Project Work 2023/24 II. semester
EEG signal processing using neural networks

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Introduction

The aim of this project was to explore and improve the processing and analysis of EEG data using advanced machine learning models. This work was a collaborative effort within the ELTE AI Research Group. After becoming familiar with EEG in a medical context, my primary contributions focused on implementing the experimental pipeline. This included configuring models, selecting EEG channels, logging experiment results, and generating plots for model evaluation.

About EEG data

Electroencephalography (EEG) data is recorded using electrodes placed on the scalp to measure the electrical activity of the brain. A major challenge in analysing EEG data is the presence of significant noise. This noise can come from a variety of sources, including muscle activity, eye movements and external electrical interference. This makes it difficult for mathematical models to extract meaningful information from EEG signals.

Importance of EEG signal processing

EEG signal processing is a crucial aspect of brain research, offering insights into the brain's electrical activity and functioning. For individuals suffering from epilepsy, advanced EEG analysis can lead to significant improvements in their quality of life. Enhanced detection and prediction of epileptic seizures could allow these individuals more freedom, such as the possibility of driving, which is often restricted for them for safety reasons.

Usual methods

Typically, researchers have mostly used classical machine learning methods for tasks such as seizure detection and sleep stage classification. There haven't been many attempts to use deep learning models, but some early results look promising. In this project, we aim to use deep learning techniques to analyze EEG data.

Accessible datasets

TUH EEG

The TUH EEG dataset is a large and publicly available EEG dataset compiled by Temple University Hospital (TUH) in Philadelphia, Pennsylvania. It is one of the largest public EEG datasets in the world and is an important resource for researchers working on EEG signal processing.

The data set contains thousands of EEG recordings, ranging in length from a few minutes to several hours. The size of each file varies considerably depending on the length of the recording and the number of channels, usually ranging from a few megabytes to several gigabytes. The TUH EEG dataset contains different types of EEG recordings, including normal and pathological conditions such as epileptic seizures, sleep disorders and other neurological problems.

Movie

The data originates from research conducted at the ELTE Institute of Psychology, where we collaborate with the research group. Currently, our primary focus is assisting with this research. The dataset consists of EEG recordings from 34 individuals, with each person undergoing two recording sessions. Each session corresponds to a different version of a short film: one with a consistent narrative and another with an inconsistent narrative. This setup allows researchers to study brain activity patterns in response to different types of film editing.

The EEG recordings were captured using 33 channels with 512 Hz recording frequency. These channels are positioned on the scalp according to the standard 10-20 system, ensuring consistent placement across all participants and sessions.

Each EEG recording session lasts approximately 10 minutes. The dataset includes a total of 68 recordings, with each recording stored as a separate file. The files are in a standard EEG data file format (BDF), with sizes varying between 20-40 Megabytes.

Current objectives

The primary question driving the research is narrative-based classification. Currently, our focus is on whether we can classify EEG data based on the films shown, as we consider this a simpler task.

Our current task involves binary classification based on segments of a given length. Specifically, we aim to classify EEG segments according to the narrative type of the films. This task is evaluated using accuracy metrics.

Experiments

Environment

The experimental pipeline was designed to ensure reproducibility and efficiency. Configuration files were employed to manage model parameters, channel selection, and other settings. Neptune.ai was utilized for experiment logging, which proved to be a valuable tool for tracking and visualizing experiment metrics. This included monitoring accuracy and plots for visualizing the models' performance on the test data.

Previous models and results

When processing and analysing the EEG data, we experimented with different models and methods to get the most accurate results. In the field of sequence processing, we first applied Long Short-Term Memory (LSTM) models, which efficiently handle long-term dependencies in time-series data. Later, we switched to the Transformer model, which has proven its outstanding performance in recent years, especially for larger data sets. Using these models, we have been able to better capture the intrinsic patterns of EEG signals, which has increased the accuracy of predictions.

We have tried different window sizes to find the optimal size for processing EEG data. We have obtained surprisingly good results even for small window sizes, which we have documented in detail for different learning rates and dropout values.

