An investigation of rapid earthquake characterization using single-station waveforms and a convolutional neural network

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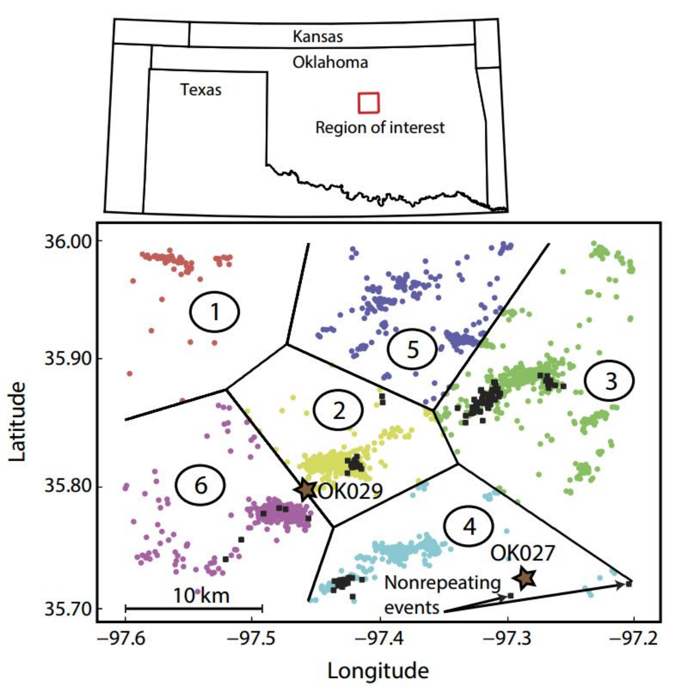
Introduction

- There is an increased need for rapid earthquake detection and characterization which is currently mainly provided by real-time analysis of seismogram waveforms using empirical and physics rule-based procedures
- Extracting information from seismograms requires a lot of processing using rule-based seismological procedures
- Development of ML techniques lead to application of ML to wide variety of waveform analysis problems
- One of the most general ML approaches is the CNN which can be successfully applied to waveform analysis problems (Perol et al., 2018.)

ConvNetQuake - Perol et al. (2018)

- ConvNetQuake, a CNN for earthquake detection and location for earthquakes that originate from a single region
- Data: noise and local events of two stations in Oklahoma, USA
- Goal: noise/event and rough geographic area classification using single-station 3C data

	Autocorrelation	FAST	ConvNetQuake (this study)
Precision	100%	88.1%	94.8%
Recall	77.5%	80.1%	100%
Event location accuracy	NA	NA	74.6%
Reported runtime	9 days, 13 hours	48 min	1 min, 1 s



CNN comparison with classical methods

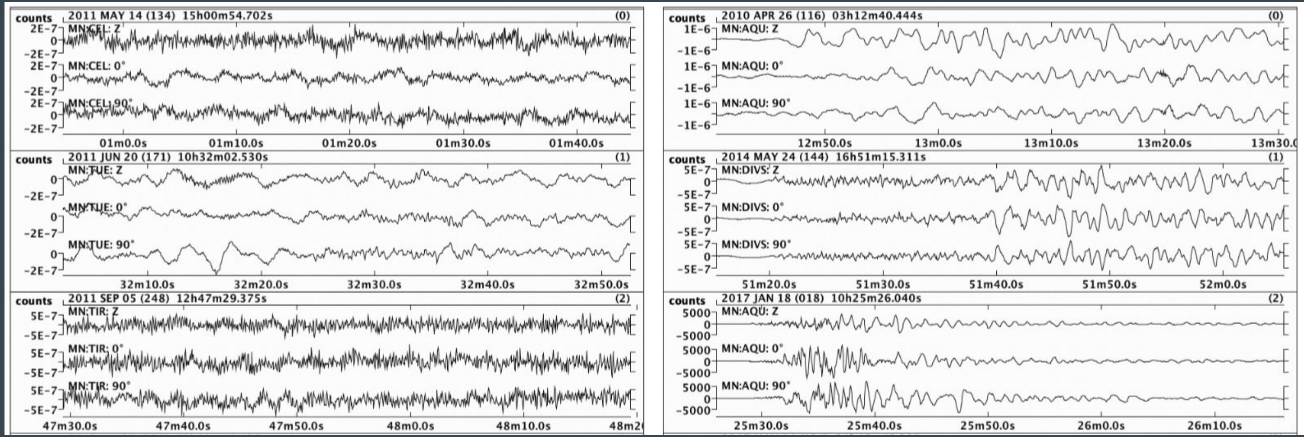
- The CNN can operate directly on the waveforms, with little pre-processing and without feature extraction such as energy detection, time-series transformation or frequency-domain analysis
- The CNN architecture is shift invariant and so not sensitive to or dependent on the time position of features such as P and S wave arrivals in the waveform
- Unlike standard regression, the CNN is not limited by assumed and simplified mathematical relations between quantities
- The CNN does not make explicit use of existing knowledge and the question remains does it learn the general physics-based principles or it remains just a high-dimensional regression

