Analysis of brain electrical signals for epileptic seizure recognition

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Introduction

This project aims to analyze a recent 'Electroencephalography (EEG) Data Set' with the objective of classifying epileptic seizure as compared to normal response. It is a time series data having 178 features against 1 categorical attribute through 11500 instances. Each data point represents a voltage signal corresponding to the brain activity at a point of time. Each of 178 features are one chunk out of a total of 23 created from 4097 digitized data points from one EEG record. 2 through 5 valued classes of the categorical attribute define various conditions and their subjects did not have epileptic seizures. Whereas the subjects of class 1 have seizure activity. An approach of classification and clustering will be undertaken for predictive analytics and pattern mining.

Literature Review

EEG as a technique

Electroencephalography (EEG) is a technique widely used to measure the functional activity of human brain. It is a noninvasive electrophysiological monitoring method that records the electrical activity of the brain by placing electrodes along the scalp. It measures the brain function as received at the surface of the brain in terms of voltage fluctuations resulting

from ionic currents within the neurons of the brain. By that, it is a graphic display of the difference in voltages from two sites of brain function recorded over time. Hence, EEG data is displayed as a continuous time series waveform of very small voltage signals as representative of brain function. In a normal brain the signals are of the magnitude of microvolts. The waveforms recorded are thought to reflect the activity at the surface of the brain, the cortex, however this activity is influenced by the activities from the brain structures underneath the cortex [1-2].

Instrument and Data Recording

The recording of EEG data is done by placing small metal plates as electrodes at specially designated places on the scalp following an international 10/20 system. For adults, there are 21 measuring electrodes and 2 reference electrodes (total 23). Each site is labelled by the combination of a letter and a number. The letter refers to the part of the brain, like F - frontal lobe, T - temporal lobe, C - central lobe, P – posterior lobe etc. whereas any even numbers designate the right side of the head as opposed to any odd number designating the left part of the brain, as shown in the figure below. A1 and A2 are the two reference electrodes. Voltage signals are measured with reference to the corresponding reference electrodes. Electrodes can be placed individually or by a cap that has electrodes attached onto it [3-4].

EEG machines use differential amplifier that measures the difference potentials as inputs from individual electrodes. In common reference derivation, each amplifier measures the difference of voltages between a scalp and a reference as shown in Fig. 1. The manner, in which pairs of electrodes are connected to each amplifier is called a montage. Each montage uses one of the three standard recording derivations, e.g. common reference, average reference and

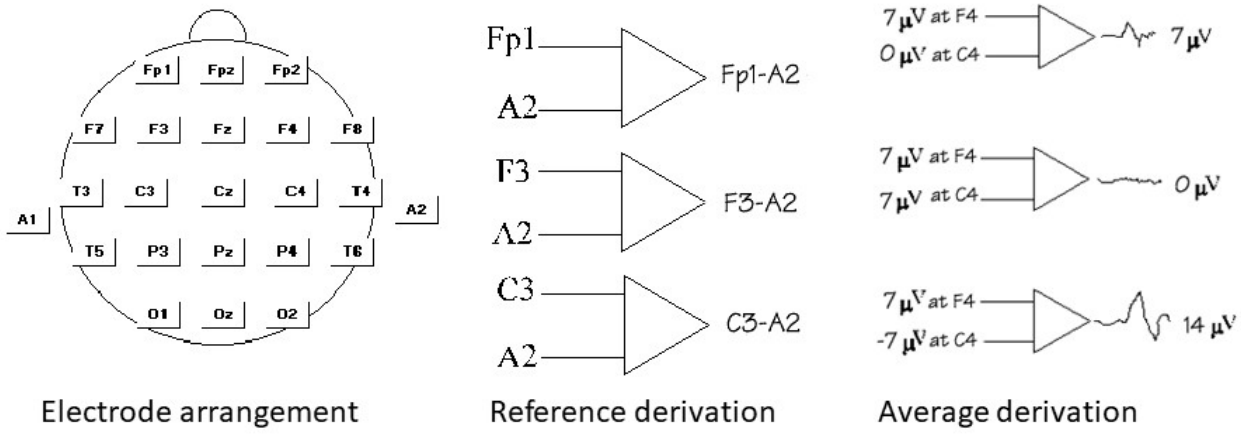


Figure 1. Electrode arrangement and reference derivation examples to record an EEG data

bipolar. The magnitude of the signal is the difference potential of which the sign depends on the sign of the higher potential. Therefore, the values at a given time can either be positive or negative voltage. This makes the correlation of the output of an individual electrode with a neurophysiological phenomenon complex. In an analog machine, the signal is recorded as a continuous pattern and in a group formed by all electrode responses, they are referred as the brain wave. Modern machines digitize the signal using an ADC which can be stored, displayed and manipulated using a computer. The rate at which the signal is digitized is called the sampling rate which typically ranges between 50 – 300 Hz [5].

What EEG data represents

Electrical signals are created when charges move within the central nervous system which originates from cerebral potential based upon the electrophysiological properties of the nervous system at the time of measurement. When neurons are activated, local current is produced due to synaptic excitations of the dendrites of many pyramidal neurons in the cerebral cortex. Differences of electrical potentials are caused due to creation of electric dipoles between soma or the body of neuron and apical dendrites or the neural branches. A current is thereby generated due to the transport of Na^{+}, K^{+}, Ca^{+2}, and Cl^{-} ions that are pumped through neuron membranes following the gradient of membrane potential [1, 6]. The signal forms wave shape that are commonly sinusoidal where peak to peak magnitude vary between 0.5 to 100 microvolts (for healthy brain) and the frequency can range from 0 to half of the sampling frequency. The signals are normally collected instructing the subjects to keep their eyes closed and be in relaxed situation. The waves are categorized into four basic groups viz. 1) Delta: 0.5 to 4 Hz, 2) Theta: 4 to 8 Hz, 3) Alfa: 8 to 13 Hz and 4) Beta: all greater than 13 Hz, as shown in the Fig. 2 [4, 7]

