Exploring Contrastive Learning Neural-Congruency on EEG Recording of Children with Dyslexia

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Abstract

Electroencephalogram (EEG) recordings of children are often used to study the underlying neural basis of causal factors of reading disorders and dyslexia. However, the inter-subject variability in EEG and the unconstrained nature of reading experiments used to elicit these factors made it challenging for traditional EEG analysis methods to extract neural components of these factors. In this work, we aim to explore the use of novel deep neural network architectures and contrastive learning methods to overcome the methodological limitations of traditional techniques and enhance the extraction process of neural components during reading tasks. Notably, we formulate a neural network architecture to extract EEG embedding using contrastive loss that maximizes the neural congruency in non-dyslexic children compared to children with dyslexia. We plan to evaluate our approach on three EEG datasets involving children with dyslexia performing Rapid Automatized Naming (RAN) and Phonological Processing (PA) tasks. The proposed contrastive learning framework will provide an enhanced tool to facilitate studying the neural underpinnings of naming speed and their association with reading performance and related difficulties.

Introduction

Dyslexia is the most prevalent reading disorder, affecting between 15-20% of children, and often persists through adulthood (Moats et al., 2008). Due to its high prevalence and societal impact, the determinants of dyslexia have been studied from different facets, ranging from cognitive (such as phonological awareness), genetic, and environmental (Theodoridou et al., 2021) to neural factors (Christoforou et al., 2021). However, despite these intensive research efforts, there is still a substantial debate regarding the underlying causes of dyslexia (Parrila et al., 2020), particularly the neural underpinnings of such factors.

Electroencephalogram (EEG) recordings have been a gateway to studying the underlying neural basis of causal factors of reading disorders and other cognitive processes. On the other hand, traditional EEG analysis methods average EEG signals across trials to improve the signal-to-noise ratio of the stereotypical waveforms evoked in response to brief stimuli (Breznitz, 2005) or explore the power of the signals at different frequency bands (i.e., frequency analysis). On the other hand, machine-learning-based approaches learn spatial projections across sensors that optimize a desired signal property, such as maximum variance, statistical independence, power-ratio differences and amplitude differences, among others (Parra et al., 2005; Dyrholm et al., 2007, Christoforou et al. 2008). However, components extracted using these approaches do not necessarily capture neural activity relevant to cognitive factors associated with reading and do not generalize across subjects due to the inter-subject variability of EEG signals (Christoforou et al., 2010)

Recently, the neural-congruency EEG analysis framework has been proposed to extract reading-specific neural components from EEG (Christoforou et al., 2021a, 2021b, 2022a, 2022b). The framework uses machine learning to extract linear neural components that maximize the similarity of EEG responses across control group participants (i.e., typical readers) during reading tasks. The extracted components have been shown to capture differences between children with dyslexia and controls in several reading tasks capturing phonological processing (Christoforou et al., 2023a), naming speed (Christoforou et al., 2023b) and phonological abilities (Christoforou et al., 2023c). However, the neural-congruency framework focuses primarily on within-group similarities, ignoring across-group differences, and it is sensitive to cofactor impurities of the control group purity for cofactors to control group purity selection and variations across tasks.

In the neural network literature, contrastive learning has recently gained popularity as a method to generate vector embeddings, such that congruent observation pairs (often from different modalities, i.e., image -text) are proximal and non-congruent observation pairs are more distal from each other in the embedding space (Chen et al. 2020). Contrastive learning achieved state-of-the-art performance in downstream tasks of various fields, such as computer vision and medical informatics (Li et al. 2021) and natural language processing tasks (Zhang et al. 2022).

Motivated by the success of the neural-congruency framework in extracting reading-specific neural components and the potential of contrastive learning as a general framework for capturing non-linear mappings in both congruent and incongruent observations, in this work, we aim to formulate a neural network architecture to extract reading-specific EEG embedding using contrastive loss that maximizes the neural congruency in non-dyslexic children compared to children with dyslexia. We hypothesize that the contrastive learning that optimizes the neural congruency criterion will extract more informative neural components and minimize the presence of irrelevant, non-reading-related co-factor components from the embedding process. In this preliminary stage of our work, we briefly introduce the proposed contrastive network architecture, its training process, and the evaluation approach.

Methodology

An illustration of the proposed Contrastive-learning-based Neural-congruency framework is shown in Figure 1. Below, we briefly outline the overall model architecture, the contrastive learning procedure, the prediction process, and the evaluation strategy.

