Intelligent Seismic Data Processing: A Data Science Perspective

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Outline

- Background
  - Seismic waves, Seismometer network, Seismographs
- Seismic Data Processing Pipeline
  - Single Seismometer to an Array to a Network to a human readable Bulletin
- Seismic Data Collection
  - Data Sources
- Data Science Problems and Corresponding Seismology Applications
  - Semi-supervised Motif discovery: Seismic Signal Detection
  - Classification: Seismic Phase Classification
  - Regression: Depth Estimation
  - Clustering: Seismic Phase Association
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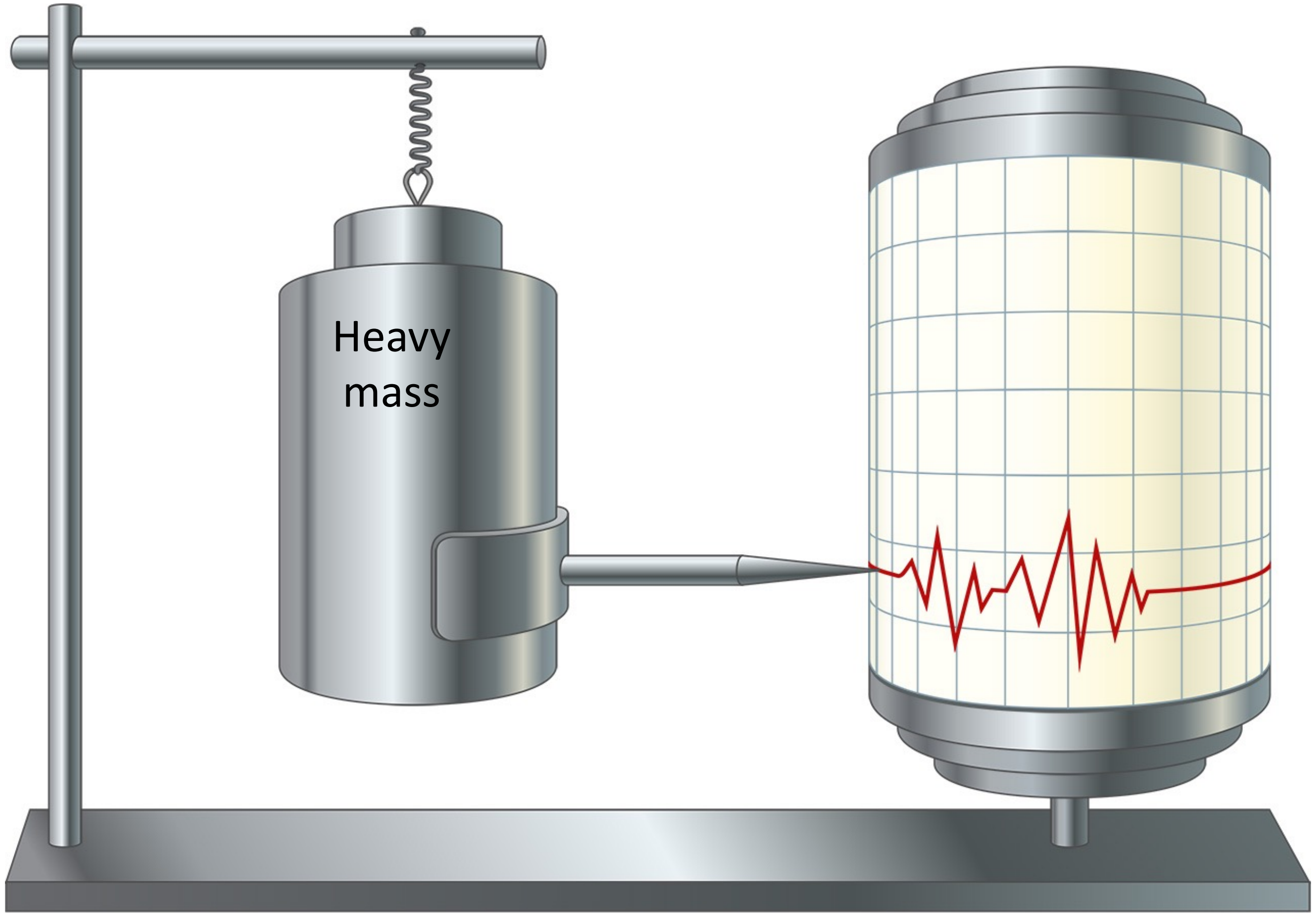
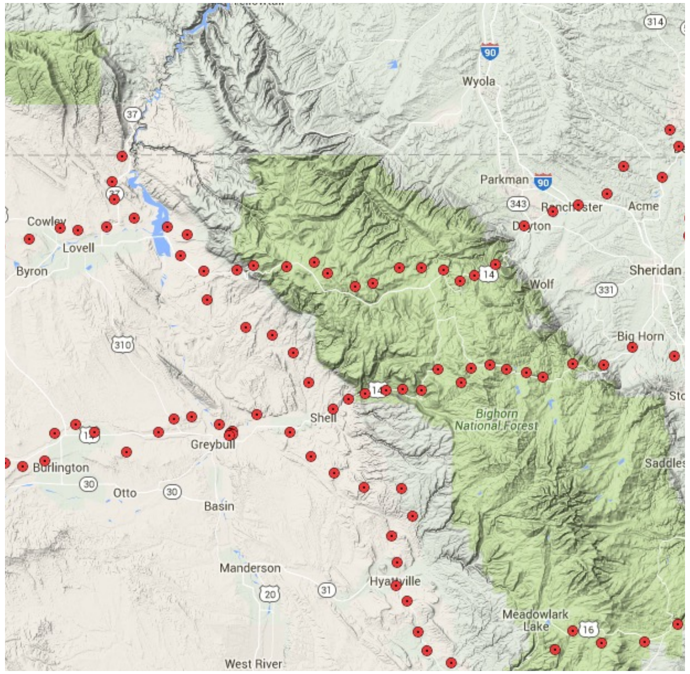
  - Similarity Search: Aftershock Detection

A Seismometer

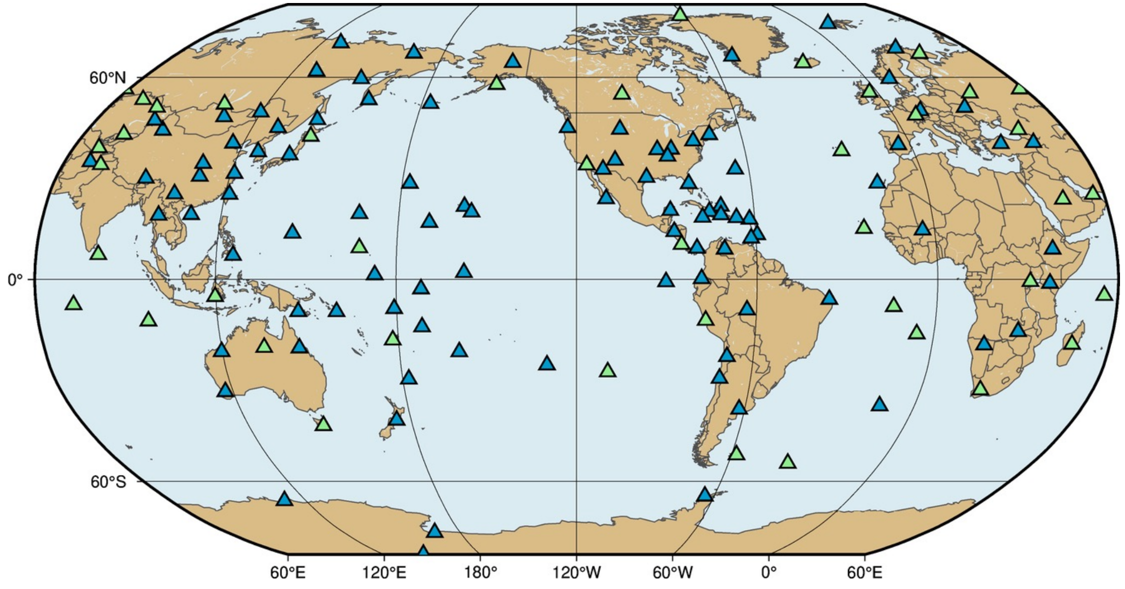


Vertical channel seismometer
The heavy mass stays in the same place while the rest of the assembly vibrates as the ground vibrates.

An Array/Network of Seismometers

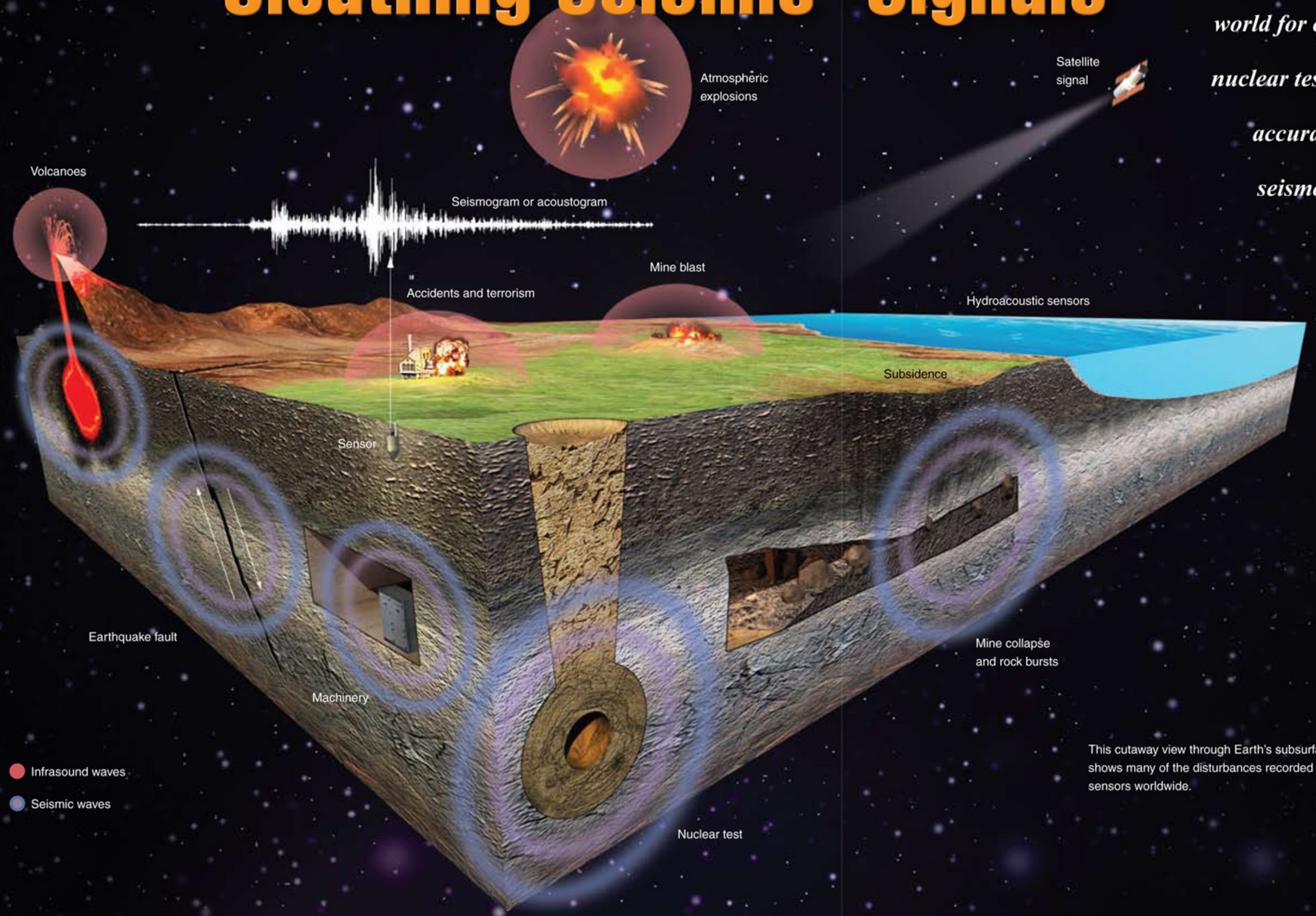


Bighorn Arch Seismic Experiment (BASE) broadband stations in Wyoming and Montana region



Distribution of Global Seismographic Network (GSN) stations.
USGS GSN sites are shown in blue and IRIS/IDA stations are shown in green.

Sleuthing Seismic Signals



This cutaway view through Earth's subsurface shows many of the disturbances recorded by sensors worldwide.

Monitoring the world for clandestine nuclear tests requires accurate forensic seismology tools.

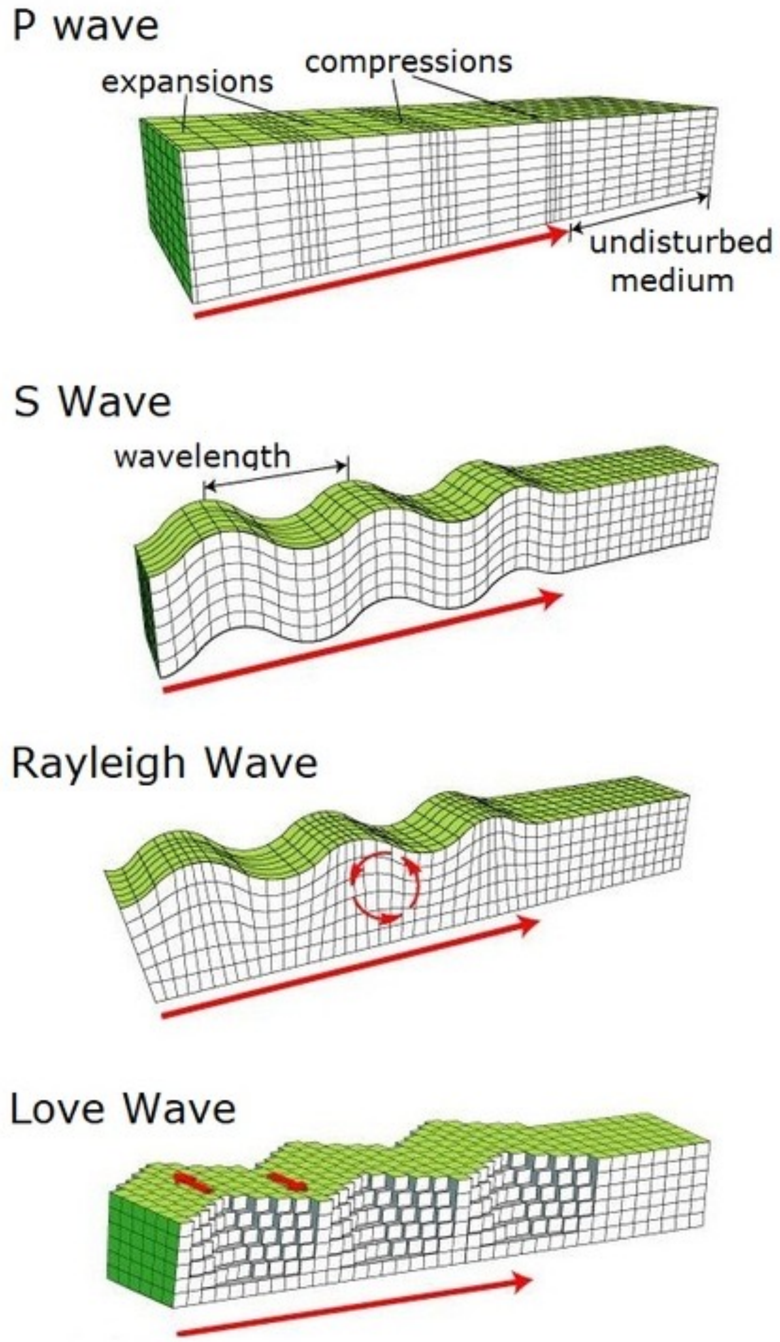
AN earthquake, a nuclear test, and a mine collapse all cause seismic disturbances that are recorded at monitoring stations around the world. However, these three types of events produce very different ground motions at their source. Earthquakes are caused by sideways slippage on a fault plane, while underground nuclear explosions push outward in all directions. A mine collapse is a massive vertical roof fall.

Lawrence Livermore is at the forefront of research to more accurately distinguish nuclear explosions from the rest of Earth's never-ending seismic activity, including earthquakes large and small, volcanoes, and waves crashing on shore. The Laboratory's work was unexpectedly put to the test following the August 2007 collapse of the Crandall Canyon coal mine in Utah, which killed six miners. Ten days later, another collapse killed three rescue workers. Both events were recorded on the local network of seismic stations operated by the U.S. Geological Survey (USGS) as well as on the USArray stations, which are part of EarthScope, a program funded by the National Science Foundation. There was considerable contention about whether the initial magnitude-3.9 event was caused by an earthquake or a collapse.

At the time, Livermore seismologists were working with colleagues from the University of California at Berkeley on a waveform-matching technique to distinguish among nuclear explosions, earthquakes, and collapse events. This technique compares seismograms produced by computer modeling with recorded data at local to regional distances (from 0 to 1,500 kilometers) for periods of 5 to 50 seconds. Livermore's analysis of the August 2007 seismograms pointed to a collapse rather than an earthquake. The important result for the Laboratory team

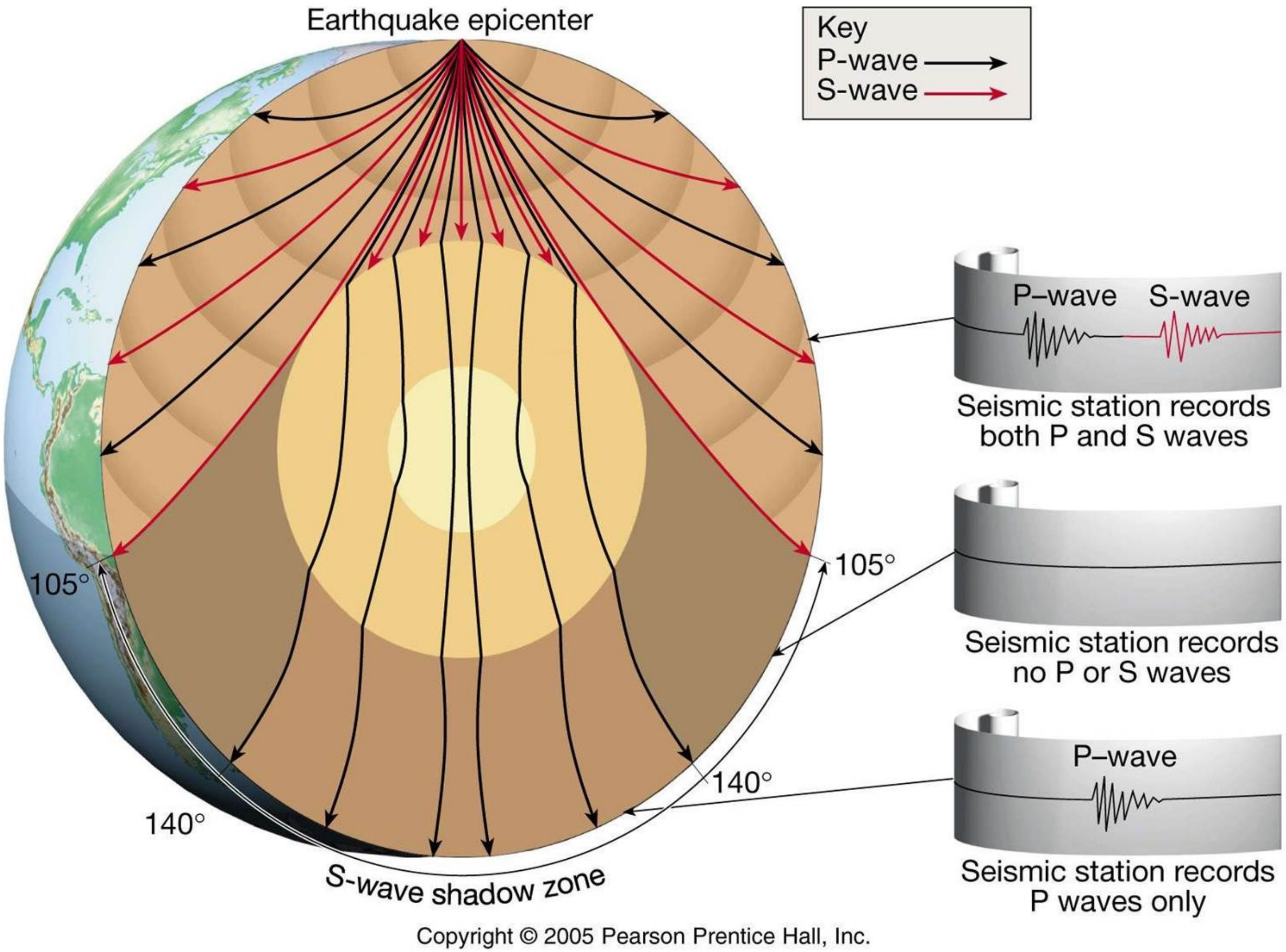
Seismic Waves

- Body waves (Linear particle motion)
  - P wave – longitudinal wave
  - S wave – transverse wave
- Surface waves (non-linear particle motion)
  - Rayleigh wave
  - Love wave

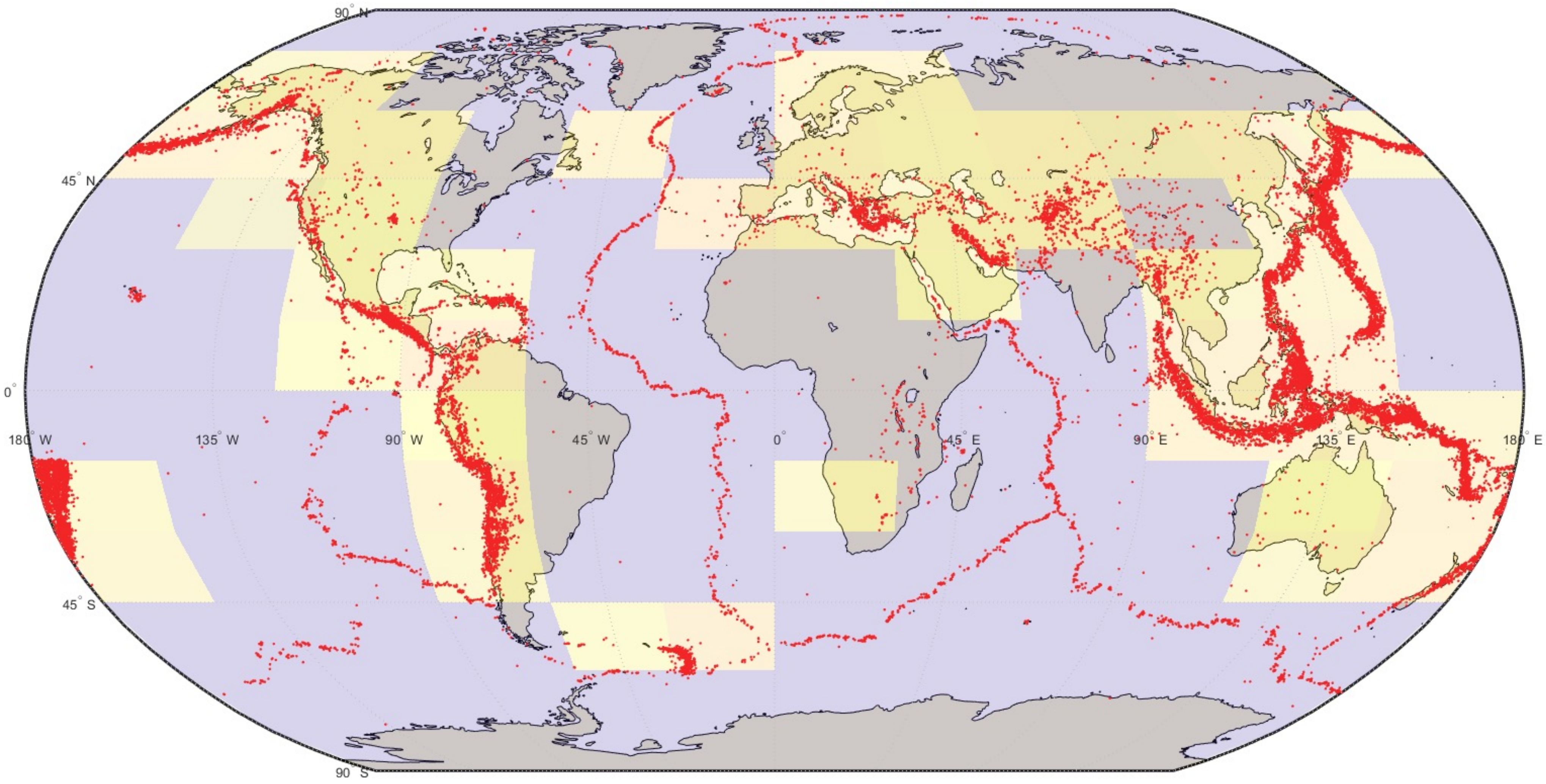


Wave propagation

- Seismic waves reflect and refract
- There are shadow zones where some waves cannot reach
- Speed of these waves varies depending on the media



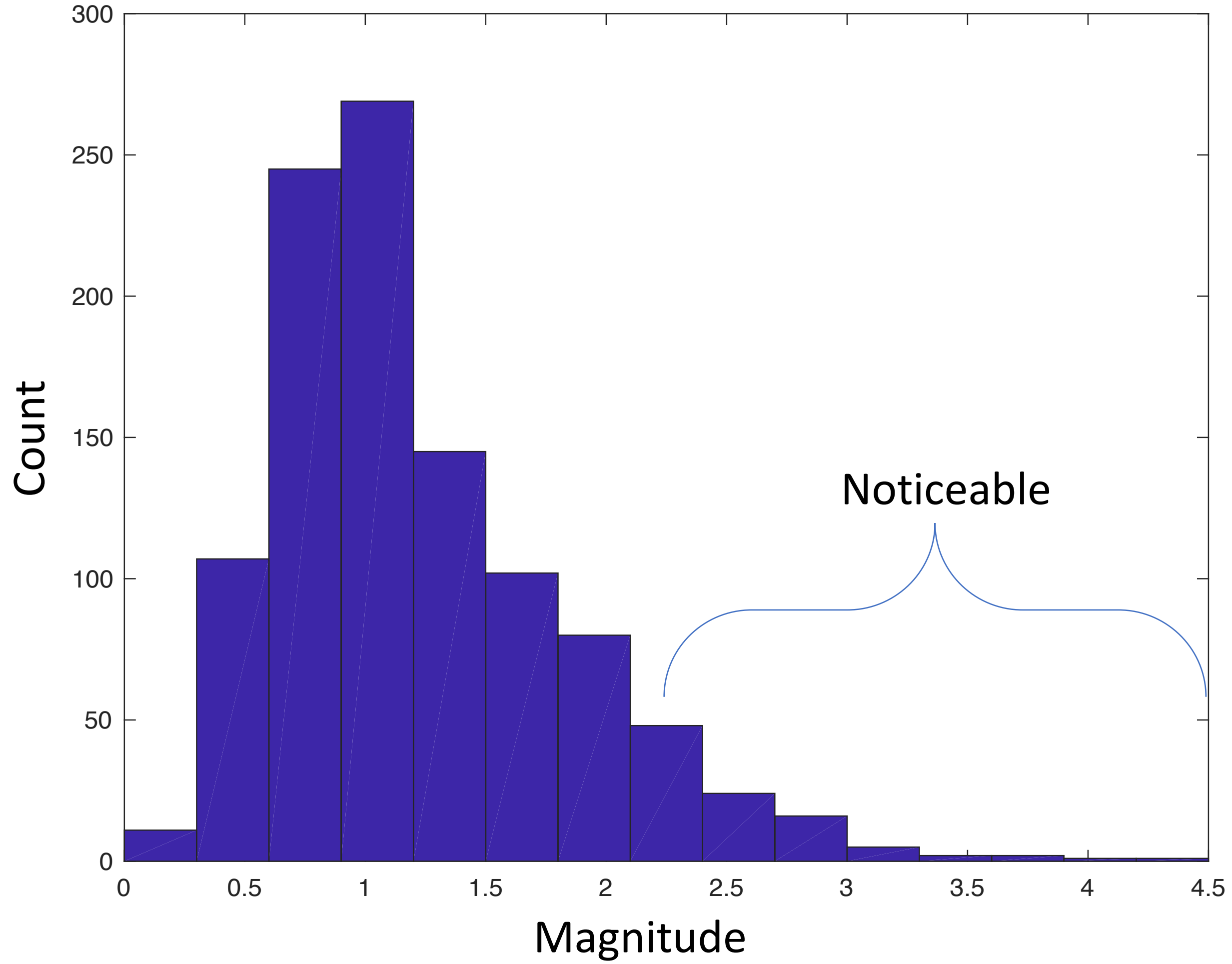
Where do earthquakes happen?



NEIC events ('14,'17,'18) are red dots.

How many earthquakes do happen?

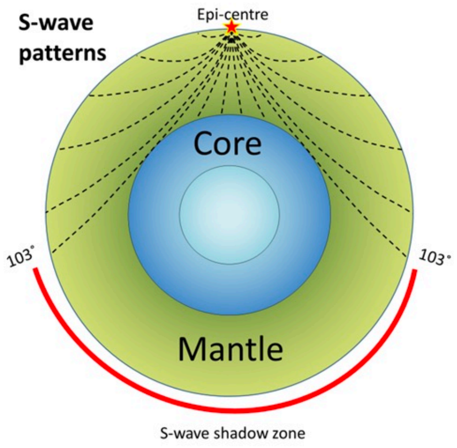
- Strong events are easy to notice, and easy to detect.
- Weaker events are rarely noticed, hard to detect, and often uncatalogued.
- Low magnitude events are frequent and potentially informative to prediction, classification and localization tasks.

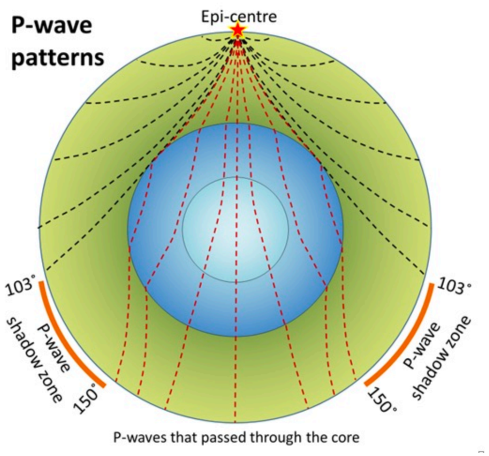


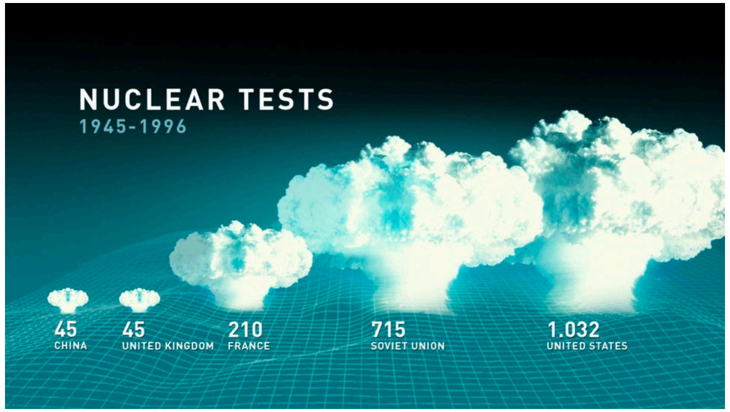
Distribution of event magnitudes in Northern California

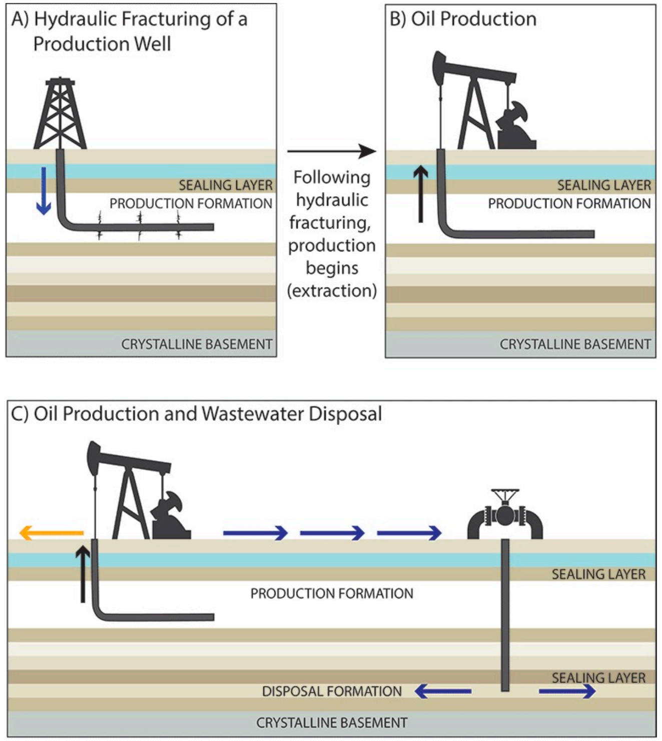
Need

- To produce early warning for damage mitigation
- To enforce Comprehensive Nuclear-Test-Ban Treaty (CTBT)
- To understand earth structure and predict large magnitude events
- To understand the effect of human induced seismicity









https://www.norsar.no
Physical Geology, by Steven Earle
Usgs.gov

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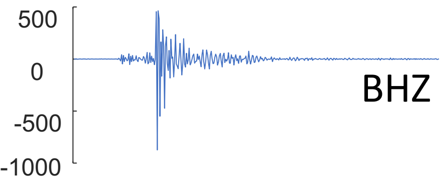
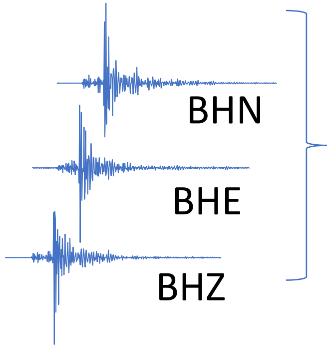
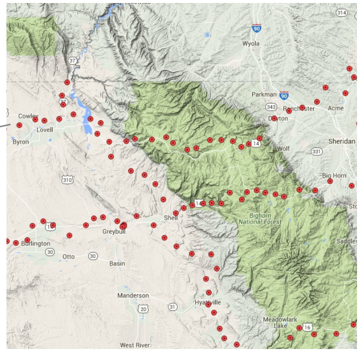
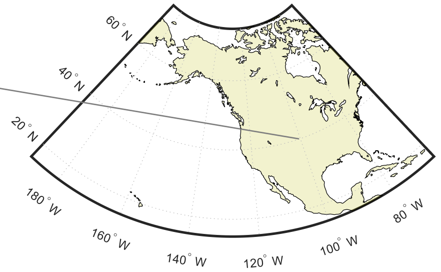
Seismic Data Processing Pipeline









- Origin time (Y-M-D H:M:S)
- Latitude (°)
- Longitude (°)
- Depth (km)
- Magnitude

Signal Detection
Identify a spike in waveform as arrival

Phase Identification
Identify phase type of the arrival

Phase Association
Group phases from the same event

Event Formation
Detect and classify all phase types

Bulletin Record
Derive attributes: magnitude, depth, etc.

