Predict Seizures In Long-term Human Intracranial EEG Recordings

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Abstract—**This is where the abstract goes**

I. INTRODUCTION

A seizure is a brain disorder which causes the brain to produce an overload of electrical activity. Generally, seizures last only a couple of minutes and cause uncontrollable muscle spasms. Spontaneous recurrence of seizures is a medical disorder called epilepsy. Epilepsy affects 1% of the human population with varying frequencies and severities.

The unpredictability of seizure occurrences also cause anxiety in epilepsy patience. Normal activities such as driving a vehicle or swimming can be unsafe for these patience. Medication can be taken to prevent convulsions, but are not effective for 20-40% of patience with epilepsy.

Seizure forecasting systems can have a positive impact on the lives of Epilepsy patiences.

II. PROBLEM

Researchers at Melbourne University have been studying epileptic seizures with the goal of accurately prediction a seizure onset up to one hour in advance. The temporal dynamics of brain activity can be classified into 4 states: Interictal (between seizures, or baseline), Preictal (prior to seizure), Ictal (seizure), and Post-ictal (after seizures).(directly from website)

Brain activity can be monitored with an electroencephalogram (EEG) machine. Electrodes are placed on the scalp to record the electrical impulses of brain waves. Intracranial EEG (iEEG) is monitored by placing these electrodes on the cereal cortex.

A public challenge was posted on kaggle.com for the data science community. The challenge is to distinguish between normal interictal activity and preictal seizure activity using several iEEG datasets.

III. APPROACH

To predict seizures we extracted features based on their power spectral density and applied linear regression techniques to create a prediction model. We tuned these models using the grid search technique.

A. Dataset

Three sets of train and test iEEG datasets were provided by Melbourne University. Each set are labeled, pre-seizure or non-pre-seizure, recordings that correspond to one epilepsy patience. Each recording is of lead seizures in which the previous seizure occurred a minimum of 4 hours before. The recordings were made using 16 EEG electrodes sampled at 400Hz were used to monitor Intracranial brain activity. The electrodes measure voltage that is referenced from the average of all 16 electrodes at the sample time. Recordings are 1 hour and 5 minutes long. The last 5 minutes ensure that predictions are made based on data 5 minutes prior to seizures.

B. Feature Extraction

30 second windows with 50% overlap. Measure power spectral density and energy trends over time.

C. LASSO GLM

Least Absolute Shrinkage and Selection Operator (LASSO), also known as the penalized regression model, is a shrinkage and variable selection method that imposes a constraint on the regression coefficients. The penalization process causes some of the regression coefficients to shrink to zero. The penalization process results in identifying the variables that minimizes prediction error. In machine learning, LASSO is a supervised learning method used to automatically select features that have greater prediction accuracy.

Generalized Linear Model (GLM) is a generalization of linear regression that allows response variables to have error distribution model.

(paragraph describing how we use LASSO GLM)

D. Linear Support Vector Machine

IV. RESULTS

V. ANALYSIS

unbalanced dataset, more non-seizure data than seizure. Evaluation based on number of correctly classified seizures.

VI. CONCLUSION

Here is a bibliographical reference [1] [2] [3] [4] [5] [6] [7] [8]

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