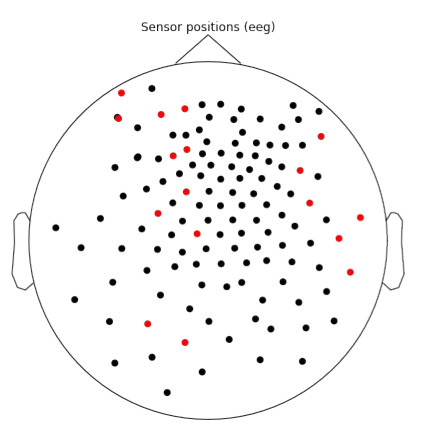
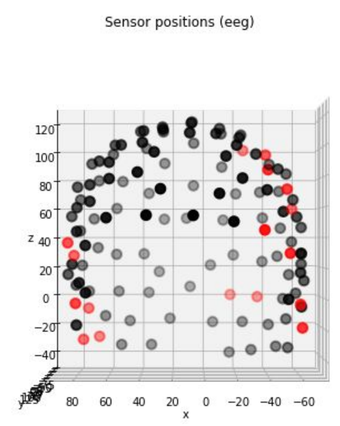
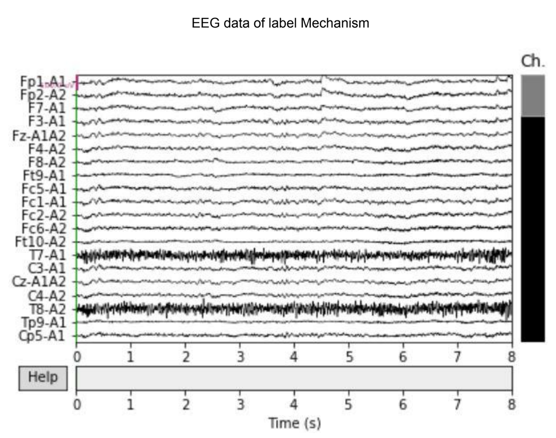
Interpreting EEG Data of Video Stimuli

Victor Ye, Jacob Wynd, Tunglin Lee
Professor Narges Norouzi

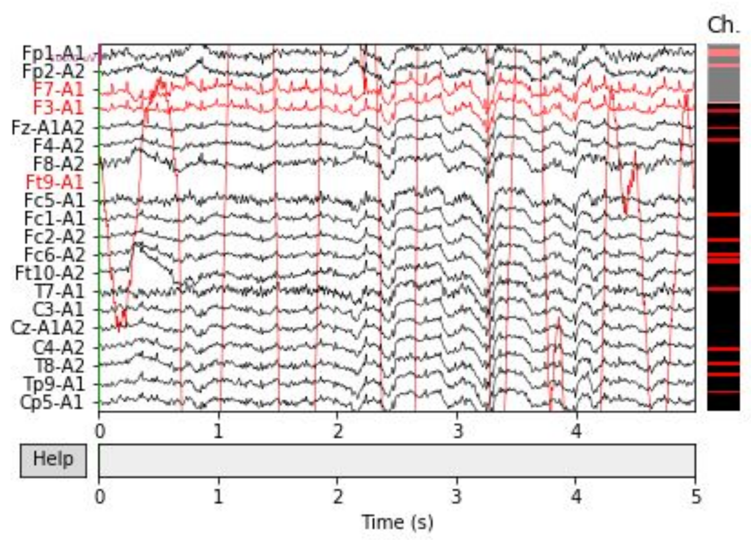
Motivation

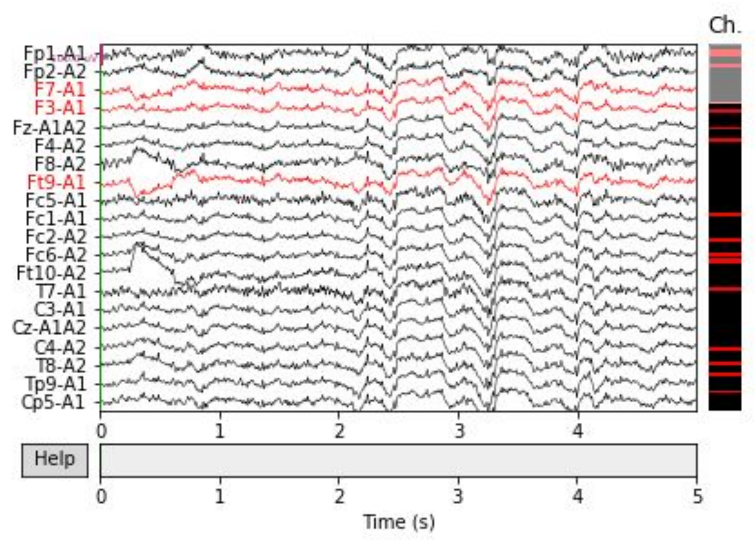
Training machine recognition of EEG patterns in response to different stimuli could have many benefits, including filtering out superfluous signals when diagnosing medical conditions, and improving the ability to interpret complex thoughts from people who have become paralyzed or are otherwise unable to communicate.

