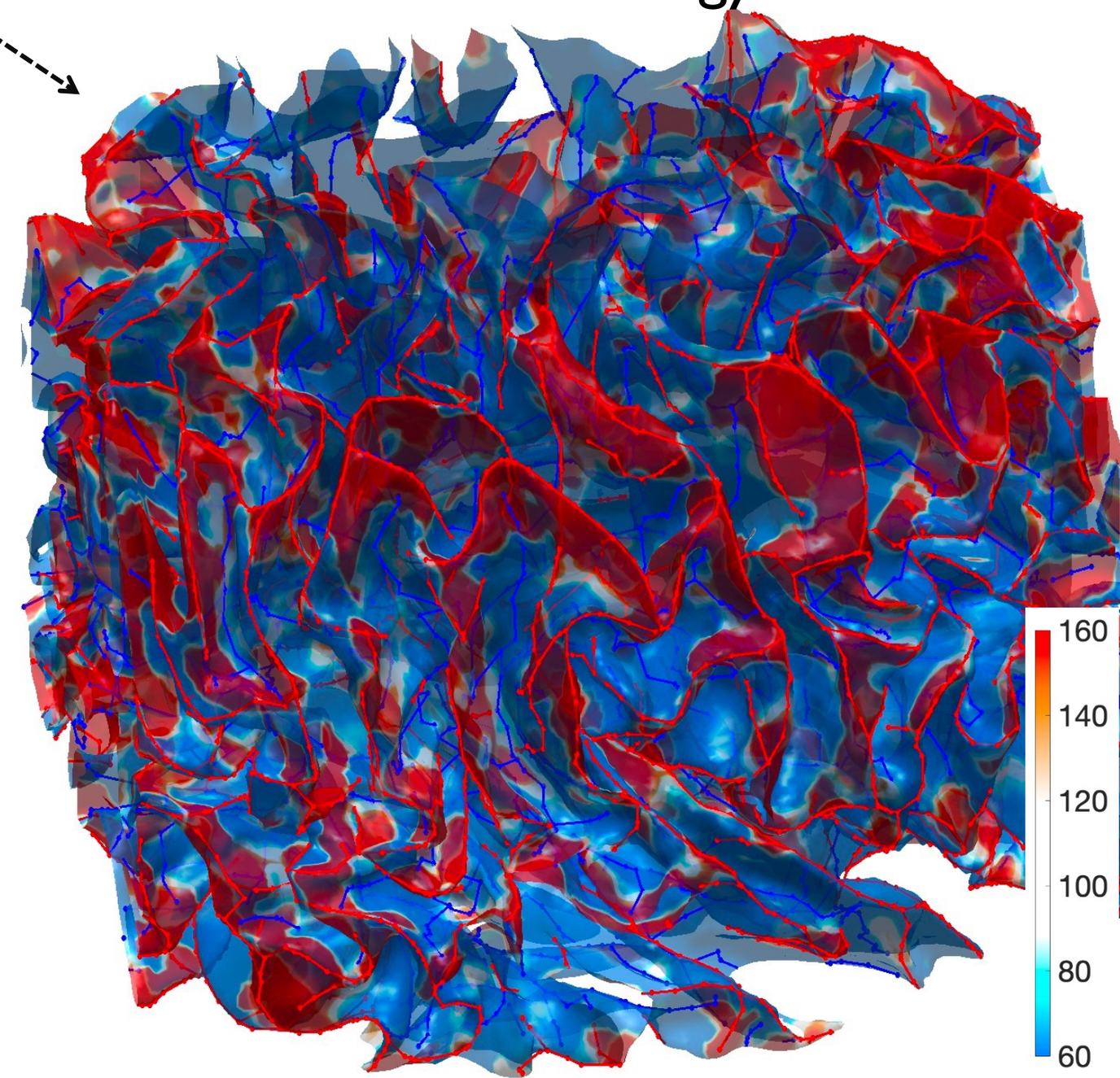
Chung et al. 2024 arXiv:2405.07835

Connectivity gradient from Gyri to Sulci

diffusionMRI → 1 million white matter tracts per subject



