#poster#

Higher-order interactions between brain regions are better at profiling tasks

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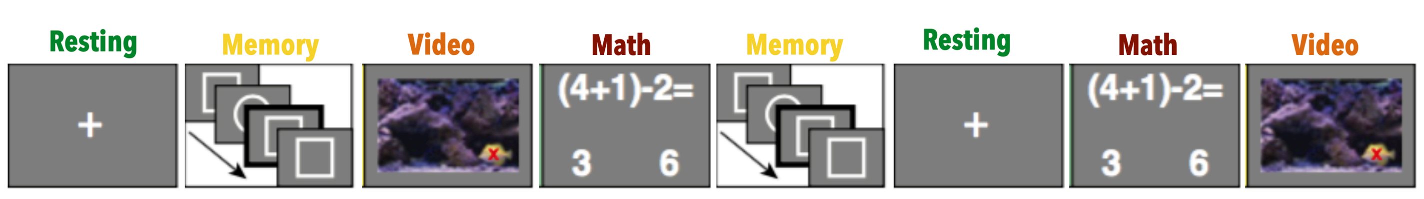
Motivation

The brain is typically characterized by a set of interactions between different regions, which govern its emergent dynamics. Most previous literature in network neuroscience has focused on pairwise interactions between brain regions, where population insights can be derived by representing and analyzing the system as a graph (Fornito et al., 2016). However, increasing evidence points towards higher-order interactions (e.g., triplets, quadruplets; denoted as HOIs) between brain regions as a major factor in shaping the dynamical properties of the brain (Battiston et al., 2021; Faskowitz et al., 2020; Owen et al., 2021). To further this line of research, two main issues need to be addressed. First, with increasing order of interaction, novel approaches are required **to better represent and characterize** the dynamical structure (or manifold) of HOIs. Second, new studies are required **to explore the nature of information** captured by different HOIs. We aim to address these issues using tools from Topological Data Analysis (TDA).

Data

Continuous multi-task fMRI data

We used a publicly available fMRI dataset (n=18)(Gonzalez-Castillo et al., 2015), to estimate time-series for different degrees of HOIs. In this fMRI dataset, participants performed a continuous multitask experiment, where they were scanned continuously for a 25 min and 24 s long session while performing four different tasks (rest, working memory, math, and video). Each task was presented for two separate 3 min blocks, with each task block being preceded by a 12 s instruction period.

