Predicting the eye state of a subject from EEG data using supervised classification algorithms

1 Description

Electroencephalogram (EEG) are one of the most common type of recordings of the brain activity. They can provide information about the mental processes which are expressed in the electrical activity of the brain. EEG data are at the core of disruptive technology as brain computer interfaces (BCIs) and also serve to diagnose mental and neurological conditions in humans. Machine learning methods have been extensively applied to classify EEG data [1, 2, 3, 4, 5, 6]. For these classification problems, feature engineering engineering techniques [7, 8, 9] and feature subset selection methods [10, 11] are essential.

2 Objectives

The goal of the project is to predict the eye state of a subject (eye-open versus eye-closed) from the analysis of his/her EEG data using a supervised classifier. One single subject is involved in the experiment. A database will be used for the analysis [1]. A supervised classifier (except a NN or DNN for which similar projects are proposed) should be created to predict the activity. Since a high variability between individuals is possible, a different classifier could be learned for each individual.

The student should: 1) Design any preprocessing of the dataset; 2) Define and learn the classifier using the training data. 3) Design the validation method to evaluate the accuracy of the proposed classification approach.

As in other projects, a report should describe the characteristics of the design, implementation, and results. A Jupyter notebook should include calls to the implemented function that illustrate the way it works.

3 Suggestions

- See relevant literature related to the general problem of EEG classification.
- Find an appropriate way to split the data between train and test sets. One suggestion is to use a contiguous set of observations (e.g., the first half of the dataset) for training and the other half for testing the classifier.
- Extracting features is a key question for this type of problems. Therefore, think about a clever way of extracting the features.
- Implementations can use any other Python library.
- If classes are not well balanced you may use performance measures different to the accuracy.

[1] The "EEG Eye State Data Set" dataset can be downloaded from `https://archive.ics.uci.edu/ml/datasets/EEG+Eye+State#`

References

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