Learning With Topological Features of Functional Brain Networks

Sourabh Palande and Bei Wang*

A summary of joint works with Archit Rathore, Keri L. Anderson, Jeffey S. Anderson, Brandon Zielinski, and Tom Fletcher

Functional magnetic resonance imaging (fMRI) measures brain activity by detecting changes in blood oxygenation levels (BOLD signals). Relating these activity measurements to behavioral and cognitive measures is a topic of great interest in neuroscience. Such relationships may lead to identification of bio-markers for various brain disorders and may also help us develop targeted treatments. However, working with fMRI data can be computationally challenging due to its size and complexity. Instead, it is common practice to extract BOLD signals corresponding to a pre-determined set of regions of interests (ROIs).

Consider a data matrix where each row represents the BOLD signal corresponding to a ROI in the brain across time. A functional connectivity network (FCN) is represented as a correlation matrix, or alternatively, a weighted graph; where each ROI is a node, and edge weights are given by correlations between the corresponding rows of the data matrix. These networks capture the synchronicity between ROIs of the brain.

Persistent homology [4] allows us to capture topological features of these weighted graphs across all scales. These topological features can be represented in the form of persistence diagrams (PDs), or transformed into objects such as persistent landscapes (PLs) [3] or persistence images (PIs) [1] which admit simple vector representations. An inner product structure can be defined directly on the space of persistence diagrams, which allows us to apply kernel methods. We give two applications of employing topological features of functional brain networks in machine learning tasks.

ASD Classification. In our first application [5], we evaluate the utility of persistence diagrams derived from FCNs in the classification of autism. Using all three representations - PD, PLs, PIs - of topological features, we experiment with classification models such as support vector machines (SVMs), random forests (RFs) and neural networks (NNs). We also propose hybrid SVM and NN models that combine correlations with topological features.

Even with a simple 3-layer architecture, our proposed hybrid NNs achieve close to state-of-the-art classification accuracy, with the best accuracy of 69.19%. Both NNs with only correlation features, and the hybrid NNs provide a significant improvement in test accuracy over SVM and RF classifiers. The three representations of topological features (PD, PI and PL) have similar performance. Kernel SVM models using four different kernels for PDs show very similar classification accuracies. However, our experiments also show that the improvement due to topological features is not always statistically significant. Therefore, we offer a cautionary tale to the practitioners regarding the limited discriminative power of topological features derived from fMRI data for the classification of autism.

*NIH grants R01EB022876, R01MH080826, and NSF grant IIS-1513616

Relating Functional Brain Networks to Cognitive Measures. Researchers have predominantly focused on studying spatial co-activation patterns captured by FCNs. However, there is a dynamic aspect to brain function that is not captured by traditional FCNs. In our second application [2], we construct networks with time points as nodes instead of ROIs. The edge weights are now given by correlations between corresponding columns of the data matrix. These networks, which we refer to as temporal functional connectivity networks (tFCNs), encode how similar the spatial patterns of ROI activations are at different time points. We derive persistence barcodes, as well as graph theoretic measurements such as modularity, characteristic path length, global efficiency and clustering coefficient, from both traditional FCNs and tFCNs. We then correlate these measures to various cognitive and personality measurements.

When comparing cognitive and personality metrics to persistence barcodes, with partial correlation with age, sex and head motion as covariates, there are significant correlations between persistent barcodes and fluid intelligence for tFCNs, with less sensitivity to head motion. For traditional FCNs, fluid intelligence is correlated with barcode values in brain regions comprising association cortex of the frontal, parietal and temporal lobes, with weaker correlations in sensory and motor regions. Of the 12 cognitive tests, 11 show significant partial correlation with persistent barcodes of traditional FCNs, and of the 5 personality factors, four show significant corrected partial correlation with persistent barcodes of traditional FCNs.

Although less intuitive than traditional functional connectivity between brain regions, our results suggest that functional connectivity between timepoints may offer new insights into aspects of cognition and neuropathology. Persistent homology in combination of temporal functional connectivities may reflect temporal duration and frequency of brain microstates, or oscillations between metastable patterns of relative brain activity; therefore providing new insights into brain network architecture and opportunities for the prediction of behavioral traits.

References

[1] Henry Adams, Tegan Emerson, Michael Kirby, Rachel Neville, Chris Peterson, Patrick Shipman, Sofya Chepushtanova, Eric Hanson, Francis Motta, and Lori Ziegelmeier. Persistence images: A stable vector representation of persistent homology. *Journal of Machine Learning Research (JMLR)*, 18(1):218–252, 2017.

[2] Keri L. Anderson, Jeffrey S. Anderson, Sourabh Palande, and Bei Wang. Topological data analysis of functional MRI connectivity in time and space domains. In Guorong Wu, Islem Rekik, Markus D. Schirmer, Ai Wern Chung, and Brent Munsell, editors, *Connectomics in NeuroImaging (Lecture Notes in Computer Science, Proceedings of International Workshop on Connectomics in NeuroImaging)*, volume 11083. Springer, 2018.

[3] Peter Bubenik. Statistical topological data analysis using persistence landscapes. *Journal of Machine Learning Research (JMLR)*, 16(1):77–102, 2015.

[4] Herbert Edelsbrunner and John Harer. *Computational Topology: An Introduction.* American Mathematical Society, 2010.

[5] Archit Rathore, Sourabh Palande, Jeffrey Anderson, Brandon Zielinski, P. Thomas Fletcher, and Bei Wang. Autism Classification Using Topological Features and Deep Learning: A Cautionary Tale. In *Medical Image Computing and Computer Assisted Intervention MICCAI 2019*, volume Part III, pages 736–744, 2019.