Earthquake Seismology and Experience in Processing Earthquake Data at ERI Tokyo

May 9th 2022

Christopher Salim

About Me

What I did:

- Alumnus of Geophysical Engineering ITS 2016
- Working as a TA for Comp. Geo., Digital Data Analysis, Math. Geo from 2019 to 2021.
- Link to my project in Tokyo (related to my undergrad thesis): https://github.com/christophersalim/ERI-Sakura-Report

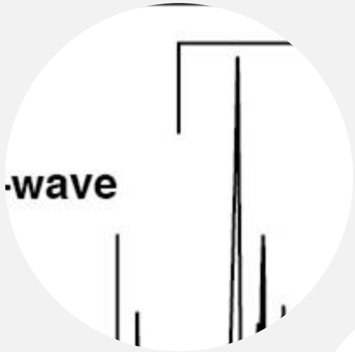
What I'm doing now:

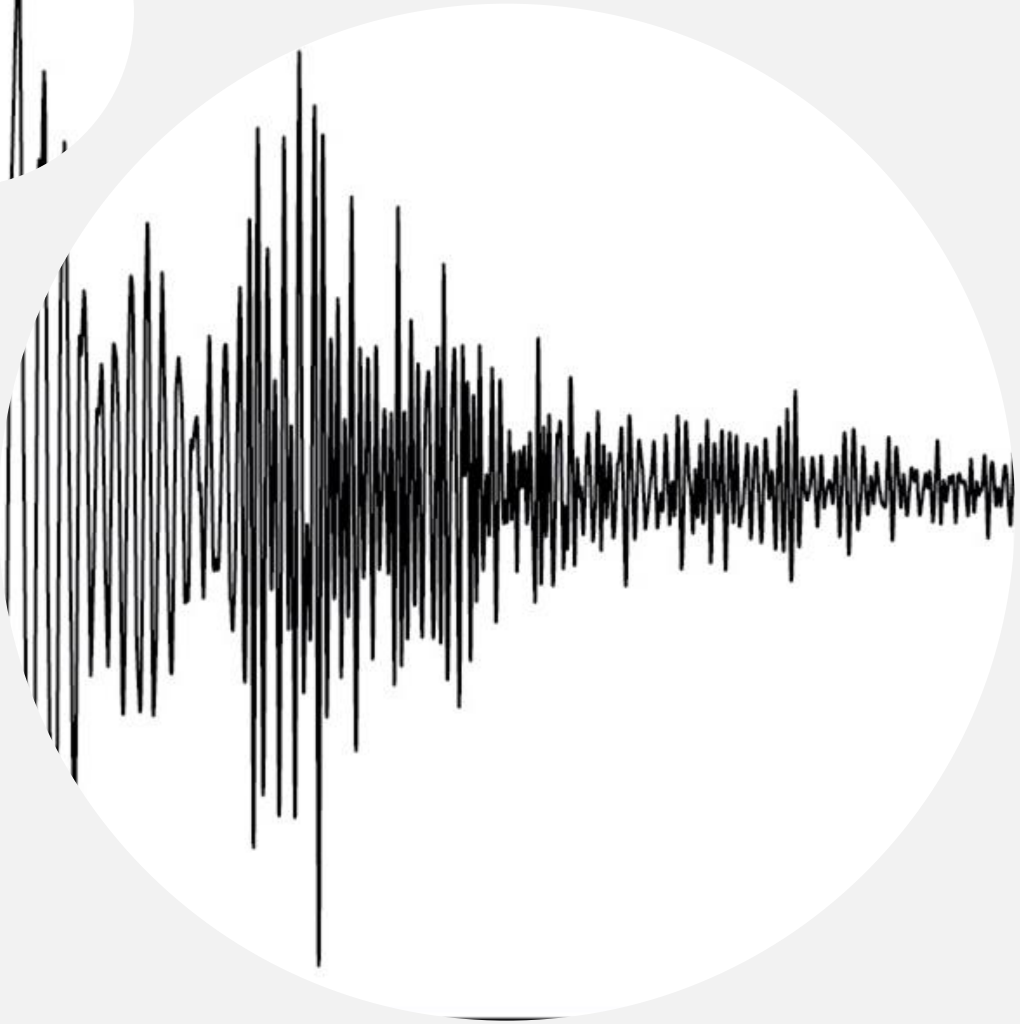
- Currently a MSc Student majoring in Statistics at Brock University (2022 – 2023 hopefully!)
- Also working as a TA and part-time Math tutor for Canada and US students.

Christopher Salim

Agenda

- Introduction
- Basic Seismology
- What is ERI Tokyo?
- Earthquake Data Processing at ERI Tokyo
- Key takeaways from the experience
- Q & A and closing

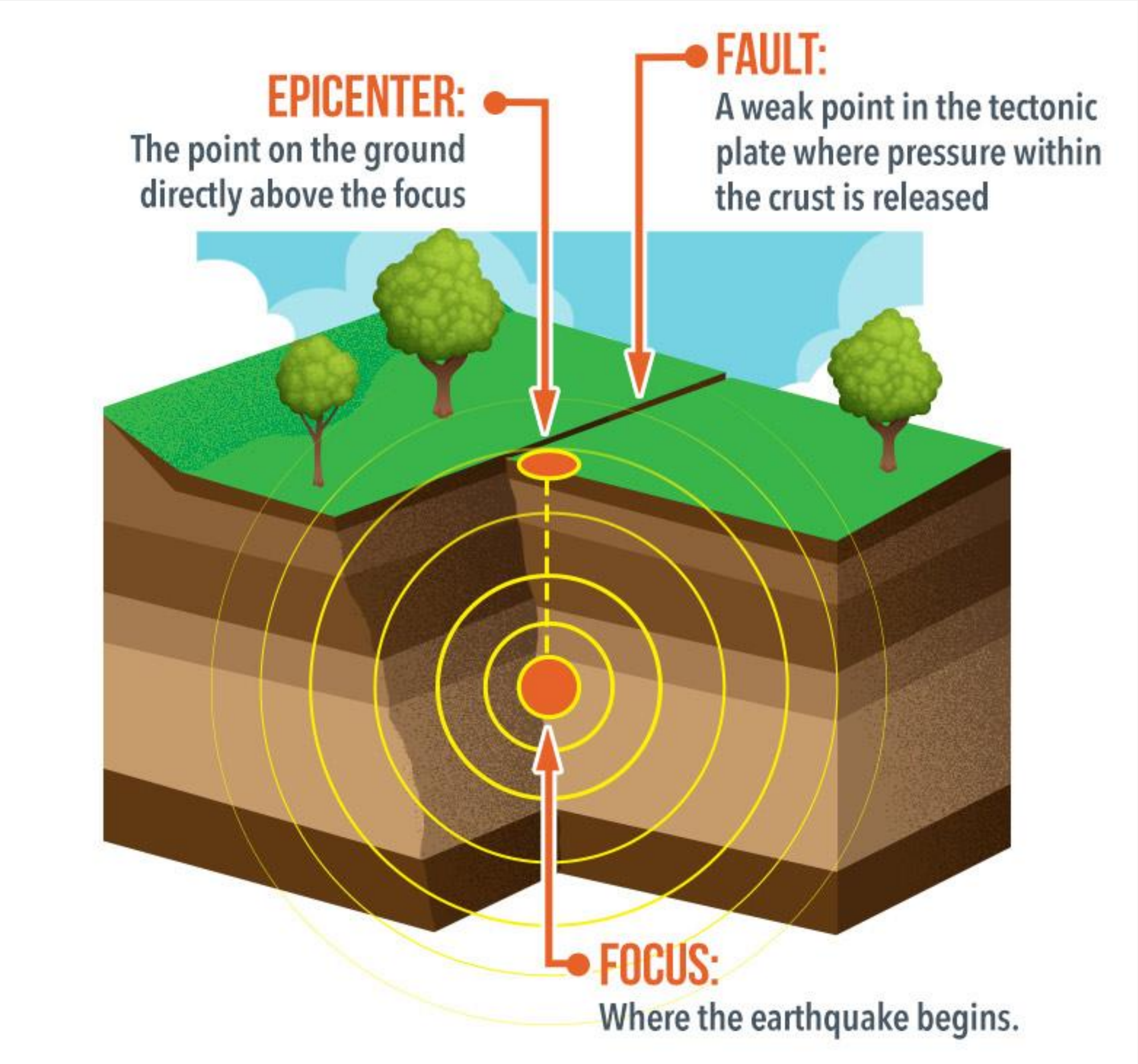




What is Earthquake Seismology?

- Seismology = study of the passage of *elastic* waves through the earth (earthquakes)
- General idea of earthquake: vibration of earth as a result of rapid release of energy (either from tectonic e.g. fault, or volcanic activities)
- When an earthquake or explosion occurs, part of the energy released is as elastic waves that are transmitted through the earth.

Earthquake Illustration



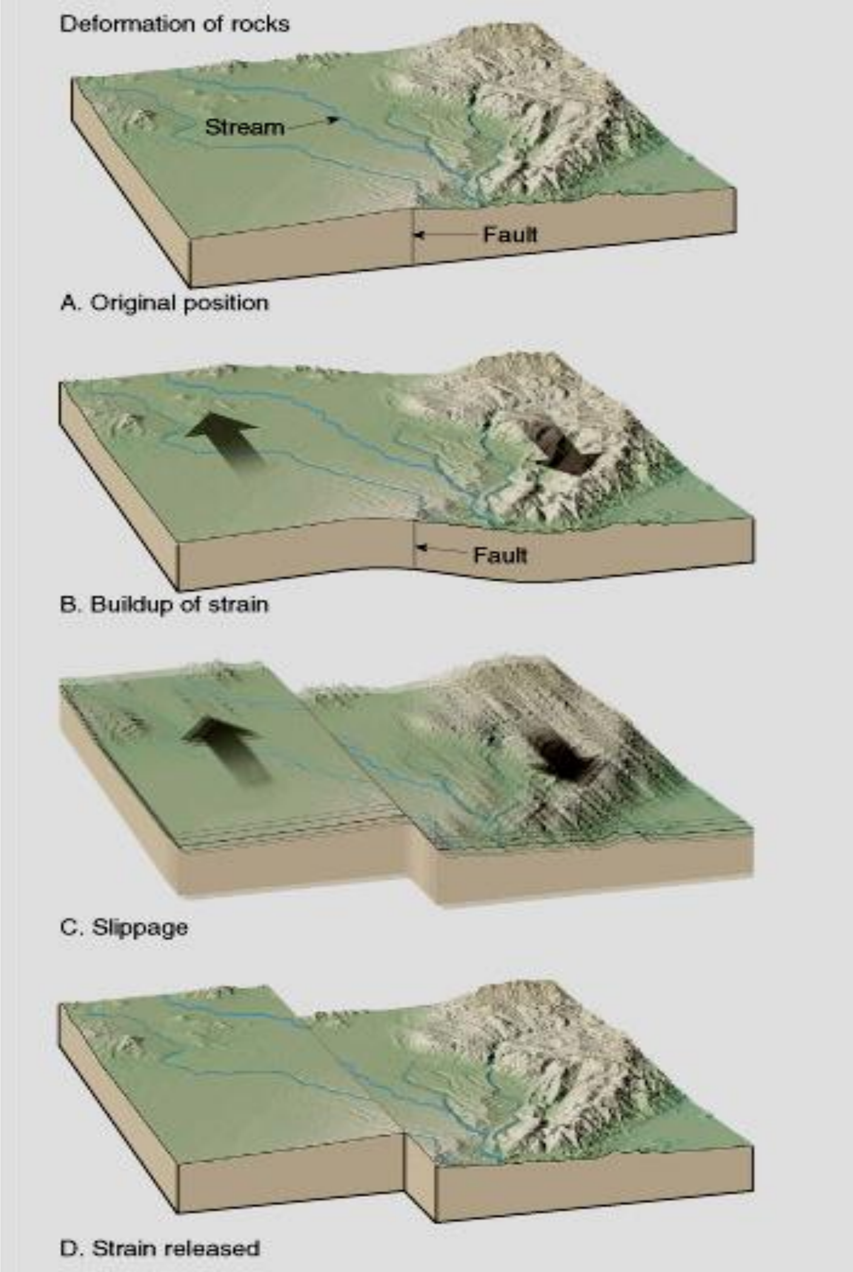
Other terms:

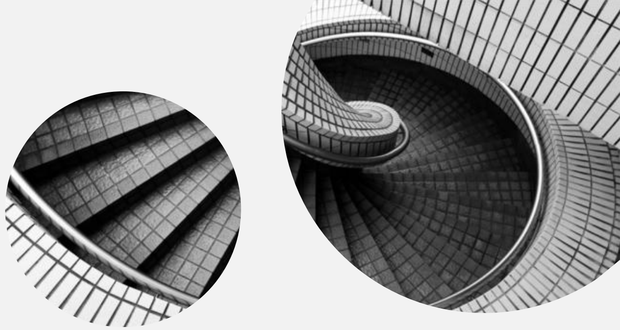
- Focal depth: the depth of focus from the epicentre, important in determining the damaging potential.
- Epicentral distance: distance from epicentre to any point of interest
- Foreshocks: smaller earthquakes pre-actual earthquake.
- Aftershocks: smaller earthquakes post-actual earthquake.

