End-to-End Earthquake Monitoring: Combining Deep-Learning-Based Detection with Physics-Constrained Association Across a Network

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Abstract

Deep learning has became one of the most effective methods for earthquake detection. However, the current methods are designed for single seismic station, treating the earthquake signal as a 1D time sequence. One remaining challenge is to simultaneously consider data from all stations inside a seismic network, which follows the spatial-temporal relationships: the relative time delays between seismic stations is determined by the station locations, the earthquake location, and the local seismic wave speed.

In this project, we develop an **end-to-end method** that combines a deep-learning-based detection with physics-constrained association across a network. Considering the detection and association stages jointly can improve the sensitivity of earthquake monitoring systems to events that are too weak to be detected by any single station in the network and also improve the robustness of earthquake monitoring systems to prevent false positive detection triggered by local noise and artifact signals at a few stations.

Traditional Method

Current earthquake monitoring systems typically treat the detection and association as **two distinct sub-problems**:

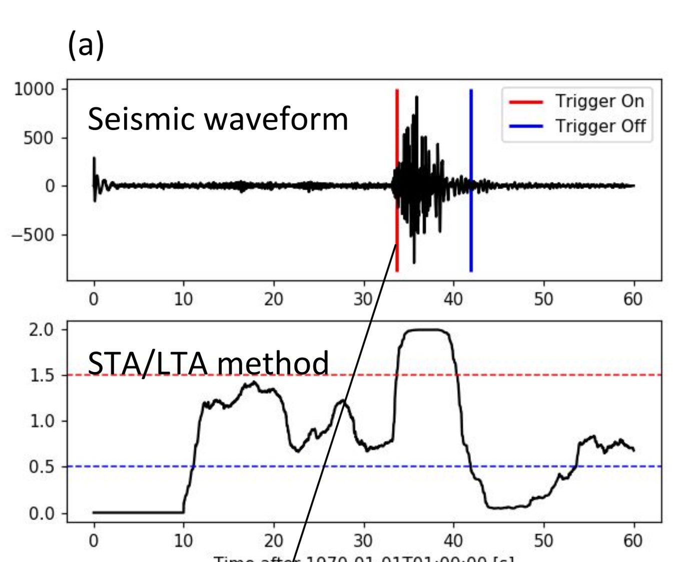
(1). an earthquake detection algorithm identifies candidate triggers at each station, using the STA/LTA (Short Time Average/Long Time Average) or neural-network-based model (ConvNetQuake).

(2). an association algorithm combines these triggers by a velocity model to determine possible earthquake times and locations.

The **disadvantages** of this two-stage approach are:

(1). it relies on accurate detection at each station -- a difficult task for low signal-to-noise ratio arrivals from low-magnitude events;

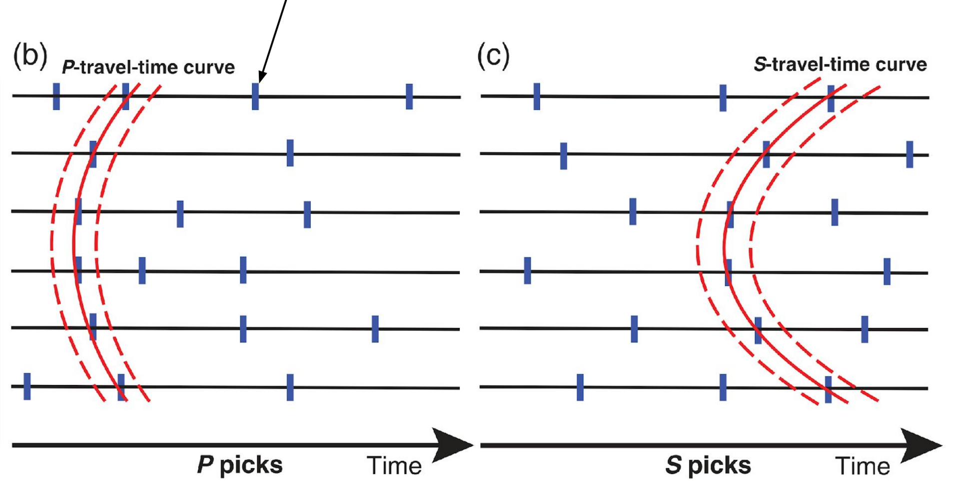
(2). the association stage typically ignores potentially informative waveform similarity features across stations.



