Learning Task-Aware Effective Brain Connectivity for fMRI Analysis with Graph Neural Networks (Extended Abstract)

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Abstract—**Functional magnetic resonance imaging (fMRI) has become one of the most common imaging modalities for brain function analysis. Recently, graph neural networks (GNN) have been adopted for fMRI analysis with superior performance. Unfortunately, traditional functional brain networks are mainly constructed based on similarities among region of interests (ROI), which are noisy and agnostic to the downstream prediction tasks and can lead to inferior results for GNN-based models. To better adapt GNNs for fMRI analysis, we propose TBDS, an end-to-end framework based on <u>T</u>ask-aware <u>B</u>rain connectivity <u>DAG</u> (short for Directed Acyclic Graph) <u>S</u>tructure generation for fMRI analysis. The key component of TBDS is the brain network generator which adopts a DAG learning approach to transform the raw time-series into task-aware brain connectivities. Besides, we design an additional contrastive regularization to inject task-specific knowledge during the brain network generation process. Comprehensive experiments on two fMRI datasets, namely Adolescent Brain Cognitive Development (ABCD) and Philadelphia Neuroimaging Cohort (PNC) datasets demonstrate the efficacy of TBDS. In addition, the generated brain networks also highlight the prediction-related brain regions and thus provide unique interpretations of the prediction results. Our implementation will be published upon acceptance.**

Index Terms—**fMRI analysis, Brain Network, Direct Acyclic Graph Generation, Graph Neural Network**

I. INTRODUCTION

Human brains play a vital role in orchestrating complex neurological systems. Understanding the mechanisms of human brains has always been a core interest in the field of neuroscience and valuable to extensive downstream biomedical applications [11], [20]. Towards this goal, functional magnetic resonance imaging (fMRI) has been acknowledged as a valuable resource of information for brain investigation, which can reflect local changes in cerebral blood oxygenation evoked by sensory, motor, or cognitive tasks [4]. There has been a significant increase of interest in utilizing fMRI for brain connectome analysis, which focuses on comprehending the brain organizations and their changes, identifying disease-specific biomarkers, as well as supporting clinical decisions such as biological sex prediction [14].

To leverage fMRI signals for neurological analysis, traditional biomedical research usually follows a two-stage approach [15]. In the first step, *functional brain networks* are generated from blood-oxygen-level-dependent (BOLD) time-series to model the interactions among regions of interests (ROIs). Then, the target classifier is stacked on top of the generated brain networks for downstream clinical predictions [8], [9]. Recently, end-to-end neural frameworks have been studied to generate *learnable brain networks* based on embedding similarity and make the prediction simultaneously [6], [18]. Thus the learned brain networks are more task-oriented under the supervision of task-specific objectives. However, two major shortcomings exhibit in both the traditional functional brain networks and the learnable ones. Firstly, these brain network generation methods focus on capturing the statistical associations between ROIs. Since correlation does not imply causation, they provide insufficient understandings of the complicated brain organization. Secondly, the connectivity in existing generated brain networks depends on the pairwise similarity between the time-series or embeddings of brain regions, which means that the constructed brain networks are fully or densely connected. The noisy signals contained in those dense networks hinder the identification of biological insights on the structure of brain networks and increase the time complexity of the downstream analysis.

Researchers have proposed a particular type of brain network, effective brain networks [3], which can overcome these two flaws. This type of brain network aims to infer causal relationships among brain regions and produce sparse connections. To construct effective brain networks from BOLD signals, there are several mathematical algorithms available, including Granger causality [1], dynamic causal modeling [5], and
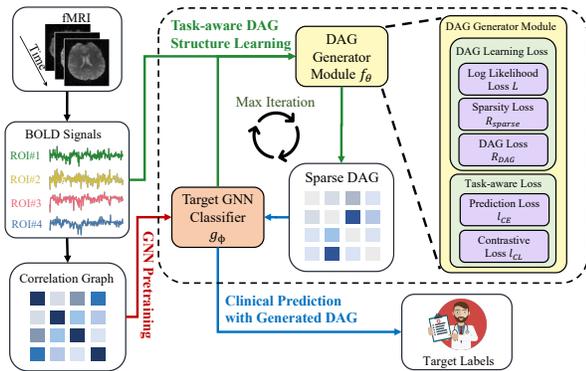
Fig. 1: The framework of TBDS.

Bayesian search methods [12]. However, there are several major drawbacks in directly adopting these techniques for brain connectivity generation tasks: (1) *Unrealistic assumptions*: these methods often model the brain connectivity with overly simplistic assumptions, such as the absence of unmeasured confounding and lack of temporal dependencies. In reality, such assumptions are hard to satisfy. (2) *Limited scalability*: existing works based on constraint- or score-based methods for brain connectivity generation [13] are usually evaluated on a selected ROI subset (less than 50 regions) for their difficulty on scalability. But in real application scenarios, there exist hundreds of ROIs, and directly adopting these methods could take several hours, or even several days for each instance. (3) *Difficulty of injecting task-specific information*: the above brain network generation methods are not customized for downstream clinical applications [7]. As a result, the mismatch between the network generation and downstream application would hurt the final performance and interpretation.

Fortunately, there is a recent trend in the machine learning community to view structure learning as a directed acyclic graphs (DAG) structure learning problem, which can be further converted to a continuous optimization constrained by additional structural regularizations to ensure acyclicity [10], [19]. Then, this optimization can be solved with some gradient-based approaches, which are efficient, flexible, and can be integrated with other deep learning models.

Motivated by these studies, we propose TBDS, a task-aware brain network generation approach via modeling the connections among different ROIs as DAGs to identify effective brain connectivities and predict the target in an end-to-end fashion. To tackle the inscalability issue, we leverage the recently proposed approach [10], [19] and reformulate the DAG structure learning task as a gradient-based optimization problem, which could benefit from GPU acceleration and scales gracefully to hundreds of brain regions. In addition, to customize the generation process with downstream task knowledge, we design a contrastive loss [17] to push the brain networks with the same label close and pull the brain networks with different labels apart [16]. Such a regularization enforces the brain networks from different classes to be more distinguishable, so that the downstream GNN classifier can

learn to make better decisions. In this manner, we can optimize the brain networks towards the downstream tasks, and provide task-specific interpretations to support clinical predictions.

We evaluate TBDS on two real-world fMRI benchmarks datasets [2], [14] for the important and accessible task of biological sex prediction. The results illustrate that TBDS achieves competitive performance when compared with advanced baselines. Besides, TBDS is able to characterize the most important brain regions for the target tasks, justifying its efficacy on providing clinically useful interpretations.

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