Mechanism for earthquakes

Elastic rebound

- Mechanism for earthquakes was first explained by H.F. Reid
- Rocks on both sides of an existing fault are deformed by tectonic forces
- Rocks bend and store elastic energy
- Frictional resistance holding the rocks together is overcome
- Then the deformed rock springs back to its original shape and releases energy.





Basic Equations

Terminologies:

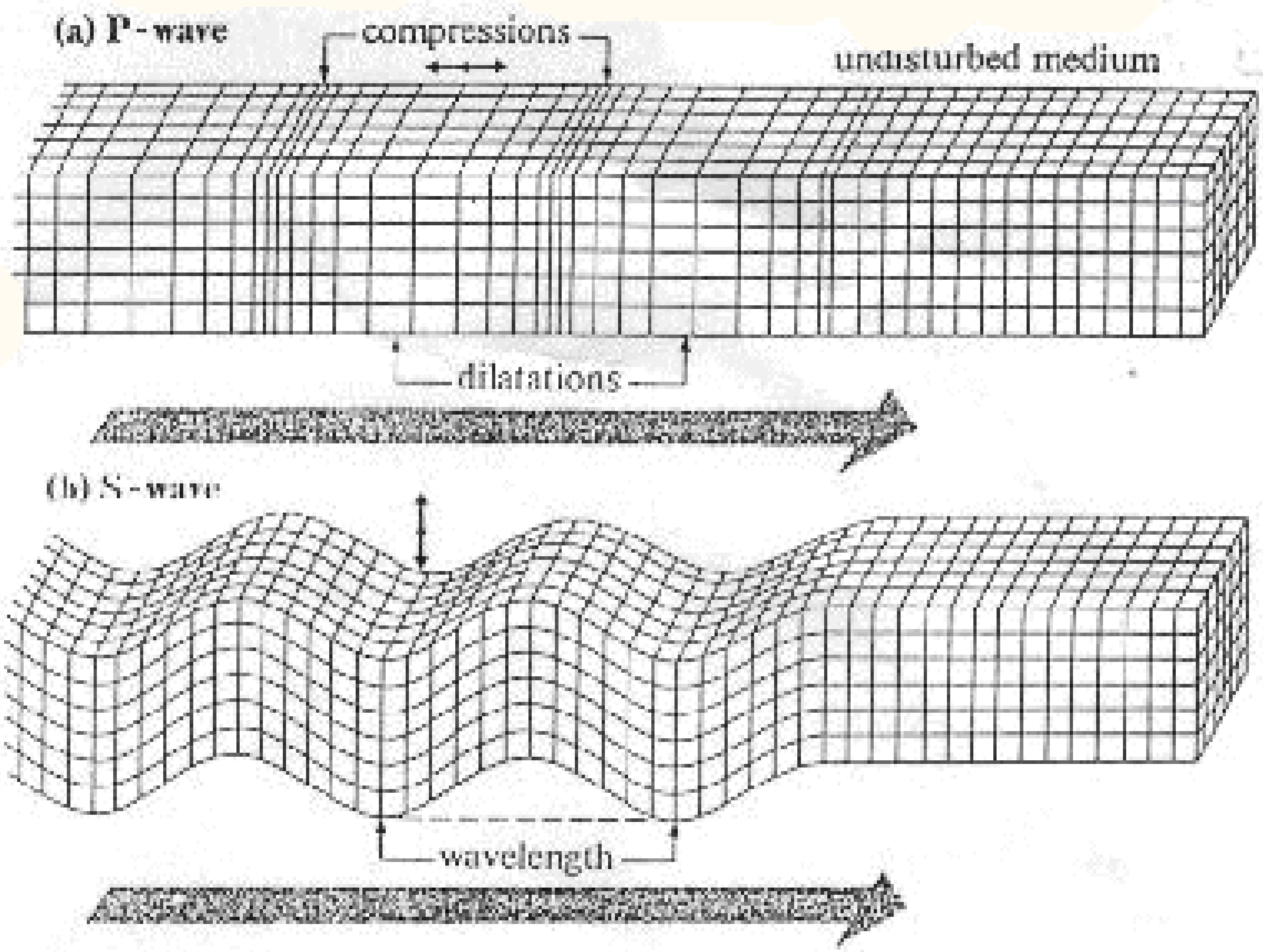
- The wavelength (λ) is the distance between two adjacent points on the wave that have similar displacements, one wavelength is the distance between successive crest.
- Amplitude (A) of the wave is the maximum displacement of the particle motions, or the height of the ripple crest.
- Period (T) is the time it takes for two successive waves to pass a reference point or the motion to complete one cycle.
- Wave equation:

$y = A\sin(\omega t\ - kx)$ where

$$\omega = \frac{2\pi}{T}\ and\ k = \frac{2\pi}{\lambda} \longrightarrow v = \lambda f = \frac{\lambda}{T}$$

Body Waves

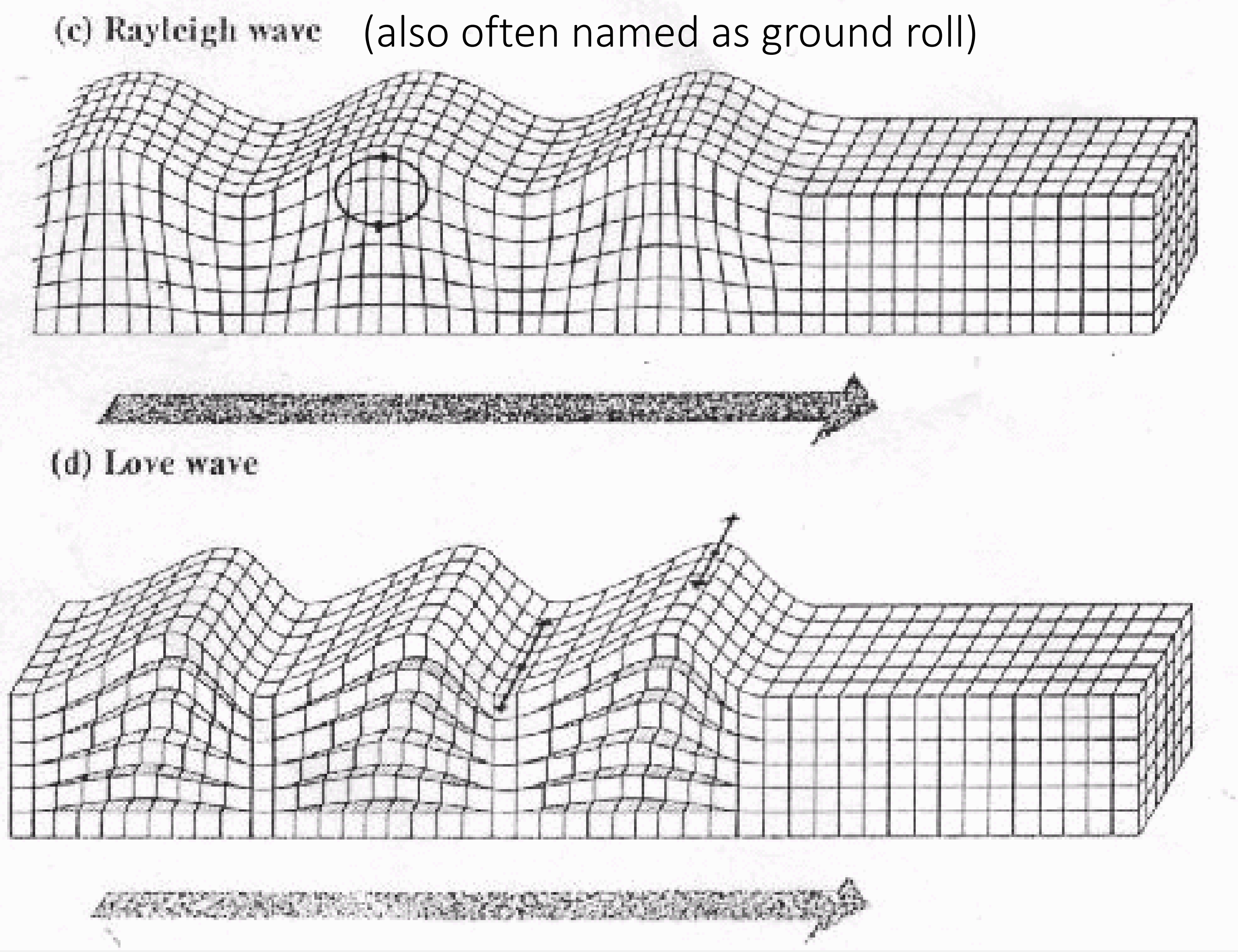
- Body waves = travel through the body of the earth.
- Side note: P-waves are faster than S-waves (~ 6 km/s vs ~ 3.4 km/s), therefore P-waves are usually detected first. -> goal in EEW is to detect P before S
- S-waves are usually more destructive.



Surface Waves

- Surface waves = travel through the surface of the earth.
- Surface waves arrive after P and S-waves.
- They are are larger in amplitude and longer in duration than body waves.

(also often named as ground roll)



