Laboratory Earthquake Prediction

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Abstract. In this paper we present a method for predicting the timing of laboratory earthquakes using machine learning. If a similar approach can be applied to improve natural earthquake prediction it will save lives. We use data collected from a laboratory experiment which exhibits similar behavior to natural earthquakes. We train a machine learning algorithm using half of the data, then predict using the other half. We compare predicted versus actual timings to measure the algorithm's accuracy. The result shows that the timing of laboratory earthquakes can be predicted up to 16 seconds in advance with 71% accuracy. The method and result demonstrates that machine learning can help if it can be scaled from the laboratory experiment to natural earthquakes.

1 Introduction

Earthquakes cause mass destruction and loss of life. Traditional earthquake prediction methods have relied on recurrence interval based models. Because the recurrences are not constant predictions can only be made within decade spanning time windows. One such model predicted that a magnitude 6 earthquake would occur between 1985 and 1993 in the Parkfield California area but no significant event occurred until 2004 [1].

Researchers imitate natural earthquakes in the laboratory by placing rocky material between steel blocks and applying shear stress to induce slipping. Recent improvements in the instruments [2] used to measure signals have enabled the collection of larger volume data from more realistic and unpredictable laboratory earthquakes. However processing the data and detecting patterns in it has become more difficult to work with. In this paper we demonstrate that machine learning can be used to detect patterns and make predictions from realistic, unpredictable laboratory earthquake data [4].

We use data which was collected by the Los Alamos National Laboratory and provided to the public via a Kaggle competition [4]. It consists of 629 million acoustic signal observations and an accompanying record of the time remaining until a laboratory earthquake (failure) occurred [2]. We calculate additional statistical measures such as variance, kurtosis and skew for each observation. We use half of the data to train a machine learning algorithm. With the remaining half of the data, using only the acoustic signal as input we calculate a prediction of the time remaining until failure. We measure accuracy by comparing the predicted to actual remaining time to failure from the original data.

The result shows that the timing of laboratory earthquakes can be predicted up to 16 seconds in advance with 71 percent accuracy.

The data, hardware and software allows us to predict impending earthquakes. However we only know 8-16 seconds before failure. Therefore practical applications may be limited. This may prove useful but only applies to laboratory experiments. This could be used in industry perhaps in researching materials for wallboard, machine parts and others.

2 Background

Statistic	Description	Formula
$\left(\frac{a^2+b^2}{c^3}\right) = 1 \quad \text{if } c \neq 0 \text{ and if } a, b, c \in \mathbb{R} \ .(1)$	Row1Col1	Row1Col2
1	Row1Col1	Row1Col2
1	Row1Col1	Row1Col2

Table 1. First Table

$$\left(\frac{a^2+b^2}{c^3}\right) = 1 \quad \text{if } c \neq 0 \text{ and if } a, b, c \in \mathbb{R} \ . \tag{2}$$

3 Data

The data we analyze is provided by LANL's 2019 Kaggle competition [4]. It was collected using a three-block assembly with two gouge layers placed in a bi-axial stress configuration. Two 5mm thick fault gouge layers were placed between the three blocks, which were held in place by a fixed normal load. The gouge material was comprised of beads with diameter 105-149 mm. The central block was sheared at constant displacement rate. The two data streams recorded were the shear stress and the acoustic signal. While the gouge material was in a critical shear stress regime, the shear stress abruptly dropped which indicated gouge failure(a laboratory earthquake). As applied load progressively increased, the recurrence of laboratory earthquakes progressively decreased. At smaller applied loads the slips became a-periodic. The acoustic particle acceleration was measured on the central block.

LANL is certain the signal recorded for analysis is the acoustic signal emanating from the fault

The acoustic data are integers ranging from -5515 to 5444 and have mean of 4.52. The time to failure is in seconds. We can see that acoustic data shows large fluctuations just before the failure and recurs cyclically. Failures can be predicted visually as cases when huge fluctuations in the signal are followed by smaller signal values. This could be useful for predicting time to failure changes from 0 to high values.