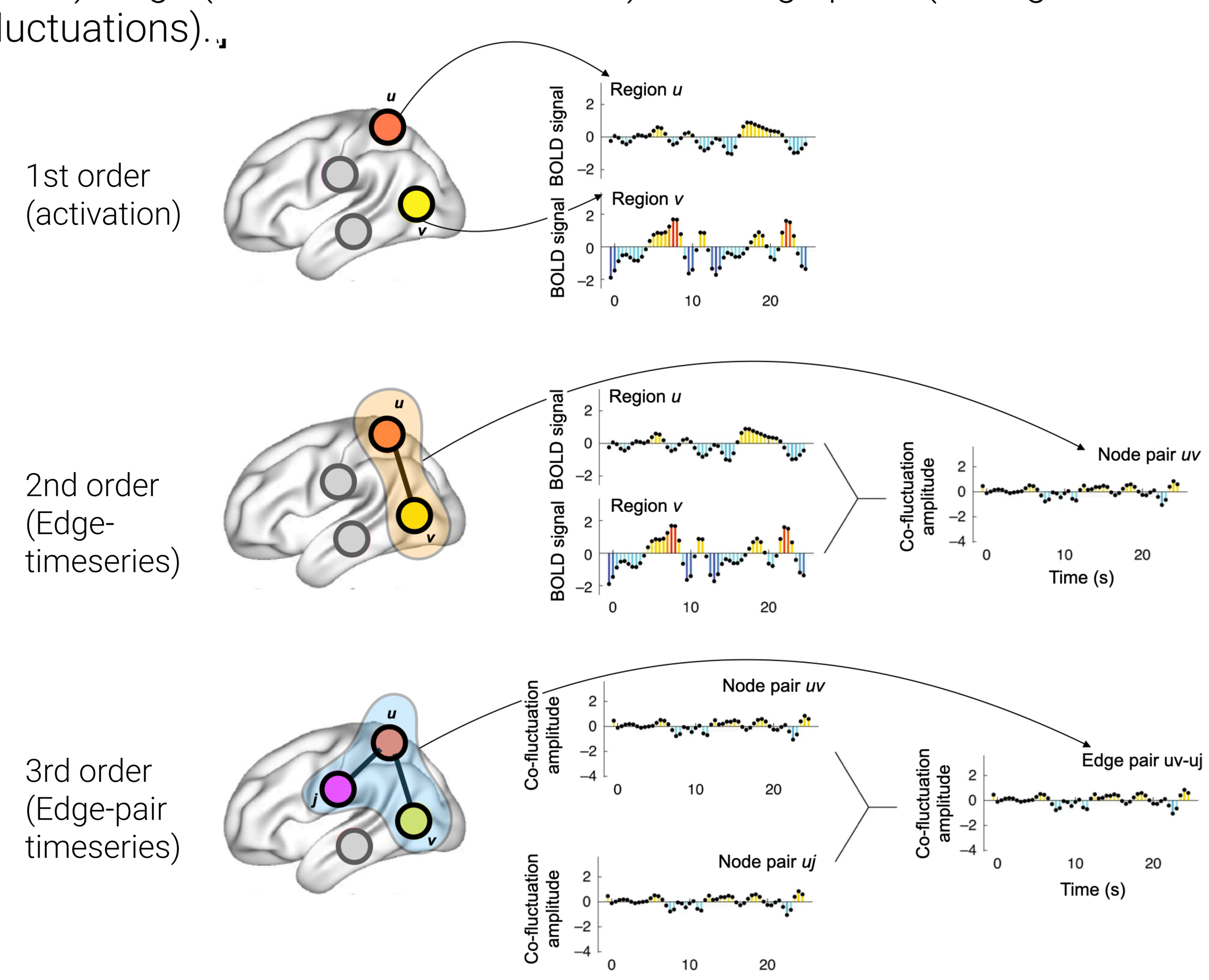


Gonzalez-Castillo et al. 2015 ***PNAS***

Methods

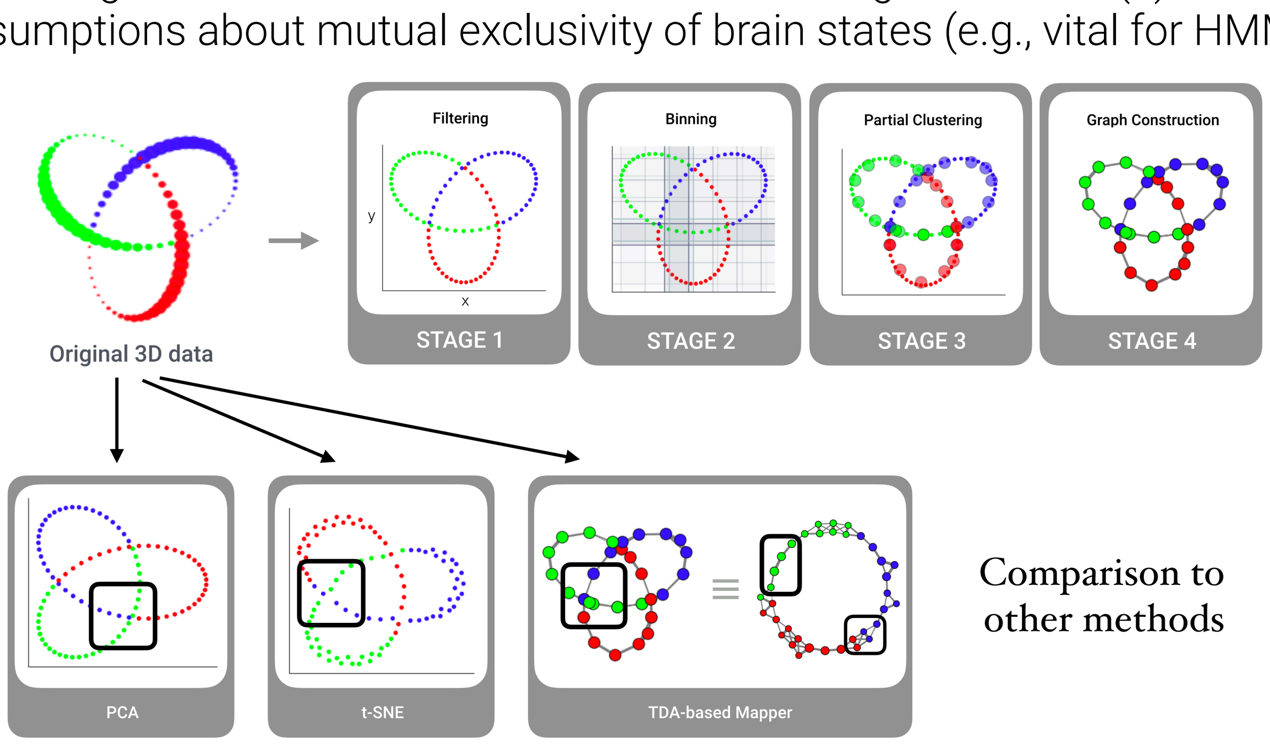
Measuring higher-order interactions (HOIs)

As shown below, we included three degrees of HOIs, i.e., nodal (or first-order), edge (or nodal co-fluctuations), and edge pairs (or edge co-fluctuations).