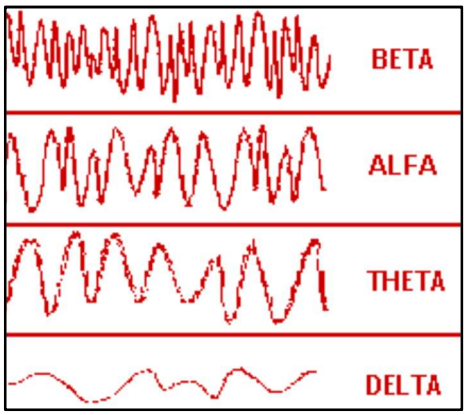


Figure 2. Types of Brain waves

Interpretation of EEG data

Interpretation of EEG signal for diagnostics is an involved task. Similar pattern can be observed for many different reasons. Widely varied patterns might result from the same

symptom as well because the signals depend on many different factors and are unique to individuals. This enables to distinguish persons by only recording their brain activity. For example, rational subjects demonstrate higher activity on their frontal left hemisphere as opposed to the intuitive subjects having strong activity on frontal right hemisphere. However, there is no thumb rule that can be formulated to be applied universally. Alpha activity is induced by closing the eyes and by relaxation and abolished by eye opening or alerting by any mechanism like, thinking or calculating. Subjects are found to be remarkably sensitive to eye closing condition, i.e. when the eyes are closed the wave pattern significantly shifts from beta to alpha waves. However, the precise origin of the alpha rhythm is still not known in detail [1, 8]. That way, EEG is sensitive to a continuum of states ranging from stress state, alertness to resting state, hypnosis, and sleep. During normal state of wakefulness with open eyes, beta waves are dominant. In a state of relaxation or drowsiness, alpha activity rises. Sleep is generally divided into two broad types: nonrapid eye movement sleep (NREM) and rapid eye movement (REM) sleep that occur in alternating cycles. Various regions of the brain do not emit the same brain wave frequency simultaneously. An EEG signal between electrodes placed on the scalp consists of many waves with different characteristics. A large amount of data received from even one single EEG recording presents a difficulty for interpretation. To deal with this complexity, it is always difficult and critical to organize a digitized EEG data for critical analysis and interpretation.

An abnormal pattern in EEG data may support diagnosis, indicate cerebral dysfunction or can be due to something different than what the study has been conducted for [1-2, 7]. Clinical applications of EEG span a very broad range of diagnostics conditions [4]. Such as,

(1) monitor alertness, coma and brain death;

(2) locate areas of damage following head injury, stroke, tumour, etc.;

(3) test afferent pathways (by evoked potentials);

(4) monitor cognitive engagement (alpha rhythm);

(5) produce biofeedback situations, alpha, etc.;

(6) control anaesthesia depth ("servo anaesthesia");

(7) investigate epilepsy and locate seizure origin;

(8) test epilepsy drug effects;

(9) assist in experimental cortical excision of epileptic focus;

(10) monitor human and animal brain development;

(11) test drugs for convulsive effects;

(12) investigate sleep disorder and physiology.

Epilepsy and EEG

This work will focus only on epileptic abnormality. Epilepsy is a chronic disorder and is distinguished by recurrent unprovoked seizures [9-10]. A person is diagnosed with epilepsy if they have two unprovoked seizures (or one unprovoked seizure with the likelihood of more) that were not caused by some known and reversible medical condition like alcohol withdrawal or extremely low blood sugar. The seizures in epilepsy may be related to a brain injury or a family tendency, but often the cause is completely unknown. The word "epilepsy" does not indicate anything about the cause of the person's seizures or their severity. Many people with epilepsy have more than one type of seizure and may have other symptoms of neurological problems as well. Sometimes, group of people having epilepsy are found to have similar clinical history, family history, outlook and EEG data. In these situations, their condition is referred as specific epilepsy syndrome. In summary, epilepsy can be characterized as follows,

1. It is the fourth most common neurological disorder and affects people of all ages.
2. It means the same as "seizure disorders"
3. Its symptom is unpredictable seizure and can also cause other health problems
4. Its control varies from person-to-person
5. There is considerable amount of public misunderstandings on epilepsy
6. Proper awareness and public educating program is still lacking.

An unusual EEG pattern can be indicative of an epileptic seizure and can act as a fingerprint to reveal which part of the brain is affected through an identification of the electrode that produced the unusual response as compared to a data from normal brain. However, in some cases the brain shows normal behavior when there is no seizure. In other cases, unusual activity is observed all the time which may be due to several reasons like tumor growth etc. Recording of an *ictal* discharge i.e. EEG pattern when the seizure occurs is often very time consuming and laborious in an outpatient setting. *Interictal* discharges are therefore recorded using portable devices in home settings. The International Federation of Societies for Electroencephalography and Clinical Neurophysiology (IFSECN) describes interictal discharges as a subcategory defined as "distinctive waves or complexes, distinguished from background activity". Interictal epileptiform has spiky morphology, however all other criteria must be verified empirically for

diagnosis [11-12]. Analysis of an interictal discharge can therefore reveal several information regarding the seizure. Sufficient number of case studies can therefore be grouped with respect to external and behavioral parameters to generate a generalized model that might help alleviate the diagnosis of unknown cases quicker and contribute in a better seizure prevention strategy.

Dataset

The data set for this project is taken from UCI Machine Learning repository. It is a multivariate timeseries having 178 features against 1 categorical attribute through 11500 instances. Each data point represents a voltage signal corresponding to the brain activity at a point of time.

The original data is composed for the study as five sets denoted by A, B, C, D, E each containing 100 single channel EEG segments of 23.6 seconds duration. Sets A and B consisted of segments taken from surface EEG recordings that were carried out on five healthy volunteers using a standardized electrode placement scheme. Volunteers were relaxed in an awake state with eyes open which is denoted as data - A and eyes closed, denoted as data - B, respectively. Sets C, D, and E originated from an EEG archive of presurgical diagnosis in Germany. The archive data is selected from five patients all of whom achieved complete seizure control after section and their epileptic zone were correctly diagnosed. The data-D was recorded from within the epileptic zone whereas data-C was collected from the hippocampal formation of the opposite hemisphere of the brain [13].

The data that is being dealt with here has been reorganized from this original data for machine learning studies as posted in UCI Machine Learning repository [14]. Each time series record A—E has been digitized to 4097 data points out of which 23 chunks have been created distributing into 178 time-features of recorded raw-voltage signals. 5 sets of 100 EEG segments thus creates (5×100×23) 11500 instances. The grouping on 23 chunks corresponds to the fact that there are 23 electrodes used in an EEG recording. A class attribute or output as 'y' is generated as follows:

Class 5 : Eyes open condition from healthy volunteer i.e. data-A, EEG is collected keeping the eyes open

Class 4 : Eyes closed condition from healthy volunteer i.e. data-B, EEG is collected keeping the eyes closed

Class 3 : Tumor is identified and located but the data is collected at the nonepileptic healthy part of the brain (archive data)