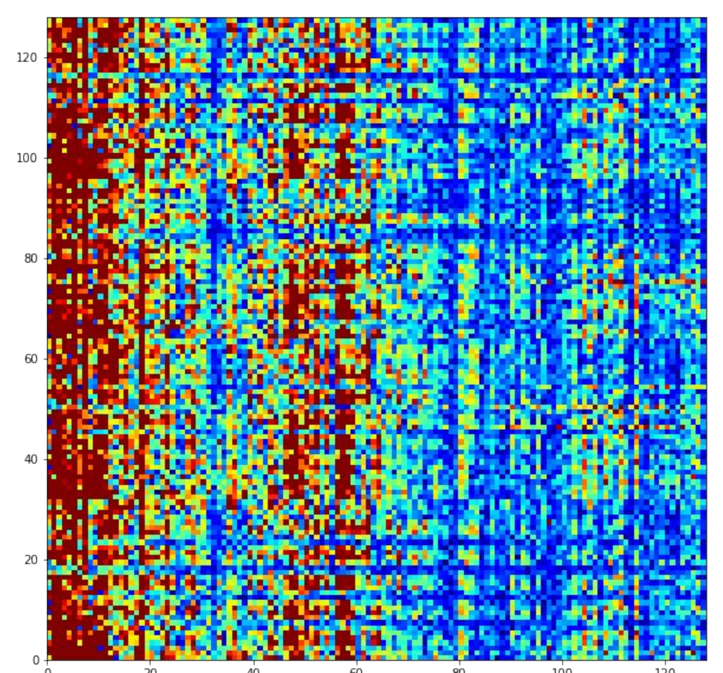
Preprocessing

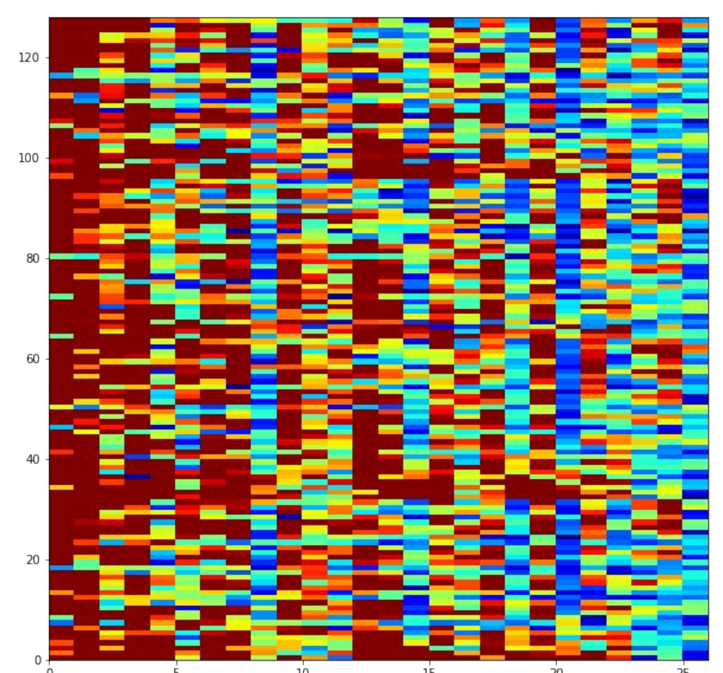
To provide uniform data to input to our CNN model, we made the videos the same length by truncating them to the shortest length found. While data is lost with this method, it allows us to more quickly understand if our model successfully learns useful classifications. Across the 17 subjects, there were many bad channels which were much noisier than their counterparts. To deal with this, we decided to interpolate the bad channels, which replaces them with the plain average of their neighbors. This allowed us to keep our data points a constant dimensionality.


Before interpolating.


After interpolating.

After interpolating the bad channels, we divided the EEG data into 6 second segments according to the time frame of the video stimulus observed, and computed for their Fast Fourier Transform (FFT) matrices. These were spliced for the first 40 frequencies (since typical brain activity occurs within that range). We also experimented with splicing for 128 frequencies so that we had a uniform square matrix. Ultimately, these were the matrices passed to our model.


