Powerful, Robust, and Explainable Deep Hypergraph Neural Networks in Brain Network Analysis for Brain Disease Diagnosis

Overview:

Analyzing neuroimaging data to construct structural and functional networks and applying graph-based methods is a major approach to diagnosis of brain diseases such as Alzheimer disease and mild cognitive impairment. One complication in human brain is that a brain region mainly interacts directly with a few of other brain regions in neurological processes, resulting in significant high-order interactions. It becomes well-motivated to derive hyper-networks and incorporate hypergraph neural networks (HGNNs) to assist in more accurate diagnosis. However, existing studies posed strong assumptions that the number of interactions is the same as the number of brain regions of interest or that all possible brain interactions involve the same number of brain regions, and thus have limited power in expressing diverse higher-order interactions between brain regions. Moreover, despite HGNNs have achieved state-of-the-art performance across a wide range of application domains, their applications are still limited by our inability to explain their behavior. Without being able to explain the patterns HGNNs rely on to make predictions, it is impossible to justify their use in brain disease diagnosis where trust and safety are critically needed. The objectives of this project are to develop high-expressive-power methods working for general hypergraphs that are essential for understanding the pathological basis of brain diseases, and to improve the explainability of deep HGNNs in brain network analysis.

Intellectual Metric:

Existing methods on applying HGNNs in brain disease diagnosis made heavy assumptions on the number or the type of interactions among brain regions. They also ignore the fact that the input neuroimaging data and the construction of hypergraphs from those data may be inherently noisy. This proposal will develop powerful HGNNs for most general hypergraph represented brain networks without such assumptions. We also plan to improve the denoising capability of existing HGNNs by developing a novel four-stage HGNN framework, accompanied with analysis on the expressive capability of the resulting methods is as compared to prior two-stage methods. Moreover, the explanations of HGNNs have remained largely unknown, although the counterpart in graph neural networks (GNNs) have attracted intensive studies recently. As far as our knowledge, it is still not clear whether and how methods designed for GNNs can be generalized to HGNNs, and how we can design HGNN explanation methods directly. This project will perform the first systematic investigation on explaining various HGNN models, providing both model-level and instance-level explanations that can explain the decision-making process for a group of patients and each individual patient, respectively.

Broader Impacts:

Neurological and psychiatric disorders include a wide range of brain diseases and disorders and affect millions globally. This project, if completed successfully, will deliver powerful and robust hypergraph learning models, which are general to be impactful not only in the brain disease field but also other hypergraph-represented networks and tasks, such as coauthorship network and visual object classification. Exposure of explanation techniques in brain disease diagnosis will allow other explainable AI research in the biomedical field to flourish. The research findings will be incorporated in at least two upper-level and graduate courses, exposing students to the latest development of AI and neuroscience. We will make all hypergraph data, models, and programs produced during the project publicly available. The PI will take advantage of the UNCG's MSI status to realize his strong commitment to underrepresented minority outreach in his research and teaching activities.