AI for Medical Time Series

Project Report

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Group Number 9

1 Introduction

Aging changes the brain and often brings changes to sleep patterns, including increased difficulty falling asleep, more frequent awakenings during the night, and earlier wake times in the morning. These changes may result in a perception of lighter sleep and reduced total sleep time. In our project we therefore want to verify this statement by using subject which are younger than 30 and subjects who are older than 80.

2 Dataset Description

We selected the Sleep-EDF dataset available open-source on PhysioNet for our study. This dataset comprises 153 recordings from 78 subjects, including 37 males and 41 females. The data were collected between 1987 and 1991 as part of a study on age effects on sleep in healthy Caucasians aged 25-101. Participants refrained from sleep-related medication during the study period.

Each participant underwent two polysomnography (PSG) recordings, each lasting approximately 20 hours, conducted over consecutive day-night periods in their homes. The recordings were made using a modified Walkman-like cassette-tape recorder. However, the first night recordings of subjects 36 and 52, and the second night recording of subject 13, were lost due to issues with the recording equipment.

The signals recorded included electrooculogram (EOG) and electroencephalogram (EEG) sampled at 100 Hz, submental electromyogram (EMG) sampled at 1 Hz, oro-nasal airflow, rectal body temperature, and event markers also sampled at 1 Hz. The EEG channels consisted of Fpz-Cz and Pz-Cz, along with one EOG (horizontal) channel, one submental chin EMG channel, and one oro-nasal respiration channel.

Each recording was manually scored in 30-second epochs by sleep experts according to Rechtschaffen and Kales scoring rules, resulting in eight classes: Wake, N1, N2, N3, N4, REM, MOVEMENT, and UNKNOWN ("sleep stage ?") . For more information check out the webpage: Sleep-EDF Database . We can also download the dataset on MNE-Python.

3 Classification Task

3.1 Task Definition

For our classification task, we aim to distinguish between participants aged below 30 and those aged over 80 based on their EEG signals during sleep. This task involves binary classification, where the target variable is whether a participant belongs to the age group below 30 (class 0) or over 80 (class 1). So this would be a Binary Classification task. We leave the opportunity open to extend this and include the sleep stages. But we could also have tasks like binary classification such as distinguishing between wakefulness and sleep, or multiclass classification tasks involving different sleep stages (e.g., wakefulness, REM sleep, NREM sleep stages).

3.2 Approach

1. Data Preprocessing:
   We will preprocess the EEG signals by applying a band-pass filter to retain frequencies of interest and ensure data quality. Since the annotation of the conditions is not so clear and we want to deal with our own - we need to rename them as well. Again the dataset includes seven channels: EEG Fpz-Cz, EEG Pz-Oz, EOG horizontal, Resp oro-nasal, EMG submental, Temp rectal, and Event marker. We need to choose some or all in our later feature engineering process but before hand clean them, since there are some "missing" annotation/conditions. The sampling frequency is 100 Hz, with a 0 Hz highpass and 50 Hz lowpass filter. We can/will filter the data with with a bandpass filter from 0.5 to 30 Hz

2. Feature Extraction:
   Using the preprocessed EEG signals, we will

compute the power spectral density (PSD) using the "Welch " method. From the PSD, we will extract features such as the average power in specific frequency bands (e.g., delta, theta, alpha, beta), or choose the choose to go with the annotated frequencies defined by experts: they defined however sleep stages differently: wake, rem, stage 1, stage2, stage 4, stage 5, unknown - we would rename them.

3. Model Selection:
   We will experiment with different machine learning models, including Random Forest, Support Vector Machines (SVM), and neural networks (e.g., Multi-Layer Perceptron). We will explore the suitability of each model for our classification task.

4. Model Training and Evaluation:
   We will train the selected models using the extracted features and evaluate their performance using cross-validation techniques. We will use metrics such as accuracy, precision, recall, F1-score (AUC-ROC) to assess the models' effectiveness in predicting participants' age groups.

5. Statistical Analysis:
   In addition to traditional model evaluation metrics, we will perform statistical tests, such as analysis of variance (ANOVA) or simple t-test, to compare the EEG features between the two age groups. This will provide insights into the significance of differences in brain activity patterns during sleep.

4 Data Insights

4.1 Age Distribution

We found that the age distribution is concentrated in the 25-30 and 80-100 ranges, indicating a balanced dataset for further analysis. We identified subjects 39, 68, 78, and 83 with missing age information and removed them from the dataset.

