Predicting Cognitive Control in Older Adults using Deep Learning and EEG Data

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Abstract. Cognitive control is characterized by mental functions that enable goal-directed interaction in a complex environment. In a recent study, researchers designed a custom video game to assess cognitive abilities and how they correlate with the aging brain. The neural basis was evaluated using electroencephalography (EEG), and signal detection metric of discriminability (d') was used to evaluate the performance. In this paper, we propose a deep learning approach to predict the task performance (d') from EEG signals. Our model begins with feature extraction in order to identify the important features, which is followed by dimension reduction using a generative model - variational autoencoder. The extracted features are then used for d' prediction with a multi-layer perceptron. Results show that the proposed model can reliably predict the task performance from EEG signals.

Keywords: Electroencephalography · Variational autoencoder · Cognitive control · Time domain signals · Medical data.

1 Introduction

Cognitive enhancement comprises activities that can help improve an individual′s abilities, such as cognitive control and skill acquisition, across their lifespan. Cognitive control allows the mind to make decisions based on an individual′s goals, and to override impulses and habits. Humans regularly challenge these control processes when attempting to simultaneously accomplish multiple goals (multitasking). It is clear that multitasking behaviour has become ubiquitous in today′s technologically dense world, and substantial evidence has accrued regarding multitasking difficulties and cognitive control deficits among aging populations. An electroencephalography (EEG) study on 60 to 85-year-old adults showed that the multitasking nature of a video game (NeuroRacer) can enhance skills such as working memory and sustained attention [1]. Games have been a proven tool in cognitive related research, for example it was used for studying human behavior in conflict situations [2], building a personalized system [3] and other medical applications [4]. In the recent studies, cognitive models were used to predict the real world dynamics of social systems [5]. Also, assessments of behavior successfully identified deficits in social competency [6].

EEG is a neuroimaging technique used to measure brain wave patterns with the help of metal discs (electrodes) placed over the scalp. The electrodes measure the electrical activity in the brain through small voltage changes that are caused by firing neurons. As a result, we can use this information about the electrical activity over space and time to understand or classify the brain state and monitor the acquisition of skills at any given moment. Moreover, EEG signals [7] can help identify the neurobiological basis of a certain task by monitoring brain activity with speed and high temporal resolution. In addition to the benefits of EEG signals, conducting EEG studies is cost-effective and readily accessible compared to neuroimaging techniques like functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG) and functional near-infrared spectroscopy (fNIRS) [8] [9]. These are conventionally used as key tools in the diagnosis and management of different types of diseases including epilepsy, tumors, sleep disorders and certain degenerative diseases.

In this paper, we build a deep learning model in order to explore how the EEG signal can act as a predictor of the skill performance (d'). Based on recent advances, deep learning algorithms are now actively used to understand the organized structures of the human brain [10]. The proposed model aims to understand the underlying activation patterns in the brain through cognitive responses in an artificial neural network and at the same time to make a prediction of performance and to monitor skills from interacting with the video game NeuroRacer [1]. The main goal is to identify the correlation between the cognitive signals and d', which is an indicator of the skill acquisition: $d' = f$(EEG time series).

2 Background

2.1 Data Description

The proposed approach used a custom-designed three-dimensional video game (NeuroRacer) to validate task performance, which exhibits a linear age-related decline from 20 to 79 years of age. NeuroRacer is a racing-game that consists of two distinct game conditions. During the first condition, "Sign Only", the participants are instructed to respond as quickly as possible to the appearance of a sign when a green circle is present, and the second condition, "Sign and Drive", involves simultaneously performing the sign task while maintaining a car in the center of a winding road using a joystick (as shown in Fig. 1). The signal detection metric of discriminability (d′), or the performance, was calculated based on how accurately the participant responded to either of the conditions. NeuroRacer was created to serve as a tool for cognitive enhancement and at the same time, calls for a deeper understanding of neurobiological processes that moderate these changes. By playing an adaptive version of this game in multitasking training mode, older adults (60 to 85 years old) reduced multitasking performance compared to both an active control group and a no-contact control group. Multitasking performance among older adults attained levels beyond those achieved by untrained 20-year-old participants, with gains persisting for 6 months [1]. The findings [1] illustrate the robust plasticity of the pre-frontal cognitive control system in the aging brain. The study also provides a custom-designed video game environment to assess cognitive abilities across the lifespan of human subjects, evaluate underlying neural mechanisms, and serve as a powerful tool for cognitive enhancement.

