Toward Optimizing Automatic KSSMN Earthquake Detection Using Machine Learning

Kentucky Geological Survey

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Introduction and Motivation

The Kentucky Seismic and Strong-Motion Network (KSSMN) is an essential facility, operated by the Kentucky Geological Survey at the University of Kentucky, to monitor earthquakes in and around the Commonwealth and to provide information on earthquakes and seismic hazards.

The KSSMN consists of 21 seismic stations, 14 of which are networked and provide recordings for near-real-time analysis (Fig. 1).

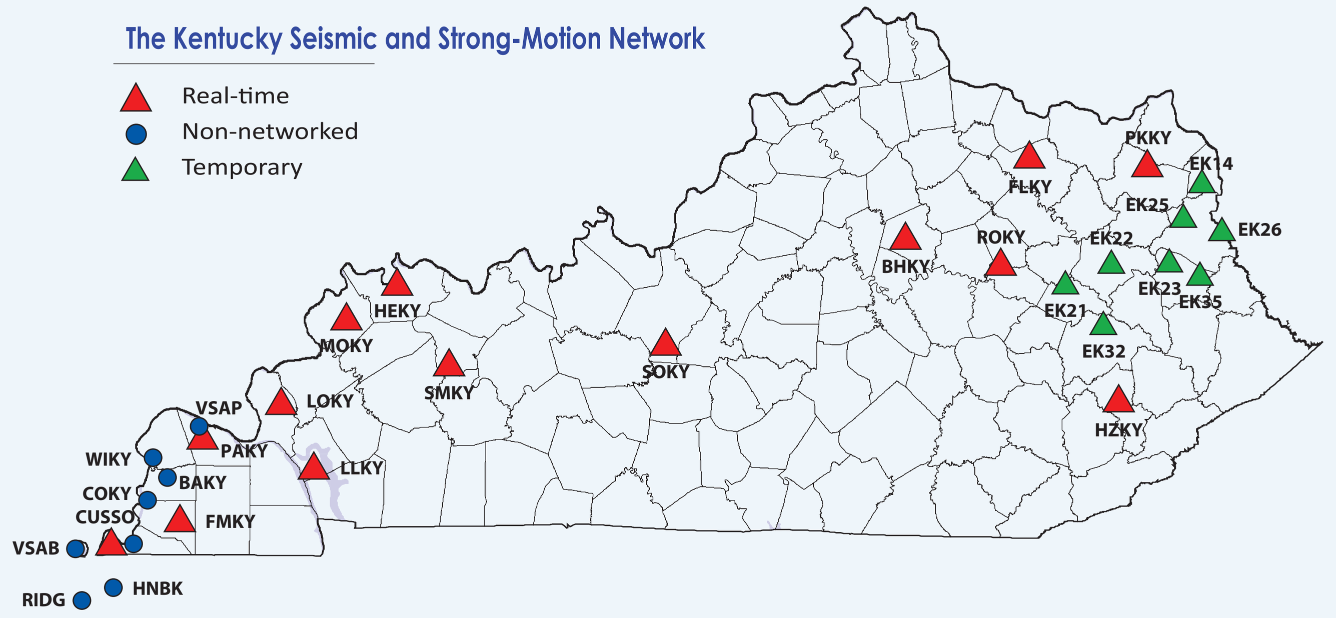


Figure 1. Permanent and currently operating temporary stations in the Kentucky Seismic and Strong-Motion Network.

The KSSMN also operates temporary stations for special projects. Currently, eight seismic stations are monitoring seismicity in Rome Trough as part of the DOE-sponsored Conasauga Shale Research Consortium (CSRC), a continuation of the 14-station KGS-sponsored Eastern Kentucky Microseismic Monitoring Project (EKMMP). The project area experiences infrequent earthquakes, but numerous mine blasts (Fig. 2; Carpenter et al., 2020).