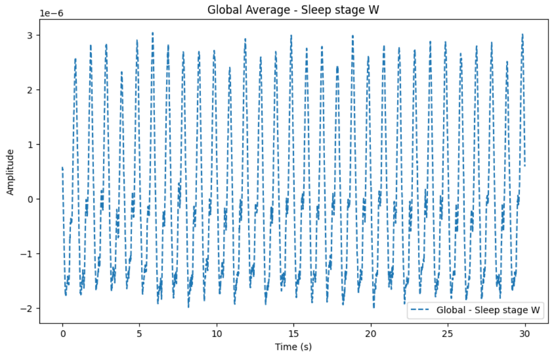

Figure 1: Age Distribution

4.2 Gender Distribution

A heatmap of gender and age distribution shows a similar distribution in the 80-100 age range. However, in the 25-30 range, there are more males than females, which might require further consideration.

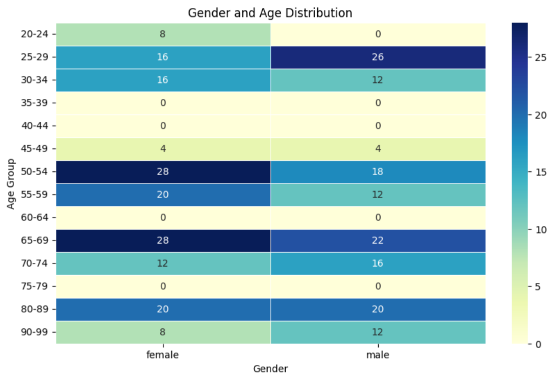

Figure 2: Gender and Age Distribution

5 Data Processing and Filtering

5.1 Channel Information

The dataset includes seven channels: EEG Fpz-Cz, EEG Pz-Oz, EOG horizontal, Resp oro-nasal, EMG submental, Temp rectal, and Event marker. The sampling frequency is 100 Hz, with a 0 Hz highpass and 50 Hz lowpass filter.

5.2 Filtering and Annotations

The data was filtered with a band-pass filter from 0.5 to 30 Hz. Events and annotations were extracted to identify sleep stages.

6 Subject 9 Analysis

6.1 Power Spectral Density

The PSD for subject 9's EEG channels is plotted below. This analysis helps identify patterns related to sleep stages. We will also use that in later steps across all subjects, however we still need to do more cleaning of missing data.

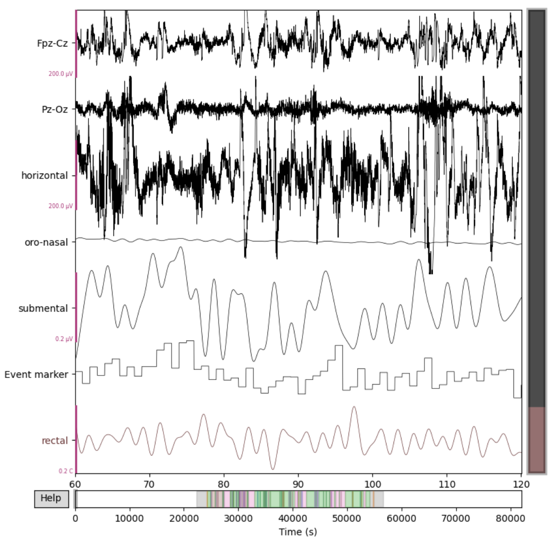

Figure 3: Raw channel data of all channels for subject 9

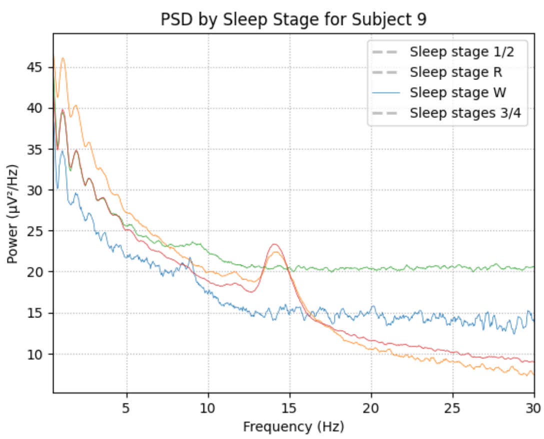

Figure 4: Raw channel data of all channels for subject 9

in Figure 4, we can see the blue line (awake stage) and the rem is green and then the deep sleep and light sleep (orange/red) unfortunately the plotting is sub-optimal and needs to be improved. However we can infer that REM and awake stages have higher power in the higher frequencies, while deep sleep stages have higher power in the lower frequencies.

6.2 Event-Based Analysis

We changed the annotations to fewer sleep stages and plotted the events for subject 9. Here one can see nicely how deep sleep has multiple events compared to other events. This will be very interesting for our futher analysis.

