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

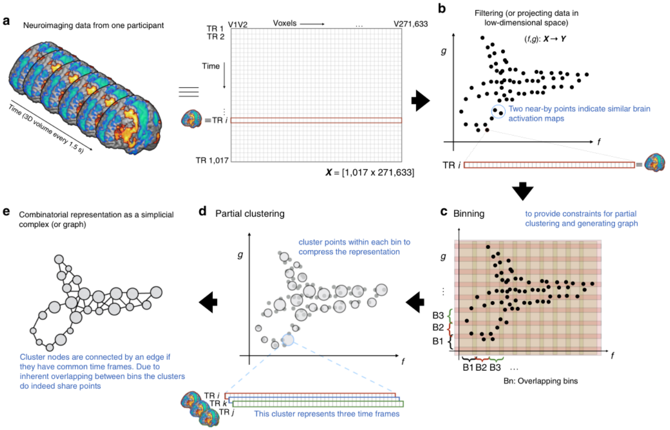

Figure: The method used to convert the 4-dimensional fMRI data into a simplicial complex. Steps b-e are a part of Mapper (the TDA-based algorithm/tool the authors used).

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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

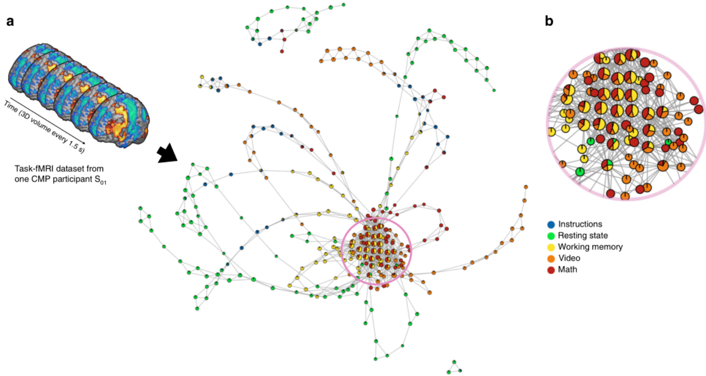

Figure: After running Mapper on an individual's fMRI data, we are left with a graph like the above.

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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

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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

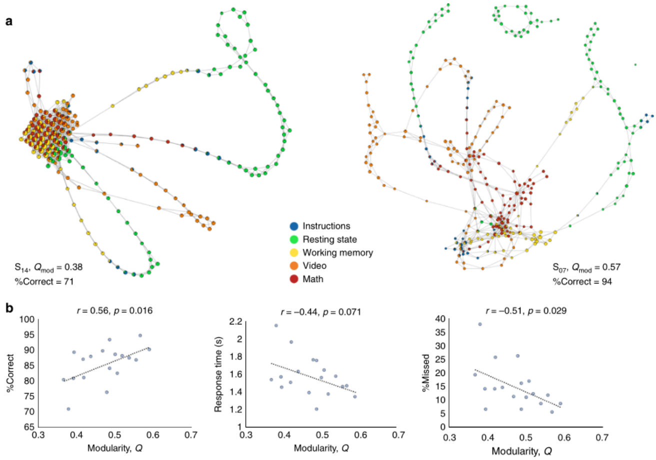

Figure: There are two different participants' shape graphs and the relations between modularity and various metrics

Analyzing the core-periphery structure of the graph

- We assign each node a coreness score (CS) by giving higher scores to nodes which lie deeper in the network

How coreness score (CS) scales

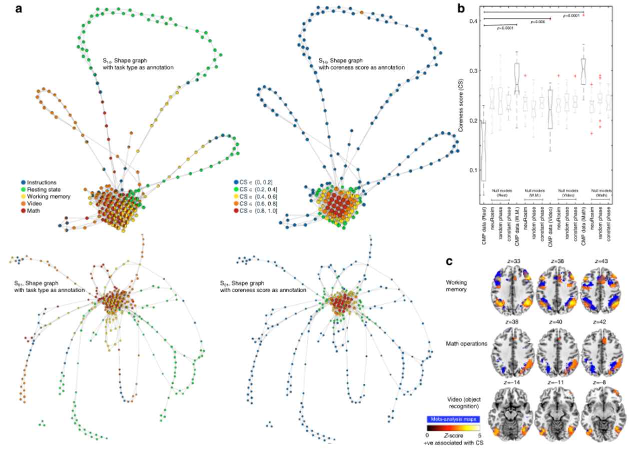

Figure: CS for two different shape graphs, CS derived from our data and the null models(neuRosim, phase randomization, and constant phase), and a diagram of regions of the brain that were associated with high coreness

Trying to explain the topological features using anatomy

Connectivity in the shape graph for different times

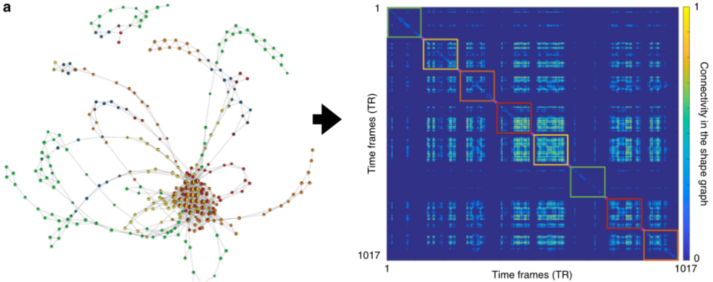

Figure: Shows which times during the scan were similar to other times by looking at the connections between times in the shape graph.

Brains are typically more connected during strenuous tasks

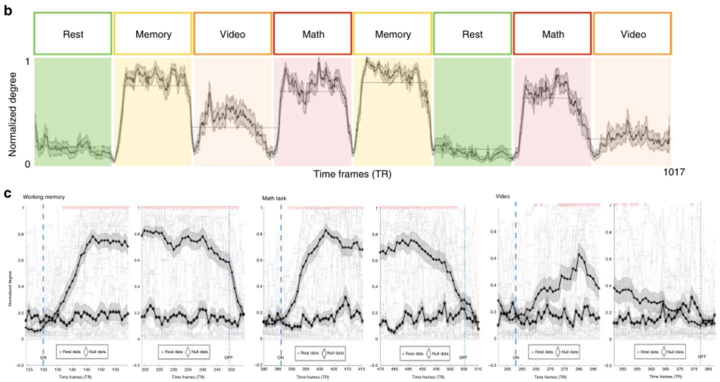

Figure: When there is a transition between tasks, this is captured by a dramatic change in the degree of the corresponding nodes. This phenomenon of nodes taken during strenuous activity having high degree is significant

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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