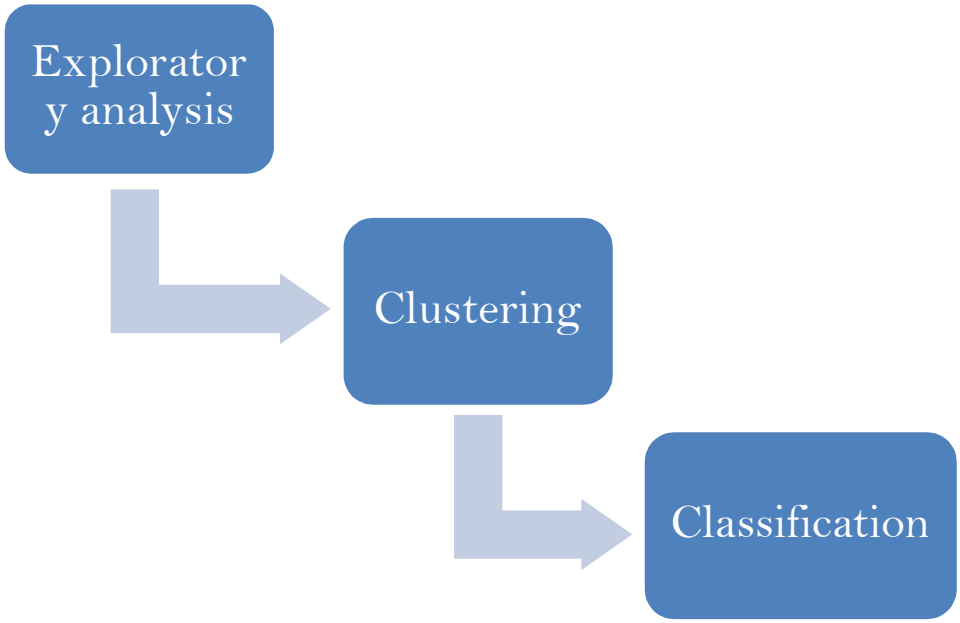
Class 2 : Tumor is identified and data is collected from the epileptic zone of the brain

Class 1 : Recording during seizure activity i.e. the *ictal* data.

As described, the data is a time stamp of recorded voltage in microvolt unit. There are no missing value in the data set.

Approach

From the structure of the data set and its class description, it appears to be a machine learning problem of classification and clustering. Subjects of class 2—4 are nonepileptic whereas only the subjects of class-1 are epileptic. Most likely treatment of a binary classification would be epileptic versus nonepileptic where all of 2 through 5 classes are designated as value 0 and class-1 as value 1. However, clustering might reveal interesting information in this regard.



Step 1: Exploratory Analysis

Exploratory analysis of the data has been done in Python. The source code is uploaded in Github repository (https://github.com/ashokbhow/Capstone-Project).

As described in 'Dataset' section, the voltage signal is received from all 23 electrodes simultaneously and has been regenerated to look like in Fig.3 shown for a sample curve over

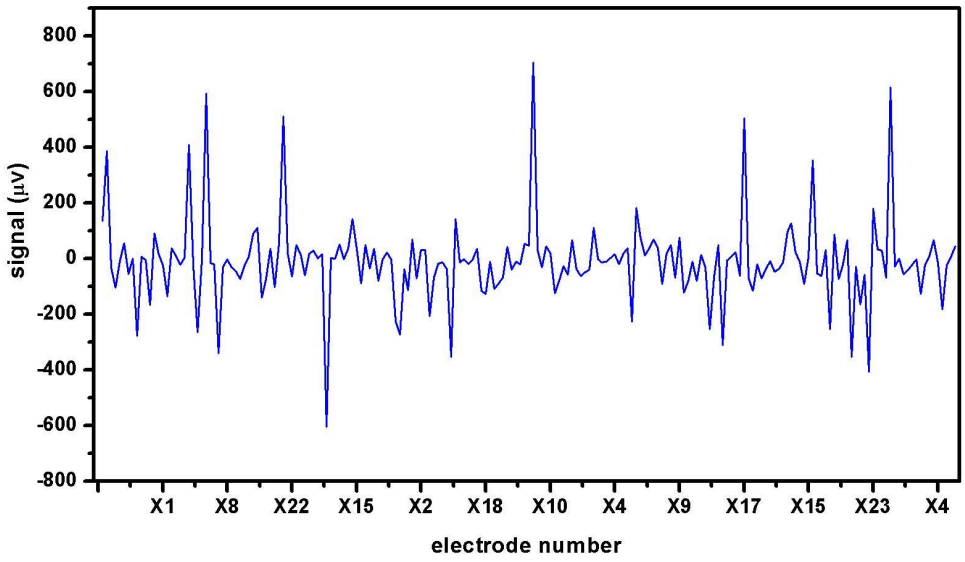


Figure 3 Tracing back the analog signal from all 23 electrodes

first 200 instances of column X1 only. Horizontal axis shows the 23 chunks representative of 23 electrodes. The plot designates how the voltages are populated on each electrode. The dataset that is being analyzed is prepared as described earlier from such apparent analog signals recorded in the detector.

Salient features of the dataset are as follows:

1. There are no missing data
2. The distribution over any attribute is smooth but not Gaussian. The range of values varies over the class (Fig 4 and Fig.5).

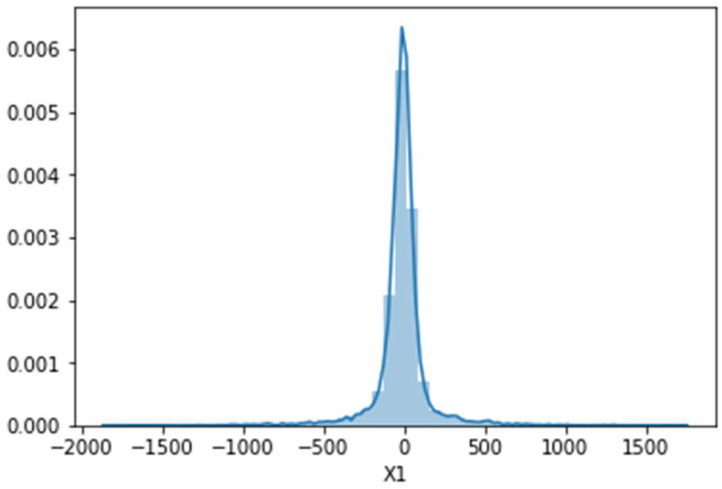


Figure 4 Histogram and distribution over an attribute

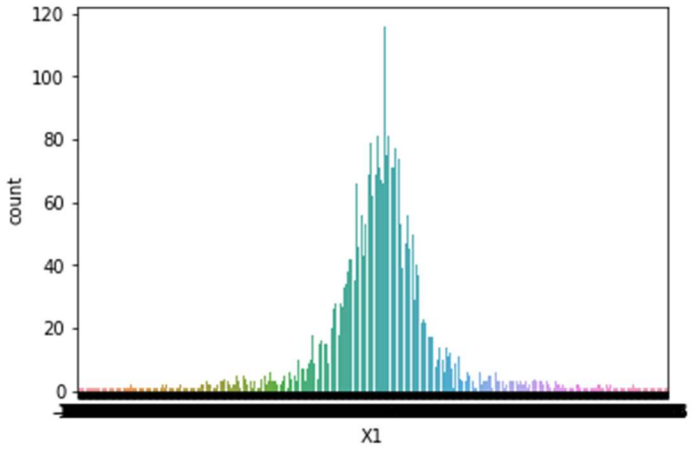


Figure 5. Count plot over a column through 11500 instances

3. Fig. 6 and 7 show plots of the instances of different classes across all the features. This shows a wide variation in maximum / minimum voltages over three orders of magnitude. The *ictal* data that represents the seizure activity exhibits larger magnitude in the range of millivolts.

