PC403 - Mini BTP Report

Classification using EEG data

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Project link :-

https://github.com/naitik-dodia/Object-Recognition-using-EEG-brain-data

Table of Contents

Abstract

The recognition of object categories is effortlessly accomplished in everyday life, yet how brain responds to it remain not fully understood. Single-trial classification to perform a categorical representation of objects in human visual cortex is used for this study. Brain responses were recorded while subject were shown a set of 72 photographs of objects with a planned category structure. For identification of spatial and temporal EEG components, we additionally performed classifications on subsets of the brain response that best discriminated object vs human face categories. Results from category-level classifications revealed that brain responses to images of human faces formed the most distinct category, while responses to images from the inanimate-object categories formed a single category cluster. Finally, object category can be decoded from purely temporal information recorded at single electrodes.

Introduction

Recognizing objects from different categories is of fundamental importance for survival.

The human visual cortex has evolved efficient mechanisms for solving this problem, and a central goal of cognitive neuroscience has been to understand how this seemingly effortless feat is accomplished.

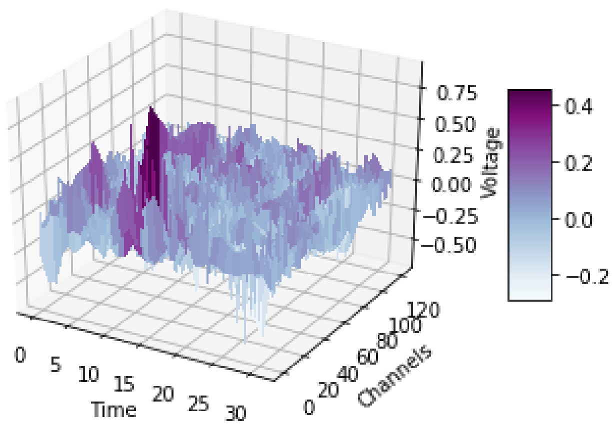
Recent electroencephalography (EEG) studies have investigated category selectivity using multivariate pattern classification.

EEG, is the physiological method of choice to record the electrical activity generated by the brain via electrodes placed on the scalp surface. According to neuroscience, each brain activity is conducted by small electrical pulses in the neurons. The effect of these small electrical signals is propagated to various parts of the brain. Similarly, these signals also propagate to the scalp. These electrical signals from the scalp are captured by placing a cap of electrodes on the subject's head. As, these captured signals are taken from the scalp, signals captured at each electrode is superposition of brain's electrical signals originated at different voxels of the brain. In this way a very diverse information is captured at each electrode and also there is correlation between the signal captured at different electrodes.

As, capturing electrical signals using electrical appliances is easy and having high frequency, EEG signals have a good temporal resolution, but a low spatial one because the 3-dimensional data i.e. exact position of generation of electrical pulses is converted to 2-dimensional data i.e. the array of electrodes placed on the surface area of the scalp. EEG's low amplitude, brief and sporadic nature, contribute to the difficulty of this problem.

EEG data carries an immense potential in various areas including human computer interaction, psychology, and neurological sciences.

EEG data can be used to diagnose neurological diseases such as epilepsy, monitoring mental disorder and brain computer interface system(BCI).



Dataset

- Preprocessed Data
- Number of subjects :- 10
- Number of experimental Trials per subject :- 5185 to 5188
- Number of electrodes or channels :- 124
- Number of time samples per trial :- 32
- Number of classes :- 6

(1=Human Body; 2=Human Face; 3=Animal Body; 4=Animal Face; 5=Fruit Vegetable; 6=Inanimate Object)

Objective

- To classify the EEG data into 6 classes using linear discriminant analysis to study the linear separability of the EEG data.
- To know how brain reacts to the two classes given below and study their linear separability.
    1) Human Face
    2) Inanimate objects
- Effects of data augmentation on the linear separability.
- Spatial and Temporal analysis of the data in both multi-class and 2-class classifications.
- Effects of data augmentation and on spatial and temporal analysis.

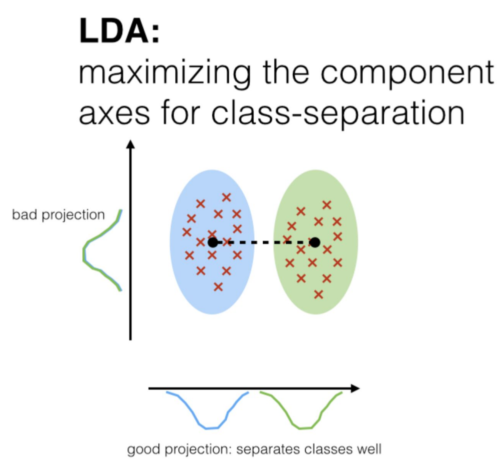
Techniques

❖ Linear Discriminant Analysis

➢ A classifier with a linear decision boundary, generated by fitting class conditional densities to the data and using Bayes' rule.

