DETECTING EPILEPTIC SEIZURES FROM EEG DATA USING NEURAL NETWORKS

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ABSTRACT

We explore the use of neural networks trained with dropout in predicting epileptic seizures from electroencephalographic data (scalp EEG). The input to the neural network is a 126 feature vector containing 9 features for each of the 14 EEG channels obtained over 1-second, non-overlapping windows. The models in our experiments achieved high sensitivity and specificity on patient records not used in the training process. This is demonstrated using leave-one-out-cross-validation across patient records, where we hold out one patient’s record as the test set and use all other patients’ records for training; repeating this procedure for all patients in the database.

1 INTRODUCTION

Collecting non-invasive health and vital signs data on a regular basis is becoming more common with advancement in bio-sensor and wearable device technology. With the right models, using such data for real-time detection of ongoing health-related events may soon become reality, enabling swift remedial action to be taken when possible.

One such application is the detection of epileptic seizures using electroencephalography (EEG). To be of practical use, models must detect seizure events quickly, with high sensitivity (minimal false negatives) as well as high specificity (minimal false positives or false alarms). This requires training models that generalize well to previously unseen data.

Many techniques are being used to build models to detect seizures. Examples include Pinho et al. (2014); Chen (2014); Page et al. (2014b); Turner et al. (2014); Page et al. (2014a) and Chander et al. (2011). We propose a technique applying feed forward neural networks trained with dropout that improves upon previous results and is demonstrated using leave-one-out-cross-validation (LOOCV) across patient records. Using LOOCV, we prove the potential of this technique to train models on a given set of patient records, and then be deployed on data from patients previously unseen by these models.

2 PROBLEM STATEMENT

Data from the CHB-MIT database, described by Goldberger et al. (2000), is used to train and validate the models. This database contains 23 multi-channel scalp EEG records collected from 22 patients over several days, sampled at 256 Hz. We classify 1-second segments of this data as being in either a normal state or a seizure state. Classification of longer segments with durations greater than 23-seconds has been studied well. Existing techniques achieve near perfect classification performance as reported by Chen (2014). However, given the length of these segments, the proposed approaches would require a significant delay for detection after seizure onset. Using short segments allows for faster detection of seizure events which would then enable swift remedial action.

Among Machine Learning approaches, neural networks have demonstrated utility on both seizure detection as well as other classification problems involving EEG, and was therefore the choice of classifier in our experiments. Our main contribution is an application of neural networks trained...
with dropout, a technique introduced by Hinton et al. [2012]. Dropout has been successfully used to improve neural network performance on commonly accepted benchmarks and several other applications. We adopt dropout as it is known to reduce over-fitting in neural networks trained on small datasets; hence improving their ability to generalize well to unseen data.

3 Solution

3.1 Dataset Creation

We use 16 patient records from the CHB-MIT database that have 14 channels in common. 1-second segments are extracted from each of these records to create training instances. These segments are non-overlapping, and temporally collocated across the 14 channels. This is illustrated in Figure 1, where each horizontal band represents an EEG channel, and each vertical band represents a 1-second segment.

Rather than using the raw EEG signal as input, the following 9 features described by Wulsin et al. [2011] are extracted from each segment in each channel: Area, Normalized Decay, Line Length, Mean Energy, Average Peak Amplitude, Average Valley Amplitude, Normalized Peak Number, Peak Variation, and Root Mean Square. These are low-level features computed from simple signal processing techniques. Hence each instance comprises 9 features x 14 channels = 126 multi-channel features. These features have previously been used with other applications such as Wulsin et al. [2011], Page et al. [2014b], Turner et al. [2014], and can serve as a baseline for future work using raw EEG data. The label for each instance is either 0 (normal) or 1 (seizure) where 1 corresponds to an ongoing seizure event within the 1-second segment.

Seizure events in a patient record are sparse, with the dominant class label in every record being 0. To eliminate this skew, each patient record is truncated to contain an equal number of positive and negative instances if it is involved in training. This is done by selecting all positive instances and randomly sampling with replacement an equal number of negative instances. This approach of sub-sampling of negative instances produces better models even though we use the entire patient record, complete with skew, during testing.

On each iteration of LOOCV, the training data is normalized such that every feature has zero mean and unit variance. This is done by subtracting the mean from each feature and dividing it by the standard deviation. The test data is normalized using the mean and standard deviation obtained while normalizing the training set.

