Epileptic Seizure Prediction

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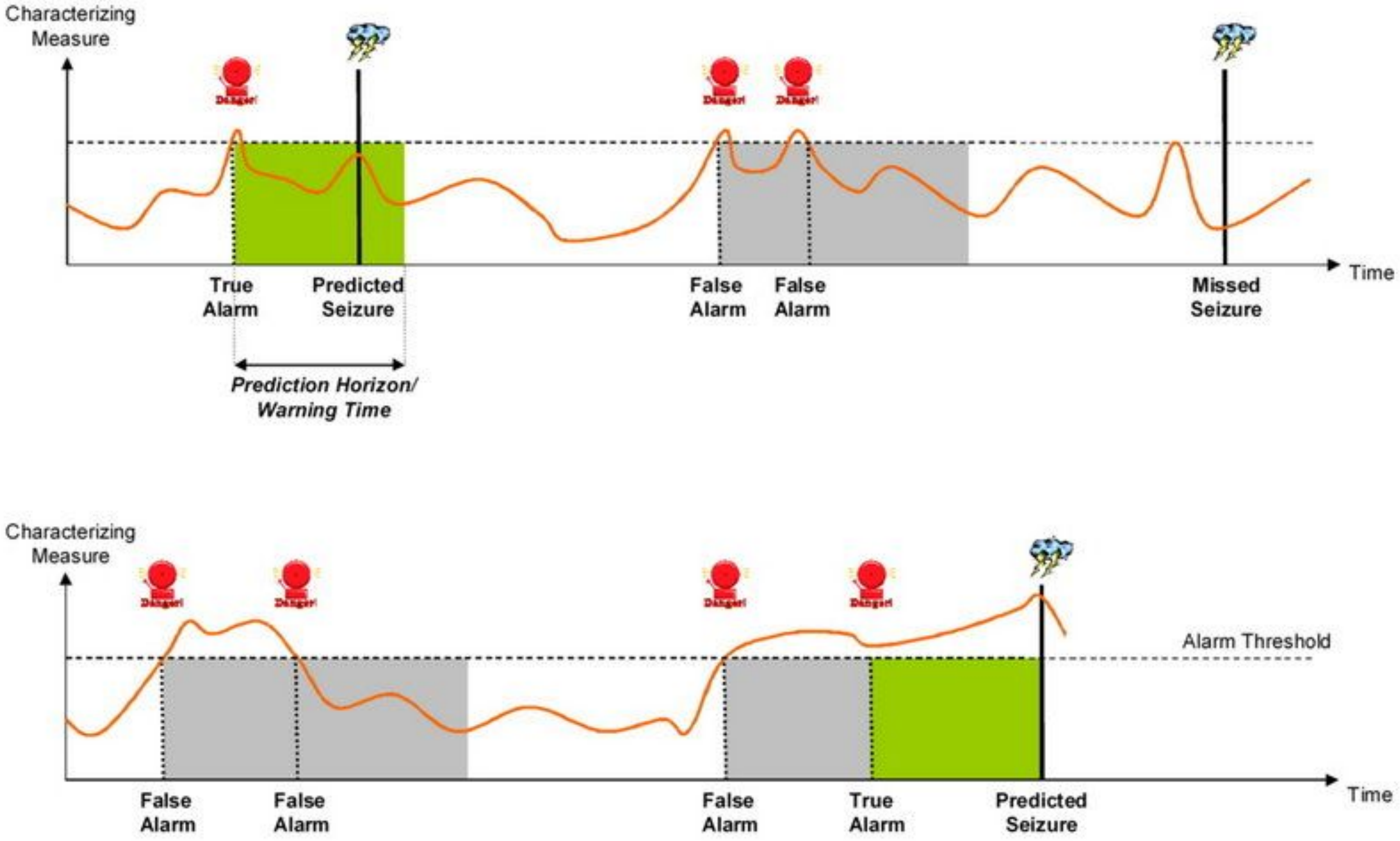
Project Background

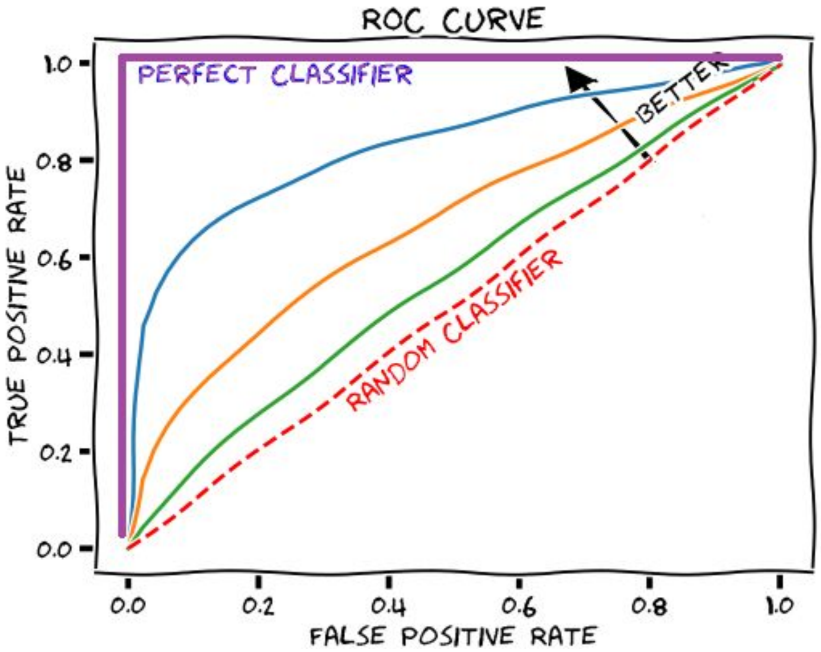
- Epilepsy and seizure onset affect a large number of people
- Emerging seizure detection & prediction applications
  - A variety of applications that prioritize different performance metrics
  - Difficult to choose hyperparameters & models
  - Thus, we want to evaluate how different model/parameters affect performance
- Seizure prediction
  - definition & metrics
- Research questions:
  - Evaluating prediction horizon:
  - Evaluating the prior: how does preictal & interictal sample sizes affect performance
  - Evaluating the model: SVM & LSTM network

