RESEARCH STATEMENT

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My research interest lies in computational neuroscience. Specifically, I am currently focusing on functional and topological data analysis of brain networks under the supervision of Prof. Moo K. Chung. In this area, the function of the human brain is studied mostly through functional magnetic resonance imaging (fMRI). Due to its complex nature and massive data, the brain network is still not fully understood.

To remedy the problem, We proposed the idea of representing the network as a manifold where connectivity is implicitly given as surface geodesics. For example, given data $\mathbf{x}_j$ at voxels $j = 1, \cdots, p$, we could embed the brain networks into S^2 by minimizing the multidimensional scaling (MDS) loss [1]

$$\mathcal{L}_{S^2} = \min_{\mathbf{y} \in S^2} \sum_{i,j=1}^{p} \left[d_{ij} - \cos^{-1} \left(\mathbf{y}_i^\top \mathbf{y}_j \right) \right]^2, \tag{1}$$

where $d_i j = \mathbf{x}_i^\top \mathbf{x}_j$ is the Pearson correlation between voxels i and j, and $\cos^{-1}(\mathbf{y}_i^\top \mathbf{y}_j)$ are simply geodesics in S^2. Using Taylor expansion, such loss can be linearly approximated and subsequently solved exactly as

$$\arg \min_{\mathbf{y}_j \in S^2} \mathcal{L}_{S^2} = \left[\frac{\mathbf{v}_1}{\|\mathbf{v}_1\|}, \cdots, \frac{\mathbf{v}_p}{\|\mathbf{v}_p\|} \right],$$

where $[\mathbf{v}_1, \cdots, \mathbf{v}_p]_{3\times p}$ are the first three rows of the matrix DU obtained by the spectral decomposition:

$$[\mathbf{x}_1, \cdots, \mathbf{x}_p]^\top [\mathbf{x}_1, \cdots, \mathbf{x}_p] = U^\top DU.$$

The target manifold is the heat kernel smoothing of the embedded points $\mathbf{y}_j$. Compared with existing embedding methods (e.g., eigenmap) that use fixed metrics, our approach uses the data to estimate the metric structure. Another highlight is how we solved (1). Most of the time, people would stop here and turn to gradient descent, while we linearized it and solved it using simple linear algebra. This greatly increases the accuracy and efficiency of implementation.

Subsequent to finding the representation of the network, our another goal is to analyze how information flows in the network. Instead of treating the network as a graph, we treat it as a simplicial complex that can encode higher-order interactions by involving faces and volumes (so that we can extend node-level analysis to edge- or even face-level) [2]. This is achieved by the boundary operator ∂_k which represents how $(k-1)-$simplicies are connected to form $k-$simplicies. Furthermore, we found that the $k-$th Hodge Laplacian (a generalization of the graph Laplacian) constructed from the boundary operators, namely

$$\Delta_k = \boldsymbol{\partial}_{k+1} \boldsymbol{\partial}_{k+1}^\top + \boldsymbol{\partial}_k^\top \boldsymbol{\partial}_k$$

contains all the necessary topological information (persistent features) in its eigenvalues and eigenfunctions. For example, the eigenvectors corresponding to the zero eigenvalues of certain subgraph Hodge Laplacians (cf. section 2.2 in [2]) would form a basis, and all cycles in this network can be represented as the linear combination of these bases. The combination coefficients can then be used for topological inferences (e.g., to test whether two networks have the same cycle structure).

Prior to joining Dr. Chung's group, I worked on clinical biostatistics under the supervision of Prof. Jin Xu during my undergraduate study. In coincidence with COVID-19, we developed a more precise method of estimating the incubation period and tested it on an observational study in north China [3]. The intuition of this study is that epidemiology reports are often subject to recall bias and that these data can be treated as censored data. Consequently, survival-analysis-based methods are the best options.

References

[1] Moo K. Chung and Zijian Chen, "Embedding of functional human brain networks on a sphere," 2022, arXiv Preprint https://arxiv.org/abs/2204.03653.

[2] Sixtus Dakurah, D. Vijay Anand, Zijian Chen, and Moo K. Chung, "Modelling cycles in brain networks with the hodge laplacian," in *Medical Image Computing and Computer Assisted Intervention – MICCAI 2022*, Cham, 2022, pp. 326–335, Springer Nature Switzerland.

[3] Tiantian Liu, Zijian Chen, and Jin Xu, "Epidemiological characteristics and incubation period of sars-cov-2 during the 2020–2021 winter pandemic wave in north china: An observational study," *Journal of Medical Virology*, vol. 93, no. 12, pp. 6628–6633, 2021.