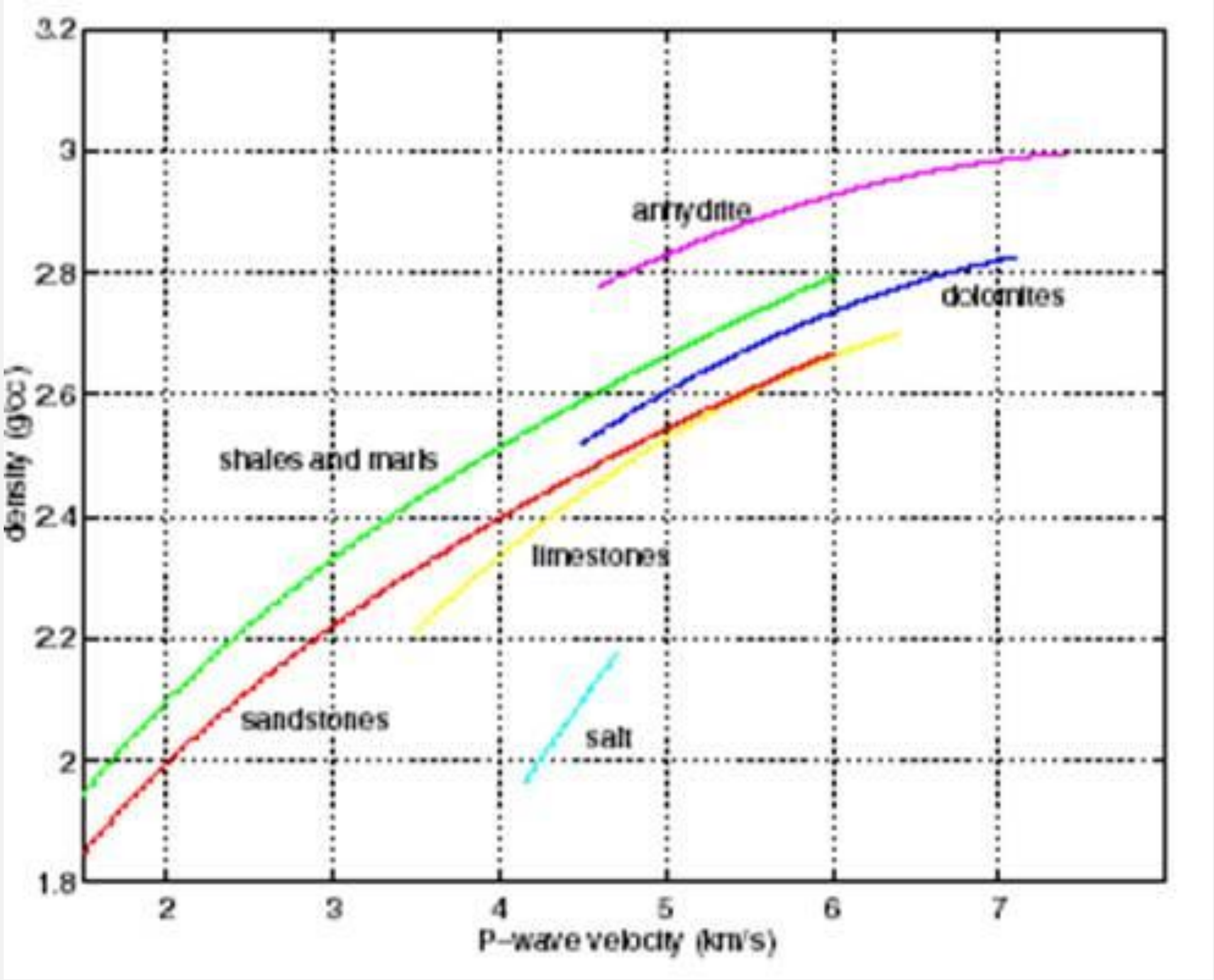
Seismic Wave Velocities

$$Vp = \sqrt{\frac{K + \frac{4}{3}G}{\rho}} \qquad Vs = \sqrt{\frac{G}{\rho}}$$

Where K = bulk modulus, G = rigidity modulus

Based from this formula, we know that Vp > Vs, and Vs = 0 when the medium is liquid.

This is how it was determined that the outer core consists of liquid.

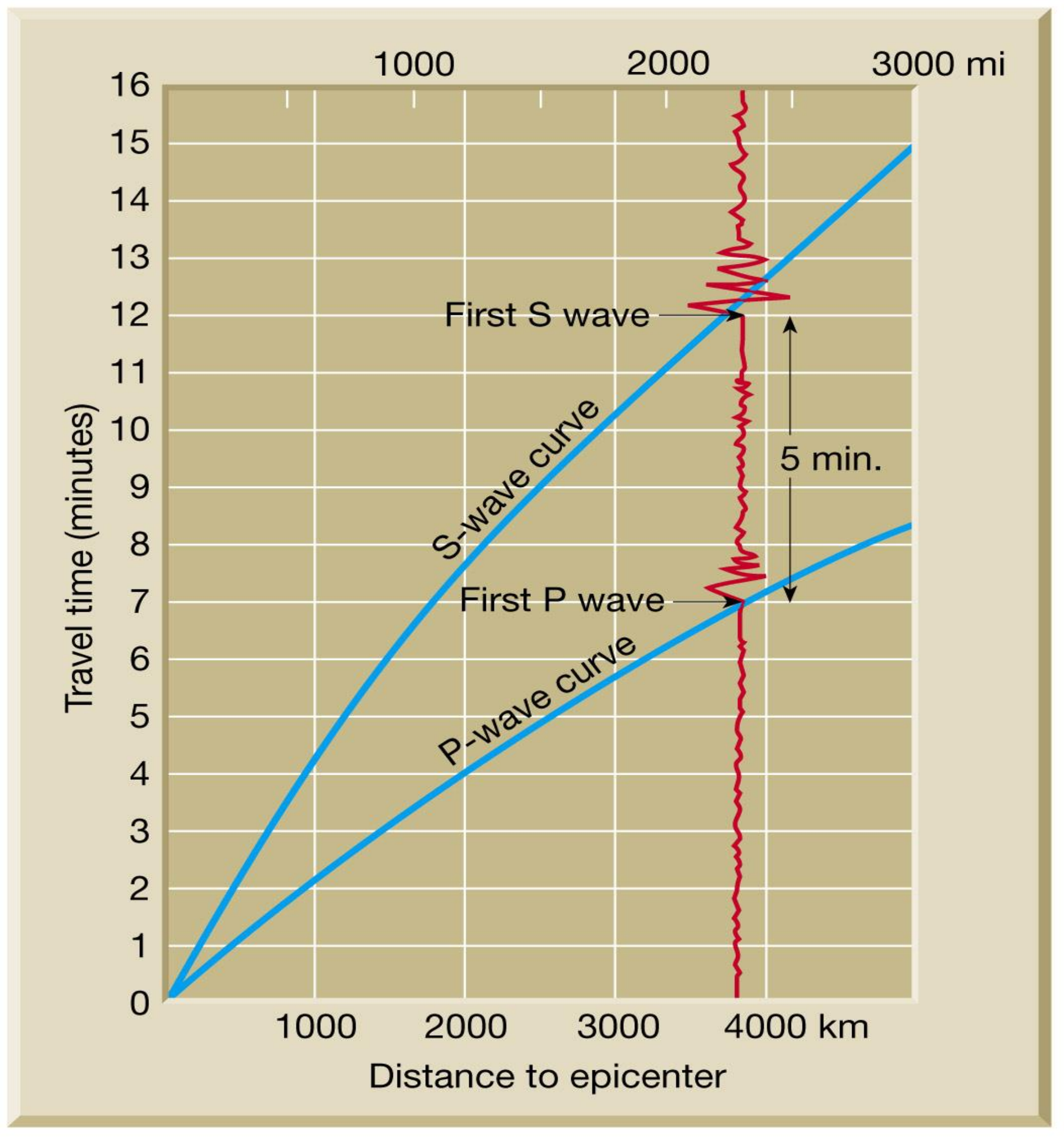


3.2
3
2.8
2.6
2.4
2.2
2
1.8
2
3
4
5
6
7
density (g/cc)
P–wave velocity (km/s)
anhydrite
dolomites
shales and marls
limestones
sandstones
salt

The P-wave and S-wave curves are used to determine the location of epicentre.

Locating the epicenter of an earthquake

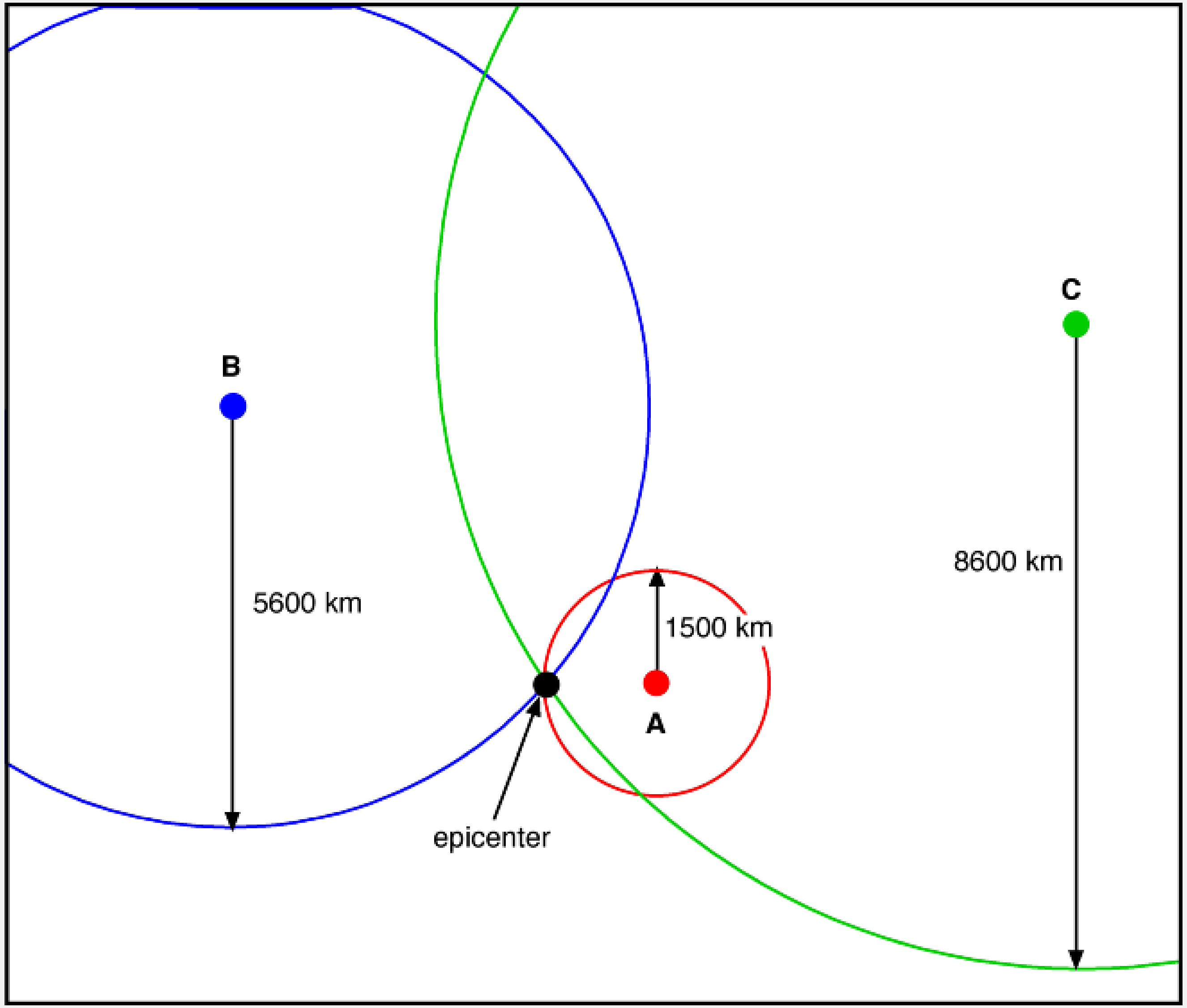
- Three station recordings are needed to locate an epicenter
- Each station determines the time interval between the arrival of the first P wave and the first S wave at their location
- A travel-time graph is used to determine each station's distance to the epicenter



Why 3 stations?

Triangulation:

To determine the location of an earthquake the distance of the earthquake must be determined from at least three seismic recording stations. Circles with the appropriate radius are then drawn around each station. The intersection of three circles uniquely identifies the earthquake epicenter.



Measuring the size of earthquakes

Two measurements that describe the size of an earthquake are

- Intensity – a measure of the degree of earthquake shaking at a given locale based on the amount of damage
- Magnitude – estimates the amount of energy released at the source of the earthquake

Measuring the size of earthquakes

Magnitude scales:

- Richter scale
- Largest magnitude recorded on a Wood-Anderson seismograph was 8.9 (earthquake in Chile, 1960
- Magnitudes less than 2.0 are not felt by humans
- Each unit of Richter magnitude increase corresponds to a tenfold increase in wave amplitude and a 32-fold energy increase

TABLE 16.3 **Earthquake Magnitude and Energy Equivalence**

Earthquake Magnitude	Energy Released* (Millions of Ergs)	Approximate Energy Equivalence
0	630,000	1 pound of explosives
1	20,000,000	
2	630,000,000	Energy of lightning bolt
3	20,000,000,000	
4	630,000,000,000	1000 pounds of explosives
5	20,000,000,000,000	
6	630,000,000,000,000	1946 Bikini atomic bomb test
		1994 Northridge Earthquake
7	20,000,000,000,000,000	1989 Loma Prieta Earthquake
8	630,000,000,000,000,000	1906 San Francisco Earthquake
		1980 Eruption of Mount St. Helens
9	20,000,000,000,000,000,000	1964 Alaskan Earthquake
		1960 Chilean Earthquake
10	630,000,000,000,000,000,000	Annual U.S. energy consumption

*For each unit increase in magnitude, the energy released increases about 31.6 times.
SOURCE: U.S. Geological Survey.

