

Analyzing Deep Learning Performance for Seismic Waveform Discrimination at Global Distances

Authors: Rayna Arora, Nimar Arora, Ronan LeBras

EGU21-1831

Introduction

- We aim to build a Deep Learning model for CTBT monitoring that discriminates explosions from earthquakes uniformly anywhere on the earth, even areas without dense seismic networks
- Therefore, this research trains and tests models on detections at 20 degrees or more
- Data from 1978-2018 was gathered from the ISC Event and Arrival Bulletins^[1] and the IRIS waveform repository^[2]
- The dataset consists of 7608 waveform samples

^[1]Storchak, D.A., Harris, J., Brown, L., Lieser, K., Shumba, B., Verney, R., Di Giacomo, D., Korger, E. I. M. (2017). Rebuild of the Bulletin of the International Seismological Centre (ISC), part 1: 1964–1979. *Geosci. Lett.* (2017) 4: 32. doi: [10.1186/s40562-017-0098-z](https://doi.org/10.1186/s40562-017-0098-z)
Storchak, D.A., Harris, J., Brown, L., Lieser, K., Shumba, B., Di Giacomo, D. (2020) Rebuild of the Bulletin of the International Seismological Centre (ISC)—part 2: 1980–2010. *Geosci. Lett.* 7: 18, <https://doi.org/10.1186/s40562-020-00164-6>

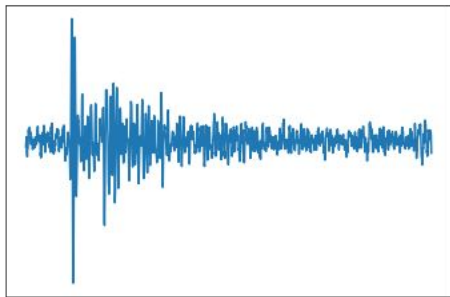
^[2]The facilities of IRIS Data Services, and specifically the IRIS Data Management Center, were used for access to waveforms, related metadata, and/or derived products used in this study. IRIS Data Services are funded through the Seismological Facilities for the Advancement of Geoscience (SAGE) Award of the National Science Foundation under Cooperative Support Agreement EAR-1851048.
All seismic data were downloaded through the IRIS Wilber 3 system (<https://ds.iris.edu/wilber3/>) or IRIS Web Services (<https://service.iris.edu/>), including the following seismic networks: (1) the AZ (ANZA; UC San Diego, 1982); (2) the TA (Transportable Array; IRIS, 2003); (3) the US (USNSN, Albuquerque, 1990); (4) the IU (GSN; Albuquerque, 1988).

Contributions

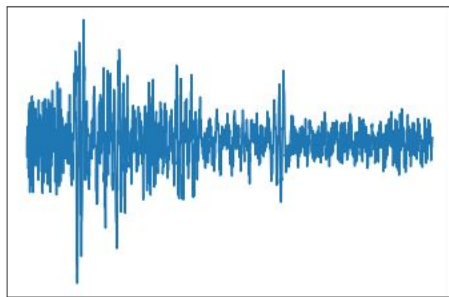
- Adapted previous work on Deep Learning with 2D spectrograms to distances greater than 20 degrees
- Developed new Deep Learning architecture for seismic classification from 1D waveforms
- Demonstrated generalization capacity for a novel class of explosions (rock bursts)

Data Processing

- Waveforms from 10 seconds before to 80 seconds after first P arrival
- Highpass filter performed at 1 Hz
- Downsampled to 20 Hz
- Eliminated data without STA/LTA value of at least 2 within 10 seconds of recorded arrival time
- Waveforms detrended and normalized
- Data included same number of earthquakes and explosions in each distance range of 10 degrees

