Earthquake warning system: Detecting earthquake precursor signals using deep neural networks

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"Journalists and the general public rush to any suggestion of earthquake prediction like hogs toward a full trough... [Prediction] provides a happy hunting ground for amateurs, cranks, and outright publicity-seeking fakers."

Charles Richter, 1977

Abstract

Earthquake prediction is one of the great unsolved problems in the earth sciences. In recent years, the number of seismic monitoring stations has increased, thereby enabling deep learning and other data-driven methods to be applied to this problem. In this study, we test the performance of 1D CNN, 2D CNN, and RNN neural networks on predicting an imminent earthquake given 100 seconds of seismic data. Preliminary results show that RNN with class weighting is preferred. We also show the performance of these methods on earthquake recognition, a simpler problem with applications to data mining earthquake statistics and early-earthquake detection.

Introduction

Earthquake seismology is a major topic relevant to understanding hazards due to natural and induced earthquakes as well as understanding physical properties of the earth's crust. In the past decade, the number of seismic monitoring stations has increased dramatically, leading the field of research to transition from an observation-based science to a data-driven science (Havskov and Ottemoller, 2010). In general, earthquake seismology problems fall into three categories: earthquake recognition for data mining and early-earthquake detection (Allen, 1978; Joswig, 1990; Satriano et al., 2011; Yoon et al., 2015; Petrol et al., 2018), earthquake prediction for a warning system (Scholz et al., 1973; Allegre et al., 1982), and probabilistic risk assessment (Nishenko and Buland, 1987; Kagan and Jackson, 2000; Moustra et al., 2011; Wang et al., 2017; Lipski et al., 2017).

In this paper, we address the earthquake recognition (P1) and earthquake prediction problems (P2) illustrated in Figure 1. We test the performance of 1D CNN, 2D CNN, and RNN neural networks on both problems using a dataset of seismic waveforms from 46 stations near the Geysers geothermal area, California. In the P1 problem, the goal is to predict whether an earthquake *has* occurred given a seismic waveform. State-of-the-art performance is generally high on this problem, largely depending on the magnitude of earthquakes considered. In the P2 problem, the goal is to predict whether an earthquake *will* occur given a seismic waveform. In contrast to the P1 problem, there is no proven analytical method to predict an imminent earthquake (Geller et al., 1997), and therefore state-of-the-art performance is non-existent.

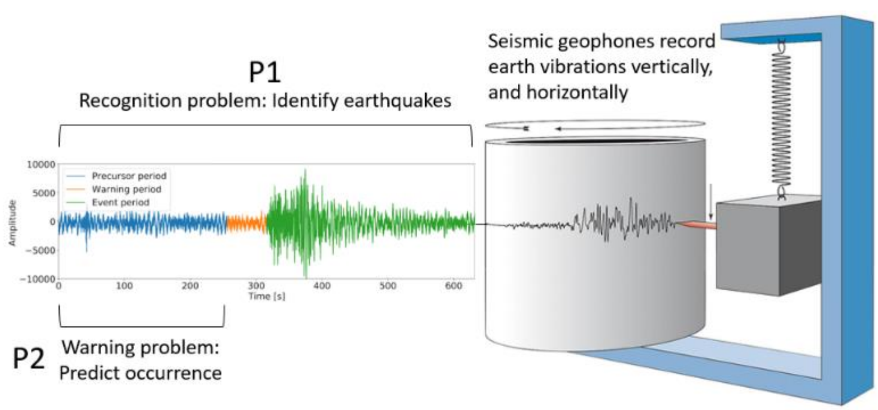

Figure 1. A schematic illustration of the problems tackled in this paper. A seismometer (geophone) records the displacement of the earth as a function of time.

Related work

In recent years, significant progress has been made towards the earthquake recognition problem using machine-learning methods. In these studies, there are several approaches to defining the model inputs. The simplest approach uses the raw time-series of the waveform partitioned into windows of equal time-steps (Perol et al., 2018). An alternative approach is to use the spectrogram of the waveform, which contains the same information as the time-series but is oftentimes a more convenient representation for machine-learning problems (Yoon et al., 2015). A final approach is to extract features from the time-series data such as summary statistics, autocorrelation at different lag values, and Fast-Fourier Transform wavelet coefficients (Chu and Mauerer, 2016; Addair, 2012). However, feature extraction has the drawback that extracted features are not informed by the prediction variable of interest, and therefore may add noise while reducing dimension of the input variable.

Datasets are generally assembled from earthquake catalogs from various seismic station networks around the world. For studies related to small-magnitude earthquakes, there are often ample earthquake events for a machine-learning or deep-learning approach. However, for studies related to large-magnitude earthquakes, which are more impactful to human lives, there are substantially fewer events to draw from. To bolster the number the number of samples, Perol et al., 2017 augmented samples by adding zero-mean Gaussian noise, which they found resulted in a regularizing effect on the model.