128 channels x 128 frequencies

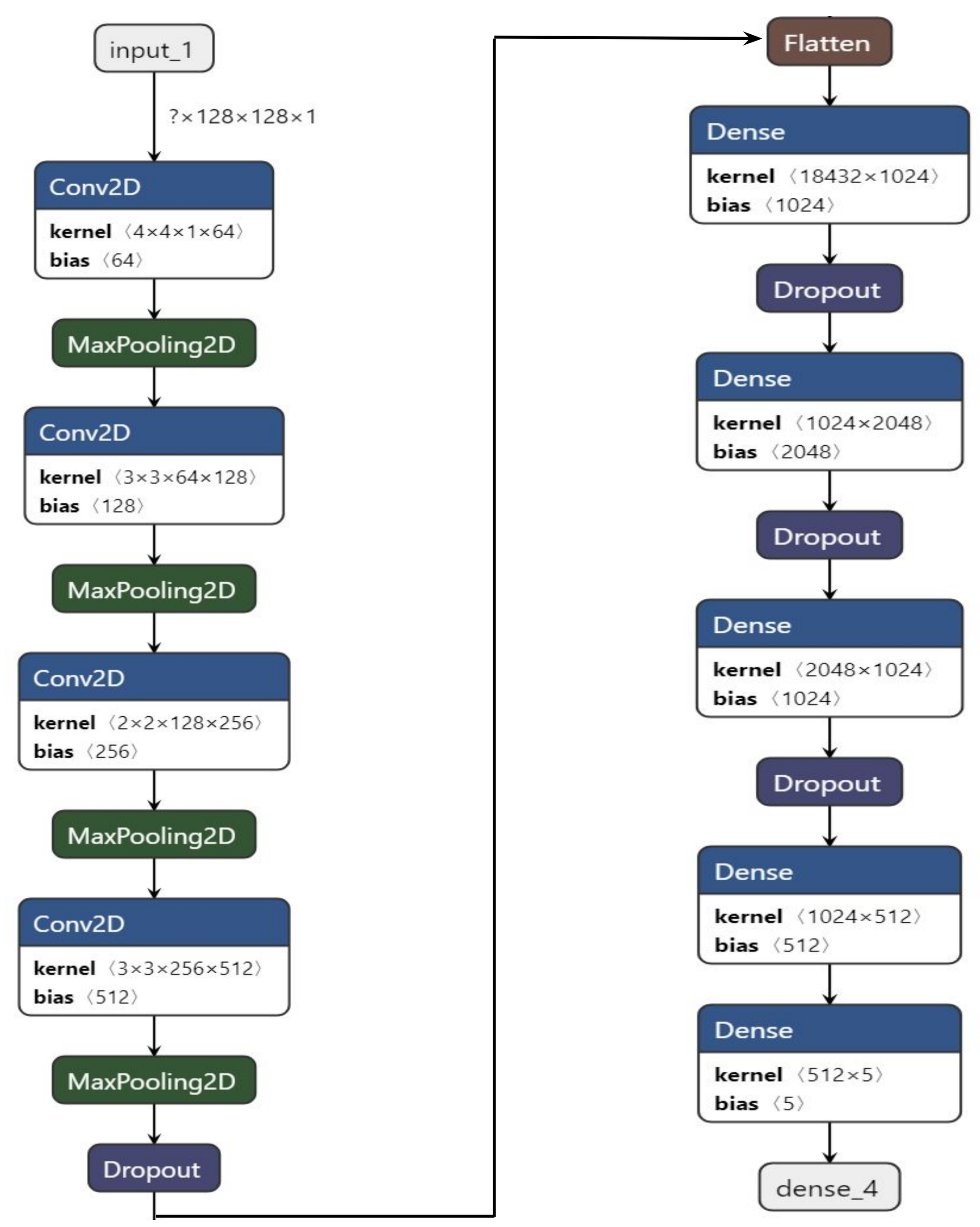

128 channels x 40 frequencies

Problem

Visual stimuli from 5 categories of videos (abstract, waterfalls, faces, Rube Goldberg mechanisms, and speed) were shown to 17 subjects, resulting in different brain wave patterns collected by an electroencephalogram (EEG) test. Our goal is to train a neural network, to identify what category the subject was looking at, based on the EEG data.

