

# Predicting cognitive state of human through FMRI image.

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## 1 ABSTRACT

The functional Magnetic Resonance Imaging (FMRI) has provided us with an approach of revealing the activity of brain. In this experiment FMRI image has been taken in three states

1. Showing a picture
2. Reading sentences
3. Ideal state (No Task)

We are trying to build a classifier such that when given a FMRI image it can predict the state of mind among the above three cases. Due to the large amount of data in FMRI studies, feature selection technique is used to select particular features for classifier. We have used two classification techniques Support Vector Machines (SVM) and Gaussian Naive Bayes (GNB) and compared the results.

## 2 EXPERIMENT

The experiment consists of a set of trials, and the data is partitioned into trails, (reading a sentence, observing a picture, and determining whether the sentence correctly described the picture). For these trials, the sentence and picture were presented in sequence, with the picture presented first on half of the trials, and the sentence presented first on the other half of the trials. Each image contains approximately 5,000 voxels (3D pixels), across a portion of the brain. There are 40 trials for each subject and images are taken every 30 secs.

## 3 FEATURE SELECTION

### 3.1 MOST DIFFERENTIATING VOXELS

The first intuition that comes to mind is to pick the top K most differentiating Voxels. However K can be learned through cross validation. However there are some limitations in this method

### 3.2 LIMITATIONS OF MOST DIFFERENTIATING VOXELS

1. Loss of Information (we will neglect rest of the voxels)
2. Redundant Information (Most Voxels in the same region will behave very similar)

Most of the voxels spatially around the most differentiating voxel will be highly differentiating and thus if K is small only these voxels are chosen thus to get a good result K should be high so that we have good amount of information with us.

### 3.3 SOLUTION TO OVERCOME THE LIMITATIONS

To avoid the redundancy and reduce K we can cluster the data together so that instead of taking a lot of voxels which are very similar to each other we can take their representative i.e a single voxels. Thus now our goal is to cluster the voxels together we have to cluster such that similar voxels can be together. We need to keep in mind that we might put two voxels which are very close to each other spatially in different clusters and vice-versa as we clustering based on similarity in properties of voxels. Here Clusters can be seen as Region of Interest, There are different ways of clustering such as K-Means and spectral clustering. We have used spectral clustering for feature selection.

### 3.4 SPECTRAL CLUSTERING

Spectral cluster could tell the intrinsic features of the data, revealing the underlying cluster. The spectral clustering algorithm is based on the concept of similarity between points.

Algorithm:

1. Merge all the trials together and make a single large matrix. Here each column of this matrix represents a voxel and each row represent the image number.
2. Find the Correlation between each voxel vector. Now we have a correlation matrix C of size  $5000 \times 5000$ . Construct Affinity Matrix A, the affinity is defined as  $A_{ij} = \exp(C(i, j)^2 / 2\sigma^2)$  if  $i \neq j$ , and  $A_{ii} = 0$ , where C(i,j) is the correlation between the two vectors of voxels.
3. Using this Affinity matrix make K clusters and find out a label vector that labels each voxel to its corresponding cluster.
4. For each cluster take the voxels vectors that lie in the cluster and average the values of these voxel vectors, the averaged value represent the value of each cluster vector.

The value of K and  $\sigma$  can be chosen using cross validation. We have taken 9 K which are {25, 50, 75, 100, 125, 150, 175, 200, 225} and 5  $\sigma$  the  $\sigma$  is chosen such that the value of  $2\sigma^2$  are  $\{10 * e^{-2}, 10 * e^{-1}, 10 * e^0, 10 * e^1, 10 * e^2\}$ .

## 4 RESULTS

1.SVM(Support Vector Machine)