Tract count within 2mm radius
around nodes on sulcal & gyral trees

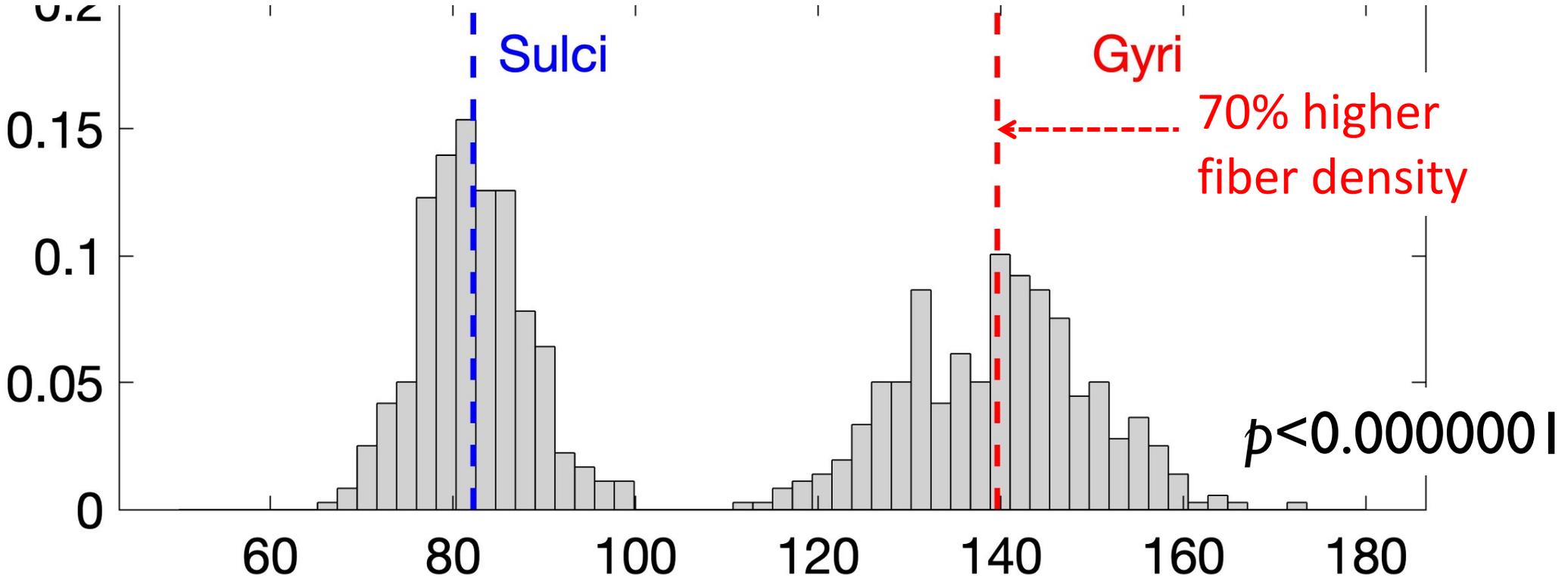


Chung et al. 2019 LNCS 11848:42-53

