Predicting Seizures in Intracranial EEG Recordings

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***Abstract*—If seizure forecasting systems could reliably identify periods of increased probability of seizure occurrence, patients who suffer from epilepsy would be able to avoid dangerous activities and lead more normal lives. The goal of this project is to differentiate between the preictal and interictal states by analyzing intracranial EEG recordings. Data for each hour are organized into six ten-minute time sequences. Logistic Regression and support vector machines (SVM) are applied to each time sequence to calculate the average test false negative rate. The idea of combining data from various time sequences is also experimented with to examine if false negative rates can be reduced. The results show that SVM provides better prediction results for patients, and that combining training examples from different time sequences does not help improve prediction results. Since the pathogenesis of epilepsy may vary across different species, applying the same training models to both dogs and patients may be problematic.**

***Keywords*—seizure, classification, logistic regression, support vector machines (SVM)**

I. Introduction

Epilepsy, characterized by the occurrence of spontaneous seizures, afflicts nearly 1% of the population worldwide. Epilepsy sometimes leads to loss of consciousness and control of bowel or bladder function, creating not only the risk of serious injury, but also an intense feeling of helplessness that strongly impacts the everyday lives of epileptic patients. If computational algorithms could reliably predict seizure occurrences, devices designed to warn patients of impending seizures would help patients avoid potentially dangerous activities. Also, medications could be taken only when necessary to reduce overall side effects.

An epileptic patient's brain activity can be classified into 4 states: Interictal (between seizures, or baseline), Preictal (prior to seizure), Ictal (seizure), and Post-ictal (after seizures). The primary challenge in seizure forecasting is to differentiate between the preictal and interictal states. Past research on seizure forecasting based on EEG has pointed out two difficulties. First, preictal and interictal EEG patterns across patients (and dogs) vary considerably. Second, EEG is highly complex and varies over time.

II. Objective

This project represents an attempt to demonstrate the existence and accurate classification of the preictal brain state in dogs and humans with naturally occurring epilepsy.

III. Data

Data used in this project, which we obtained from a Kaggle competition, are intracranial electroencephalography (EEG) recordings sampled from dogs and patients. The training data are organized into ten-minute EEG clips labeled "Preictal" for preseizure data segments, or "Interictal" for non-seizure data segments. Both the preictal and interictal training data segments are numbered sequentially. The sequence, numbered 1 - 6, represents the index of the data segment within an hour. For example, the sequence 6 preictal data segment represents the EEG data between the 51st minute and the 60th minute in the hour before a seizure occurrence. The test data, which are preictal, are also organized into ten-minutes EEG clips but are provided in random order. This allows us to pick any test data segment to verify the accuracy of every time sequence's training model.

Preictal training and test data segments cover one hour prior to seizure with a five-minute seizure horizon (Figure 1). Similarly, one hour sequences of interictal ten-minute data segments are provided.

A. EEG recording for dogs

Intracranial EEG for dogs are sampled from 16 electrodes at 400 Hz. Thus, the canine data contain 16 features, and the data for each ten-minute time sequence contain $16 \times 240,000$ data points. Each

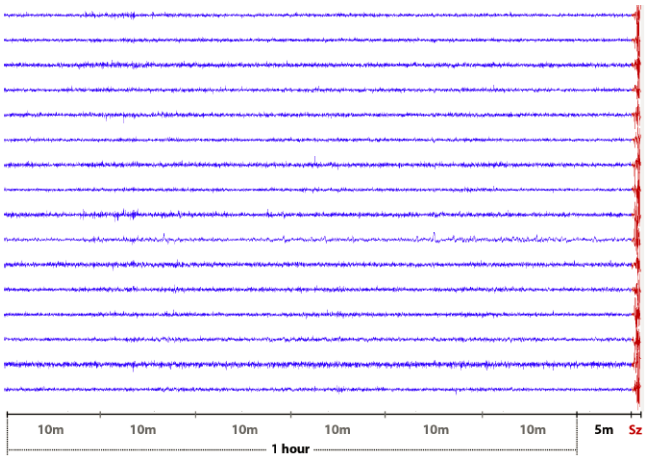


Fig. 1: EEG recordings cover one hour prior to seizure with a five-minute seizure horizon

data point represents the EEG recording for electrode i at some time t. The competition provided EEG recordings for 5 dogs. We choose to use the first hour (6 sequences) training data for dogs 1 and 5.