EEG dataset and Reading Tasks: We plan to train the proposed models on EEG epochs from a group of 30 children with dyslexia and 30 children in a control group, obtained while children perform three reading tasks, namely Rapid Automatized Naming, Spoonerism, and Phoneme Elision. For each participant *s* and each reading task, a set of *N* epoch observations is obtained, each represented as a matrix $X_n^s \in \mathbb{R}^{D\times T}$, where *n* is the epoch index, *D* is the number of EEG sensors, and *T* is the number of time points.

Generating contrastive EEG samples batches: To enforce the contrastive learning strategy, we build batches of congruent and incongruent observations pairs across subjects. Each batch comprises pairs $\boldsymbol{X}_i = (X_{n_1}^{S_1}, X_{n_2}^{S_2})$ of random samples from the dataset of all epochs and participants. A pair is labeled congruent ($\delta_i = 1$), if the participant s_1 *and* s_2 belongs to the same group, or incongruent ($\delta_i = -1$) otherwise.

EEG components Embedding Model: Motivated by the neural-congruency framework, we build a neural network architecture that extracts spatial projections in EEG. The model takes as input an EEG epoch X_n^s and generates a spatio-frequency-temporal representation tensor $H_n^s \in \mathbb{R}^{C\times F\times T}$ of each epoch, through a spatial and temporal 1D convolutions, where *C* denotes the number of spatial kernel and F is the number of temporal kernels.

Contrastive Loss: The parameters of the embedding model are trained by minimizing the contrastive loss function on the set of pairs $z_i = (Z_{n_1}^{S_1}, Z_{n_2}^{S_2})$ and their corresponding congruency designation δ_i, where $Z_n^s \in \mathbb{R}^L = vec(\ H_n^s)$ denotes the vectorization form of H_n^s, and $L = CFT$.

Multi-linear prediction model: With the embedding model parameters fixed through contrastive learning optimization, we introduce a multilinear projection architecture to classify observations. Given the output tensor of an embedding layer, the prediction model learns special, frequency, and temporal filters defined as a sequence of convolutions that are optimized using cross-entropy loss.

Future work

We plan to evaluate and compare the predictive performance of our proposed Contrastive-learning-based Neural-congruency model to the Neural-congruency Framework proposed by Christoforou et al. Evaluation will be based on the accuracy performance and the spatial interpretability of the resulting components on real EEG datasets. We hypothesize that our model's ability to factor epochs into frequency elements and then extract neural components through contrastive learning will enable extracting more "pure" neural components associated with reading-related cognitive factors.

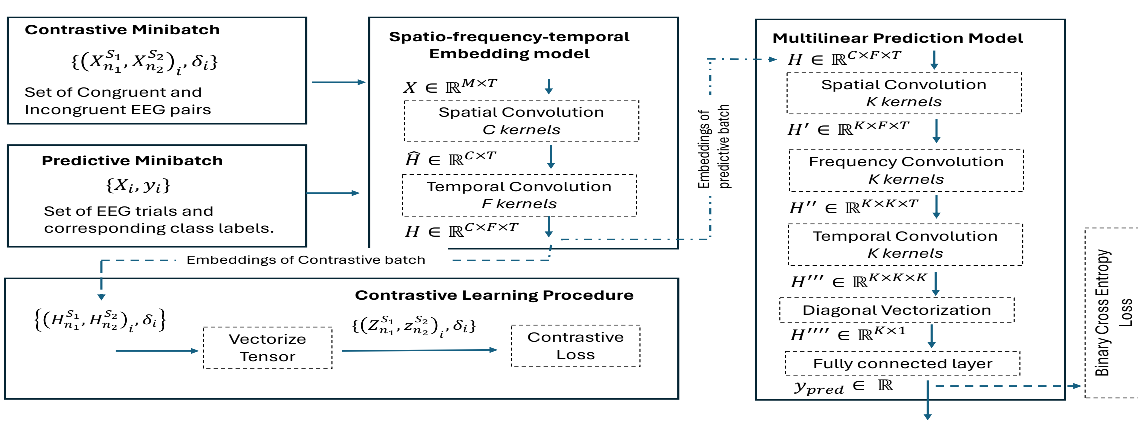

Figure 1. The illustration of the proposed Contrastive-learning-based neural congruency framework.

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