

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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- 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

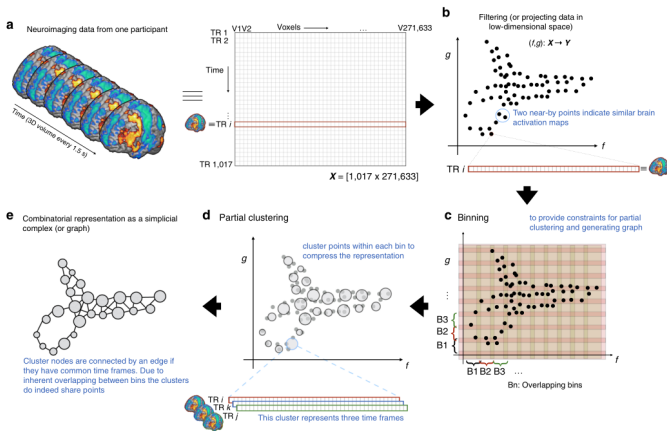


Figure: The method used to convert the 4-dimensional fMRI data into a simplicial complex. Steps b-e are a part of Mapper (the TDA-based algorithm/tool the authors used).

How Mapper works

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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

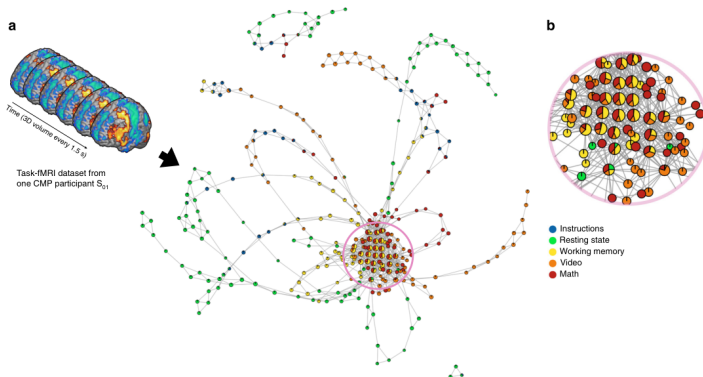


Figure: After running Mapper on an individual's fMRI data, we are left with a graph like the above.

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- *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]

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

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

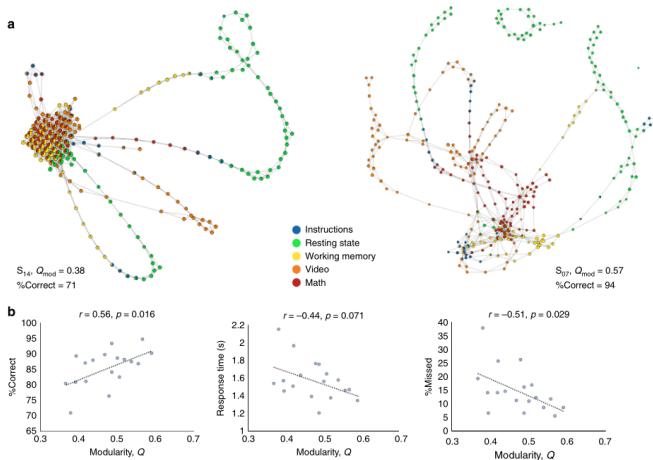


Figure: There are two different participants' shape graphs and the relations between modularity and various metrics

Analyzing the core-periphery structure of the graph

How coreness score (CS) scales

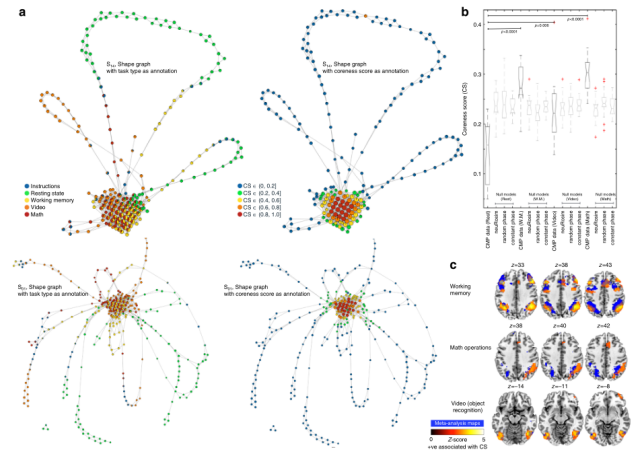


Figure: CS for two different shape graphs, CS derived from our data and the null models (neuRosim, phase randomization, and constant phase), and a diagram of regions of the brain that were associated with high coreness

Trying to explain the topological features using anatomy

Connectivity in the shape graph for different times

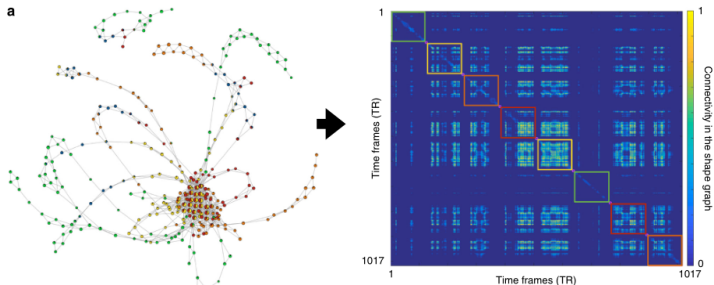


Figure: Shows which times during the scan were similar to other times by looking at the connections between times in the shape graph.

Brains are typically more connected during strenuous tasks

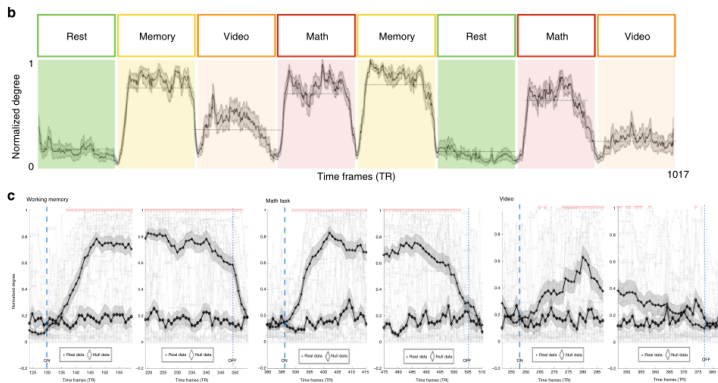


Figure: When there is a transition between tasks, this is captured by a dramatic change in the degree of the corresponding nodes. This phenomenon of nodes taken during strenuous activity having high degree is significant

References I

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