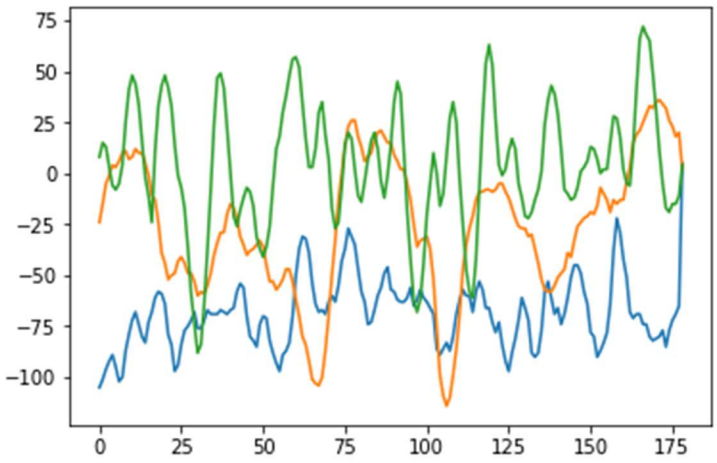


Figure 6. Variation across the features regenerating the timestamp. Class-1: ictal data in blue, Class-2: Probe in epileptic zone in orange, Class-3: Probe in healthy part of brain (Class descriptions are given in section-Dataset)

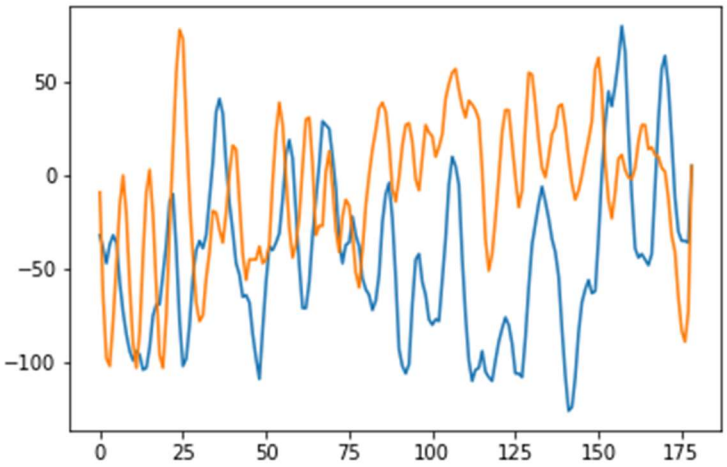


Figure 7. Similar plot for Class 4 in blue and Class 5 in orange

4. However, as instances over the same class might vary on range of values, the data has been grouped over their class values and variation of mean across all features are shown in Fig. 8 for the 3 prime classes.

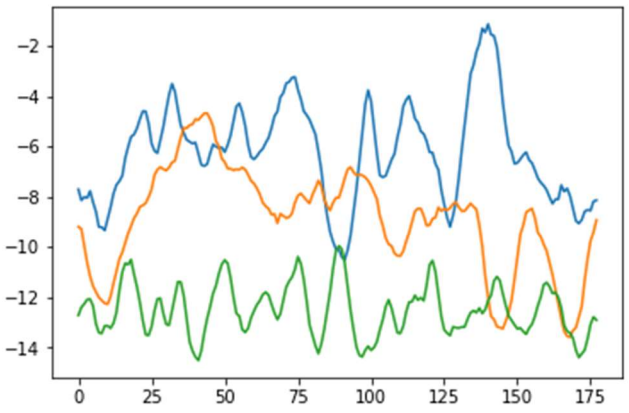


Figure 8. The timestamp of the mean values of Class-1 (green), Class-2 (orange) and Class-3 (blue). X-axis are the number of attributes and Y-axis shows the voltage in microvolts

The standard deviation across the features clearly distinguishes the seizure class from the rest as shown in Fig. 9.

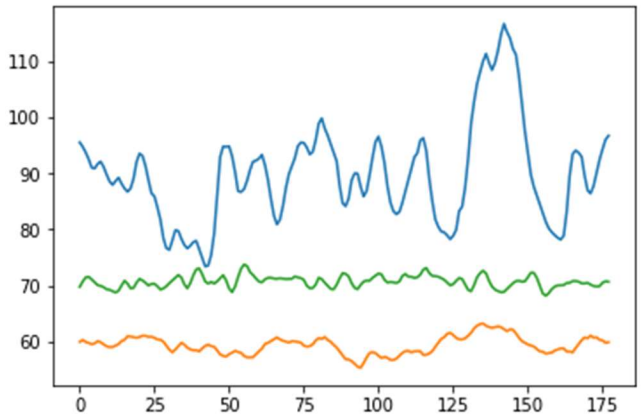


Figure 9. Standard deviation across features for Class-1 (blue), Class-2 (orange) and Class-3 (green). Epileptic seizure has high fluctuation in standard deviation compared to any non-epileptic classes.

5. Apparently, a box plot of any attribute (column) might look like that there are outliers. However, these are the maximum/minimum values of the voltage and are relevant information to determine the degree of seizure. Besides, these data points are well within the distribution pattern and not suggestive of removing. Maximum ± extent might help to determine the extent of damage to the cells due to intense seizure activity. Hence, no data points are removed identifying as an outlier. Fig. 10 shows the variations in max values across features. Notice, that the max value apparently shows a saturation flattening at 2 milivolt which might be due to the detection limit of the difference amplifier, indicating that the seizure spike might shoot over the limit. Such

intense electric pulses are damaging to brain cells and is a subject to study the permanent damage caused due to epileptic seizure.

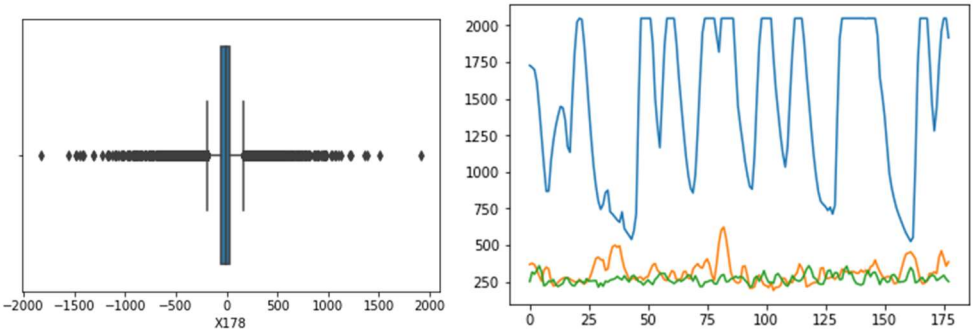


Figure 10. A boxplot of a feature showing apparent outliers. These are the positive and negative maximums and relevant to interpretation. The maximum voltage surge is shown beside for Class-1 (blue), Class-2 (orange) and Class-3 (green).