In contrast to the earthquake recognition problem, earthquake prediction has not seen significant progress due to the inability to identify earthquake precursor signals in seismic data (Geller et al., 1997; Uyeda et al., 2009). In addition to looking at the seismic signal, researchers have also studied possible earthquake precursors related to emittance of radon gas (Teng, 1980), ultra-low frequency electromagnetic signals (Karakelian et al., 2002), and abnormal animal behavior (Bhargava et al., 2009). Nevertheless, the application of deep learning is rare in earthquake prediction studies, and therefore may offer a new avenue forward.

Datasets and features

Continuous seismic waveform data is available through many publicly funded seismic station networks that monitor and catalog seismic events. Because there is no proven method for identifying earthquake precursors, there is little information about how to create an optimal dataset for the earthquake prediction problem. Therefore, we wrote a python script that generates multiple datasets for specified 1) seismic stations across different regions, 2) minimum earthquake magnitude, and 3) single (vertical displacement measurements) or multi-channel waveforms. After some initial experimentation, we determined that using many stations clustered in a geologically similar environment offered the best balance of containing a large number of samples drawn from the same distribution. We also decided to use a balanced dataset of positive and negative samples based on the conclusions of Buda et al. (2017) who found that training a convolutional neural network on undersampled negative samples yielded the best result.

The procedure used in the python script is as follows: 1) for each seismic station, we query the catalog for all earthquakes above a minimum magnitude and within ~10 kilometers of the station; 2) for each earthquake, we estimate the time of arrival of the seismic wave using the "iasp91" earth model; 3) we then download the seismic waveform for a specified period of time around the arrival time of the earthquake; and 4) we download a random seismic waveform from the same station to create a balanced dataset of positive and negative samples. The final datasets used in this paper included 1671, 614, and 176 positive samples (single-channel, vertical displacement) for minimum earthquake magnitudes of 3, 3.5, and 4 respectively. These samples are retrieved from 46 stations from the Berkeley Geysers Network (NCEDC, 2014), located ~110 kilometers north of the Bay Area, California (Figure 2). The region is seismically active and with a relatively dense array of monitoring stations.

Figure 3 shows an example seismic waveform for the 1D CNN model. For the earthquake prediction problem, the "precursor period" is used as input, whereas for the recognition problem a small window centered around the earthquake event is used as input. For the 2D CNN and RNN models, the spectrogram of the time-series data is used as input (spectrogram is a representation of the signal energy at different frequencies). Both input types - the raw time series and the spectrogram - are normalized using the z-score transformation.

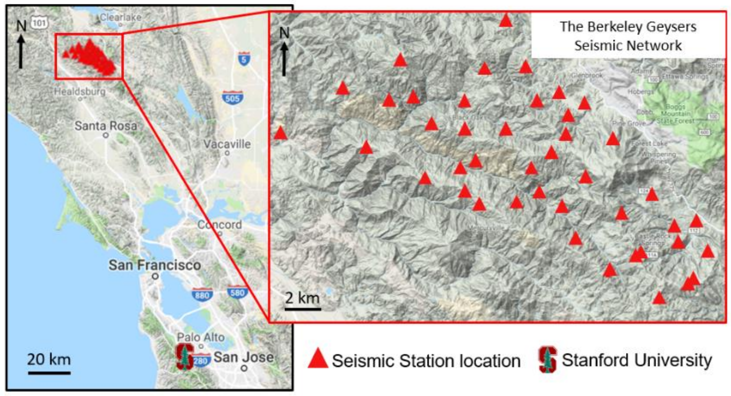

Figure 2. Location of the study area (the Geysers) and the seismic stations used to collect the dataset.

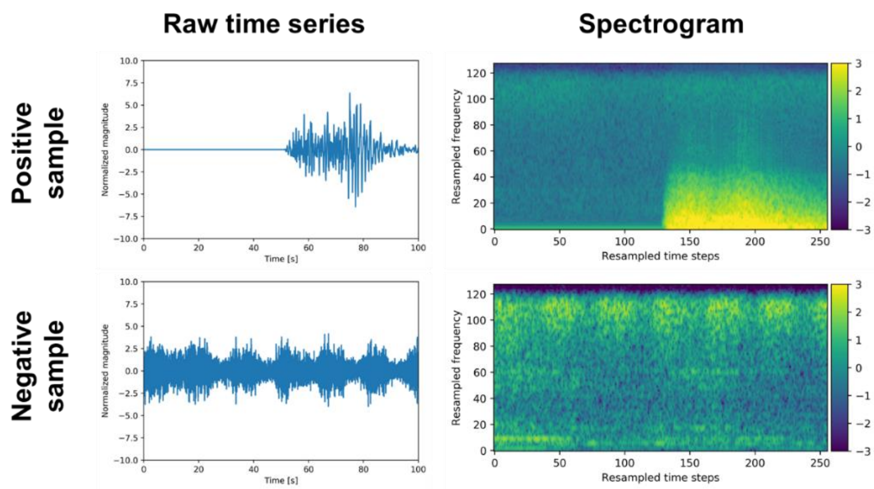

Figure 3. Examples of the raw data and spectrogram. A negative example in which there is not earthquake during the event period. (Bottom) A positive example in which an earthquake occurs during the event period.