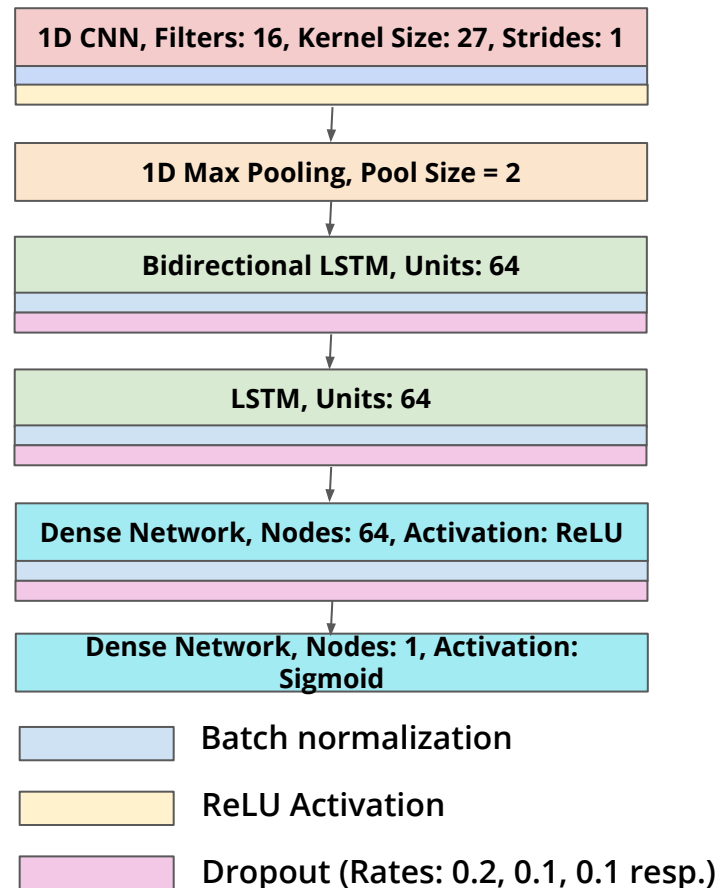


Explosion
(76 degrees, 5.1 mb)



Earthquake
(61 degrees, 5.5 mb)

Model Architecture



Recent Related Work

- Mousavi, S.M., Zhu, W., Sheng, Y. et al. CRED: A Deep Residual Network of Convolutional and Recurrent Units for Earthquake Signal Detection. *Sci Rep* 9, 10267 (2019).
<https://doi.org/10.1038/s41598-019-45748-1>
 - This research uses a Deep Learning network on spectrograms for P phase detection
 - Results only available for detections within 50 km
- Linville, L., Pankow, K., Draelos, T. Deep Learning Models Augment Analyst Decisions for Event Discrimination. *AGU Geophysical Research Letters* (2019).
<https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2018GL081119>
 - This research tests a Convolutional Neural Network(CNN) and Recurrent Neural Network(RNN) on spectrograms for discrimination between earthquakes and quarry blasts.
 - Results only available for detections within 400 km.

Both methods require many more parameters because they process 2D spectrograms rather than 1D waveforms.

Results

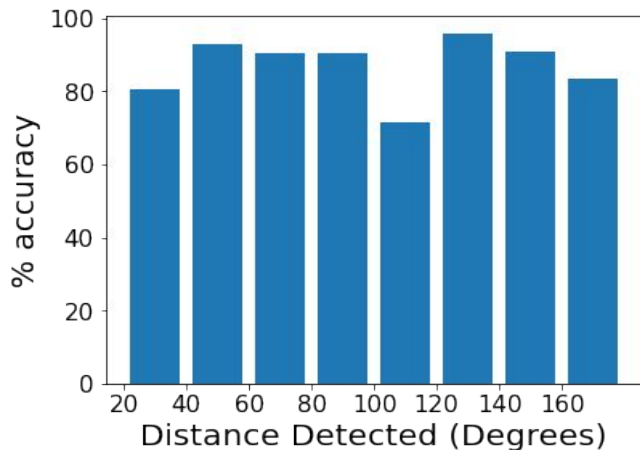
Models from related work were reproduced and trained and tested on the corresponding spectrograms for the dataset of our proposed method.

Model	Best Accuracy	AUC*	Parameters
Proposed Method	89.5%	0.962	96,641
Mousavi et al. (CRED)	89.7%	0.957	208,273
Linville et al. CNN	83.9%	0.896	456,237
Linville et al. RNN	80.9%	0.894	375,425