Example

Given the intensity of two earthquakes and the magnitude of one of them, we can find the magnitude of the other earthquake. For example:

Earthquake A is 15 times stronger than earthquake B. Earthquake B is estimated to be 2.3 on the Richter scale. What is Earthquake A on the Richter scale?

$$M_A - M_B = \log\left(\frac{I_A}{I_B}\right)$$

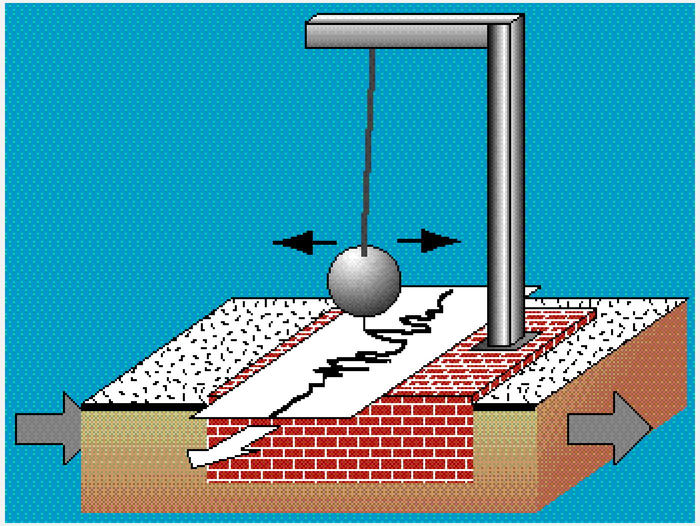
$$M_A - 2.3 = \log(15)$$

$$M_A = \log(15) + 2.3$$

$$M_A \doteq 3.5$$

Seismograms and how the data look like

- Earthquakes are detected and recorded by seismograms, which measure, amplify and record the motion of the ground.



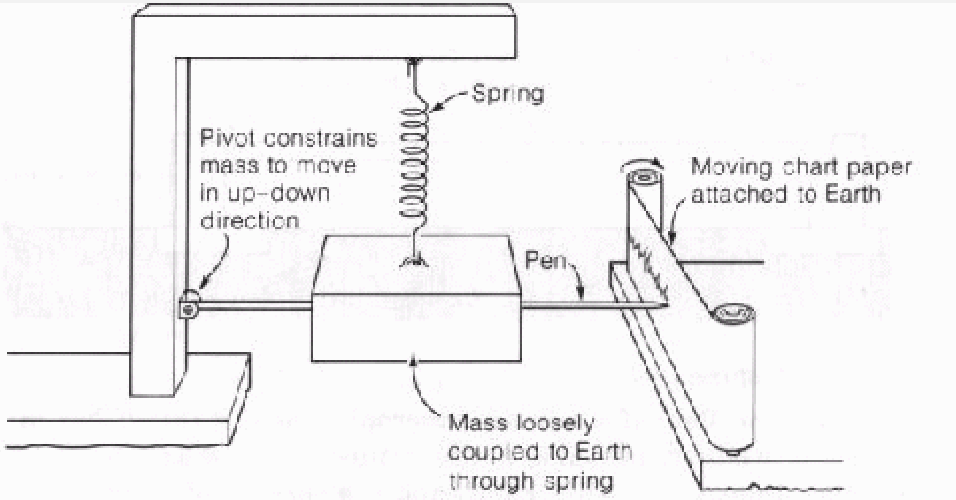
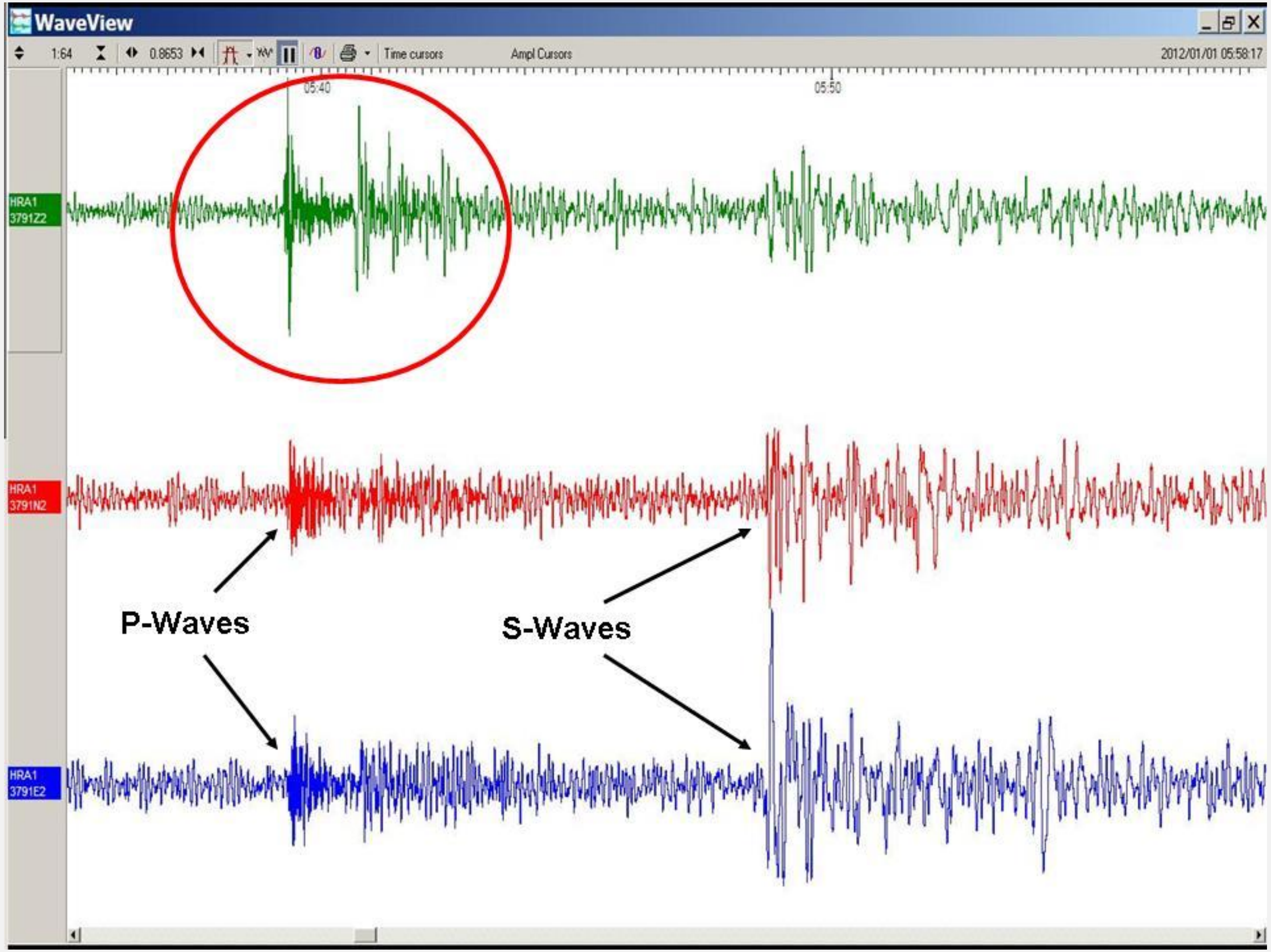


Figure 18-2

Spring-mounted seismograph to record vertical ground motion.



- Either 3 components of velocity or acceleration are recorded (east-west, north-south, and vertical)

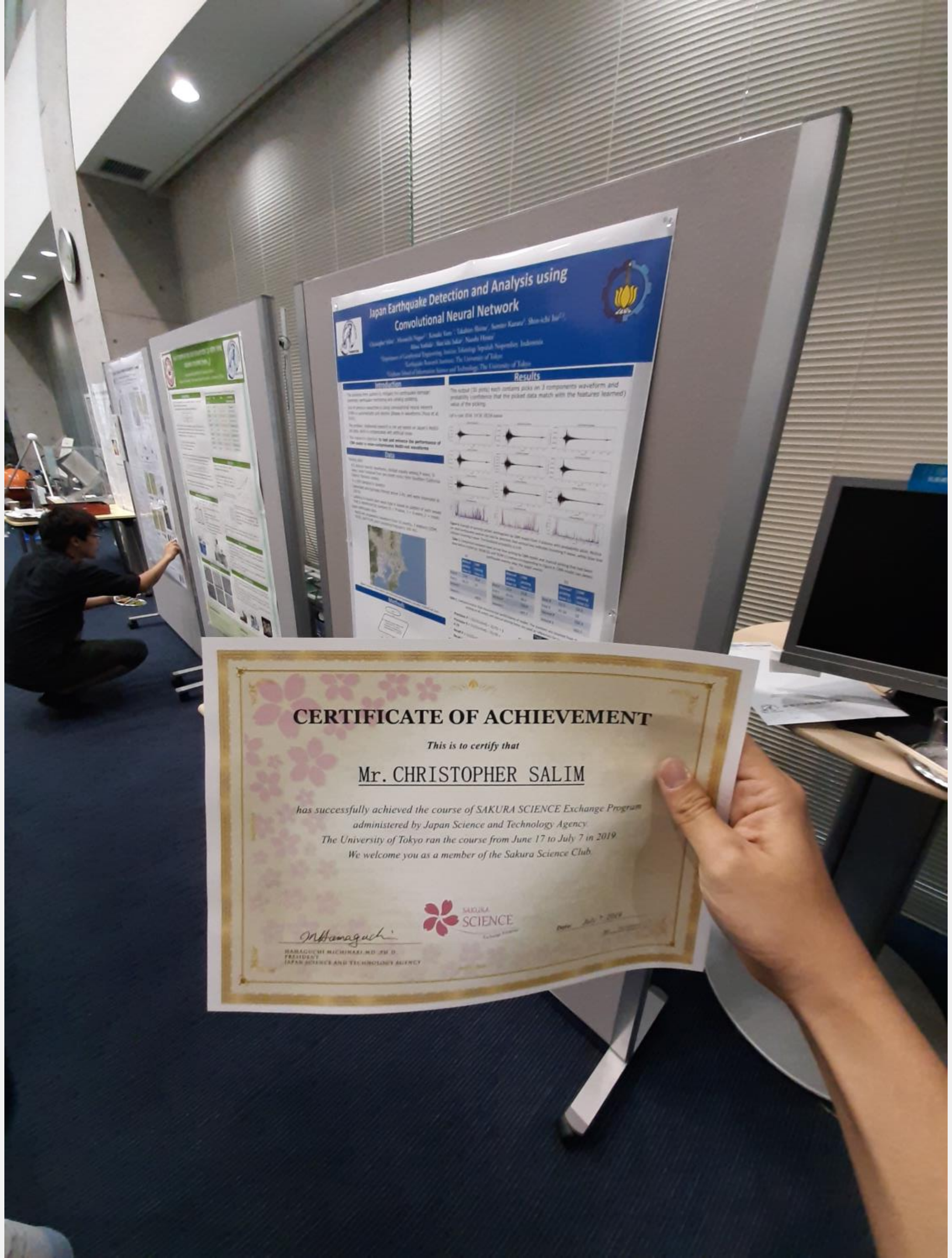
What is picking?

Picking: determining which ones are the start of P-waves and S-waves, usually by drawing a vertical line in that specific timestamp.

Used to be done only manually, but more and more technologies have allowed us for automatically picking the earthquake signals.