Two-stage method:

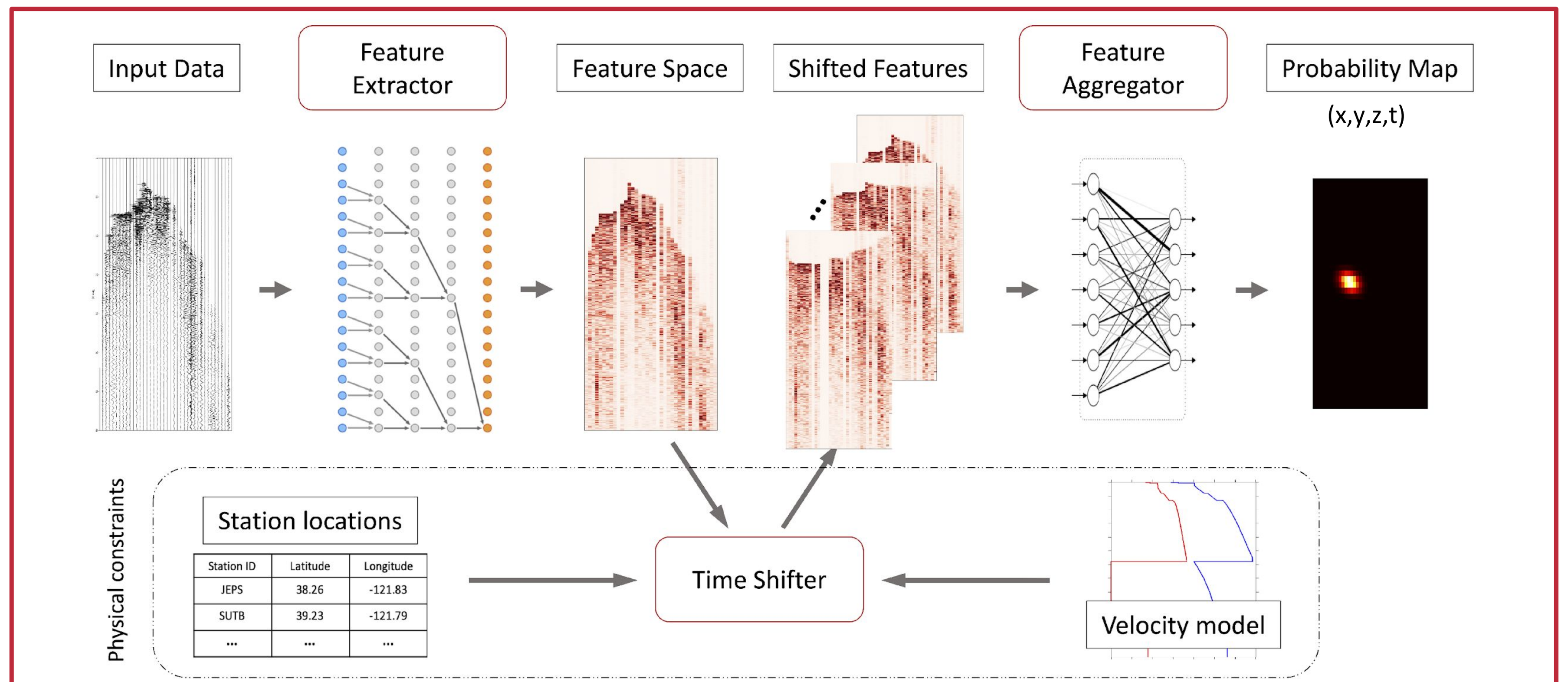
(a). Earthquake detection on a single station, producing a sequence of triggers.