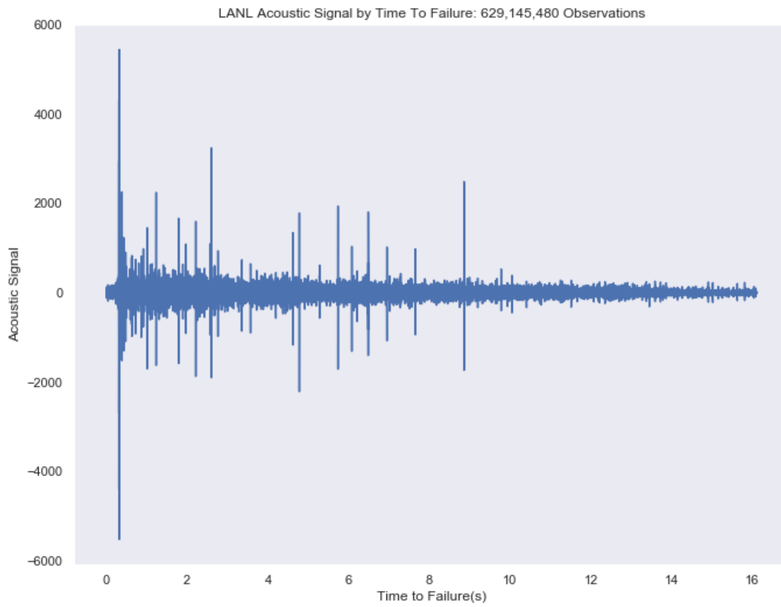


Fig. 1. The magnitude of each seismic signal and the time remaining before the next laboratory earthquake. There are 16 lab earthquakes. The shortest time to failure is 1.5 seconds for the first earthquake and 7 seconds for the 7th, while the longest is around 16 seconds.

Table 2. Sample of Data Provided

Index	**Seismic Signal**	**Time to Failure**
0	12	1.469099998474121
1	6	1.469099998474121
2	8	1.469099998474121
3	5	1.469099998474121
4	8	1.469099998474121

4 Methods and Experiments

Our goal is to predict the time remaining before the next failure using only moving time windows of the acoustic data. We divide our data into windows containing 150,000 observations each (0.0375 seconds of seismic data)therefore 4194 windows. From each time window, we compute a set of 98 potentially relevant statistical features (e.g., mean, variance, kurtosis). We apply machine learning techniques such as the Random Forest Regressor, XGB Regressor, Decision

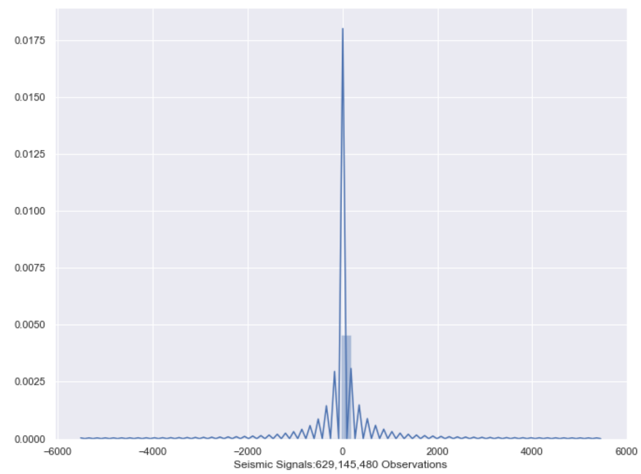


Fig. 2. The distribution of seismic signal measurements by LANL

Table 3. Seismic Signal Stats

Index	**Seismic Signal**
count	6.29145480
mean	4.47708428
std	2.61278939
min	9.55039650
25	2.62599707
50	5.34979773
75	8.17339516
max	1.61074009

Tree Regressor, LGBM Regressor, Extra Trees Regressor to the new continuous windows of values.

Similar to the LANL study we create new features separated into two main classes: Distribution of signal's energy: we use couple of higher order moments of the acoustic data to capture the evolution of the signal's energy. Within each time window we compute the signal's normalized mean, minimum, maximum and higher moments (variance, skewness, kurtosis).

Precursors: the system enters a critical state when close to failure. We rely on different percentiles and thresholds to monitor this precursory activity. We use the 1st - 9th and 91th - 99th percentiles. Our thresholds measure the count of observations that the acoustic signal spends over a threshold value f0 and under a threshold value f1.