Experience at Earthquake Research Institute, The University of Tokyo, Japan

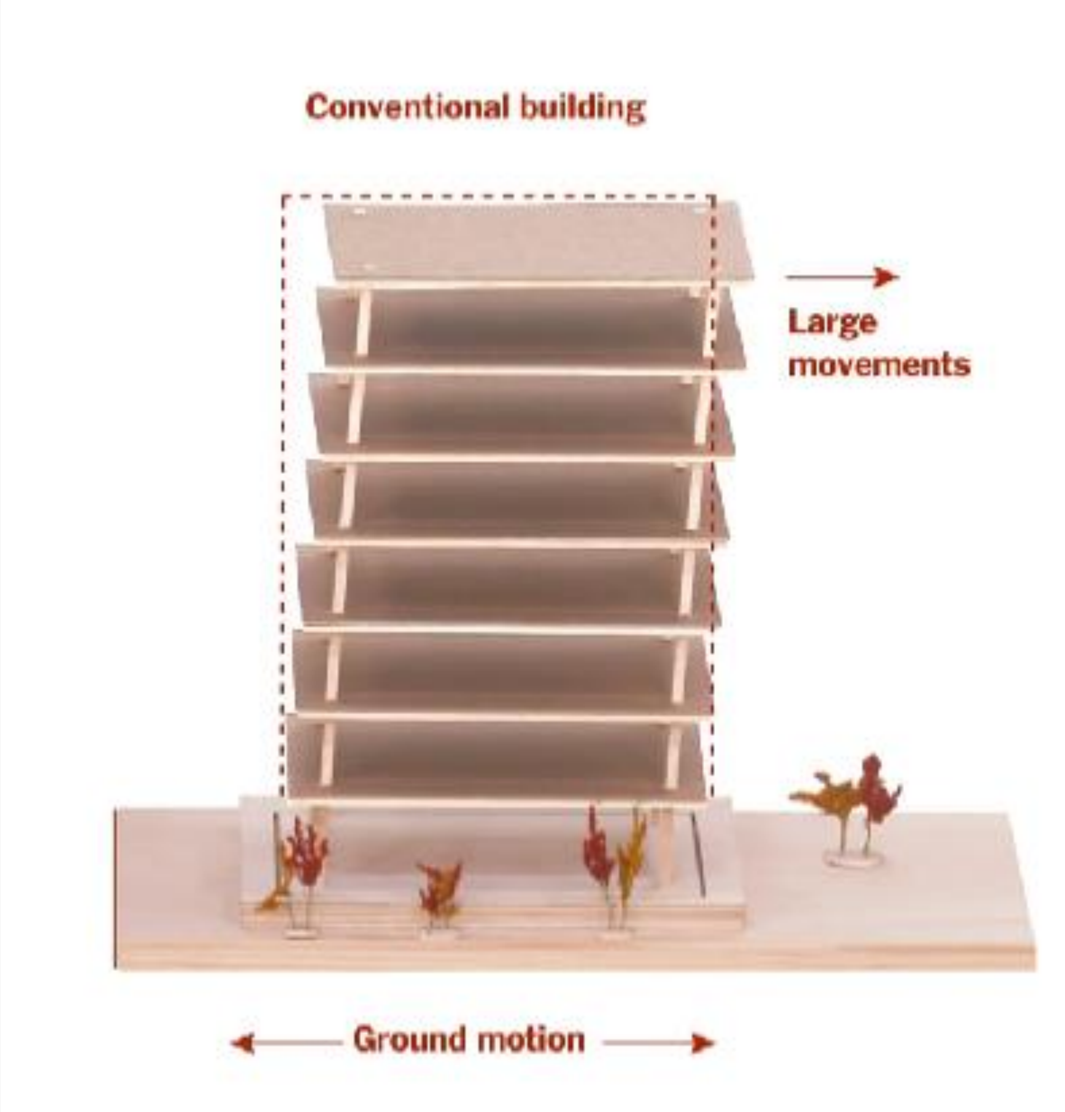
- 3 weeks (June 16th to July 9th 2019)
- Fully-funded by Japan Science and Technology Agency (JST) under Sakura Science program
- Supervisor at ITS: Ir. Mariyanto, S.Si. M.T.
- Host supervisor: Dr. Hiromichi Nagao

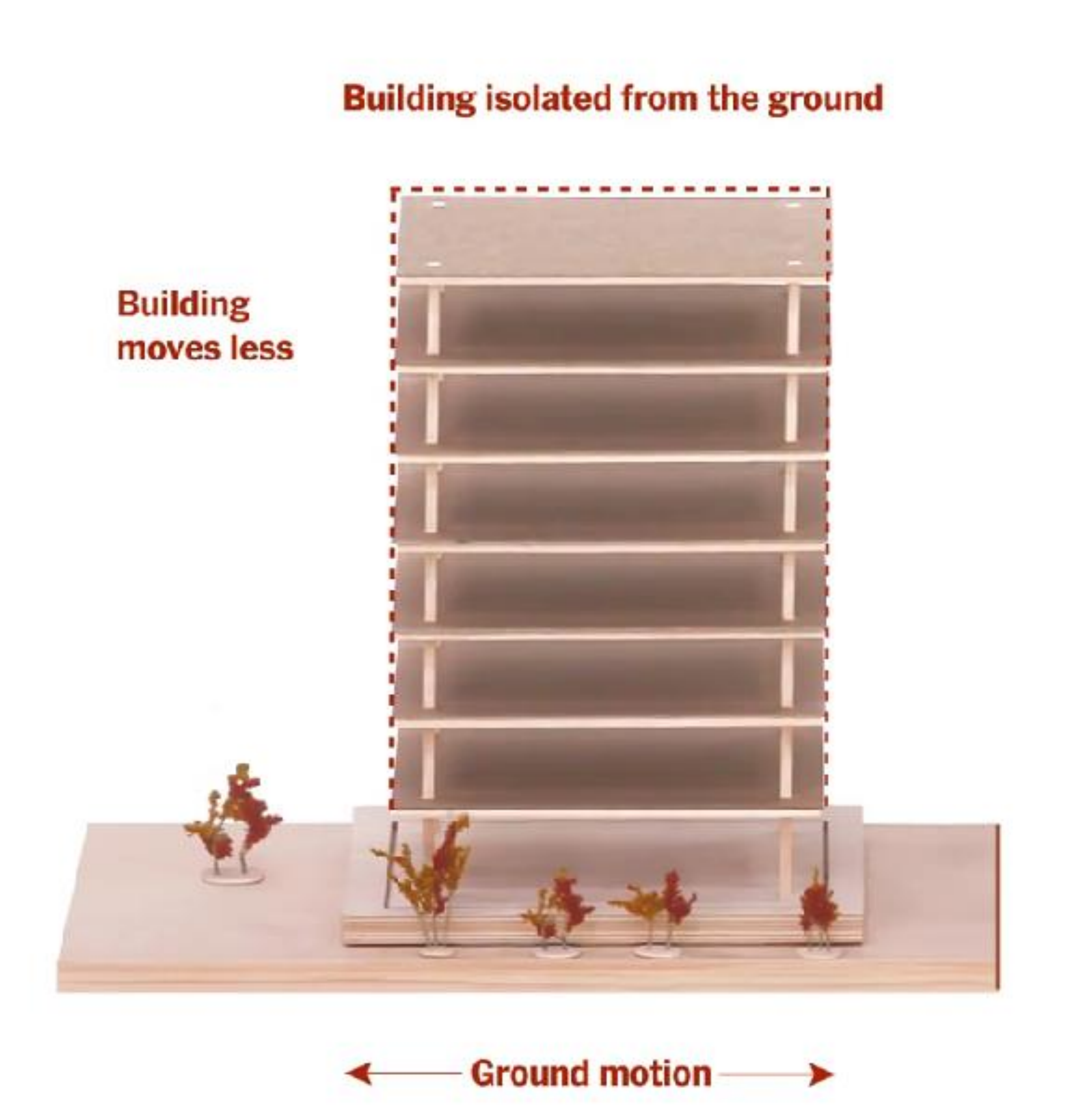

Japan Earthquake Detection and Analysis using
Convolutional Neural Network
Introduction
Results
CERTIFICATE OF ACHIEVEMENT
This is to certify that
Mr. CHRISTOPHER SALIM
has successfully achieved the course of SAKURA SCIENCE Exchange Program
administered by Japan Science and Technology Agency
The University of Tokyo ran the course from June 17 to July 7 in 2019
We welcome you as a member of the Sakura Science Club.
SCIENCE

The secret behind Japan's resiliency to earthquakes:

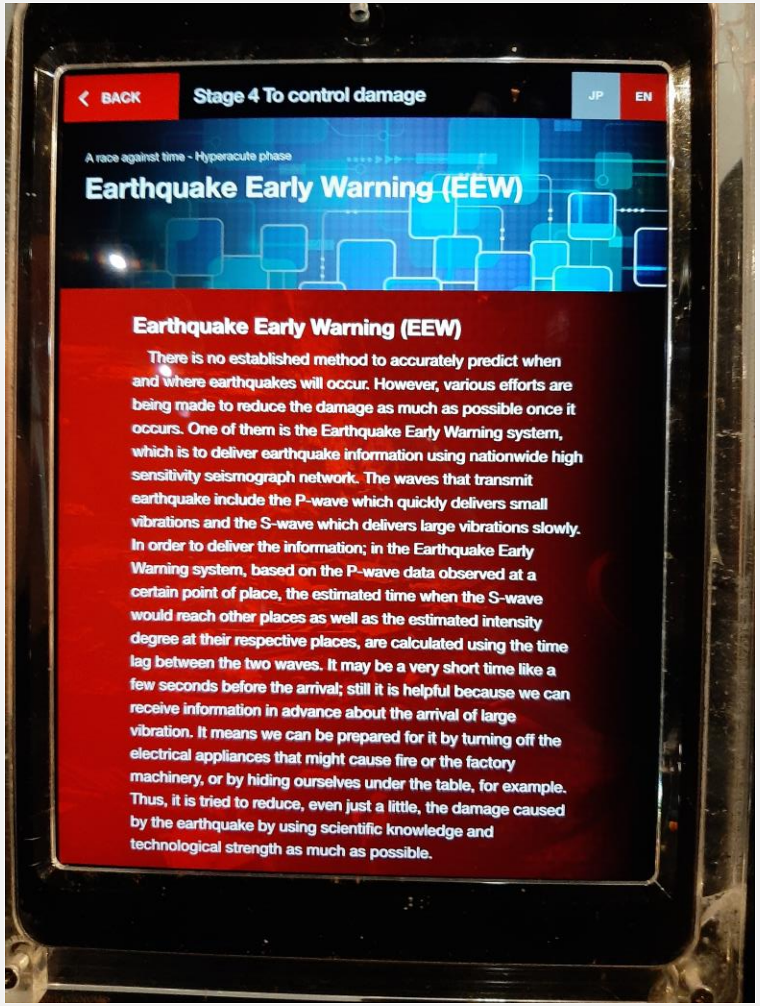
- Yes, I experienced an earthquake too back in Japan.
- Shock absorbers are designed and distributed equally spaced so they absorb seismic energy.
- Comparison on the next slide

The consequence:





Besides improving our resiliency to earthquakes, then what?



Japan Earthquake Detection and Analysis using Convolutional Neural Network

TOPHER SALIM[1] , HIROMICHI NAGAO[2,3], KEISUKE YANO [3], TAKAHIRO SHIINA[2], SUMITO KURATA[3], SHIN-ICHI ITO[2,3],
MIWA YOSHIDA[2], SHIN'ICHI SAKAI[2], NAOSHI HIRATA[2]
[1]DEPARTMENT OF GEOPHYSICAL ENGINEERING, INSTITUT TEKNOLOGI SEPULUH NOPEMBER, INDONESIA
[2]EARTHQUAKE RESEARCH INSTITUTE, THE UNIVERSITY OF TOKYO
[3]GRADUATE SCHOOL OF INFORMATION SCIENCE AND TECHNOLOGY, THE UNIVERSITY OF TOKYO

Introduction

- The solutions from authors to mitigate the earthquake damage: automatic earthquake monitoring and catalog updating.
- One of previous researches is using convolutional neural network (CNN) to automatically pick seismic phases in waveforms (Ross et al, 2018).
- The problem: mentioned research is not yet tested on Japan's MeSO-net data, which is contaminated with artificial noise.
- This research's objective: **to test and enhance the performance of CNN model in noise-contaminated MeSO-net waveforms**

Data

Training data:

- 4.5 millions velocity waveforms, divided equally among P-wave, S-wave, noise (obtained from pre-event noise) from Southern California Seismic Network catalog.
- 4 s (400 samples) in duration
- Detrended and high-pass filtered above 2 Hz, and were resampled at 100 Hz.
- Labeling to classify each wave type is based on pattern of each waves that is determined by numbers (0 = P-wave, 1 = S-wave, 2 = noise).

Japan earthquake data:

- MeSO-net acceleration waveform from 10 events, 3 stations (IIDM, TACM, and TK2M) each (sampling frequency 200 Hz).

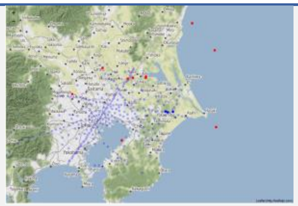


Figure 1. Location of the stations (dark blue dots) and hypocenters (red dots) of MeSO-net Data.