(b, c). Association of triggers from all stations based on P-wave or S-wave speeds.



The triggers (blue vertical lines) from a true earthquake should follow the P-wave or S-wave travel-time curves (red curves). The rest false positive triggers are filtered out.

End-to-End Method

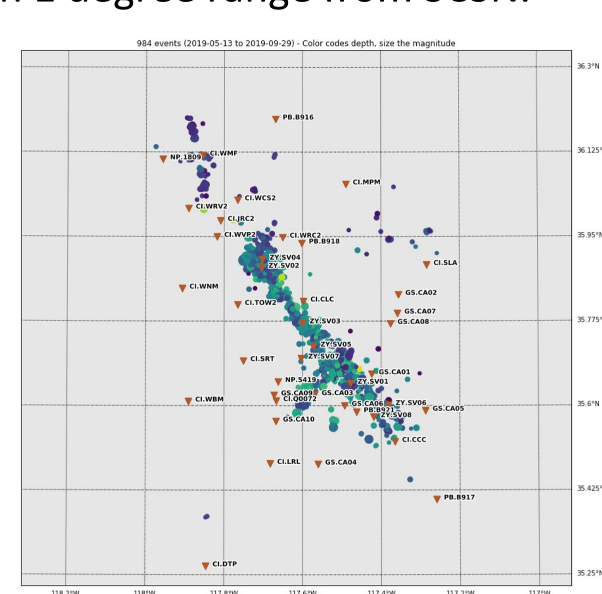


End-to-end model has three modules: Feature Extractor, Feature Aggregator, and Time Shifter.

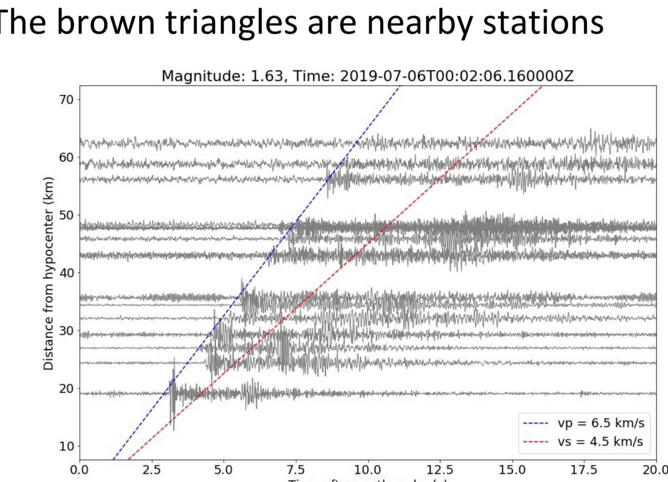
- Feature Extractor and Feature Aggregator are neural-network based, optimized to learn
  - the features to detect earthquakes on one single station
  - the rules to combine the features from all the stations together.
- Time Shifter imposes the physical constraints in the feature space based on the station locations, the seismic wave velocity model and candidate earthquake locations.
- The features will only align using the correct earthquake time and location.

Dataset & Training

Two large earthquakes (M6.4 and M7.1) happened this summer near Ridgecrest, which triggered a large sequence of aftershocks (~2000 earthquakes/day). We collected **23,110 earthquakes** reported by Southern California Seismic Network (SCSN) from April 1st to October 1st and downloaded the **continuous seismic waveforms** from the seismic stations within 1 degree range from SCSN.

