Decoding Hypnotic Experience from Raw EEG using a Multi-Output Auto-Encoder

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Abstract

In this study, we propose a novel approach for quantifying brain-to-brain coupling during a hypnosis induction. Our approach uses a multi-output sequence-to-sequence deep neural network applied to raw EEG data recorded from 51 participants using 59 electrodes. Specifically, we use a long short-term memory (LSTM) encoder to extract an embedding, which is then utilized for two downstream heads: one head to predict the hypnotist's brain activity, and the other head to classify the level of hypnotic depth. We found that removing the head that predicted the hypnotist's brain activity substantially decreased the accuracy of the classification head, indicating that this head plays a critical role in achieving better classification performance. These results highlight the importance of shared representations in shaping social interactions. Ultimately, this work can help us better understand the dynamics of verbal communication.

Keywords: Deep learning; sequence embedding; brain-to-brain coupling; hypnosis; EEG

Introduction

The brain's ability to couple with external stimuli as well as other brains is a crucial process that enables us to extract information about the state of the world and other minds, facilitating social interaction, effective communication, and social bonding (Hasson, Ghazanfar, Galantucci, Garrod, & Keysers, 2012). Hypnotic interaction is a remarkable example of effective communications, where the hypnotist can induce profound changes in the person's feelings and perceptions using only words. Despite the growing interest in this phenomenon, the neural mechanisms underlying hypnotic induction and its impact on the brain remain largely unexplored. Recent evidence from two-person neuroscience suggests that a multi-brain approach could lead to a breakthrough in our understanding of the neural mechanism of social interactions (Redcay & Schilbach, 2019). Deep neural networks, on the other hand, have emerged as a powerful tool in cognitive science, offering not only predictive capabilities but also providing insights into how the human brain functions (Cichy & Kaiser, 2019). Unsupervised algorithms, such as sequence-to-sequence models, are particularly useful when there are no explicit labels for classification. These models have shown promise in decoding brain state from multichannel EEG, including decoding emotional processes (Li et al., 2020) and predicting cognitive workload levels (Zheng, Yin, Wang, & Zhang, 2023). The current work aims to train a sequence-to-sequence model based on raw EEG data to decode participants' mental state during a hypnotic induction (whether they were in deep or shallow hypnosis) while optimizing the model's weights to reconstruct the hypnotist's brain activity.

Methods

Data collection and preprocessing This study included 51 participants (39 females) with an average age of 24.5 years. During the experiment, participants listened to a hypnotic relaxation technique (Elkins & Elkins, 2013) while their brain electrophysiological activity was recorded. The induction and rest period lasted approximately 10 minutes, with the induction segment being 5 minutes long. This segment was analyzed for the study.

After the hypnotic session, participants were asked to rate their level of hypnotic depth on a scale from 0 to 10, with 10 indicating the highest level of depth and zero indicating the lowest. Participants who rated below 5 were considered shallowly hypnotized, and those who scored 5 or higher were considered deeply hypnotized.

In a separate session, the brain activity of the hypnotist was recorded during a real hypnotic session, while his voice was recorded for the experimental session. Such an offline recording method has been used in previous studies (e.g. (Silbert, Honey, Simony, Poeppel, & Hasson, 2014)).

The data of participants and hypnotist was resampled to 128 Hz. We kept the preprocessing of EEG data minimal, and only included the interpolation of bad channels and re-referencing to the average of electrodes. Next, we scaled data over electrode dimension using Lp normalization from PyTorch.