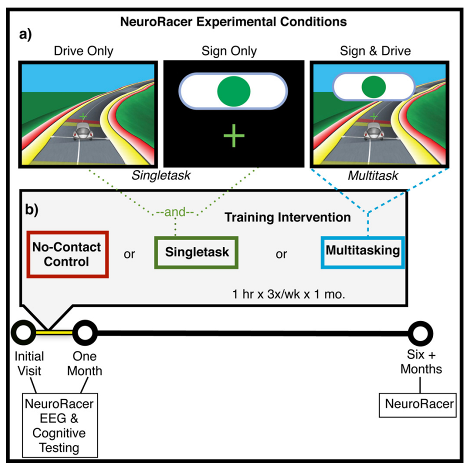


Fig. 1: NeuroRacer experimental conditions and training design. a, Screen shot captured during each experimental condition. b, Visualization of training design and measures collected at each time point. (original figure from [1])

The datasets were provided as part of the IEEE Brain Data bank hackaton that was held at the 2018 IEEE Big Data conference[4]. It consists of the EEG dataset for every epochs and event-related potentials, and measure of performance (d') collected during the NeuroRacer game[5] from 30 non-gamer participants. Among them were 8 males and 22 females ranging from 60 to 83 years in age. Data collection had been done during one day of training. NeuroRacer game aims to challenge players on two tasks, navigating and responding to specific signs in order to stimulate the brain to perform multi-tasking activities.

There are two conditions in the game: " Sign Only" and Sign and Drive". Each participant completed three blocks of trials for each condition of the game.

[4] https://ieee-dataport.org/competitions/ieee-brain-data-bank-hackathon-2018-ieee-big-data-conference

[5] https://neuroscape.ucsf.edu/technology/

EEG signals were recorded using an active two-head cap (Cortech Solutions) with a BioSemiActiveTwo 64-channel EEG acquisition system in conjunction with BioSemiActiView software (Cortech Solutions). Signals were amplified and digitized at 1024 Hz with a 16-bit resolution. Anti-aliasing filters were used and data were band-pass filtered between 0.01–100 Hz during data acquisition [1].

The epochs dataset that we used consists of 60 datasets: 30 for Drive Shoot and 30 for Shot Only conditions.

The average raw EEG data for a period from -1000 to +1000 msec was provided for a total of 2000 msec window of data. In this case the stimuli was presented at time 0. The total number of epochs is 200 for each mode of the game. [1]

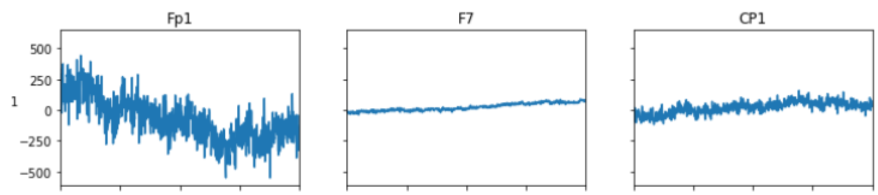


Fig. 2: Dynamic of three electrodes: 'Fp1', 'F7', CP1' for Drive-Shoot game mode for person ID 2002.

Event-Related Potentials (ERPs) dataset is measured by means of EEG epochs dataset. The ERPs dataset also consists of 60 datasets: 30 for Drive-Shoot and 30 for Shoot Only conditions with the time period of -1000 to +1000 msec.

2.2 Application of Deep Learning in Modeling EEG Data

In recent years, deep learning has gained immense attention, especially in the field of computer vision and natural language processing. However, owing to the capacity of deep learning algorithms to approximate functions and increased accessibility to computation power, it has been extended to other domains. One such modern application is to answer some of the long-impending research questions in the field of cognitive neuroscience. Khaligh et. al [10] briefly discussed how the architecture of a state-of-the-art deep learning model trained to do image recognition is similar to the inferior temporal cortex organization in the human brain. This result influenced researchers to apply these algorithms to create machines that can learn and think like human [11]. Recent advances in artificial intelligence can be used to get insights into how cognitive abilities are represented and can be enhanced.

