Predict sex from brain rhythms : project report

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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.
We experimented two different strategies to solve the problem of class imbalance : first, we assigned different weights to each sample, following the approach described in [4]. On the other hand, we tried undersampling the majority class (i.e men) to have the same amounf of men and women in our dataset. The drawback of this approach is that we reduce the size of an already small dataset. Indeed, since there are 209 women in the original file x_train, the dataset after

undersampling includes 209 men and 209 women i.e 418 subjects compared to 946 initially.

2 Features of EEG data during sleep

Contrary to the data used in the article [9], 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[8] and Dosed[1]. These two libraries follow different approaches and are detailed below.

YASA This library is based on the work done in [6] 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.

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

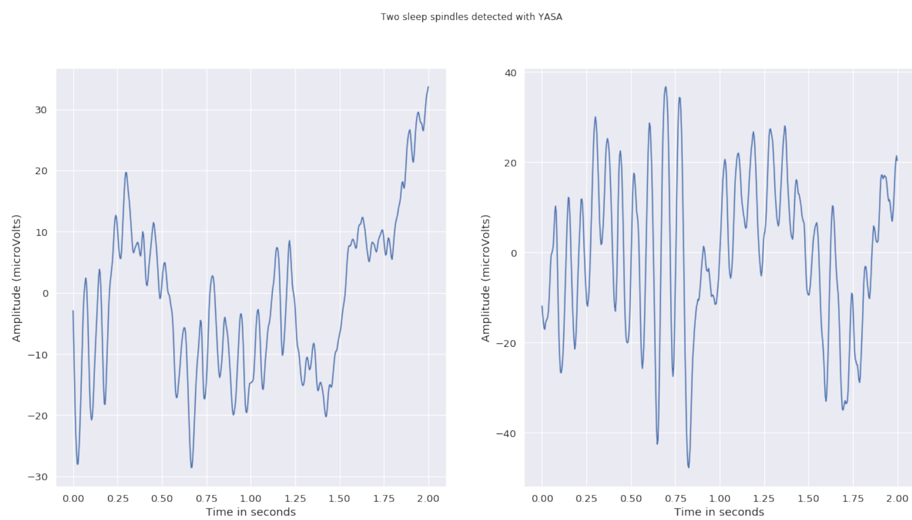

Figure 1: Example of two recordings showing sleep spindles, from revised x_train.h5 file. Left : subject 1, sample 12, channel 4. Right : subject 3, sample 16, channel 5. We can clearly observe the oscillatory behavior lasting for about half a second.

each of the 946×40 recordings : the 7×7 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 [9] describes an architecture based on a previous architecture designed by Krizhevsky et al. to work on ImageNet [5].

3.1 Reproducing the article's network

The first of this project was to reproduce the results presented in[9].

Data formating The authors of[9] 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 [9], 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 braindecode, described in [2] and which is specialized in classification of EEG recordings using deep-learning and built on top of the Pytorch library. In the original article, the authors applied this library to another task than sex prediction, namely the decoding and classification of imagined or executed movement from EEG recordings. Experiments on various tasks showed competitive results compared to more traditional techniques such as Filter Bank Common Spatial Pattern (FBCSP) [3].

Deep vs shallow network

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 $\{x_0, \ldots, x_{KQ-1}$ of size KQ into K segments disjoint of size Q, *i.e.* $(\{x_{k(Q-1)}, \ldots, x_{(k+1)Q-1}\})_{k=1}^{K}$, 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.

Nevertheless, we perform a simple classification

Linear classifier using DWT

5 Conclusion

References

[1] Stanislas Chambon, Valentin Thorey, Pierrick J Arnal, Emmanuel Mignot, and Alexandre Gramfort. A deep learning architecture to detect events in EEG signals during sleep. In *MLSP 2018 - IEEE International Workshop on Machine Learning for Signal Processing*, Aalborg, Denmark, September 2018.

[2] Schirrmeister et al. Deep learning with convolutional neural networks for brain mapping and decoding of movement-related information from the human EEG. *CoRR*, 2017.

[3] Kai Keng Ang, Zheng Yang Chin, Haihong Zhang, and Cuntai Guan. Filter bank common spatial pattern (fbcsp) in brain-computer interface. In *2008 IEEE International Joint Conference on Neural Networks (IEEE World Congress on Computational Intelligence)*, pages 2390–2397, June 2008.

[4] Gary King and Langche Zeng. Logistic regression in rare events data. *Political Analysis*, 9:137–163, Spring 2001.

[5] Sutskever Hinton Krizhevsky. Imagenet classification with deep convolutional neural networks. *Neural Information Processing Systems*, 25, 2012.

[6] Karine Lacourse, Jacques Delfrate, Julien Beaudry, Paul Peppard, and Simon C. Warby. A sleep spindle detection algorithm that emulates human expert spindle scoring. *Journal of Neuroscience Methods*, 316:3 – 11, 2019. Methods and models in sleep research: A Tribute to Vincenzo Crunelli.

[7] Federica Latta, Rachel Leproult, Esra Tasali, Elisa Hofmann, and Eve Van Cauter. Sex differences in delta and alpha eeg activities in healthy older adults. *Sleep*, 28 12:1525–34, 2005.

[8] Raphael Vallat. raphaelvallat/yasa: v0.1.9, February 2020.

[9] Arns van Putten, Olbrich. Predicting sex from brain rhythms with deep learning. *Scientific Reports*, 2018.