Detecting Seizures From EEG data

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Synopsis

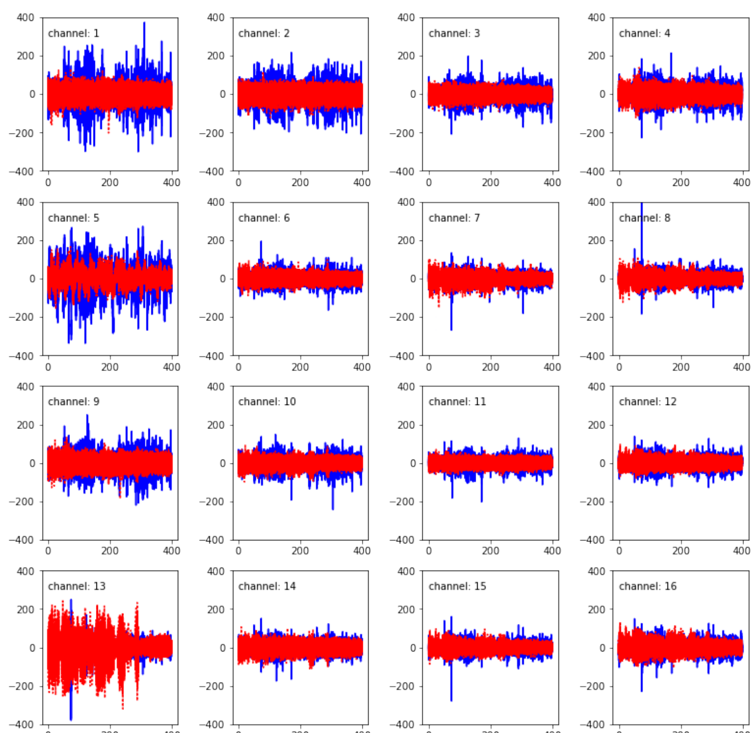
The aim of this project is to detect onset of epileptic seizures from electroencephalogram (EEG) recordings. Epileptic seizures are unexpected and most patients have to be on constant medication, leading to significant side effects. Using wearable electronics, it could be possible to predict seizures before they onset and warn the patient in a timely manner to take necessary precautions. This would significantly improve patients' life and open up possibilities for alternative treatments.

The techniques developed in the project can also be used in other time-series data that arise in medical settings, including hearth rate, blood pressure and body temperature for a variety of applications.

The project is intended to serve clients in medical device manufacturing, wearable electronics and medical research centers.

Data collection and processing

The data collected for this project is obtained from a Kaggle competition, which provide EEG recordings for 5 dogs and 2 human subjects with naturally occurring epilepsy. The data comes in ".mat" format used in Matlab, and includes labeled EEG segments. The *preictal* segments are those with an oncoming seizure (positive class) and *interictal* segments are without (negative class) any seizure. Each segment contains recordings in a number of channels with a given frequency.



An example EEG recording from the first dog subject is provided in the figure above. The figure shows EEG recordings in 16 channels for a duration of 400 seconds recorded with a frequency of 600 Hz (600 recordings per second). The red lines represent *preictal* segments, while the blue lines represent *interictal* segments.

The segments corresponding to each subject is parsed using a Python script and features are engineered by processing the time-series data. Two different approaches are used to process the data to be fed into the machine learning algorithms:

Manually Engineered Features

Several different features are tested before a final decision has been made based on the best predictive accuracy obtained. The final set of features are engineered by using power spectra at 6 frequency bands (0.1-4, 4-8, 8-12, 12-30, 30-70, 70-180 Hz) computed at blocks of 60 seconds on each EEG segment. The power spectra are then used to engineer the following features:

1. Eigenvalues of the correlation matrix between bands and channels within each block
2. Shannon's entropy for the power within each block
3. Power at dyadic levels, the eigenvalues of their correlation between channels and Shannon's entropy
4. Hjorth parameters
5. Skewness and Kurtosis within each block

Tensor Input for LSTM Networks

The raw time series data is reshaped into a tensor to be fed into a long-short-term memory (LSTM) network. Since the time-series is very long, a one-dimensional convolution operation is used to reduce the size of the sequence to be able to help LSTM training.

Other datasets being employed

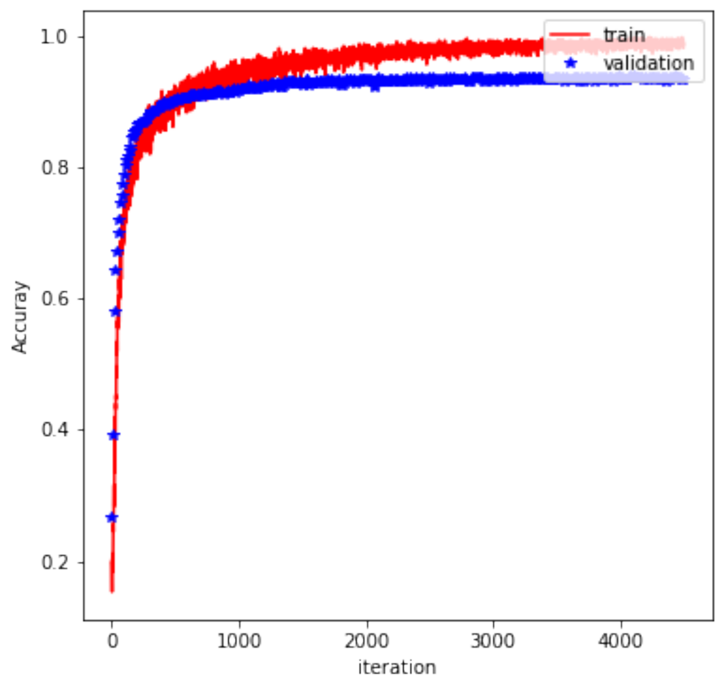
We have also employed the well-known Human-Activity-Recognition (HAR) dataset, which offers an analogous task, but with a much cleaner and simpler time-series data. We have tested several deep-learning architectures on this dataset successfully before tackling the more difficult problem of EEG classification.

Potential datasets that will be employed include other EEG measurements available publicly, as well as the PhysioNet challenge on classifying normal/abnormal hearth sounds dataset.

Initial Findings

The engineered features scored on average 0.95 AUC score for all the five dogs and two humans. Instead, the initial tests on LSTM networks were only able to achieve around 0.70 AUC. The reason for the low score is understood by the fact that the one dimensional convolution we have employed to reduce the sequence length was providing only a single filter. A better approach would involve learning multiple filters through the network architecture. This approach is tested for the case of the HAR dataset and successful results were obtained.

The figure below shows the accuracy of Convolutional Nets trained on the HAR dataset which achieved around 98% accuracy, surpassing methods based on manually engineered features.



Next Steps

The network architecture used successfully in the HAR dataset will be adopted (with relevant modifications) in the EEG data. Further experiments will be performed to push the accuracy of the deep learning based models close to or above the model based on engineered features.

The methods will also be used in other datasets that provide similar challenges.