One Trace

Multiple Channels

Multiple Stations

Multiple Arrays

24/7 analysts

Seismic Data Collection

- Event data from an already produced bulletin
  - Generally queried by ranges of time and location of events
  - All regional networks distribute bulletin: SCEDC, NCEDC, UU, NEIC
- Waveform data at a station
  - Generally queried by range of time
  - https://service.iris.edu/fdsnws/dataselect/1/
- Real-time data at a station
  - No query
  - https://ds.iris.edu/ds/nodes/dmc/services/seedlink/

Key Challenges

- Real-time Data Processing
  - 40Hz-100Hz data rate
  - Large network with many stations
- Machine learning
  - Planet scale learning
  - Lack of ground truth!
  - Location sensitivity
  - heterogeneity in sensors and networks
- Constrained processing in defense applications
  - Single station
  - Far from the Event
- Monitoring Challenges
  - No or few human involvement
  - Variable system load

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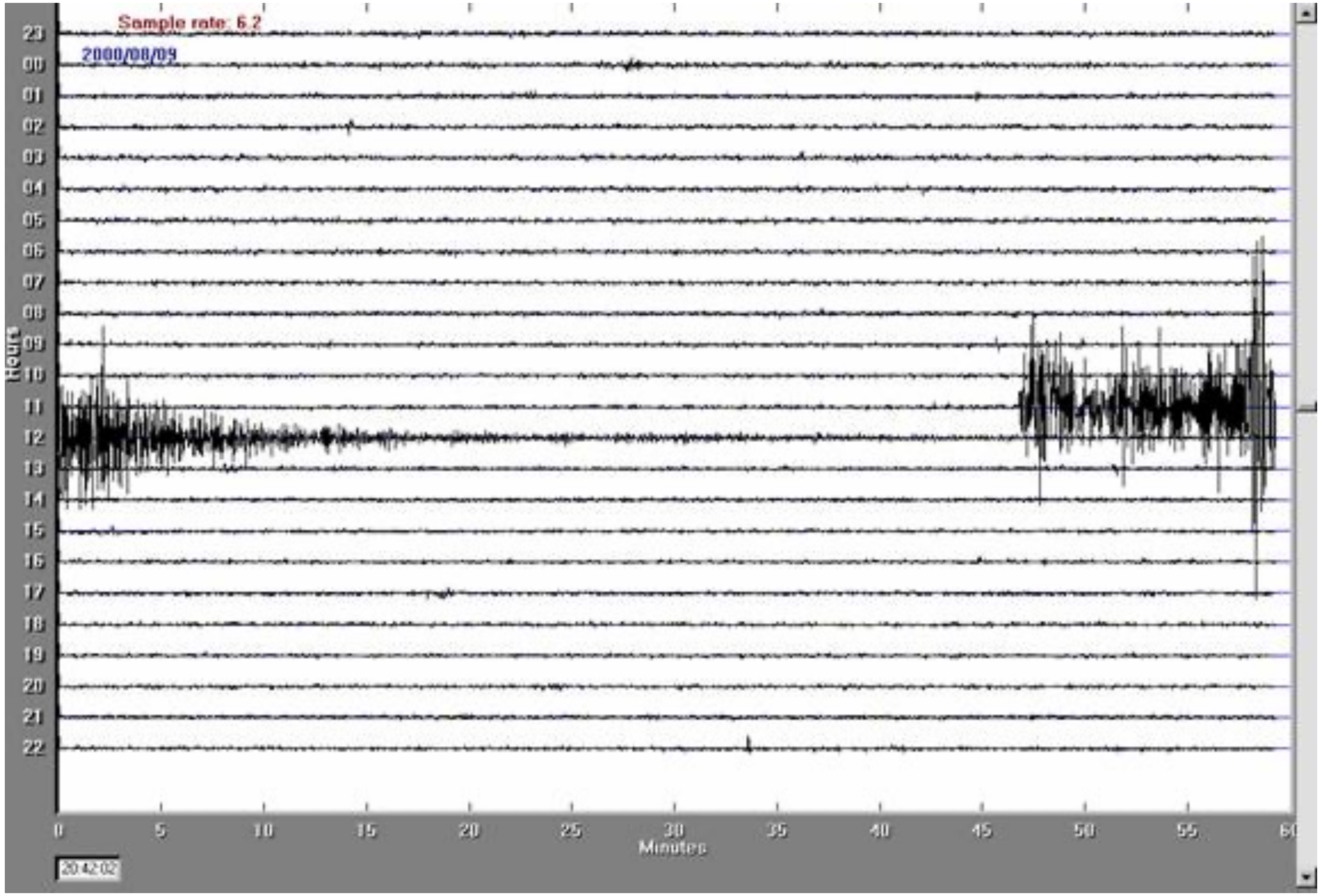
Automated Seismic Signal Detection



The Problem: Given a long seismograph, spot the low magnitude seismic events.

Signal Processing Technique

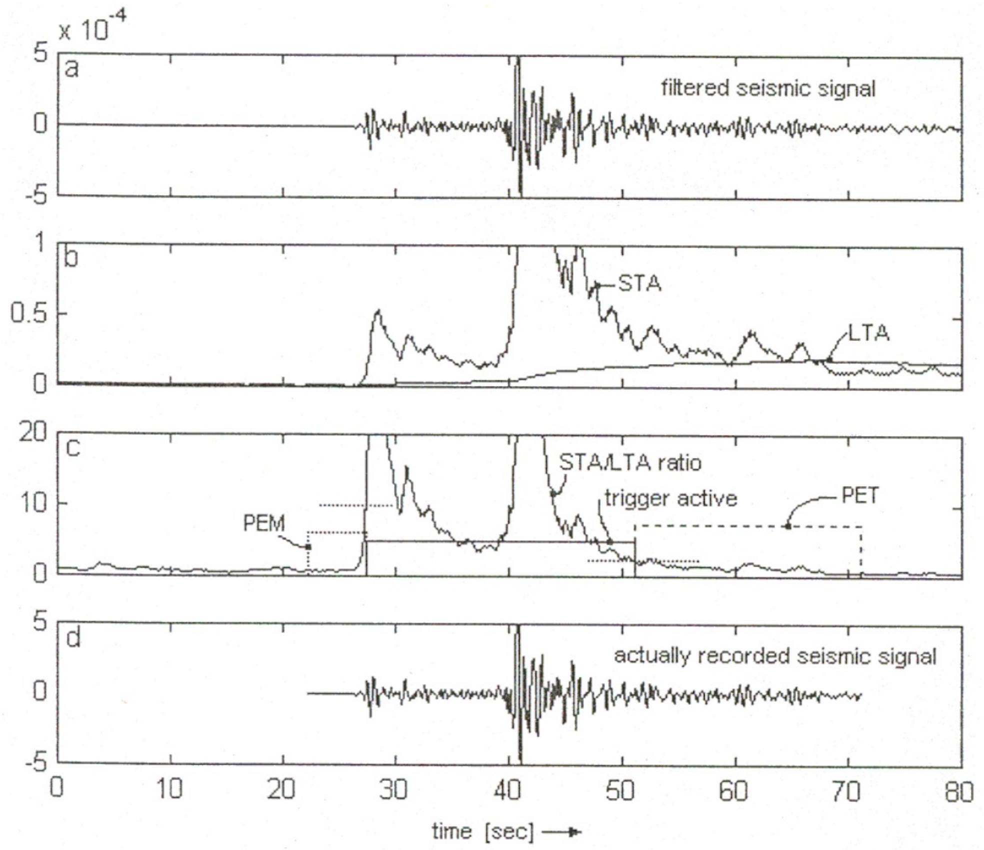


Figure 1 Function and variables of STA/LTA trigger calculations (see text for explanations).

List of parameters

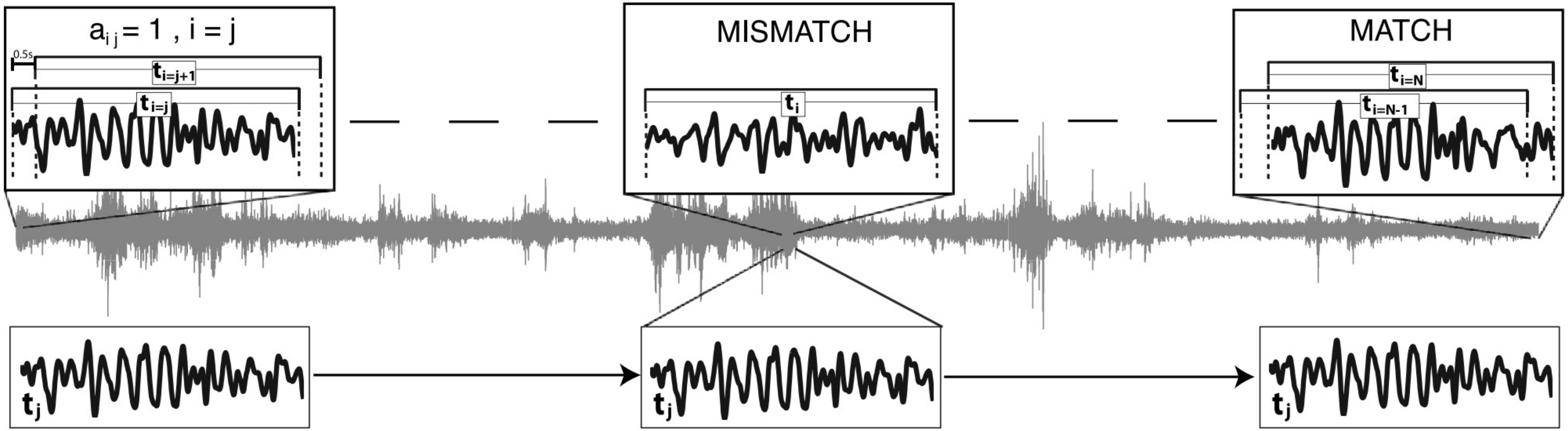
- STA window duration
- LTA window duration
- STA/LTA trigger threshold level
- STA/LTA detrigger threshold level.
- Trigger filters
- Pre-event time (PEM)
- Post-event time (PET)

Very high false detection rate.

Understanding and parameter setting of STA/LTA trigger algorithm, Amadej Trnkoczy

Auto-correlation Technique

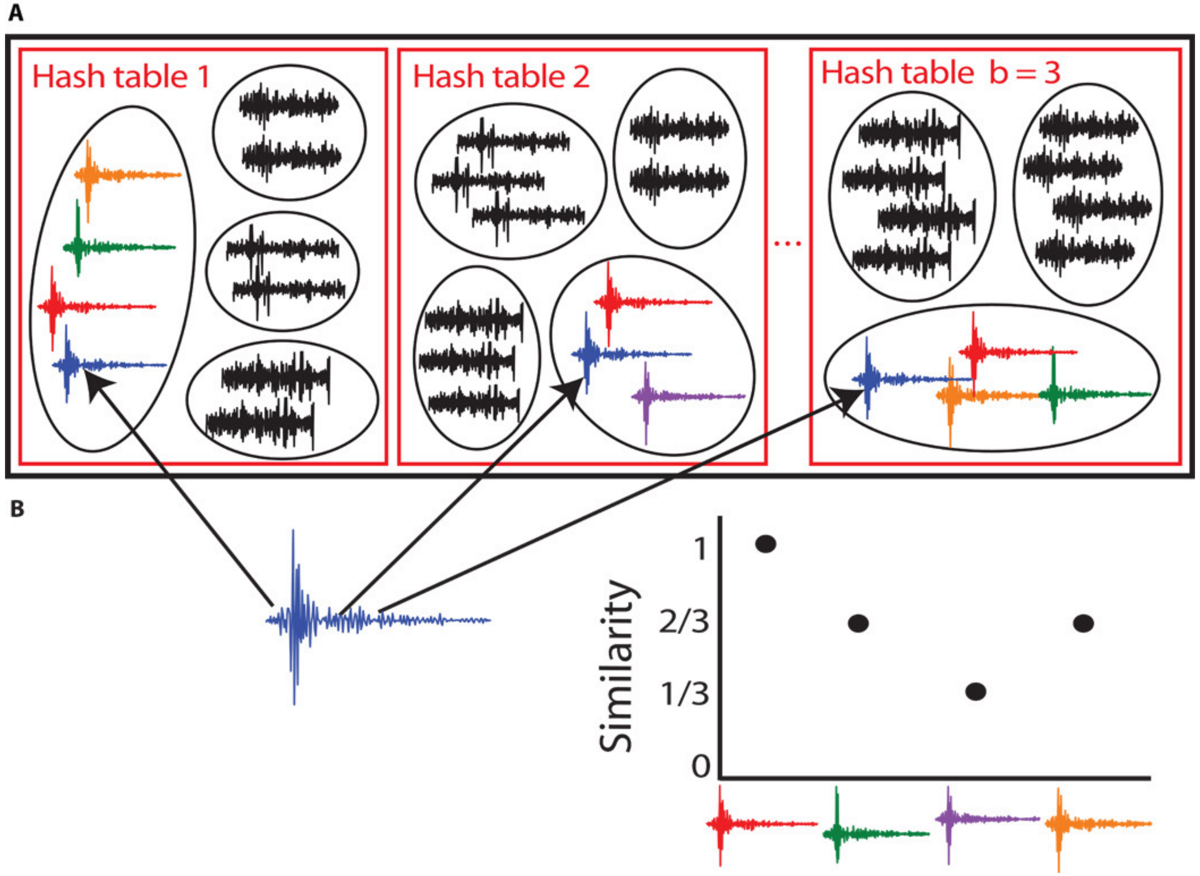
High correlation indicates identical dynamics at the source(s).

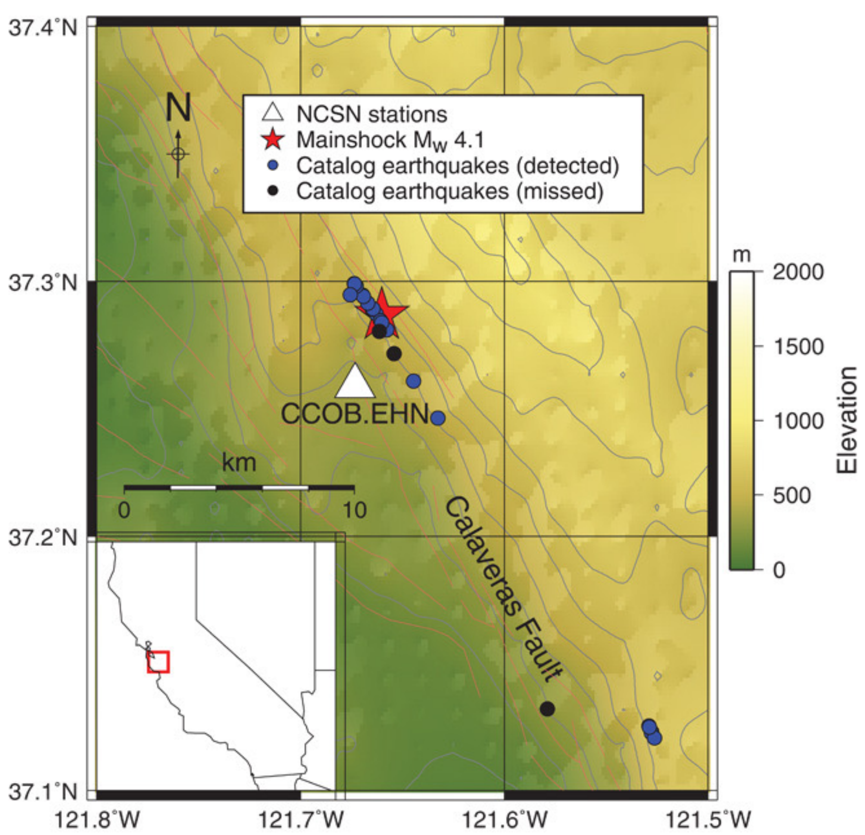


One parameter, high accuracy, time consuming.

An autocorrelation method to detect low frequency earthquakes within tremor, J.R. Brown, G.C. Beroza, and D.R. Shelly, Geophysical Research Letters, 2008

Approximate Correlation

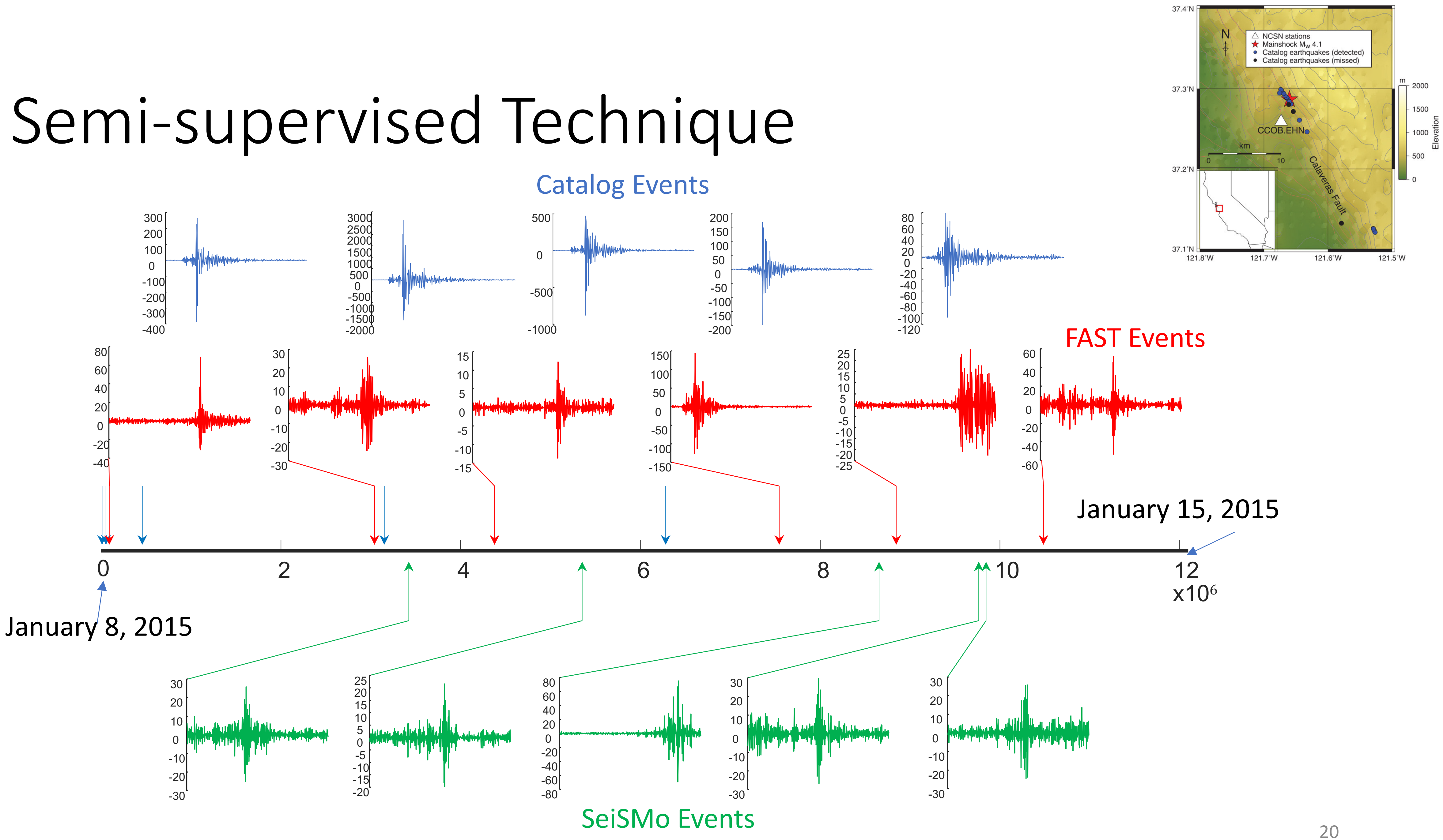




Very FAST algorithm, admits few false detection.

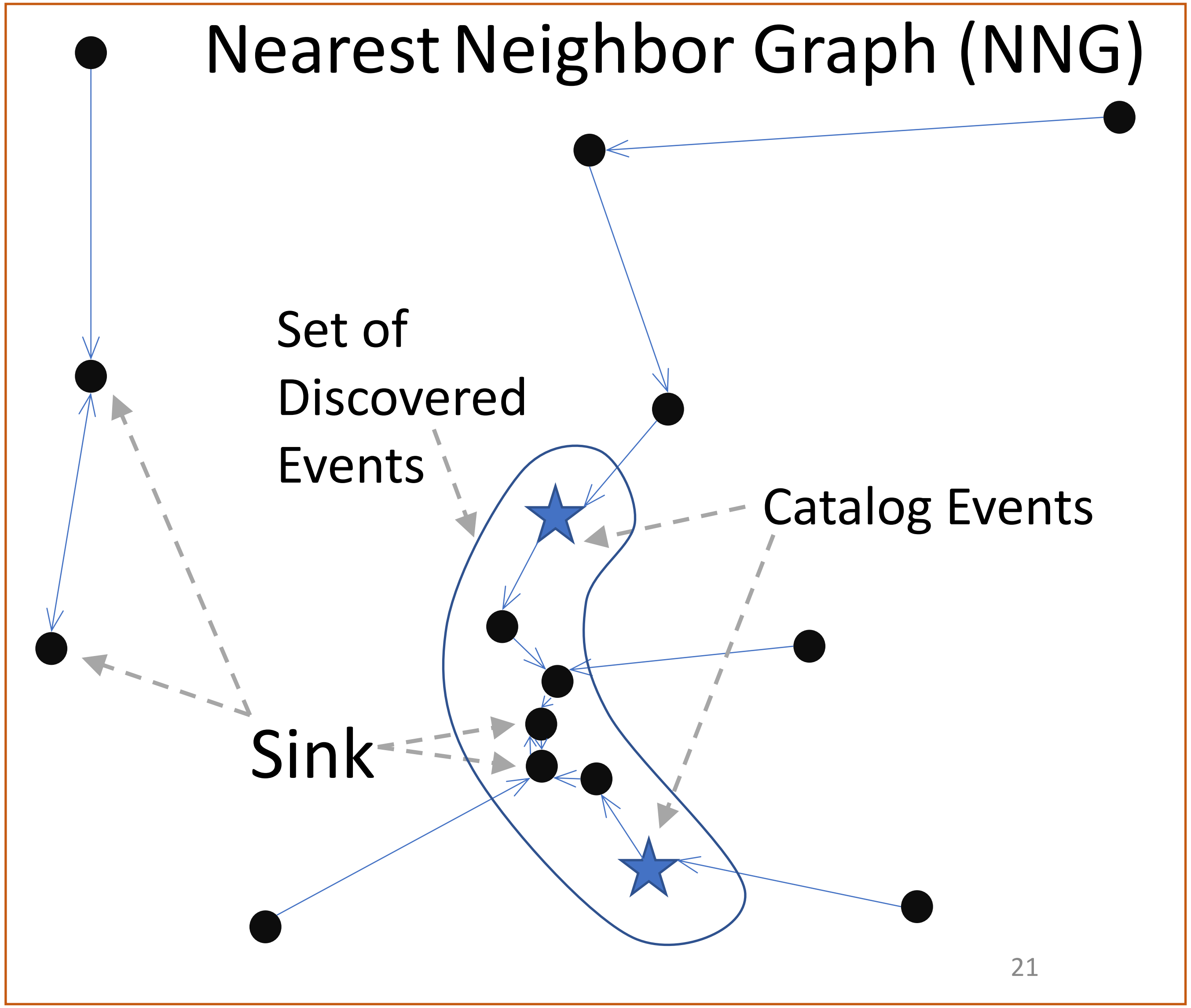
Earthquake Detection Through Computationally Efficient Similarity Search
Clara E. Yoon, Ossian O'reilly, Karianne J. Bergen, Gregory C. Beroza *Science Advances*, 2015 : E1501057

Semi-supervised Technique

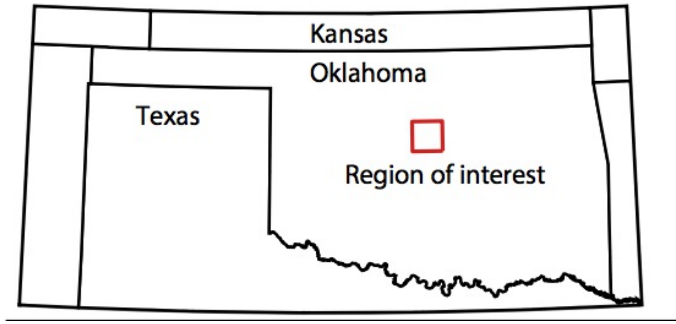


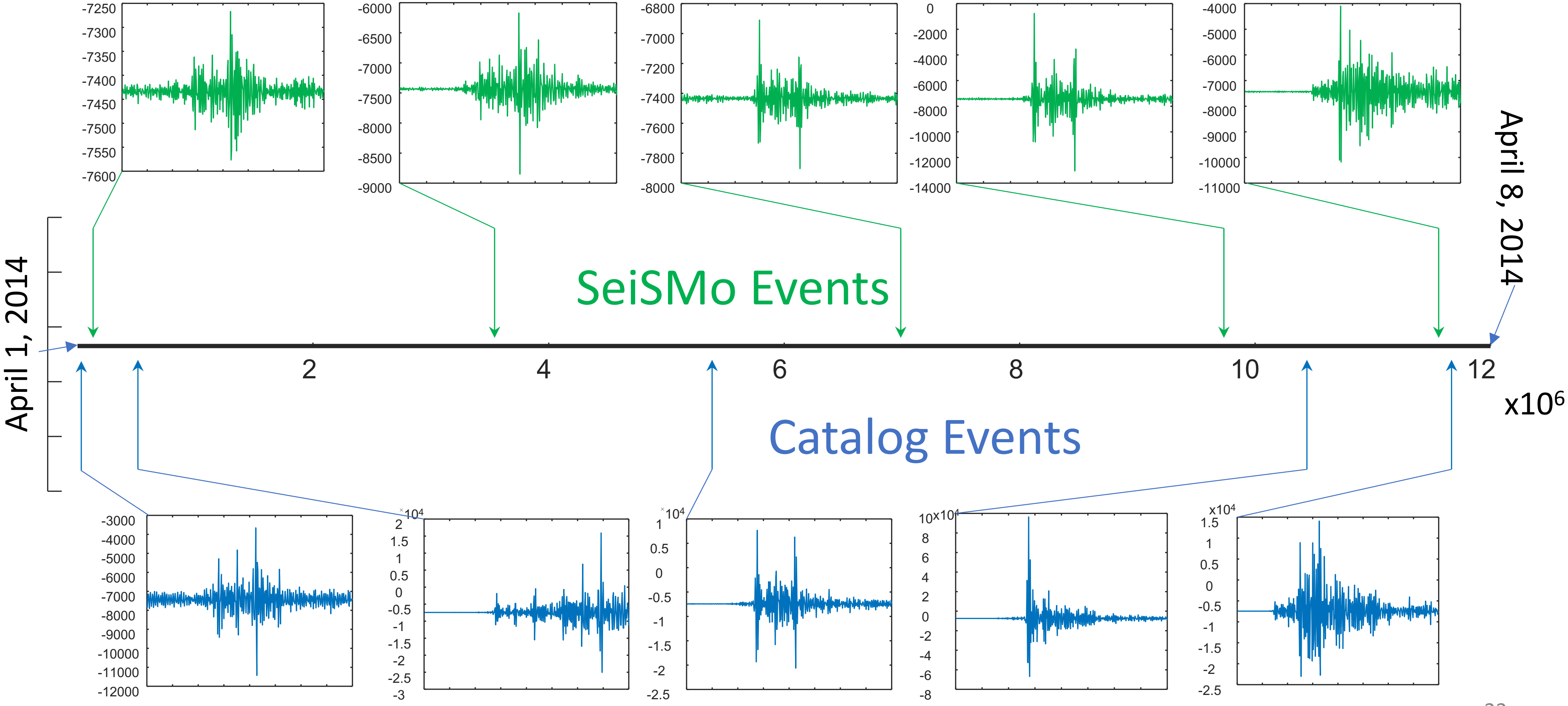
SeiSMo: Semi-supervised Motif Discovery

- Create NNG
- Find sinks
- Count support of each sink
- If support is high enough report all nodes on the paths from any given node to the sink



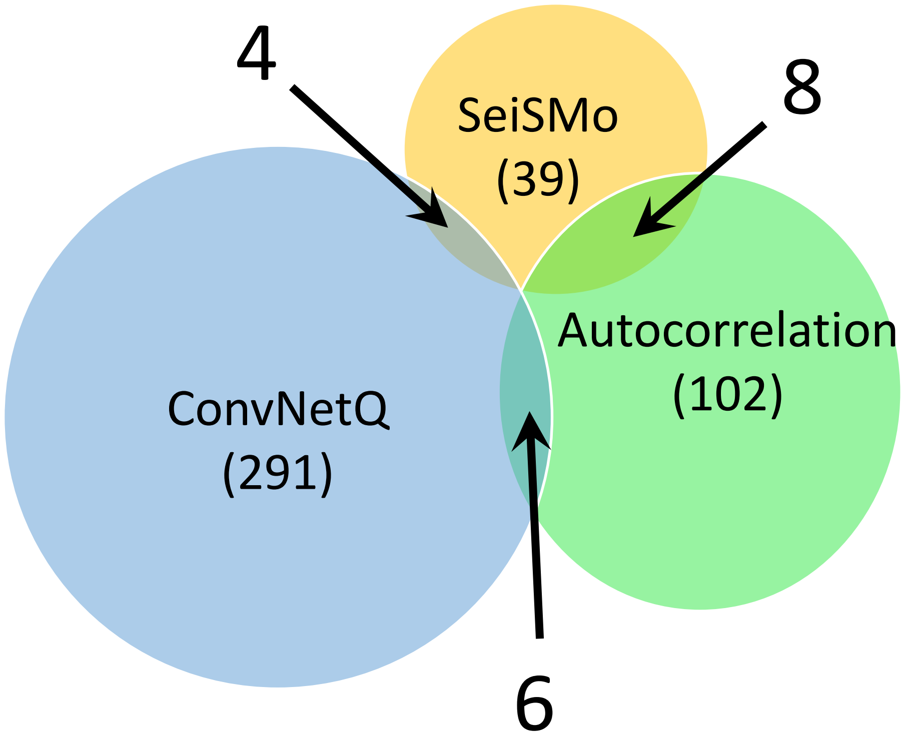
SeiSMo on OK



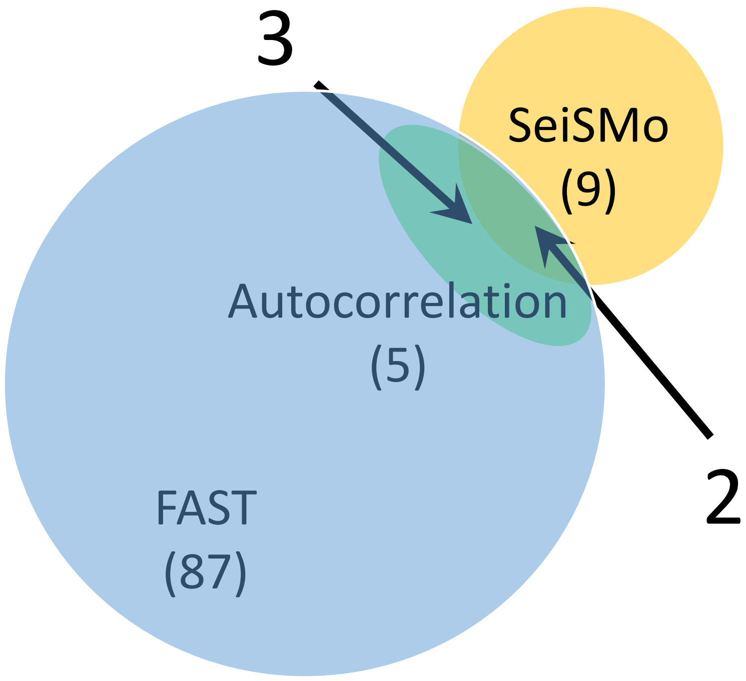


Convolutional neural network for earthquake detection and location, **Thibaut Perol, Michaël Gharbi and Marine Denolle**
Science Advances 14 Feb 2018: Vol. 4, no. 2, e1700578 DOI: 10.1126/sciadv.1700578

Novel Events



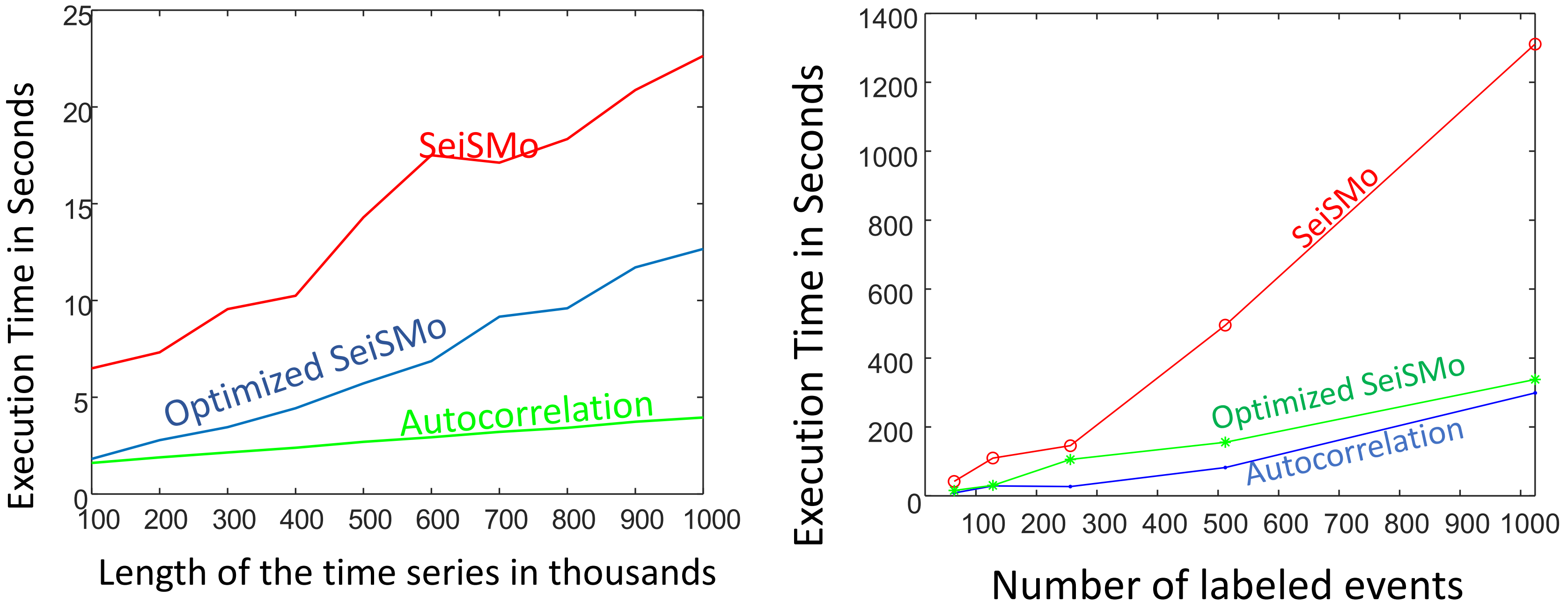
Oklahoma



California

SeiSMo has detected novel events that existing methods missed.