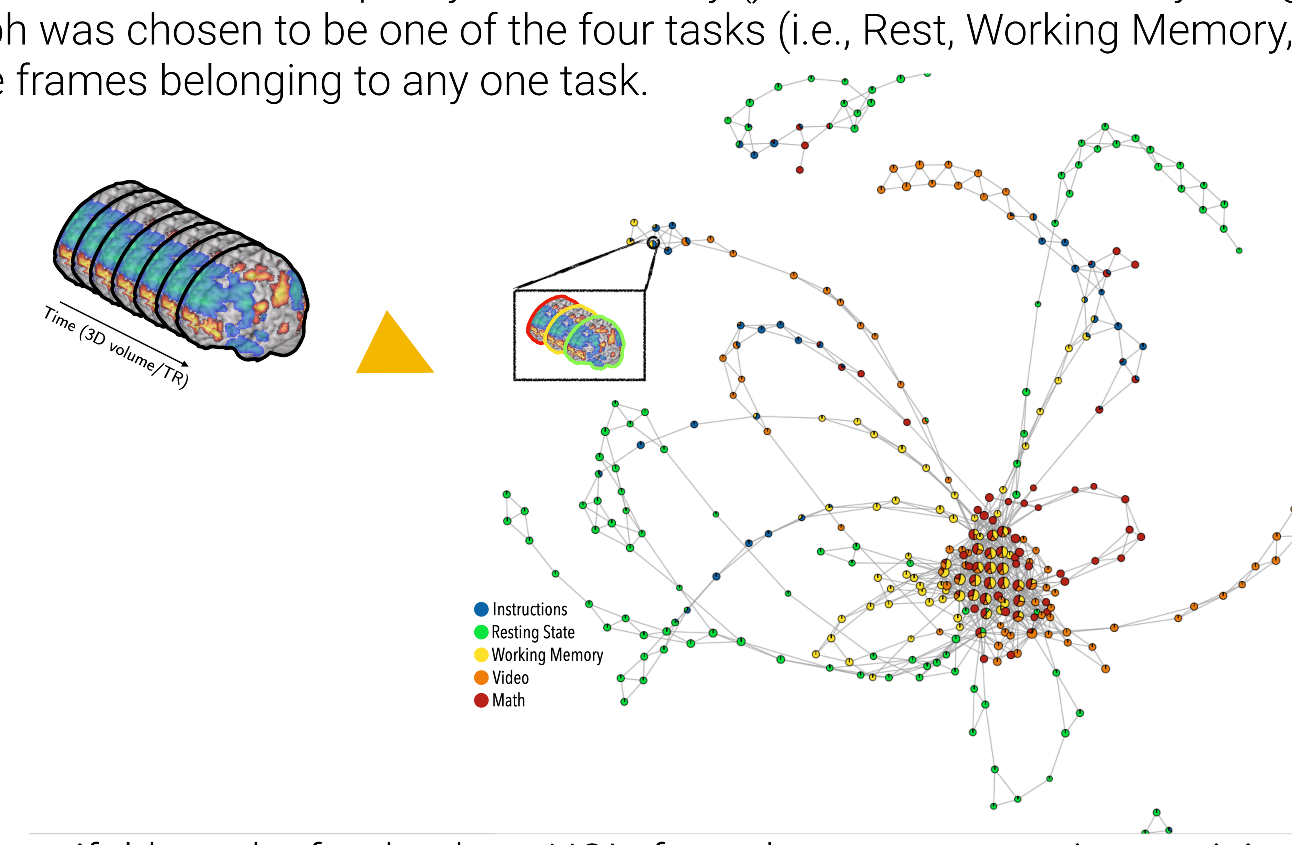
Characterizing HOIs using Topological Data Analysis

To characterize the dynamical structure of different HOIs, we fed the time-series from each HOI into the TDA-based Mapper pipeline (Saggar et al., 2018, 2021; Singh et al., 2007). Mapper has been previously shown to capture task-evoked transitions in the whole-brain activity patterns at the highest spatiotemporal resolution (Saggar et al., 2018). Unlike previous time-varying analytics, Mapper does not require (1) splitting or averaging data across space or time (e.g., windows) at the outset; (2) a priori knowledge about the number of whole-brain configurations; or (3) strict assumptions about mutual exclusivity of brain states (e.g., vital for HMMs).



Annotating Mapper-generated graphs using task type

Lastly, to characterize the Mapper-generated manifold graphs from each HOI, we annotated nodes in the graph by task type. The nodes with time frames from multiple tasks were visualized using pie charts to appropriately depict the proportion of time frames from each task (Fig. 1C). To examine the degree of separation between different task types, we estimated the quality of modularity (), where the community assignment for each node in the manifold graph was chosen to be one of the four tasks (i.e., Rest, Working Memory, Video, and Math) based on most time frames belonging to any one task.



