CSE 512 Machine Learning
Learning Cognitive states using Brain fMRI Mid-Way Project Report

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1 Introduction

Functional Magnetic Resonance Imaging (fMRI) has emerged as a powerful tool to collect vast quantities of data from the human brain. The data produced from the fMRI image is 3 dimensional. The data represents the neural activity level of different regions of the brain. This local neural activity is measured using blood oxygenated level. The 3 dimensional image of the brain is made up of voxels. The voxels represent cells or group of cells which are activated due to a cognitive response. The blood oxygenated level of each voxel is recoreded in the fMRI image. There are approximately 15000 voxels collected once per second. This yields tens and millions of observations. This project aims at using Machine Learning techniques to analyze data from the fMRI to study the cognitive state of the human brain.

2 Objective

The objective of the project is to apply machine learning techniques on the fMRI data and classify different cognitive activities based on the BOLD (blood oxygenated level dependent) response of the voxels. The study involves the evaluation of various machine learning techniques and the analysis of their results, to better understand their behaviour on high-dimensional data.

3 Data

The Data is obtained from http://www.cs.cmu.edu/afs/cs.cmu.edu/project/theo-81/www/ . The data consists of fMRI BOLD responses from 6 different subjects. Each subject data consists of 54 trials, where each trial is a sequence of images representing the fMRI BOLD responses of voxels. Due to differences in the shape and size of each subject's brain, the number of voxels recorded varies based on the subject. During each trial the subject is presented with two stimuli - a sentence and a picture - in two phases, during which the BOLD response is sampled every 0.5 seconds. For the first phase a stimulus is displayed for 4 seconds, followed by a rest period of 4 seconds. This consists of first 16 records in each trial. The neural activity of the voxels is retained after the stimulus has been withdrawn and it lasts for 9-12 seconds. The period without the stimulus is thus considered to have similar neural activity as that of the previous stimulus. The second phase is the following 16 records consisting of neural activity of the brain for next 8 seconds. In the two phases the subject is given a stimulus of either a picture or a sentence. This provides the labelling necessary for classification.

4 Feature Selection

The data processing involves segregation of the records based on the stimulus. The approach used is to classify the records based on the neural activity of the voxels, represented by BOLD levels. The number of voxels thus provides the number of features, resulting in very high dimensional data (5000 voxels sampled twice per record for a period of 27 seconds, across 54 trials). Feature selection utilized voxel activity across Regions of Interest(ROI), which are specific anatomically defined sections of the brain. The ROI are collected by segregating the voxels based on a scheme called parcellation, which identifies the overlapping areas in the structural and functional MRIs. Feature selection was employed based on the suggestions provided in the original paper. Three different types of feature selection were used.

- **Based on Average BOLD responses in ROI:** Average BOLD response in ROI consists of super voxels. This level indicates the mean activation of the voxels within that ROI
- **Based on the activity level of each individual voxels**
- **Based on specific set of ROI:** Voxels consisting of certain Regions of interests. For classifying the cognitive state, the following ROIs were chosen based on the suggestion in Mitchell(2004): 'CALC','LIPL','LT','LTRIA','LOPER' 'LIPS','LDLPFC'.

5 Classification

Three different types of classifier was studied with the feature selection employed on the data. The classification was carried out on a single subject.

- **Support Vector Machines.** The classification process is a binary classification task. The dimensionality of the data provided the motivation to go for SVM. It is also one of the classifiers evaluated in the original paper. The classifier was cross validated using bucket sizes in the multiples of 16, so that each bucket contains equal distributions of the data from both the classes. The classifier performed the best when the feature selection was based on active voxels.
- **Gaussian Naive Bayes.** The feature selection strategy provided valuable insight on the reduction of the dimension of the data. Gaussian Naive Bayes helps us in studying the correlation between independent voxels and the cognitive activity. Gaussian Naive Bayes performed with a similar average accuracy with every feature selection method employed.
- **K nearest neighbour Classification.** The primary reason for the use of k-nearest neighbor algorithm for classification is to study and understand the effect of the activity level of a group of voxels on the classification task. The euclidean distance measure of similarity was used for the grouping. Different values of the parameter k was used in cross validation and it was found that the classifier performed better when the k value was set at 7. The k- value of 7 continued to perform well with every feature selection strategy.