➢ This method maximizes the ratio of between-class variance to the within-class variance. $\frac{Between\ class\ variance}{Within\ class\ variance}$

➢ The model fits a Gaussian density to each class, assuming that all classes share the same covariance matrix.



➢ The ‘**eigen**’ solver used with LDA is based on the optimization of the between class scatter to within class scatter ratio, it also supports shrinkage.

Bayesian Classifier Equation :- $$P(Y_k|X) = \frac{P(X\,|Y_k)P(Y_k)}{P(X)}$$

For given test pattern X; class k is the arg $max_k\ P(Y_k|X)$

$P(X|Y_k)$ is need to be known or estimated from training data

If $P(X|Y_k)$ assume Gaussian distribution with equal variance across the classes

Bayesian classifier ➔ linear discriminant analysis

Shrinkage is a tool to improve estimation of covariance matrices in situations where the number of training samples is small compared to the number of features.

❖ Data Augmentation

➢ Data augmentation refers to creation of data points by taking mean of a specific number of data points, all of which belong to same class, randomly :-
  - With Replacement - While creating new data points previously used data point can be used more than once to create more new data points. Here, we can control the number of new samples to be created. To compare the results of classification on the augmented data the new number of samples to be created is kept same as the original number of samples.
  - Without Replacement - While creating new data points once a data point is used, it cannot be reused. Here, as the data points cannot be reused, the maximum number of new samples to be created from the original data is fixed. Here the number of samples created is $\frac{n}{degree\ of\ augmentation}$ (degree of augmentation refers to the number of samples to be averaged for creating a new sample).

➢ Data augmentation increase accuracy by decreasing intra-class variance.

➢ For each classification the degree of classifications to be analyzed are [2,4,6,8]

❖ Cross Validation

For validating the stability of our machine learning model, we have used k - fold cross validation technique. The steps for this technique are as follows:

- Shuffle the dataset randomly.
- Split the dataset into k groups
- For each unique group:
  - Take the group as a hold out or test data set

    - Take the remaining groups as a training data set
    - Fit the model on the training set and evaluate it on the test set
    - Retain the evaluation score and discard the model
- Summarize the skill of the model using the sample of model evaluation scores

In this process the knowledge of all of the data is not used to evaluate our model so this process is repeated *n* number of times in which each time the partitions are created randomly. This way we get n different accuracy scores. All these *n* accuracy scores are averaged to get a single accuracy score which is now more robust as it has been (here as all the accuracy scores are measured from the data belonging to same population i.e. considering the original data as population and the k partitions as samples) calculated using all the data and as it is averaged, any chance of randomly getting high or low accuracy minimized.
For our model: $k = 5$; $n = 8$.

❖ Univariate Analysis

Electrode-wise Univariate

Each trial consists the signals of 124 electrodes taken during 32 contiguous time samples. For each trial a single electrode can predict the class. To study this, each electrode is taken separately and every one of them is assigned the same class as of the whole trial. So now we have 124 datasets to train (individually) for the same subject.

Electrode-wise analysis is helpful in studying the area of the which are responsible for visual recognition in the brain.

Time-wise Analysis

Each trial consists the signals of 124 electrodes taken during 32 contiguous time samples. For each trial a single time-step can predict the class. To study this, each time-step is taken separately and every one of them is assigned the same class as of the whole trial. So now we have 32 datasets to train (individually) for the same subject.

Time-wise analysis is helpful in studying the time at which brain responds the most and the time-step most responsible for classification of objects.

Results & Analysis

Multiclass results:

For 6 class classification using LDA, the accuracy is 34.4% averaged across all subjects with standard deviation of 2.9%.

