A semi-supervised deep learning algorithm for abnormal EEG identification

Subhrajit Roy, PhD[1], Kiran Kate, MS[2], and Martin Hirzel, PhD[2]
[1]IBM Research Australia; [2]IBM Research, Yorktown Heights, NY, USA

Abstract

Systems that can automatically analyze EEG signals can aid neurologists by reducing heavy workload and delays. However, such systems need to be first trained using a labeled dataset. While large corpuses of EEG data exist, a fraction of them are labeled. Hand-labeling data increases workload for the very neurologists we try to aid. This paper proposes a semi-supervised learning algorithm that can not only extract meaningful information from large unlabeled EEG datasets but also perform task-specific learning on labeled datasets as small as 5 examples.

Introduction

Brain-related disorders such as epilepsy can be diagnosed by analyzing electroencephalograms (EEGs). However, manual analysis of EEG data is time-consuming due to the relatively low availability of expert investigators. Hence, automatic EEG interpretation by machine-learning algorithms has gained popularity recently. However, typically such algorithms require a large labeled dataset to train on. It is not always possible to obtain such a dataset, since there is a limited number of certified EEG labelers. This paper tackles this problem by proposing a semi-supervised learning algorithm for classifying EEGs, comprising an unsupervised learning phase followed by supervised learning. The unsupervised phase trains a Deep Markov Model (DMM)[1] to learn non-linear sequential dependencies in EEG signals from a large set of unlabeled EEG data. The supervised phase uses the trained DMM and a small set of labeled EEG data to obtain latent features for training a k-Nearest Neighbors (kNN) algorithm. Using kNN helps explain predictions by returning similar cases. This paper concentrates on one of the first steps in interpreting an EEG session: identifying whether the brain activity of a patient is abnormal or normal. To train and evaluate the proposed system, we use the TUH EEG Abnormal Corpus dataset[2], which consists of 1,488 abnormal and 1,529 normal labeled EEG sessions. The dataset was reorganized into a training set (1,361 abnormal/1,379 normal) and a test set (127 abnormal/150 normal).

Methods

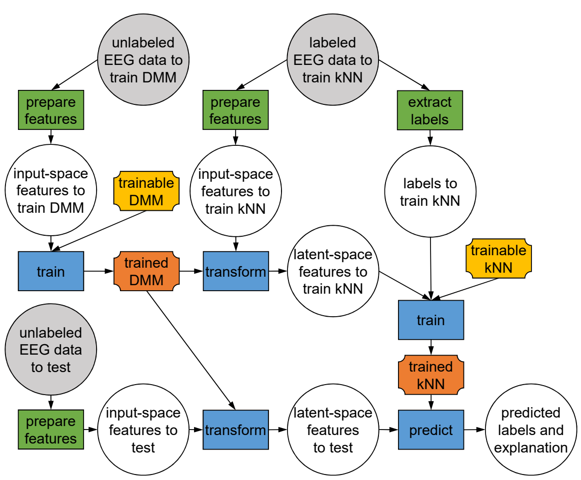

Figure 1: Workflow of proposed semi-supervised learning algorithm for abnormal EEG identification.

Figure 1 summarizes the complete training and evaluation process. Neurologists typically classify an EEG session into either normal or abnormal by examining only its initial segment[3]. Hence, like Lopez et al.[3], we extracted only the first minute of each EEG session from the training and test set. Next, we converted the recorded raw EEG signal into the transverse central parietal (TCP)[3] montage system for accentuating spike activity. We extracted four standard features (power in the alpha, beta, theta, and delta band) from each second of data. Figure 1 refers to these as input-space features. The training dataset consists of a large unlabeled set and a small labeled set. We trained a Deep Markov Model (DMM) on the unlabeled training dataset to model the dynamics of the EEG features over time. Compared to a Markov model, a DMM is flexible enough to integrate highly non-linear dynamics. This is because in a DMM, the transition probabilities that govern the dynamics of the latent variables as well as the emission probabilities governing how the observations are generated by the latent dynamics are parameterized by deep neural networks. This makes a DMM particularly well-suited for modeling EEG data. The specific DMM architecture we used was proposed by Krishnan et al. for modeling temporal dependencies[1]. We trained the DMM for 50 epochs with a batch size of 32 and learning rate of 0.001. We used the stochastic variational inference strategy and ADAM optimization algorithm. Our implementation is based on the auto-gradient computation framework of the Pyro library[4]. Once the DMM is trained, we use the labeled training samples and extract their corresponding latent-space features from the trained DMM. Next, these latent features are used to train the k-Nearest Neighbors (kNN) algorithm for identifying abnormal EEG sessions. During evaluation, we first pass the test set through the trained DMM and obtain the features from the latent space. Next, we use the trained kNN algorithm to obtain the predictions. If requested by neurologists, the model can also return the nearest neighbors from the labeled training data as explanation. The hyperparameters of kNN were explored and optimized by the HyperOpt library[5].

