A semi-supervised deep learning algorithm for abnormal EEG identification

Subhrajit Roy, Kiran Kate, and Martin Hirzel IBM Research roy.subhrajit20@gmail.com, kakate@us.ibm.com, hirzel@us.ibm.com

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 workflow that can not only extract meaningful information from large unlabeled EEG datasets but also make predictions with minimal supervision, using labeled datasets as small as 5 examples.



Figure 1: Proposed semi-supervised learning workflow for abnormal EEG identification.

1 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^{1–3}. 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 workflow for classifying EEGs, comprising an unsupervised learning phase followed by supervised learning

Machine Learning for Health (ML4H) Workshop at NeurIPS 2019 - Extended Abstract



Figure 2: TSNE visualization of the input-space (left) and the latent-space features learned by the DMM (right). Red dots correspond to normal EEGs and blue dots correspond to abnormal EEGs.

(similarly to Kingma et al.'s M1 workflow⁴). The unsupervised phase trains a Deep Markov Model (DMM)⁵ 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 dataset⁶, 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).

2 Methods

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 segment⁷. Hence, like López et al.⁷, 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)⁷ 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 DMM⁵ on the unlabeled training dataset to model the dynamics of the EEG features over time. DMM is a high-dimensional, non-conjugate model designed to be fit to large data sets. The number of latent variables in a sequence depends on the input data. Compared to a Markov model, a DMM is flexible enough to capture 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 (hence the name Deep Markov Model). This makes a DMM particularly well-suited for modeling EEG data. We used Krishnan et al.'s DMM architecture for modeling temporal dependencies⁵. Figure 2 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 shows the the DMM architecture, comprising a *generative* and an *inference* model. The *generative model* takes a sequence \vec{z} of latents and generates the corresponding observations \vec{x} . The model's transition and emission functions are modeled by multi-layered perceptrons (MLPs). The transition module uses a gated transition function without being conditioned by the observations, similar to the Markovian properties of the latents. The *inference network* serves as a variational guide^{8,9}, taking an observation sequence \vec{x} to propose corresponding latents \vec{z} . The guide is structured upon the factorization of the posterior latent distribution. The factorization is followed by using a backward (right to left) recurrent neural network (RNN), which outputs a hidden unit h_i for each time step i. A combiner function uses h_i and z_{i-1} to propose the approximate latent z_i .



Figure 3: Deep Markov Model (DMM) graphical model and guide.



Figure 4: Test accuracy (a, c) and AUROC (b) vs. size of labeled dataset (top horizontal axis: number of samples, bottom axis: percentage of full training data). Each data point shows the average and standard deviation obtained across 5 runs. (c) is the comparison of best classification performance among 11 classifiers on input-space features and latent-space features to our approach (k-NN+DMM).

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 library¹⁰. 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. We used the scikit-learn implementation¹¹ of the kNN algorithm. We chose the kNN algorithm since it offers a certain level of interpretability by explaining its classification decisions to neurologists via examples.

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. Given an unlabeled sample, the *kneighbors* method from the scikit-learn implementation of kNN returns the indices of the *k* labeled samples that are nearest to it in latent space. Using those indices, we can retrieve the corresponding labeled points in input space as a visual explanation for the prediction. We used the Hyperopt library¹² to explore and optimize the hyperparameters of kNN.

3 Results and discussion

To analyze the performance of our proposed workflow, we conduct two experiments, both using the train/test split discussed in Section 1. 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 classifier and obtain classification performance on the test dataset.

Our first experiment reports classification accuracies and AUROC on the test dataset when kNN is used as a classifier as proposed in our system. These results, reported in Figure 4(a) and 4(b), show that our system can achieve reasonable performance even at low amounts of labeled EEG



Figure 5: ROC curves of 5 runs for different sizes of the labeled dataset.