Huang et al. 2020 IEEE Transactions on Medical Imaging

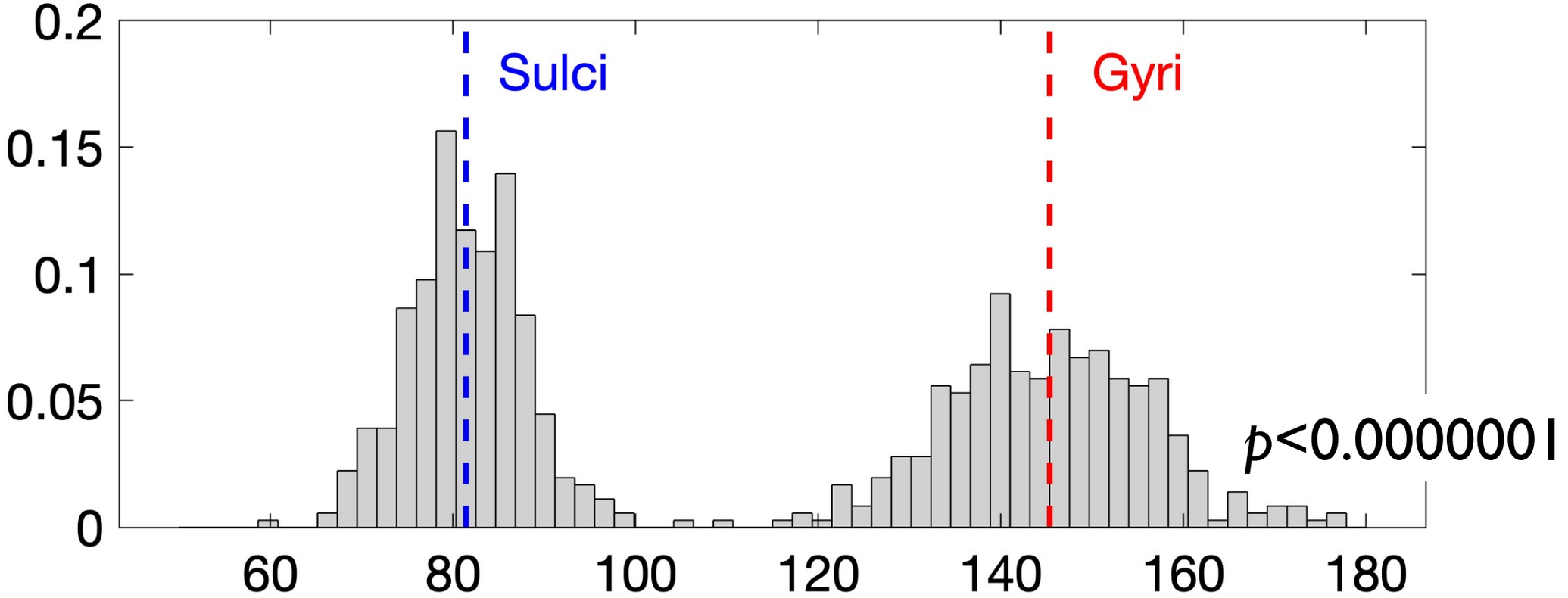
Differential functional connectivity between sulci and gyri

