Graph Neural Network for fMRI Analysis

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Understanding the relationship between specific brain regions and a particular neurological disorder has been a pivotal focus of neuroimaging research, primarily within the realm of noninvasive medical neuroimaging. This field of study has generated numerous insights into brain connectivity and our idea is to bring the new trends in Graph Neural Networks (GNN) to this field.

1 Objective

Neuroimaging techniques must effectively encompass morphological, structural, and functional brain connectivities. Leveraging its capacity to handle non-Euclidean data types, the Graph Neural Network (GNN) framework offers a sophisticated approach for modeling the intricate graph structures inherent in the study of neuronal activities within the human brain, commonly referred to as the "brain graph."

In this study, our objective is to investigate the utility of the Graph Neural Network (GNN) framework for the analysis of Functional Magnetic Resonance Imaging (fMRI) data, with a particular focus on the identification of neurological biomarkers. Specifically, we aim to employ a GNN-based framework to delineate regional and cross-regional functional activation patterns for classification tasks. These tasks include distinguishing between neurodisorder patients and healthy control subjects, as well as performing cognitive task decoding.

2 Methods

Our framework integrates the simultaneous learning of Region of Interest (ROI) clustering and subsequent whole-brain fMRI analysis. This approach not only mitigates predefined errors but also adapts to specific clustering patterns relevant to downstream tasks. More precisely, the model parameters we estimate allow us to extract ROI clustering patterns. Additionally, our Graph Neural Network (GNN) design enhances model interpretability by incorporating a loss term to govern intermediate outputs. This feature offers flexibility in choosing between individual-level and group-level explanations.

3 Results

In this work, we introduce a graph learning model for the analysis of brain networks. Our approach excels in both predictive capability and interpretability. Furthermore, it offers a notable advantage in terms of model size compared to methods utilizing convolutional neural networks, positioning it as a promising research tool for identifying biomarkers through the analysis of whole-brain fMRI data.

Our proposed method also affords researchers the opportunity to delve into neural network decision-making processes. A central challenge in the application of deep learning models to neuroimaging research has been their inherent "black box" nature, making it unclear how these models arrive at their conclusions. Our method not only aids in understanding the inner workings of the model but also plays a critical role in unraveling the complexities of the human brain network.

4 Conclusions

In this study, we present an interpretable graph neural network tailored for fMRI analysis. This model receives neuroimage-derived graphs as inputs and provides both prediction outcomes and interpretation insights. Our approach was applied to the Biopoint dataset. With its built-in interpretability, our model not only outperforms alternative methods in terms of prediction accuracy but also identifies key brain regions linked to predictions and uncovers patterns within brain communities. This demonstrates its superiority over alternative graph learning and machine learning classification models.

These advantages hold significant promise for the advancement of precision medicine, enhancing our comprehension of neurological disorders, and ultimately contributing to the progress of neuroimaging research.