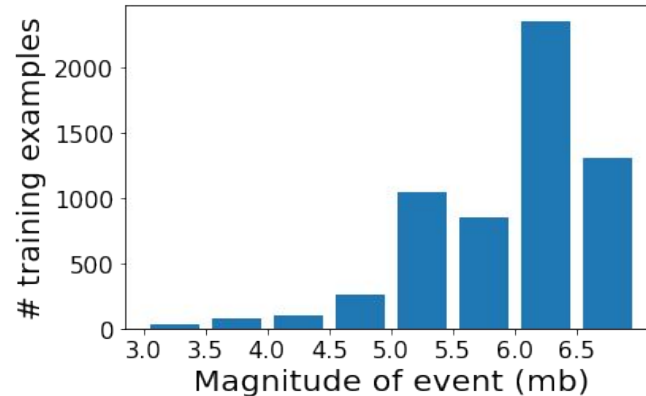
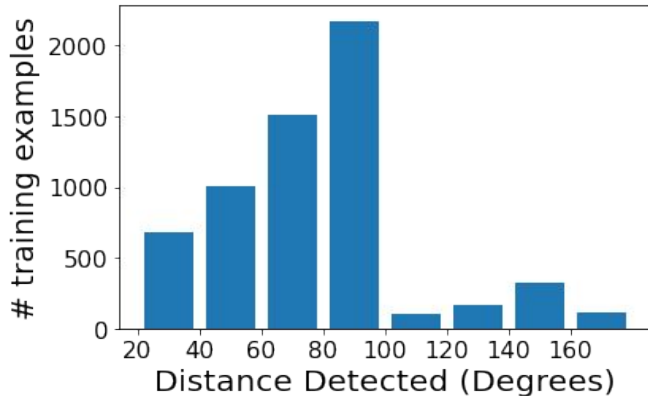
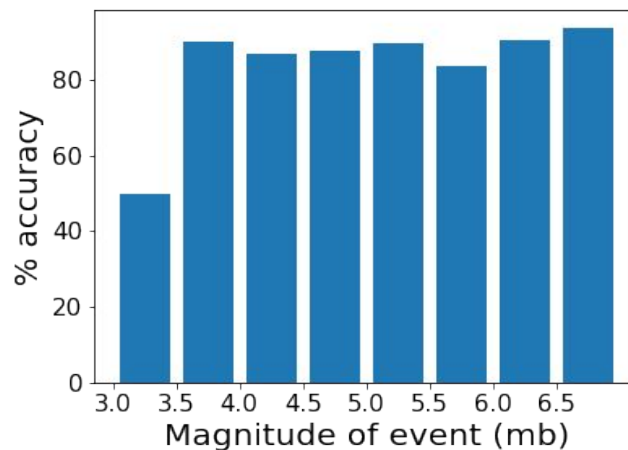
*Area under the Receiver Operating Characteristic curve

Proposed Method Results

Accuracy by distance detected

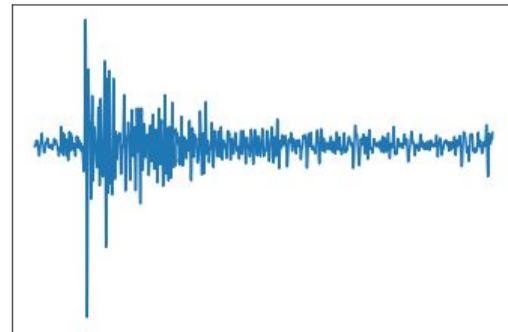


Accuracy by magnitude



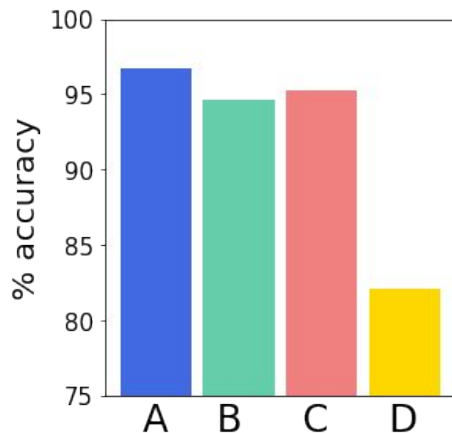
Rock Burst Results

- Rock bursts are spontaneous explosive ejections of rocks in mines caused by high stress.
 - Our model was not trained on rock burst data, but a separate test was performed to assess how well the model generalizes
 - Rock bursts were treated as explosions
 - Our model obtained 96.7% accuracy on over 2000 rock burst waveform samples



Rock Burst
(50 degrees, 5.3 mb)

Rock Burst Accuracy



A	Proposed Method
B	CRED
C	Linville et al. CNN
D	Linville et al. RNN

Conclusion

- We demonstrated that even with limited data, Deep Learning methods worked well for discriminating between earthquakes and explosions at teleseismic distances (over 20 degrees), yielding nearly 90% accuracy
- Using seismic waveforms rather than spectrograms as model inputs, it was possible to train a model with far fewer parameters that generalizes better for unseen inputs such as rock bursts