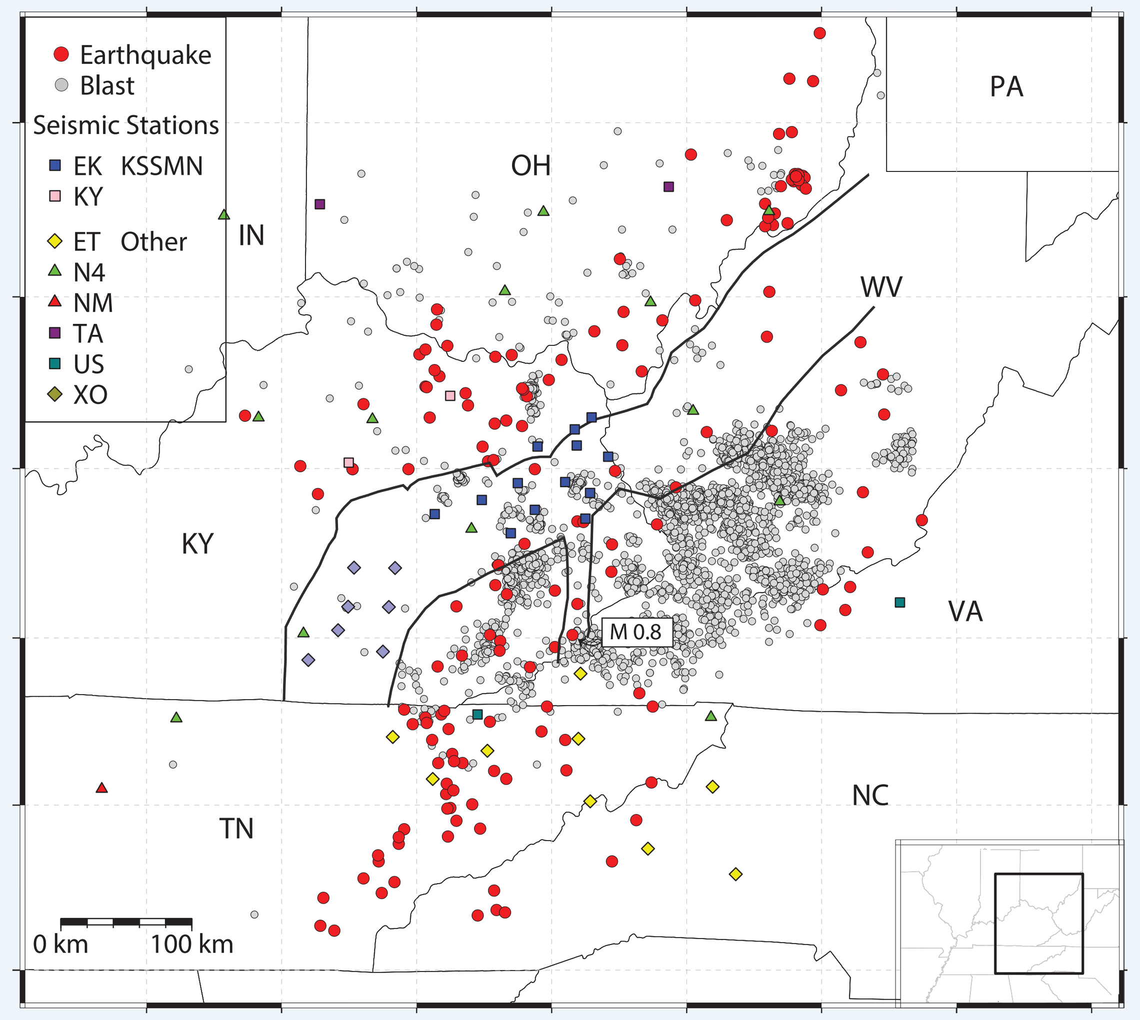
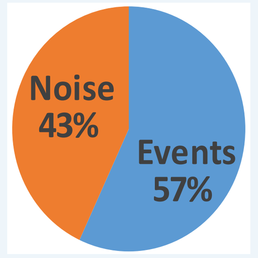


