

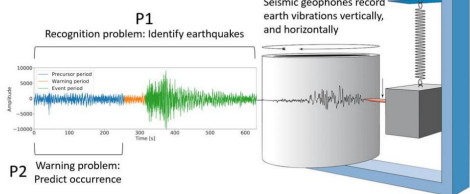
ABSTRACT

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.

INTRODUCTION

"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

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.



Two binary classification problems addressed:

(P1) Given a seismic waveform, **has** an earthquake occurred?

The earthquake recognition problem is useful for data mining massive volumes of seismic data in which smaller magnitude earthquakes may not have been previously detected. State of the art performance is high, ~87% accuracy is achievable [1].

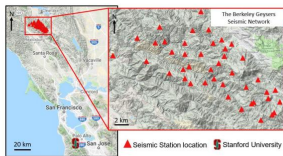
(P2) Given a seismic waveform, **will** an earthquake occur?

The earthquake warning problem is important for developing a warning system that can alert people to an imminent earthquake. Although long-studied in the field of seismology, there is no proven analytical method to predict earthquakes before they occur [2].

STUDY AREA

The Geysers study area:

- The area is seismically active.
- 46 seismometer stations.
- Single channel (vertical).
- Decades of monitoring data.
- An enhanced geothermal system program (EGS) began in 2009 and seismic data was recorded before and after water injection to study induced seismicity.

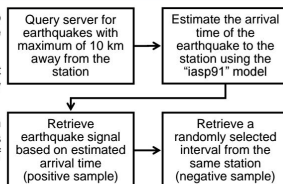


DATASET AND FEATURES

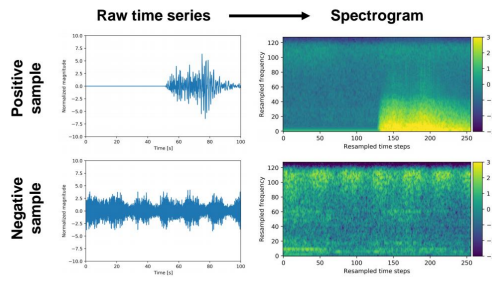
We used the Obspy library [3] to assemble the dataset through the procedure outlined.

We experimented with different datasets, determining that tightly clustered stations is preferred.

Three datasets are assembled with 1671, 614, and 176 earthquakes using a minimum magnitude (M) of 3, 3.5, and 4 respectively.



Spectrogram (a representation of energy of the signal at different frequencies) is calculated and used as an input for the 2D CNN and the RNN network architectures.

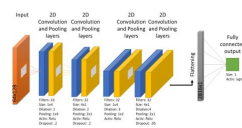
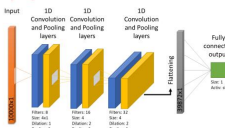


DEEP LEARNING APPROACH

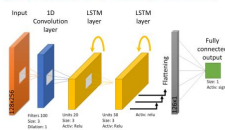
Multiple neural network architecture were tested starting with a simple 1D CNN on the raw time series data to an RNN on the spectrogram data.

(A1) 1D CNN on raw time series

(A2) 2D CNN on spectrogram data



(A3) RNN on spectrogram data



Hyperparameters explored include:

- Number of layers
- Filter and pooling size - CNN only
- Number of epochs (ep)
- Learning rate (lr)
- Class weights (cw)
- Dropout rate
- Dilatation rate - CNN only
- Spectrogram upscaling size
- Number of units - RNN only

RESULTS & DISCUSSION

(P1) Earthquake recognition:

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%

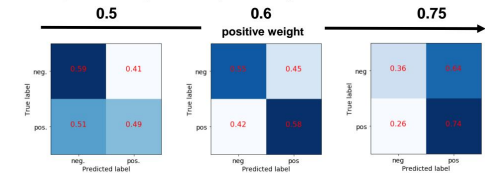
(P2) Earthquake prediction:

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%

• Our results demonstrate high performance on the earthquake recognition problem (P1) but low performance on the prediction problem (P2).

• 2D CNN and RNN models both performed better than the 1D CNN model. This is expected as the spectrogram is a more convenient representation of the data and information contained in the signal.

• Preliminary results suggest that slightly penalizing false positives might improve model performance up to a critical point where performance start to decrease.



CONCLUSIONS

• 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

- Experiment with cleaner and bigger datasets.
- Study the neural layers that activate for the true positive cases in the prediction problem (P2).
- Explore the relationship between warning time and prediction accuracy.

REFERENCES

1. Yoon, C.E., O'Reilly, O., Bergen, K.J., and Berzosa, G.C., 2015, Earthquake detection through computationally efficient similarity search: Science Advances, 13 p.
2. Geller, R.J., Jackson, D.D., Kagan, Y.Y., and Mulargia, F., 1997, Earthquakes cannot be predicted: Science, vol. 275, 1 p.
3. Krischer, L., Magies, T., Barsch, R., Beyreuther, M., Lecocq, T., Caudron, C., Wassermann, J., 2015, ObsPy: a bridge for seismology into the scientific Python ecosystem: Computational Science & Discovery.