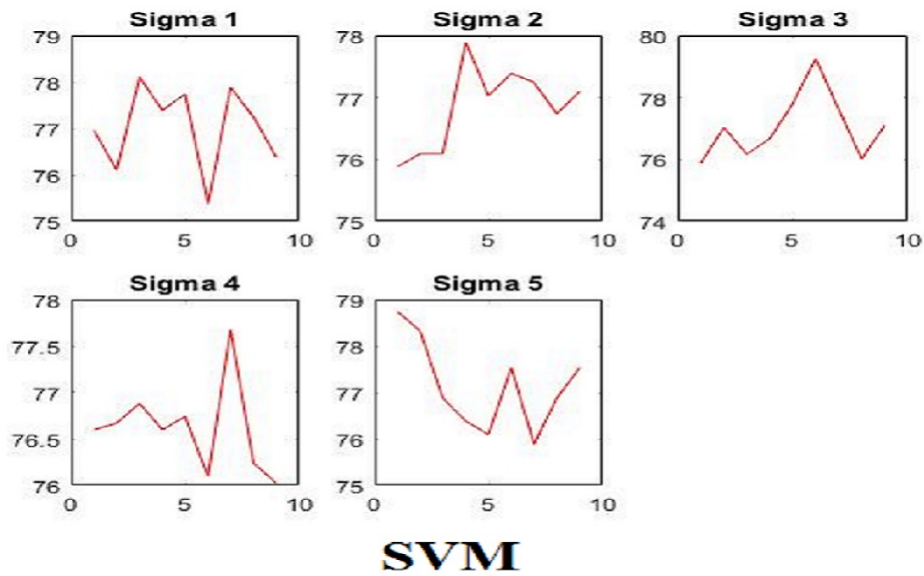
Accuracy Before Feature Selection - 75.38

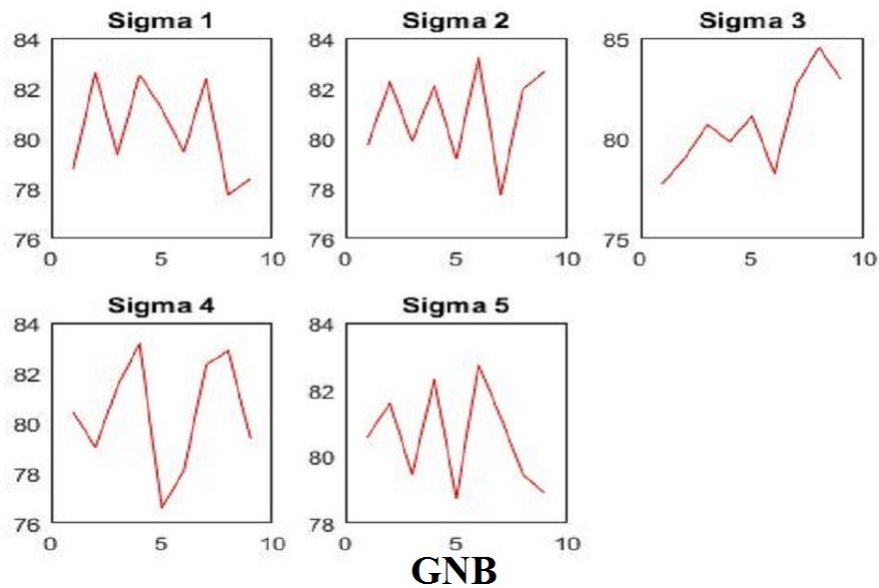
Accuracy After Feature Selection - 79.31 (K=150  $2\sigma^2 = 10 * e^0$ )

2.GNB(Gaussian Naive Bayes)

Accuracy Before Feature Selection - 77.42

Accuracy After Feature Selection - 84.54 (K=200  $2\sigma^2 = 10 * e^0$ )





These graphs show the accuracy for different sigma and different K for SVM and GNB. Both SVM and GNB have 5 graphs where for 5 different Sigma accuracy of 9 different K are plotted in each graph.

## 5 FUTURE WORK

1. Explore more Feature Selection and classification techniques.
2. Training on Subject X and testing on Subject Y (Training cognitive state of a human and testing on other humans)

## 6 REFERENCES

1. Learning to Decode Cognitive States from Brain Images (<http://www.cs.cmu.edu/~tom/mlj04-final-published.pdf>)
2. Classifying Instantaneous Cognitive States from FMRI Data (<http://www.cs.cmu.edu/~tom/amia2003-final.pdf>)
3. Training FMRI Classifiers to Detect Cognitive States across Multiple Human Subjects (<http://www.cs.cmu.edu/~tom/nips03-submitted.pdf>)
4. Feature Selection for FMRI Classification (<http://www.cs.cmu.edu/~epxing/Class/10701-06f/project-reports/wu.pdf>)