COGS 189 Project Group 33

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Introduction and Motivation

Objective: Advances in technology have brought new operating environments in which the role of human actors has been reduced to passive observation. While opening up new boundaries for productivity and lifestyle, this environment also creates hazards related to the inability of individual humans to maintain attention and focus in passive control tasks. Using EEG brain activity imaging and machine learning data analysis, a passive brain-computer interface (BCI) is developed for monitoring the mental attention states of human individuals. Our main purpose for this project is to analysis EEG mental attention state detection. It is important to distinguish mental attention states of human via en EEG-based passive BCI using machine learning or deep learning methods. We want to investigate the relationship between human attention and other EEG signals such as the alpha and beta waves.

Related Work

"A passive brain-computer interface for monitoring mental attention state"

https://ieeexplore.ieee.org/document/8404612

- develop a passive brain-computer interface (BCII) for monitoring individual mental attentional states by using electroencephalogram (EEG) brain activity imaging (EEG) using machine learning data analysis method of support vector machine (SVM).
- It has been established that the changes in frontal and parietal brain activity in the 1 ~ 5 Hz and 1015 Hz bands are related teno the changes in attentional states.
- Our tests also cover the results of the work done that will guide the design of future systems that monitor the operator's status through EEG brain activity data.

"Generalized of EEG-based Mental Attention Modeling with Multiple Cognitive Tasks"

https://ieeexplore.ieee.org/document/9176346

- Attention is the foundation of a person's cognitive function. Attention levels can be measured and quantified from electroencephalography (EEG).
- There was no statistically significant difference in classification accuracy among the three different cognitive tasks. Our study highlights that EEG based attention recognition can be generalized to all subjects and cognitive tasks.

Data Resources

Due to the covid-19, our group member were study online in different cities. Therefore, we decided to find our required dataset from Kaggle. This dataset is the EEG data of different students who are watching different video lectures online, which are in the similar situations of our group.

Here is the link of the dataset:

https://www.kaggle.com/saptarshineogi/eegdata?select=EEG_data.csv

Data Exploration

By the data overview, there are 12811 data points. Looking into the column heads, we suspect that there are ten students attending different lectures.

Also there are given data of the attention and mediation. We supposed that those data are provided by the Neurosky Headsets. Hence, we would compare our prediction with the provided attention data.

Before we trained our dataset, we need to clean the data into idealized format.

- First, we normalized the training set x and target y to bring all the variables in the same range (0,1). This was done to prevent data that are ranging to far away from each other. Which might cause significant variations between models.
- Then we need transform the input data in required type for different methods.

Methods

There are two methods we used in our project to analysis EEG mental attention state detection. We also tried RNN model but failed on the training model step.

Method I is **Deep Neural Network**; We want to know what the relationship is between EEG signals and output attention. Our first method is to generate a model between the signals Delta, Theta, Alpha1, Alpha2, Beta1, Beta2, Gamma1, and Gamma2. Output y variables should be attention.

Method II is **SVM**; we use support vector regressor for working with continuous values and compare the original data and the prediction.