Using EEG signals in a deep learning model is challenging for many reasons. The noise in the electrical activity, the high dimensional representation of time-space domain and the interference among channels are important modalities to be considered when applying EEG data. Also, deep learning generally thrives on a large amount of data samples [12], especially when the dimension is less than the number of available samples to intrinsically learn the non-linear relationships within the data that might be unattainable by an ordinary linear model. Recent attempts to use deep learning with EEG data include using convolutional neural networks (CNN) [13] for features extraction and variational autoencoder (VAE) for classification. Similarly, CNN was applied on raw EEG signals to distinguish ictal, preictal, and interictal segments for epileptic seizure detection [14]. EEG data has also been used to predict metric values such as the cognitive workload of subjects while they are undertaking intelligence tests [15]. In this paper, we present a deep learning approach to predict the multitasking performance from EEG data of a subject playing the NeuroRacer video game. In addition to the model, we also identify the electrodes that are actively involved during the study. The electrode information can provide insights about which brain regions are active for a specific condition. This provides us with the ability to make forward-reverse inference [16] maps of the different brain regions for various game conditions.

3 Methodology

We aimed to find the correlation between the EEG signals and discriminability metric, such that $d' = f(\text{EEG signals})$. The main challenge was a low number of discriminability metric samples (1 sample per subject for one mode of the game) comparing to a high dimensionality of EEG data (64 features $\times$ 200 epochs $\times$ 2000 time steps in one epoch for a subject for each type of the game). In order to cope with a difference in dimensionality and low number of d' samples, our framework consists of two main steps:

- Feature learning. The goal of feature learning is to extract more discriminative features from handcraft EEG features using deep learning part to decrease the dimensionality of the data. In our framework we applied Variational Autoencoder technique (Sec. 3.1).
- Real value prediction. The goal of this step is to train the universal approximator to map latent features of EEG and d'. We built a multi-layer perceptron (Sec. 3.2).

3.1 Variational Autoencoder

Variational Autoencoder (VAE) has been introduced in 2013 [17] as an unsupervised learning method for nonlinear dimensionality reduction. The architecture involves two parts: encoder and decoder. The encoder reduces the dimension of data by compressing them to latent features and the decoder produces the data from any values of latent features. The generator of the VAE is a probabilistic model that assumes that the data was generated from some conditional distribution and an unobserved variable z in latent space.

To perform efficient inference and learning in directed probabilistic models, in the presence of continuous latent variables with intractable posterior distributions and large dataset we used VAE. In this model the goal is to maximize the probability of each X in the training set under the entire generative process.

$$P(X) = \int P(X|z;\theta)P(z)dz \tag{1}$$

where X is the training data; z is the latent variable; θ is learning parameters; $P(X)$ is the probability distribution of the data; $P(z)$ is the probability distribution of latent variable; $P(X|z;\theta)$ is the distribution of generated data given latent variable and learning parameters.

$P(X|z;\theta)$ is a distribution, that allows to make the dependence of X on z explicit. In VAE the output can be described as Gaussian distribution $P(X|z;\theta) = \mathcal{N}(X|f(z;\theta), \sigma^2 * I)$, where $f(z;\theta)$ is a mean, a covariance is equal to explanation in order of σ^2 and identity matrix I.

One of the ways to measure the difference between the original and reconstructed distributions is to use Kullback-Leibler (KL) divergence (Eq. 2).

$$D[Q(z)||P(z|X)] = E_{z \sim Q}[\log Q(z) - \log P(z|X)] \tag{2}$$

The loss is defined as a combination of reconstruction loss of autoencoder and KL divergence. For the reconstruction loss we used mean squared error (MSE), that is defined as follows, $MSE = \frac{1}{n}\sum_{i=0}^{n}(X_i - \hat{X}_i)^2$, where X_i is an input value; $\hat{X}_i$ is a reconstructed value and n is a number of samples.

3.2 Multilayer Perceptron

A Multilayer Perceptron (MLP or Artificial Neural Network) with a single hidden layer can be viewed as a logistic regression classifier where the input is first transformed using a learned non-linear transformation Φ. This transformation projects the input data into a space where it becomes linearly separable. The intermediate layer is referred to as the hidden layer. A single hidden layer is sufficient to make MLP a universal approximator.

One hidden-layer MLP is a function $f : R^D \longrightarrow R^L$, where D is the size of input vector x and L is the size of the output vector $f(x)$, such that $f(x) = g^{(2)}(b^{(2)} + W^{(2)}(g^{(1)}(b^{(1)} + W^{(1)}x)))$, where $b^{(2)}, b^{(1)}$ are bias vectors; $W^{(2)}, W^{(1)}$ are weight matrices and $g^{(2)}, g^{(1)}$ are activation functions.

