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

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- They observe that the revealed individual differences in the dynamical organization of the subject were predictors of the task performance

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- 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

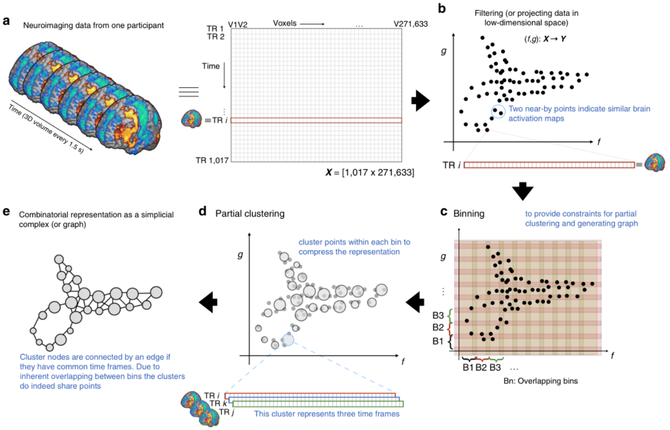

Figure: The method used to convert the 4-dimensional fMRI data into a simplicial complex. Steps b-e are a part of Mapper (the TDA-based algorithm/tool the authors used).

How Mapper works

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

Filtering in Mapper

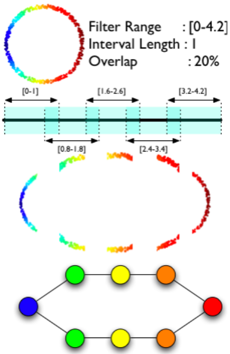

Figure: Toy example of applying a filter to data[4]. The data is sampled from a noisy circle, and the filter used is $f(x) = ||x - p||^2$, where p is the left most point in the data. We divide the range of the filter into 5 intervals which have length 1 and a 20% overlap. For each interval we compute the clustering of the points lying within the domain of the filter restricted to the interval, and connect the clusters whenever they have non-empty intersection. At the bottom is the simplicial complex which we recover whose vertices are colored by the average filter value. Our paper uses a very different filter function. They use something called the Neighborhood Lens function to take their 271633-dimensional data into $\mathbb{R}^2$. This function is part of a patented software that appears to be standard.

Example

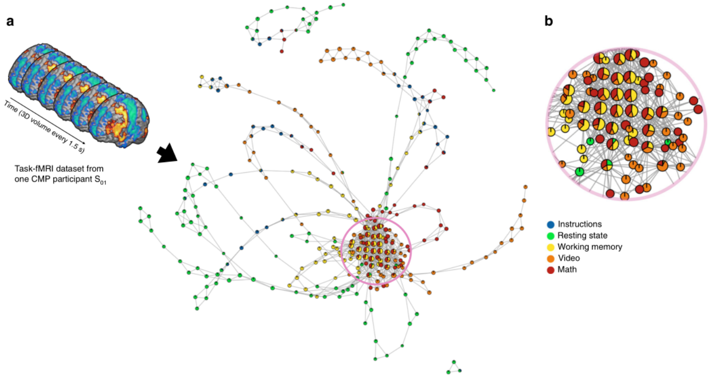

Figure: After running Mapper on an individual's fMRI data, we are left with a graph like the above.

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- Two likely possibilities: the weight between two nodes is the number of timeframes they shared, or the weight is something that depends on the mean distance between the timeframes constituting the nodes

Analyzing the community structure of a graph

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

$$Q_{\mathrm{mod}} = \sum_{i,j} (A_{ij} - P_{ij})\, \delta(g_i, g_j)$$

where A is the adjacency matrix, $P_{ij} = \frac{k_i k_j}{\sum_{ij} A_{ij}}$, k_i is degree of i, g_i is the community that i belongs to, and δ is the Kronecker delta.