Work goals

- We extend the work of Perol et al. to detect and determine the location of global earthquakes at any distance over a large range of magnitudes and depths
- The inputs are single-station, 50 seconds, 3 component 20 Hz waveforms from all the stations within the regional MedNet network
- The outputs are classification event/noise and binned, probabilistic estimates of the distance, azimuth, depth and magnitude of an event
- The goal is to examine how well the network can detect and characterize earthquakes and how well can it generalize to unseen data(regions)

Data

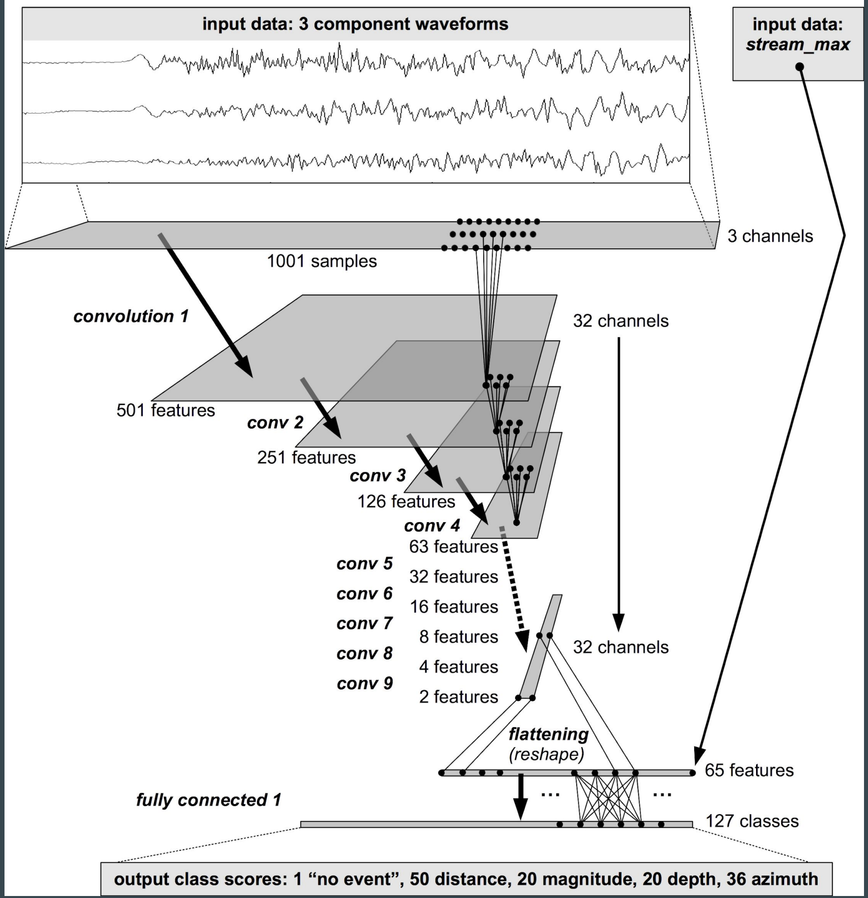
- Downloaded noise and event data for MedNet stations using FDSN webservices
- Minimal pre-processing: trim event waveforms to start 5 sec prior to P arrival, normalize to global maximum of all 3 traces and store the normalization value so it can be appended to the input