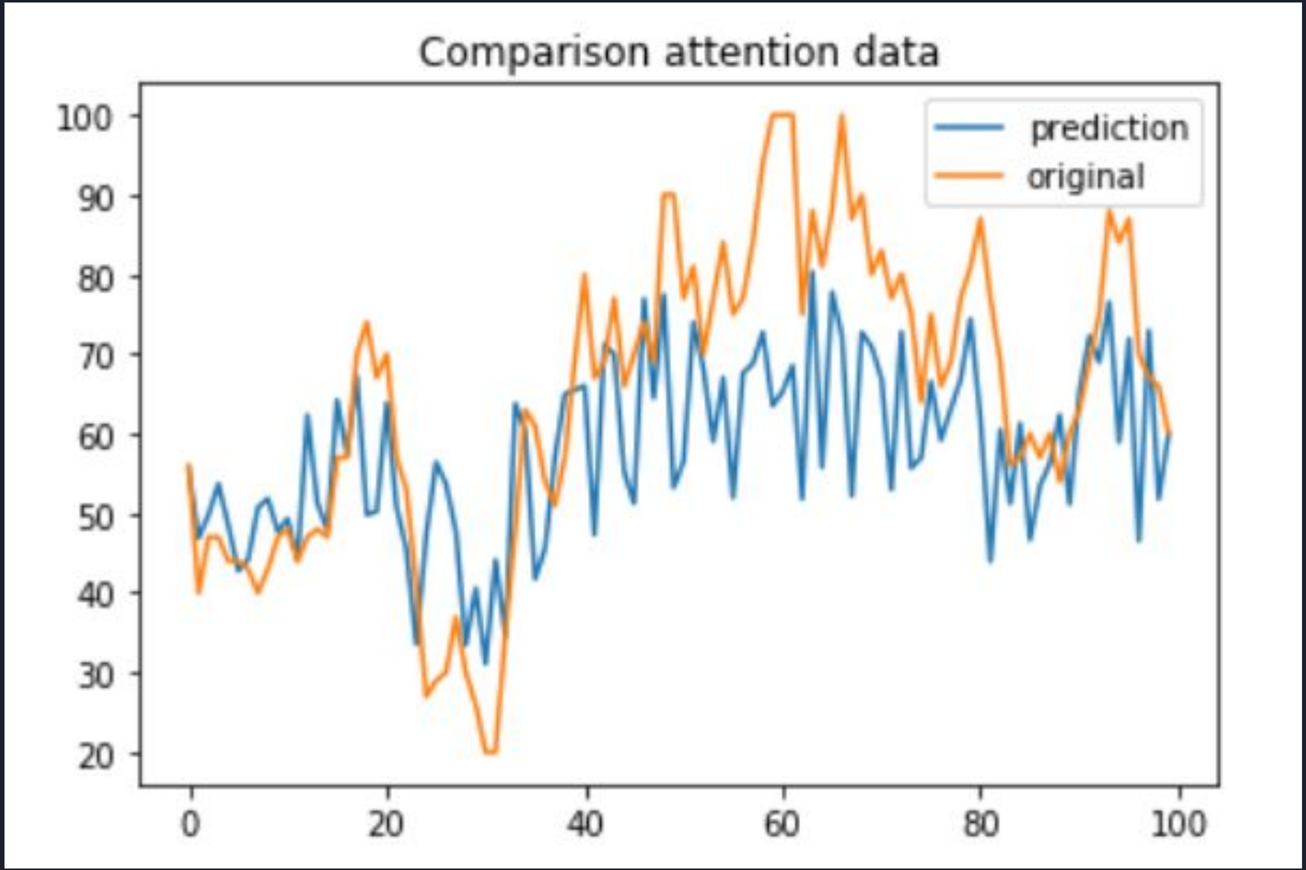
Method I: Deep Neural Network

Advantages:

- Lower loss
- Higher Accuracy

Disadvantages

- Time consuming
- Overfitting


Comparison attention data
prediction
original
100
90
80
70
60
50
40
30
20
0
20
40
60
80
100