Window size	**Accuracy**
5	0.917795
10	0.998754
25	0.998895
50	0.999094
100	0.998851
150	0.999487
200	0.998993
500	0.999908
750	0.999777
1000	0.998623

Table 1: Accuracy of various LSTM models with different window sizes

Dropout	**Learning rate**	**Accuracy**
0.0001	0.1	0.998896
0.001	0.1	0.999843
0.0001	0.3	0.9804
0.001	0.3	0.999987
0.0001	0.5	0.999123
0.001	0.5	0.999897
0.0001	0.7	0.998533
0.001	0.7	0.999881
0.0001	0.9	0.998781
0.001	0.9	0.999729

Table 2: Some measurements made with fixed window sizes (50)

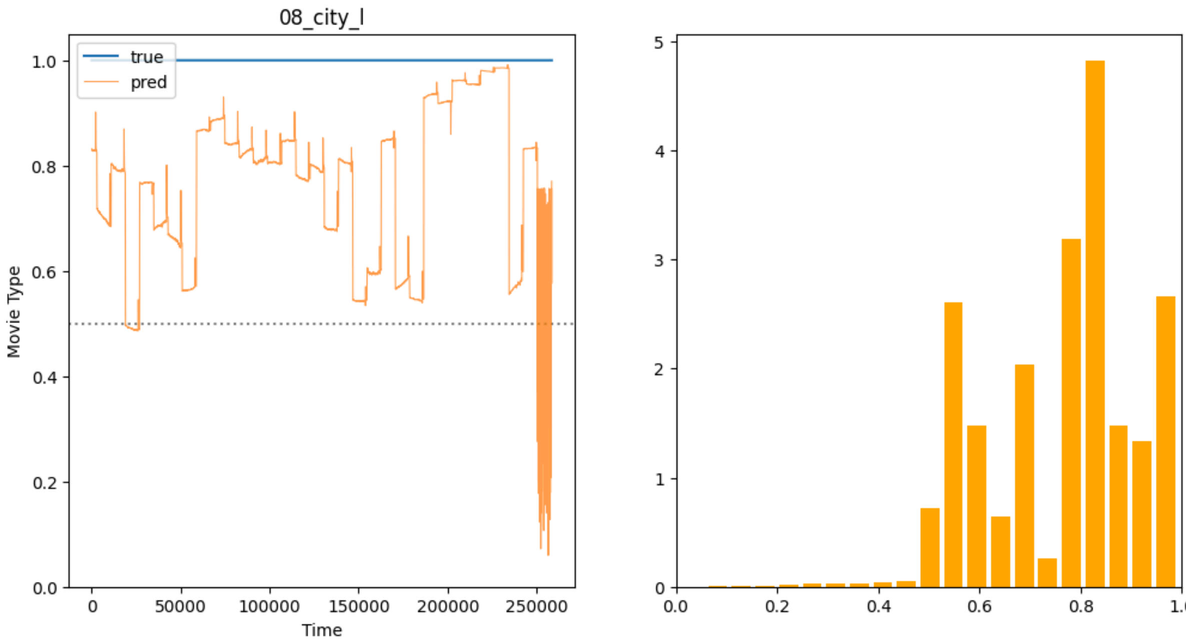

Figure 1: Sample plot generated by the experiment pipeline for inspecting the evaluation of the model on a specific test file.

Recently, however, it has become clear that these promising results were largely due to a specific channel, Status. The Status channel contains human annotations of movies projected onto subjects during EEG recordings. These annotations added significant information to the dataset that made it easier for the models to make accurate predictions. This discovery prompted us to re-evaluate our previous results and to investigate the performance of the models without the Status channel to get a true picture of the generalization ability of the models and the processing capabilities of real EEG signals.

Currently we are focusing on this problem. There have been attempts made to preprocess the data (e.g., extracting the Fourier coefficients of the channels), but we were unable to achieve a significantly better model than a random one.

Future work

Currently, we are attempting to adapt an existing general-purpose model, BENDR, but we have encountered difficulties. This model is appealing because it comes with pretrained weights, making it potentially suitable for transfer learning. Our hope is to utilize this capability in our project.

Our long-term goals beyond this smaller task involve leveraging the TUH EEG dataset, which is significantly larger than the Movie dataset we are currently working with. We aim to explore how we can use this dataset for tasks similar to our current project or how the experience gained from this project can be applied to identify epileptic seizures.

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