The network

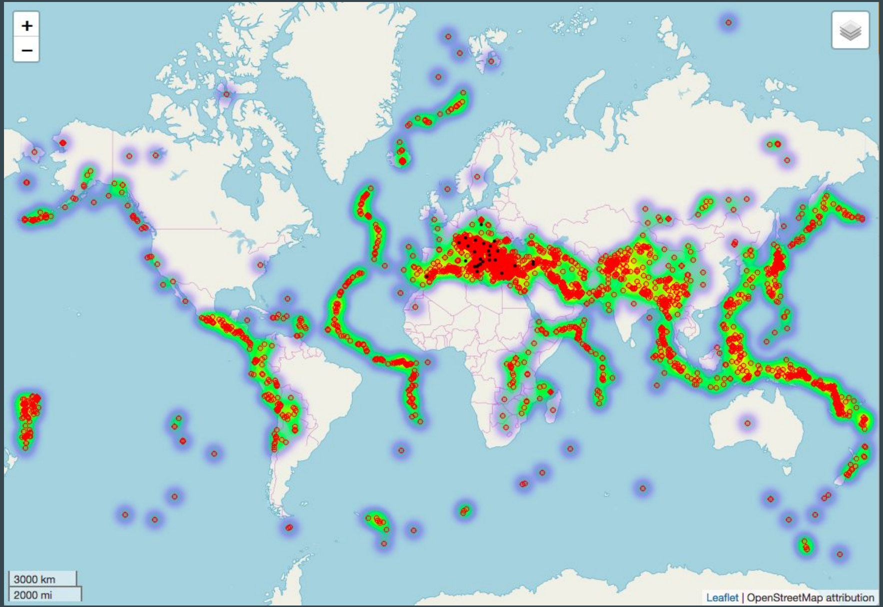
- The network ConvNetQuake_INGV is a CNN with 9 convolutional layers, each with 32 channels and half the number of features as the preceding layer, and two fully connected layers at the end
- The final, fully connected layer, contains an event node, 50 distance nodes, 20 magnitude nodes, 20 depth nodes and 36 azimuth nodes
- The ReLu activation function is used in CNN layers and softmax function is applied to the output fully connected layer class scores to obtain a properly normalized probability distribution over classification bins
- For training, ConvNetQuake_INGV uses an L2-regularized cross-entropy loss(misfit) function and the Adam Optimizer algorithm

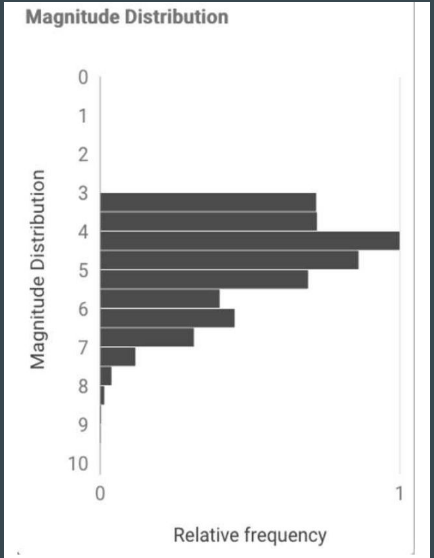
CovNetQuake_INGV Architecture

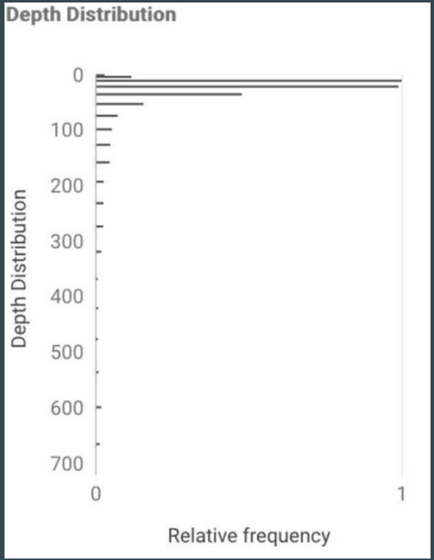


Training

- For training: 15200 event and 10724 noise waveforms starting from year 2010 to year 2018; Validation: 1773 event and 1198 noise waveforms, same timespan