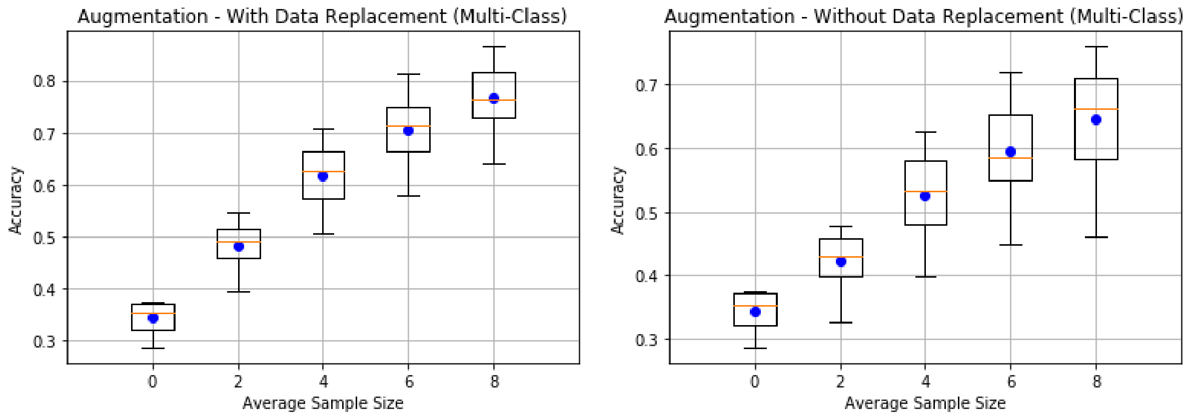


Fig 1: Accuracy vs averaging sample size. The accuracy scores averaged over subjects are shown by blue points and the box plots are of accuracy score across all subjects. (left) Data taken by averaging with replacement and (right) without replacement.

From the results it is clear that in both the cases as the degree of averaging increases the variance in accuracy between subjects increases. This is because random samples are taken for averaging. Also the accuracy for augmentation with replacement for any degree of averaging is higher than that of augmentation without replacement.

The each degree of augmentation the variance in augmentation without replacement is more than that of in augmentation with replacement. This is because the signal to noise (SNR) ratio is decreased in augmentation with replacement. This effect becomes more prominent because the number of augmented samples with replacement are maintained to the same number of samples as before. Therefore the intra class variance decreases while keeping the mean same. This further results into more linear separability. This effect, in the case of augmentation without replacement is seen less. So the resulting variance is higher than in its counterpart.

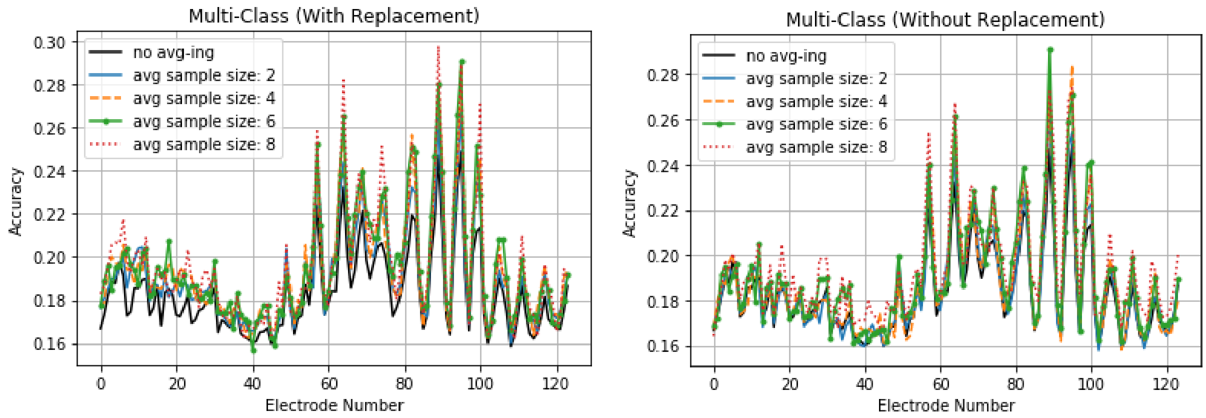


Fig 2: Electrode-wise analysis a) (left) Accuracy scores taken Electrode-wise analysis and augmentation with replacement. b) (right) without replacement.

In Electrode-wise analysis we can see that the electrodes ranging from number 58 to 100 are having majority accuracy. This electrodes are responsible for the visual recognition cortex. Here the effect of augmentation is seen for each of the electrodes. As the degree of augmentation increases the accuracy increases. As seen before the accuracy in augmentation with replacement is more than that of augmentation without replacement.