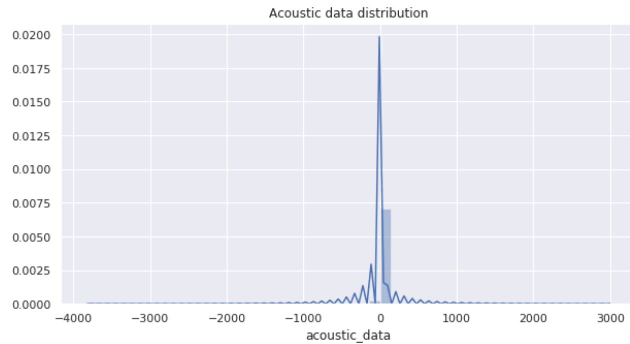


Fig. 3. 1% random sample from 629,143,480 observations

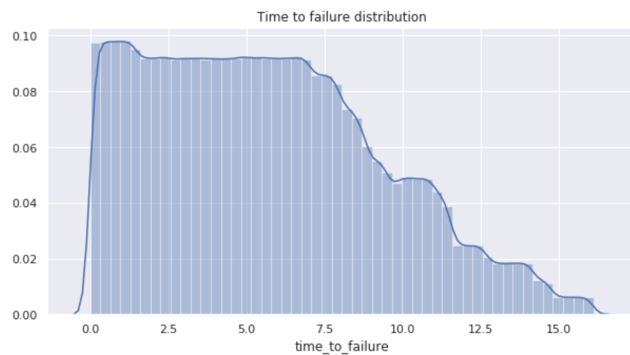


Fig. 4. The min value is very close to zero and the max is 16 seconds.

In order to avoid correlation between new features we applied principal component analysis. Instead of using 98 features, we created just 10 that represented 99.9 percent of the full data variation. We use a 70/30 random split of the full time series as training and testing data sets respectively. We compute regularization hyper-parameters for each machine learning predicting technique by random grid search based on a 3-fold cross-validation.

4.1 Data Transformations

The distribution of time to failure is right skewed. We apply a square root transformation to normalize it and improve the prediction models. It is still not ideally normal, but has improved.

Fig. 5. We checked how both variables changed over time. The red line is the acoustic data and the blue one is the time to failure. On a plot above we can see, that training data has 16 earthquakes. The shortest time to failure is 1.5 seconds for the first earthquake and 7seconds for the 7th, while the longest is around 16 seconds.

4.2 Algorithms

4.3 Recursive Neural Network

LSTM is a type of RNN that helps us deal with vanishing or exploding gradients (incorrect slope). For example most of our acoustic signal observations are within x however more extreme signals occur just before failure. The extreme differences between these observations can skew the accuracy of more traditional RNN algorithms.

LSTM separates the long term(fault slip) from short term (slow slip) Hidden state= memory from prior observations Typical RNN input+priorhiddenstate¿tanh (-1,1) activation function¿new hidden state LSTM is same but includes gates to determine what information is included in hidden state and what is not.

The gates are rnn's themselves.

input+priorhiddenstate¿sigmoid (0,1) activation function¿new hidden state. 0, 1 allows us to forget or remmeber Patrick Yam: LSTM cannot handle data with 150000 sequence length therefore we wavenet in the earlier layers as feature extraction and reduce the sequence length to 150.

Forget gate decides what to include 1, or exclude 0. https://www.youtube.com/watch?v=2GNbIKTKCfE https://www.youtube.com/watch?v=8HyCNIVRbSU

4.4 Auto Regressive integrated Moving Average (ARIMA)

The data shows evidence of non-stationarity (the mean, variance change over time). We use an ARMIA model to analyze the changing means and variance. This this model also can also account for white noise.

ARIMA(0,0,0)