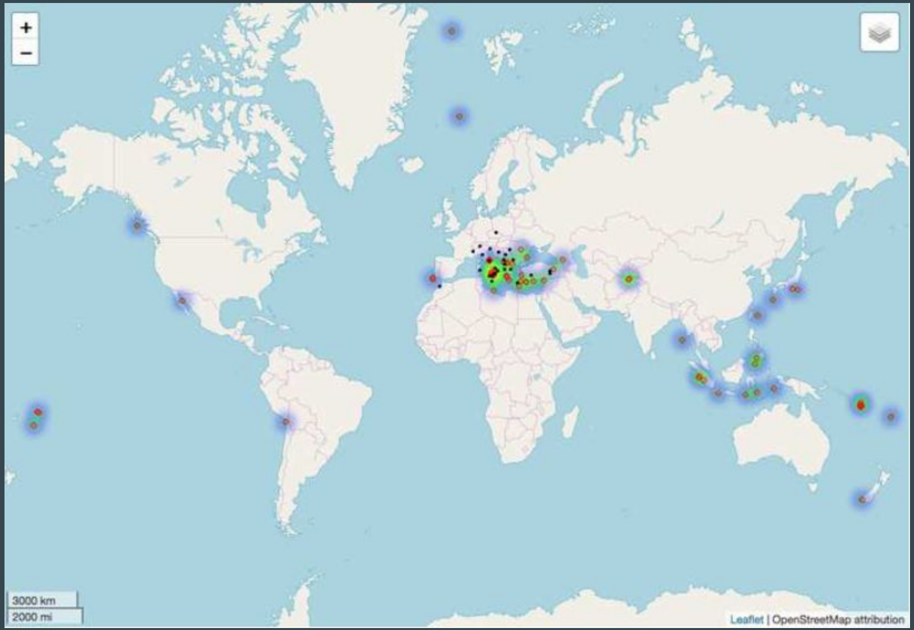


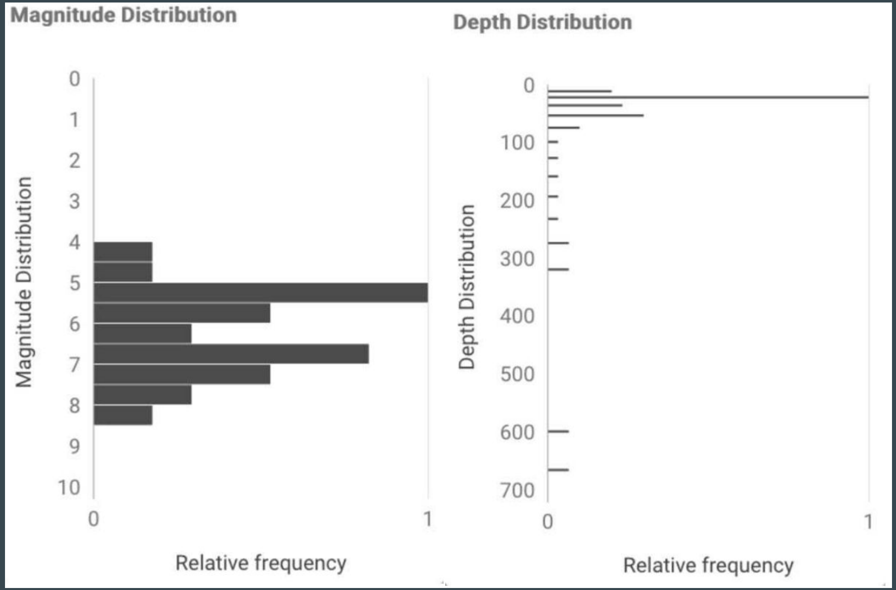


Event epicenter map showing events (red dots), event heat (density) map and MedNet stations (black dots)