Performance



SeiSMo can process hours long seismographs in seconds.

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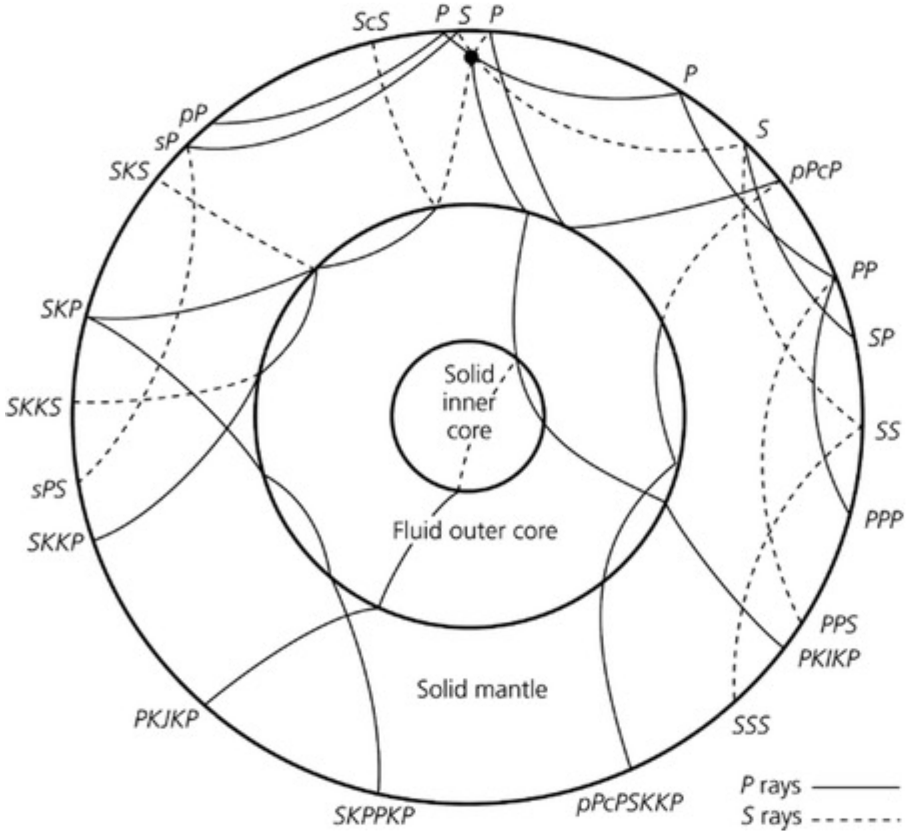
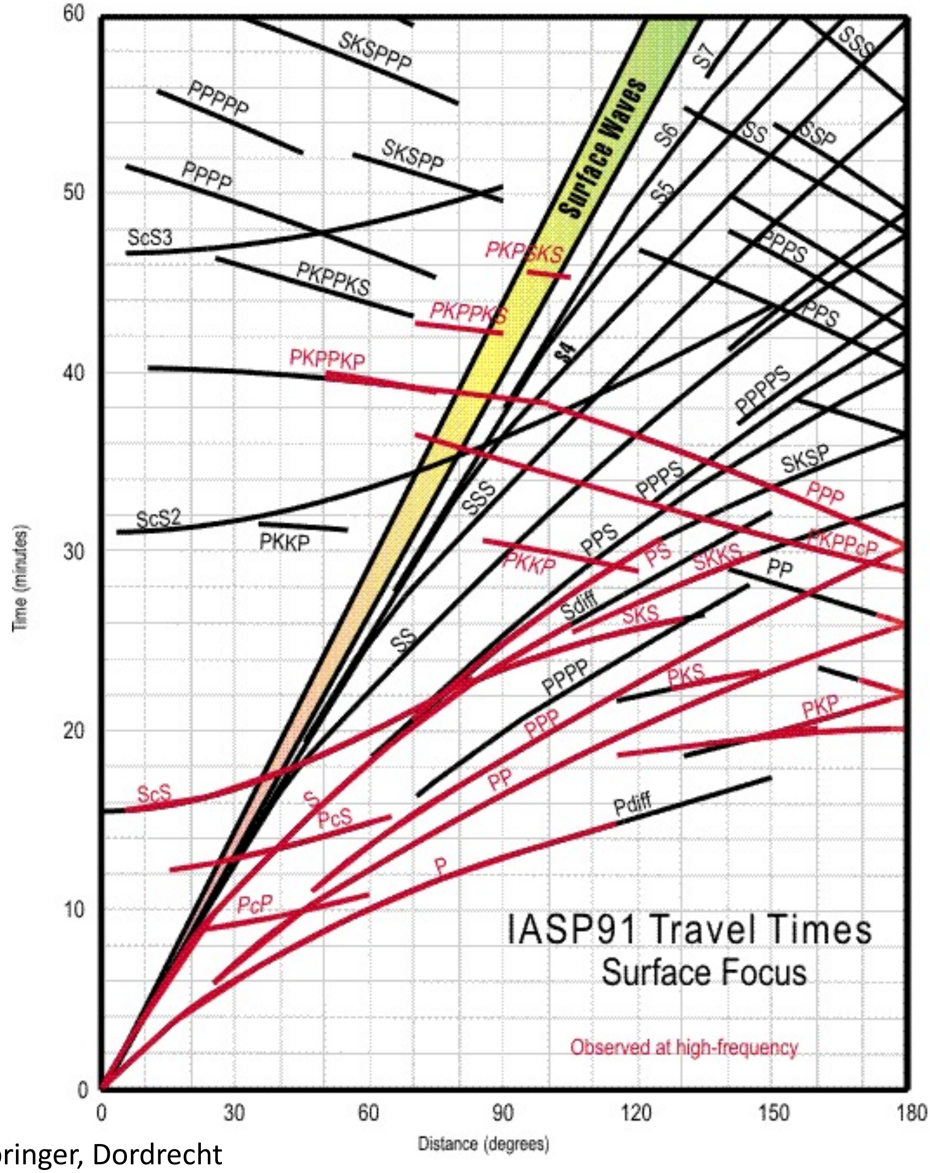
Phase Classification

- The Problem: Identify the phase in given waveforms from a three-component station with vertical, north-south, east-west channels at the arrival time.
- We consider only 3-C stations without any corroboration with other stations in the arrays.
- New monitoring stations are unlikely to be arrays and more likely to be uncalibrated 3-C stations.

Seismic Phases

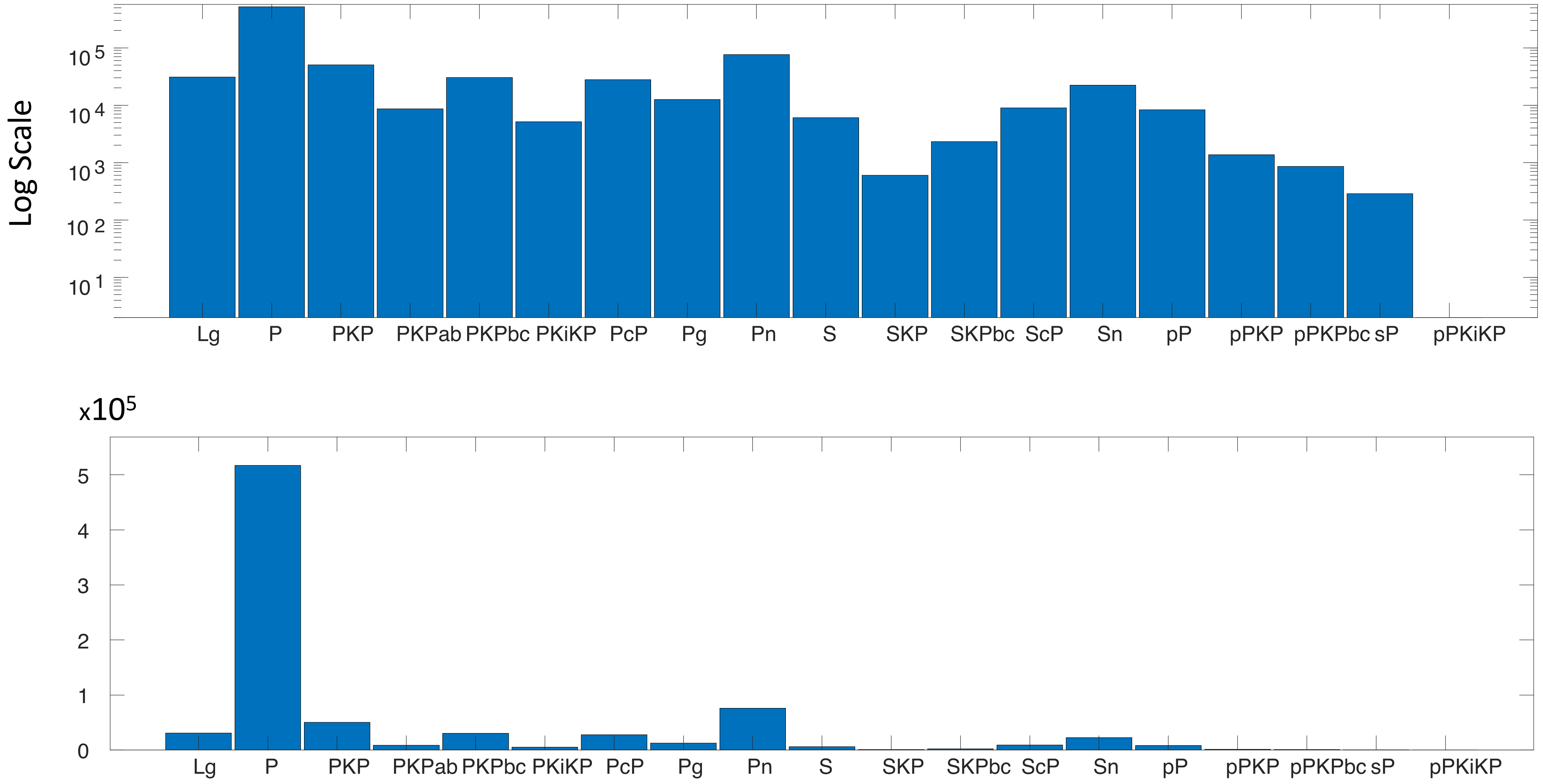
- Six phases: P, Pg, Pn, S, Sn, Lg
- We consider the final phase that arrived at a station, ignoring path. For example, *pPcP* is considered as *P*.





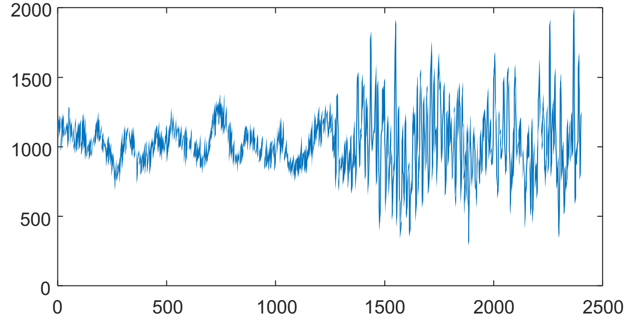
Havskov J., Ottemöller L. (2010) Earth Structure and Seismic Phases. In: Routine Data Processing in Earthquake Seismology. Springer, Dordrecht
USGS.gov

Phase Distributions

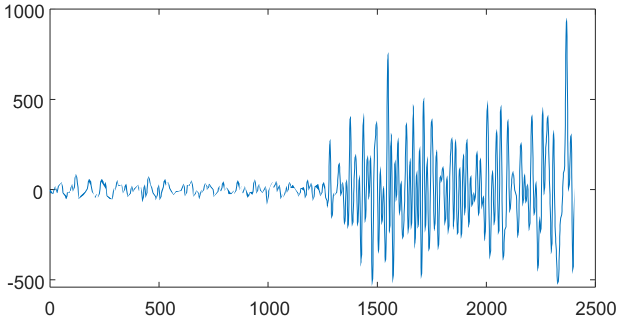


Continuous Wavelet Transform

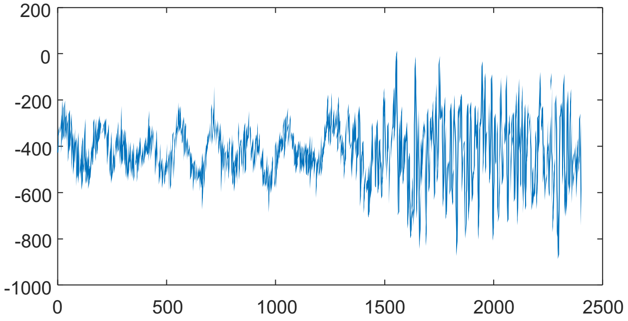
BHZ

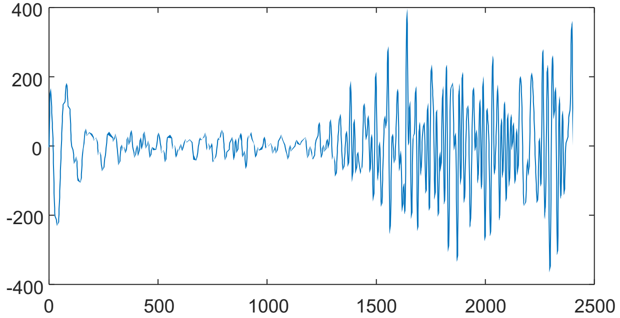


0.4 – 10Hz

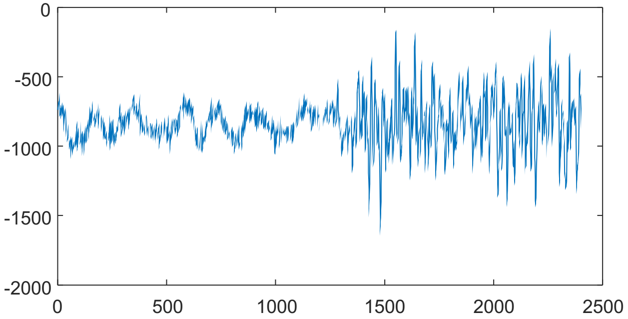


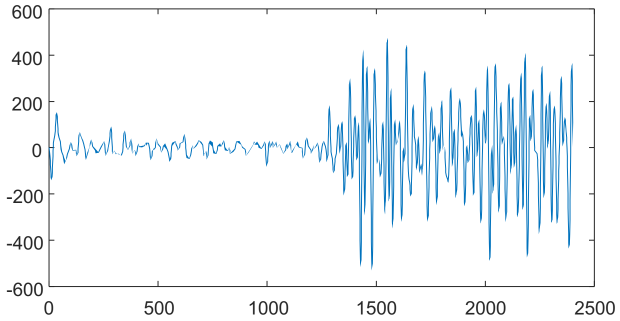
BHE



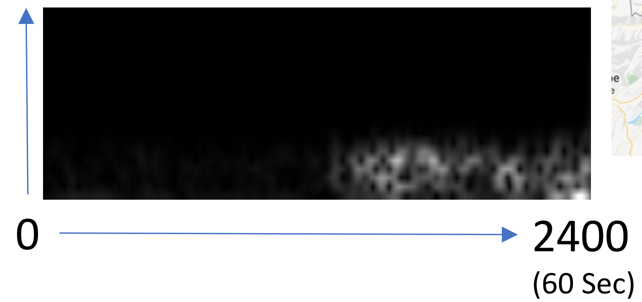


BHN



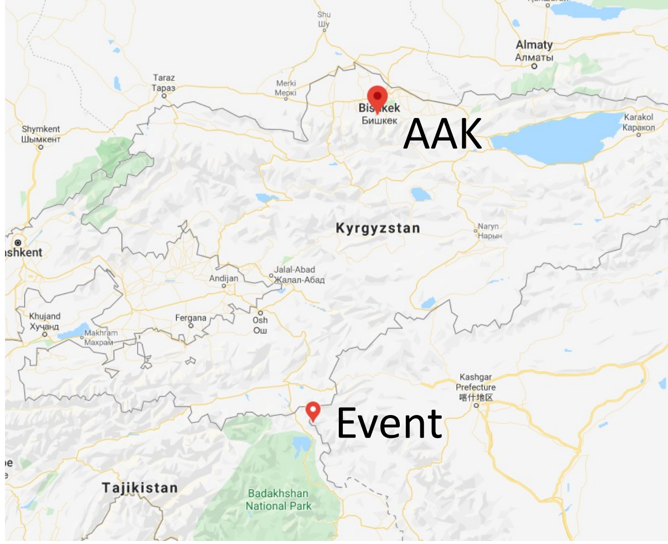


Red

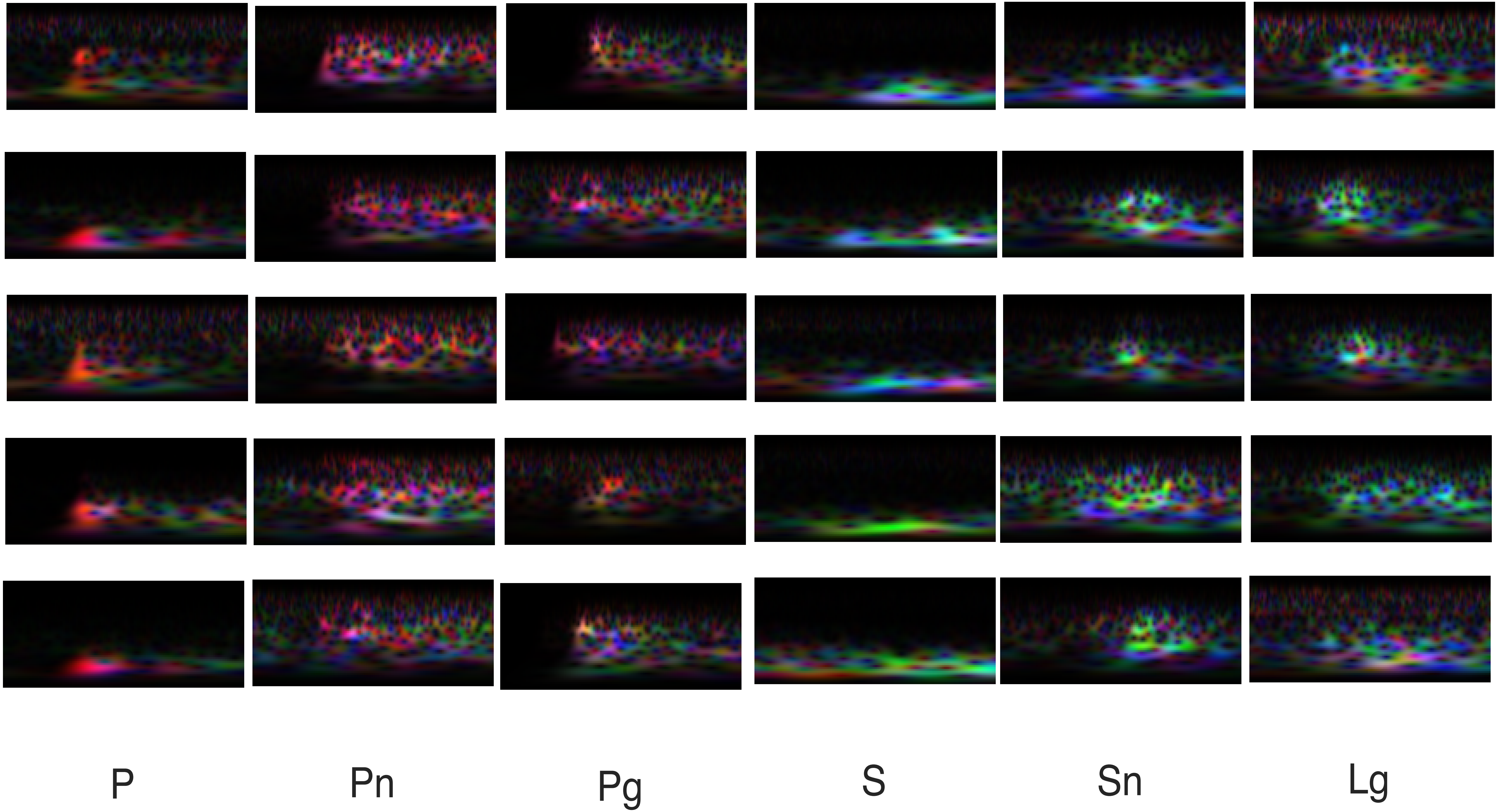


Green

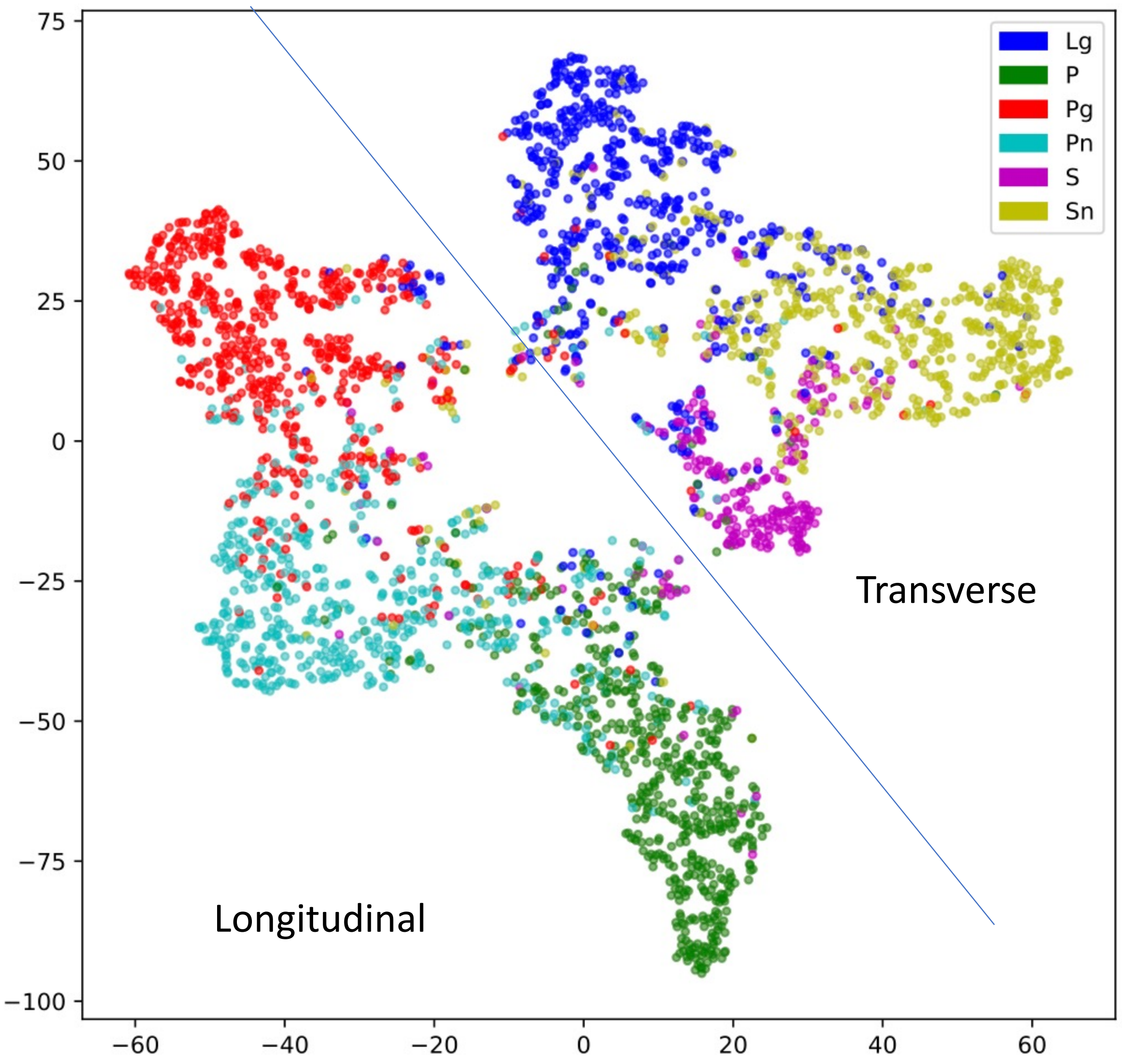
Blue



Phase: Pn
Station: AAK
Distance: 3.43 degree
Depth: 0

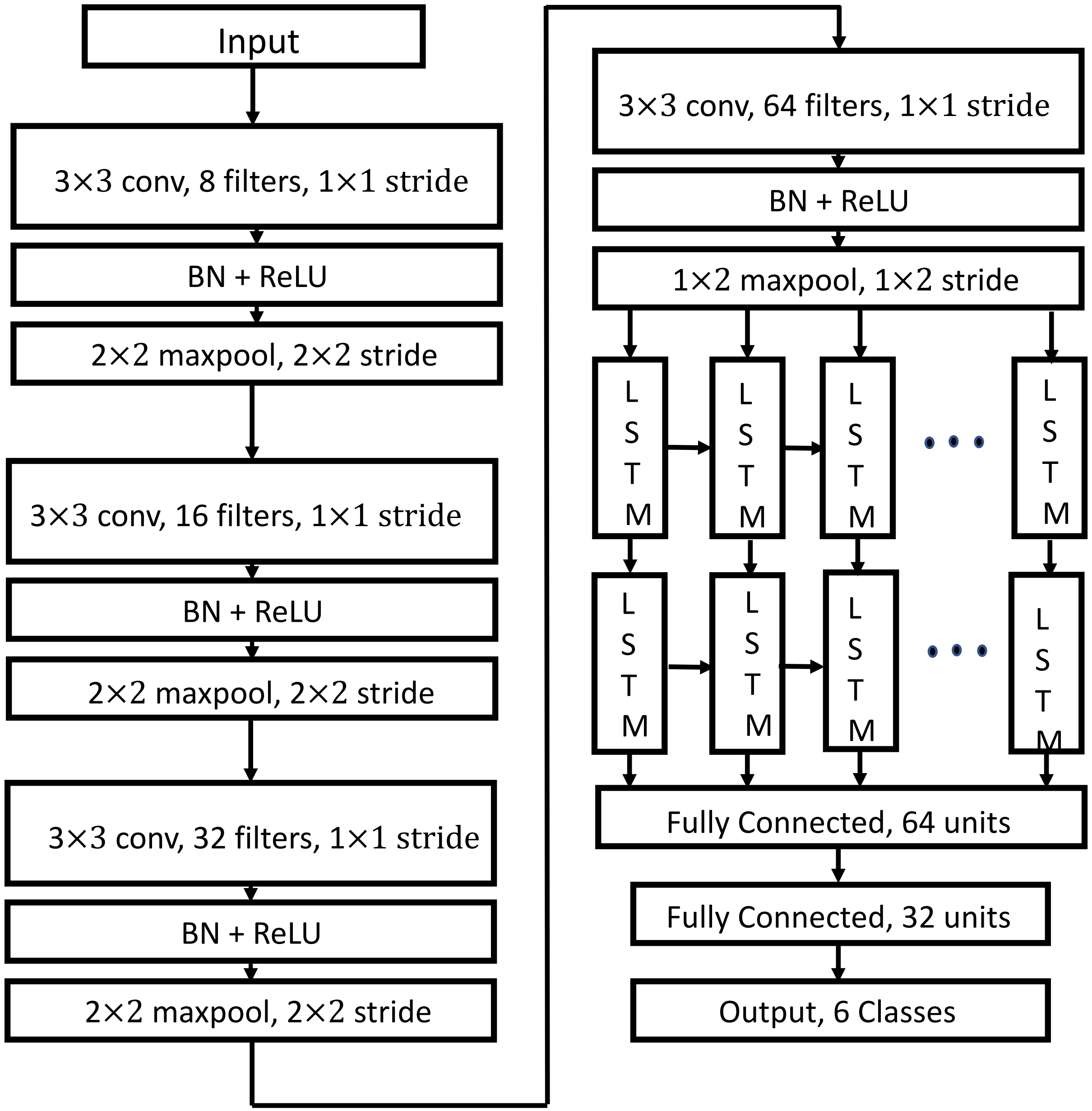

P
Pn
Pg
S
Sn
Lg

t-SNE visualization of the feature space



https://lvdmaaten.github.io/tsne/

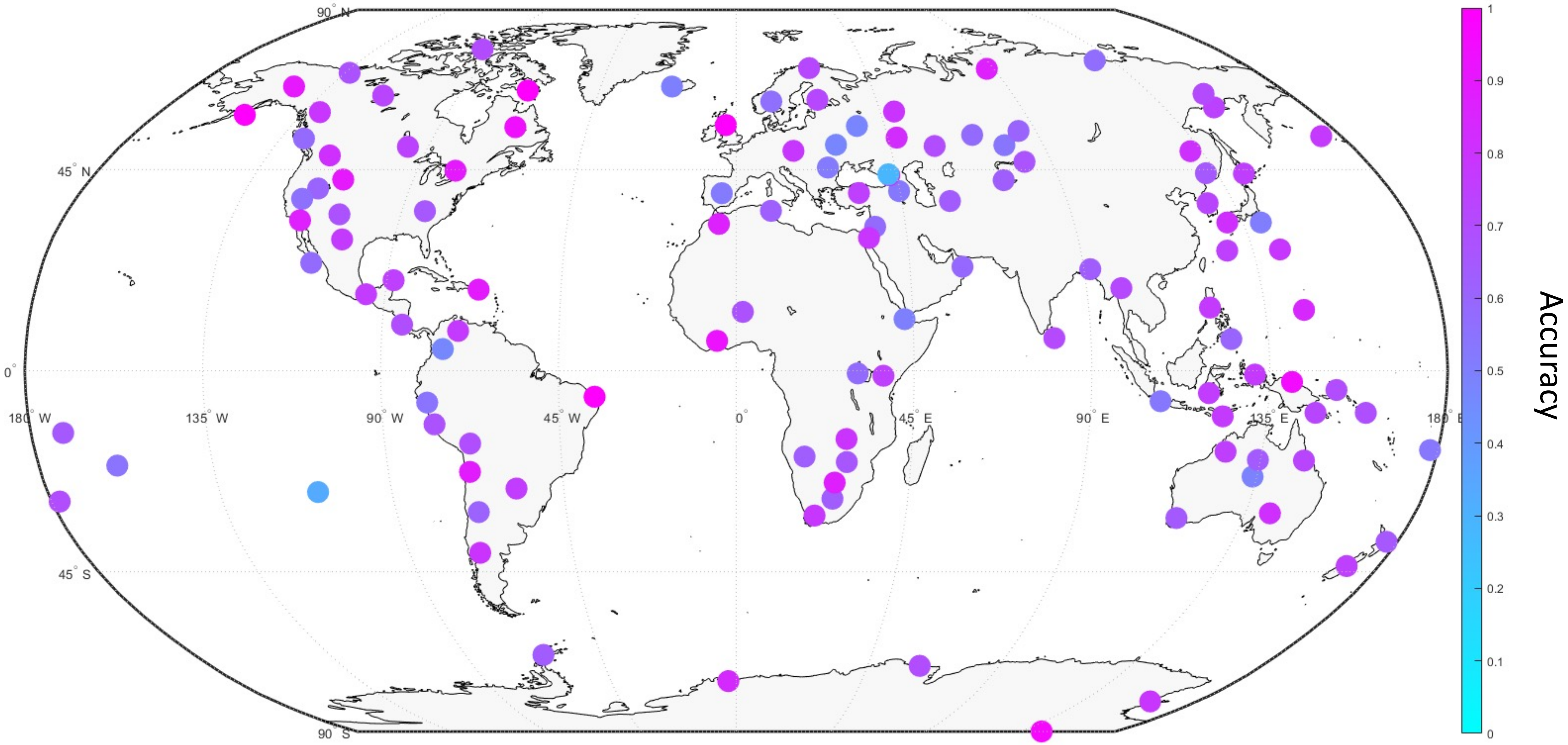
FASER: A Deep Neural Network for Seismic Phase Classification