Methods

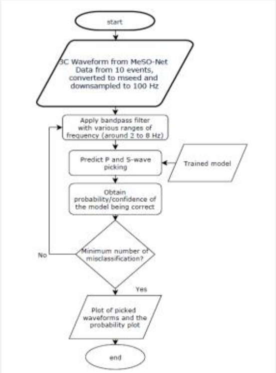


Figure 2. Flowchart of how the MeSO-net data is analyzed using the CNN model.

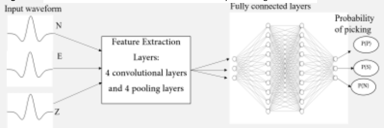


Figure 3. CNN architecture for training the model (Ross et al, 2018).

Results

The output (30 plots) each contains picks on 3 components waveform and probability (confidence that the picked data match with the features learned) value of the picking.

Left to right: IIDM, TACM, TK2M station

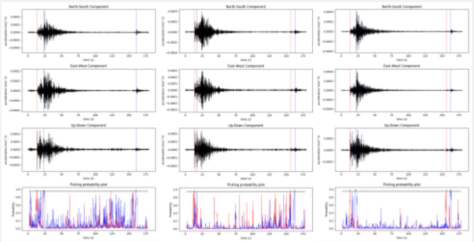


Figure 4. Example of correctly picked seismograms by CNN model from 3 stations with probability plots. Notice the small earthquakes swarms can also be detected. Red vertical line indicates incoming P-wave, while blue line indicates incoming S-wave. The threshold probability is 0.95.

Table 1. Comparison between wave arrival time picking by CNN model and manual picking that had been done before in IIDM (a), TACM (b), and TK2M (c) station corresponding to Figure 4. CNN model can detect earthquake swarms after the major events.

(a)

	Manual picking time (s)	CNN picking time (s)
First P	13.8	13.4
First S	23.21	23
Second P	-	-
Second S	-	160.9

(b)

	Manual picking time (s)	CNN picking time (s)
First P	13.4	13.6
First S	22.53	16.2
Second P	-	156.6
Second S	-	161.7

(c)

	Manual picking time (s)	CNN picking time (s)
First P	13.2	13.2
First S	22.16	22
Second P	-	156.3
Second S	-	162.5

Table 2. Confusion matrix that measures the performance of model. The numbers are counted from the amount of picking on all events and manual picking times are used as references for true label.

Precision P = 32/(32+0+0) = 32/32 = **1**
Precision S = 31/(31+0+8) = 31/39 = **0.79**
Recall P = 32/(32+0+1) = 32/33 **= 0.97**
Recall S = 31/31 **= 1**

	True P	True S	True Noise
Predicted P	32	0	0
Predicted S	0	31	8
Predicted Noise	1	0	

Discussion

- Major earthquakes were successfully detected with this CNN model and the time at which the events were detected proved to be accurate overall.
- Several different filters did not eliminate some false positives
- Main cause: other type of noises such as noise from traffic are not available in large quantity in the training data set.
- Mislabel because model does not know noise type in MeSO-net data
- Experimented with frequency range for bandpass filter to optimally cut out the noise as much as possible.
- After careful filtering by analyzing the noise frequency range with spectral analysis, the precision and recall score increases significantly that the model is able to give reliable predictions.

Conclusions

- Major earthquake events automatic detection from MeSO-net data were successfully done by the CNN. It could also detect earthquake swarms.
- Signal processing, especially frequency range for the filter, is important prior to feeding the waveform to the model. The most reliable frequency range for bandpass filter in our experiment was 2.5 Hz to 6 Hz.
- Train with wide variety of noise to improve its model performance.
- This CNN can prove to be useful as a tool for earthquake monitoring and earthquake catalog generation.

Recommendations

- Include waveforms with artificial noise to the training data so the noise can be distinguished more accurately.
- Improve the CNN model to be more efficient when used in less-sophisticated computer hardware to democratize AI in geoscience.
- Apply CNN to automatically detect earthquakes in Indonesia (no researches about it has been done)

Acknowledgement

- Japan Science and Technology Agency (JST) for funding this Sakura Program.
- The University of Tokyo components and Sakura Program students who helped us to finish this project.

References

Ross, Z. E., Meier, M.A., Hauksson, E., & Heaton, T. H. (2018). Generalized seismic phase detection with deep learning. *Bulletin of the Seismological Society of America, 108*(5A), 2894–2901.

JAPAN EARTHQUAKE DETECTION AND ANALYSIS USING CONVOLUTIONAL NEURAL NETWORK (CNN)

Poster Handout

Christopher Salim[1] , Hiromichi Nagao[2,3], Keisuke Yano [3], Takahiro Shiina[2], Sumito Kurata[3], Shin-ichi Ito[2,3],

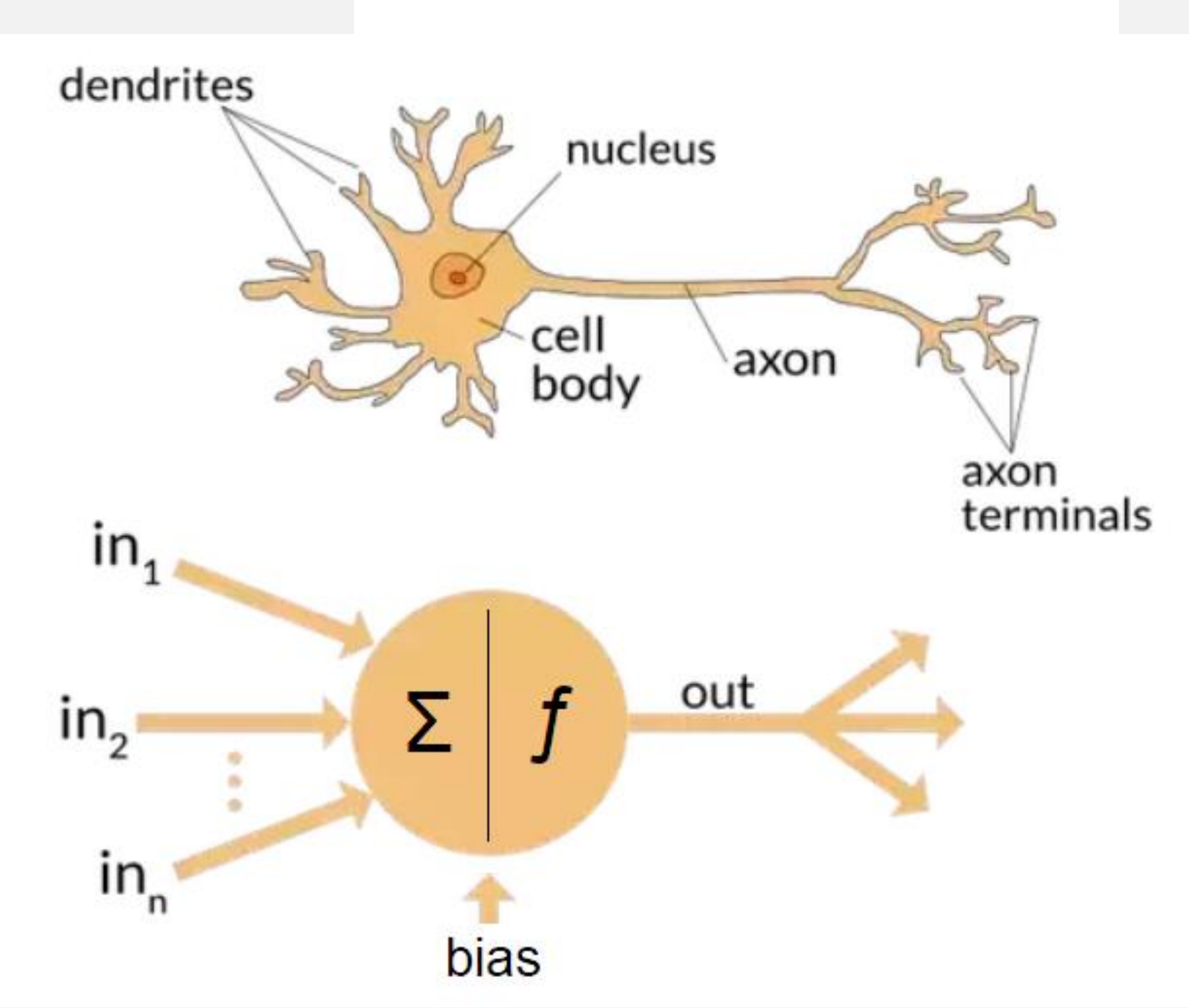
Miwa Yoshida[2], Shin'ichi Sakai[2], Naoshi Hirata[2]

[1]Department of Geophysical Engineering, Institut Teknologi Sepuluh Nopember, Indonesia

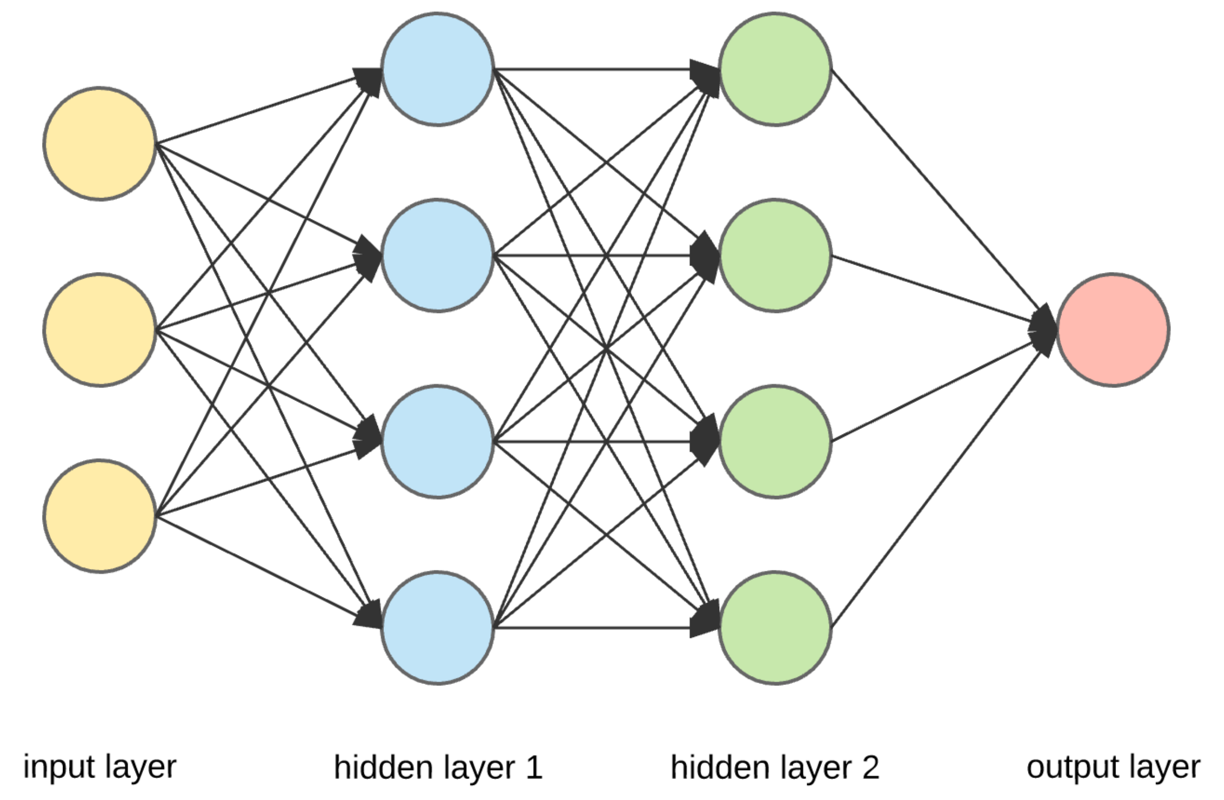
[2]Earthquake Research Institute, The University of Tokyo

[3]Graduate School of Information Science and Technology, The University of Tokyo

NEURAL NETWORK MIMICS HOW OUR BRAINS LEARN SOMETHING!



