TASK-DRIVEN GRAPH NEURAL NETWORK PRE-TRAINING: A PATH TO ROBUST EEG REPRESENTATIONS IN MOTOR PLANNING

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1 INTRODUCTION

Motor learning, the process of acquiring and refining motor skills, is central to understanding human behavior and neural dynamics (Krakauer et al., 2019). Electroencephalography (EEG) provides a non-invasive method to measure neural activity during motor tasks, but the data's high dimensionality and noise pose significant challenges for understanding underlying phenomena. Graph Neural Networks (GNN) are increasingly used to model EEG as graphs, with nodes representing EEG channels and edges encoding channel relationships (Hou et al., 2022; Han et al., 2023). While promising, previous GNN applications for EEG have focused on simple and static tasks, such as motor imagery, limiting their ability to capture the complexity of real-world neural phenomena.

In this work, we investigate the motor planning phase of a task performed in an Embodied Virtual Reality setup, where participants executed pool shots under varying conditions (Nardi et al., 2024a). Specifically, the task involves different shot directions and participant experience, which introduce different contexts under which motor learning occurs. To enhance GNN performance and its ability to extract task-relevant neural representations, we introduce a data-driven pre-training strategy that leverages these complementary task dynamics. By pre-training on participants from opposite shot conditions before fine-tuning on the target group, the model would learn representations that capture stable motor planning dynamics across task variations, rather than adapting only to specific conditions.

2 METHODOLOGY

The dataset consisted of 14-channel EEG recordings collected during a motor learning task in an Embodied Virtual Reality setup (Haar et al., 2021; Nardi et al., 2024a). 32 participants performed billiard shots under varying conditions while exposed to partial reward-based visual feedback, and their neural activity during the motor planning phase was recorded. For each shot, the EEG data from the 2-second window preceding the shot was used to predict the outcome (successful or unsuccessful) of the previous trial. The data was preprocessed to remove artifacts and represented as a graph, where nodes correspond to EEG channels containing cleaned time-series data, and edges encode the spatial proximity of the channels based on the fixed electrode layout. This representation preserves the spatial structure of neural activity, which is critical for studying motor learning dynamics.

We employed the same GNN architecture as in Nardi et al. (2024b), which processes brain data using temporal and graph convolutional layers to capture spatio-temporal dependencies. To enhance model generalisation and mitigate data scarcity, we introduced a pre-training strategy that leverages complementary task dynamics. For each target group, the GNN was initially pre-trained on participants from the opposite condition: when analysing *left* pocket shots, we pre-trained on *right* pocket

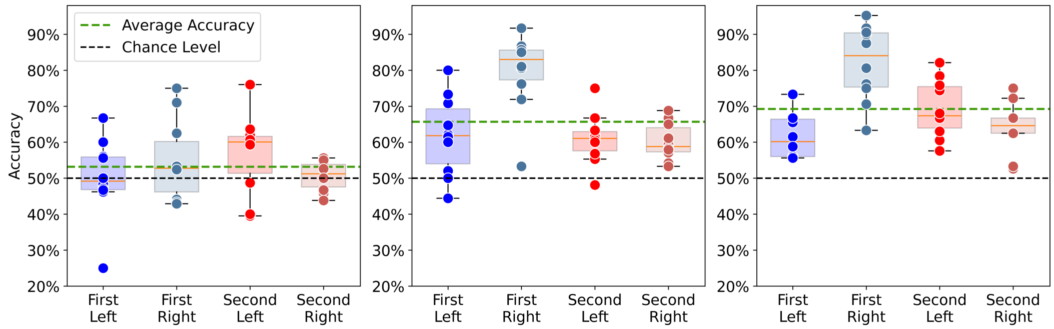

Figure 1: Performances of GNN models with (**A**) no pre-training, (**B**) pre-training on opposite *Round*, (**C**) and pre-training on opposite *Pocket*. The 10-fold cross validation accuracy distributions of the four groups are displayed separately for each pre-training. Black dashed line represents chance level, while the green dashed line shows average accuracy across groups for the individual mode.

data, and vice versa; similarly, when analysing *first* round performance (naive participants), we pre-trained on *second* round data (non-naive participants), and vice versa. This pre-training on opposite conditions encourages the model to extract common motor learning dynamics that persist across task variations, rather than features that are specific to a single condition. After pre-training, the GNN was fine-tuned separately on each target group, aiming to predict the previous trial outcome based on the EEG data of the following trial. As a baseline, we compared the pre-trained model to a GNN trained directly on an individual group without any pre-training on the others. This comparison evaluates whether pre-training enhances the model's ability to generalise across task conditions.

3 Results

The performance of the GNN was evaluated using 10-fold cross-validation accuracy as the primary metric. Using the same model pipeline as Nardi et al. (2024b), pre-training on complementary task dynamics led to a significant improvement in accuracy compared to training without any pre-training. In particular, all groups apart from two showed significant improvements (paired Wilcoxon signed-rank tests, $p < 0.05$), while the remaining two were close to significance. Indeed, pre-training on participants performing opposite rounds (*first* vs *second*) increased average accuracy from 0.53 to 0.66, while pre-training on opposite pockets (*left* vs *right*) further improved average accuracy to 0.69. This level of improvement suggests that pre-training successfully enhances representation learning by allowing the model to transfer knowledge between task conditions.
The accuracy gain highlights the potential of pre-training as a powerful tool for enhancing EEG-based modelling, particularly in dynamic tasks with inherent variability. These findings underscore the ability of pre-training to uncover generalisable neural patterns across groups, offering a step toward meaningful representations in motor learning tasks.

4 Discussion

The proposed pre-training strategy highlights the importance of leveraging diverse task features, such as shot direction and participant experience, to enhance Graph Neural Networks performance on EEG-based motor tasks. By pre-training on opposite task-specific dynamics, the approach reinforces shared neural representations between conditions rather than introducing irrelevant features to the models. Extending this strategy to additional task variations, such as different feedback modalities, could further strengthen learned representations and provide deeper insights into motor planning and learning. Moreover, additional analysis of model insights and enhancement of the pre-training strategies, for instance through contrastive learning, could improve the generalisability of learned representations across conditions. By comparing tasks within the same paradigm, pre-training enables the model to learn more meaningful EEG representations, identifying motor planning dynamics that remain stable despite task-specific variations. This suggests that even without complex modifications, a simple data-driven pre-training strategy can improve the robustness of EEG-based models in dynamic environments. The ability to extract meaningful representations from diverse yet related tasks highlights the broader applicability of this approach for studying motor learning and neural adaptation.

Meaningfulness Statement

A meaningful representation of life captures the shared patterns and dynamics of underlying complex behaviours, enabling generalisation across diverse yet related tasks. In this work, we focus on understanding motor planning through EEG-based neural representations, leveraging variations within a controlled paradigm to uncover commonalities in brain activity. By pre-training Graph Neural Networks on complementary task dynamics, we demonstrate that even simple strategies can extract robust and generalisable features, offering insights into the neural basis of motor learning and its adaptation to varying conditions.

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