Methods

Three neural network architectures – 1D CNN, 2D CNN, and RNN – were developed using the Keras library for both earthquake recognition and prediction problems. Figure 4 illustrates architecture configurations and the hyperparameters explored during training. The 1D CNN model consists of a series of 1D convolution and pooling layers, and uses the time-series of the seismic waveform as the input variable. The 2D CNN model is similar but uses the spectrogram of the seismic waveform as the input variable. Finally, the RNN model consists of a 1D convolution layer followed by two LSTM layers, and also uses the spectrogram of the seismic waveform as the input variable. In all models, binary crossentropy is used for the loss.

Models were tuned by exploring several hyperparameters using a training/validation/test set approach. The dataset is first split into training/test sets using a 9/1 ratio, and then 10% of the training set is used as a validation set. Hyperparameters are tuned by computing accuracy on the validation set. For example, the optimum values of dropout rate and number of epochs were determined such that the model does not overfit the training data. We used dilation rate in the 2D CNN model to explore a larger area of the spectrogram without increasing the filter size. We used class weights in the RNN model to force increasing accuracy in a specific class.

Several different datasets and window sizes for the seismic waveform were explored to increase performance of the models. For example, using a smaller window (~1 minute before and after the earthquake) was found to increase the accuracy of the recognition model, suggesting that selection of the window size is an important pre-processing step. In the case of the prediction problem, selecting the window size is more complex because of the computation cost of using a larger spectrogram. Generally, increasing the size of the time interval while fixing the resolution of the spectrogram results in decreasing accuracy of the model.

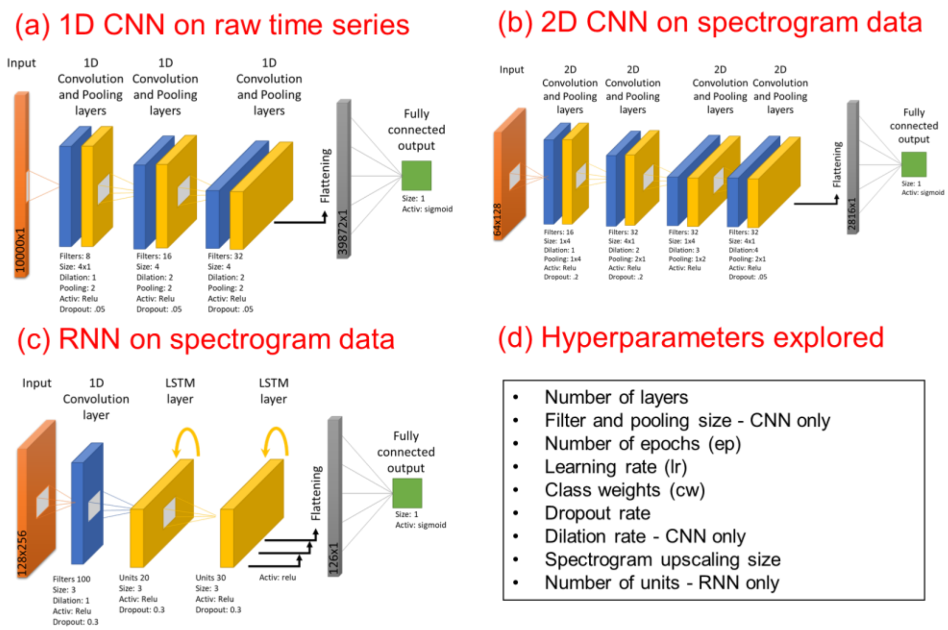

Figure 4. Three neural network architectures (a, b, c) and network hyperparameters explored (d).

Results and discussion

Table 1 shows selected results for the earthquake recognition problem (P1 in Figure 1). Overall, all the architectures performed well (>90% accuracy), and 2D CNN and RNN obtained 100% test accuracy. This indicates that neural networks can be reliably trained to identify earthquakes in seismic waveform data.