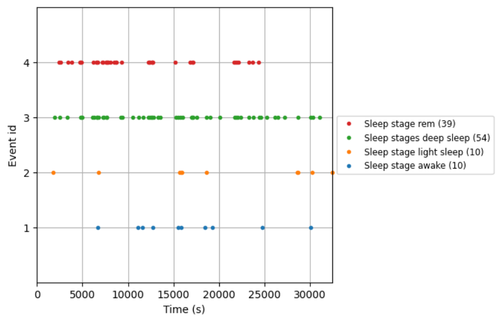

Figure 5: Events and Sleep stages for subject 9

7 First analysis

7.1 Averaging for Condition "Sleep stage W"

We computed the global average for the "Sleep stage W" condition across the first 5 subjects.

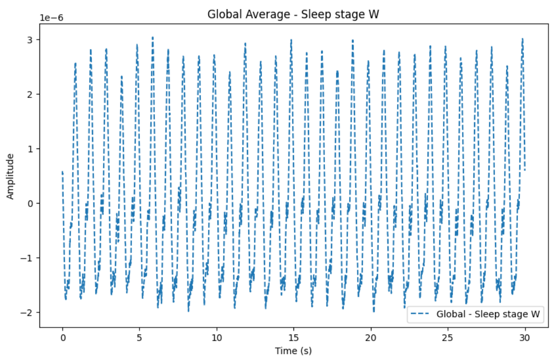

Figure 6: 2 channels EEG average response for first 5 subjects for condition: awake

In Figure 5 we see how spread out the global average response for the sleep stage "W" - wake is now we plot "R" - Rem and average them over those 5 subjects: See Figure 6. It seems to be very similar.

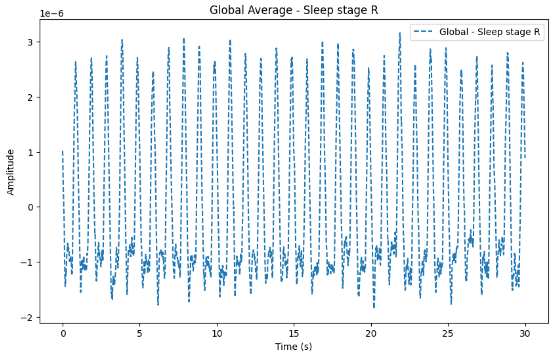

Figure 7: EEG average response of first 5 subects over condtions: REM

If we however plot the sleep stage 4, refering to "deep sleep" and averge the response over all those 5 subjects we get a very different pattern, see Figure 8.

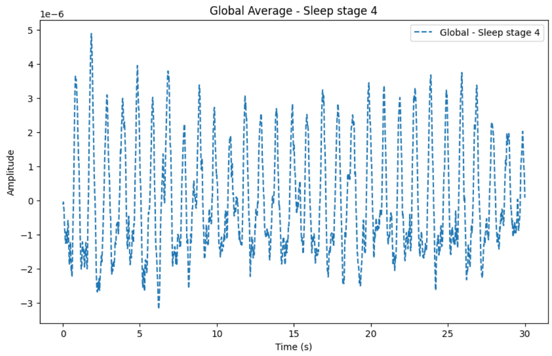

Figure 8: Deep sleep: sleep stage 4, average response over all 5 subjects

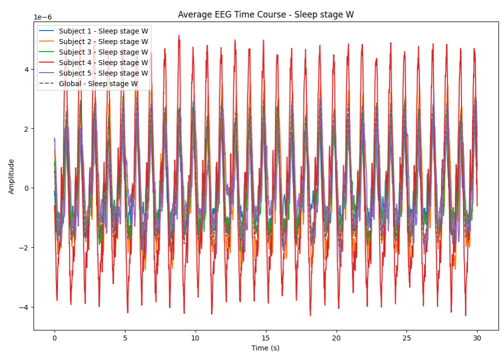

Figure 9: 2 channels EEG response for first 5 subjects for condition: awake

7.2 Average for All Conditions

Next, we computed the overall global average across all conditions for the first 5 subjects.

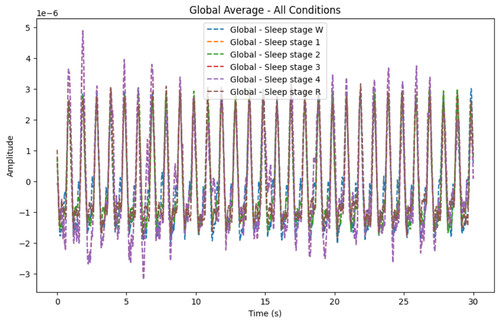

Figure 10: Overall average for 5 subjects across all conditions

8 Conclusion

In our report we presented first insights into the EEG data, with some average plotting, due to the amount of data and since there needs still be be some "clean-ups" done within the data, where we exclude certain conditions that are not always present in all subject we did not use all data. But we visualized age and gender distribution over all, and presented an individual subject analysis, and some first global averages (over all conditions and over "awake" condition) of the first 5 participants/subjets . The analysis provides a basic understanding of our data and our future proceeding.