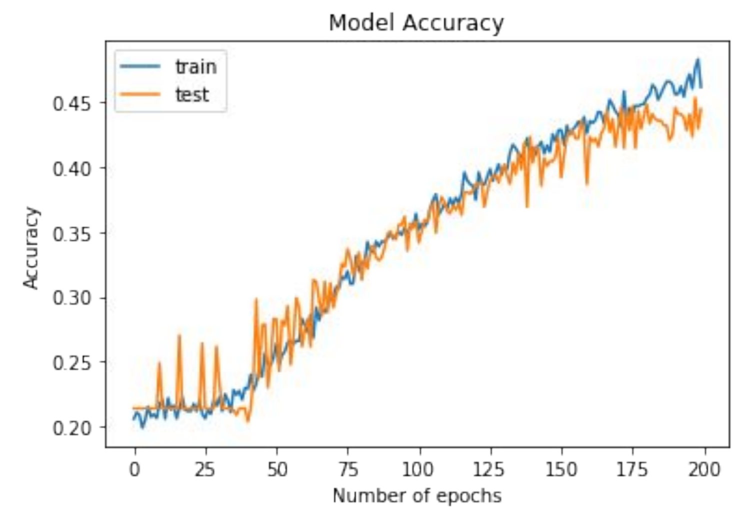

Examples of video frames from each of the stimuli categories

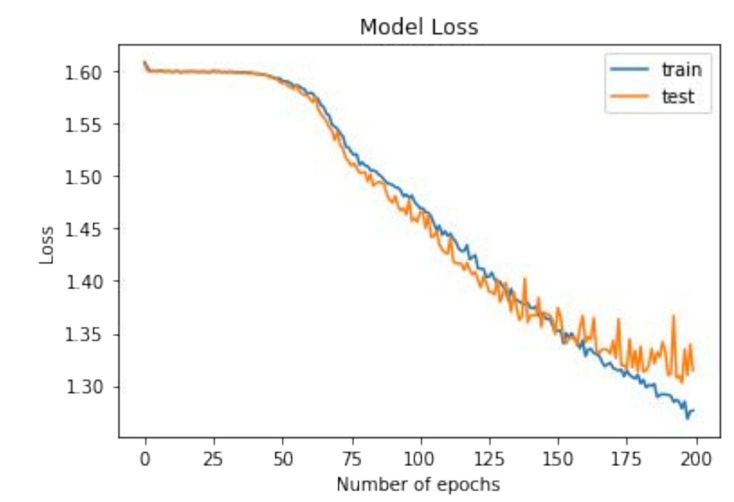
Neural Network



Results

After training on the CNN, we were able to achieve a test accuracy of 45% with a loss of approximately 1.3. While this is not accurate enough to be reliable, it is significantly better than what would be expected if labels were assigned at random. With further research and more complex networks, higher accuracies may be achievable.





Challenges

- EEG data is prone to noise, therefore one of our primary challenges was to find a method of normalizing the data in such a way as to filter bad data, such as those produced by bad channels, and false stimuli caused by eye blinks and other factors.
- The data provided was for videos of varying length, but our neural network required input of fixed size. We truncated the data down to the size of the shortest video (about 6 seconds), because it was the simplest solution to implement that would provide the CNN with longest uninterrupted EEG scan examples.
- Converting the EEG data from the .edf files to a format usable by the CNN proved challenging as few resources were provided with the initial dataset.
- The documentation for spectrograms, FFT, and other EEG concepts were extremely dense and often required lots of prior knowledge. Though their implementation syntax was not entirely difficult, we found it challenging to verify correctness.
- Attempts to change the neural network to improve accuracy proved difficult as resource limitations on the systems that we were using prevented us from exploring all possible variations.
- Due in part to initial optimism regarding how much we could accomplish in the time available, we were unable to implement different types of neural networks.

Analysis

Our convolutional neural network achieved a maximum accuracy of 45% on test data. The model is therefore correct twice as often when identifying the type of video being watched based on the EEG data than random chance would suggest. In an attempt to bring more accuracy to the neural network, more dense layers were added after the first, which produced more accurate results. It is possible that with longer training or more samples, such a network could become more effective than the current model. In addition it is worth noting that while it took longer to train, using 128✕128 version of the data yielded significantly better results.

Looking Ahead

As the EEG data is presented as a time series, it is possible that more accurate classification could be achieved using a recurrent neural network (RNN). In addition, it would likely be beneficial to train on more varied data, while there were several thousand individual segments of EEG data to analyze, there were only 17 subjects as part of the initial study. More data would likely allow the neural networks to train more precisely distinguish the useful data from the noise. Finally, as you may be able to see from the volatile spikes in the charts, our data was not thoroughly cleansed. In future endeavors, we could incorporate independent component analysis to unmix signals for a cleaner dataset.

Acknowledgments

We would like to thank our professor Dr. Narges Norouzi, and our TA Jonathan Scott for their support during this project.