6. Similarly, the extent of -ve surge is clearly very high for seizure activity as compared to that in any non-epileptic classes (Fig. 11).

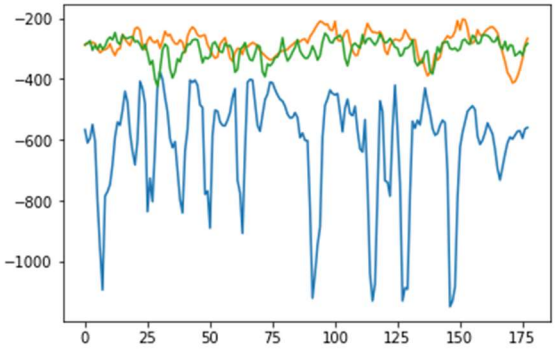


Figure 11. The -ve maximum voltage surge for Class-1 (blue), Class-2 (orange) and Class-3 (green). The reason for + and - voltages is described in previous section.

7. The distribution of mean and standard deviation of Class-1 seizure (ictal) data on a linear scale is shown in Fig, 11.

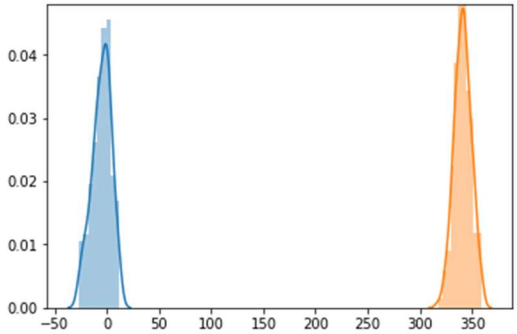


Figure 121. The mean and sd of Class-1 data.

8. There are 2300 instances in each class chosen to have an equal distribution of number of instances, however mingled together in the dataset.

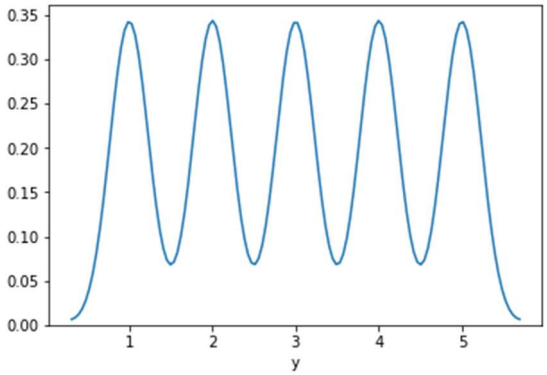


Figure. 12. Distribution of instances in each class.

Step 2: Clustering

Even though the class attribute is assigned in the original data, it is always suggestive to explore the inherent grouping in the data as a part of exploratory analysis by applying

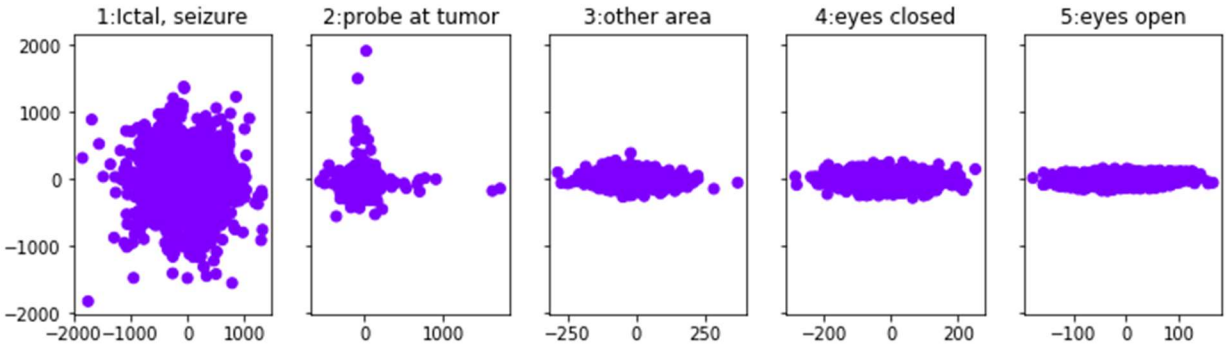


Figure 13. Scatterplots of class values exhibiting their comparative ranges.

unsupervised machine learning. Dropping the class attribute, Fig. 13 shows the scatterplot of the data for all the classes exhibiting the extent of variation in values. A few values of non-seizure class-2, when the probe is placed at the epileptic zone, do compare to that of class-1 seizure data, however it does not show as any trend. These 4 values could be considered as true outliers, depending on the condition of data acquisition.

Normal k-means clustering does not reveal any natural grouping within the data. For this, the data has been subjected to hierarchical clustering analysis. However, very large variation in values over 3 orders of magnitude necessities the data to be normalized for calculating a possible dendrogram revealing the inherent classes. Fig. 14. Shows the dendrogram revealing 5 classes at level 15. Cross verified with the non-ictal classes giving 4 hierarchies at the same level, shown in the Python source code given in github repository. The distance calculation method = 'ward' is used in the analysis. Single-link, complete-link and average-link methods do not work well.

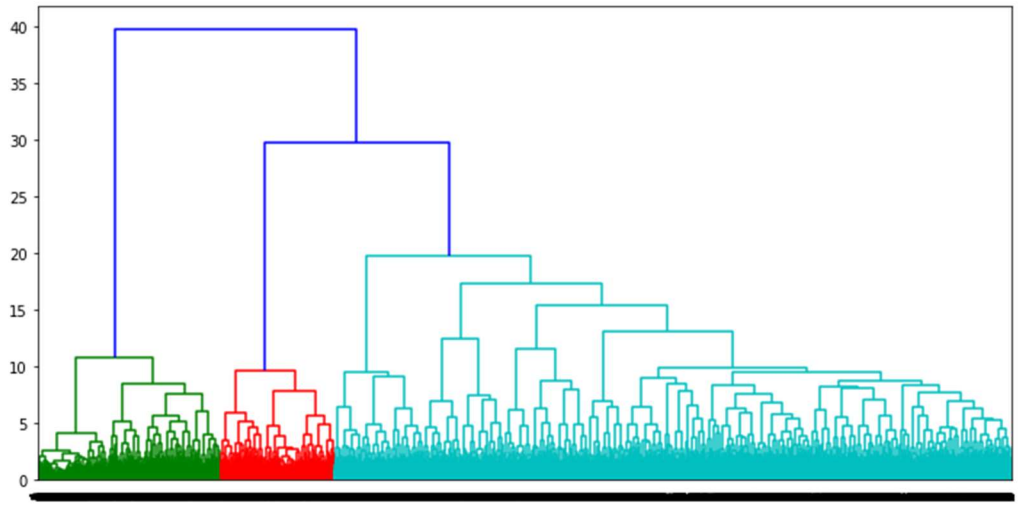


Figure 14. Hierarchical clustering using method = 'ward' revealing 5 classes at level 15.

