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Report

Challenge by Dreem / Master MVA

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1. Introduction

Presentation The goal of this data challenge is to predict a subject's gender (*i.e.* male or female) from the electrical activity of its brain during sleep. The dataset provided by Dreem for this challenge is divided into a *training set* and a *test set*. The training set and the test set both contains EEG measurement for 946 subjects. On each of these subjects, the EEG signal has been recorded on 7 channels on 40 time intervals of 2 seconds. The sampling frequency of the signal is 250 Hz. As a consequence, each subject is associated with an input array of size $(40, 7, 500)$.

Notation Hereafter, male subjects will be denoted as « class 0 » and female subjects will be assigned « class 1 ».

Previous work The challenge webpage was presented with a reference article [**?**]. In this work, the author applied a deep-learning model to the prediction of the gender from EEG recordings. Using a convolutional neural network, the authors achieved 81% of accuracy.

Data balancing The repartition of genders in the training set is 737 men and 209 women, i.e male subjects represent 78% of the training set. As a consequence, a trivial classifier returning 0 will have 78% accuracy on the training step. It is natural to ask whether or not the test set is also imbalanced. Since, we do not have access to the true classes of the test set, we simply submitted a solution on the challenge webpage where all the predictions where male, and obtained and accuracy of around 77.5%. Thus the test set has this 77.5% of male subjects and is quite imbalanced like the training set.
There are two possibilites to counter the imbalance : we can either oversample the class 1 to adjust the class distribution or assign different weights to each class.

2. Electrophysiology of sleep

Whilst sleep is commonly viewed as an homogeneous phenomenon through which restorative tasks are being carried by our organism, EEG recordings of normal subjects show that sleep actually comprised different stages which correspond to different electrophysiological regimes. In what follows, we begin with a rough introduction of those different regimes by presenting some of their defining characteristics. Doing so pertains to us as a paramount step toward building interpretable predictive models, as this allows for a better understanding of the underlying geometry to the sheer data. We then mention some current literature discussions on gender-based differences of sleep EEG, so as to make our way into assembling a first evidence-based predictive model.

Sleep cycle. The sleep cycle divides into two defining regimes, namely the *Rapid Eye Movement* sleep (REM) and the non-REM sleep. The REM sleep regime is distinguishable, as hinted by its very denomination, by the presence of erratic and rapid movements to the subject's eyes. In REM sleep, the EEG recordings are very similar to that of the awake state (*i.e.* low-voltage and high-frequency electrophysiological activity), to the extent that REM sleep also bears the name of *paradoxal sleep*. The non-REM sleep phase is divided into four stages, namely:

- *Stage I*. This stage is characterized by brainwaves of medium frequencies ($4-8$ Hz) with increasing amplitudes ($50-100$ μV) compared to the waking state, which is characterized by high-frequency ($15-60$ Hz) and low amplitude (~ 30 μV) activity, the so-called *beta waves*.
- *Stage II*. This stage is characterized by the presence of *sleep spindles*, which are sudden burst of oscillatory brain activity, corresponding to frequencies bandwidth $10-15$ Hz and amplitudes $50-150$ μV. Research indicates that those sleep spindles stem from the interactions between thalamic and cortical neurons. Another type of defining brainwaves for the stage II non-REM phase are the so-called *K-complex*, which, unlike the sleep spindles, are waves of low frequencies ($0.5-4$ Hz) and large amplitude that react to external stimuli while sleeping.
- *Stage III*. This stage, which represents moderate to deep sleep, is characterized by slower waves at $2-4$ Hz with amplitudes $100-150$ μV.
- *Stage IV*. In this final stage of the non-REM sleep phase, which represents the deepest level of sleep, the predominant EEG activity displays brainwaves of low frequency ($1-4$ Hz) and high-amplitudes, the so-called *delta waves*.

After reaching Stage IV, the sequence reverses itself and a period of REM sleep ensues. This pattern is repeated

Toward gender-based differences of sleep physiology

3. Deep learning-based classification

In this section, we develop the deep learning pipeline used for the gender classification.

Braindecode [?]

4. Classification with linear models

Linear classifier using DFT. Recall that a signal $x(t) \in L^2(\mathbb{R})$ is entirely characterized by its Fourier transform $\widehat{x}(\omega) \in L^2(\mathbb{R})$ and vice-versa (*i.e.* $x(t) \mapsto \widehat{x}(\omega)$ is a bijective isometry of $L^2(\mathbb{R})$). Therefore, by working on the frequency-signal $\widehat{x}(\omega)$ rather that on the time-signal $x(t)$, we do not lose (*a priori*) any relevant information concerning the recorded time-signal. Because the EEG data at our disposition is not time-stamped, the temporal structure is so to say inexistant, which advocates for carrying the computations into the frequency-domain. Given a discrete time-signal $\{x_0, \dots, x_{N-1}\}$, the *Discrete Fourier Transform* (DFT) is defined as the frequency-signal $\{\omega_0, \dots, \omega_{N-1}\}$, where

$$\omega_k := \sum_{j=0}^{N-1} x_j \exp(-i2\pi kj/N), \quad k = 0, \dots, N-1.$$

Because the recordings are our disposal each only spans for a short duration T across time (*i.e.* $T = 2$ sec), there exists a lower-bound ω_{low} in the frequency-domain below which the Fourier transform is simply unable to perform anymore, that is $\omega_{low} = 1/T$ (*i.e.* 0.5 Hz in our context). This is a well-known drawback to the short-time Fourier transform. Nevertheless, because of the nature of our data as presented above, we shall not be expecting such low-frequency features in the EEG signal.

Inherent to any dataset obtained through physical-acquisition is the presence of measurement noise. For each EEG channel, we want to estimate the *power spectral density* (PSD) (*i.e.* the quantity $|\widehat{x}(\omega)|^2$) as accurately as possible. One way to proceed is the *Bartlett's method*, which consists in splitting the recorded signal $\{x_0, \dots, x_{KQ-1}$ of size KQ into K segments disjoint of size Q, *i.e.* $(\{x_{k(Q-1)}, \dots, x_{(k+1)Q-1}\})_{k=1}^{K}$, to compute the spectral density for each segment through a certain weight function (*i.e.* the window) and to average over the segments. This allows for a smaller variance in the measurement (*i.e.* less measurement noise). An improvement of the Bartlett's method is the so-called *Welch's method* which introduces a overlap of user-defined size D between the different segments s_k's (*i.e.* $|s_k \cap s_{k+1}| = D$). Since the windows are generically more sensitive to the data at the centers of the segments, the Bartlett's method results in a loss of information, which here is alleviated by the overlapping.

Using Welch's method, we compute the PSD of men and women over different splits of the training set (we average over the 40 samples for each subject). First, *(i)* we observe trends for each channel that are quite similar from split to split, which indicates a common underlying geometry to the data (*i.e.* the data is consistent across all subjects). Over some splits, *(ii)* we observe a mild but nevertheless significant difference between genders. Nevertheless, *(iii)* some splits yield very similar results for both male and female, which therefore tends to indicate that the variance of the Welch estimator is rather to be sought in inter-subject variability than in inter-sex variability.

Linear classifier using DWT