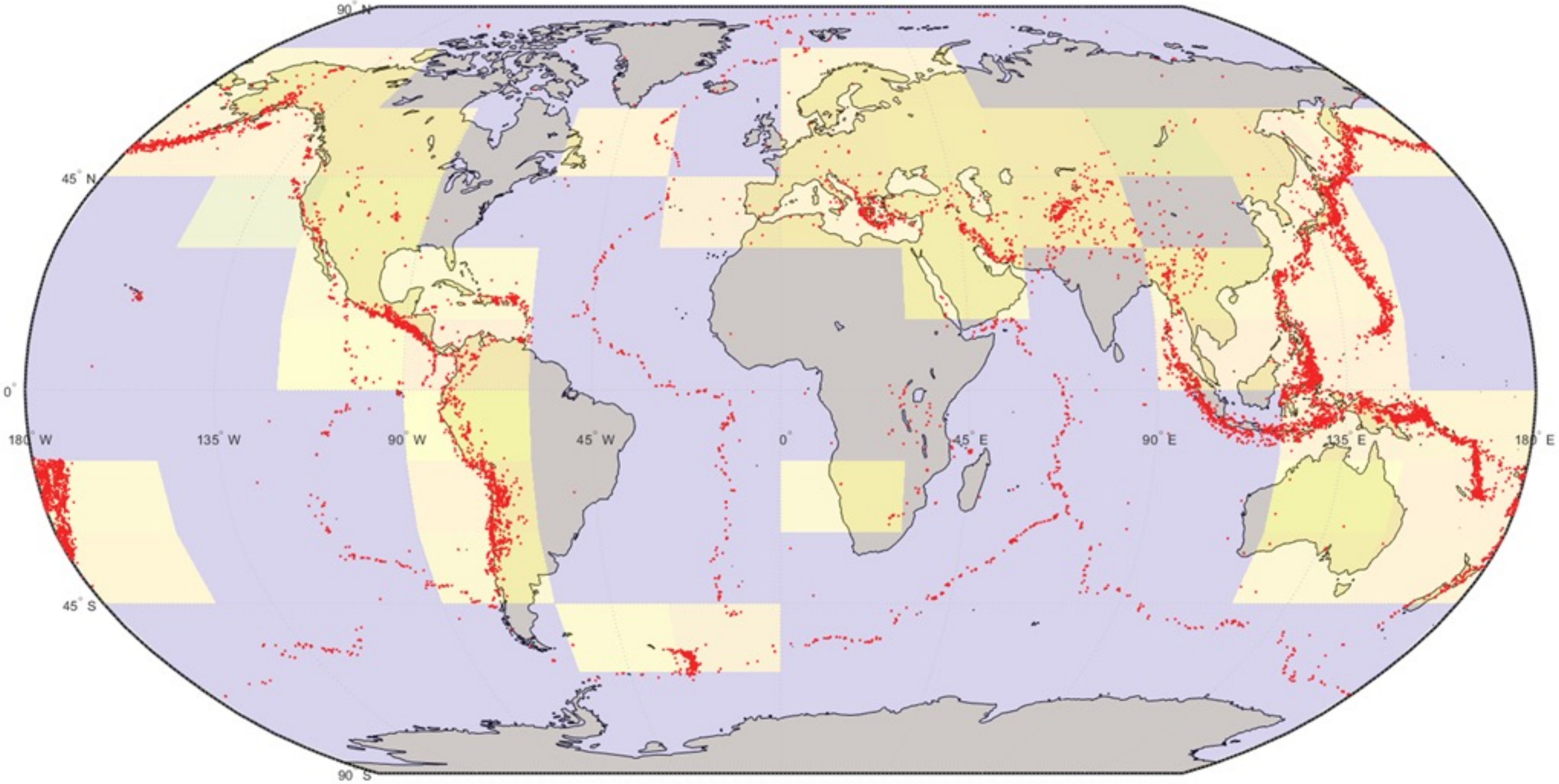
Comparison to other ML Classifiers

	Precision	Recall	F1-Score	Accuracy
XGBoost	68.4	67.2	67.2	67.2
MLP	76.2	75.6	75.3	75.6
CNN	75.2	75.2	75.2	75.2
LSTM	75.7	74.3	75	75.3
CNN-Bi-LSTM	81.3	80.2	80.7	81.5
FASER	84.6	81.6	83.1	82.8

Model Performance on Held-out IMS Stations



Model Performance on Held-out Source Regions



Average accuracy is 0.7727 with standard deviation 0.0413

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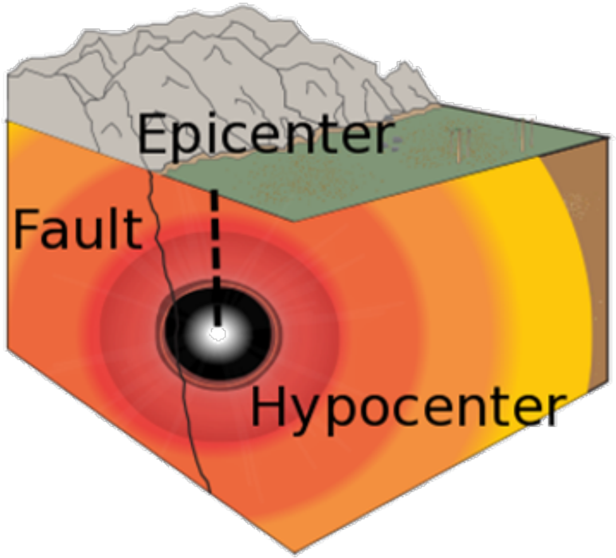
Motivation

- Seismic depth helps us separate natural vs man-made seismic activity
- Current depth estimation is deterministic and requires high quality data
- The Problem: Predict depth of a seismic event given waveforms at various stations

Challenges

- Recording station should be right above the hypocenter
- Lack of accurate training data
- Multiple reference points for ground truth



1

[1] redsismica.uprm.edu

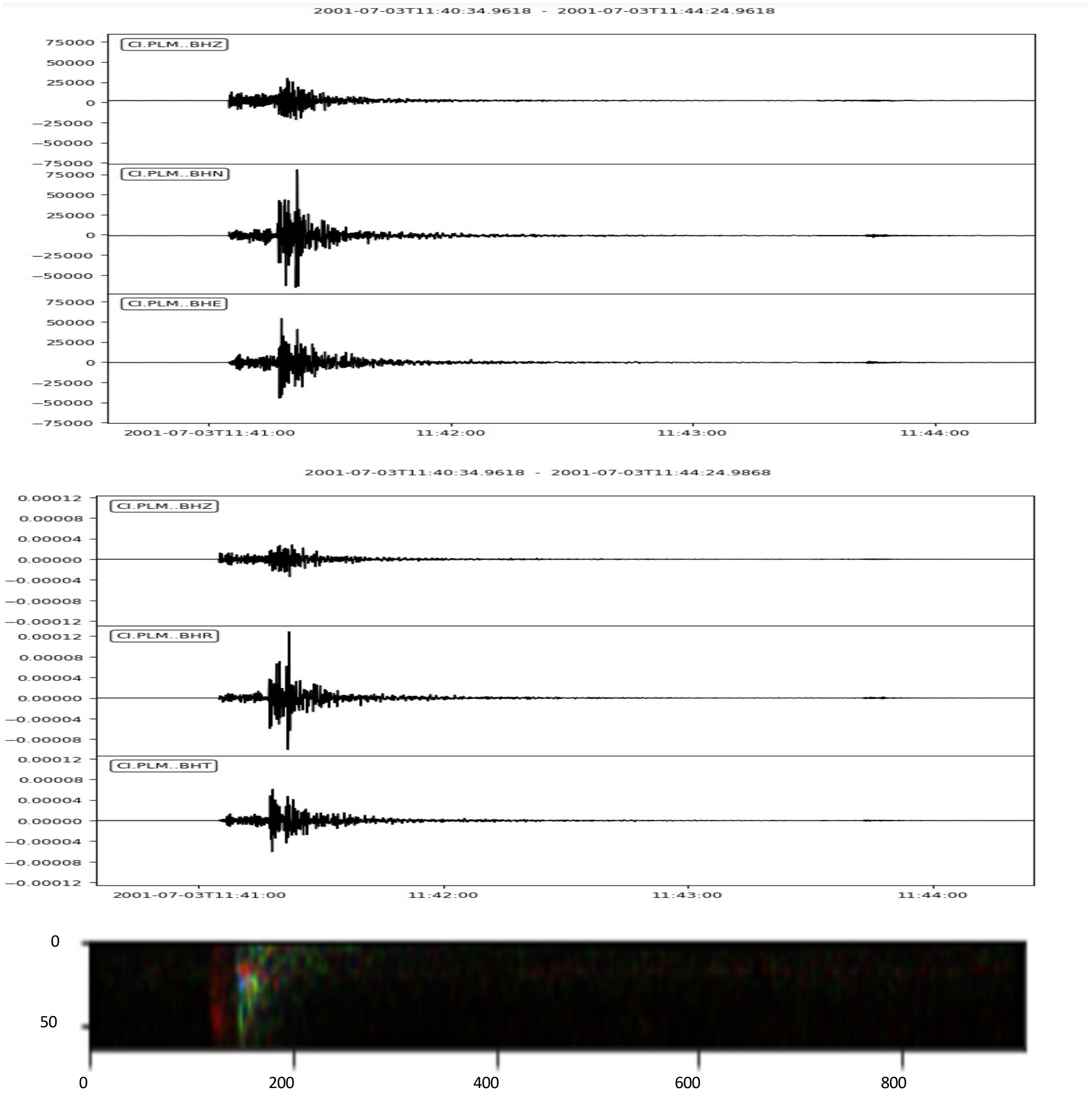
Southern California dataset[1]

- Relocated earthquake depth
- 627,669 seismic events in the catalog
- 423 seismic stations
- ~40 years (1981 - 2019)
- Magnitude range: 2 - 4
- 8359 events collected
- Each arrival has 230 seconds (9200 sample) long waveform from 5 closest stations

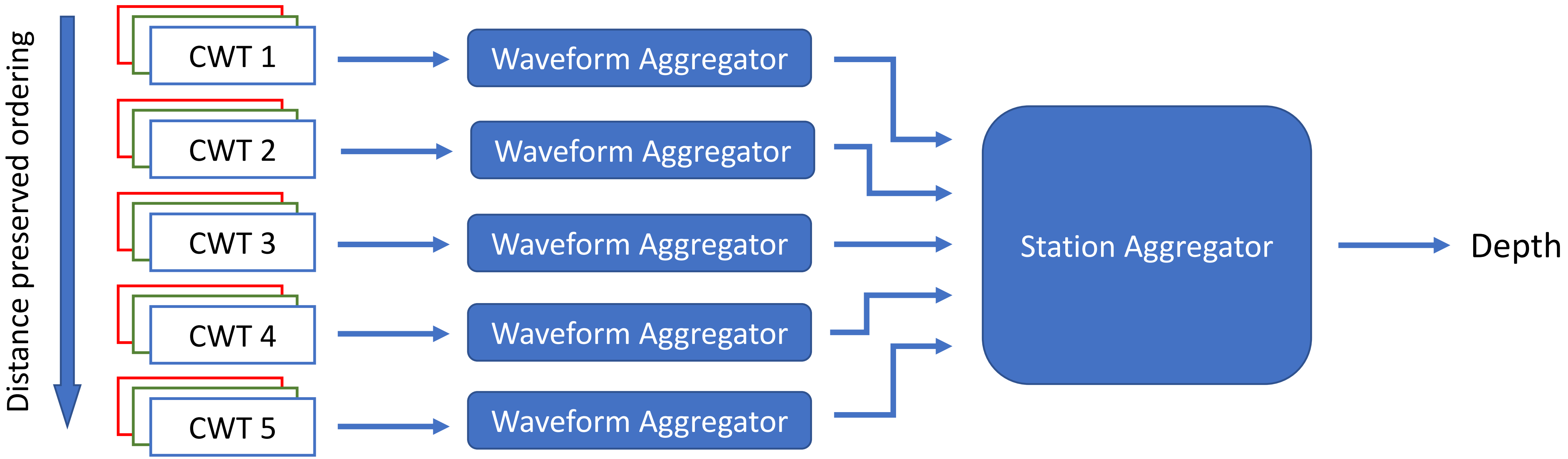
1. https://scedc.caltech.edu/research-tools/alt-2011-dd-hauksson-yang-shearer.html

Preprocessing

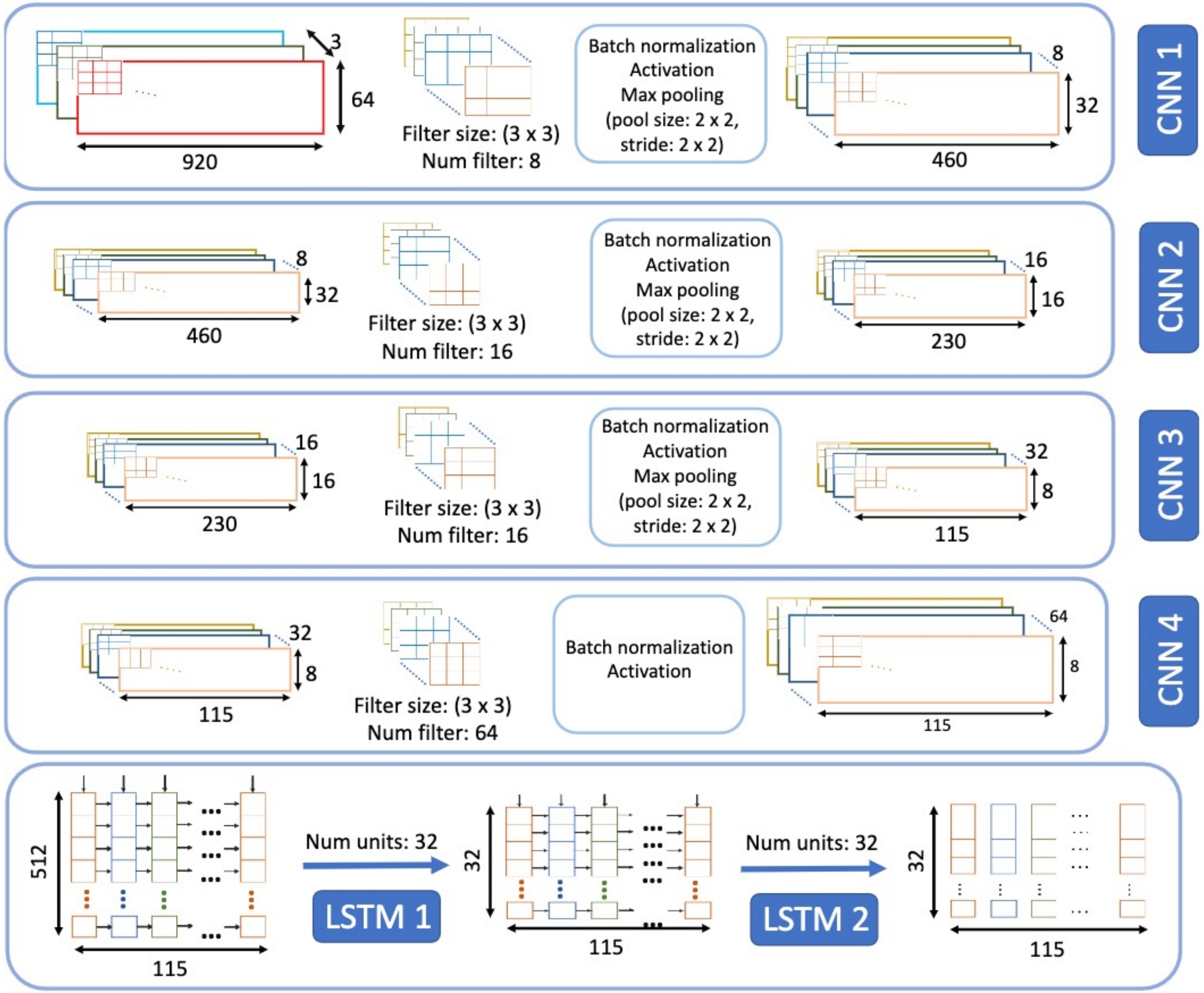
- Filtering (0.5-10 Hz)
- Down sample (40 samples/sec)
- Zero mean, min-max normalization
- Convert to ZRT components
- Continuous Wavelet Transform (CWT)



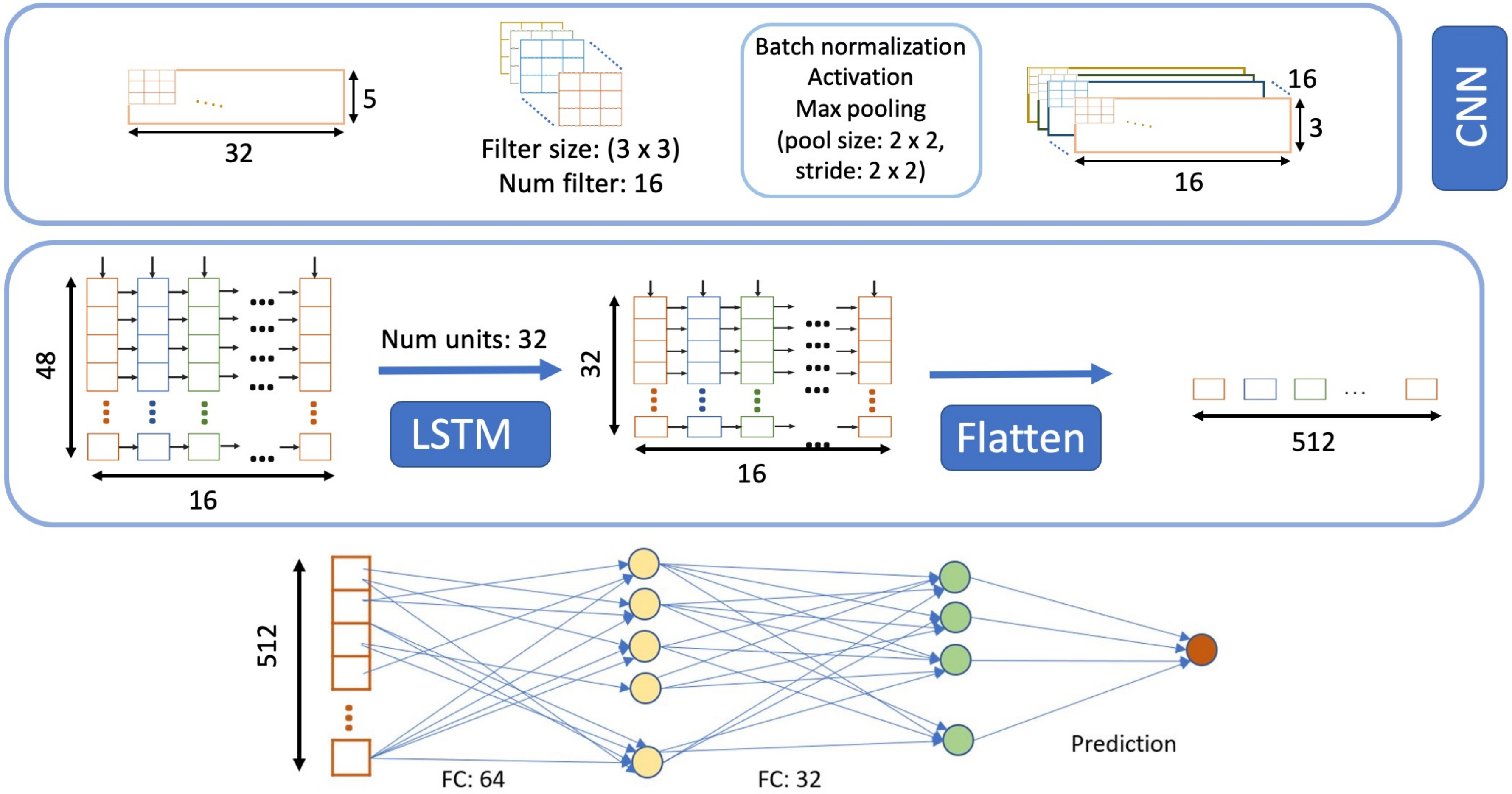
Septor model



Waveform aggregator



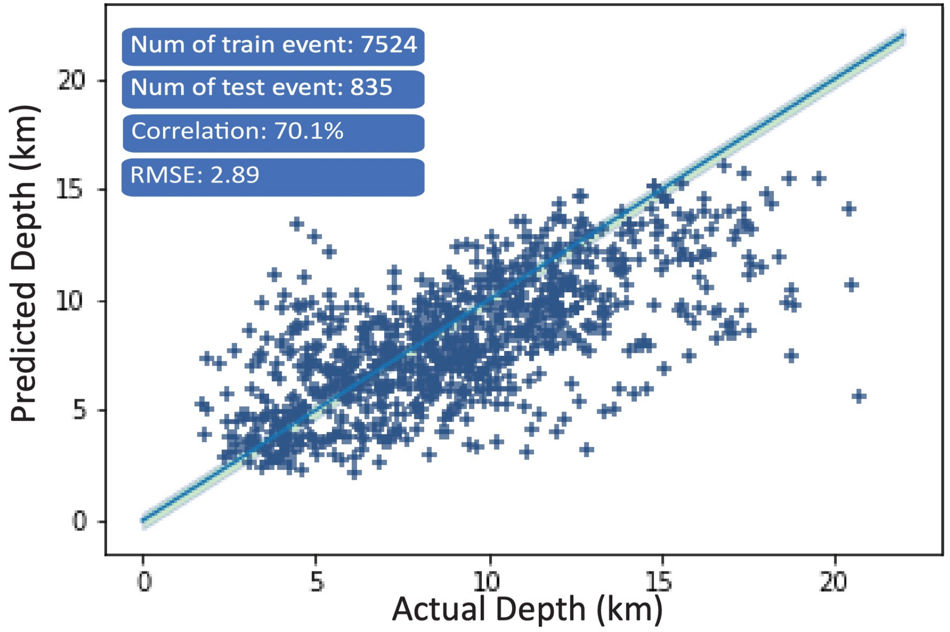
Station aggregator



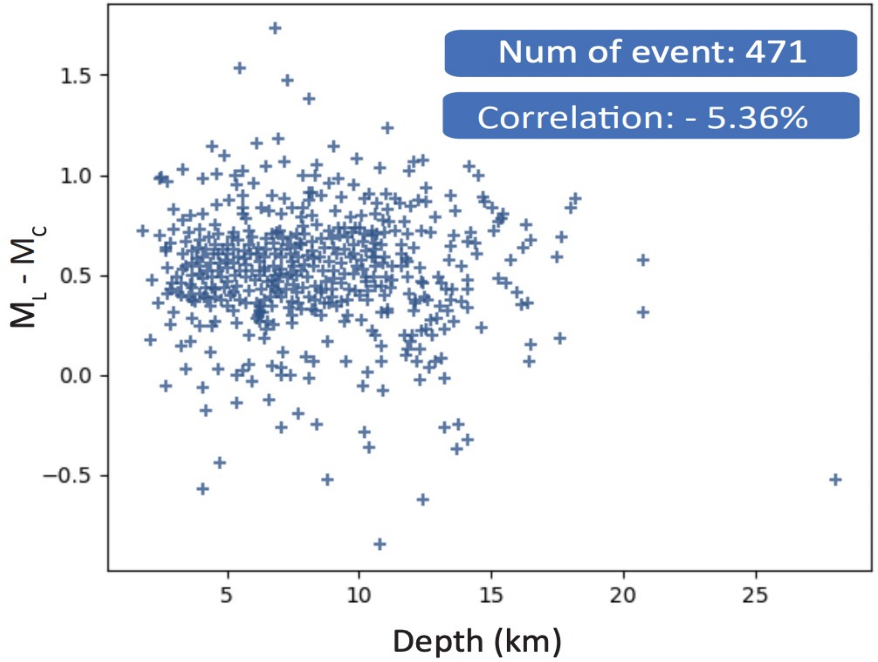
Experimental Setup

- Comparison with physics-driven methods
- Comparison with state-of-the-art data-driven methods
- Performance of Septor as binary classifier
- Experiment on transferability across region

Results



Septor



Baseline [1]

Septor outperforms physics-informed features

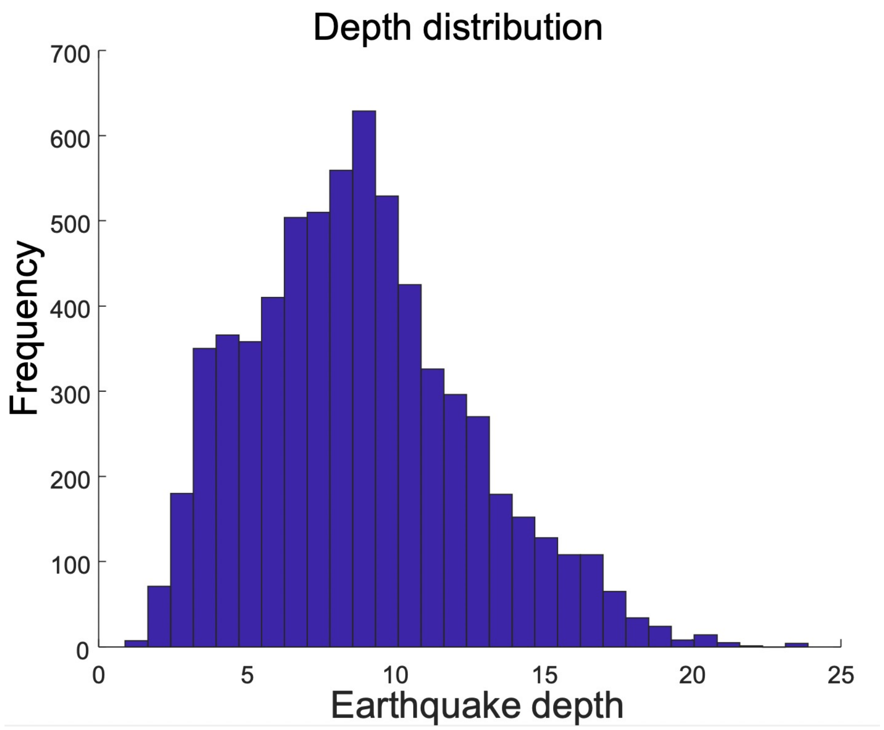
[1] Holt et al. 2019

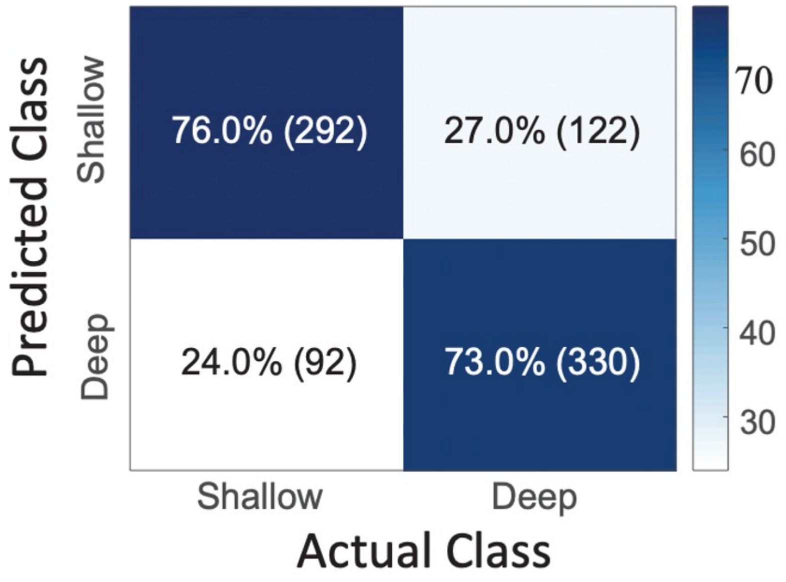
Results (cont.)