Step 3: Classification

This data with its specific class attribute is ideal for the predictive approach using supervised machine learning techniques. The research questions are:

1. Is it possible to predict epileptic seizure from measurement when there is no seizure i.e. from non-epileptic parameters? If so, with what level of accuracy?
2. Which non-epileptic class values are the best predictor? This will enable doing unnecessary measurements saving time, money and resources.

The data being multiclass, the task is harder and not easy to work through all classifiers. However, the research question requires the seizure cases to be classified with respect to, (i) any of the non-epileptic classes or (ii) all the non-epileptic classes together as one class. For this, the

original data file has been split into many separate binary class files using R (source code given in github). Binary classification studies have been done using Logistic, XGBoost, Support Vector Machine algorithms whereas the multiclass classification is done using GLMulti, Decision Tree, KNN, Random Forest and Multilayer Perceptron (MLP) algorithms. Studies have been done on both original and principal components using PCA transformation. All classification calculations are done using cross validation techniques.

1. **Binary Classification**

The most important class being Class-1 in the dataset which correspond to the seizure activity, it is pertinent to split the dataset into two major classes viz. seizure (or epileptic) and non-seizure (or non-epileptic). By that, the task in hand reduces to predicting the seizure activity with respect to a combined effect of all other classes. However, it is also imperative to reduce the dimensionality of the data to obtain better prediction accuracy in classification. Two different methodologies have been tried in this regard. One, doing a logistic classification of 1 vs. all class where all of class 2, 3, 4, 5 are put to '0' value and then removing the unimportant attributes by noting the significance score (refer. Github R code). Finally, doing a logistic only with highly significant attributes. About 10 odd features (X4, X7, X9, X10, X23, X24, X26, X99, X100, X102) are thus selected, however the accuracy is not significant. It is therefore suggestive to consider the effective contribution of all features by doing Principal Component transform (PCA). From Python variance ratio plot, first 50 components are retained for classification analysis as the variance shows saturation beyond that. 10-fold cross validation is applied in splitting the data into training and test sets. The accuracies obtained are shown in Fig. 15. The selectivity and sensitivity calculations are given in respective codes.

Fig. 15 also shows the results of XGBoost and Support Vector Machine classifications on the same organized datasets. XGBoost turns out to be the winning classifier for this dataset. It maybe worth mentioning here that the dataset does not have any sort of correlation between any two features (refer to the R-code and R correlation plot file: corr_plot.jpg in Github). The prediction accuracy for cross validated 67% training and 33% test split of first 50 PCA transforms, the accuracy obtained is 98.1% with a selectivity of 99.03%. Support vector machine classification on the other hand renders better results with raw scaled data than the principal components. Predictive accuracy of class-1 with respect to class-3 is superior than that of class-

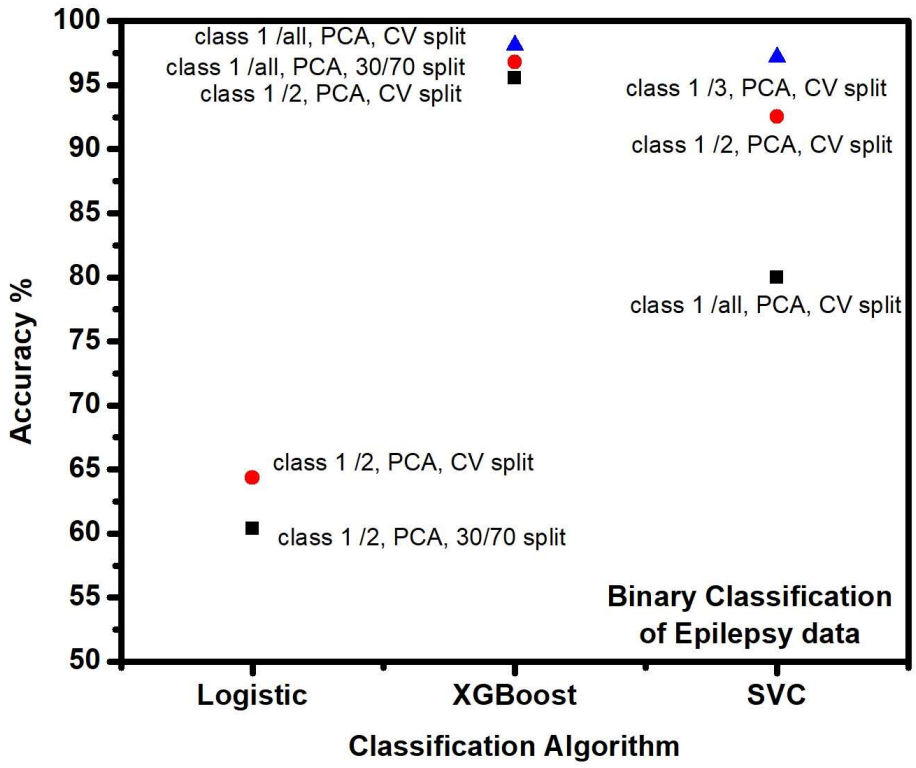


Figure 15. Binary classification predicting epileptic seizure w.r.t. all other non-epileptic classes and class-2 and class-3 values as well, to understand decipher the more relevant class in predictive analytics.

2, suggesting that class-3, when the probe is placed on the healthy tissue of the brain at the opposite lobe of the tumorous zone, is a better predictor than the values obtained by probing at the tumorous zone during a period of non-seizure. The receiver operating characteristic (ROC) curves of Logistic classification benchmarking seizure at threshold probability >= 0.5, however does not reveal much of a superiority of class-3 as better predictor of seizure than class-2 (Fig. 16).

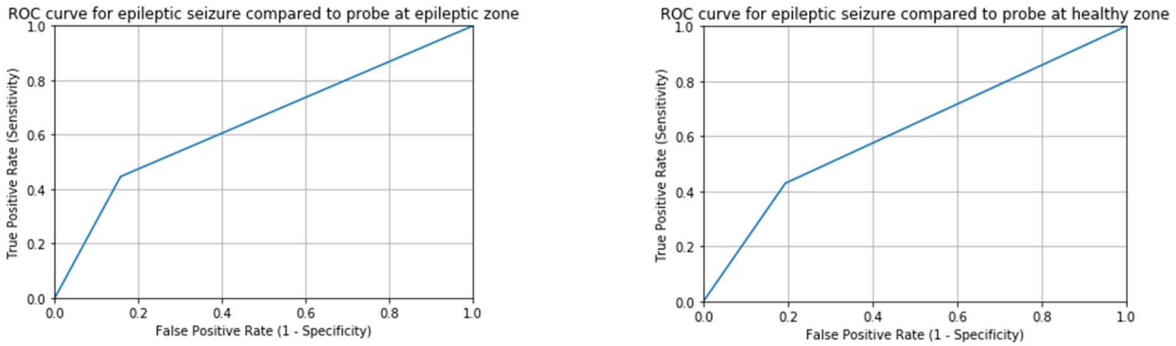


Figure 16. The ROC curves from Logistic classification of class 1 vs. 2 and class 1vs. 3.