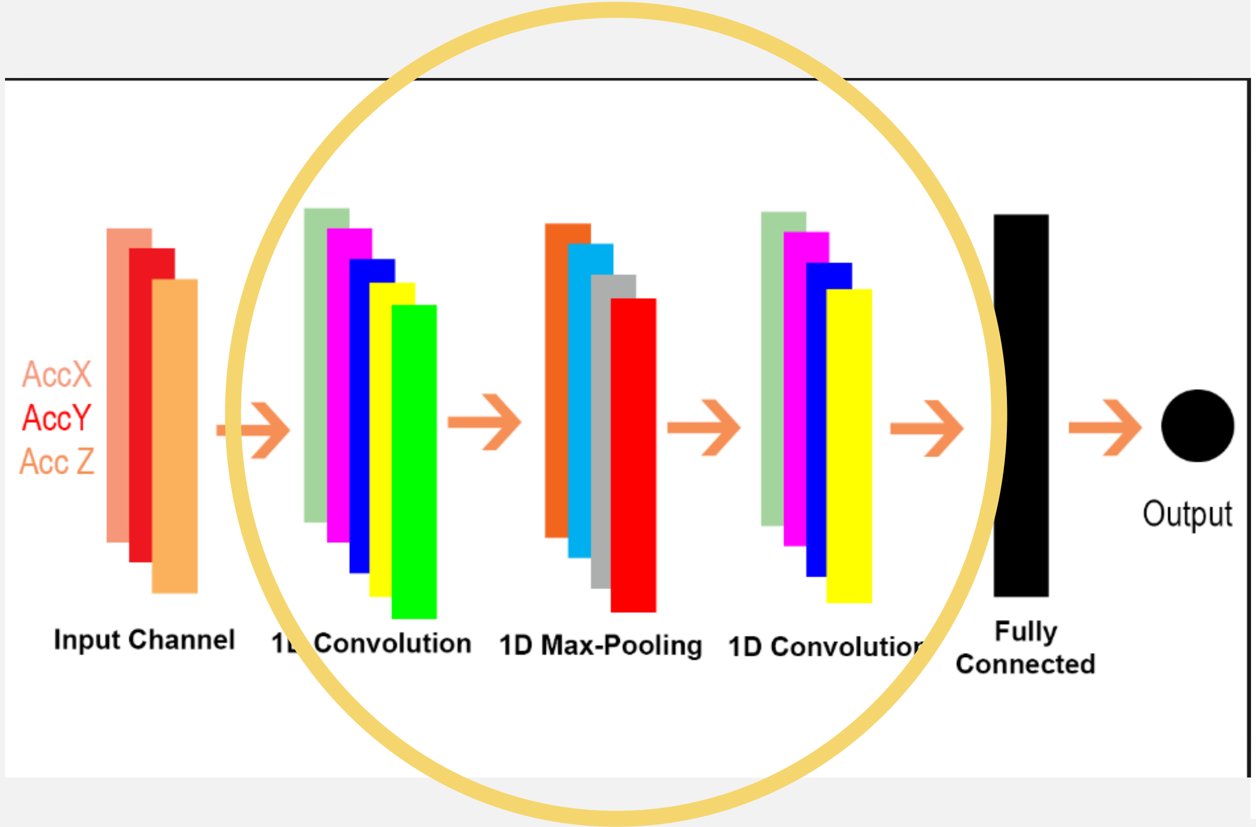
ORDINARY NN



- Not shown: activation function, bias, weight.
- Calculate the numbers of parameter using multiplication.
- The parameters will be updated to find best parameters.

Source: towardsdatascience.com

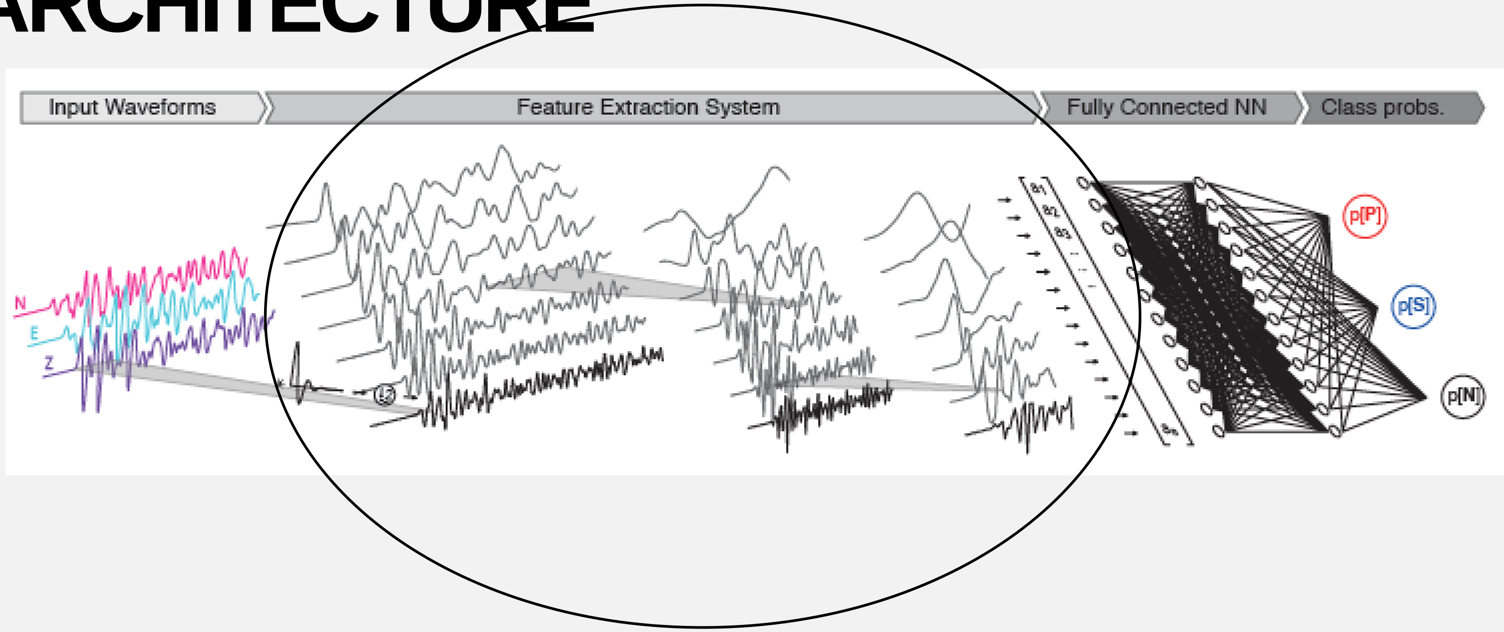
CNN



Source: stackoverflow.com

- Unlike NN, CNN has feature extraction.
- Convolution layer: performs convolution between input and filter
- Pooling layer: for downscaling the image.

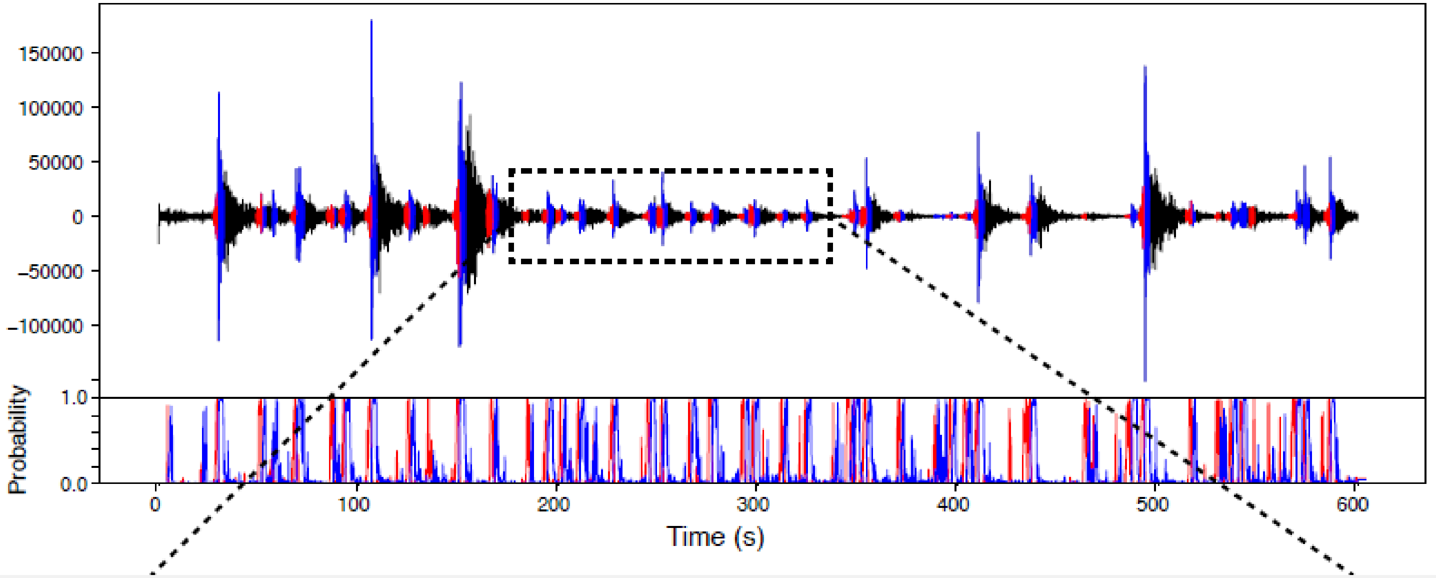
CNN ARCHITECTURE



- Can be treated as 1D CNN input with three components being RGB component equivalent.
- Using ReLU activation layer so the output is always positive.
- Using pooling so the amplitude and window length does not matter in identification.
- 4 convolutional layers, 2 fully connected layers

EXPECTED OUTPUT

- Wave picking and classification
- Probability of each wave type
- Inference to whether earthquake happens or not -> early earthquake warning



