Predict sex from brain rhythms : project report

CLARTE Lucas, LELLOTTE Rodrigue

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1 Introduction

1.1 Presentation

The goal of this project is the prediction of a subject's gender from its brain rhythms. The dataset provided by Dreem for this project 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 $(40, 7, 500)$. The recordings were made during the night.

Notation In the following, male subjects will be associated with the class 0 and female subjects will be assigned class 1.

1.2 Previous work

The challenge webpage was presented with a reference article [7]. 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.

1.3 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 use undersampling /

oversampling to adjust the class distribution or assign different weights to each class.

A trivial classifier The ranking on the data challenge website[1] was based on the accuracy of the predictions on the public test set. It is easy to realize that the test set suffers of the same class imbalance as the training set : 77.59% men and 22.41% women. As a consequence, we obtained an accuracy of 77.59% by submitting a trivial classifier whose prediction is always 0 (men's class), beating the benchmark by 1%.

2 Features of EEG data during sleep

Contrary to the data used in the article [7], our challenge used EEG data recorded during the night. However, nocturnal brain rhythms present different caracteristics than diurnal ones. In this section, sleep spindles and K-complexes are studied : Sleep spindles are bursts of activity in the frequency range of 11-16 Hz and whose duration is 0.5 - 1.5 seconds. Note that the short duration of our EEG recordings makes it harder to efficiently detect sleep spindles, because the duration of latter is almost the same as our recordings. In other works, 10-seconds recordings are used.

2.1 Brain rhythms

The work studied in this challenge claimed Previous work such as [**?**] showed evidence of a higher neural activity in the alpha and delta frequency range.

2.2 Sleep spindles

Several Python libraries are able to compute sleep spindles. In our work, we studied two of them : YASA[6] and Dosed[1]. These two libraries follow different approaches and are detailed below.

YASA This library is based on the work done in [4] and detects sleep spindles using four well-chosen features : the absolute sigma power, the relative sigma power, the sigma covariance and the sigma correlation. Applying this algorithm on the 264880 2-seconds recordings of our training set, 441 sleep spindles were detected. Figure (1) shows two examples of sleep spindles present in the training dataset.

Dosed Contrary to YASA, this Python library trains a deep learning model to identify sleep spindles. It thus requires training using annoted recordings where sleep spindles are already identified. Because of our lack of time, we limiteed ourselves to YASA for our experiments, as it does not require supplementary data for training and was overall easier to use in our own codebase.

[1] https://challengedata.ens.fr/participants/challenges/27/

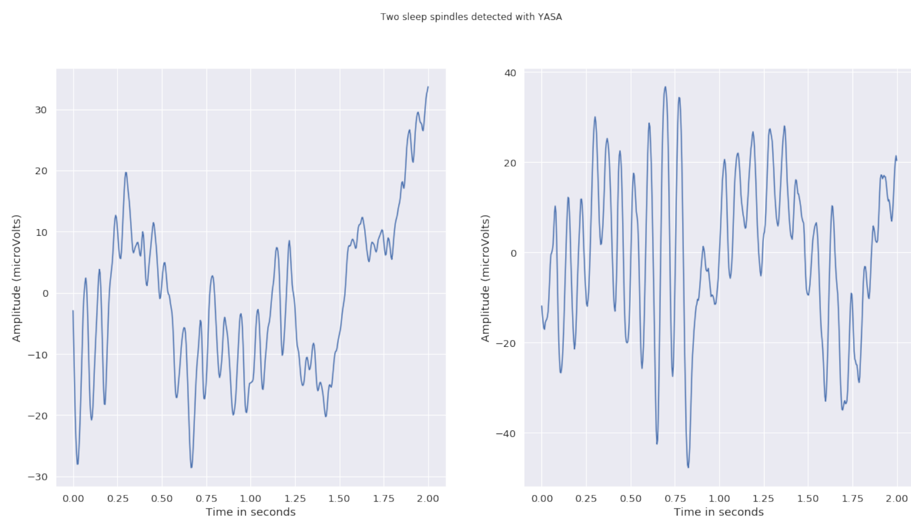

Figure 1: Example of two recordings showing sleep spindles, from revised x_train.h5 file. Left : subject 1, sample 12, channel 4. Right : subject 3, sample 16, channel 5. We can clearly observe the oscillatory behavior lasting for about half a second.

2.3 K-complexes

2.4 Correlation between sensors

Observing the data leads us to observe a strong correlation between some channels : indeed, the pairs of channels (1, 5), (2, 6) and (3, 4) seem to show strongly correlated signals. To verify this fact, we computed a correlation matrix M for each of the 946 $\times$ 40 recordings : the 7 $\times$ 7 matrix M stores the value returned by the `numpy` function `np.correlate`(s_i, s_j) for the signals of two sensors s_i, s_j. In our case, this function simply returns the cross product of the 500 dimensional vectors corresponding to each sensor. Then, for each row i of M, we simply compute the sensor j that maximizes the cross product with i (other than i itself). Doing this for all the recordings, we confirm the observation stated above.

3 Deep learning-based classification

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

The original article on which the challenge is based proposed [7] describes an architecture based on a previous architecture designed by Krizhevsky et al. to work on ImageNet [3].

3.1 Reproducing the article's network

The first of this project was to reproduce the results presented in[7].

Data formating The authors of[7] studied EEG recordings of 2 seconds with a sampling frequency of 128 Hz and 24 channels, thus having data formatted as 24 x 256 matrices. Since our input data has the shape of 7 x 500 matrices, we decided to resize them to match the the network's input shape.

Reordering channels We saw in section 2.4 that some sensors were sontrgly correlated with one another. To take into account these correlations, we swapped rows of our dataset so that these strongly correlated channels are consecutive in the dataset : namely, we swap the channels 2 and 5. While we have no rigorous mathematical justification for this reordering, we have an intuitive justification : indeed, as explained in the article [7], the neural network architecture used is inspired by previous work on image datasets such as ImageNet. However, in images, nearby pixels are strongly correlated for the sole reason that two pixels belonging to the same object will have very similar color. If the EEG recordings are treated the same way as images, we want nearby pixels to be as correlated as possible.

For hyperparameter tuning, the python library `keras-tuner` was used.

3.2 Braindecode library

In addition, we used the Python library [**?**], which is specialized in classification of EEG recordings using deep-learning and built on top of the Pytorch library.

4 Classification with linear models

5 Conclusion

References

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