The tradeoff between benefit (TP) and cost (FP) does not therefore exhibit substantial difference between class-2 and 3 in logistic classification. It therefore justifies the use of higher classifier like XGBoost and SVC to examine the effectiveness in predicting the seizure activity from non-seizure data. As epileptic seizure is highly unpredictable in occurrence, it is important to have a best possible predictive model from EEG measurements on healthy tissue in addition to symptomatic diagnostics of probable candidate patients.

2. Multinominal Classification

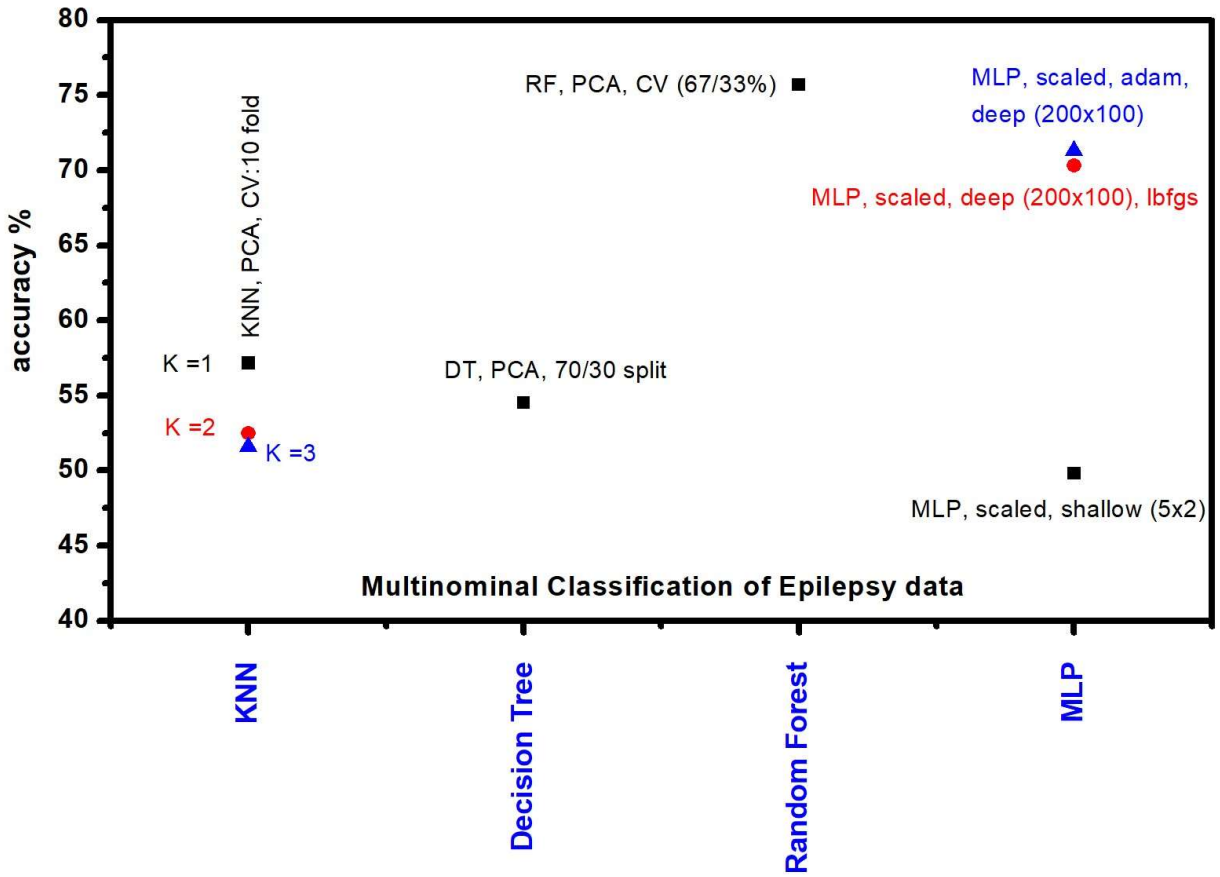


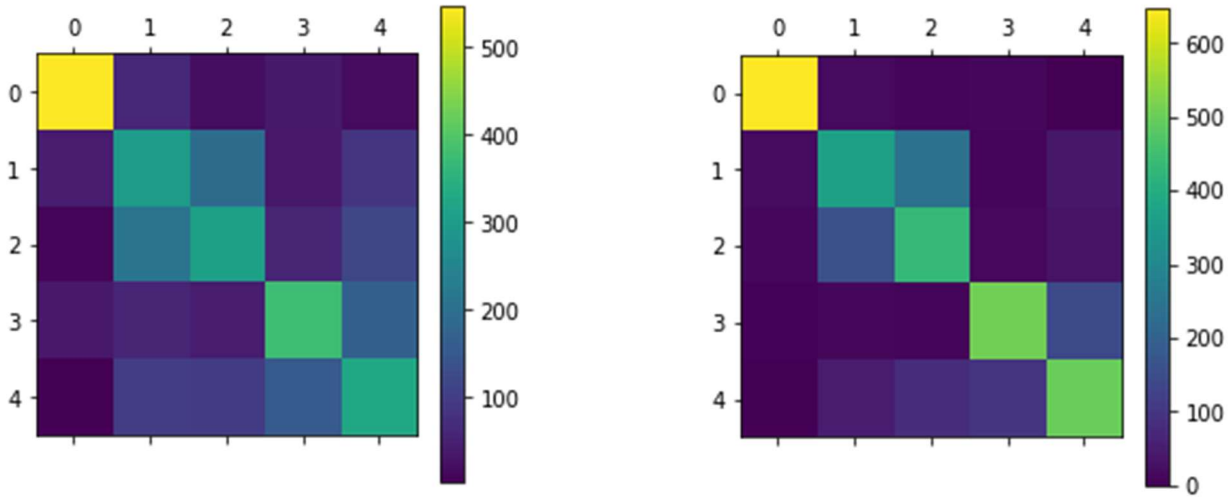
Figure 17. Multinomial classification (Python)

Fig. 17 shows the accuracy obtained by subjecting the data into multinomial classification. Quite obviously, KNN does not work, neither the Decision Tree classifier. The K vs. CV-accuracy plot (refer Python source code in Github) does not show any trend of reviving back till K=30. Decision Tree confusion matrix is shown in the source code. For class-1 seizure

cases, the sensitivity = 95.4% and selectivity = 93.9%, however the prediction scores for other classes renders a lower overall accuracy.