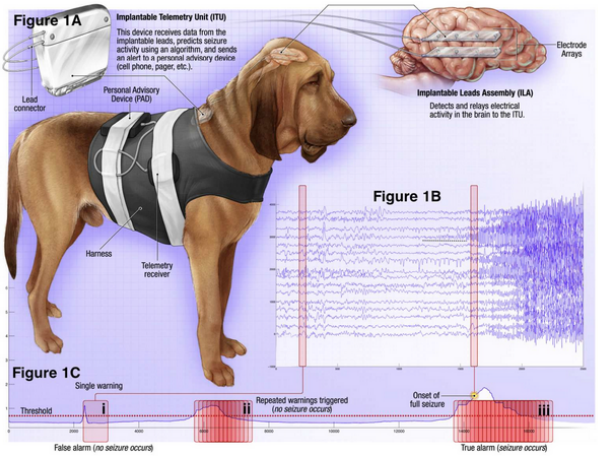


Fig. 2: EEG recordings cover one hour prior to seizure with a five-minute seizure horizon

B. EEG recording for patients

Intracranial EEG for patients are sampled from 15 electrodes at 5,000 Hz. Thus, the human data contain 15 features, and the data for each ten-minute time sequence contain $15 \times 3000,000$ data points. The competition provided EEG recordings for 2 patients. We choose to use the first hour (6 sequences) training data for patient 1.

IV. Models

A. Logistic Regression

This is a binary classification problem, so the first intuitive choice is logistic regression with sigmoid function $h_\theta(x)$. We apply stochastic gradient ascent to the following equation:

$$\theta_j := \theta_j + \alpha(y^{(i)} - h_\theta(x^{(i)}))x_j^{(i)}$$

$$\text{where} \quad h_\theta(x) = g(\theta^{\mathrm{T}}x) = \frac{1}{1+e^{-\theta^{\mathrm{T}}x}}$$

A fixed learning rate α is used, and the implementation slowly decreases α to some value around zero to ensure the algorithm converges to the global minimum.

B. Support Vector Machine (SVM)

The goal of SVM classification is to establish and test a mapping $x \mapsto y$ from EEG spectral features to either a preictal or an interictal label. To achieve this goal, we use C-support vector classification which solves the following primal optimization problems:

$$\min_{w,b,\xi} \quad \frac{1}{2}w^{\mathrm{T}}w + C\sum_{i=1}^{l}\xi_i$$

$$\text{subject to} \quad y_i(w^{\mathrm{T}}\phi(x_i) + b) \geq 1 - \xi_i,$$
$$\xi_i \geq 0, i = 1, \ldots, l,$$

where $\phi(x_i)$ maps x_i into a higher-dimension space and $C > 0$ is the regularization parameter. We use the radial basis function (RBF) kernel:

$$K(x_i, x_j) = \exp(-\gamma\|x_i - x_j\|^2)$$

There are two model parameters: C and the kernel factor γ. Using the grid search approach, we try all combinations of C and γ, and select the combination that produces the maximum classification accuracy. The search range for $\log C$ is from -1 to 6, and for $\log \gamma$ is from -3 to 4.

We then run C-SVM with the selected C and γ. We use the same C and γ for each (individual and combined) time sequence.

C. Calculating False Negative Rates

Data for dogs and patients are categorized as either preictal or interictal. For logistic regression, we label preictal data examples as positive ("1"), and interictal data examples as negative ("0"). For SVM, we label preictal data examples as positive ("1"), and interictal examples as negative ("-1"). All test examples should be predicted as preictal, which is positive ("1"). We are interested in the false negative rate, which is the fraction of the preictal test examples that the algorithm incorrectly predicts to be interictal. A small false negative rate implies a high probability of seizure occurrences. In the following equation, R_{FN} stands for false negative rate.

$$R_{FN} = \frac{\text{\# of test examples predicted to be interictal}}{\text{\# of test examples}}$$

We apply logistic regression to a time sequence 10 times using 10 different test data segments, and compute the average of the 10 false negative rates. We repeat this step for the other five time sequence and compare the average false negative rates. (For SVM, the process is the same except we use 5 different test data segments). The time sequence with the lowest average false negative rate is the best in predicting seizures. We then combine some continuous or randomly selected ten-minute sequences, and run the algorithms again, calculate and compare the average false negative rates to observe whether combining time sequences improves the accuracy of seizure predictions.