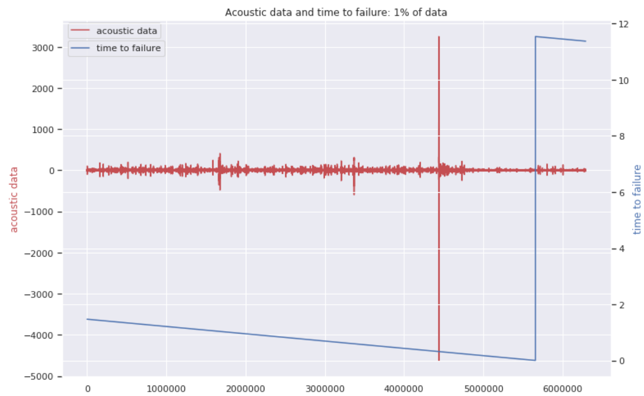


Fig. 6. On this zoomed-in-time plot we can see that actually the large oscillation before the failure is not quite in the last moment. There are also trains of intense oscillations proceeding the large one and also some oscillations with smaller peaks after the large one. Then, after some minor oscillations, the failure occurs. Interesting thing to check is the time between high levels of seismic signal and the earthquakes. We are considering any acoustic data with absolute value greater than 1000 as a high level

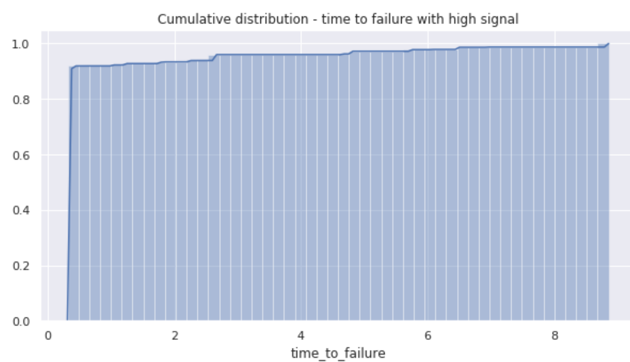


Fig. 7. More than 90% of high acoustic values are around 0.31 seconds before an earthquake

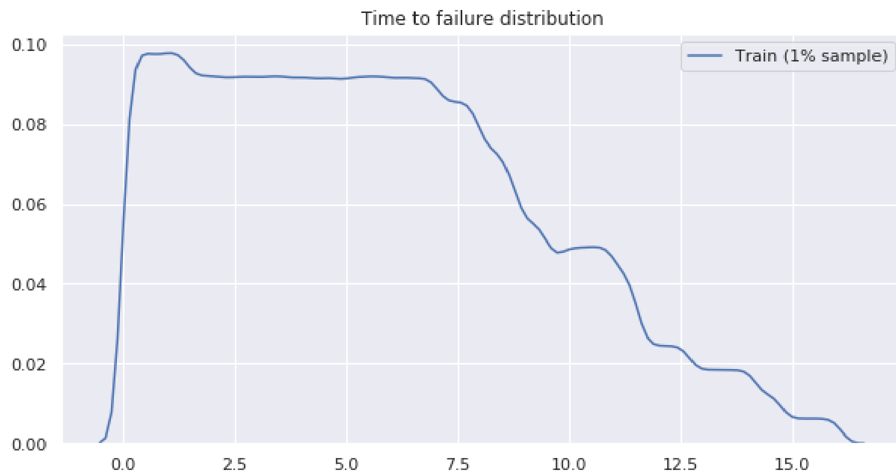


Fig. 8. Distribution of Time to Failure showing right skew

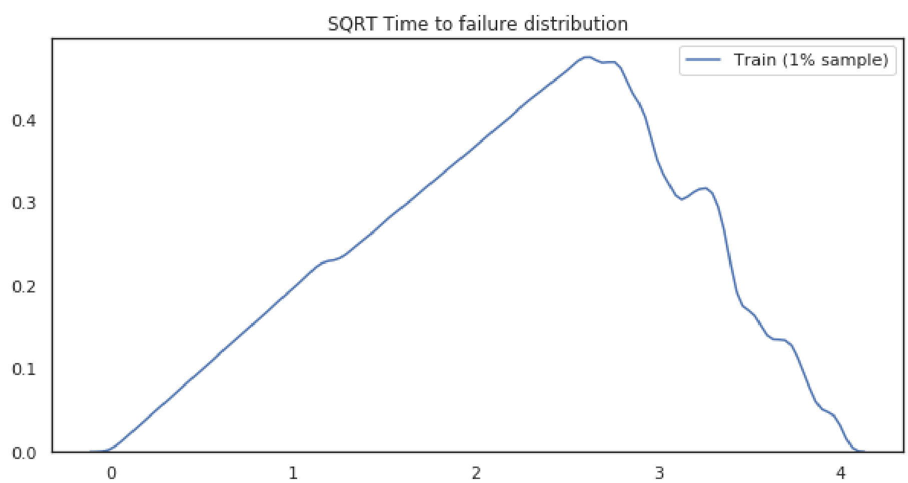


Fig. 9. Distribution of Time to Failure showing improved normality after applying square root