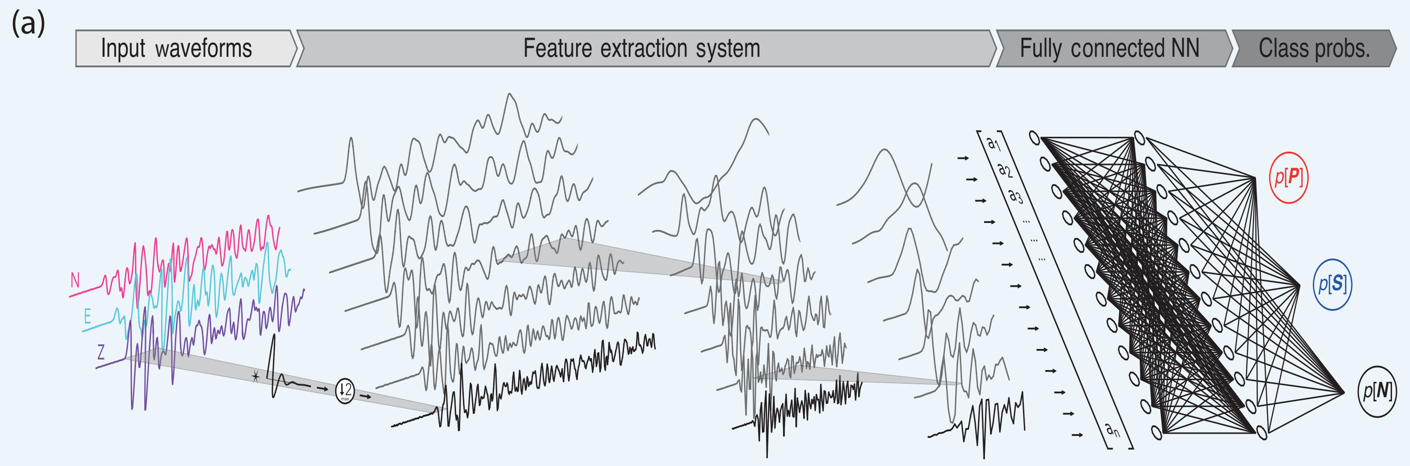
Figure 2. Earthquakes and blasts from June 2015 through April 2019, located as part during the EKMMP. Seismic stations EK are temporary stations installed for this study, KY are permanent KSSMN stations used in this study. Stations from other networks that were used for event analysis are also shown.

Problem: Attempting to detect small earthquakes results in numerous noise triggers:
Of the ≥ 65,000 triggers recorded during the EKMMP, 43%, or ~28,000 were noise.



Improving Seismic Monitoring with Machine Learning: Event Detection

Event Detection: GPD Picker (Ross et al., 2018)