V. Results

A. SVM parameter selection

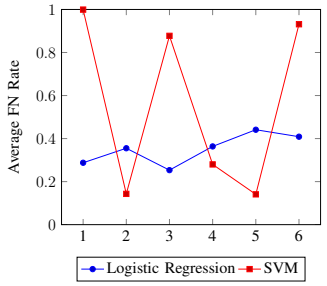
Because of the extremely long training time, we select the last $16 \times 80,000$ examples in the canine data, and the last $15 \times 100,000$ examples in the human data to grid-search the optimal values of C and γ.

	C	γ	Accuracy
Dog 1	8	2	77.8919%
Dog 5	8	2	84.9231%
Patient 1	1	2	100.0%

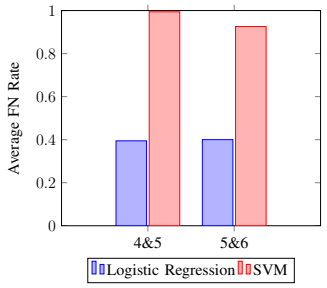
TABLE I: Cross Validation Results for C and γ

B. Dogs

We use all the canine data, $16 \times 240,000$, to run logistic regression. Due to the aforementioned time constraint, we use only the last $16 \times 80,000$ canine training examples in each time sequence to run SVM. We then combine sequences 1, 6 and sequences 3, 6 to examine if the accuracy can be improved. See Figure 3, 4, and Table II for Dog 1 and Dog 5 results.



(a) Sequences 1 to 6

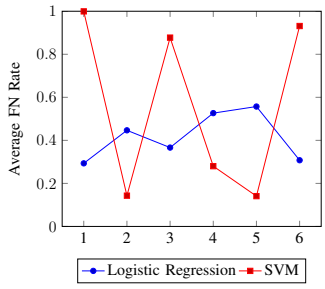


(b) Combined Sequences

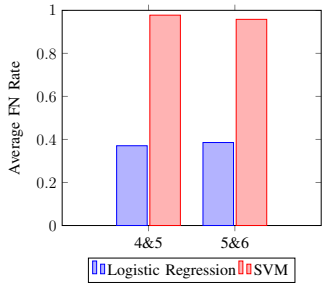
Fig. 3: Dog 1 Results

Dog 1	Logistic Regression	SVM
seq 1	0.287635	0.999345
seq 2	0.355074	0.143058
seq 3	0.253306	0.877420
seq 4	0.363520	0.279950
seq 5	0.441084	0.140827
seq 6	0.408698	0.931298
seq 1&6	0.394584	0.977588
seq 3&6	0.400128	0.958088
Dog 5	**Logistic Regression**	**SVM**
seq 1	0.293179	0.999345
seq 2	0.446686	0.143058
seq 3	0.366449	0.877420
seq 4	0.526572	0.279950
seq 5	0.557142	0.140827
seq 6	0.307605	0.931298
seq 1&6	0.370788	0.977588
seq 3&6	0.385755	0.958088

TABLE II: Dogs 1 and 5 Results



(a) Sequences 1 to 6



(b) Combined Sequences

Fig. 4: Dog 5 Results

C. Patients

We use all the human data, $15 \times 3,000,000$, to run logistic regression. Due to the aforementioned time constraint, we use only the last $15 \times 100,000$ training examples in each time sequence to run SVM. We then combine sequences 4, 5 and sequences 5, 6 to examine if the accuracy can be improved. See Figure 5 and Table III for Patient 1 results.