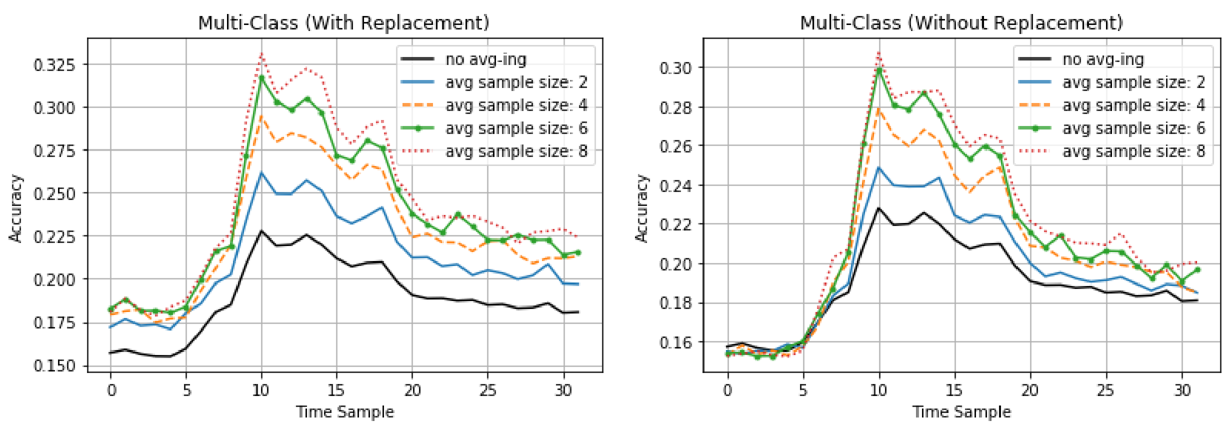


Fig 3: Time-wise analysis a) (left) Accuracy scores taken for Time-wise analysis and augmentation with replacement. b) (right) without replacement

In time-wise analysis, we can see that the time mostly responsible for classification is from the time-step 7 and afterwards. So we can say that the brain activates and shows more activity at these time steps.

Binary - class results:

For human-face v/s class classification using LDA, the accuracy is 76.2% averaged across all subjects with standard deviation of 0.08%.

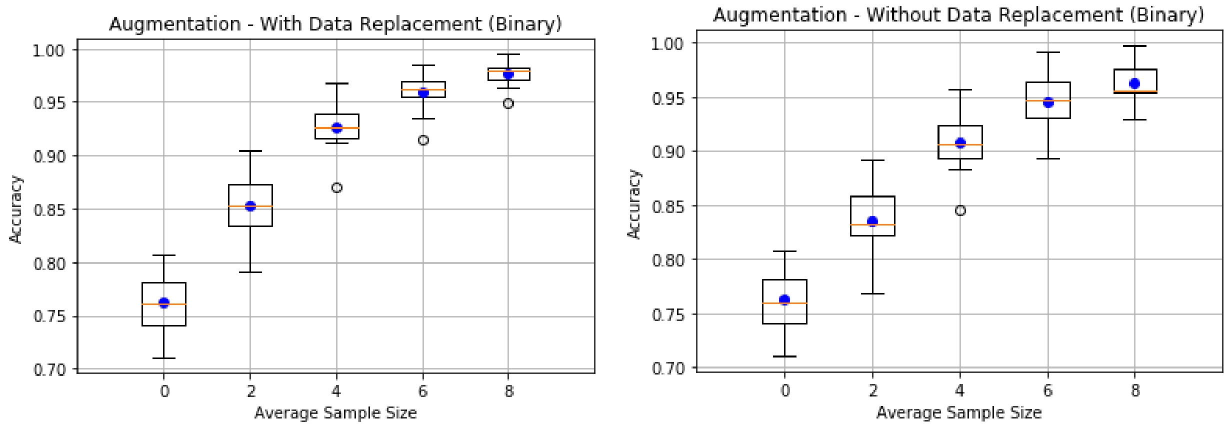


Fig 4: Accuracy vs averaging sample size. The accuracy scores averaged over subjects are shown by blue points and the box plots are of accuracy score across all subjects. (left) Data taken by averaging with replacement and (right) without replacement.

From Fig 4, it is clear that as degree of averaging increases the variance in accuracy over subjects decreases; which implies that the brain sees human face and the inanimate objects very distinctively. And the effects of augmentation are same as in the case of multi-class classification.