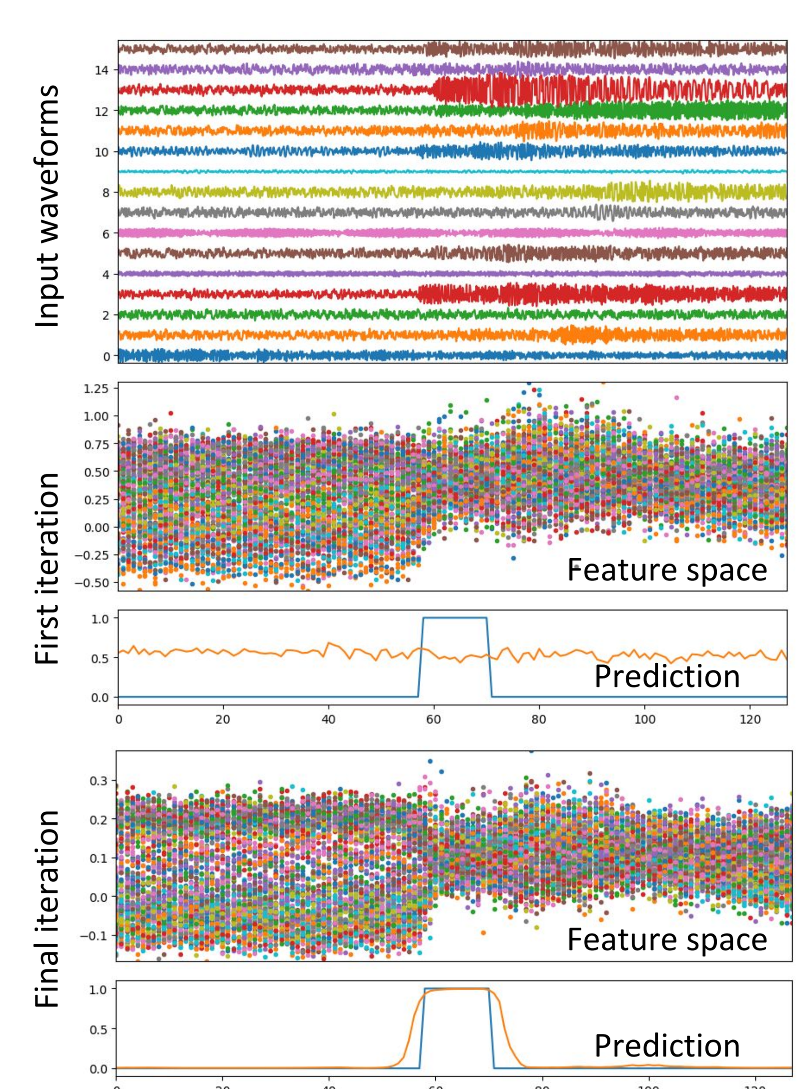


The colored dots are locations of earthquakes. The brown triangles are nearby stations