Results

Mapper-generated manifold graphs for the three HOIs from three representative participants are shown in Fig. 2A. Qualitatively, for these participants, as the degree of interaction increases so did the segregation of task-types in the graph. Thus, suggesting that higher-order interactions better characterized differences across task types. This result was quantitatively summarized, across all participants, using a one-way ANOVA ($F(2,53)=15.32$, $p=6.14 \times 10\text{-}06$). Further, post hoc t-tests revealed increasing segregation (modularity) with an increasing degree of interaction (all ps <0.05; Fig. 2B).

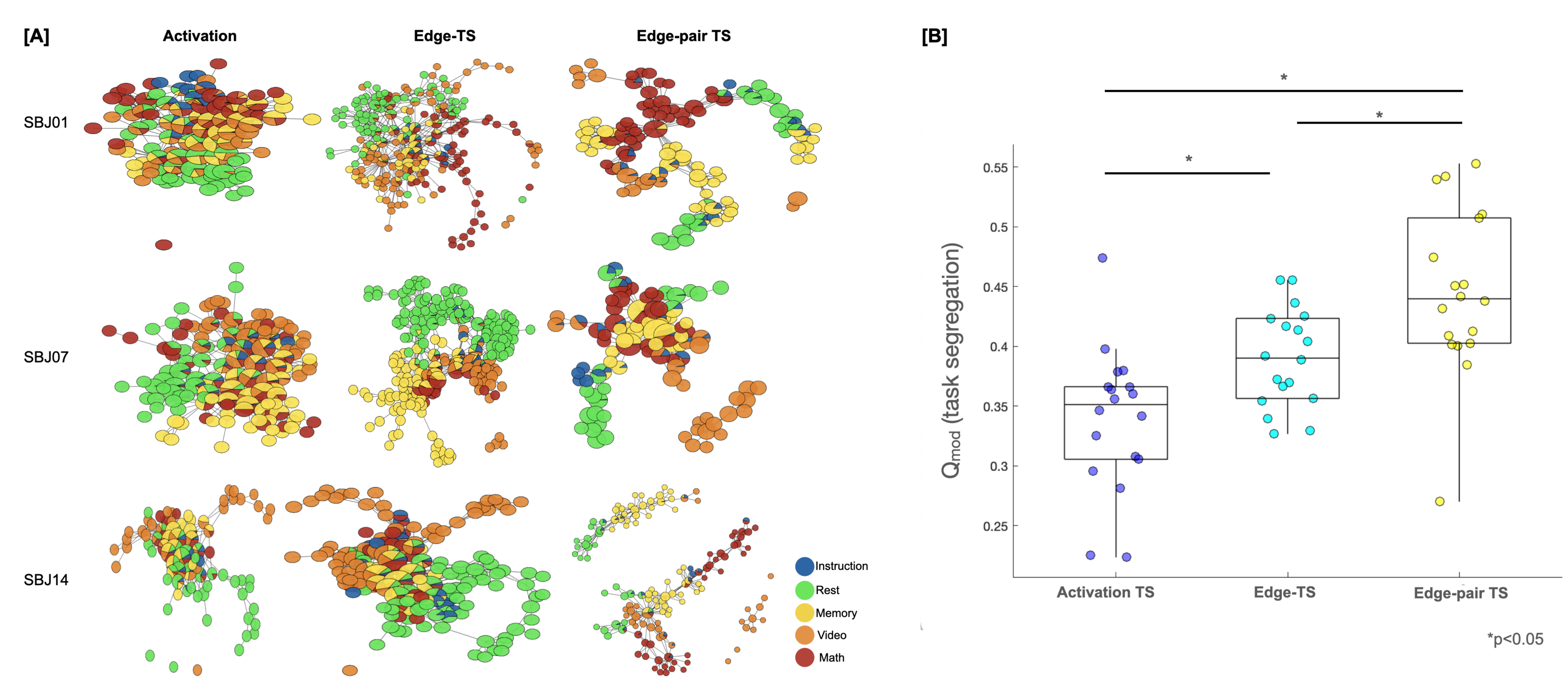


Figure 2: [A] Mapper-generated manifold graphs annotated by task types for three representation participants (SBJ01, 07, and 14) as well as for each order of interaction. As evident qualitatively, with increasing order of interaction the graph nodes of different task types are more segregated, indicating that higher-order interactions might be better at profiling tasks. **[B]** Quantitative analysis of task-segregation on graphs using quality of modularity as a metric.

Conclusions

In this proof-of-concept study, we provide evidence that TDA-based Mapper approach effectively represents and characterizes HOIs in the brain. Importantly, our results further amplify previous work suggesting that HOIs might better represent cognitive processes than nodal or pair-wise interactions. Future work is needed to validate these results against carefully crafted null models as well as across different datasets.

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