With an observation that the data does not response well with any branching structure, the ensemble method like Random Forest has been attempted which nonetheless, gives better overall prediction accuracy of approximately 76%. However, the computing time is much higher compared to any other classification task. Mean absolute error turns out to be 0.58 degrees. It would have been nice to have a graph done on any estimator value. But the graphing of Random Forest tree needs more work to explore in Python.

Lastly, Multilayer Perceptron (MLP) has been tried. It does not work well with principal components and therefore the calculation is done using original data with feature scaling. For binary classification between class-1 vs. class-2, the accuracy obtained is 95%. However, the classifier is extra sensitive to feature scaling. For a shallow net with 2 hidden layers consisting of 5 nodes, the prediction accuracy is < 50%. A deep net of 100 hidden layers of 200 nodes (200x100) provides better accuracy of 70.32%. However, following 'stochastic gradient descent method (solver= 'adam' in Python), the accuracy increases by 1% than what is obtained by using method 'lbfgs'. Thereby, the ensemble method Random Forest provides best predictive accuracy for seizure cases in multinominal classification.



Confusion Matrix: Decision Tree (left) and MLP (right)

R-GLMulti has also been tried for multinominal classification. R-source code provides the details. However, the computation takes excessively large time to converge if more than 4 features are put together. By that, principal component scores were chosen as features by noting the aic-scores and a best IC profile is shown is Fig. 18.

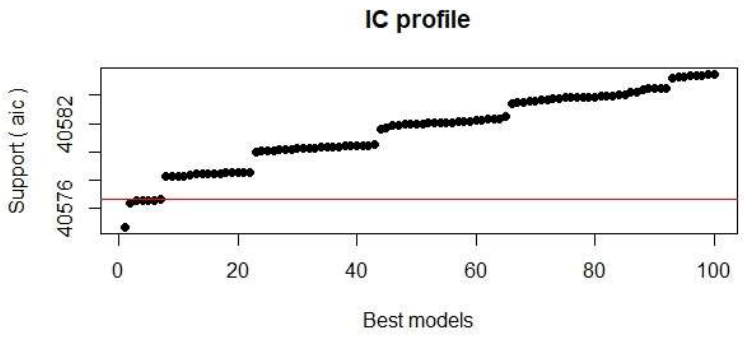


Figure 18. R-GLMulti best classification

Final best value is provided by selecting PCA components 1, 17, 29 and 38 and the best model, *y ~ 1 + Comp.17 + Comp.29 + Comp.38 + Comp.29:Comp.1 + Comp.29:Comp.17 + Comp.38:Comp.17*. By this, the data can be effectively reduced as 4 dimensional principal components for mult inominal predictive analysis.

Step 4: Recommendations

Even though, answering the research question, how efficiently epileptic seizure can be predicted from all other non-epileptic electroencephalographic (EEG) measurements (or scans), depends on several scientific parameters for a medical judgement, a data based predictive modelling can assist to determine effective preventive strategies for patients from pre-symptomatic evidences. The analysis on this open source EEG data, attempts to qualify such a predictive scenario, that might be further modified and specified with real life medical data. So long this dataset is concerned, the following points might be mentioned,

1. The class-2 data is redundant and may be excluded.
2. Class-3 data is the only requirement for a seizure prediction which is advantageous because it is collected by probing the healthy part of the brain at opposite lobe to the tumorous zone.

3. Class-4 and 5 may be useful to develop pre-symptomatic signatures, however further evidences should be worked out in this regard.
4. It is better to consider binary classification between relevant classes than trying multinomial classification. XGBoost classifier in this regard, turns out to be the winning approach.
5. A combination of several classifiers may however be worked out for better multinomial classification [16]. But again, any approach needs to be substantiated with actual ground reality of medical cases.
6. As epileptic seizure is highly unpredictable in its occurrence, collection of ictal data is a major challenge. In this regard, other similar brain conditions may be relevant to be studied, for example, extremely deep substance intoxication from severe drug/alcohol addictions.

Step 5: Future work: Entropy analysis

A Bayesian approach will be studied for an entropy analysis on class-1 seizure data and correlated with various types of seizure cases [15] if possible. In the neural network framework, Boltzmann Machine and Deep Autoencoders may be applied to explore the possibility of unsupervised learning within a supervised framework.

References / Literature

[1] William O. Tatum, Handbook of EEG Interpretation – Normal EEG, (2008), Demos Medical Publishing LLC, ISBN-13: 978-1-933864-11-2 (pbk: alk paper)

[2] Niedermeyer E., da Silva F. L., (2004), Electroencephalography: Basic Principles, Clinical Applications and Related Fields, Lippincott Williams & Wilkins, ISBN 0-7817-5126-8.

[3] https://medlineplus.gov/ency/article/003931.htm

[4] M. Teplan, Measurement Science Review, 2, (2002), Section 2

[5] E. J. Smith, in http://www.ebme.co.uk/articles/clinical-engineering/56-introduction-to-eeg

[6] H. L. Atwood, W. A. MacKay. 1989. Essentials of neurophysiology, B.C. Decker, Hamilton, Canada.

[7] Selim R. Benbadis, Handbook of EEG Interpretation – Abnormal Nonepileptiform EEG EEG, (2008), Chapter 2, Demos Medical Publishing LLC, ISBN-13: 978-1-933864-11-2 (pbk: alk paper)

[8] R.D. Bickford. 1987. Electroencephalography. In: Adelman G. ed. Encyclopedia of Neuroscience, Birkhauser, Cambridge (USA), 371-373.

[9] William O. Tatum and Selim R. Benbadis, Handbook of EEG Interpretation – Abnormal Nonepileptiform EEG EEG, (2008), Chapter 3, Demos Medical Publishing LLC, ISBN-13: 978-1-933864-11-2 (pbk: alk paper)

[10] https://www.epilepsy.com/learn/about-epilepsy-basics/what-epilepsy

[11] https://emedicine.medscape.com/article/1138880-overview#a1

[12] Bergamini, M. Dondey, D. W. Klass, M. Lennox-Buchthal and I. Petersén, Electroencephalogr. Clin. Neurophysiol. 37(5), 1974, p. 538

[13] Ralph G. Andrzejak, Klaus Lehnertz, Florian Mormann, Christoph Rieke, Peter David, and Christian E. Elger, Phys. Rev. E, 64 (2001) p.61907-15

[14] Qiuyi Wu and Ernest Fokoue, School of Mathematical Sciences, Rochester Institute of Technology, UCI Machine Learning Repository, Date uploaded: May 24 2017

[15] N. Kannathal, Min Lim Choo, U. Rajendra Acharya, P. K. Sadasivan, Computer Methods and Programs in Biomedicine, 80 (2005) p.187

[16] Stefan Lessmann, Student Member, IEEE, Bart Baesens, Christophe Mues, and Swantje Pietsch, IEEE Transactions on Software Engineering, 34(4), (2008), p.485