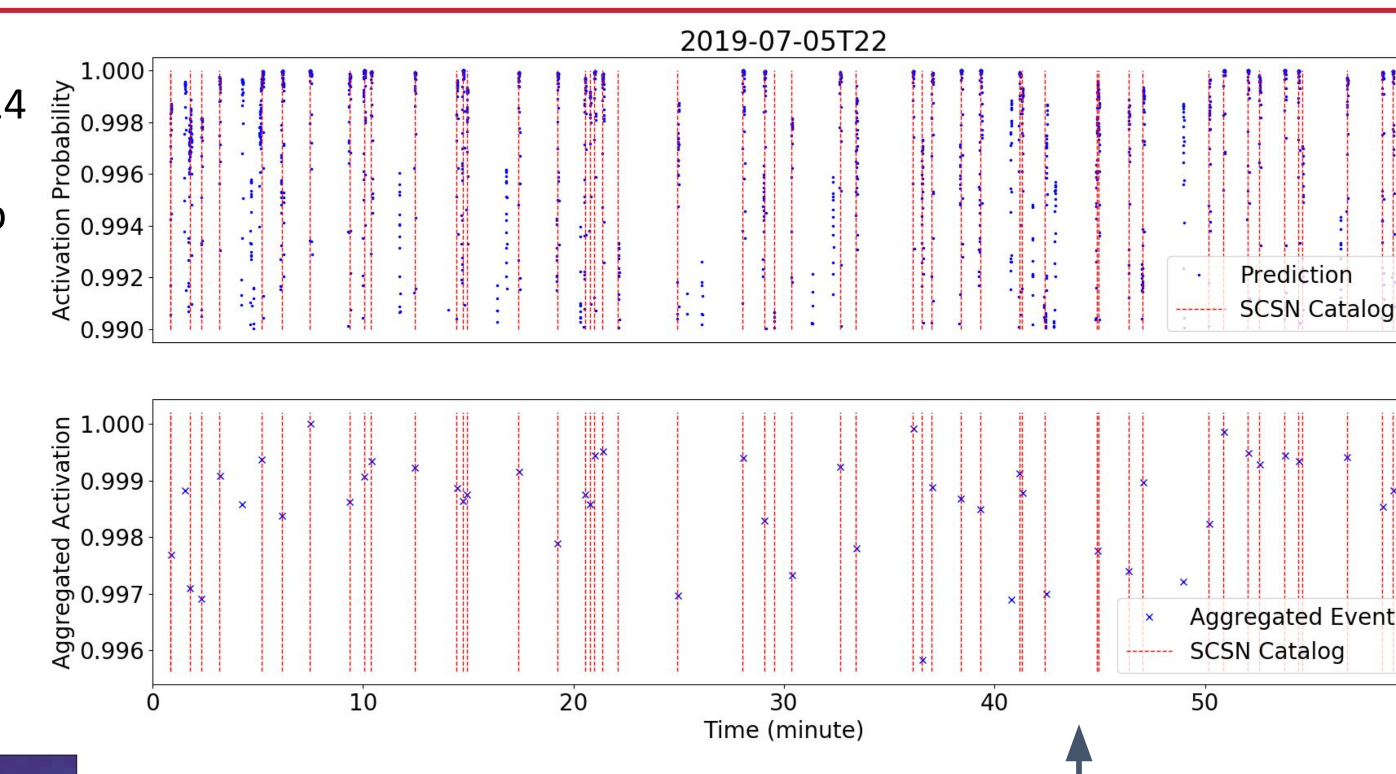
Example of seismic waves (P-wave and S-wave) received by nearby stations. The arrival times of the waves are determined by the distance from earthquake to station and the seismic wave speed

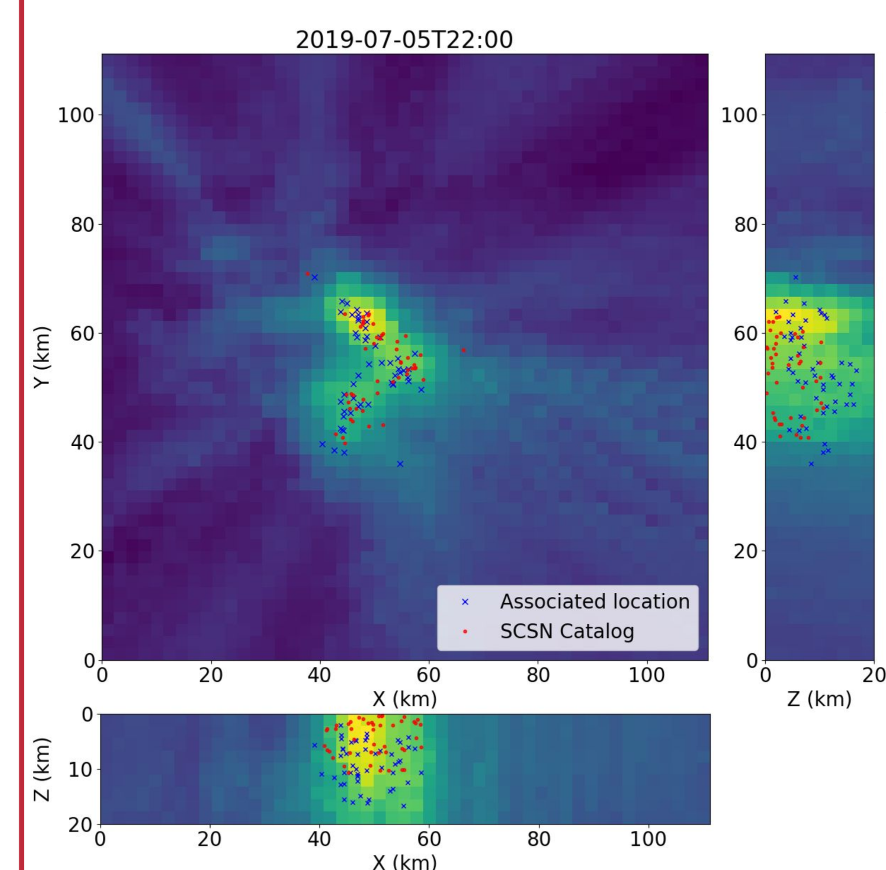
Example of the features and predictions in the first iteration and last iteration during training. The blue rectangle is the training target for the case when the features align.