Results and discussion

To analyze the performance of the proposed algorithm, we conduct the following experiment. We split the TUH corpus into a training set and a test set. We use the full training set without labels to train the DMM. Then, we pick a random stratified subset of the training set for the supervised phase. We vary the amount of data used in the supervised phase for training the kNN and obtain classification accuracies on the test dataset. These results, reported in Figure 2 (DMM+kNN), show that our system can achieve reasonable performance even at low amounts of labeled EEG data and the performance gets better as it increases. At 20% labeled data, our model reaches a similar performance to that reported by Lopez et al.[3], who used a similar pre-processing technique and trained on 100% of the data. Moreover, Figure 2 shows that if, instead of training the kNN on the latent features extracted from the trained DMM, we directly train it on the input space, then the performance is worse. This shows that the DMM is learning meaningful representations during the unsupervised training process.

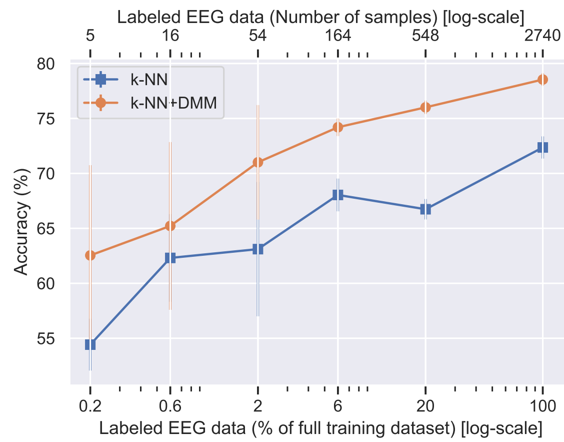

Figure 2: Test accuracy (averaged over 5 runs) vs. size of labeled dataset (top horizontal axis depicts the number of samples and bottom axis represents the percentage of full training data).

Furthermore, Figure 3 shows the t-distributed stochastic neighbor embedding (TSNE) visualization of the input space and the features learned by the DMM where blue and red dots correspond to normal and abnormal EEG respectively. The latter qualitatively depicts that the DMM learns more discriminative features in the latent space as compared to the input space.

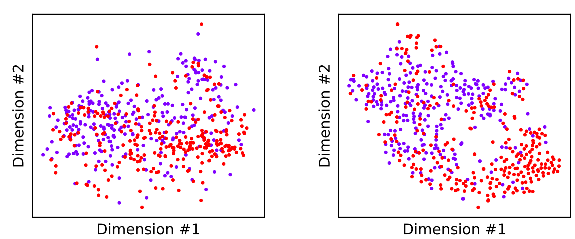

Figure 3: TSNE visualization of the input-space (left) and the latent-space features learned by the DMM (right).

Conclusion

We propose a semi-supervised learning algorithm for automated abnormal EEG identification. We envision that the proposed algorithm might be applicable to other time-series datasets which we will explore in future.

References

1. Krishnan RG, et al. Structured Inference Networks for Nonlinear State Space Models. arXiv:1609.09869. 2016.
2. Dataset Link. Temple university EEG corpus. Link: https://www.isip.piconepress.com/projects/tuh_eeg/.
3. Lopez S. Automated Interpretation of Abnormal Adult Electroencephalograms. MS Thesis, Temple University. Link: https://www.isip.piconepress.com/ publications/ms_theses/2017/abnormal/, 2017.
4. Uber. Pyro, 2017. URL http:// pyro.ai/. (Retrieved February 2019).
5. Bergstra J, et al.: Hyperopt: a Python library for model selection and hyperparameter optimization. Computational Science & Discovery. 2015;8:e014008.