Model architecture Our multi-output auto-encoder consists of an LSTM encoder to extract an embedding from the raw EEG data collected from participants, and a LSTM-based decoder to reconstruct the input data (Figure 1). The decoder comprises LSTM layers and fully connected linear layers

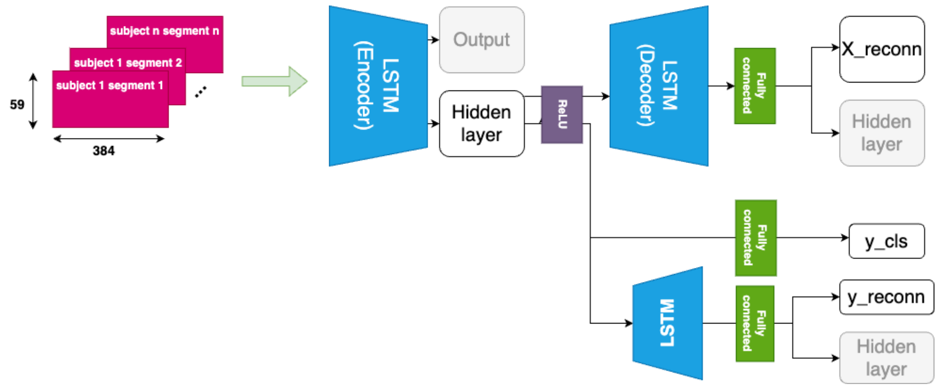

Figure 1: Multi-output auto-encoder architecture. The LSTM auto-encoder extracts an embedding from participants' raw EEG data, which is then used by the downstream decoders for hypnotist's EEG data prediction and hypnosis depth level classification. Abbreviations: X-reconn: reconstructed participants' brain activity; y-reconn: reconstructed hypnotist's brain activity; y-cls: level of hypnotic depth (shallow vs. deep)

to decompress input data. The extracted embeddings of this autoencoder are then fed into two downstream heads: a LSTM decoder and fully connected layer for hypnotist's brain prediction (Brain-to-brain or B2B head) and a fully connected layer for participants' hypnosis depth prediction. Using this approach, the network is able to classify the brain states of participants while also reconstructing the hypnotist's brain from participants' brains, which takes into account the similarity between the two brains. To determine if this information about two brains coupled activity affected the classification task, we trained two models: one with and one without the B2B head.

Training and evaluation We trained the model using a combination of mean squared error (MSE) loss for the decoder heads and cross-entropy loss for the classifier head. To evaluate the performance of the model, we split the dataset along the time dimension, using 80% of the data for training and the remaining 20% for validation. We segmented the EEG data into 3-second intervals before feeding it into the model. The model was trained for 1000 epochs using the Adam optimization algorithm with a learning rate of 0.001 and a batch size of 256.

Results

The model that included the B2B head achieved an average accuracy of 76% in predicting hypnotic depth and an average MSE of 0.002 in predicting the hypnotist brain activity patterns on the validation set (Figure 2). However in the model that does not include B2B head, the classification accuracy drops to 58%. Several runs with different random seeds were conducted to eliminate the possibility that randomness and different starting points could have contributed to the observed performance decrease when the B2B head was removed. In all cases, the model combining both heads performed better than one containing only the classifier head.

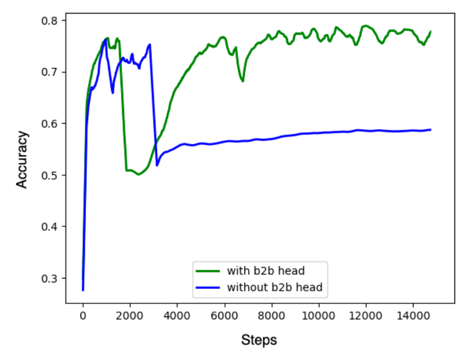

Figure 2: Performance of two multi-output LSTM auto-encoders models in predicting hypnosis depth after 1000 epochs of training

Discussion

Our study demonstrated that incorporating information about the brain state of the hypnotist in a multi-output sequence-to-sequence deep neural network outperformed a model without this information. The B2B head might play a crucial role in improving classification performance by capturing essential information that is relevant for classification task. For example, the B2B head could determine the participant's brain state based on similarity between their brains activity and the hypnotist's brain activity. Moreover, the B2B head could act as a regularizer, thereby preventing overfitting of the model.

To further understand the underlying reasons of the improved performance, we plan to use explainable methods to investigate the features learned by the B2B head and their contribution to the performance of the classification head. Specifically, we aim to identify the brain areas where brain coupling occurs, which will provide insights into the neural basis of interpersonal communication.

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