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Sleep Stage Prediction Using Smartwatch and EEG Data

Abstract:

Sleep is an integral part of the human experience and is vitally important for cognitive functions such as learning, creativity, and memory. In order to study the importance of sleep on the brain, it is very useful for researchers to be able to categorize the stages of sleep a participant is in during a given time. This information is crucial to sleep research due to different sleep stages contributing various benefits for the brain, but current researchers are limited to using EEG devices to categorize participants' sleep cycles. This limitation makes running sleep studies very difficult. Here, in hopes of finding a more accessible alternative for sleep classification, we build a neural network model to classify a participant's sleep stage at a time point from data that is retrievable from smart watch devices. Using heart rate, accelerometer motion, and gyroscope motion data as our inputs and EEG classification data as ground truth, we developed a convolutional neural network that predicts a participant's sleep stage at a given second with 60% accuracy. Our model consists of two 1D Convolutional layers and one Dense layer of 128 units. Developing a reliable model for classifying sleep stages can make sleep research easier to run, with the chance of longer studies in the comfort of people's homes at a much lower cost. This also opens up the possibility to have an accessible sleep tracker for anyone to be able to run on their smartwatch devices.

Additional Details:

For training and testing our model, we used 963,120 data points from a dataset of a previous sleep study. In this study, participants wore an electroencephalogram (EEG) device to measure the electrical brain signals at each second, as well as a Fitbit smartwatch that measured heart rate, accelerometer motion, and gyroscope motion sampled at 1 Hz. The EEG device categorizes a participant's sleep stage per second and provides us with the ground truth to be used for training and testing. The five stages of sleep categorized are wake, N1, N2, N3, and REM. We matched the Fitbit smartwatch data and EEG device data based on timepoints to be used for this project.

Along with the heart rate, accelerometer, and gyroscope motion data, Fast Fourier Transform (FFT) values were computed for each signal over a minute of data at 1Hz frequency resolution. This is in hopes to provide the model with more information about each signal over the past minute of data for each timestamp which could aid in classification, since it is easier to determine sleep stages using information from a small chunk of time versus a singular second of data. We used around one million data points which roughly represents 35 different sleep sessions, and split the data with 80% used for training and 20% used for testing. Our main challenge in building this model was the imbalance in data for each category, as some sleep stages last for five minutes, and others might last up to 40 minutes. We decided to add more N1 data into our dataset so that it was closer in size to the second smallest class, and then used class weights to further balance our dataset during training. Our final dataset consisted of: (1) 137,679 in wake, (2) 112,079 in N1, (3) 341,155 in N2, (4) 152,417 in N3, and (5) 219,790 in REM.

We experimented with different inputs and models in order to find the best classification accuracy. We originally tried to use a Long Short-Term Memory (LSTM) recurrent neural network with time series sequences of 800 data points in order to analyze our sleep data as a time series. However, training sequentially overfit the model to the sleep stage with the most data (N2). We found that shuffling the data and using a Convolutional Neural Network (CNN) model worked better for this dataset. Our model consists of: (1) 1D Convolutional Layer with 32 filters of kernel size 5 (2) 1D Max Pooling Layer of size 3 (3) 1D Convolutional Layer with 64 filters of kernel size 5 (4) 1D Max Pooling Layer of size 3 (4) Dense Layer of 128 units (5) Output Dense layer of 5 units. We train our model over 50 epochs with a batch size of 64. We chose our parameters based on the size of our dataset and the number of features being passed in, as well as from experimenting with different values.

Figure 1

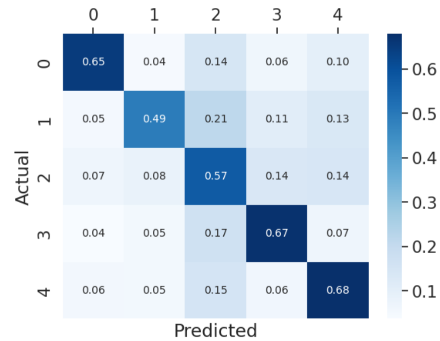

Figure 2

After training over 50 epochs, our model was able to predict our test data with 60% accuracy, 3 times greater than chance accuracy (see Figure 1). These results are comparable to existing smartwatches that classify sleep stages whose models are not publicly available. Training loss consistently declined with increased training, improving by over 20% by 50 epochs (see Figure 2). While implementing our model, we decided to analyze the Equivariance principle and Manifold view by visualizing the first channels of both of our Conv1D layers, and performing Principal Component Analysis on the second to last layer outputs as seen in Figures 3-6.

Our project concludes that we were able to build a model that can classify sleep stages of a participant based on smartwatch data at 60% accuracy. In future work, we plan to try our model on a larger and more balanced dataset and experiment further with learning rates, kernel sizes, and hidden layers to find the optimal model. We believe this could be a useful tool for research as well as an accessible alternative for individuals to be able to track their sleep patterns.

Figure 3

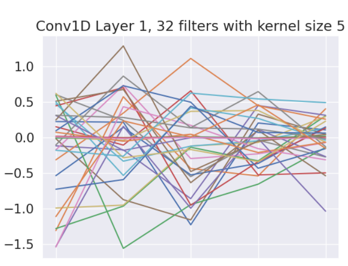

Figure 4

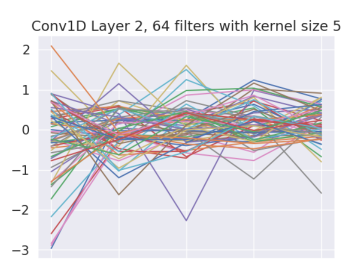

Figure 5

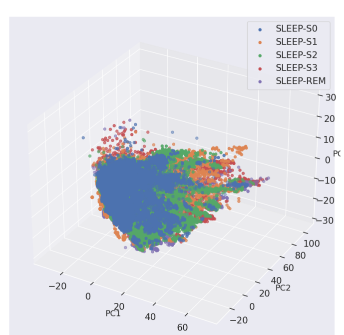

Figure 6