6 Intermediate Test Results

The test data used for this case was a collection of 100 BOLD records randomly selected and separated from the dataset before training. The classifiers have all been trained on a single subject.

The graphs report the 16-fold cross validation accuracy on the test data.

Classifier	Active1500	SelectROI	AverageROI
SVM	0.701388	0.694444	0.541666
GNB	0.666667	0.673611	0.520833
KNN	0.666667	0.569444	0.625

Table 1: Test Accuracies over classifier with Feature selection on single subject

7 Plots for Cross validation Accuracies with feature selection on multiple classifiers

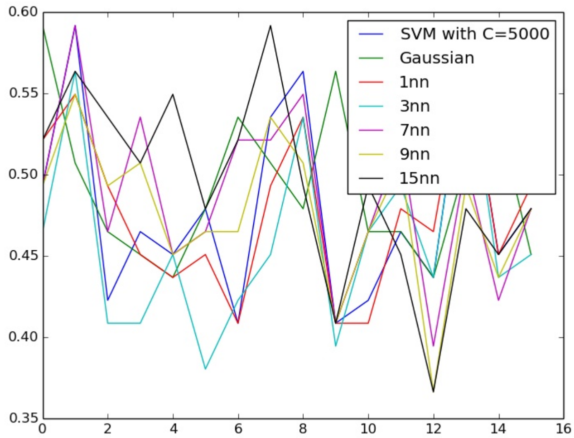

Figure 1: Cross Validation Accuracies across Classifiers, Feature Selection: Most-active 1500 voxels

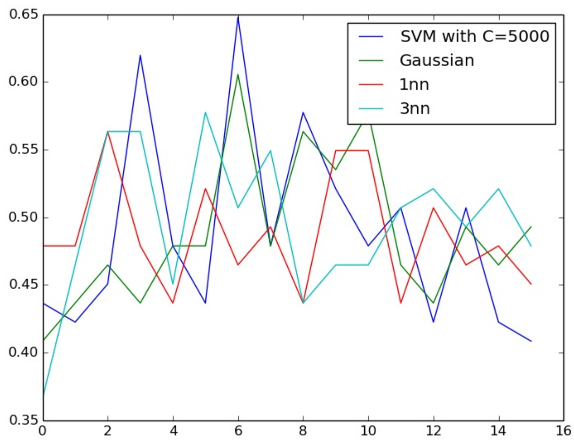

Figure 2: Cross Validation Accuracies across Classifiers, Feature Selection: Time Average over ROI voxels

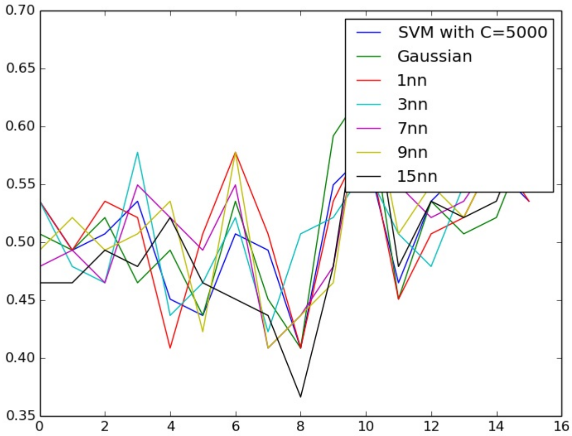

Figure 3: Cross Validation Accuracies across Classifiers, Feature Selection: Select ROI voxels

8 RoadMap

The next step in the project is to employ the Tree Augumented Naive Bayes classifier on the data. This is based on the intuition that there exists a structural dependency between voxels which could influence the classification task. The structural independence between voxel activity, assumed by naive bayes, is nullified and a bayesian network is constructed using structural learning. Once the structure is learnt, inference is done based on the conditional probabilities to obtain a classification for the new data. Additionally the single-subject classifiers can be extended to operate across multiple subjects.

References

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[3] N. Friedman, D. Geiger, and M. Goldszmidt *Bayesian Network Classifiers. Machine Learning 29:131-163 (1997).*

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