Model	Data resolution	RMSE (km)	Corr. (%)
CNN	Multi-channel	3.26	56.0
LSTM	Multi-channel	3.38	52.0
XGBoost	Single-channel	3.53	37.0
XGBoost	Multi-channel	3.58	36.0
XGBoost	Multi-station	3.39	44.3
Rocket	Single-channel	3.11	46.2
Rocket	Multi-channel	3.12	46.0
Rocket	Multi-station	3.51	36.5
Septor	**Multi-station**	**2.89**	**70.1**

Septor outperforms ML based regressors

Performance of binary classifier

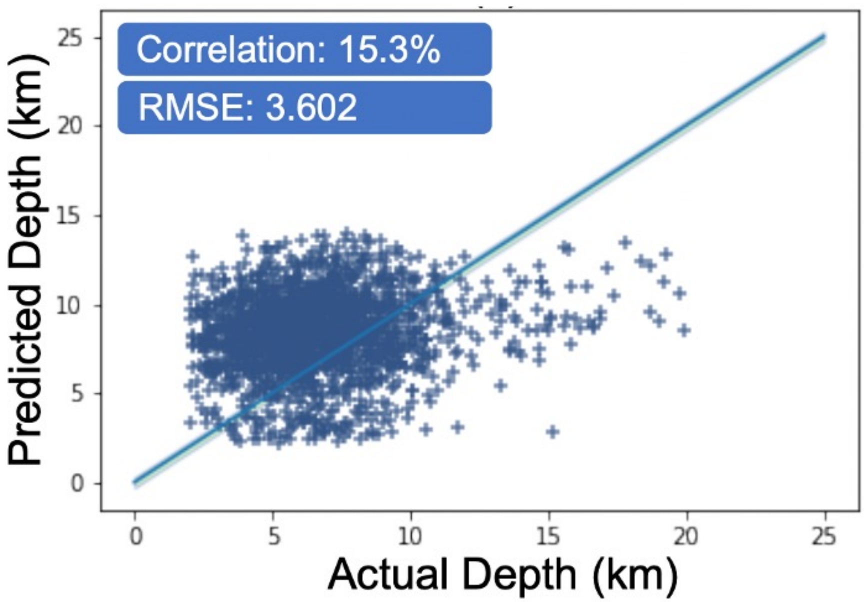




Accuracy	Precision	Recall	F1 score
73.0	78.2	75.5	86.5

Septor performance as binary classifier

Case study: Novel geographical region



Septor performance degrades for novel geographical region

[1] geology.com

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  - Regression: Depth Estimation
  - Clustering: Seismic Phase Association
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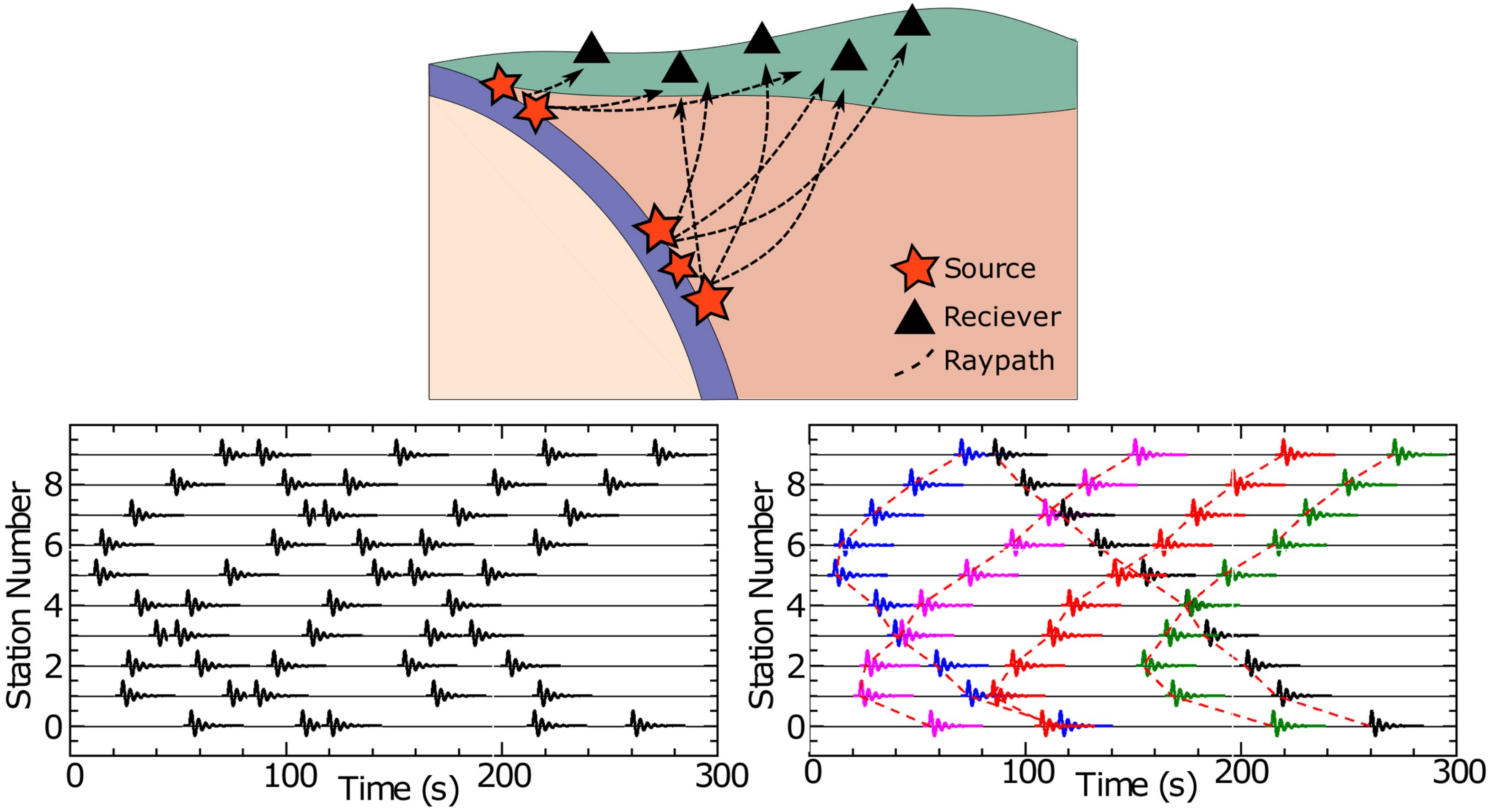
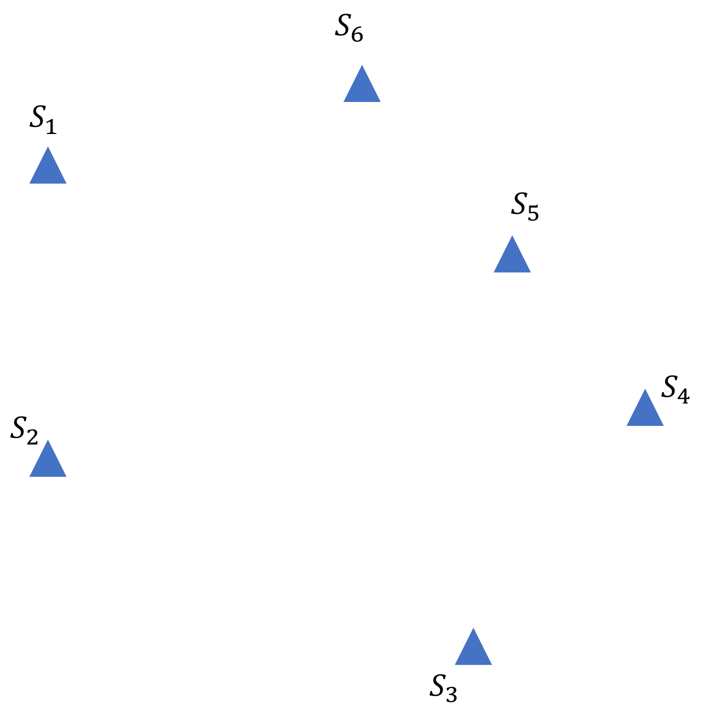
Earthquake Arrival/Phase Association



The Problem: Given a set of phases at a set of stations, cluster/associate the phases such that no station repeats in a cluster and the phases in a cluster obey physical travel-time laws.

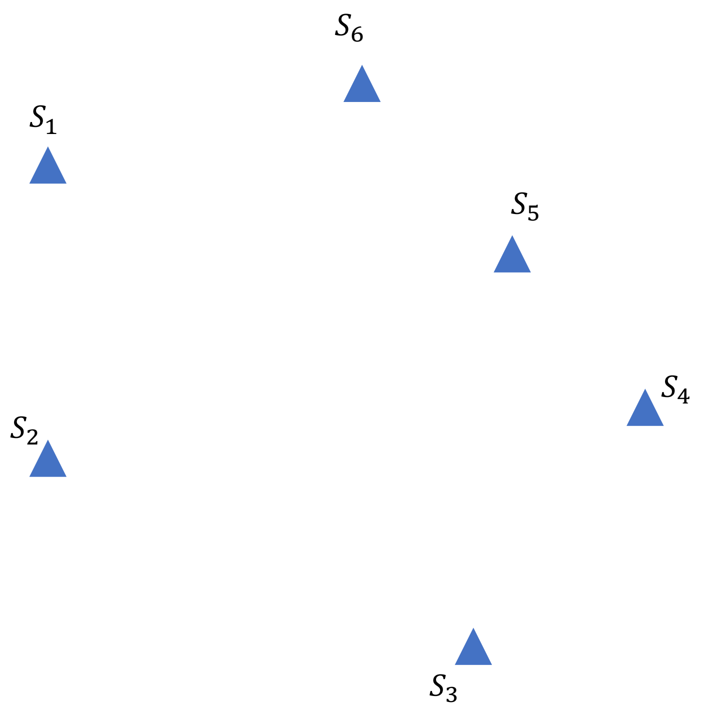
Ian W. McBrearty, Joan Gomberg, Andrew A. Delorey, Paul A. Johnson; Earthquake Arrival Association with Backprojection and Graph Theory. *Bulletin of the Seismological Society of America* 2019;; 109 (6): 2510–2531.
doi: https://doi.org/10.1785/0120190081

Consider six sensors on a 2D plane

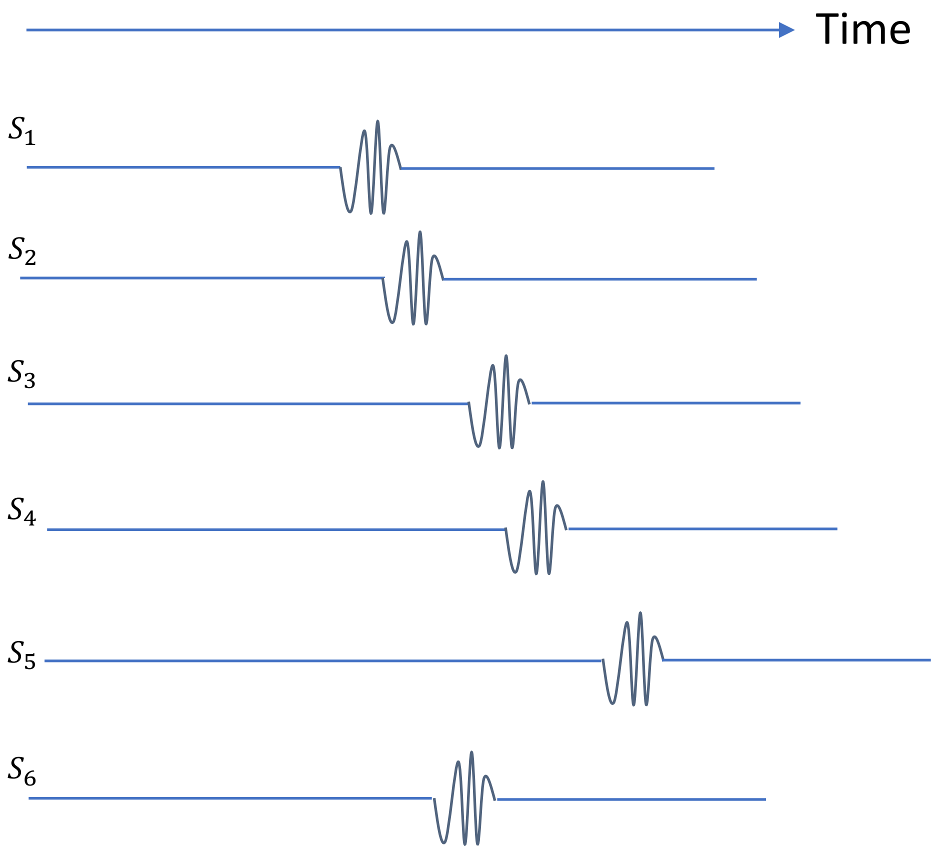


Six sensors are on a 2D plane

Consider the signals observed at these sensors

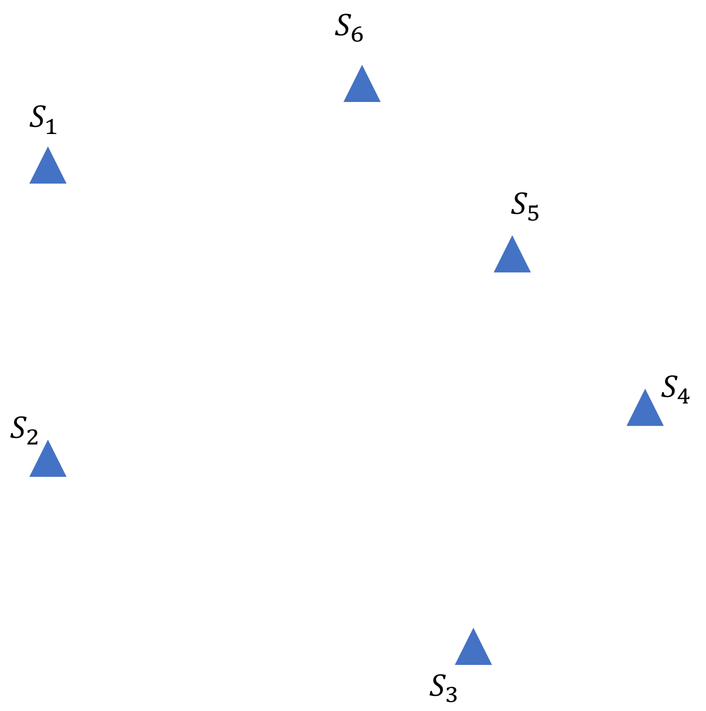


Six sensors are on a 2D plane

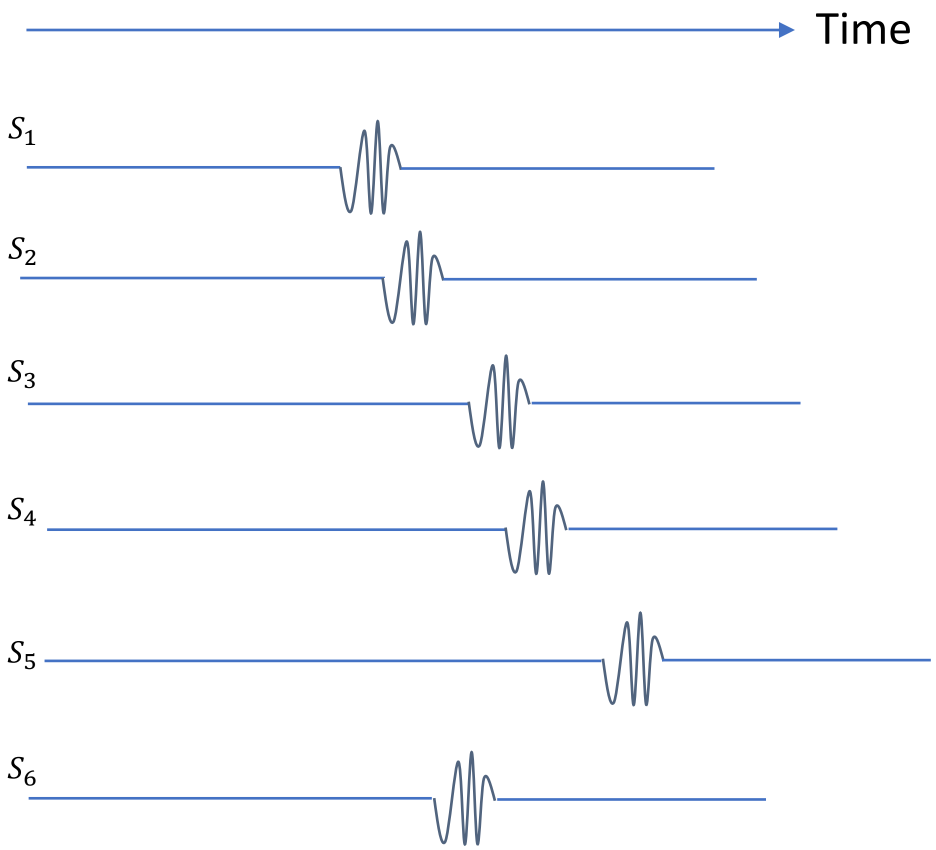


Observed Data – Each signal blip is a wave arrival at the sensor.

Where, when and how many events happened to produce this data?

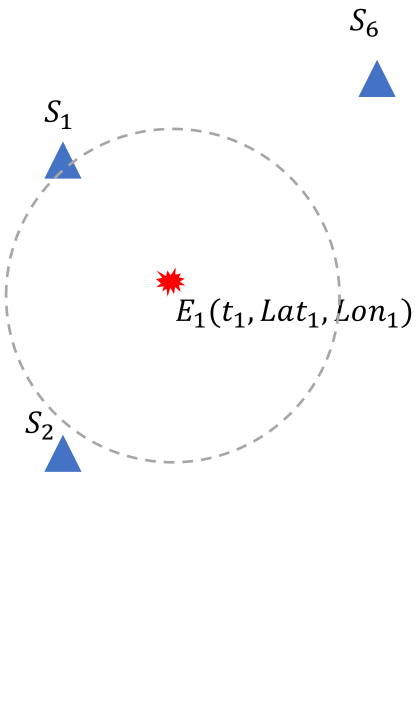


Assuming uniform wave propagation speed.

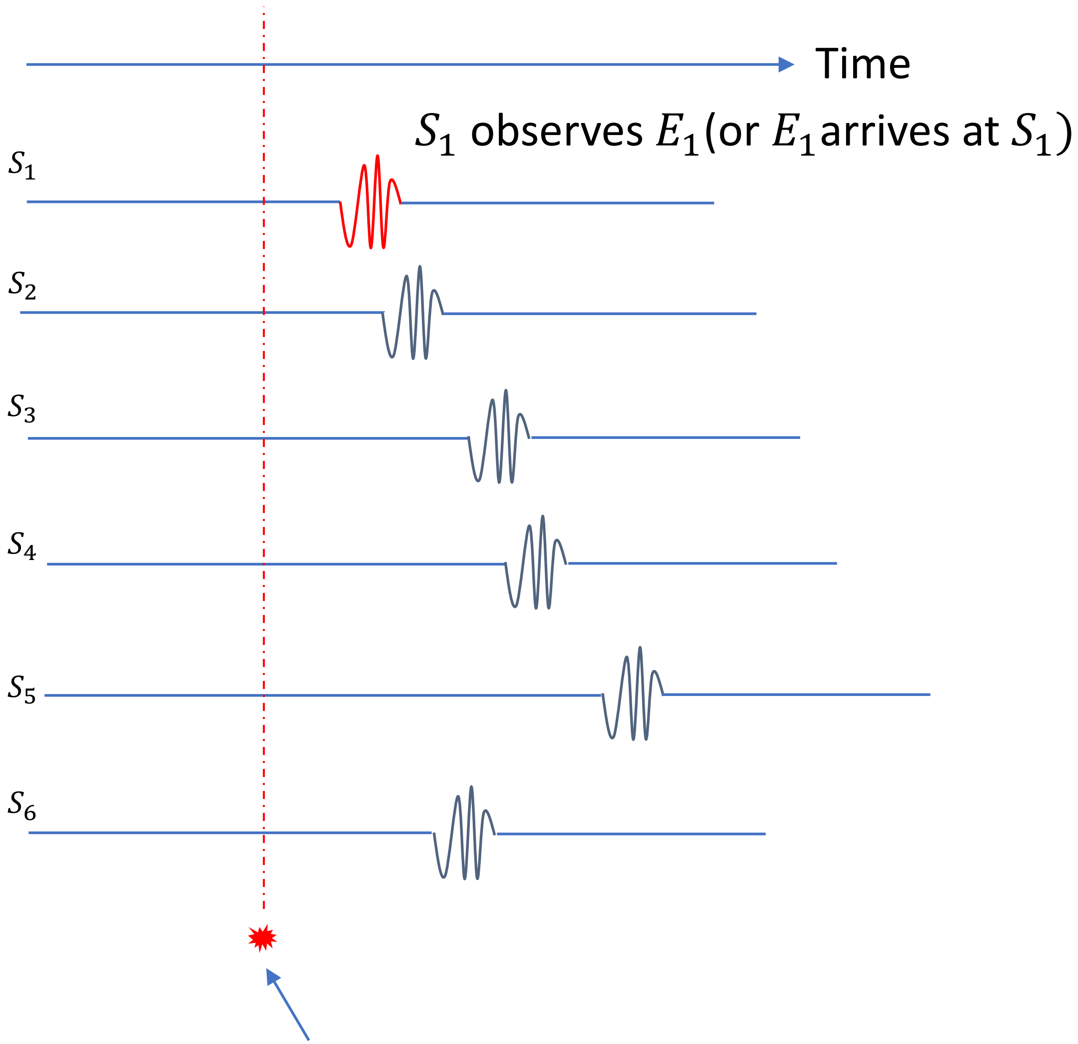


Observed Data – Each signal blip is a wave arrival at the sensor.

Let us try an example E_1

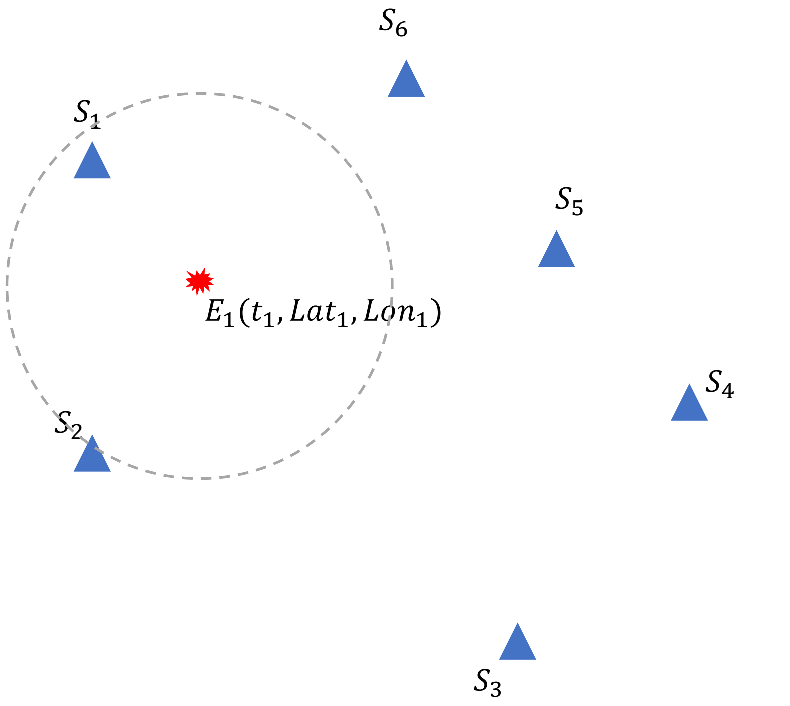


Assuming uniform wave propagation speed.

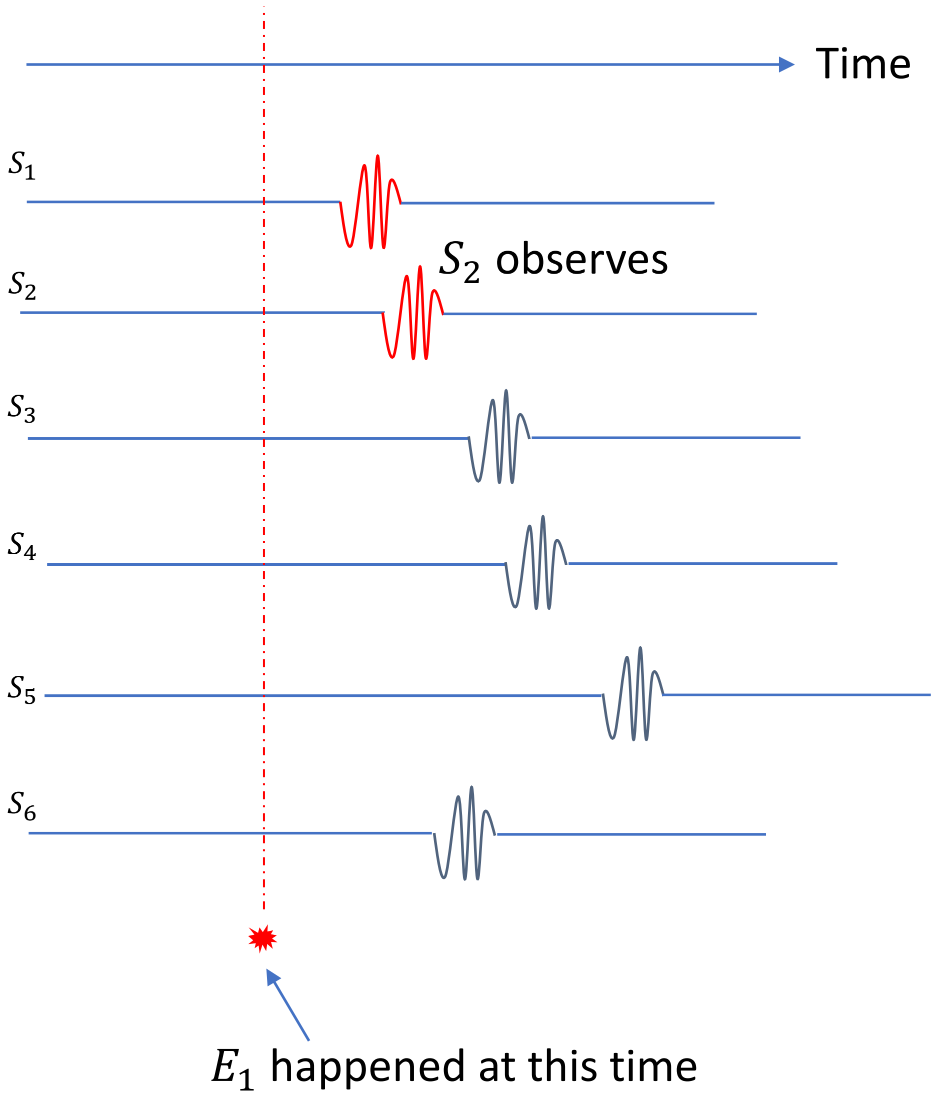


E_1 happened at this time

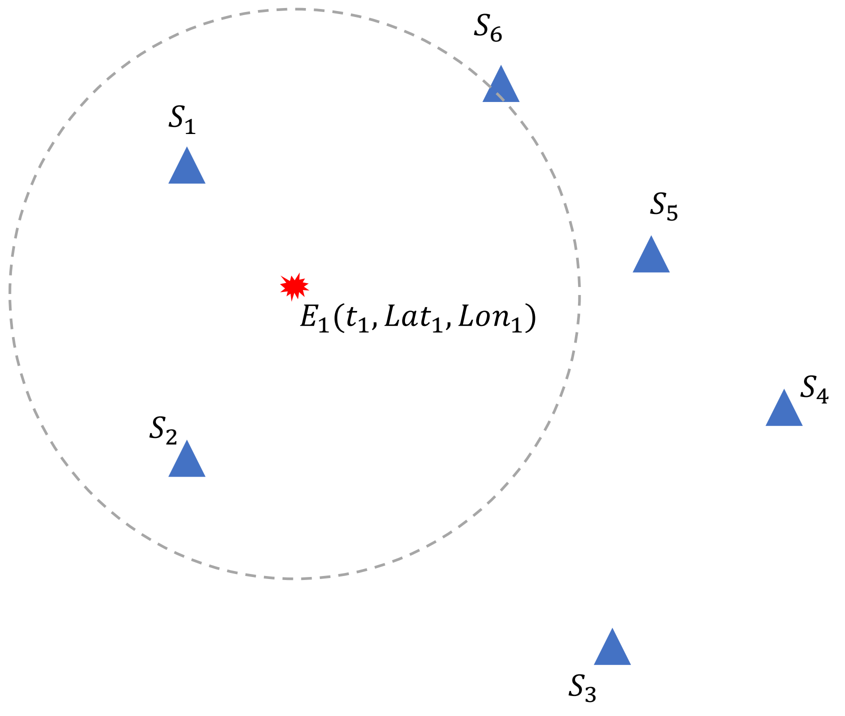
Let us try an example E_1



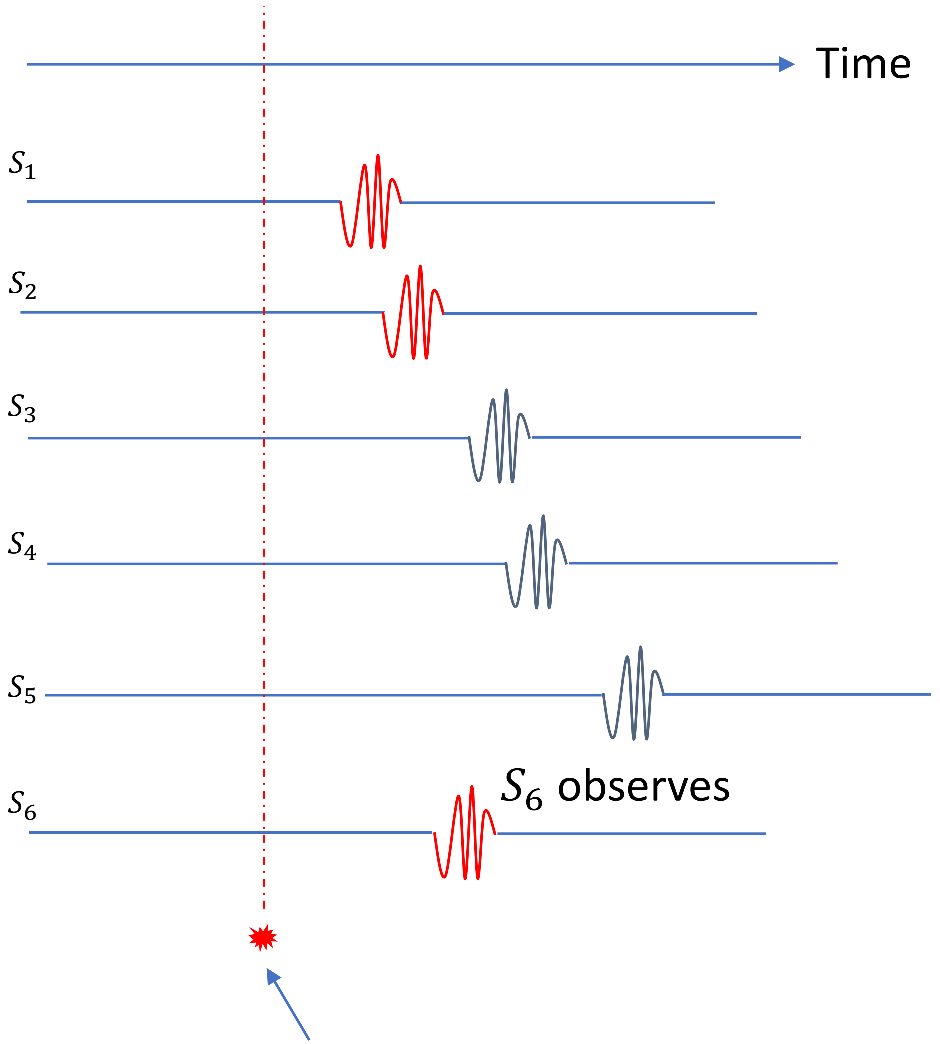
Assuming uniform wave propagation speed.



Let us try an example E_1

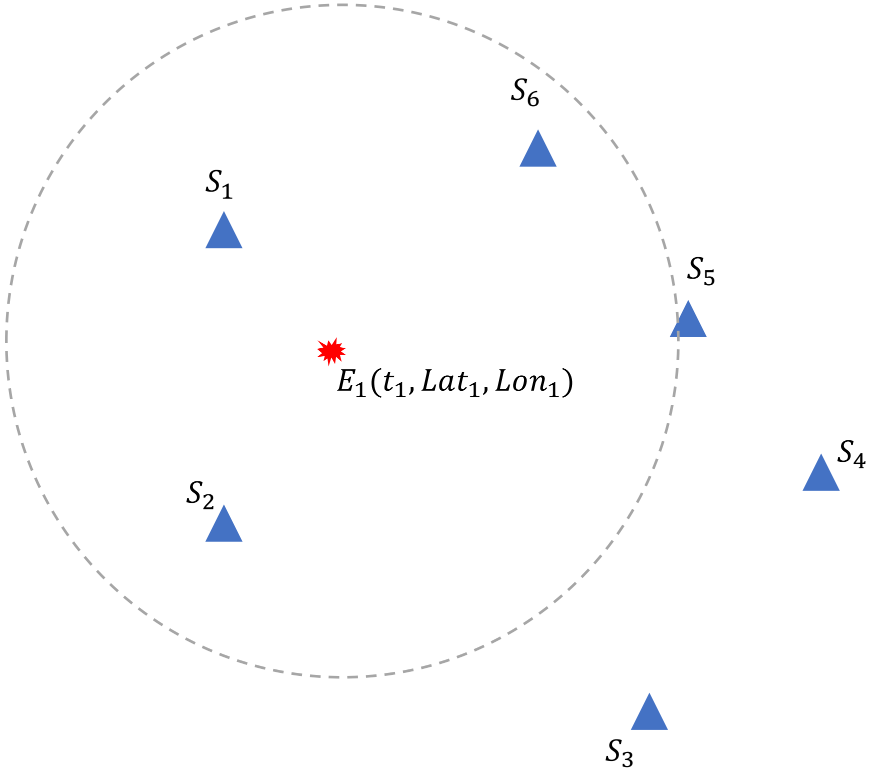


Assuming uniform wave propagation speed.