Left



White matter fiber density

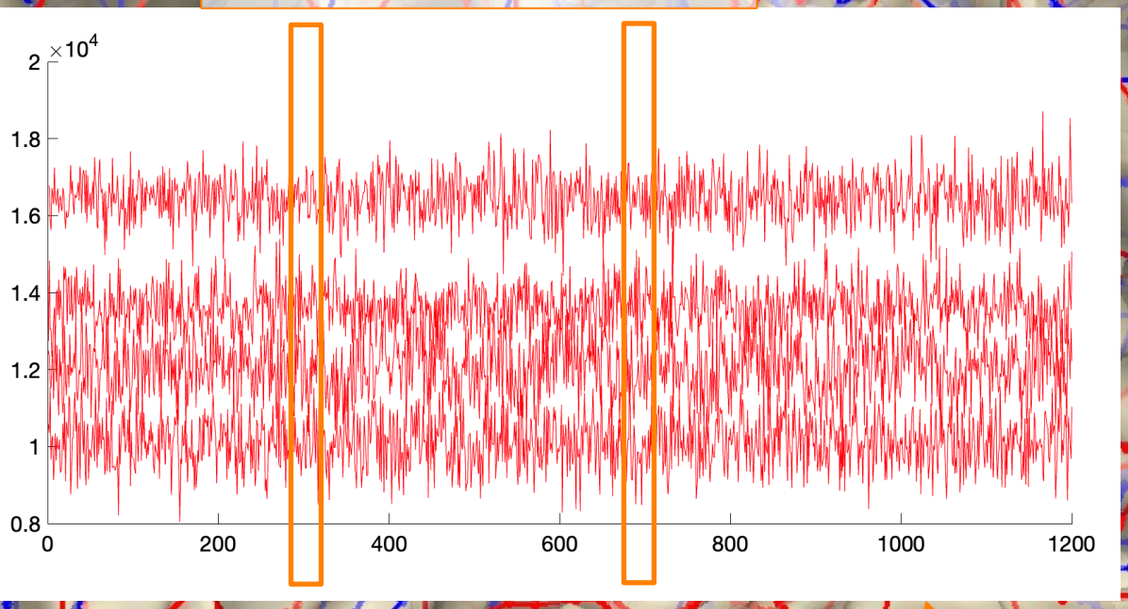
Right



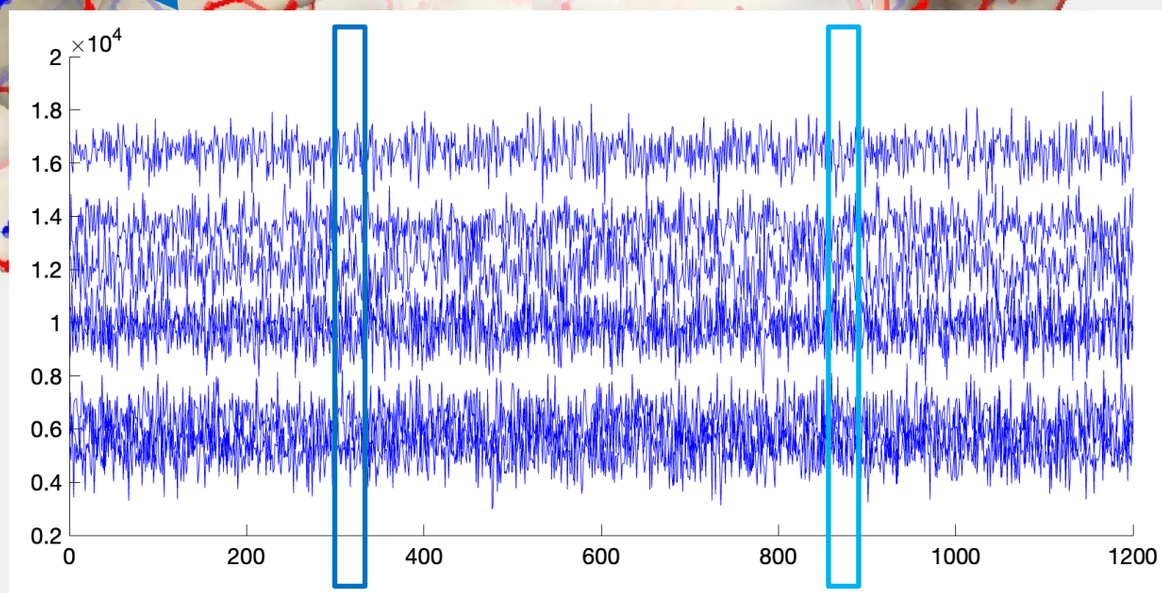
358 subjects

~200000 rs-fMRI time series

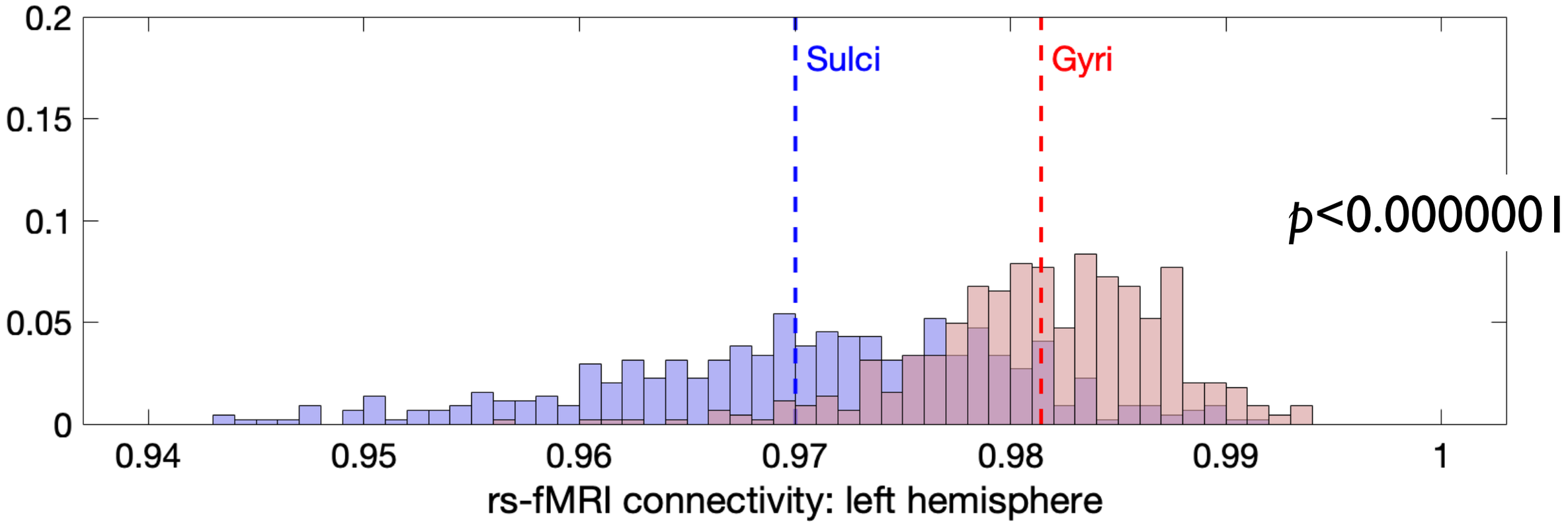