3.2 Model and Experiments

Each instance in the pre-processed training data, which corresponds to a 1-second segment of a multi-channel EEG signal, is fed as input to the neural network. The number of hidden layers

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1We experimented with artificially increasing the number of positive instances in the training set using bootstrap sampling; however, this did not have any observable effect on training performance.
The activation function used at each node of the hidden layer is the rectified linear unit (ReLU), introduced by Nair & Hinton (2010). This activation function is known to improve training speed over using sigmoid activation functions, while simultaneously encouraging sparsity.

We use dropout during training, a technique introduced by Hinton et al. (2012) where the activations of a random set of nodes in the neural network are set to zero, and hence don’t participate in the training process. This set of dropped-out nodes is unique to each presentation of each training instance during the training procedure. The dropout-rate, which is the probability that a node drops out, is an additional hyper-parameter. After training, the weights are multiplied by \((1 - \text{dropout-rate})\) before testing or deployment.

The models are trained using gradient descent, with early stopping through validation on a subset of the training set.

Hyper-parameter optimization is conducted on each iteration of LOOCV, where 300 architectures with differing hyper-parameters are trained using a subset of the training data for a maximum of 200 iterations of gradient descent. The hyper-parameters are sampled at random from the following ranges: number-of-layers \(\sim [2, 5]\), layer-width \(\sim [10, 100]\), dropout-rate \(\sim [0.1, 0.5]\), and learning-rate \(\sim [0.01, 0.1]\). The three best architectures, evaluated by validation set error, are chosen for complete training.

3.3 Results

Table 1 shows performance of models tested on the held-out record on each iteration of LOOCV. Since multiple architectures are trained in each iteration, we report the mean performance across these architectures. Both sensitivity and specificity are seen to be consistently high across all iterations. The high variance in precision, and hence in the F-score, may be explained by the sparsity in the data. To illustrate, a single false alarm in a record with a single seizure event would reduce the precision to 0.5 in an otherwise perfect detector.

| Patient record | Sensitivity | Specificity | Precision | F-score |
|----------------|-------------|-------------|-----------|---------|
| 1              | 0.9842      | 0.9986      | 0.7702    | 0.8504  |
| 2              | 1.0         | 0.9914      | 0.2291    | 0.3502  |
| 3              | 0.999       | 0.9803      | 0.1956    | 0.3057  |
| 5              | 0.9839      | 0.9986      | 0.7677    | 0.8539  |
| 6              | 1.0         | 0.9999      | 0.9444    | 0.9712  |
| 7              | 1.0         | 0.9987      | 0.7644    | 0.8265  |
| 8              | 1.0         | 0.9923      | 0.678     | 0.7509  |
| 10             | 1.0         | 1.0         | 1.0       | 1.0     |
| 11             | 1.0         | 0.984       | 0.7084    | 0.7409  |
| 12             | 0.7447      | 0.9992      | 0.8395    | 0.7696  |
| 14             | 1.0         | 0.9996      | 0.8203    | 0.8991  |
| 15             | 1.0         | 0.998       | 0.8798    | 0.9273  |
| 20             | 0.9951      | 0.9998      | 0.9417    | 0.9661  |
| 21             | 0.9983      | 0.9985      | 0.7634    | 0.817   |
| 22             | 1.0         | 0.9471      | 0.4344    | 0.4916  |
| 23             | 0.9837      | 1.0         | 0.9888    | 0.9861  |
| Mean           | 0.9806      | 0.9929      | 0.7329    | 0.7816  |
| Standard Deviation | 0.078   | 0.023       | 0.33      | 0.29    |

Standard deviations for each LOOCV iteration are not shown for purposes of brevity.
This is an improvement on the most recently reported results on this database by [Pinho et al., 2014], who also predicted seizure events on 1-second segments, and provided test results for 6 patient records that have 23 channels of EEG data. Comparing the results reported here for patient records that have 23 channels (records 1, 2, 3, 5, 7, 8, 10, and 23), the mean false positive rate (which is 1−specificity) improved from 5% to 0.5%, and the mean false negative rate (which is 1−sensitivity) improved from 0.8% to 0.62%.

These results provide a good baseline for ongoing and future experiments using raw data as input. Much remains to be improved in terms of precision of the classifier. Also, using the proposed classifier to detect seizure onsets is still a work in progress, where such a technique involves aggregating classifier outputs on multiple contiguous segments to achieve higher sensitivity and specificity.

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3It is not clear exactly which 6 patient records were tested.