4.5 Gradient Boosting Decision Tree

5 Results

We run 5 different techniques on a train data set (70 percent of the full data) before principal component analysis and after. Principal component analysis did not improve our findings significantly, that is why we are not represent those results here. For each model we provide hyper-parameters details for future reproducibility (Table 2). When making a prediction (red curve), we emphasize that there is no past or future information considered: each prediction uses only the information within one single time window of the acoustic signal. We quantify the accuracy of our model using R2 (the coefficient of determination) and MAE (mean absolute error), applying predicting model on a 30 percent of the full data (test data).

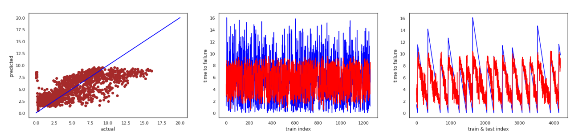
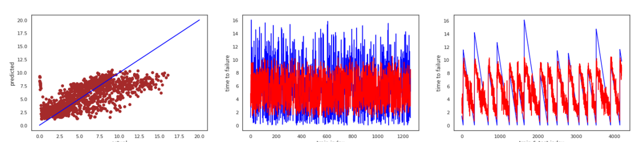
Method	Results
RandomForestRegressor 'min_samples_split': 12, 'min_samples_leaf': 4, 'max_features': 'sqrt', 'max_depth': 8 n_estimators=1000	mean_absolute_error: 2.0322193397002044 r2_score: 0.4953230388182709 
XGBRegressor 'colsample_bytree': 0.9059046706163597, 'gamma': 4.395361343977617, 'learning_rate': 0.22367318773362826, 'max_depth': 21, 'min_child_weight': 69.30113404571125, 'reg_alpha': 7.681525516492065, 'subsample': 0.8919123509453631 nthreads=-1, n_estimators=1000	mean_absolute_error: 2.0634676560951557 r2_score: 0.48347777795889124 

Fig. 10. Results by Model

6 Analysis

The most accurate results with coefficient of determination 0.5 and mean absolute error 2.03 we got using Random Forest Regressor. The most important

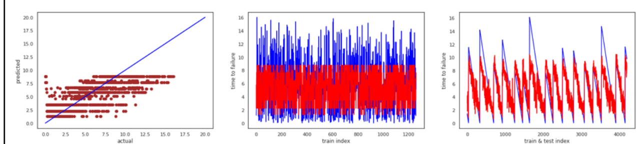
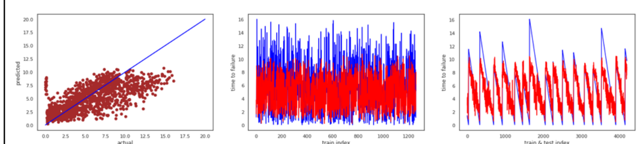
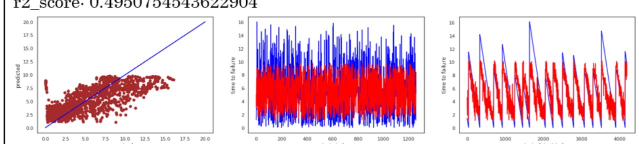
DecisionTreeRegressor 'max_depth': 4, 'max_features': 'sqrt', 'min_samples_leaf': 12, 'min_samples_split': 70	mean_absolute_error: 2.066672622791363 r2_score: 0.4703327918288054 
lgb.LGBMRegressor 'feature_fraction': 1, 'lambda_l1': 0.6, 'lambda_l2': 0.4, 'learning_rate': 0.05, 'max_depth': 8, 'min_data_in_leaf': 10, 'min_gain_to_split': 0.01, 'num_leaves': 44, 'random_seed': 13, 'subsample': 0.9 n_estimators=10000	mean_absolute_error: 2.089058482904736 r2_score: 0.43881088754719744 
ExtraTreesRegressor 'max_depth': 11, 'max_features': 'auto', 'min_samples_leaf': 40, 'min_samples_split': 200, 'min_weight_fraction_leaf': 0.010872755116371424, 'n_estimators': 200	mean_absolute_error: 2.0338440361453003 r2_score: 0.4950754543622904 