 1
 from lale.lib.sklearn import GaussianNB, GradientBoostingClassifier as GradBoost, KNeighborsClassifier as KNN, \

 2
 RandomForestClassifier as RF, ExtraTreesClassifier, QuadraticDiscriminantAnalysis as QDA, \

 3
 PassiveAggressiveClassifier as PAC, DecisionTreeClassifier as DT, LogisticRegression as LR

 4
 from lale.lib.tgboost import XGBClassifier as XGB

 5
 from lale.lib.lightgbm import LGBMClassifier as LGBM

 6
 from lale.lib.lale import HyperoptClassifier

 7
 planned_pipeline = GaussianNB | GradBoost | KNN | RF | ExtraTreesClassifier | QDA | PAC | DT | LR | XGB | LGBM

 8
 clf = HyperoptClassifier(planned_pipeline, cv = 3, max_evals = 150)

 9
 trained_clf.clf.tit(X_train, y_train)

 10
 predictions = trained_clf.predict(X_test)

 11
 accuracy = accuracy_score(y_test, predictions)

Figure 6: Code for CASH experiment discussed in Section 3.

data and the performance gets better with more labels. At 20% labeled data, our model reaches a similar classification accuracy to that reported by López et al.⁷, who used the same dataset, a similar preprocessing technique, and trained on 100% of the data. Moreover, Figure 4 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, it performs worse. This shows that the DMM is learning meaningful representations during the unsupervised training process. To further demonstrate the advantages of the proposed method, we dive deeper and show the ROC curves obtained at different levels of the size of the labeled dataset for the 5 runs in Figure 5. The ROC curves confirm the AUROC results and demonstrate that our method performs better across the spectrum of true/false positive trade-offs.

Our second experiment tests the suitability of kNN as a classifier. While kNN is an important choice for explainability, we would want to make sure that classification performance is not affected negatively. We performed combined algorithm selection and hyperparameter tuning (CASH) on 11 popular classifiers: 9 from scikit-learn¹¹ along with the XGBoost Classifier¹³ and the LightGBM Classifier¹⁴ as shown in Figure 6. We used a Python library Lale¹⁵ that simplifies CASH using Hyperopt. We used the same CASH budget of 150 Hyperopt trials as the previous experiment. Figure 6 shows a code snippet of this experiment. Figure 4(c) shows that for low amounts of labeled EEG data, our proposed approach still outperforms even the best classifier trained on input-space features. Even in the case with 100% labeled data, we gain interpretability at slightly worse performance. Interestingly, kNN on the latent space performs better than the best classifier for the latent space found using CASH. While kNN was among the 11 classifiers used, with limited budget and other classifiers in the mix, Hyperopt could not tune it to the same extent as in the first experiment.

4 Conclusion

We propose a semi-supervised learning workflow for automated abnormal EEG identification. In hospitals, while large volumes of EEG data exist, typically they are not used to design machine learning systems due to the absence of annotations. Since this data can only be reviewed by certified investigators, the amount of annotated data is bounded by the time these clinicians have. Our solution addresses this issue by using less annotated data while also extracting relevant features from the entire unlabeled corpus. We envision that the proposed workflow might be applicable to other time-series datasets which we will explore in future.