3.3 VAE-MLP Framework for EEG signals

In this subsection we describe our framework for predicting d' from EEG signal and determine the influence of every particular electrode on d'. The model consists of two parts. Firstly, we do feature learning (Sec. 3.1), that extracts the latent variable and thus reduce the high-dimensional EEG signals. Secondly, the extracted low-dimensional features are fed into MLP (Sec. 3.2) for regression prediction. The deep learning architecture is shown at Fig. 3.

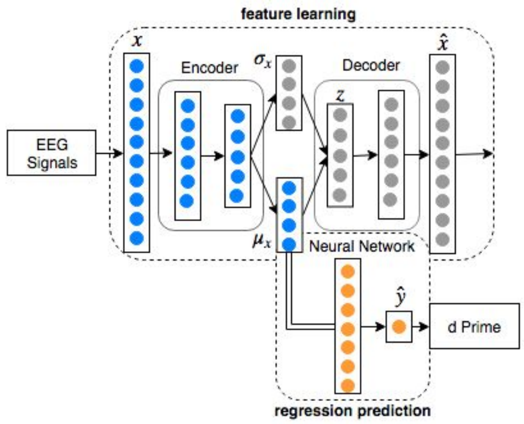


Fig. 3: Architecture of the deep learning model for d' prediction from EEG data. EEG signals ($\mathbf{x}$) are inputs to the model. $\hat{x}$ is the reconstructed vector of the original data. $\mathbf{z}$ is the vector to be decoded, which is obtained by reparameterization. μ_x and σ_x are the mean and the standard deviation of data distribution respectively. μ_x is the input vector for 1-hidden layer neural network. $\hat{y}$ is the output from the neural network, corresponding to the d'.

4 Experiments

In this section, we conducted extensive experiments on the EEG Dataset to evaluate the proposed VAE-MLP framework in finding the correlation between the EEG data and d'. All the experiments were run on the GPU instance incorporated NVIDIA Tesla K80 Accelerator, running a pair of NVIDIA GK210 GPUs with 12 GB of memory each, and 2,496 parallel processing cores.

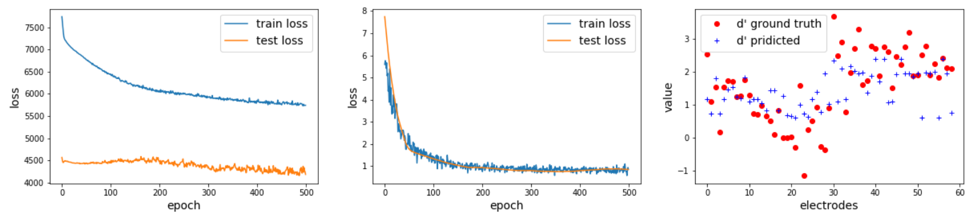
4.1 Data Preprocessing

For feature learning we used epochs EEG dataset that has 200 epochs of training for each of the participant, the time ranges from -1000 to +1000 msec, the tracking is done every other second. For our experiment we chose the data for time starting from 0 msec, since at the beginning of each epoch there might be some noise involved.

4.2 Results

The results of VAE training is presented at Fig. 4a. VAE loss was calculated as a sum of reconstruction loss and KL divergence for each data in minibatch (Eq. 2). As we can see the VAE model showed good results in capturing the stochastic dynamic of EEG signals.

At Fig. 4b we can see the results of applying non-linear functions to predict d'. The ground truth and predicted d' values are mapped on Fig. 4c.



(a) (b) (c)