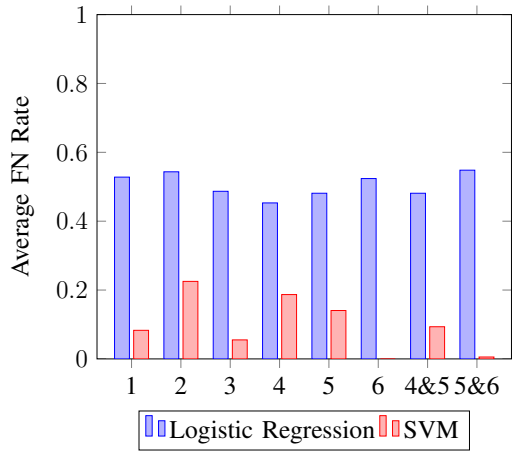


Fig. 5: Histogram of Patients 1 Results

VI. Discussion & Conclusion

Based on the results of dogs and patients, we observe that combining time sequences does not improve the results. None of the combined sequences produce false negative rates smaller than the minimum of the individual sequences' false negative rates. Although this contradicts the intuitive conjecture that adding more data should improve results, the finding is not entirely surprising because previous research has pointed out that EEG is highly complex and varies over time. If there is little correlation between any time sequences, continuous or random selected, then combining sequences would only add noise to each model and should not be expected to yield better predictions.

Patient 1	Logistic Regression	SVM
seq 1	0.527982	0.083046
seq 2	0.543429	0.225166
seq 3	0.486822	0.055214
seq 4	0.453055	0.186868
seq 5	0.481161	0.140582
seq 6	0.523835	0
seq 4&5	0.481130	0.093442
seq 5&6	0.548151	0.005538

TABLE III: Patient 1 Results

Interestingly, while sequences 1, 3, 6 in the human data give low SVM false negative rates, sequences 1, 3, 6 in the canine data give surprisingly high SVM false negative rates (close to 1). Our surmise is that logistic regression may not have classified the preictal and interictal states correctly because we omitted the process of cross validation before performing logistic regression.

We observe some patterns from the results of the two dogs. The logistic regression false negative rates fluctuate (increase, decrease, increase, and finally decrease), while the SVM false negative rates exhibit an entirely opposite, and much more volatile trend. These trends may be evidence that pre-seizure brain activities exhibit a high degree of fluctuation. If future medical devices can detect such fluctuation, then warning epileptic patients of impending seizures may be achievable. This approach may be more effective in forecasting seizures than solely focusing on the false negative rates of specific time sequences.

According to the results of patient 1, SVM outperforms logistic regression as expected. SVM results are all $< 25\%$. This means that we are able to predict seizures with reasonable accuracy. However, all logistic regression false negative rates are around 50%. Such relative "uniformity" makes it difficult to interpret which time sequences are better in seizure

forecasting than others. The 0 false negative rate for sequence 6 is surprising. However, since sequence 6 closely precedes seizures, the brain's behavior is expected to differ drastically from that during non-seizure periods, thus the low false negative error.

After comparing the results between dogs and patient, we observe that sequence 6 has the lowest false negative rate for patient 1 but not for dogs. This inconsistency implies that the pathogenesis of epilepsy may be different across different species. Hence, applying the same training models to both dogs and patients may be problematic.

VII. Future

- This competition also provided data for another three dogs and one patient. Furthermore, for each dog and each patient, multiple hours' worth of data are available. We could run the same algorithms several more times to observe patterns and anomalies. The new results could be used to verify our conclusions.
- Instead of 6 sequences, we could divide an hour into 12 or more sequences. That would give us a better understanding of the pathogenesis of epileptic seizures and the variation of the prediction results within shorter time intervals.
- Logistic regression does not work well for patient 1. The reason might be that human brains are much more complicated than canine brains. We could apply logistic regression with regularization to ameliorate the high variance problem.
- SVM does not work well for dogs at sequences 1, 3 and 6. The cause is the large number of support vectors. Since the the number of support vectors determines the maximum number of misclassified data points, we could apply ν-SVM instead of C-SVM, and set $\nu = 0.5$. This approach would force only half of our data to be support vectors and implicitly adapt C.

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