Towards a new approach to reveal dynamical organization of the brain using topological data analysis

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- The approach of this paper is able to probe within and between task transitions of about (4-9 seconds)
- They observe that the revealed individual differences in the dynamical organization of the subject were predictors of the task performance

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- Previously, this data has typically been used in models after some kind of "averaging" procedure
- The previous approaches have been unable to reveal the optimal temporal and spatial scales which best probe clinically and behaviorally relevant brain dynamics
- Additionally, they are unable to determine if the brain dynamics are best thought of as continuous or discrete or able to tell whether a particular brain activity is healthy or not

Pipeline

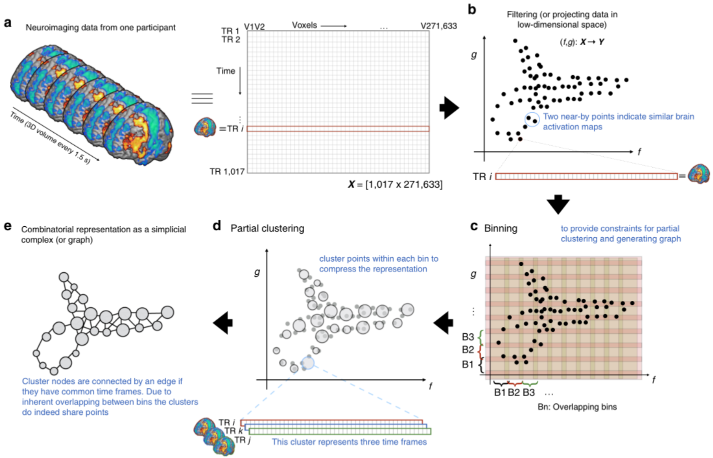

Figure: The method used to convert the 4-dimensional fMRI data into a simplicial complex. Steps b-e are a part of Mapper (the TDA-based algorithm/tool the authors used).

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- Step e treats each cluster as a vertex of a graph and adds an edge between two vertices if they shared a point[4]

Example

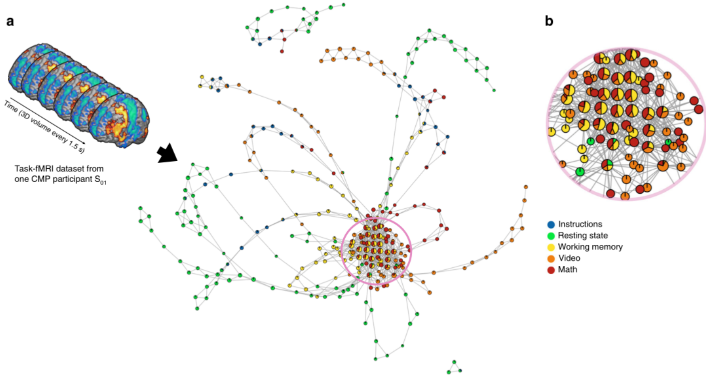

Figure: After running Mapper on an individual's fMRI data, we are left with a graph like the above.

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- The most commonly analyzed mesoscale structures are community structures and core-periphery structures
- *need to explain the structure of the graph out of the mapper pipeline does it have weights on the edges? What are the strengths on the nodes?

Analyzing the community structure of a graph

- You can think about the community structure as the measure of if there are many "communities" of densely connected nodes (not necessarily cliques) where there are only a few connections between communities

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- Q_{mod} is the most commonly used metric to assess the community structure of a graph[1]

$$Q_{\mathrm{mod}} = \sum_{i,j} \left(A_{i,j} - \frac{k_i k_j}{\sum_{ij} A_{ij}} \right) \delta(g_i, g_j)$$

where A is the adjacency matrix, k_i is the strength of the node i, and g_i is the community that i belongs to.

How Q_{mod} scales

Figure: There are two different participants' shape graphs and the relations between modularity and various metrics

Analyzing the core-periphery structure of the graph

How coreness score (CS) scales

Figure: There are two different participants' shape graphs and the CS of their nodes, CS derived from our data and the null models(neuRosim, phase randomization, and constant phase), and a diagram of regions of the brain that were associated with high coreness

References I

[1] Santo Fortunato. "Community detection in graphs". In: *Physics Reports* 486.3-5 (2010), pp. 75–174. DOI: 10.1016/j.physrep.2009.11.002. URL: https://doi.org/10.1016%2Fj.physrep.2009.11.002.

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[3] Maria Giulia Preti, Thomas AW Bolton, and Dimitri Van De Ville. "The dynamic functional connectome: State-of-the-art and perspectives". In: *NeuroImage* 160 (2017). Functional Architecture of the Brain, pp. 41–54. ISSN: 1053-8119. DOI: https://doi.org/10.1016/j.neuroimage.2016.12.061. URL: https://www.sciencedirect.com/science/article/pii/S1053811916307881.

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