Results

- Test data: **seismic data on July 5** (one of the most active days with 1224 reported earthquakes)
- Output: a 4D **(x,y,z,t) probability** map for earthquake locations and times.
  - Detect earthquake time: sum over locations (x,y,z) (the right figure)
  - Detect earthquake location: choose the grid with the maximum association weights (the figure below).



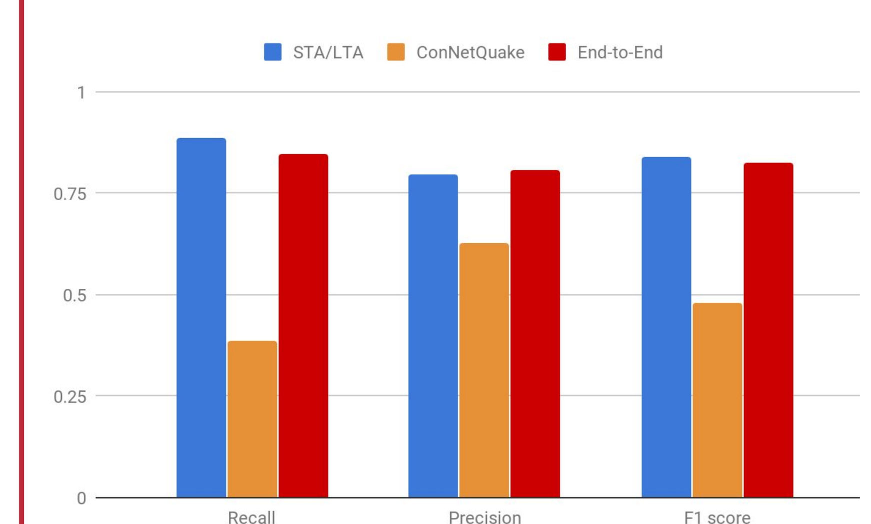


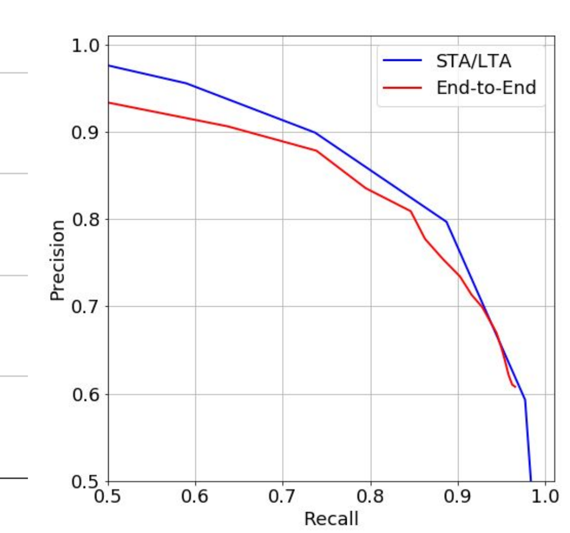
Detected Earthquake Location

- The background color represent the association weights by summing over the time axis (t).
- The brighter color indicates locations with higher earthquake probabilities.
- For each detected earthquake, we choose the grid with the maximum association weight as the earthquake location (blue x). The associated earthquake locations agree well with those (red dots) from the SCNC catalog.

