Detecting Epileptic Seizures in Electroencephalogram Data

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I) Task
Overview: Affecting fifty million people worldwide, epilepsy is a chronic disorder of the central nervous system characterized by recurrent seizures. During a seizure, aberrations in the brain's electrical activity produce physical symptoms ranging from unresponsiveness to loss of memory to unconsciousness. An electroencephalogram (EEG) is a record produced by electrophysiological monitoring of the electrical activity of the brain. Electrodes are placed on the scalp and measure voltage fluctuations between the nodes as the not effect of millions of neurons in the brain. EEGs are used for diagnosis of a number of neurological disorders, including epilepsy, sleep disorders, comas and more.

Our goal is to train a single neural network to classify on epochs of EEG data from any patient as being seizure or non-seizure. Previous attempts at EEG classification have failed short by:
1. Building separate models for each patient
2. Using data sets of only certain seizures and non-seizure activities.
3. Yielding low data positive rates

We hope to overcome these shortcomings by using vastly more data than previous attempts. For example, Miao (2009) used 23 patients and 844 EEG files, whereas we have access to 12,385 patients and 136,303 EEG files.

II) Dataset
Put briefly, our data set is large and heterogeneous. The data set consists of 136,305 electroencephalograms from adults measured at the Stanford Hospital and the Lucile Packard Children's Hospital. Each electroencephalogram is stored in a hierarchical data format (HDF) containing anonymized data about the patient, metadata about the EEG read, the raw signals of the EEG read to matrix with shape number of channels by length of EEG, and accompanying annotations with timestamps for the EEG. The data is remarkably heterogeneous:
- 74% intracranial and scalp
- 26% routine, long-term
- EEG, ambulatory, etc.
- Length: 5 seconds to 24 hours
- Frequency: 30 Hz to 500 Hz
- Age: 0 to 100+
- Channels: 1 to 6

Because the data is not explicitly labeled as seizure and non-seizure, we use the norm annotations as a proxy for seizure labels.

III) Data Pre-Processing

Given the heterogeneity of the data, we filtered our data by:
- Only including scalp EEG i.e., excluding intracranial records.
- Taking reads only from the nodes in the International 10-20 System.
- Limiting length to minimum time of seizure: 50 seconds.
- Only including files with a sampling rate of 200 Hz.
- Standardizing each waveform to have mean 0 and standard deviation 1.

With these filters in place, we defined our seizures and non-seizure data:
- Seizure: Every time a file contains a seizure annotation, slice the following 50 seconds.
- Non-seizure: For each file without a seizure annotation, randomly sample a 50-second slice. Randomly sample from all such slices to get 25,830 non-seizure reoccurrences.

The result is 51,700 matrices shaped 25x200 with a binary label.

IV) Proposed Architectures

We trained four different model architectures:
1. Baseline: Flatten the matrix and run logistic regression via a one-layer neural network with no hidden layers.
2. Dense Network: Flatten the matrix and run through two hidden layers with ReLU activation functions before outputting a single neuron with a sigmoid activation function.
3. Convolutional Network: Run matrix through five 1-dimensional convolutional layers each with 96 filters, 3x1 pooling, and exponential linear units. Flatten the remaining matrix and run it through one layer with batch norm, dropout, and ReLU before a final layer with a sigmoid activation function. This model is based off Schirrmeister’s work (2017) on EEG decoding.
4. Recurrent Network: Process each of the 2000 inputs into two bi-directional LSTM units followed by mean pooling, a dense layer with batch norm and ReLU, and a final layer with a sigmoid activation. This is based on many-to-one recurrent networks on temporal data.

V) Results

- As expected, the worst performing architecture was the logistic regression model: With just 50,000 parameters, it couldn’t fit a lot beyond guessing.
- Our top performing architecture on the test set was the densely connected feed-forward neural network, achieving an accuracy and F1 score of 90.8% and 0.97, respectively. The architecture’s flexibility likely was key to its success with over 1 billion parameters to tune.
- The convolutional neural network also performed impressively. It achieved the highest training accuracy and F1 score of 96.9% and 0.97 respectively. However, this model may have over fit given its poor test performance.
- From preliminary error analysis, this difference seems to be an error in the convolutional evaluation code.
- The bidirectional LSTM network performed okay with an accuracy around 66%. Its classifier performance is expected given the known challenge of training an LSTM with such a large number of time steps. These results are at apparent convergence after 70 epochs of training.

VI) Discussion and Next Steps

Our top-performing architectures were the densely-connected and the convolutional networks. Both achieved accuracy and F1 scores over 90%, well beyond the results of published work for a general EEG classifier used on any patient to classify any of the types of seizures. This is especially remarkable given the heterogeneity of the data, which contains ample non-seizure activity, many types of seizures, and many patients. That said, we see four major areas of improvement for this task:
1. Improve Labels: The current seizure annotations are not completely trustworthy nor complete. We can apply labeling functions to generate sound training data as described in Rainer et al. (2017).
2. Improve Embeddings: We currently use the raw waveforms. However, Busharini et al (2016) propose using EEG “video” as discussed in Figure 5 that may better capture temporal and spatial information.
3. Improve Network: Our proposed models have been relatively shallow compared to what Du et al (2016) suggest is necessary to capture all information from raw waveforms.
4. Segmentation: We would love to expand our efforts to other time points of a seizure or segmentation of an EEG file into seizure and non-seizure activity. Unfortunately, the annotations usually only mark seizure start, so this is difficult.

This work is already clinically useful as a tool to identify seizures in EEGs. An ambitious additional goal is to forecast a seizure 7 seconds ahead of time. We plan to try this but do not expect great results as even the best clinicians cannot forecast seizures from EEG data.

VII) References and Code
My code can be found at [https://github.com/chanbean/c230-eeeg](https://github.com/chanbean/c230-eeeg)

References cited in the paper are (see report for all sources):
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