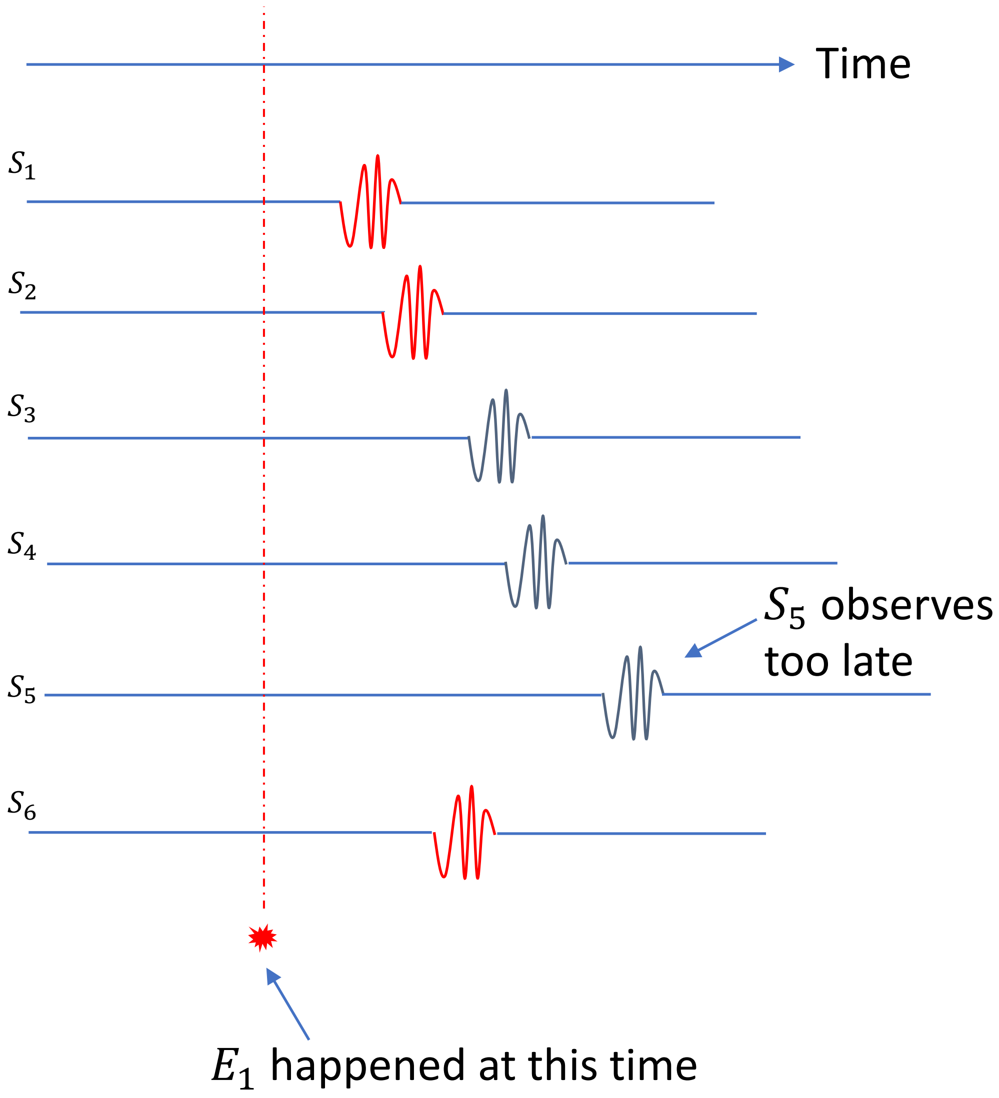


E_1 happened at this time

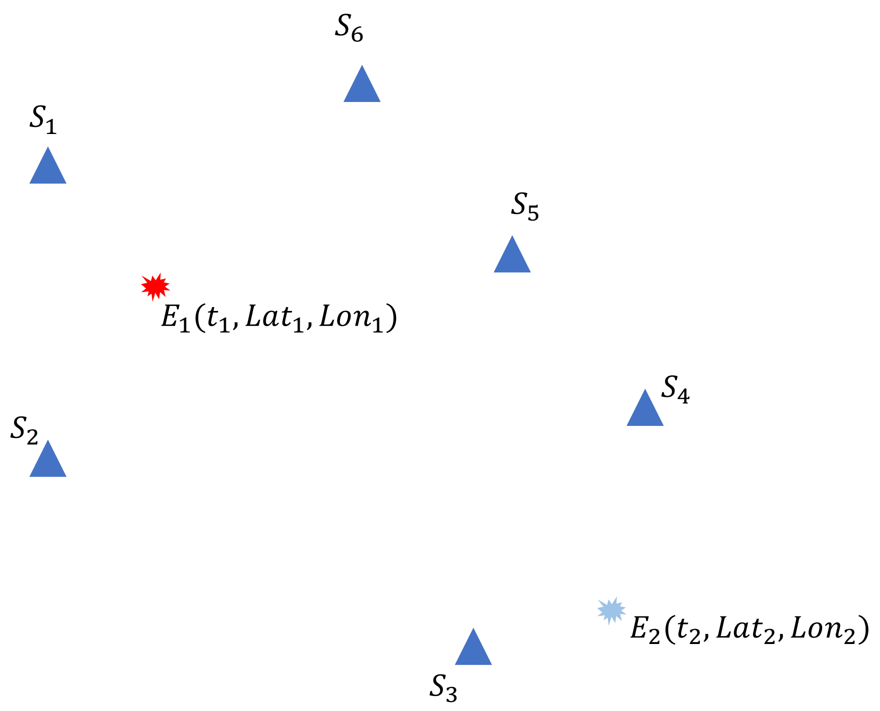
Let us try an example E_1

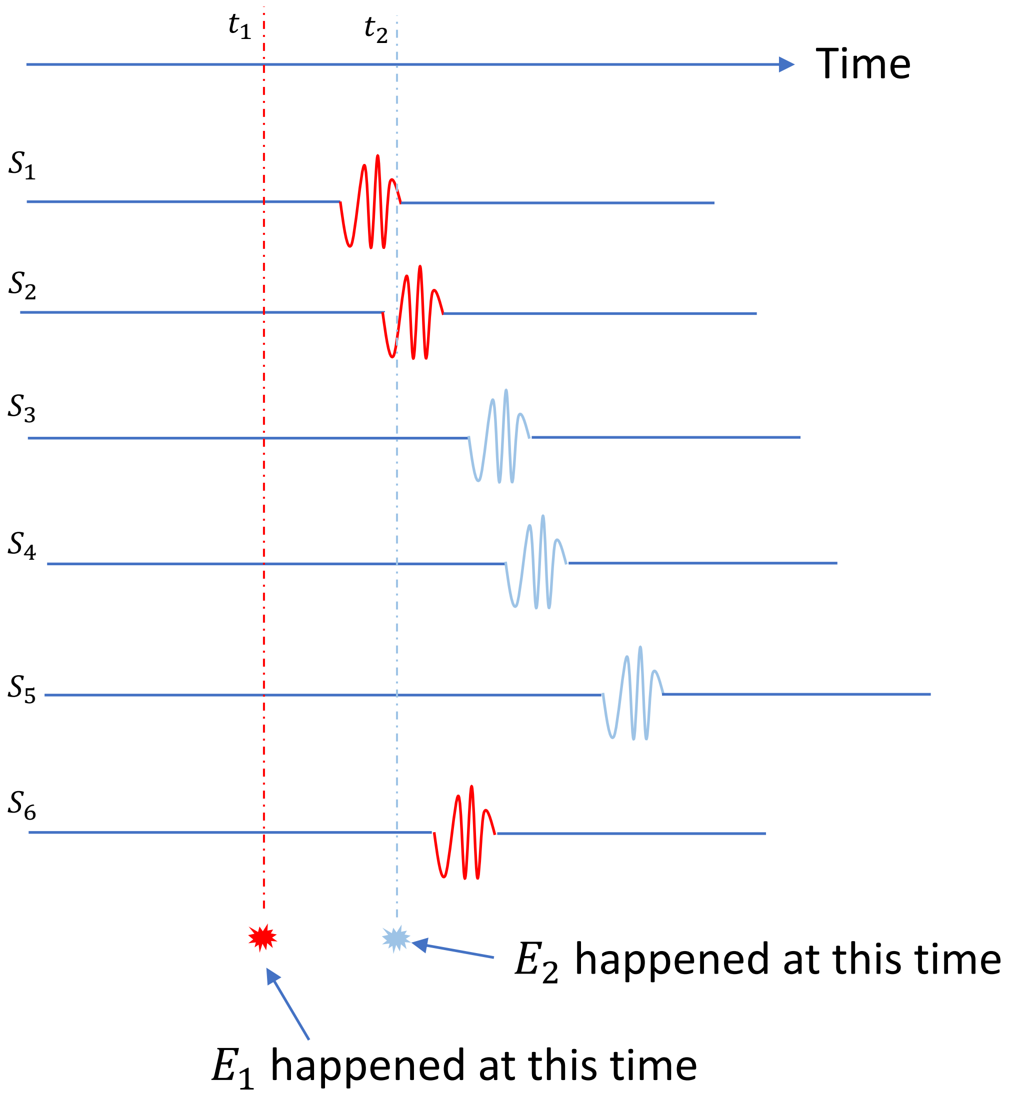


We can prove that one event cannot produce this data by solving a system of linear equations to find no real root.



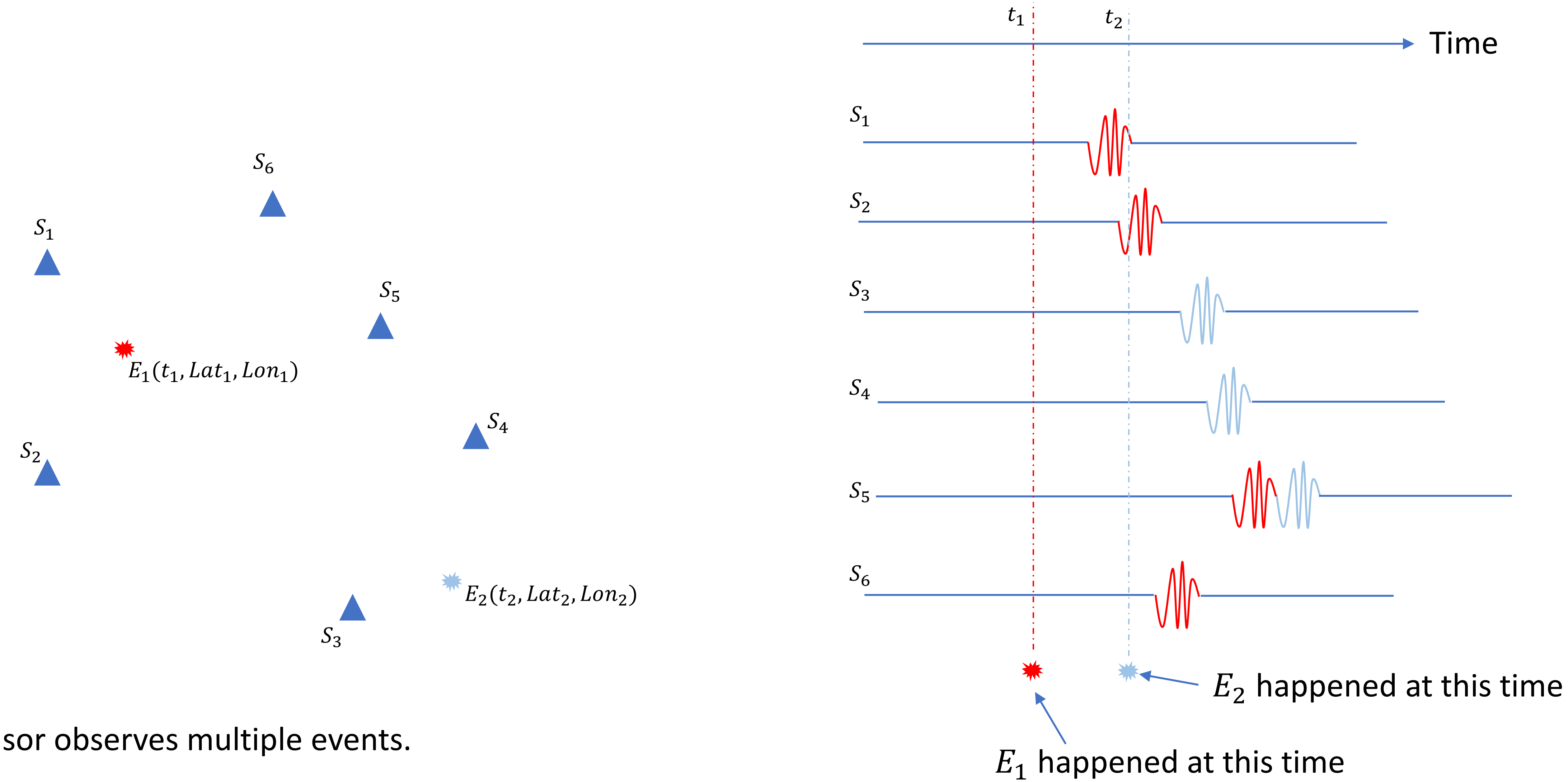
Let us try two example events E_1 and E_2





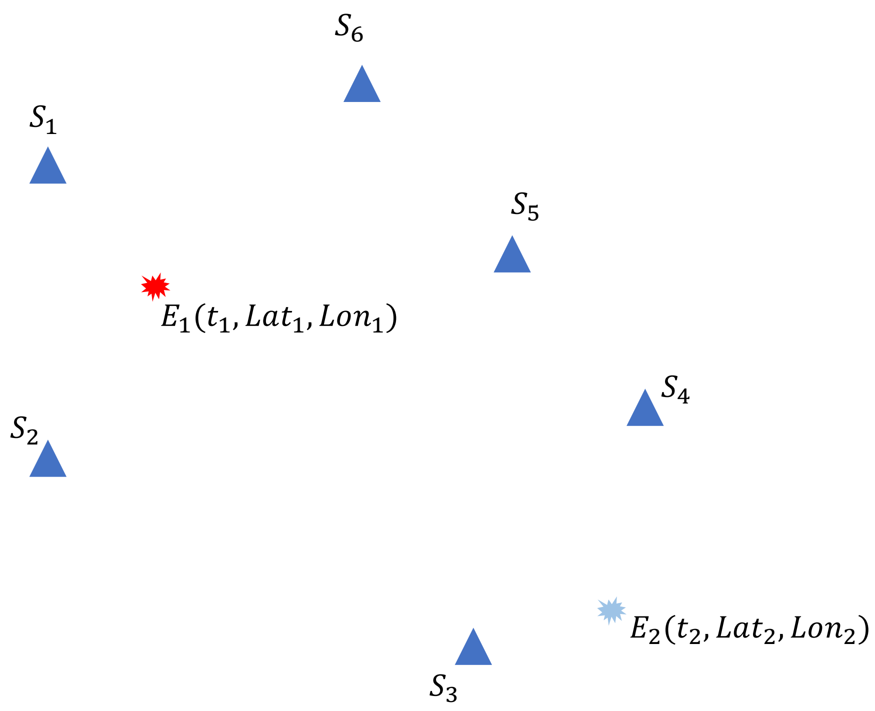
These two events show a plausible explanations of the observed data. However, we assume that E_1 does not reach beyond S_6 and E_2 does not reach beyond S_5.

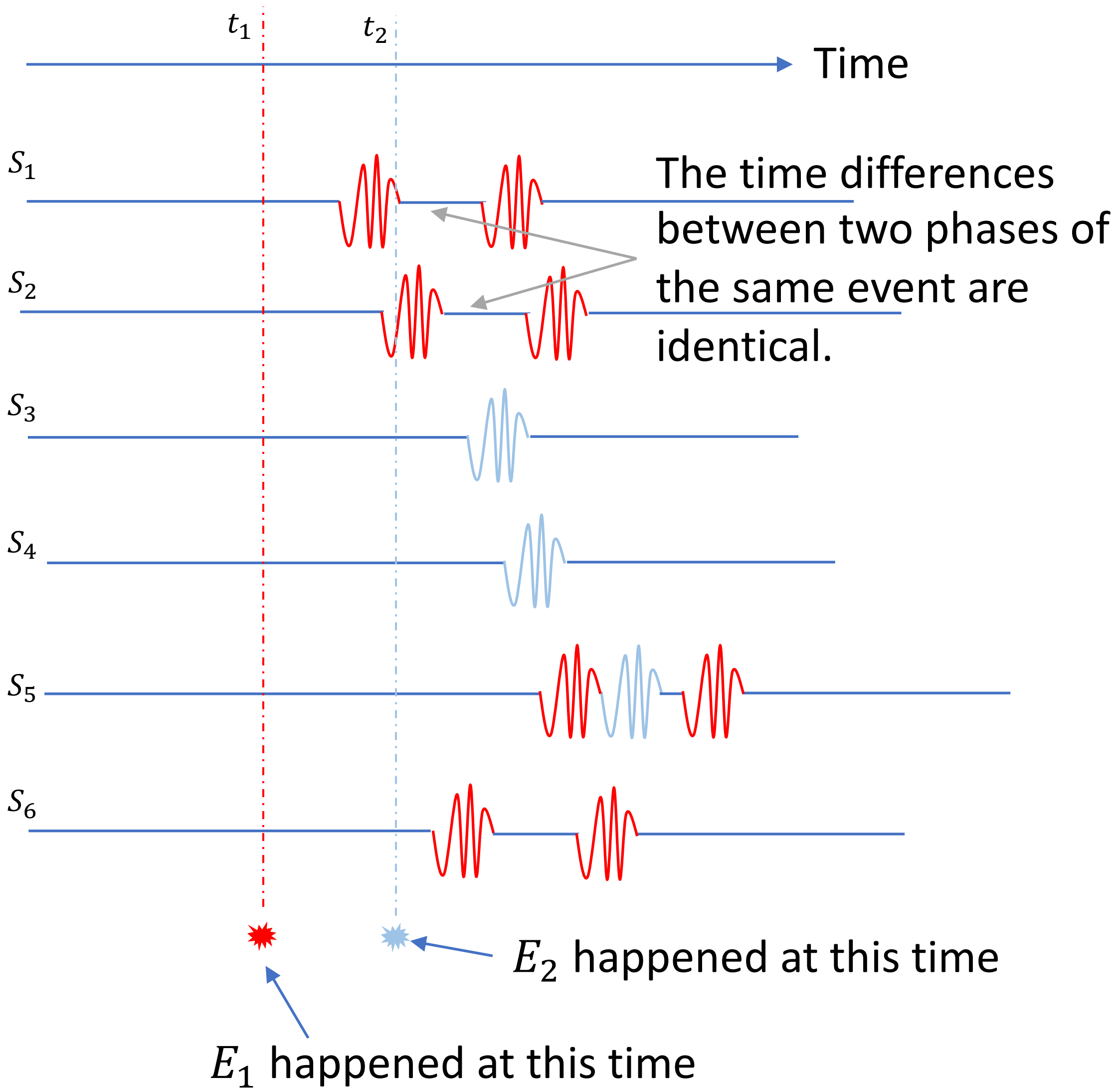
What happens when E_1 reaches S_5 ?



A sensor observes multiple events.

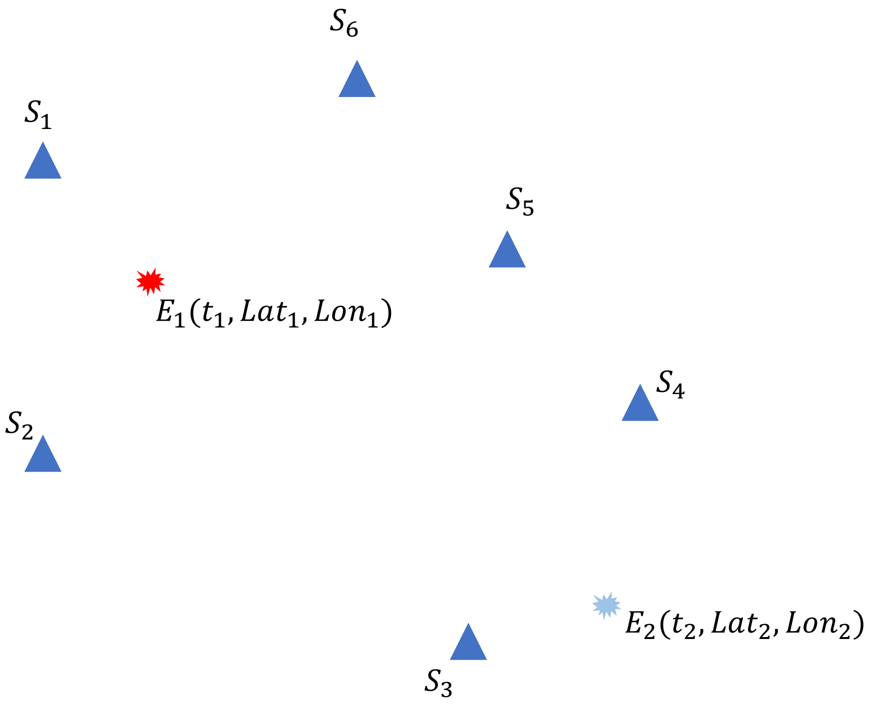
What happens when E_1 generates multiple phases?

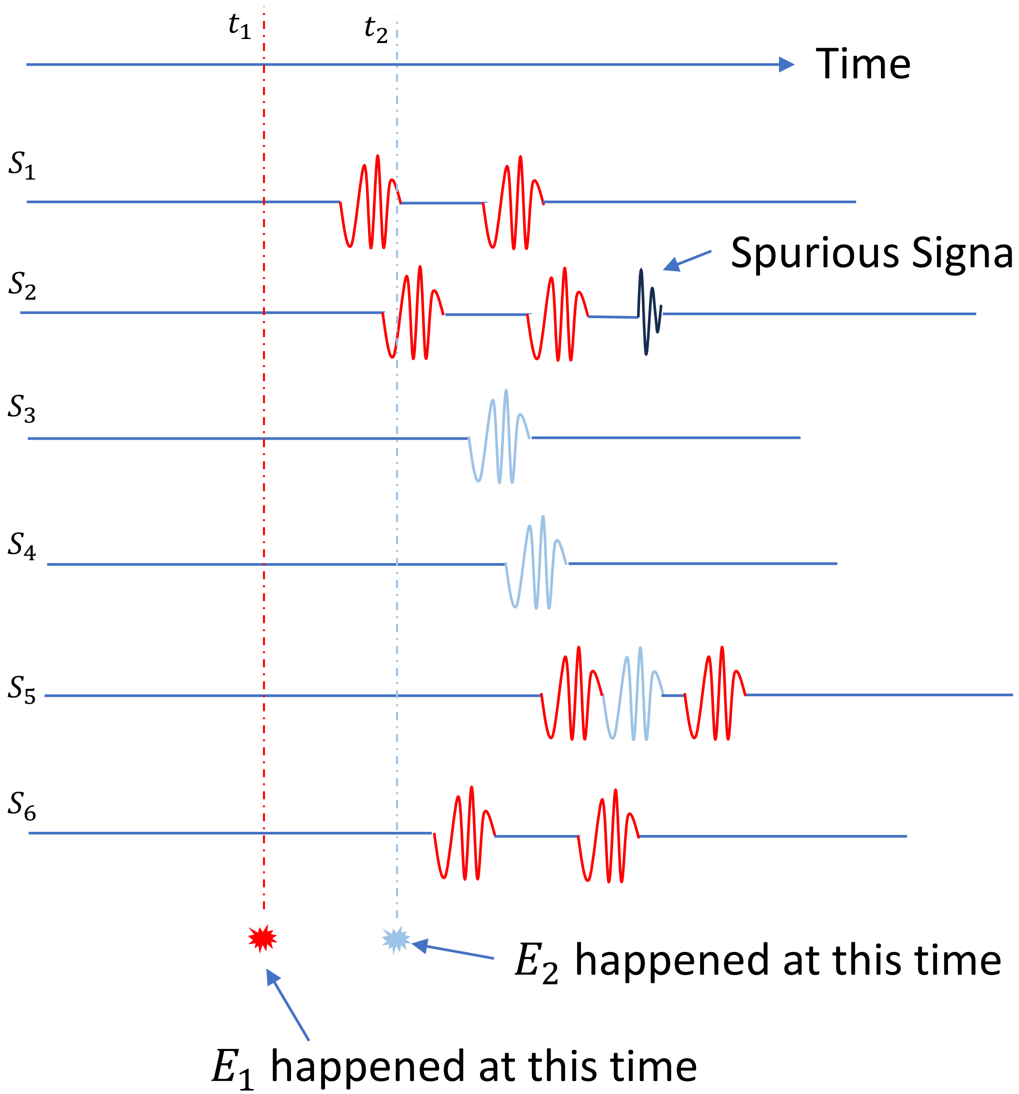




A sensor observes the same event multiple times based on the distance and dynamics of the event.

Spurious signals are observed at random time and location…





A sensor observes the same event multiple times based on the distance and dynamics of the event.

ML attempts to solve this problem

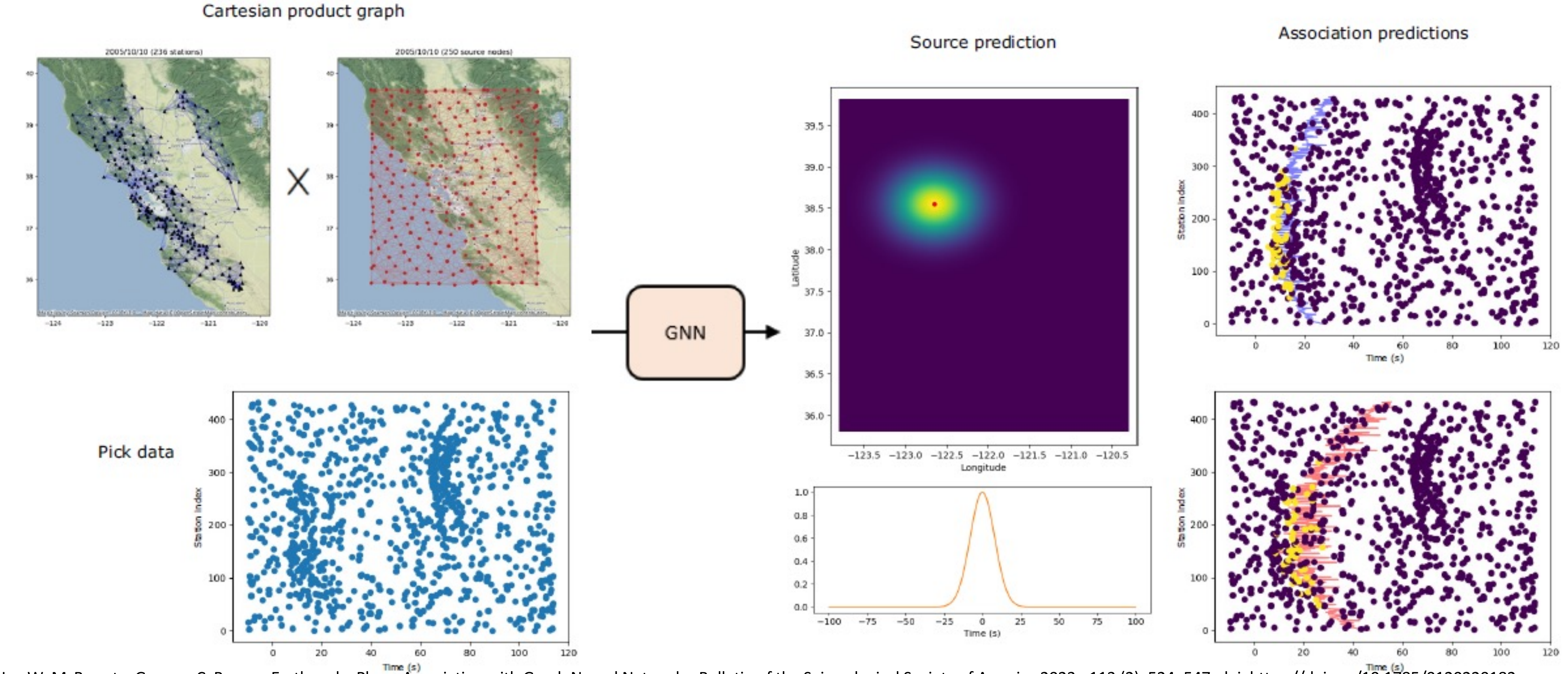


Figure 2. Schematic of the GNN model's input and output. On the upper left are input station and spatial graphs, and on the lower left a window of input pick times. This input is mapped through the GNN to provide a spatial and temporal prediction of the source likelihood (represented as space–time Gaussians), and individual source-arrival association likelihoods for each pick. Out of the large number of picks within the input pick window, the GNN is trained to identify only the small subset of *P* (top right) and *S* (bottom right) picks that are associated to the true source, as marked in red in the spatial heat map. On the right-side panels, the yellow arrivals are the true *P*- and *S*-wave arrivals, whereas all other picks are false. The color version of this figure is available only in the electronic edition.

Ian W. McBrearty, Gregory C. Beroza; Earthquake Phase Association with Graph Neural Networks. Bulletin of the Seismological Society of America 2023;; 113 (2): 524–547. doi: https://doi.org/10.1785/0120220182

Challenges

- The number of earthquake events (and their locations) are unknown.
- Many observations/arrivals can be false, with uncertain pick times.
- Multiple earthquakes can occur nearby in time and space.
- Dozens or hundreds of stations must be processed.
- Station/sensor coverage and event distribution are highly heterogeneous.
- Most events are small and only observed on a small subset of stations/sensors.
- Sensors on earth are assumed to be on the surface of a sphere instead of the 2D plane in these examples.

- Rare but possible challenges:
    - Sensors are not always operational.
    - Sensors may change locations.

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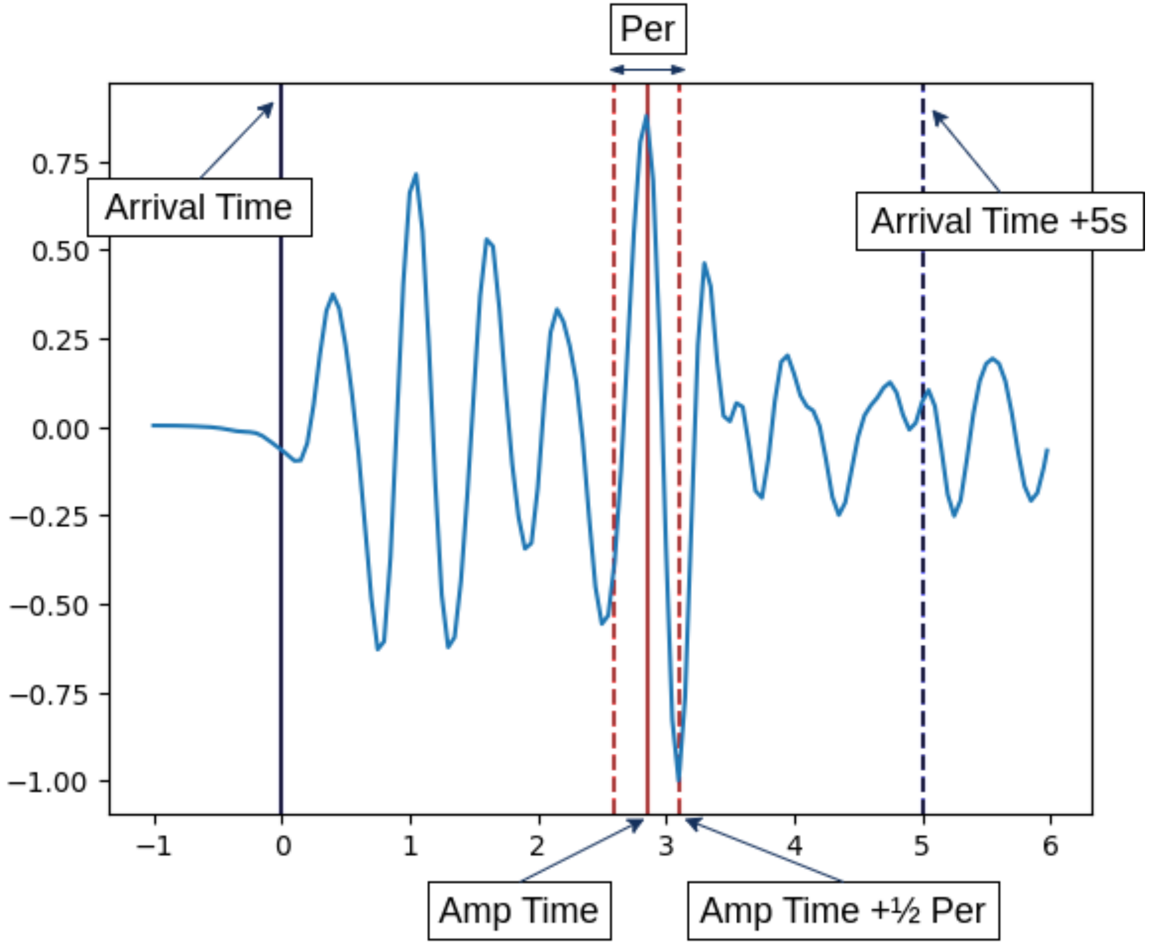
Amplitude Window



The period and amplitude are measured at the largest, uninterrupted half-cycle in the seismograph.

The Problem: Find the largest uninterrupted half-cycle in the waveform.

ARA Labeled Dataset

Derived 'ground-truth' labeled metadata from EVAL1 bulletin

Extracted matching signal windows from International Data Center (IDC) 2017 – 2018 continuous waveform data.