Some intuition for Q_{mod}

- It is based on the idea that a random graph is not expected to have a cluster structure, so the possible existence of clusters is revealed by the comparison between the actual density of edges in a subgraph and the density one would expect to have in the subgraph if the vertices of the graph were attached regardless of community structure
- This expected edge density ($P_{ij} = \frac{k_i k_j}{2m}$ where $m = \sum_{ij} A_{ij}$) depends on the chosen null model, i.e. a copy of the original graph keeping some of its structural properties but without community structure[1]
-

How Q_{mod} scales

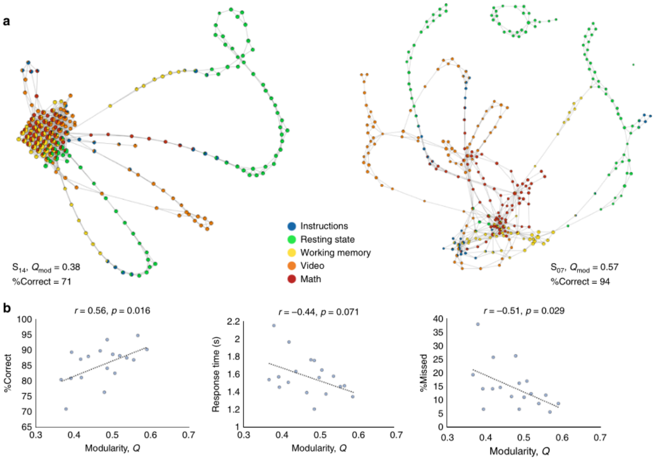

Figure: There are two different participants' shape graphs and the relations between modularity and various metrics

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

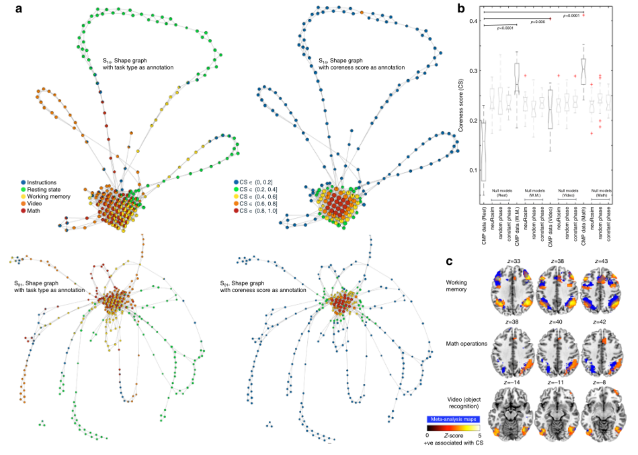

Figure: CS for two different shape graphs, CS derived from our data and the null models(neuRosim, phase randomization, and constant phase), and a diagram of regions of the brain that were associated with high coreness

Trying to explain the topological features using anatomy

Connectivity in the shape graph for different times

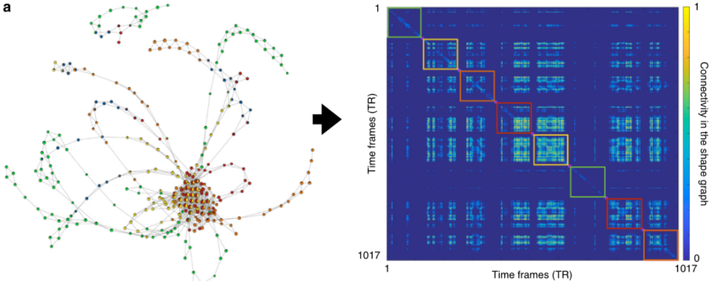

Figure: Shows which times during the scan were similar to other times by looking at the connections between times in the shape graph.

Brains are typically more connected during strenuous tasks

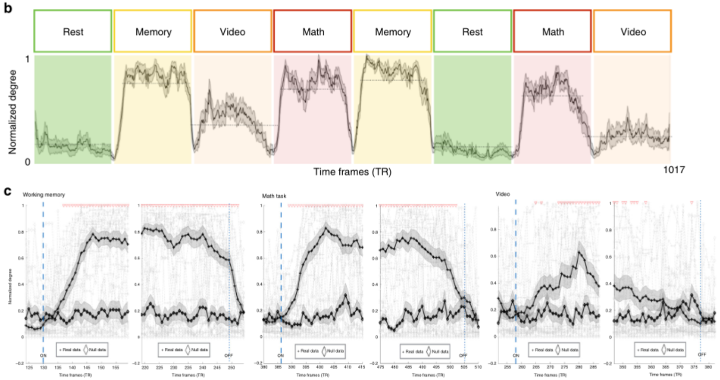

Figure: When there is a transition between tasks, this is captured by a dramatic change in the degree of the corresponding nodes. This phenomenon of nodes taken during strenuous activity having high degree is significant

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