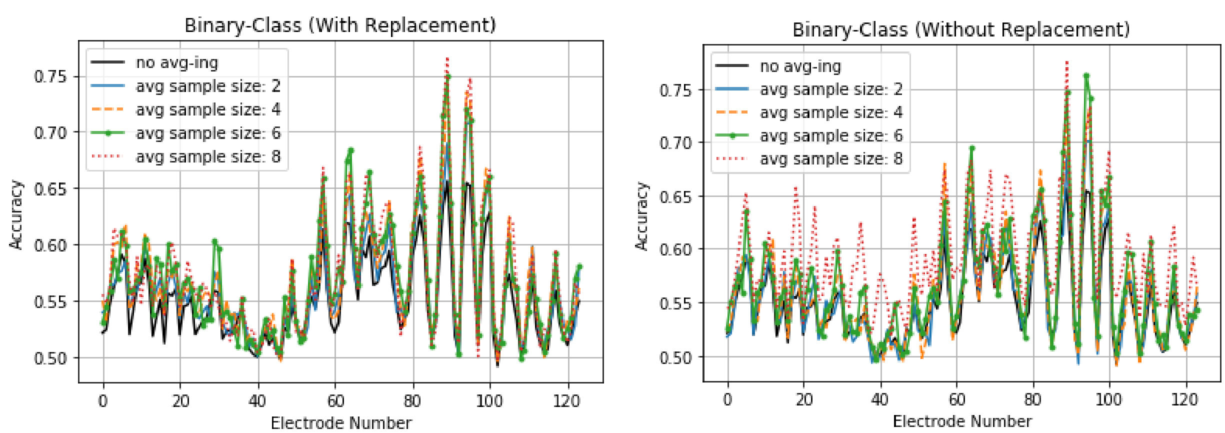


Fig 5: Binary Classification Electrode-wise analysis a) (left) Accuracy scores taken for Electrode-wise analysis for binary class and augmentation with replacement. b) (right) without replacement

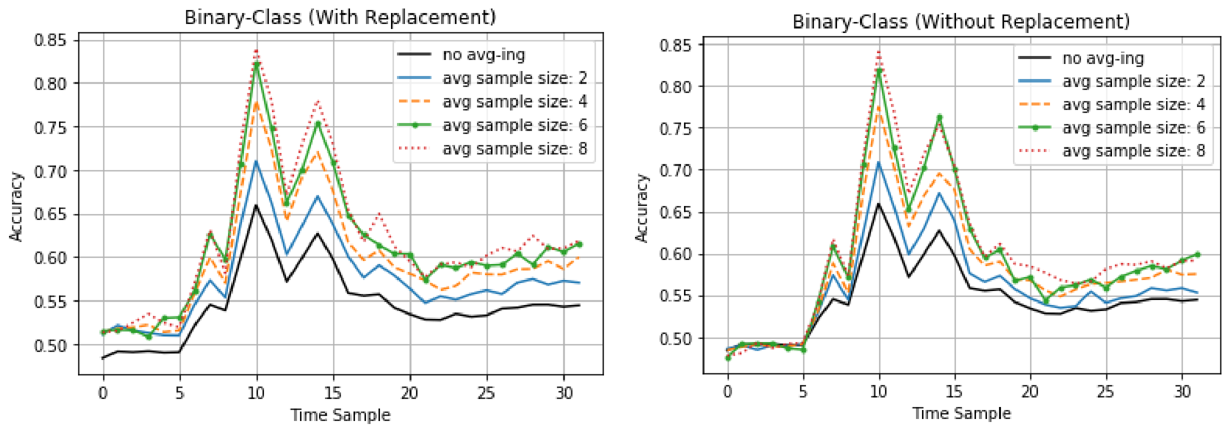


Fig 6: Binary Classification Time-wise analysis a) (left) Accuracy scores taken for Time-wise analysis for binary class and augmentation with replacement. b) (right) without replacement

The trends in electrode-wise analysis and time-wise analysis in binary classification follows the same trend as of their counterparts in multi-class classification.

References:

Blair Kaneshiro, Marcos Perreau Guimaraes, Hyung-Suk Kim, Anthony M. Norcia, and Patrick Suppes (2015). A Representational Similarity Analysis of the Dynamics of Object Processing Using Single-Trial EEG Classification. PLoS ONE 10:8, e0135697

Dataset - Blair Kaneshiro, Marcos Perreau Guimaraes, Hyung-Suk Kim, Anthony M. Norcia, and Patrick Suppes (2015). EEG data analyzed in "A Representational Similarity Analysis of the Dynamics of Object Processing Using Single-Trial EEG Classification". Stanford Digital Repository. Available at: http://purl.stanford.edu/bq914sc3730