True and False Warnings



Performance Metrics

- Confusion matrix
  - Sensitivity
  - # seizure with alarm / total # seizure
  - Specificity
  - # false positive per hour
- Receiver Operating Characteristics
  - Area under ROC curve



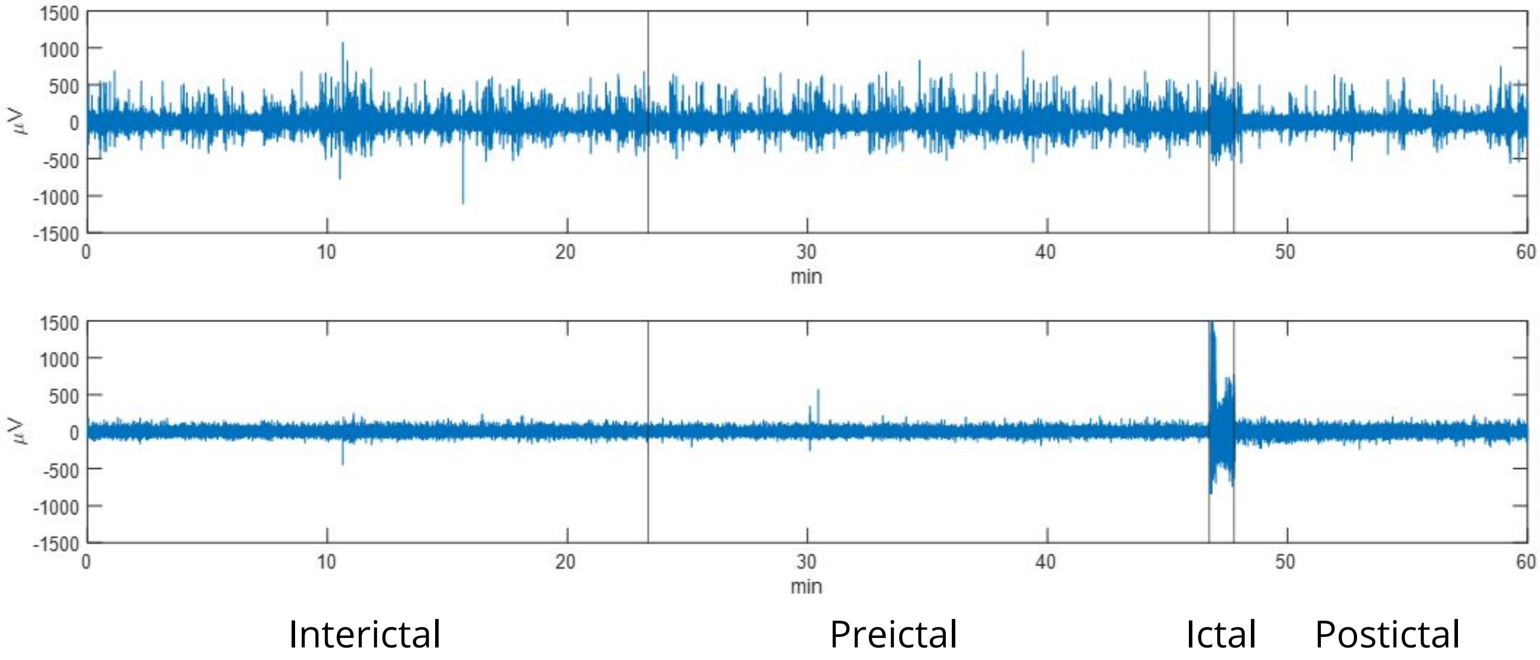
Methods

- Data labeling & preprocessing
  - Remove artifacts
- Feature Extraction
  - Spectral power selected based on standard EEG frequency bands are calculated using sliding 20-second-long and half-overlapped windows [3]
- Classification Models
  - Support Vector Machine (SVM)
  - Long Short-term Memory (LSTM) network
- Hyperparameters to Evaluate
  - Prediction Horizon (PH) or Warning time
  - Priors for interictal class & preictal class: ratio of interictal sample/preictal sample