Table 2 shows selected results for the earthquake prediction problem (P2 in Figure 1). The results obtained are higher than 50% (i.e. the expectation of random guessing). This suggests that there is some pattern in the precursor signal that is indicative of earthquake occurrence in the next minute. The reported results are typical and not merely the best obtained results in our model training. In some runs, the test accuracy obtained reached 62% (using the dataset with higher magnitude earthquakes). However, because higher-magnitude earthquake occurrence is sparse, the dataset is small, and therefore the test accuracy may not reflect the true accuracy of the model.

Model	Parameters	Training Accuracy	Test Accuracy
1D CNN	M = 3.5, lr = 0.001, ep = 10	97.5%	94.4%
2D CNN	M = 3.5, lr = 0.001, ep = 10	100%	100%
RNN	M = 3.5, lr = 0.001, ep = 50	100%	100%

Table 1. Selected results of earthquake recognition problem (P1). M: minimum earthquake magnitude, lr: learning rate, ep: number of epochs.

Model	Parameters	Training Accuracy	Test Accuracy
1D CNN	M = 3, lr = 0.002, ep = 40	56.0%	54.2%
2D CNN	M = 3, lr = 0.001, ep = 12	60.0%	52.6%
RNN	M = 3, lr = 0.001, ep = 100, cw = [0.5, 0.5]	82.5%	54.5%
	M = 3, lr = 0.001, ep = 100, cw = [0.4, 0.6]	83.8%	56.4%
	M = 3, lr = 0.001, ep = 100, cw = [0.25, 0.75]	74.7%	53.9%

Table 2. Selected results of earthquake prediction (P2). M: minimum earthquake magnitude, lr: learning rate, ep: number of epochs.

In the RNN model, modifying the class weights was found to increase the overall test accuracy. As illustrated in the confusion matrices (Figure 5), penalizing the network to prefer true-positive accuracy to 0.6 resulted in an overall increase in accuracy. However, further increasing the true-positive accuracy to 0.75 then decreased the overall accuracy.

Although our results indicate improvement over random guessing, the test accuracy of the models is quite low. Possible issues include: 1) there is simply no physical mechanism prior to an earthquake that generates a seismic signal; 2) the precursor signal cannot be isolated in our dataset; or 3) the network architectures are not suitable for the setup of our problem. If there is no signal that is generated before the earthquake (issue 1), then the problem is unsolvable in its current formulation. If the precursor signal cannot be isolated in our dataset (issue 2), then assembling a better dataset might yield a better accuracy. If the network architectures are unsuitable (issue 3), then a more complex architecture might be useful.

After considering the different issues, we think that issue 2, the dataset, is likely the most important issue. A possible next step is to manually pick the arrival times of each earthquake rather than relying on the "iasp91" earth model, which might result in a more precise dataset. Then, we could experiment with using shorter "warning periods" (Figure 1) to test whether accuracy improves with shorter warning times. This would suggest that we can isolate when the precursor signal exists, and then explore the characteristics of the precursor signal.

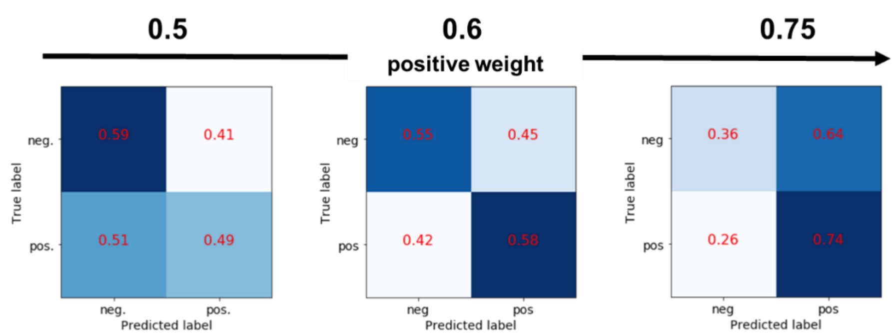

Figure 5. Confusion matrices with different class weights for the RNN network applied on a dataset with a minimum magnitude (M) of 3.5

Conclusions and final remarks

All of the presented neural network models achieved high performance on the earthquake recognition problem (P1). Predicting earthquakes before they occur (P2) is still a challenging problem. Based on the current analysis, some seismic precursor signal may exist. Future work planned includes: 1) experimentation with cleaner and bigger datasets, 2) studying the neural layers that activate for the true positive cases in the prediction problem (P2), and 3) exploring the relationship between warning time and prediction accuracy.

Code availability

The current code of the project can be found in: https://github.com/MosGeo/TerraeMotus

Contributions

Mustafa Al Ibrahim: Dataset retrieval and preprocessing; Neural network code transfer to keras, testing and writing.
Jihoon Park: Focused on preparing CNN codes, neural network testing, hyperparameters optimization and writing
Noah Athens: Focused on organizing and writing the report, background research, and generating figures.

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