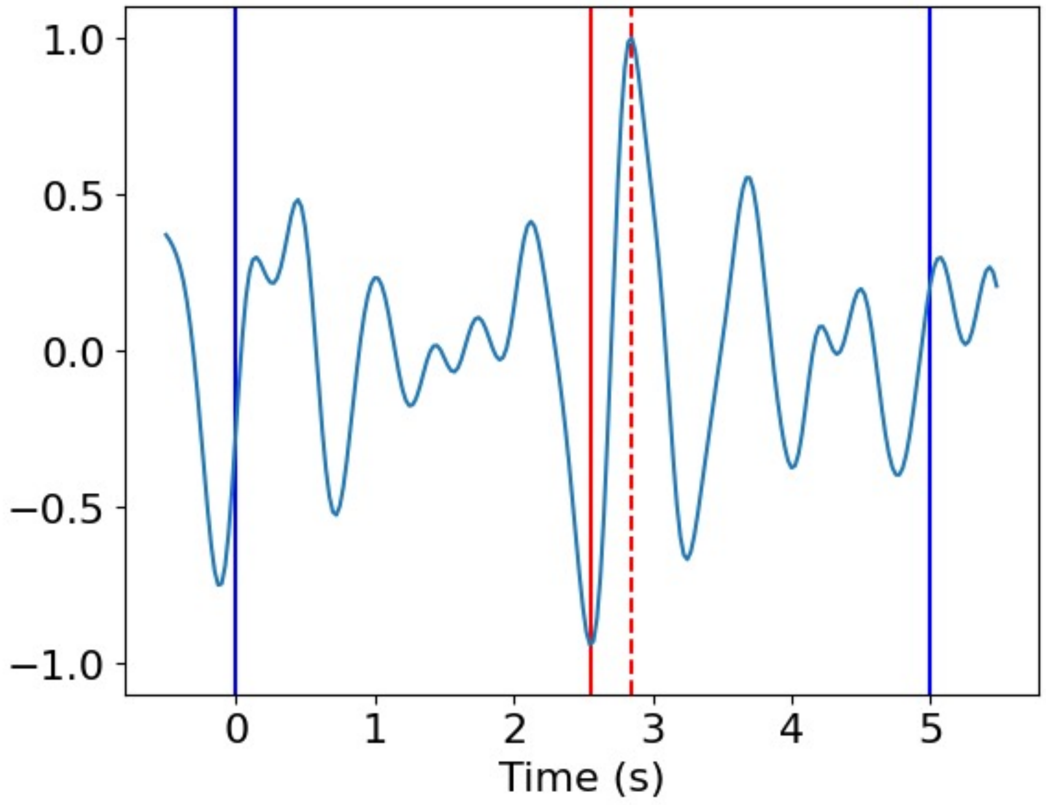
Metadata Filtering Criteria	Counts
Total arrival IDs	5,912,699
Arrivals with P or Pn phase label from preferred origins in 2017 or 2018	525,605
Arrivals with specified filtering parameters	197,670
AMP-Per window in signal window	175,481

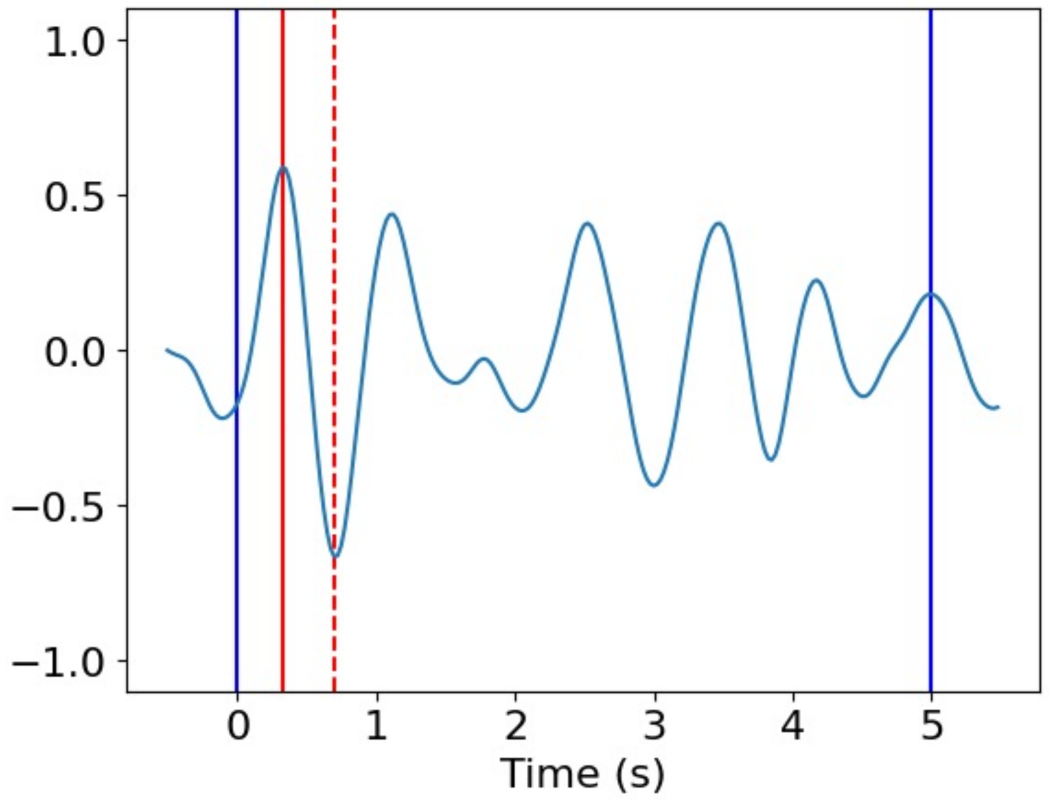
Final AM-P Dataset

51,800 BHZ time windows (3-C stations)

123,681 SHZ time windows (array beams)

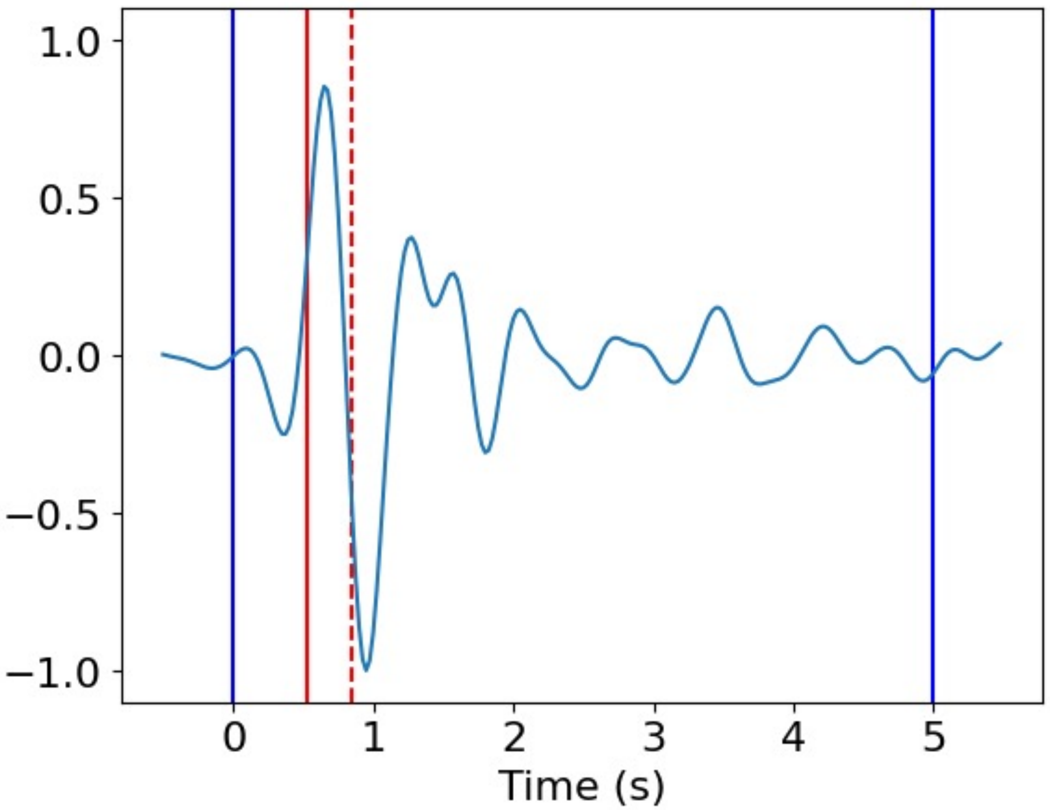
Examples…

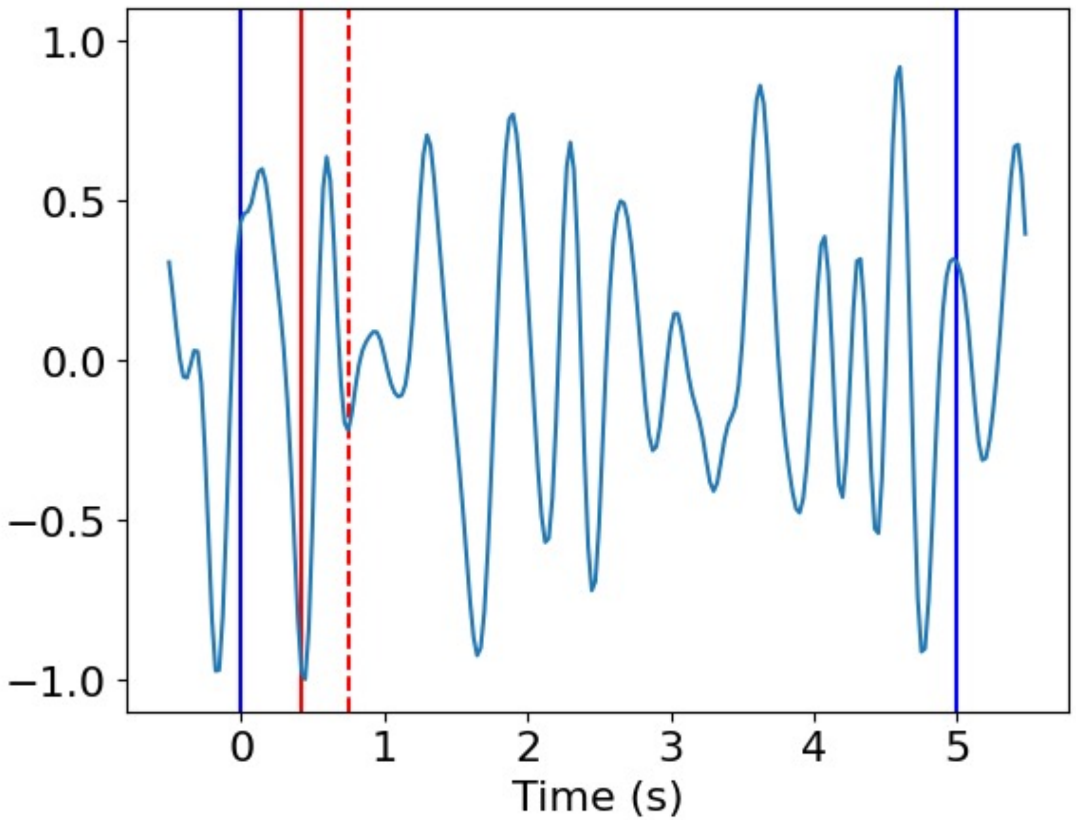




Some examples clearly shows a half-cycle ...

Examples…



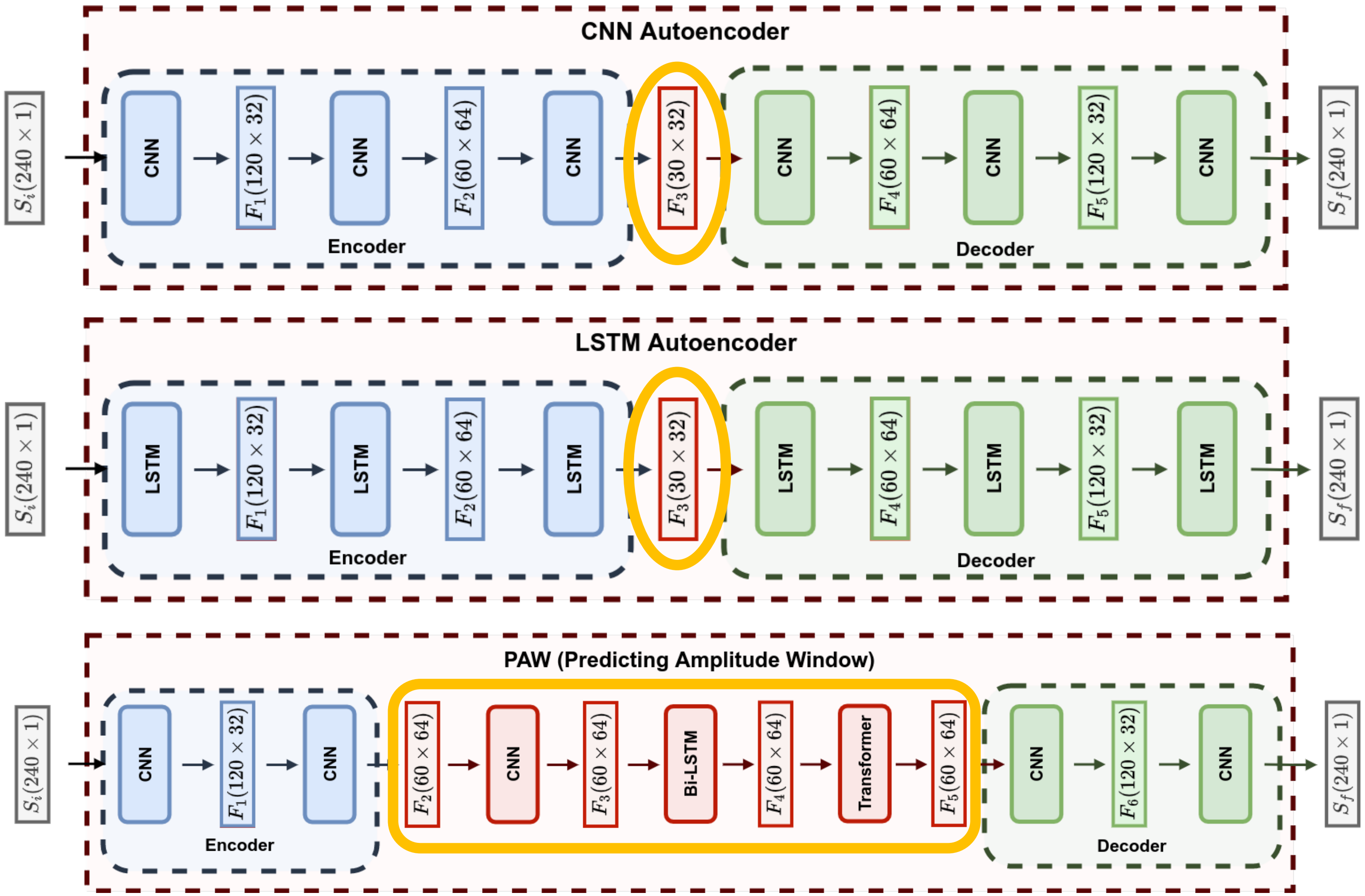


… and some are not intuitive.

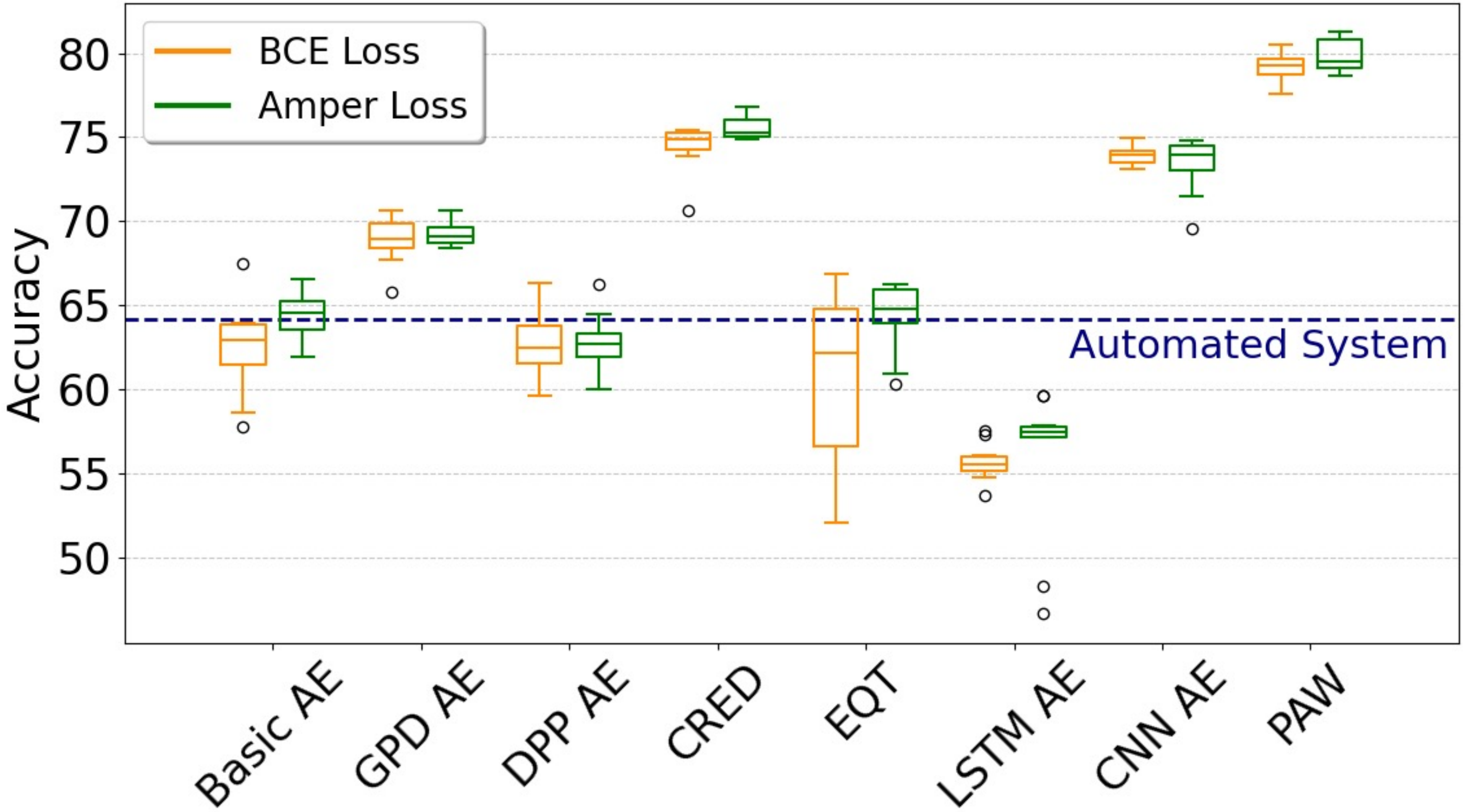
Autoencoder Models

Directly decode the latent representation

Transformations in latent space



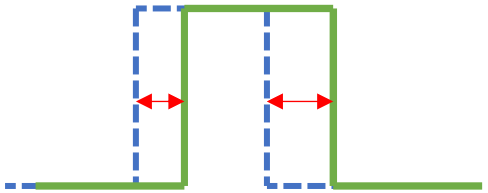
Comparison to other approaches…



PAW achieves higher accuracy compared to other AE and regressor methods

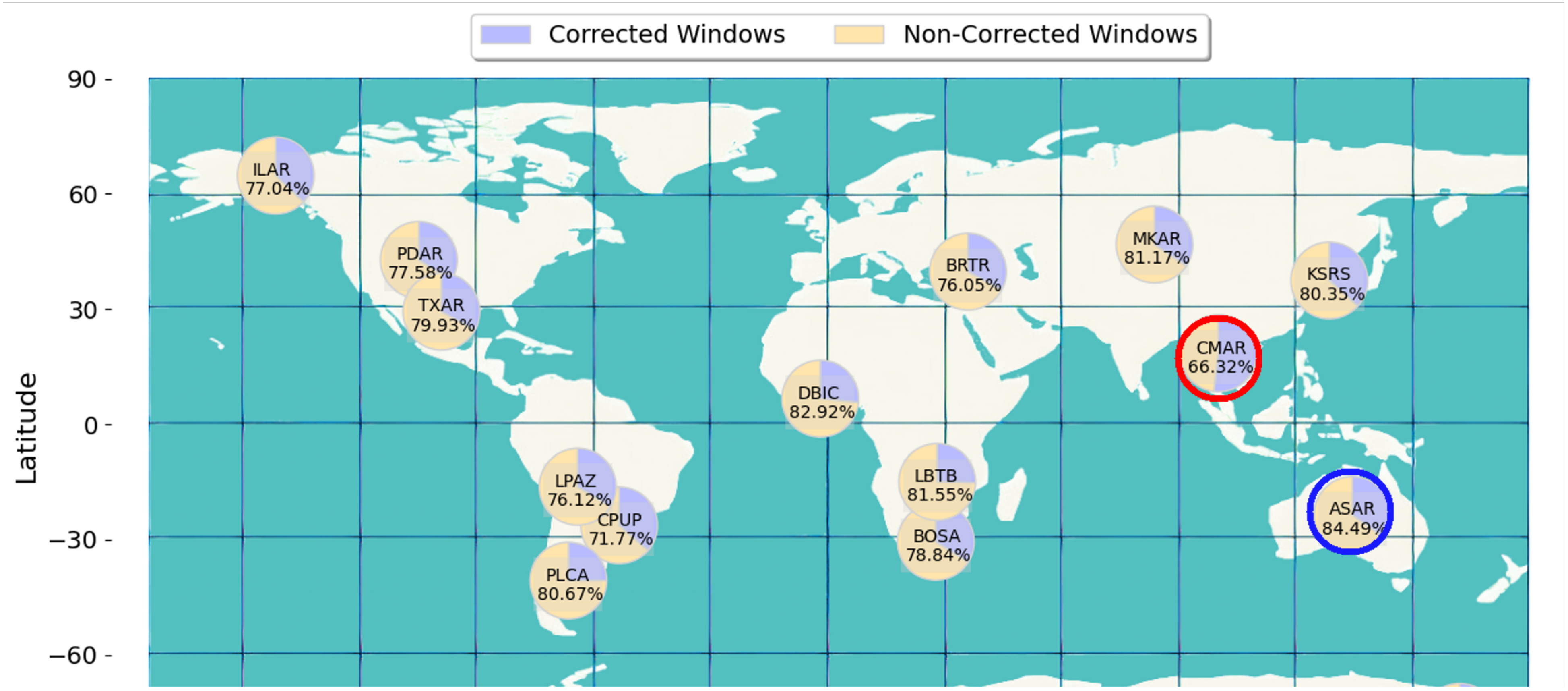
Amper Loss considers error in amplitudes and periods estimated from the predicted window (training converges faster)

Binary Cross Entropy (BCE) looks at window error only



Window error is the sum of red deltas.

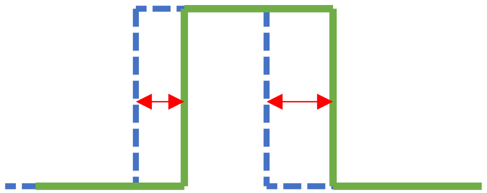
Performance on held-out stations



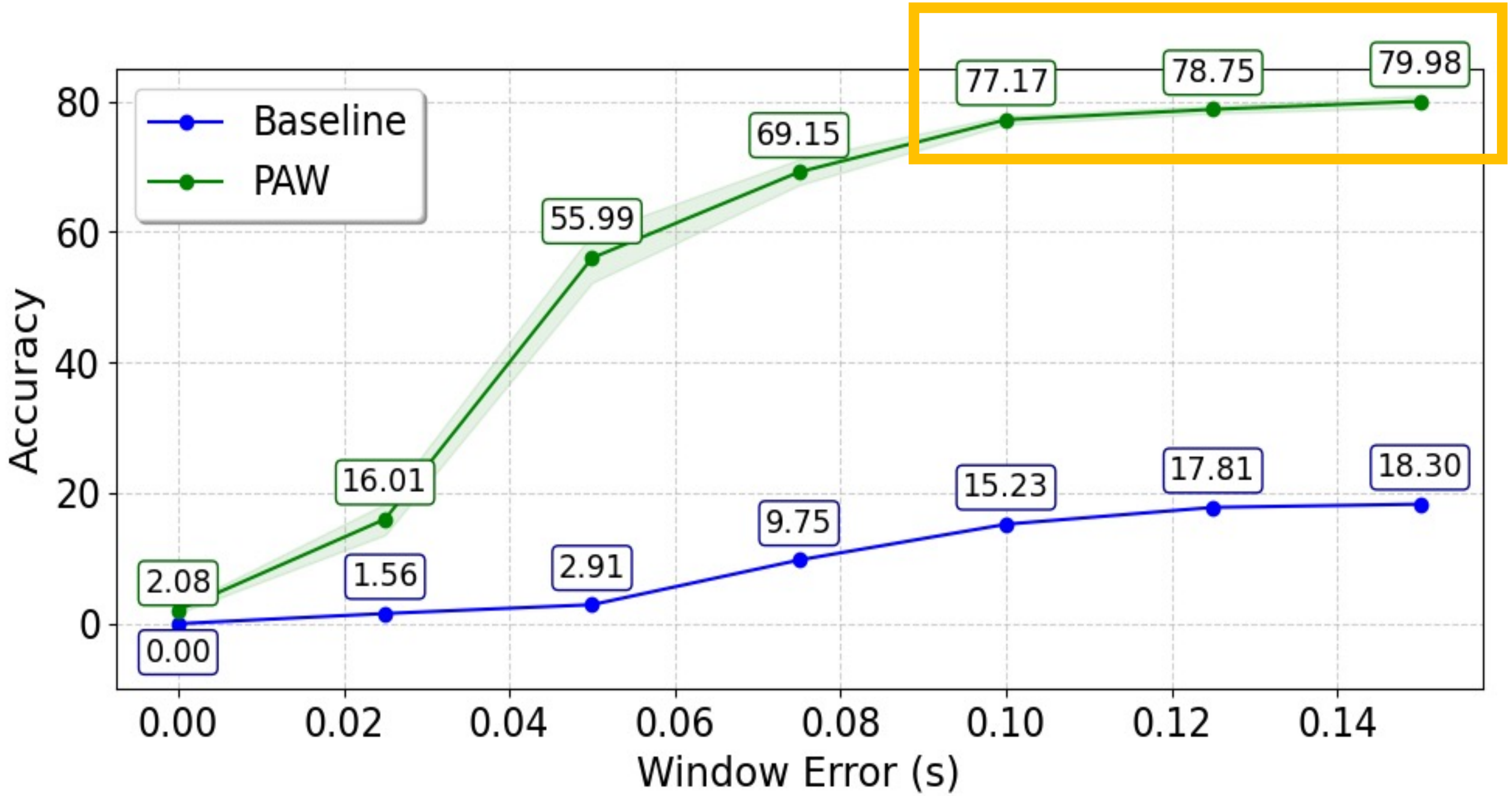
Relationship between the corrected windows and accuracy

	3C Stations							Array Beam Points							
STA	BOSA	CPUP	DBIC	LBTB	LPAZ	PLCA	VNDA	ASAR	BRTR	CMAR	ILAR	KSRS	MKAR	PDAR	TXAR
Adjusted	33.91%	36.36%	26.61%	25.44%	33.75%	25.00%	28.95%	34.81%	32.97%	51.92%	37.11%	36.61%	34.42%	33.89%	33.01%
Accepted	66.09%	63.64%	73.39%	74.56%	66.25%	75.00%	71.05%	65.19%	67.03%	48.08%	62.89%	63.39%	65.58%	66.11%	66.99%
Proportion	1.74%	0.99%	1.24%	1.14%	1.60%	1.68%	2.28%	22.84%	4.64%	10.17%	15.17%	4.89%	16.50%	7.82%	7.30%
WA	78.84%	71.77%	82.92%	81.55%	76.12%	80.67%	79.05%	84.49%	76.05%	66.32%	77.04%	80.35%	81.17%	77.58%	79.93%

Low sensitivity to window error



Window error is the sum of red deltas.

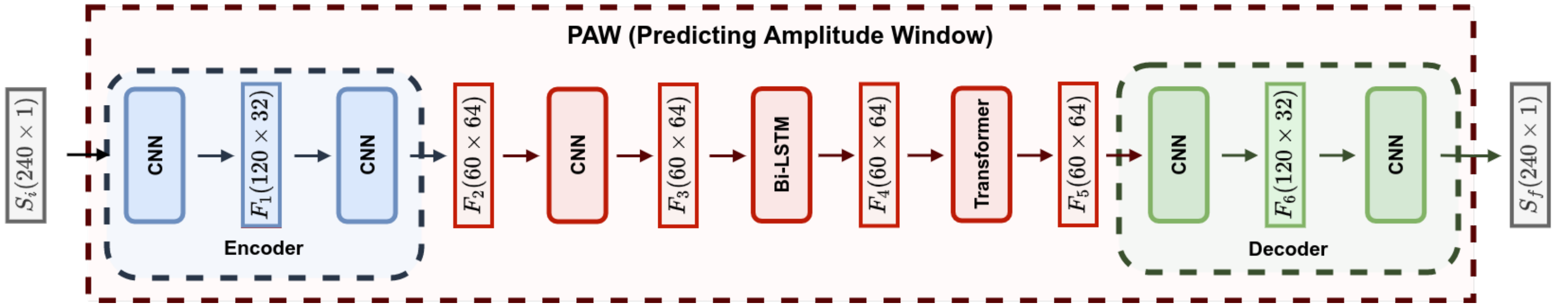


Above 0.1s window error, we reach an accuracy plateau close to 80%!

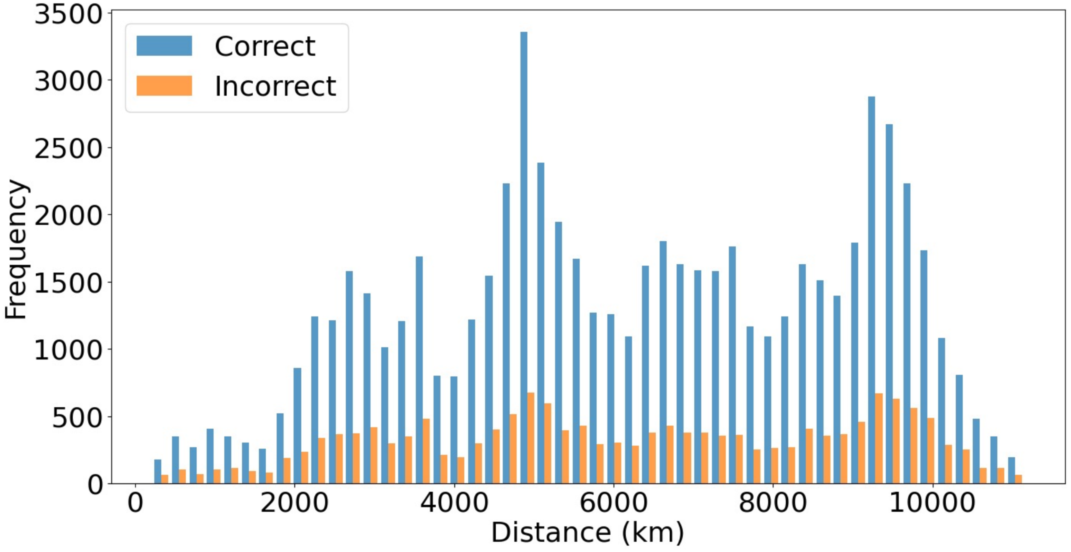
0.1s is equivalent to 4 samples in the entire window

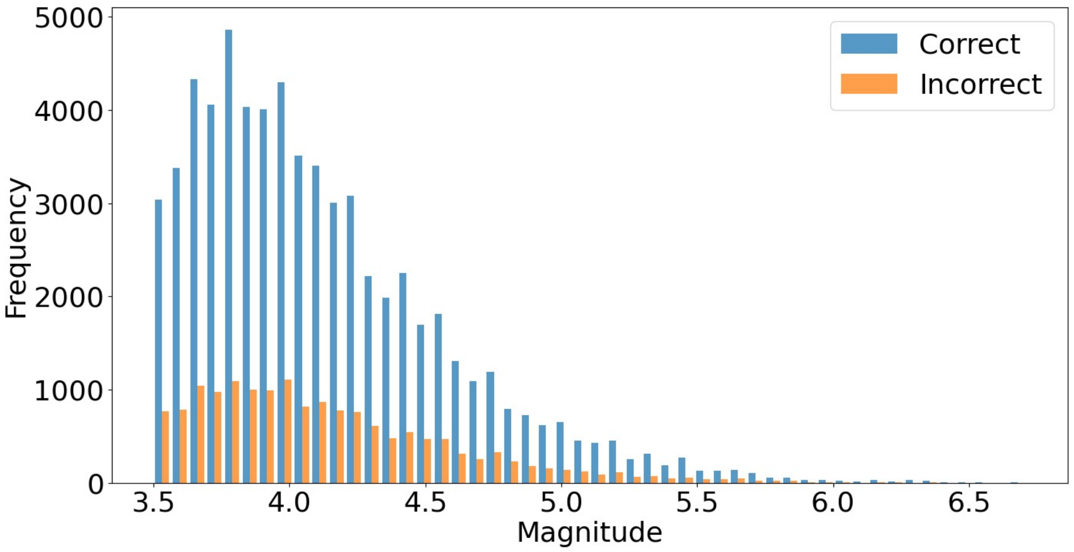
Ablation Study

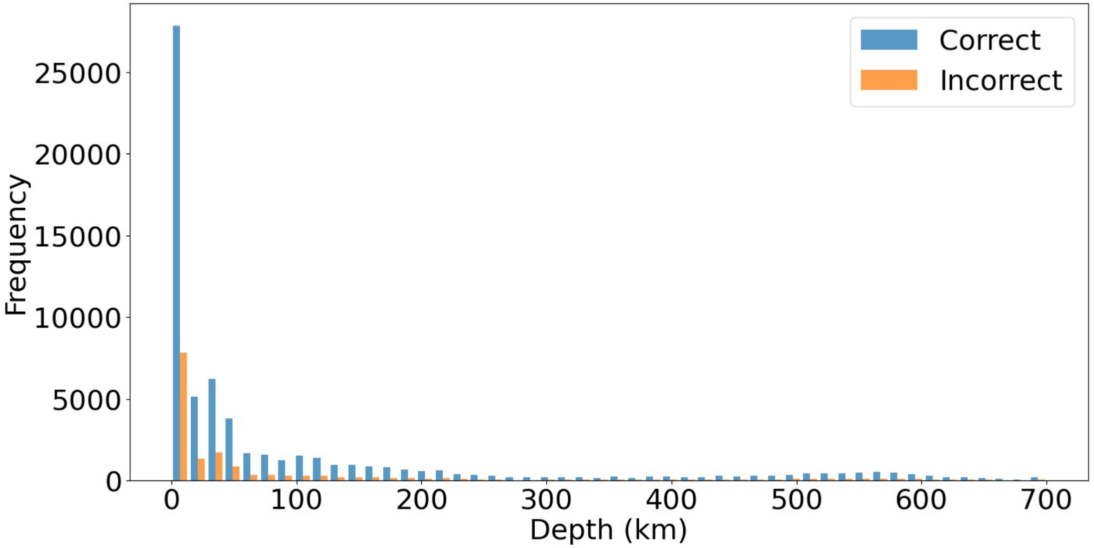
PAW Model Components				RMSE				Window Accuracy		
CNN AE	LSTM	Transformer	Symmetry	Window	Amp	Per (s)	Mag	Test	Adj	Acc
✓				0.1537	0.0715	0.2158	0.3804	75.54%	71.05%	80.48%
✓	✓			0.1526	0.0699	0.2024	0.3783	76.83%	72.25%	80.14%
✓		✓		0.1514	0.0694	0.2107	0.3792	76.04%	69.92%	82.19%
✓	✓		✓	0.2712	0.2864	0.5386	1.0083	18.31%	14.43%	22.67%
✓	✓	✓		**0.1445**	**0.0683**	**0.1686**	**0.3573**	**79.84%**	**73.28%**	**87.28%**