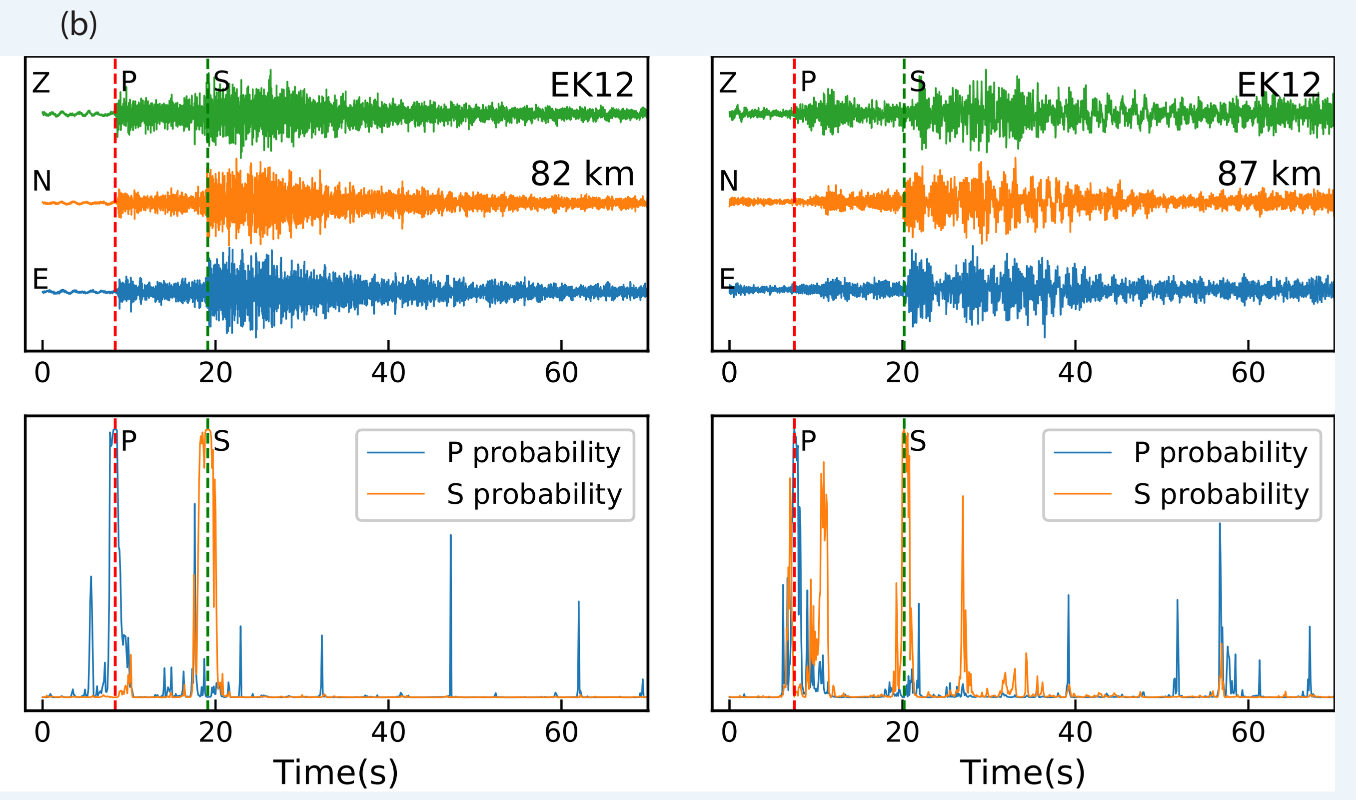


Figure 3. Probabilistic seismic event detection using GPD Picker. (a) Extraction of features from three-component seismograms (Z, N, and E) via decimations and applications of multiple filters. Features are input into a trained connected convolutional neural network and probabilities of P-wave, S-wave, or noise are output. (b) Example of phase arrivals and detection probabilities for an earthquake (left column) and a blast (right column) at EK station EK12.

Improving Seismic Monitoring with Machine Learning: Detection Association

The GPD picker is skilled, but also detects noise that resembles seismic waves. This is problematic when detecting microseismicity with few seismic stations: low probability detections may be required from few stations and thus transient noise may cause false triggers. Associating detections using predicted travel times helps to remove noise detections. We are evaluating two recently developed (Python) associators: PhasePApy (traditional time-based) and PhaseLink (deep-learning-based)

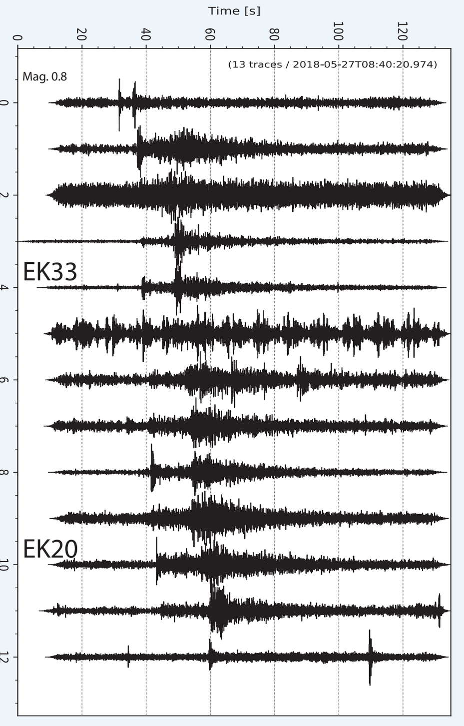


Figure 4. Seismograms from a mag. 0.8 earthquake (Figure 2).