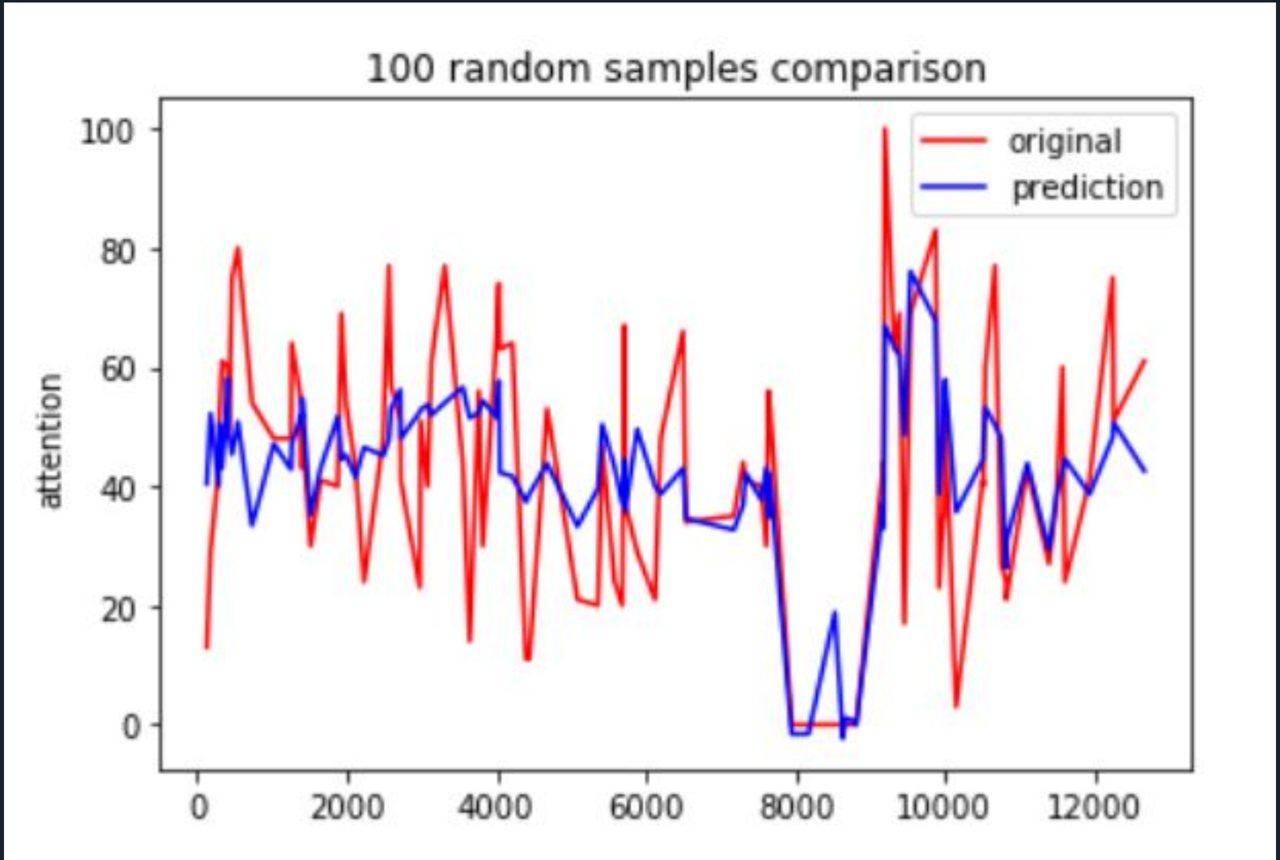
Method II: SVM

Advantages

- Train Fast, especially when we are using a polynomial kernel with lower degrees.
- Can avoid overfitting.

Disadvantages

- Accuracy is lower compared to the Neural Network.
- The function seems too complex to be modeled well by SVM.


100 random samples comparison
original
prediction
attention
100
80
60
40
20
0
0
2000
4000
6000
8000
10000
12000

Results

- From our first method of generating a deep learning model using tensor flow, we can see that our prediction is overfitting the original data. Meaning that our model learns the detail and noise in the training data to the extent that it negatively impacts the performance of the model on new data. The problem is that these concepts do not apply to new data and negatively impact our model's ability to generalize.
- From our second method of performing an SVM, although the training process is very rapid, the result is underfitting the data: the predicted results does not align with the labels in the test set. It is probably due to a SVM model that is too simple.

Discussion

What did we learn?

- Deep neural networks modeling and machine learning algorithms

What can be done better?

- Sequential data like this can further be modeled with a Recurrent Neural Network (RNN), to exploit its temporal feature.
- Better and more complete datasets