Testing

- Testing has been done on 1003 event and 621 noise events from 2009



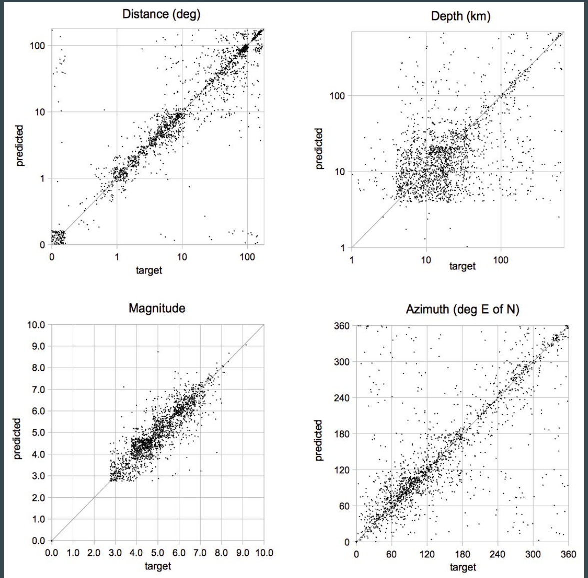


Detection results

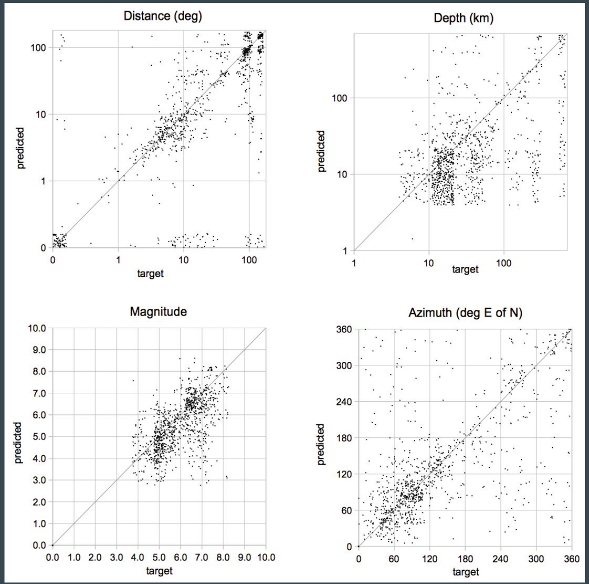
- detection accuracy (correct detections / total number of waveforms): 0.87
- detection precision (number of correct event detections / total number of predicted event detections): 0.97
- recall (number of correct event detections / total number of events): 0.81
- F1 score (2 * precision * recall / (precision * recall)): 0.88.

Results

- Test results are similar to, but notably more scattered than the validation results; validation events include many aftershock, swarm and other events with similar waveforms; suggests difficulty in generalizing