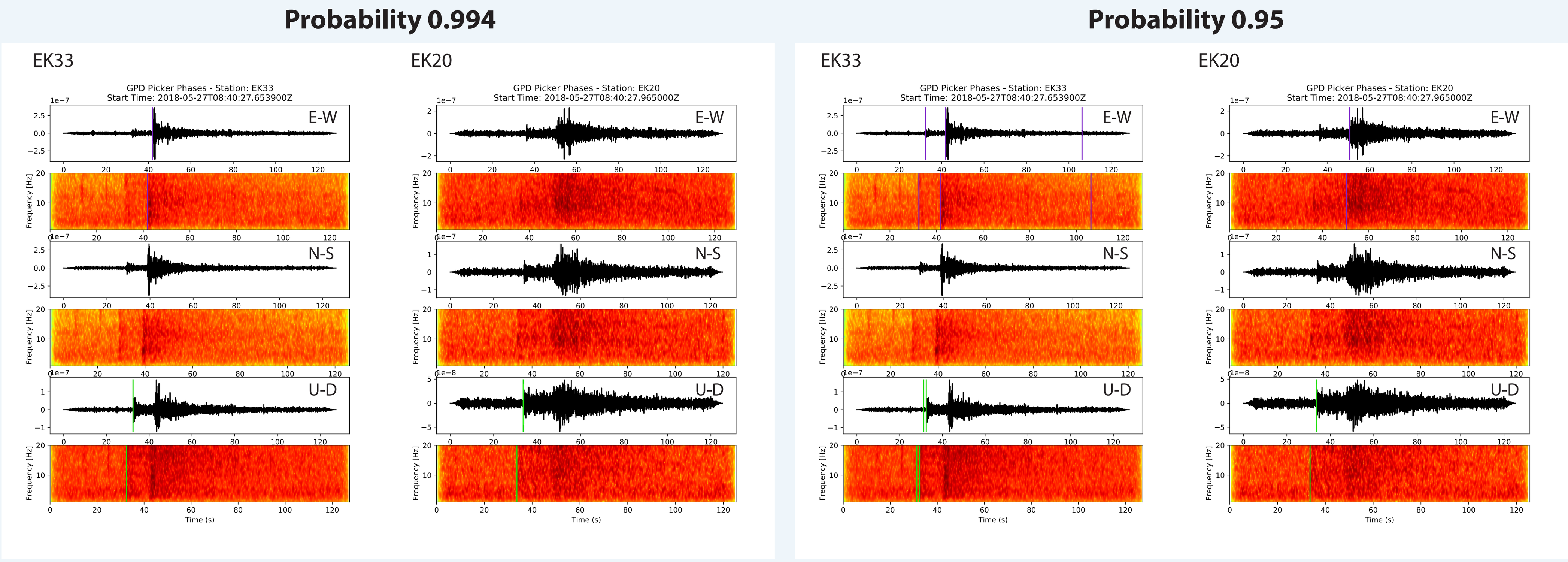


Figure 5. Example GPD detections for two probability thresholds: 0.994 (left) and 0.95 (right) at two Rome Trough stations EK33 and EK20. Three component seismograms (Horizontals: E-W, N-S; Verticals: U-D) and corresponding power-frequency-time plots (spectrograms) are shown. Higher probability detections are more reliable, but some are missed. Lower-probability detections include seismic waves, but more noise.