PAW is Unbiased to Depth, Magnitude and Distance







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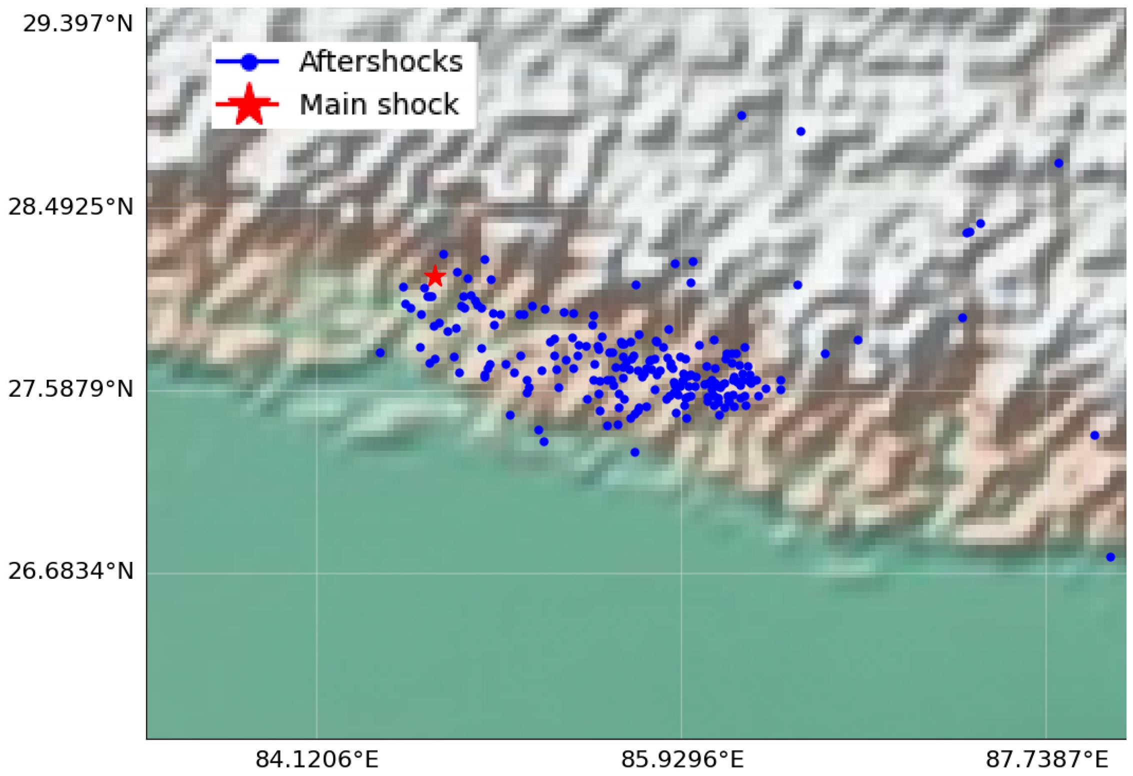
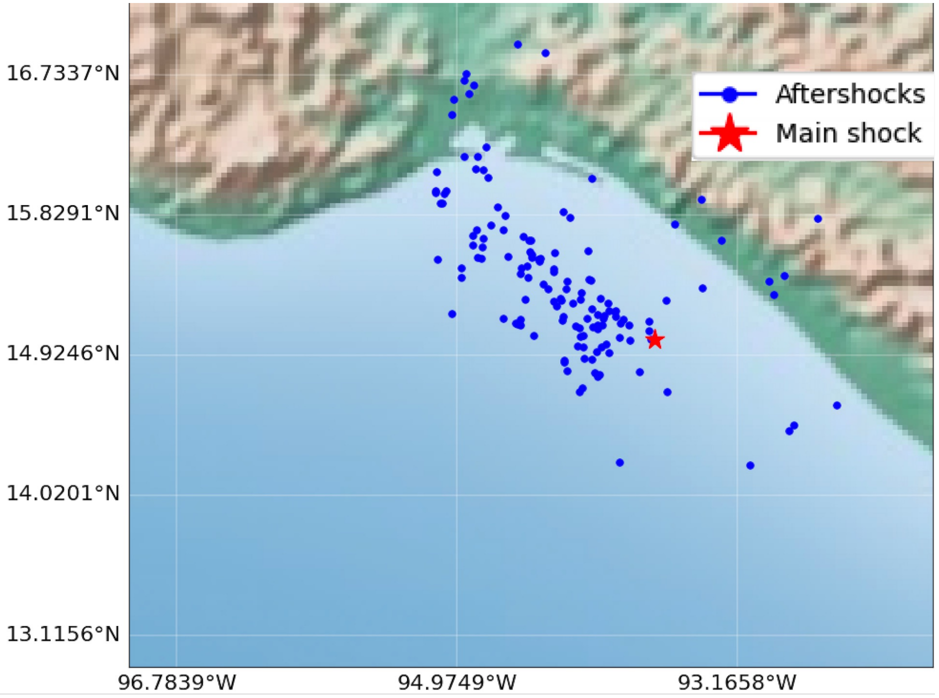
Introduction -- Online event detection

- Motivation:
  - Seismic monitoring systems
    - Not fully automated
    - Human analysts to confirm
  - Aftershocks:
    - Not interesting
    - Increase analyst workload by 10x
  - Solutions:
    - More analysts: **Redundant**
    - Delay reporting: **Vulnerability**
    - A real-time automated aftershock detector.



Challenges

- An unseen event: different data distribution.
- Only first few events are available.
- Computational efficiency is required for real-time performance.
- Concept drift.



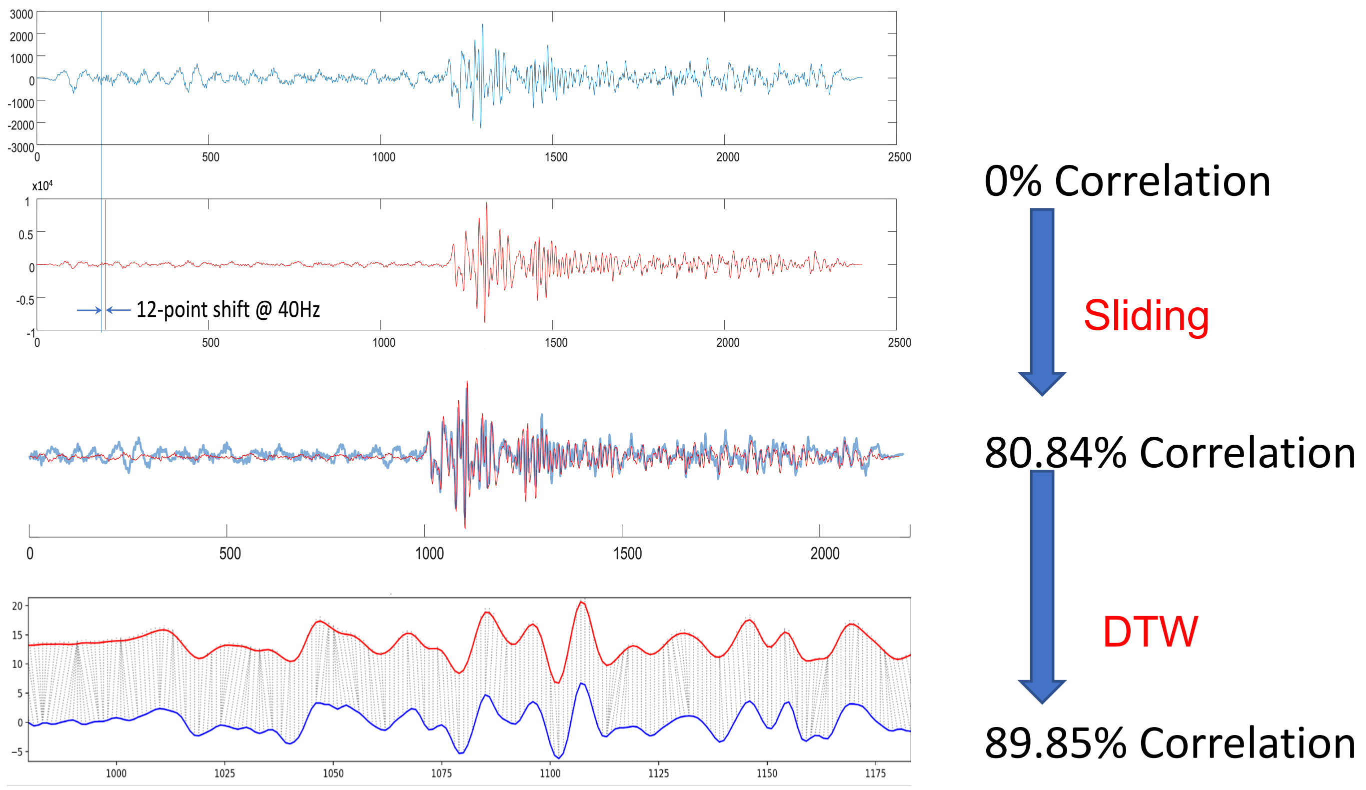
FewSig

- Highlights:
  - Trained on a few positive samples.
  - Adapt to the new positive instances iteratively.
  - Efficiently enough for real-time usage.

	FewSig	Offline supervised classification model	Offline semi-supervised model
Few positive signals	✓	✗	✓
Concept drift	✓	✗	✓
Real-time	✓	—	—
Invariant to orders	✓	✗	✗

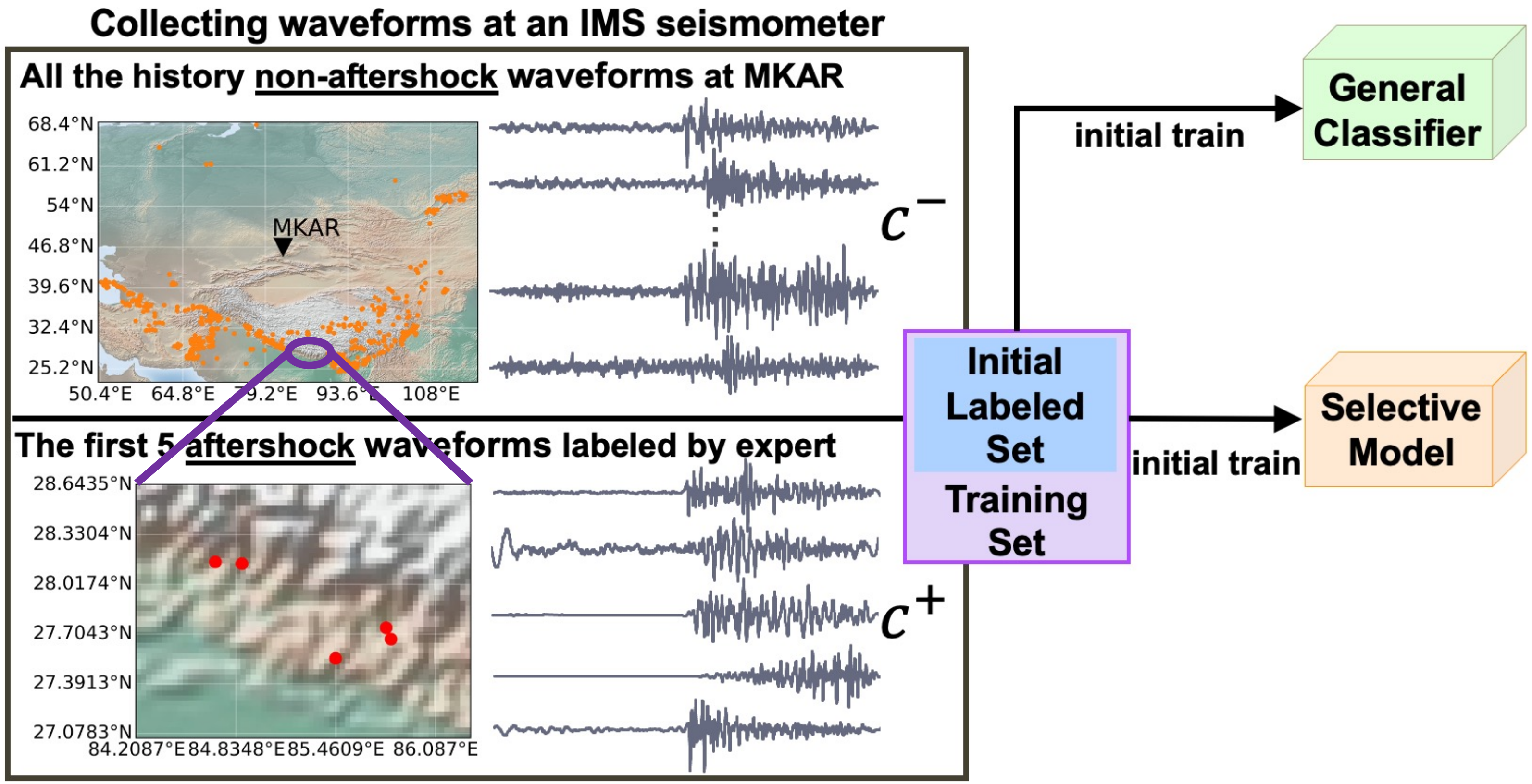
Distance computation

- **Sliding DTW**
  - Sub-sequence search with DTW
  - Reduce two types of errors:
    - Misalignment error.
    - Warping error.
- Parameters:
  - Sub-sequence length
  - Search-range
  - Warping band
- Learning strategies:
  - Minimize intra-class distance
  - Maximize inter-class distance

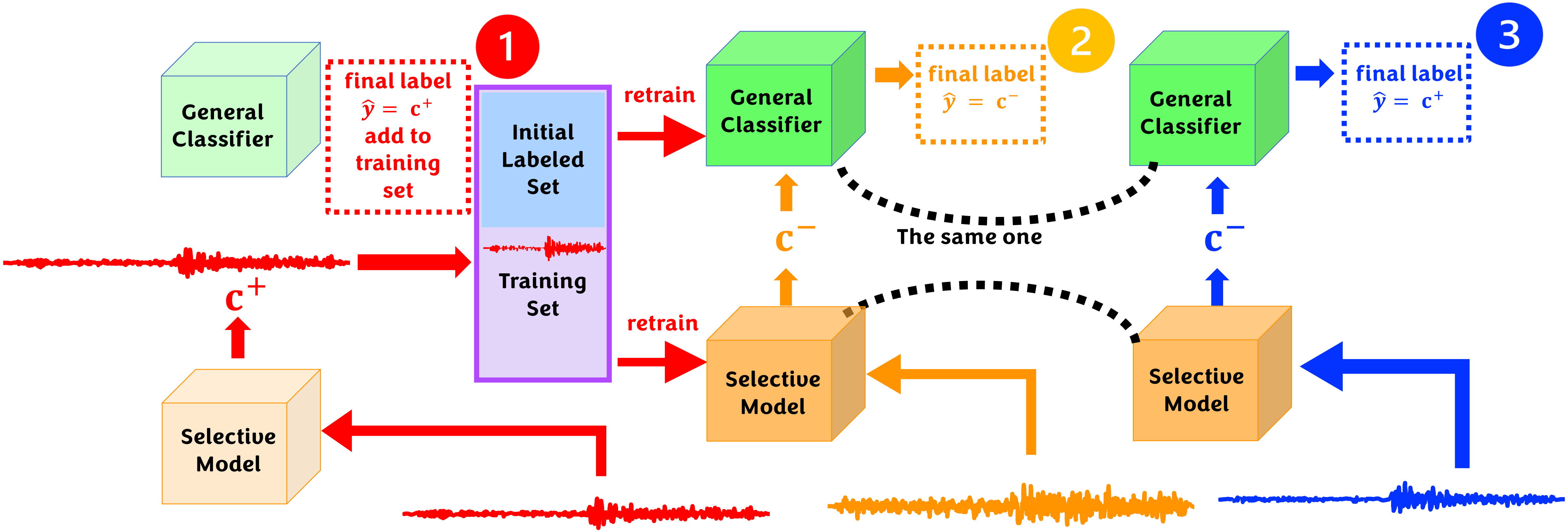


Initial Stage

M 7.8 - 67 km NNE of Bharatpur, Nepal
•2015-04-25 06:11:25 (UTC)
•28.231°N 84.731°E



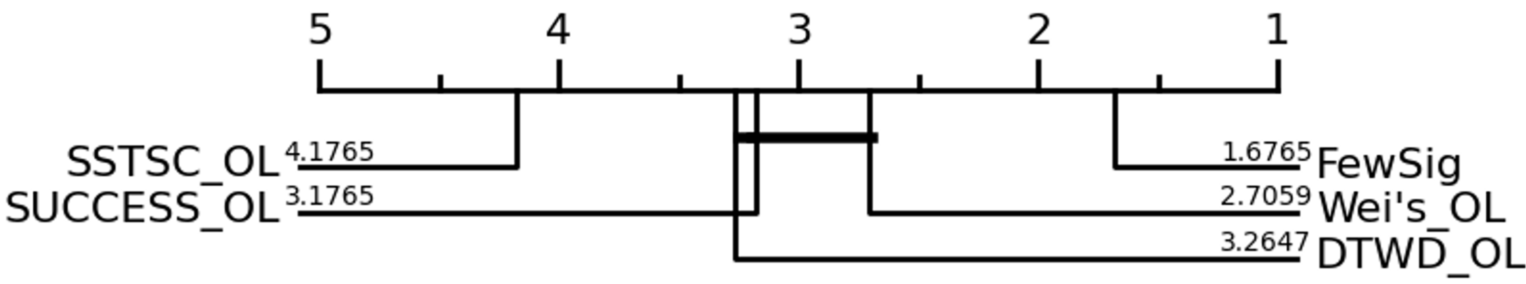
How FewSig works



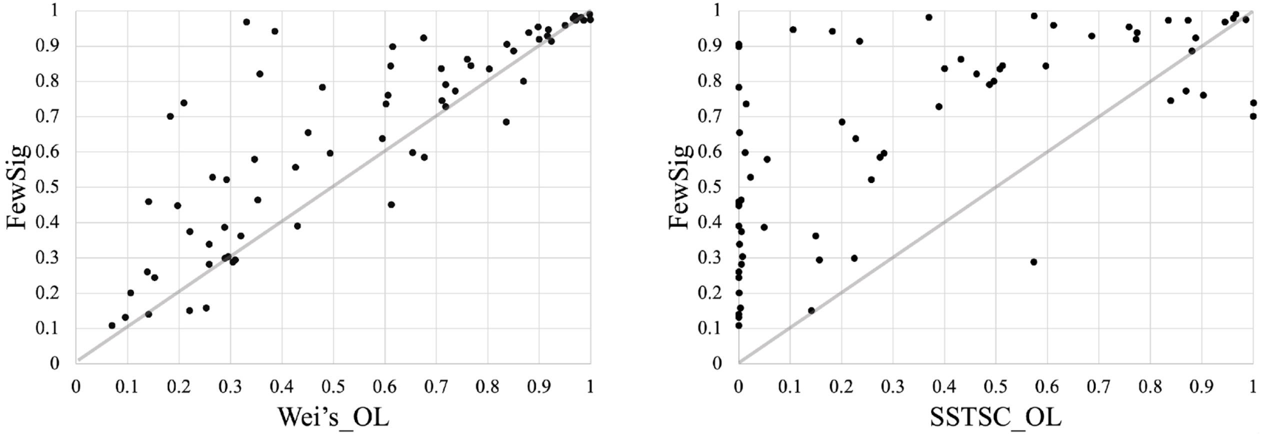
FewSig Sanity-check

- Other semi-supervised model modified for online version:
  - Wei's Algorithm
  - DTWD
  - SUCCESS - SOTA
  - SSTSC - SOTA

- We tested on 68 univariate time series datasets from the UEA/UCR repository that covers various domains.

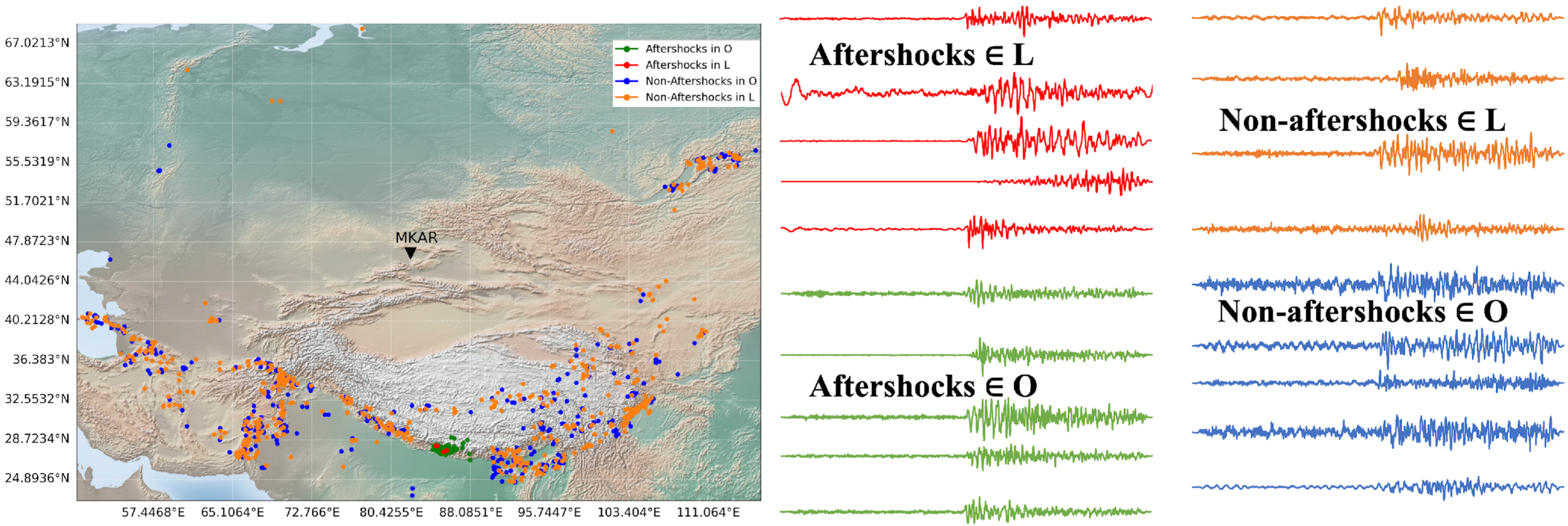


Critical difference diagram of 5 models, the ranking is based the average F1 score



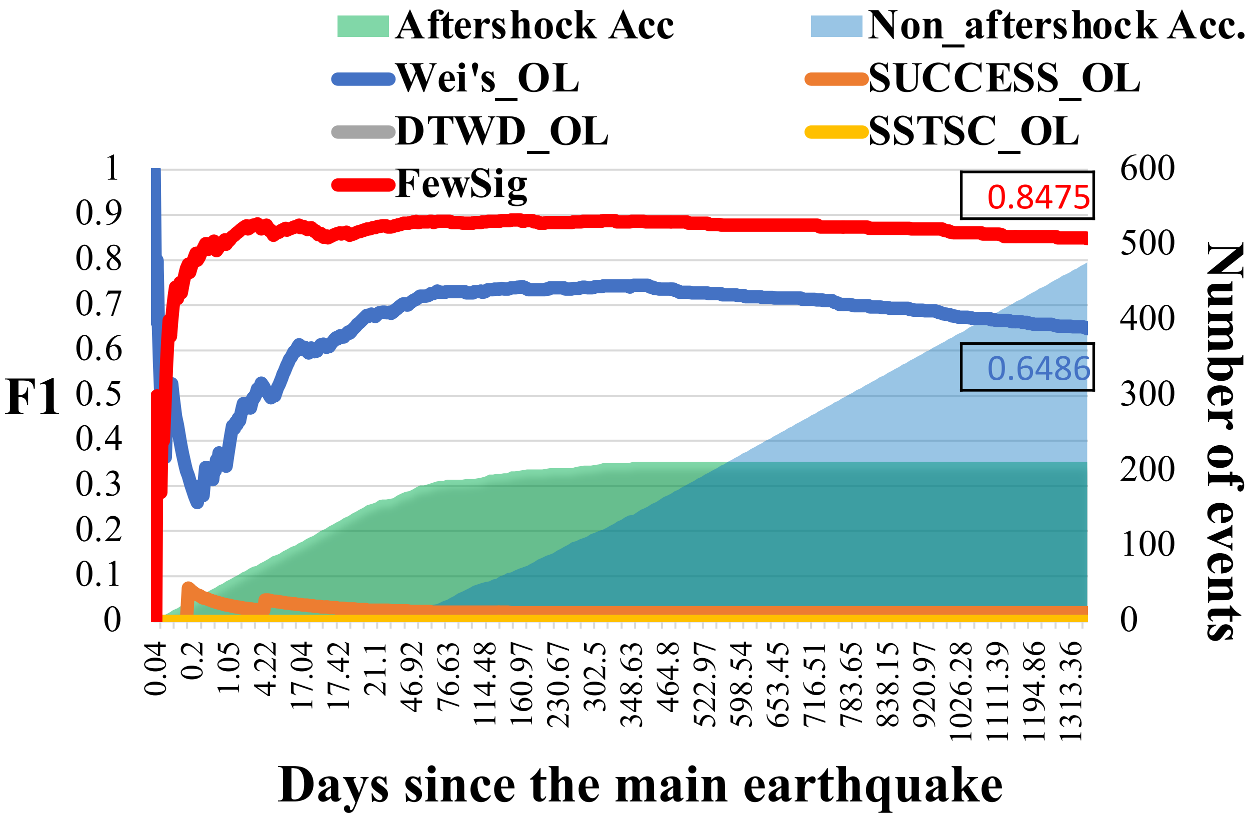
F1 scores of 68 datasets comparison between FewSig and Wei's model (left) and SSTSC (right).

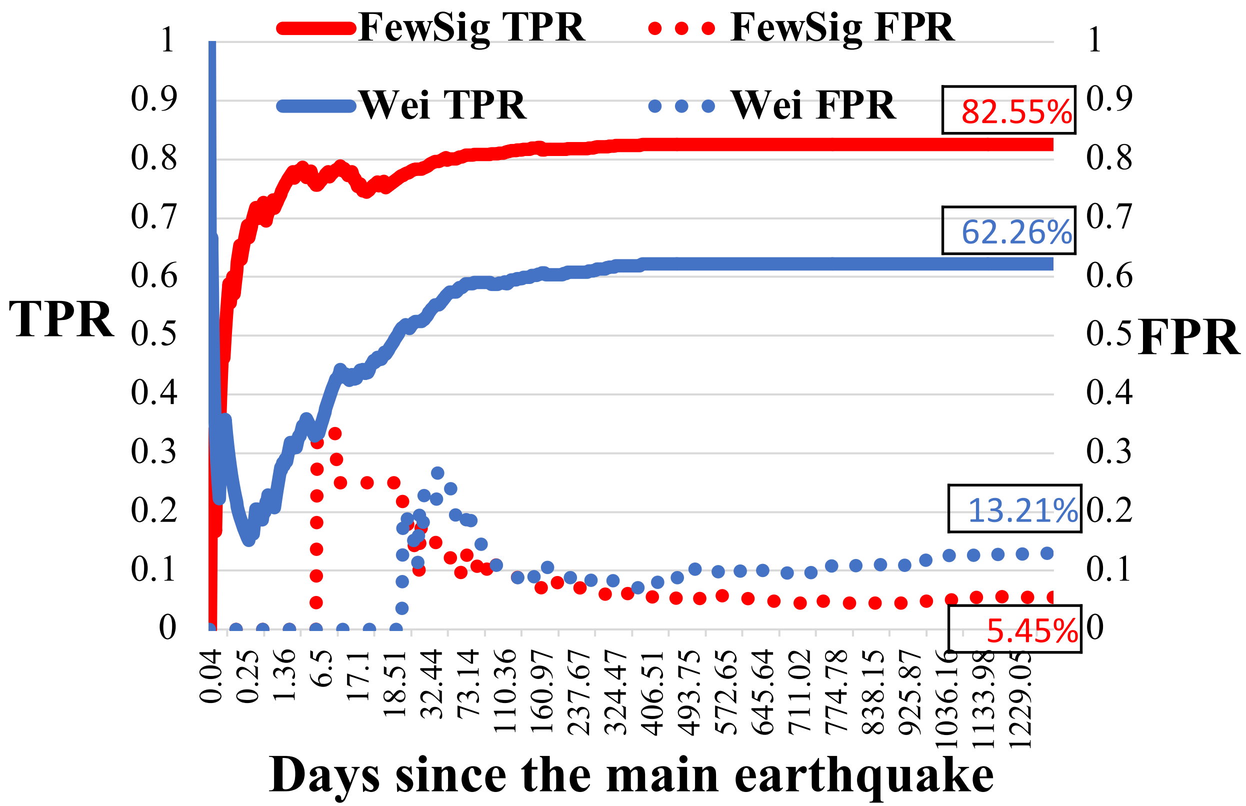
Nepal aftershocks on MKAR



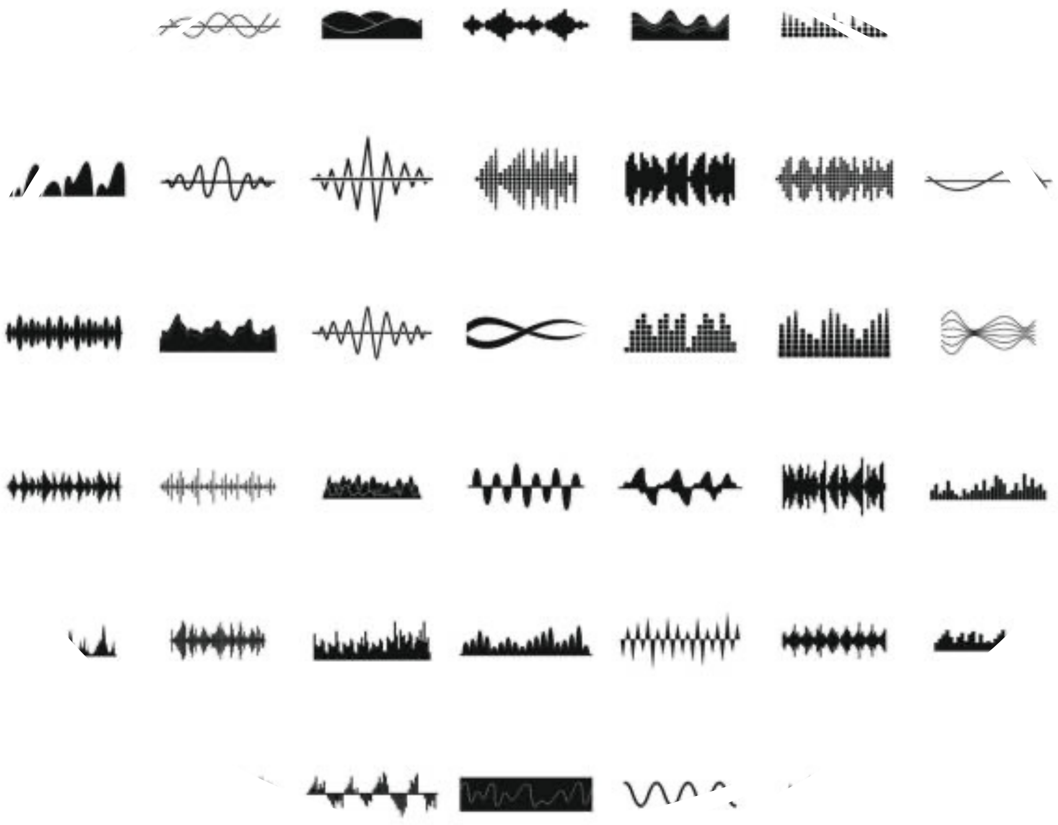
- Left figure shows the geographical distribution of origins for valid arrivals at MKAR.
- The right figure shows some example waveforms for aftershocks and non-aftershocks from L and O. The first 5 aftershocks are in red. The BHZ waveforms recorded at MKAR are shown. They were filtered with a 0.4Hz to 10Hz Butterworth bandpass filter.

Results for 2015 Nepal Earthquake





Online performance for classifying Nepal aftershock sequence at MKAR. TPR, FPR, and F1 scores of different models are shown on the solid or dotted curves. A point on a curve shows the score when testing the events at and before the time on the x-axis. The accumulated number of testing aftershocks and non-aftershocks are represented by the light green and blue shaded areas respectively. Both SUCCESS_OL and SSTSC_OL have F1 scores of zero throughout. We only use Z channel time series data for SSTSC_OL since it only supports univariate time series.



Thank you!