MULTI-TASK LEARNING FOR BRAIN CONNECTOME ANALYSIS IN THE ABCD STUDY

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Neuroimaging studies increasingly use network-oriented analysis to understand the human brain in healthy and diseased individuals. Neuroscience research has provided ample evidence that these neural circuits play a crucial role in explaining the differences in brain function between populations [1]. The Adolescent Brain Cognitive Development (ABCD) study [2] is the largest and long-term study of brain development and child health in US. It provides a vast brain development dataset in a diverse population, including fMRI and abundant biological and behavioral survey results. This dataset offers an opportunity to explore the relationship between intricate brain connections and rich behavioral data.

There is a recent trend of using brain networks derived from neuroimaging data such as fMRI to predict various clinical outcomes.These models are then analyzed to determine the potential correlation between functional brain networks and clinical outcomes. For instance, Li et al. [3] proposed a GNN model to predict clinical targets and then discovered task-specific neurological biomarkers. Furthermore, Chen et al. [1] built individual models for each behavior task in the ABCD study and analyzed these models to capture relations across the various behaviors.

Instead of training an individual model for each task, in this work, we simultaneously train 35 tasks together with the rest-state functional brain networks from 7327 samples in the ABCD study via Multi-task Learning (MTL). MTL is a framework that enables multiple learning tasks to share their knowledge, resulting in improved generalization abilities. The backbone model used is the Brain Network Transformer [4]. The overview of the MTL model architecture is shown in Figure 1: Brain Network Transformer converts a brain network into graph-level embedding, which is then fed into different task-specific fully connected networks (FCN) for each prediction target. The model is trained end-to-end across all targets using Adam optimizers, with Mean Squared Error applied to calculate loss and evaluate performance. In addition, we trained 35 separate Brain Network Transformers, one for each task, for comparison purposes.

We include 35 tasks in total from the ABCD study, categorized into 3 categories (domains): *cognition prediction (15 tasks)*, *personality prediction (9 tasks)*, and *mental health prediction (11 tasks)*. Our experimental results show that MTL performs significantly better than single-task models for most cognition prediction tasks, indicating a strong promise of leveraging tasks from similar domains to enhance the training of predictive models. However, most tasks in the other two domains, namely personality and mental health predictions, show similar or even decreased performance with MTL. Upon more thorough analysis, we find that the model's coefficient of determination on the test set is close to or less than 0 for these tasks, indicating strong difficulties of connectome-based predictions, possibly due to the weak correlation between resting-state fMRI and the personality and mental health outcomes evidented in neuroscience literature [1]. This phenomenon calls for novel MTL frameworks that can robustly learn essential brain connectome features even under irrelevant tasks.

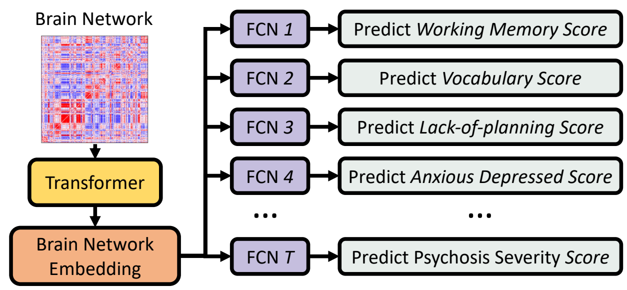

Fig. 1. Overall framework of our Multi-task Learning model.

1. REFERENCES

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