Correlation

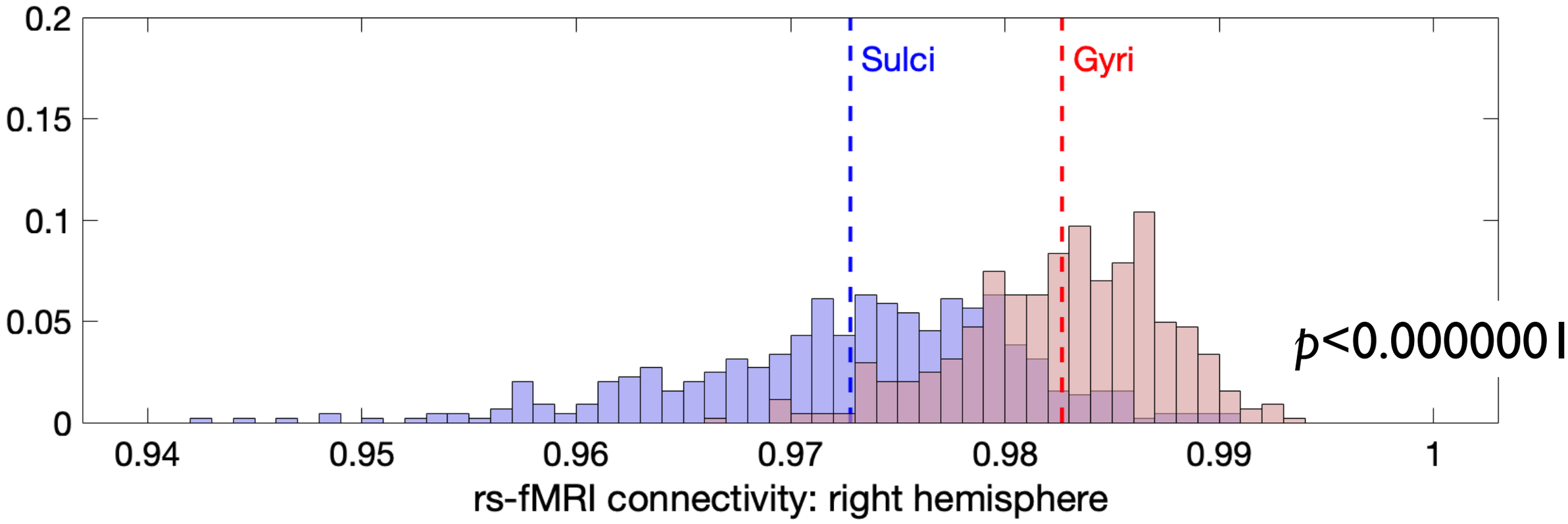


Correlation



Differential functional connectivity between sulci and gyri





443 subjects

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