

Deep Learning - Project 1

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Abstract—The goal of this project is to train and test a predictor of finger movements (left or right hand) from Electroencephalography (EEG) recordings. We decided to construct several solutions, starting from simple baseline models and then escalating to complex deep neural networks.

I. INTRODUCTION

This project consists in a two-class classification problem to predict the laterality of incoming finger movements 130ms before key-press. The electrical impulses that generate the finger movement starts a fraction of second before the actual movement, giving us the possibility to predict which hand the subject is going to move through an EEG analysis.

The following sections give an overview of the tried techniques to construct a predictor. Section II briefly describes the dataset of EEG recordings and the experiment that was performed to obtain them; Section ?? proposes a first approach to the problem by using a series of simple classification models (baselines); Section IV goes to more complex solutions exploiting Fully Connected Neural Networks and Convolutional Neural Networks; Section V compares the results obtained with the most performance models.

II. EXPLORATORY DATA ANALYSIS

The dataset was provided by Fraunhofer-FIRST, Intelligent Data Analysis Group (Klaus-Robert Müller), and Freie Universität Berlin, Department of Neurology, Neurophysics Group. It was first given in the "BCI competition II" (May 2003) with a sample of 416 epochs, divided in 316 train records (labeled) and 100 test records (unlabeled). The experiment performed to construct the dataset consists in a normal subject sitting on a chair in a relaxed position, while he is typing a computer keyboard in a self-chosen order. 3 sessions of 6 minutes each were taken, all conducted the same day with a small break in between and with an average typing speed of 1 key/second. The EEG records were made using 28 electrodes to monitor the brain electrical activity. They measured a time slot of 500ms, ending 130ms before the keypress and sampled at 100Hz and 1000Hz. In our project we used the records sampled

at 100Hz, imported as a 28 (electrode's measurements) x 50 (time frames) matrixes. We also tested the 1000Hz records after we identified the best predictor model. An example of a record with the respective label is shown in figure 1 – Da mettere

III. BASELINE MODELS

All the baseline models were tested with cross-validation and we iterated over a range of values for some parameters in order to find the best score. We implemented the following models (from sklearn library): - Logistic Regression, tested with a grid search on the regularization parameter. Surprisingly, this model has good performances in our classification problem as shown in figure 2, despite the fact that it is much more simple than other models we tried. - Random Forest Classifier, with iteration over the max depth of the trees. - K-Nearest Neighbors, with multiple values for K. Moreover, before training this model, we normalized the input and applied a PCA to reduce the dimensions (we kept the 95% of the signal energy) - SVM - Linear Discriminant Analysis

Result obtained DA FARE

IV. DEEP NEURAL NETWORKS

We designed different models, starting from a Fully Connected Neural Network and then moving to Convolutional and Fully Convolutional Neural Networks. The increasing complexity of these models allowed us to get better performances on the test set, at the price of more time and resources needed.

V. RESULTS

The traditional CNN was trained for 1000 epochs, each consisting of 25 batches of 4 images, on a NVIDIA GeForce GTX graphics card with 2 GB of VRAM, obtaining an F1 score of 0.833. While the U-Net was trained for 10000 iterations with a learning rate $\lambda = 10^{-3}$ which led to an F1 score of 0.9385 on the test set submitted on Kaggle. To compare different techniques we used the Precision Recall method (PR) which focuses on the relevance of the prediction on the labels of a test set. To compute the PR values we split the training dataset into two subsets, one used for training and one

used to compute the PR curve. The latter is computed by gradually increasing the threshold (used to establish, given its probability, if a pixel is a road) to compute different PR values. By doing so, we obtain the graph in Figure 1.

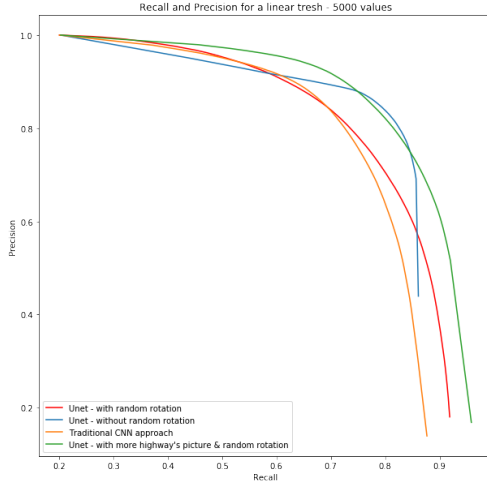


Figure 1. Precision and recall evolution regarding our different methods

We can observe three important things in this plot . Since the yellow curve is below every others, we can say that Unet is performing better than the traditional approach. The second observation is that the green curve is above the red one. Considering this we can conclude that adding more highway images and getting rid of the seaside images was a good thing. The third observation is about the blue curve. We can see that in some cases the blue curve is above the green one. In fact when we are not rotating the image the network learns better how to detect vertical and horizontal lines but the results are worse when predicting the others. That explains why the blue curve goes above the yellow one between 0.6 and 0.8. We concluded that the yellow curve corresponds to the best model and therefore the one we used for the Kaggle competition.

VI. CONCLUSION

Both models proved to be versatile and effective in achieving good predictions. However, our traditional CNN model failed in recognizing narrow roads, especially when they are covered by shadows, those types of roads are indeed almost inexistent in the training set while present in many images of the test set. Moreover, the train and test datasets were mainly restricted to cities. To obtain a model that would efficiently work with a wider range of input images such as images with snow, country images or on different meteorological conditions, we would require a bigger and diverse training set. In addition, without any preprocessing other than data augmentation, both models outperformed the baselines and confirmed their superiority in solving this kind of problem.