Dataset

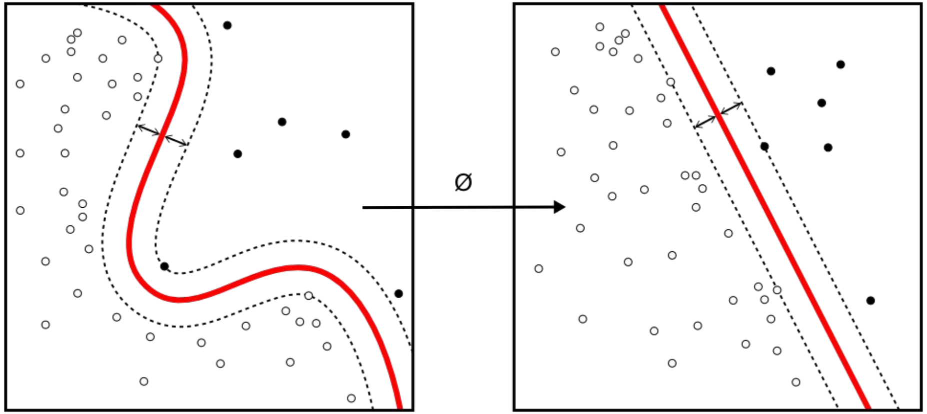
- CHB-MIT Scalp EEG Database
  - "Application of machine learning to epileptic seizure onset detection and treatment"
    - By Ali Shoeb
  - Manually labeled by clinicians
- 23-electrode EEG recordings
  - Choose 6 channels that best differentiates preictal & interictal class
- 24 subjects, each with 24 hours of recording
  - Preictal samples: epoch from time period of length P before seizure onset
  - Interictal samples: epoch from randomly selected time of length H

Epileptic Seizure Time Series Data



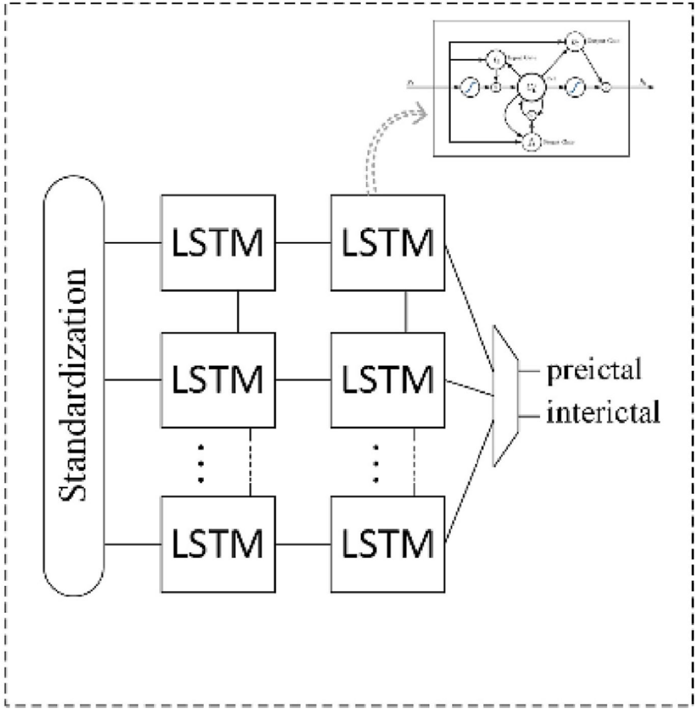
SVM

- Supervised binary classifier based on constraint optimization
- Maximizes margin between decision boundary
- Fully specified by support vectors



LSTM [4]

- Assesses the significance of each feature
- Internally evaluates feature space for each patient
- Assigns entire sequence of EEG segments instead of each individual EEG segment



Expected Core Results

- Area under ROC curves VS prediction horizon length
    - How the values in confusion matrix change as PH changes
    - A guidance to choose prediction horizon length for different applications
    - Compare area under curve for each classifier
- Prediction discrepancy rate VS prediction horizon length
    - Characterize the precision of onset prediction
    - Discrepancy rate = difference between PH and (actual onset - alarm) / PH

Discussion & Future Work

Things to improve with current evaluations:

- Patient specific to a generalized model for all patients that account for different types of seizures
- Considering all channels / choose best channels for each patient
- More features such as mean spike rate

Citations

1. Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, Mietus JE, Moody GB, Peng C-K, Stanley HE. PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals (2003). Circulation. 101(23):e215-e220.
2. Ali Shoeb. Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment. PhD Thesis, Massachusetts Institute of Technology, September 2009.
3. Park, Y., Luo, L., Parhi, K.K. and Netoff, T. (2011), Seizure prediction with spectral power of EEG using cost-sensitive support vector machines. Epilepsia, 52: 1761-1770.
4. Kostas M. Tsiouris, Vasileios C. Pezoulas, Michalis Zervakis, Spiros Konitsiotis, Dimitrios D. Koutsouris, Dimitrios I. Fotiadis, A Long Short-Term Memory deep learning network for the prediction of epileptic seizures using EEG signals, Computers in Biology and Medicine, Volume 99, 2018, Pages 24-37.