References

- Meysam Golmohammadi, Saeedeh Ziyabari, Vinit Shah, Silvia Lopez de Diego, Iyad Obeid, and Joseph Picone. Deep architectures for automated seizure detection in scalp EEGs, 2017. http://arxiv.org/abs/1712.09776.
- [2] Robin Tibor Schirrmeister, Jost Tobias Springenberg, Lukas Dominique Josef Fiederer, Martin Glasstetter, Katharina Eggensperger, Michael Tangermann, Frank Hutter, Wolfram Burgard, and Tonio Ball. Deep learning with convolutional neural networks for brain mapping and decoding of movement-related information from the human EEG, 2017. http://arxiv.org/ abs/1703.05051.
- [3] Subhrajit Roy, Isabell Kiral-Kornek, and Stefan Harrer. ChronoNet: A deep recurrent neural network for abnormal EEG identification. In *Conference on Artificial Intelligence in Medicine (AIME)*, pages 47–56, 2019. https://doi.org/10.1007/978-3-030-21642-9_8.
- [4] Diederik P. Kingma, Shakir Mohamed, Danilo Jimenez Rezende, and Max Welling. Semisupervised learning with deep generative models. In *Conference on Neural Information Processing Systems (NIPS)*, pages 3581-3589, 2014. http://papers.nips.cc/paper/ 5352-semi-supervised-learning-with-deep-generative-models.
- [5] Rahul G. Krishnan, Uri Shalit, and David Sontag. Structured inference networks for nonlinear state space models. In *Conference on Artificial Intelligence (AAAI)*, pages 2101–2109, 2017. https://aaai.org/ocs/index.php/AAAI/AAAI17/paper/view/14215.
- [6] Temple University EEG corpus, 2015. https://www.isip.piconepress.com/projects/ tuh_eeg/ (Retrieved Sept, 2019).
- [7] Silvia López de Diego. Automated interpretation of abnormal adult electroencephalograms. Master's thesis, Temple University, 2017. https://www.isip.piconepress.com/ publications/ms_theses/2017/abnormal/.
- [8] David M. Blei, Alp Kucukelbir, and Jon D. McAuliffe. Variational inference: A review for statisticians. *Journal of the American Statistical Association*, 112:859–877, 2017. https: //arxiv.org/abs/1601.00670.
- [9] Guillaume Baudart, Martin Hirzel, and Louis Mandel. Deep probabilistic programming languages: A qualitative study, April 2018. https://arxiv.org/abs/1804.06458.
- [10] Eli Bingham, Jonathan P. Chen, Martin Jankowiak, Fritz Obermeyer, Neeraj Pradhan, Theofanis Karaletsos, Rohit Singh, Paul Szerlip, Paul Horsfall, and Noah D. Goodman. Pyro: Deep universal probabilistic programming. *Journal of Machine Learning Research (JMLR)*, 20:1–6, 2019. http://www.jmlr.org/papers/volume20/18-403/18-403.pdf.
- [11] Lars Buitinck, Gilles Louppe, Mathieu Blondel, Fabian Pedregosa, Andreas Mueller, Olivier Grisel, Vlad Niculae, Peter Prettenhofer, Alexandre Gramfort, Jaques Grobler, Robert Layton, Jake VanderPlas, Arnaud Joly, Brian Holt, and Gaël Varoquaux. API design for machine learning software: Experiences from the scikit-learn project, 2013. https://arxiv.org/ abs/1309.0238.
- [12] James Bergstra, Brent Komer, Chris Eliasmith, Dan Yamins, and David D. Cox. Hyperopt: a Python library for model selection and hyperparameter optimization. *Computational Science & Discovery*, 8(1), 2015. http://dx.doi.org/10.1088/1749-4699/8/1/014008.
- [13] Tianqi Chen and Carlos Guestrin. XGBoost: A scalable tree boosting system. In Conference on Knowledge Discovery and Data Mining (KDD), pages 785–794, 2016. http://doi.acm. org/10.1145/2939672.2939785.
- [14] Guolin Ke, Qi Meng, Thomas Finley, Taifeng Wang, Wei Chen, Weidong Ma, Qiwei Ye, and Tie-Yan Liu. LightGBM: A highly efficient gradient boosting decision tree. In *Conference on Neural Information Processing Systems (NIPS)*, pages 3146–3154, 2017. http://papers.nips.cc/ paper/6907-lightgbm-a-highly-efficient-gradient-boosting-decision-tree.
- [15] Martin Hirzel, Kiran Kate, Avraham Shinnar, Subhrajit Roy, and Parikshit Ram. Type-driven automated learning with Lale, May 2019. https://arxiv.org/abs/1906.03957.