Detected Earthquake Time

- The upper panel shows the activations (blue dots) from all earthquake locations (x,y,z). The activations accurately align with the earthquake time (red lines) reported by SCSN catalog. We can observe activations from new detected earthquakes, too.
- The lower panel shows the aggregate events (blue x) by averaging the activations within the same time range.



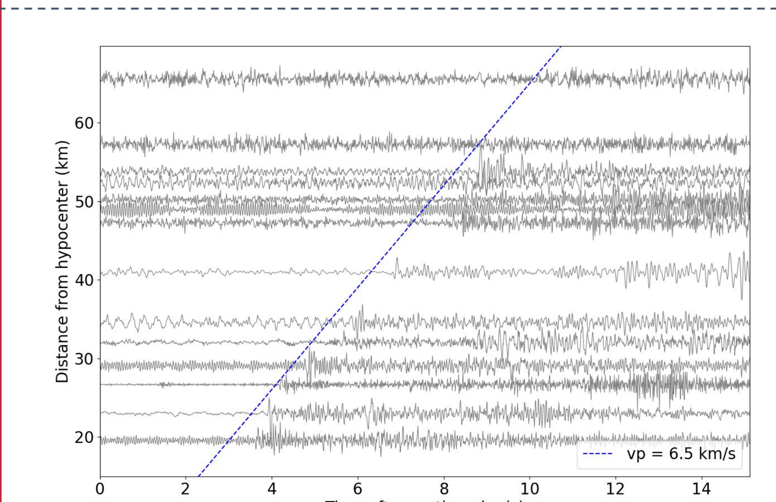


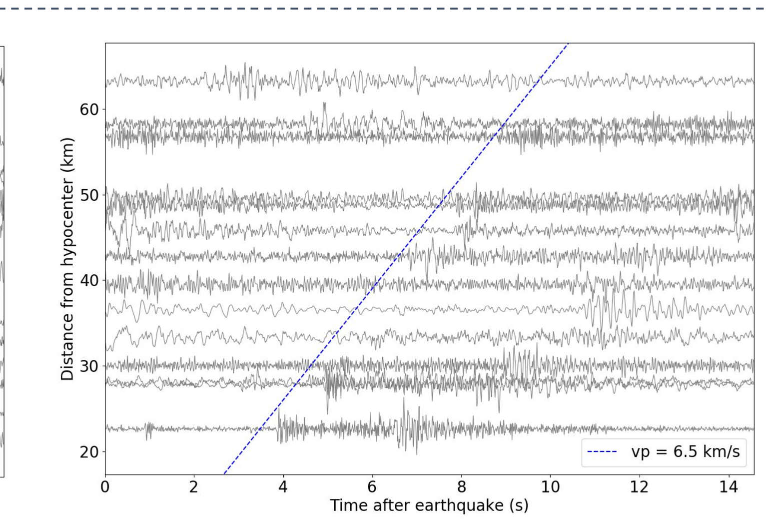
Performance Comparison.

We assume the SCSN catalog is the ground truth and compare the **precision**, **recall**, and **F1 score**. The result shows our end-to-end method has similar performance as STA/LTA method and better performance than ConvNetQuake.

Future improvements:

- Data augmentation, i.e., adding noise, stacking multiple earthquakes.
- Filtering out bad data in SCSN catalog
- Improving training hyperparameters.





New Detected Earthquakes.

Many weak earthquakes that were not reported by the SCSN catalog are detected by our end-to-end method. The examples on the left show two newly detected small earthquakes. The incompleteness of the SCSN catalog can cause the low prediction of our end-to-end method.

References

T. Perol, M. Gharbi, and M. Denolle. Convolutional neural network for earthquake detection and location. Science Advances, 4(2):2–10, 2018.

M. Zhang, W. L. Ellsworth, and G. C. Beroza. Rapid Earthquake Association and Location. Seismological Research Letters, 90(6), 2019.