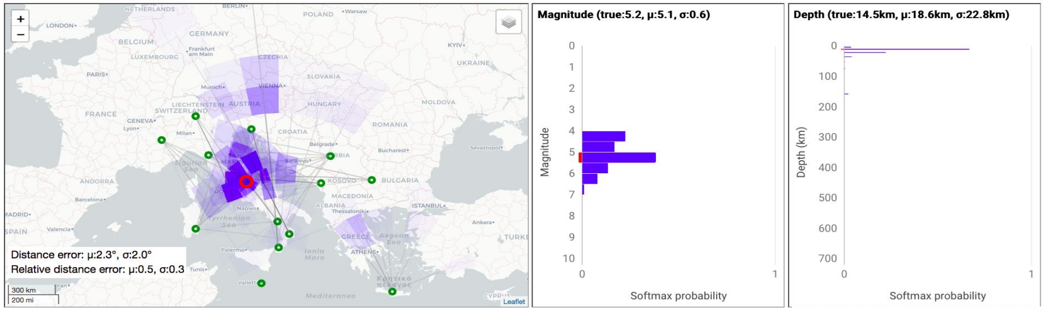


Predicted vs True for validation data set classification

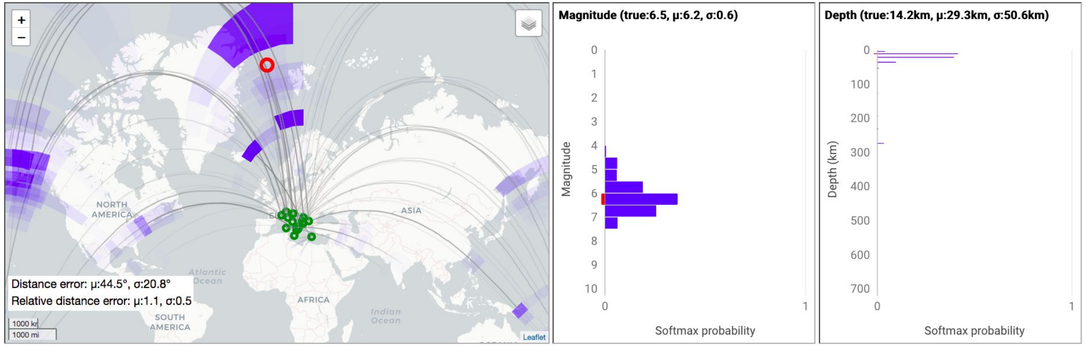


Predicted vs True for test data set classification

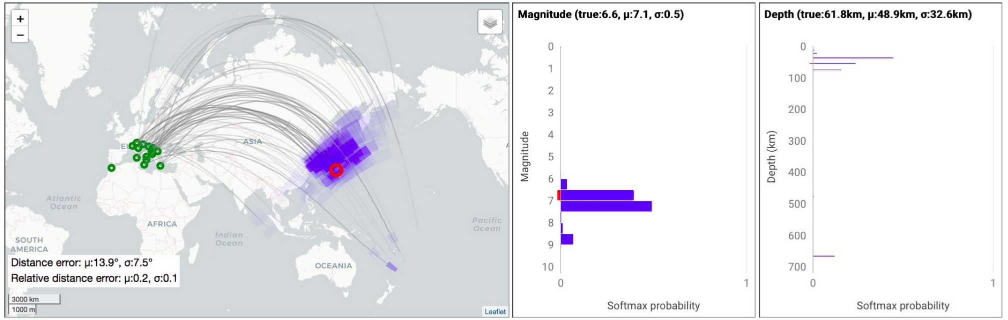
M=5.2 CENTRAL ITALY 2009-04-09T19:38:18.890000 Lat:42.5157 Lon:13.3575 Depth:14.5km



M=6.5 NORTH OF SVALBARD 2009-03-06T10:50:30.160000 Lat:80.3143 Lon:-1.9637 Depth:14.2km

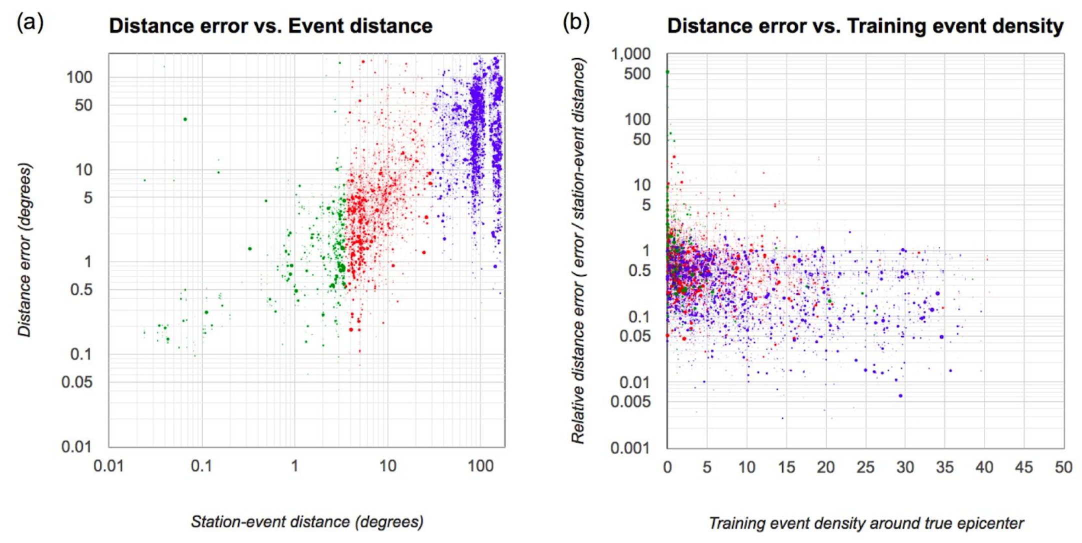


M=6.6 SOUTHEAST OF HONSHU, JAPAN 2009-08-12T22:48:52.100000 Lat:32.8133 Lon:140.4279 Depth:61.8km