Detection Association: PhasePApy (Chen and Holland, 2016)

Operational principles:
- Requires both P- and S-wave detections for a given station
- Calculates distances and event times from t_s - t_p
- Associates clusters of stations with common event times.
- Trigger declared for ≥3 stations in cluster

Detriments to performace:
- Requires P- and S-wave detections at a station
- Associator cannot manage numerous low-probability detections

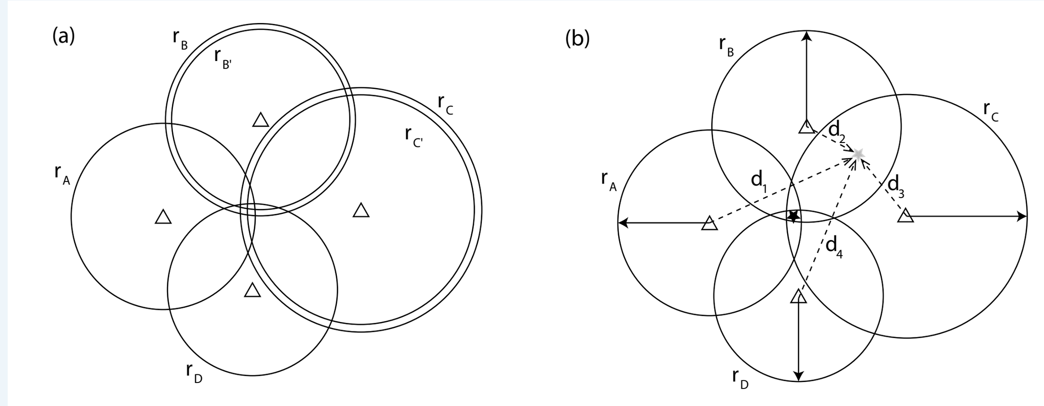


Figure 6. Illustration of PhasePApy detection clustering. (a) 12 detections at 4 stations have similar predicted event times. Only the best-fitting at a given station are retained. (b) The location whose distance to each station best fits the t_s - t_p distance (black star) is assigned. Modified from Chen and Holland (2016)

Detection Association: PhaseLink (Ross et al., 2019)

