BrainGB: A Benchmark for Brain Network Analysis with Graph Neural Networks (Extended Abstract)*

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***Abstract*—Mapping the connectome of the human brain using structural or functional connectivity has become one of the most pervasive paradigms for neuroimaging analysis. Recently, Graph Neural Networks (GNNs) motivated from geometric deep learning have attracted broad interest due to their established power for modeling complex networked data. Despite their superior performance in many fields, there has not yet been a systematic study of how to design effective GNNs for brain network analysis. To bridge this gap, we present BrainGB, a benchmark for brain network analysis with GNNs. BrainGB standardizes the process by (1) summarizing brain network construction pipelines for both functional and structural neuroimaging modalities and (2) modularizing the implementation of GNN designs. We conduct extensive experiments on datasets across cohorts and modalities and recommend a set of general recipes for effective GNN designs on brain networks. To support open and reproducible research on GNN-based brain network analysis, we host the BrainGBwebsite at https://braingb.us with models, tutorials, examples, as well as an out-of-box Python package. We hope that this work will provide useful empirical evidence and offer insights for future research in this novel and promising direction.**

***Index Terms*—Brain network analysis, GNNs, geometric deep learning for neuroimaging, datasets, benchmark**

I. Introduction

Human brains are at the center of complex neurobiological systems in which neurons, circuits, and subsystems interact to orchestrate behavior and cognition. Understanding the structures, functions, and mechanisms of human brains has been an intriguing pursuit for researchers with various goals, including neural system simulation, mental disorder therapy, as well as general artificial intelligence. Recent studies in neuroscience and brain imaging have reached the consensus that interactions between brain regions are important for neural development and disorder analysis Li et al. (2021); Farahani et al. (2019). Inspired by graph theory, brain networks are developed to describe the interactions among brain regions.

The human brain can be scanned through various medical imaging techniques, including Magnetic-Resonance Imaging (MRI), Electrogastrography (EGG), Positron Emission Tomography (PET), and so on. Among all these acquisitions, MRI data are the most widely used for brain analysis research. There are also different modalities of MRI data such as functional MRI (fMRI) and Diffusion Tensor Imaging (DTI), from which functional and structural brain networks can be constructed respectively. Specifically, the connectivity in functional brain networks describes correlations between time-series signals of brain regions, while the connectivity in structural brain networks models the physical connectivity between gray matter regions Osipowicz et al. (2016).

Previous work on brain network analysis has studied shallow models based on graph theory Bullmore and Sporns (2009); Sporns (2022) and tensor factorization Liu et al. (2018) extensively. Methodological developments in graph research enable us to quantify more topological characteristics of complex systems. On the other hand, deep learning models have become extraordinarily popular in machine learning, achieving impressive performance on regular data in 1D/2D/3D Euclidean spaces such as images, videos, and speech. In contrast, the irregular structural and functional brain connectivity networks constructed from neuroimaging data are more complex due to their non-Euclidean characteristics. In recent years, Graph Neural Networks (GNNs) have attracted broad interest due to their established power for analyzing graph-structured data Kipf and Welling (2017); Xu et al. (2019); Veličković et al. (2018). Several pioneering deep models have been devised to predict brain diseases by learning the graph structures of brain networks. For instance, Li et al. (2021) proposed BrainGNN to analyze fMRI data, where ROI-aware graph convolutional layers and ROI-selection pooling layers are designed for neurological biomarker prediction. Kawahara et al. (2017) designed a CNN framework BrainNetCNN composed of edge-to-edge, edge-to-node, and node-to-graph convolutional filters that leverages the topological locality of structural brain networks. However, they mainly experiment with their proposed models on specific local datasets. Due to the ethical issue of human-related research, the datasets used are usually not publicly available, and the details of imaging

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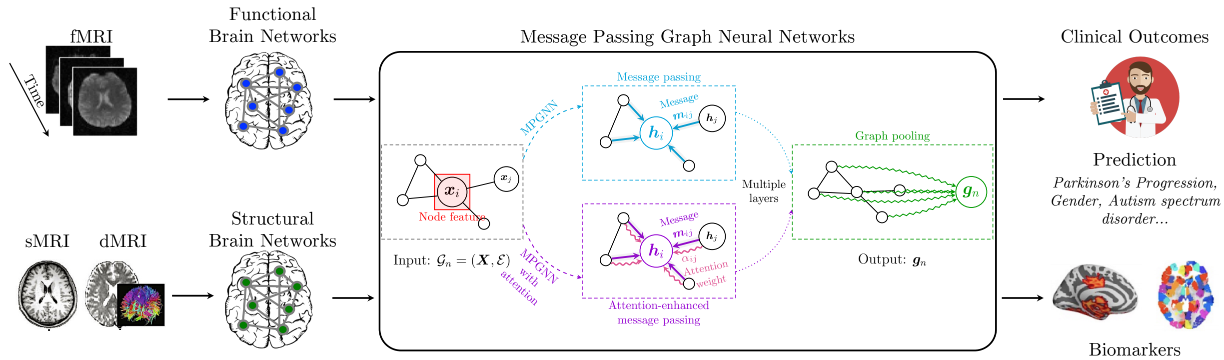

Fig. 1. An overview of BrainGBframework for brain network analysis with graph neural networks.

preprocessing are not disclosed, making it hard to reproduce the results and evaluate on new datasets.

To address the aforementioned limitations, there is an urgent need for a public benchmark platform to evaluate deep graph models for brain network analysis. However, it is non-trivial to integrate different components within a unified benchmarking platform. Current brain network analyses are typically composed of two steps. The first step is to construct brain networks from neuroimaging data. Then, in the second stage, the resulting brain connectivity between all node pairs is used to classify individuals or predict clinical outcomes. The difficulties in the initial stage are mostly due to restricted data accessibility and sophisticated brain imaging preprocessing and network construction pipelines that differ across cohorts and modalities. The difficulty of the second stage is to establish a standard evaluation pipeline based on fair experimental settings, metrics, and modular-designed baselines that can be easily validated and extended for future research. In this work, we propose Brain Graph Neural Network Benchmark (BrainGB)—a novel attempt to benchmark brain network analysis with GNNs. The overview of BrainGB is demonstrated in Fig. 1 and the main contributions are four-fold:

- A *unified*, *modular*, *scalable*, and *reproducible* framework is established for brain network analysis with GNNs to facilitate reproducibility. It is designed to enable fair evaluation with accessible datasets, standard settings, and baselines to foster a collaborative environment within computational neuroscience and related communities.
- We summarize the preprocessing and construction pipelines for both functional and structural brain networks to bridge the gap between the neuroimaging and deep learning community.
- We decompose the design space for GNN-based brain network analysis into four modules: (1) node features, (b) message passing mechanisms, (c) attention mechanisms, and (d) pooling strategies. Different combinations in these four dimensions are provided as baselines, and BrainGB can be easily extended to new variants.
- We conduct a variety of empirical studies and suggest general recipes for effective GNN designs on brain networks, which could be a starting point for further studies.

To foster future research, we release the source code of BrainGB at https://github.com/HennyJie/BrainGB and provide an out-of-box package that can be installed directly, with detailed tutorials available on our hosted website at https://braingb.us. Preprocessing instructions and models are provided for standardized model evaluations. We enable the community to collaboratively contribute by submitting their own custom models, and we will maintain a leaderboard to ensure such efforts will be recorded.

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