Analysis of epicentral errors

- Figure a): increase in distance error with distance; sharp and strong increase in maximum error beyond about 3.5° indicates reduced distance accuracy when there is no S arrival in the waveform window
- Figure b): Mild reduction of distance error with increasing training event density around true epicenter

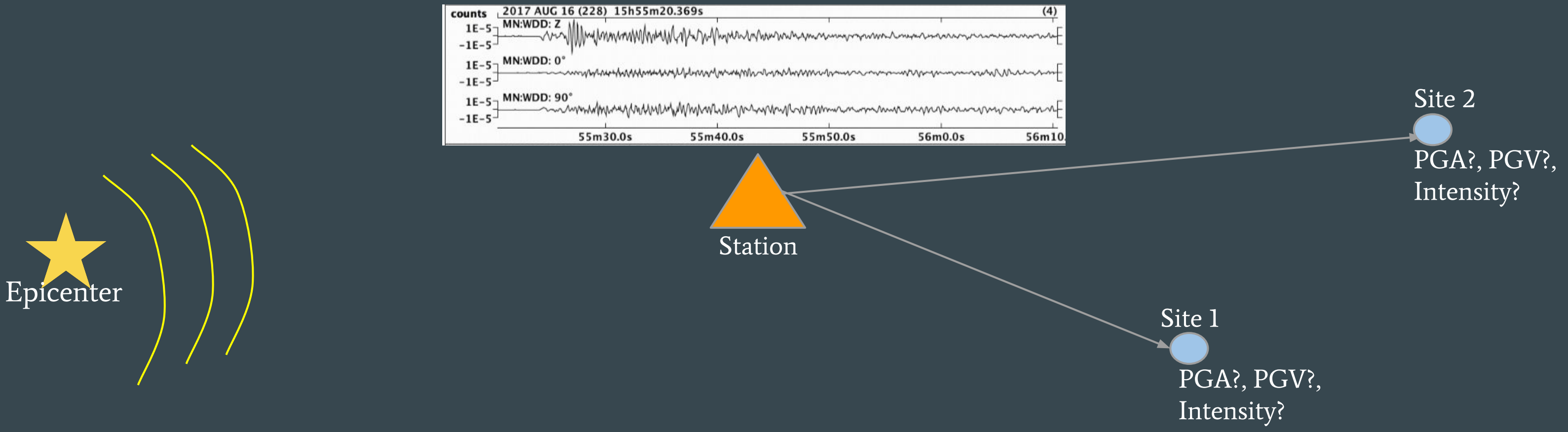


Summary

- CNN for single station broadband seismograms over a large span of event types, distances, magnitudes and depths
- Performs very well in detecting events whose waveforms are dissimilar to any in the training data
- Event characterization does not show the same performance, with a tendency to overfit to areas with high event density, and with lot of outliers; there is, however, some generalization of the determination of the event parameters
- Not a practical monitoring tool, but allows investigation into rapid detection and characterization for short, single-station waveforms

Outlook

- Incorporate new machine learning techniques (CNN + LSTM...)
- Use additional metadata about the stations (V_s30, f_0...)
- Use two or more stations
- Move to ground-motion prediction



Thank you for your attention

Citations

- Perol, T., M. Gharbi, and M. Denolle (2018). Convolutional neural network for earthquake detection and location, Science Advances, 4:2, doi:10.1126/sciadv.1700578
- Lomax, A., A. Michelini, and D. Jozinović (2019). An investigation of rapid earthquake characterization using single-station waveforms and a convolutional neural network. In press in SRL.
- FDSN web services at http://cnt.rm.ingv.it/webservices_and_software