Fig. 11. Results by Model

features, shown on Fig. 7, suggest to check our data for correlated features, since rolling standard deviations show the same patterns. Plus in order to improve our predicting model, we need to get rid of features that have importance equal to 0 or close to 0, such as hypermoment, minimum, maximum and some of the rolling means. Currently we are working on improving of the model to make prediction for the beginning and the end of the one quake cycle. As you can see on a Fig. 1, seismic waves with small voltage are in our interest. Random forest model accurately predicts failure across load level, but hardly can predict outliers. It means that we still need to think about new features that we missing. Precursors that we choose during feature engineering were not good enough when the system enters a critical state close to failure.

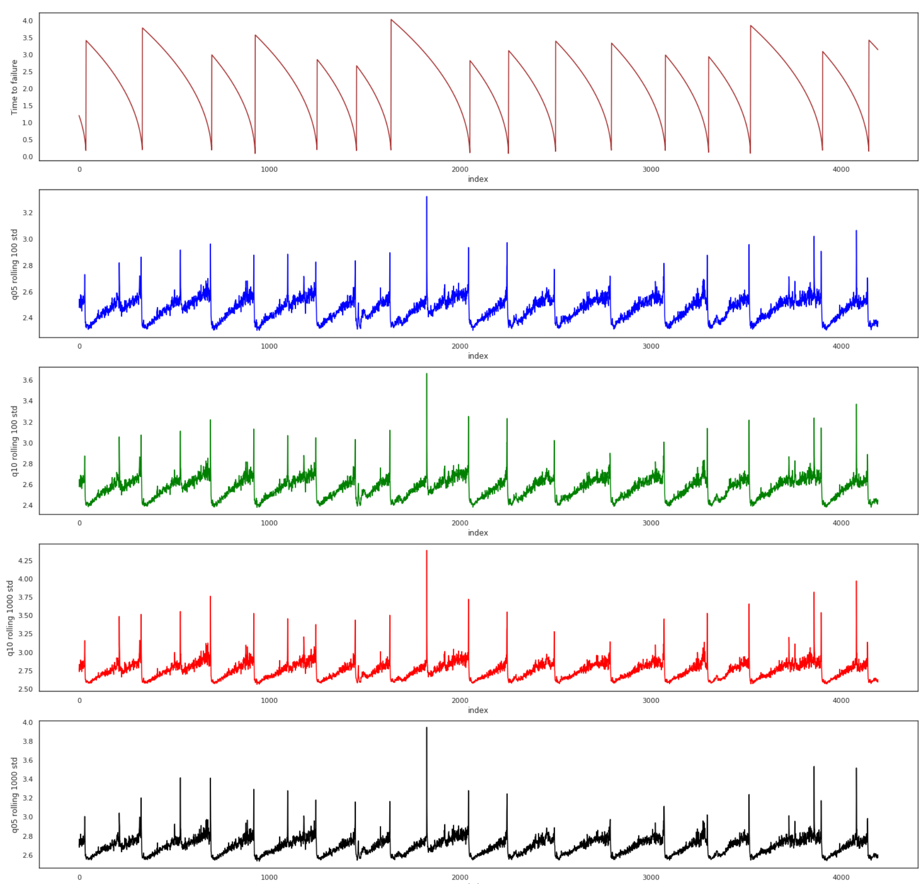


Fig. 12. Predictions by Model

7 Ethics

Our responsibility to report our results has to be weighed with our responsibility not to cause social disturbance. If the method demonstrated in this paper is scaled and applied to predict natural earthquakes this balance must be considered. Unwarranted predictions could have affects on personal property value while failure to report warranted predictions could result in loss of life. [8].

8 Conclusions

The results show that laboratory earthquakes can be predicted with 71% accuracy up to 16 seconds in advance. The acoustic signal measurement is an indicator of imminent failure. The recurrence interval is not needed to achieve the 71% accuracy prediction.

In this study we are using only 157 seconds of data. Future work should introduce higher volumes of data to determine if accuracy can be improved. Also the combination of the acoustic signal and the recurrence interval should be tested to determine it's affect on accuracy.

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