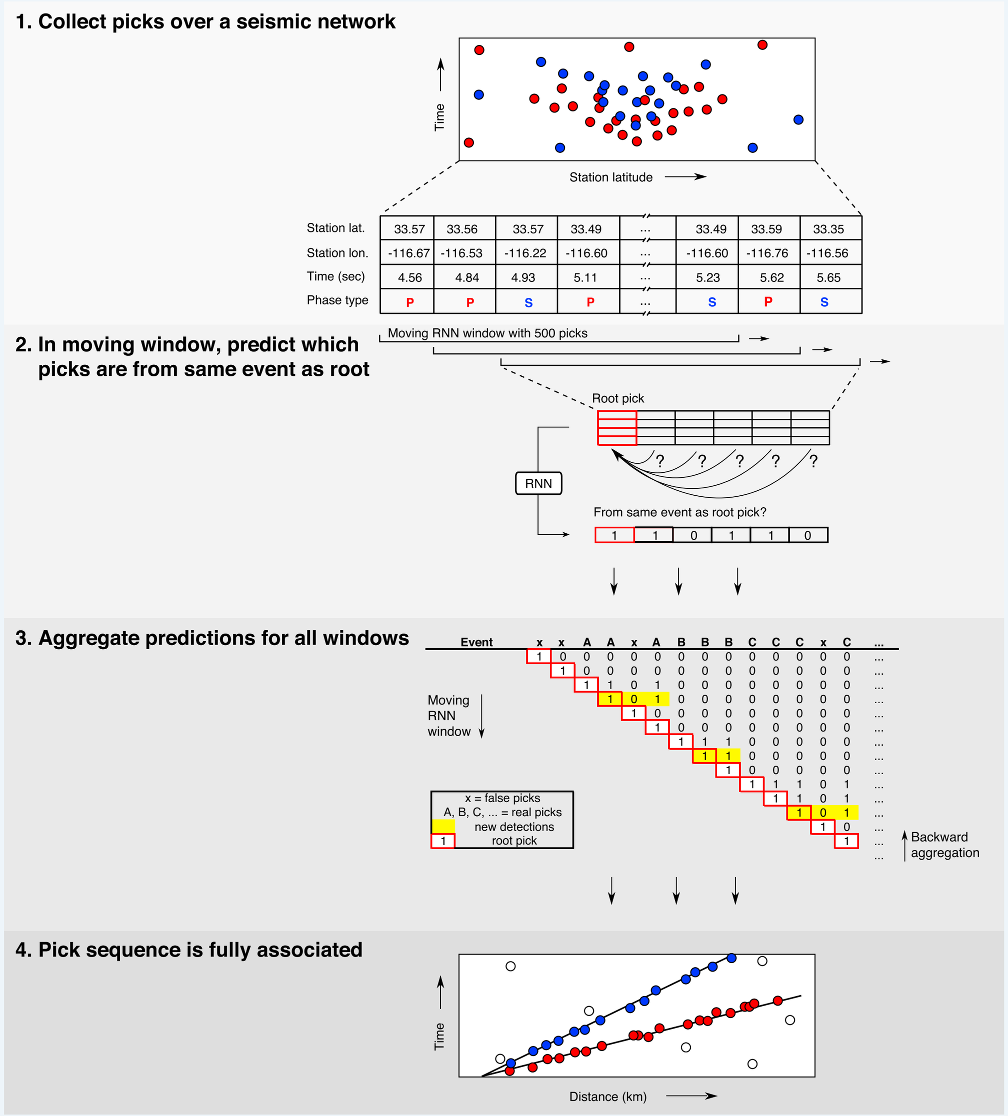


Figure 7. (left) Illustration of PhaseLink Recurrent-Neural-network- (RNN) based detection association. From Ross et al. (2019)

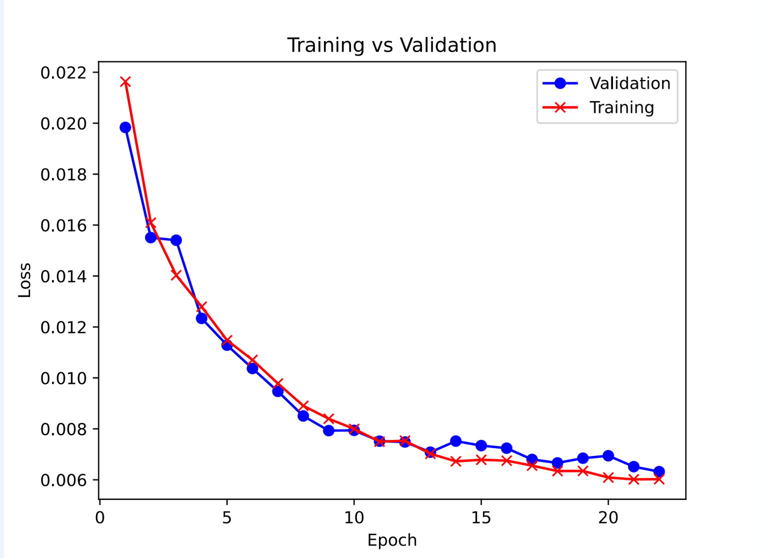


Figure 8. Reduction of loss while training PhaseLink on synthetic data created for multiple earthquake scenarios and using an earth model appropriate for Kentucky and station locations shown in Figure 2.

Next steps with PhaseLink

- Determine optimal GPD detection probability
- Optimize PhaseLink association. E.g.:
  - Synthetic earthquake scenarios
  - Number of detections per window
  - Number of stations needed to trigger
  - Simultaneous-event merging
  - Maximum detection error (time uncertainty)
  - Maximum distance to closest station
- Assess entire CSRC dataset.

References

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