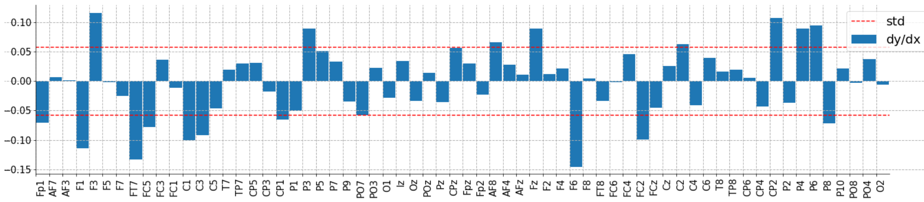
Fig. 4: Results of the ensemble models training, following the architecture presented at Fig. 3. Fig. 4a shows VAE Loss. The loss for training batch varies from 7737 to 6015, the loss for validation batch fluctuates from 4568, which shows that the model was able to catch the latent variables of the EEG data structure. Fig. 4b shows Neural Network Loss. The loss goes down from 8.32 to 0.69 for training loss and from 7.98 to 0.67 for validation loss after 500 epochs, which shows that the model was able to learn the non-linear correlation of the EEG and d'. Fig. 4c represents mapping the ground truth d' (red circles) and predicted d' (blue pluses) for each electrode. The absolute difference ranges from 0.003 to 1.9.

4.3 Correlation between EEG electrodes and d'

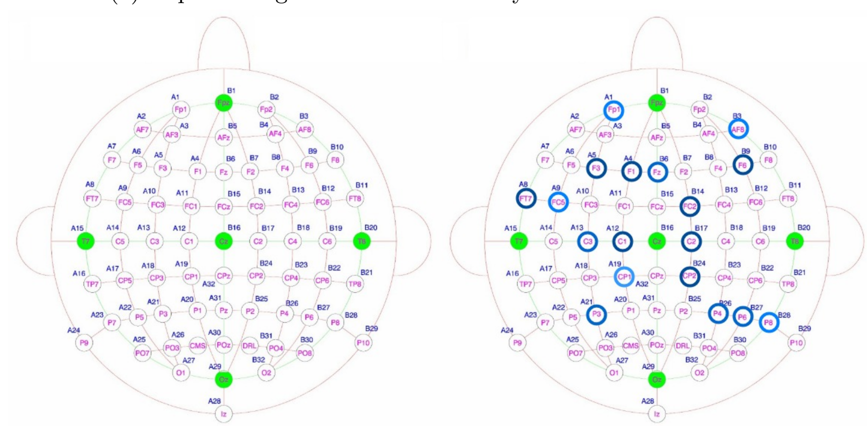
EEG does not have a high spatial information such as functional magnetic resonance imaging (fMRI). However, the identified electrodes can give insight on an abstract level regarding the regions of the brain were involved in a certain task. These electrodes are the important electrodes that helped determine the multitasking performance in the NeuroRacer game. Based on 5a, we identified increased sensors in Frontal (F), Central (C), Central-parietal (CP), Frontal-temporal (FT) and Parietal (P) cortex. Parietal cortex includes sensory information including the sense of space, navigation and somatosensory integration of senses such as touch while the frontal cortex is responsible for planning, motor control and other executive functions. We would like to highlight two important observations. First, the sensors in the occipital lobe which is responsible for visual processing were not identified as important electrodes. This clearly validates the fact that there was no significant change in the the visual processing in NeuroRacer game during either conditions. Second, the activity in parietal cortex is skewed towards right side of the brain when compared to the left which might indicate that the input information could have been presented or processed more on the left. While we cannot conclude all possible neuroscience facts from the presented results, we provide a tangible solution to interpret observed patterns in electrode activation through deep learning.

5 Conclusion

In this paper, we presented a novel approach on predicting skill performance (d') values from cognitive signals. The framework we used combines a varia-



(a) Representing the influence of every electrode on d' value



(b) BioSemi Layout 64+2 electrodes was used for collecting the data.

(c) Representation of electrodes, that have gradient changes higher than the standard deviation. The color gradient shows the level of influence each electrode, the darker - the more influence.

Fig. 5: Calculating gradient for the VAE-MLP framework to catch how each electrode influence d'.

tional autoencoder for feature extraction of the high-dimensional data and a multi-layer perceptron for real-value prediction of d'. In addition, we have also identified the electrodes that have the highest influence on d′. The proposed framework serves as a foundation for future research, especially in scenarios in which we are expected to learn values from high-dimensional space. One way in which this study may be advanced could involve a reverse inference experiment to understand how the high influence electrodes can be mapped back to specific brain regions and how to interpret them. While the methods detailed in the paper facilitate the identification of electrodes, further research may require a more substantive study of electrodes during skill acquisition. A potential advancement for this field would involve extending deep learning to other models of neuroimaging, like functional magnetic resonance imaging. Ultimately, the proposed model serves as a stepping stone to understanding the representation of cognitive abilities in human brain leading to the development of near human-like machines.

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