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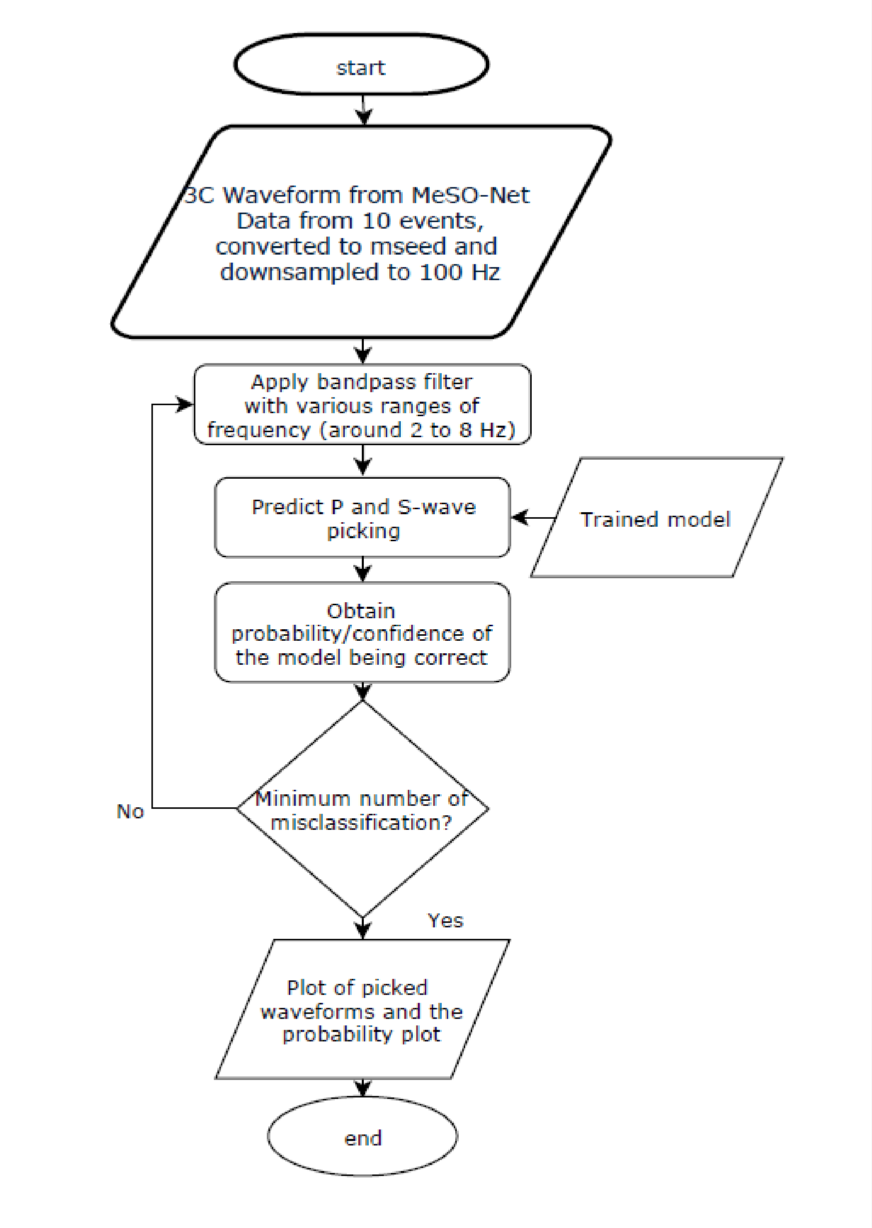
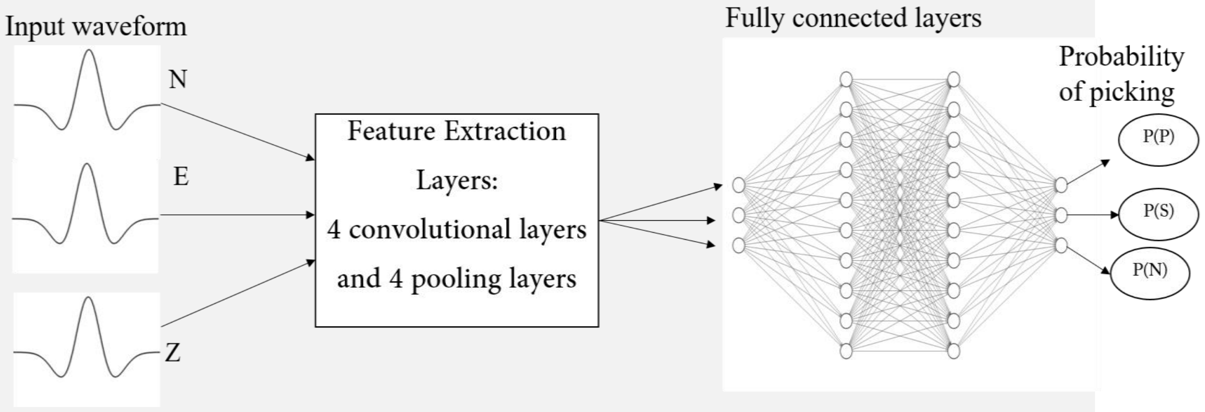
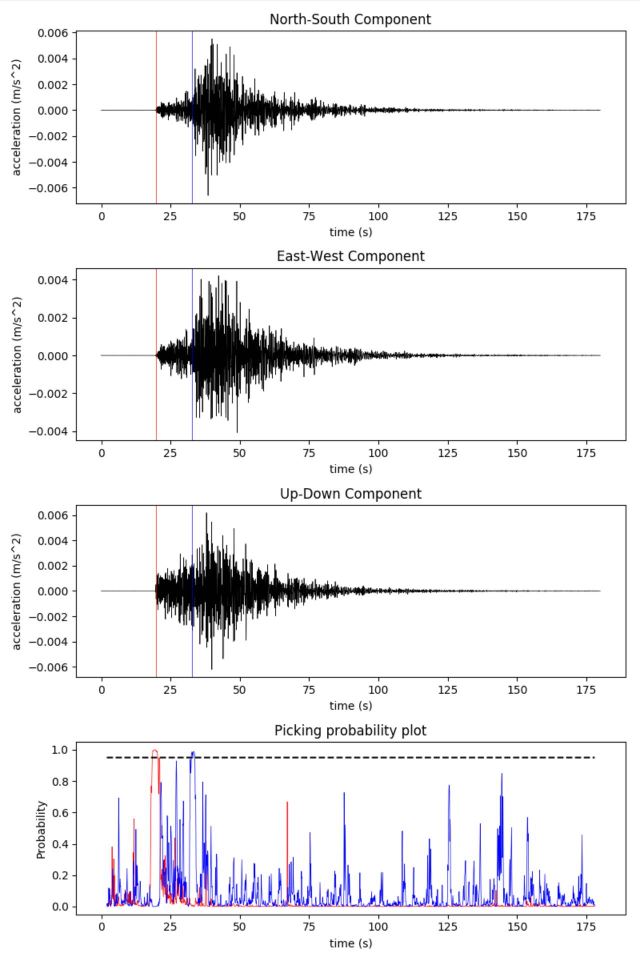


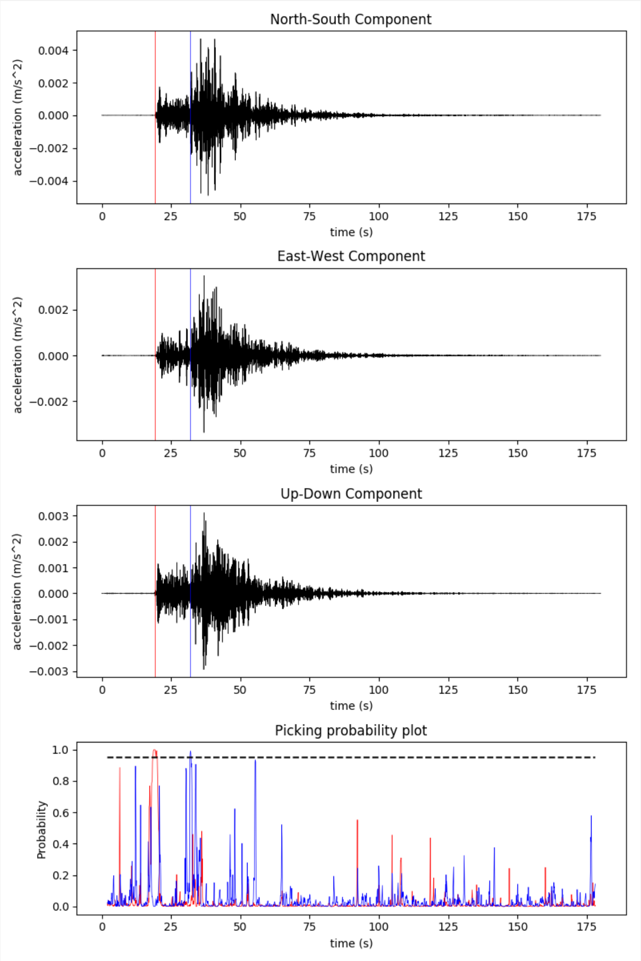
Flowchart of how the MeSO-net data is analyzed using the CNN model.

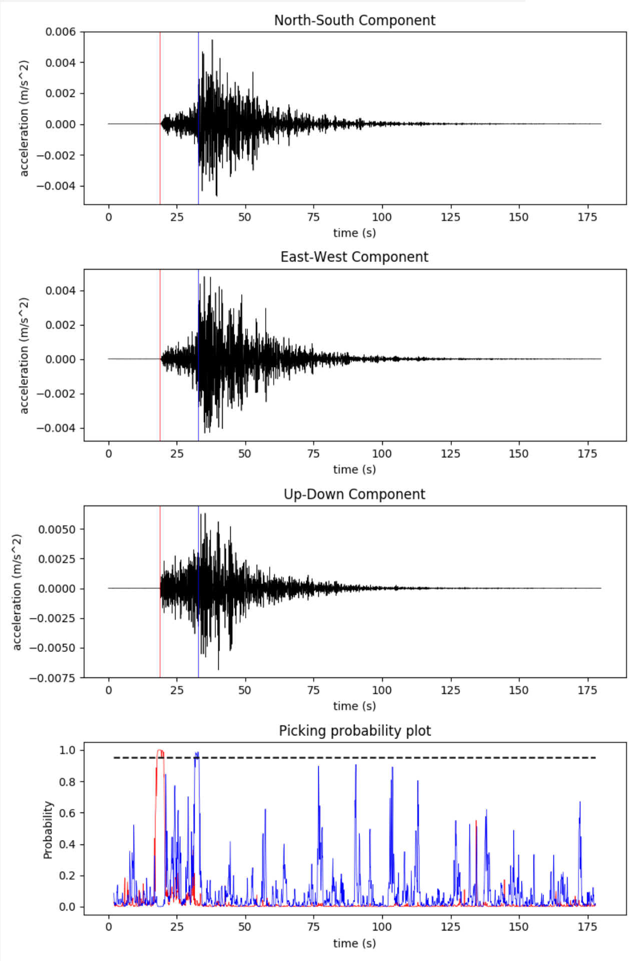


CNN architecture for training the model (Ross et al, 2018).

FIRST EVENT: 11-09-04 05:52:47 *Left to right: IIDM, TACM, TK2M stations*







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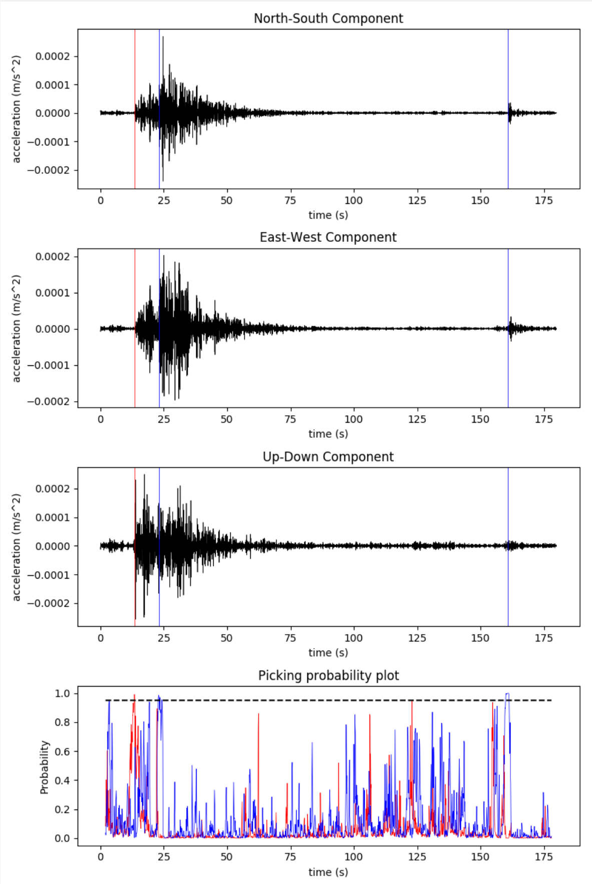
	Manual picking time (s)	CNN picking time (s)
First P	19.2	19.2
First S	33.3	32

	Manual picking time (s)	CNN picking time (s)
First P	19	18.7
First S	32.9	32.7

SECOND EVENT: 11-09-04 18:42:18

Left to right: IIDM, TACM, TK2M station



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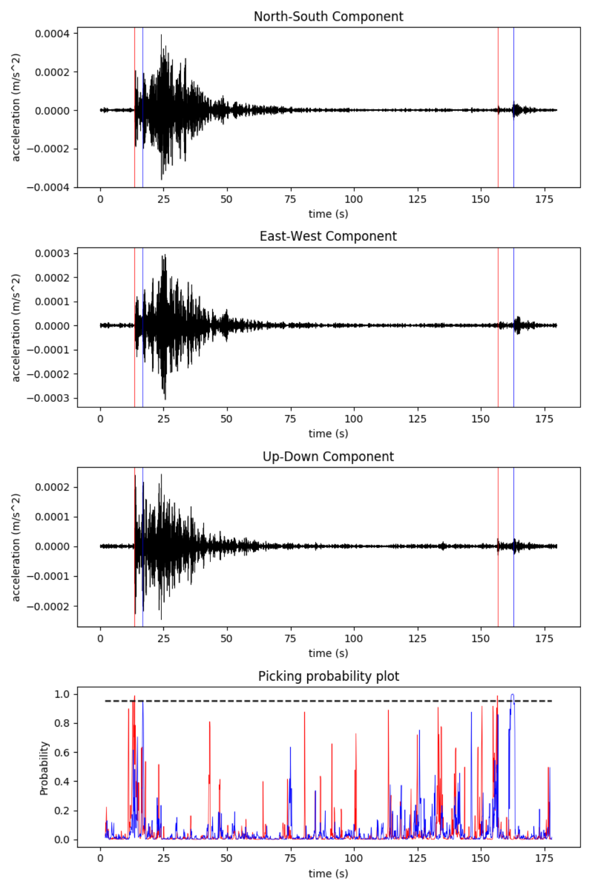

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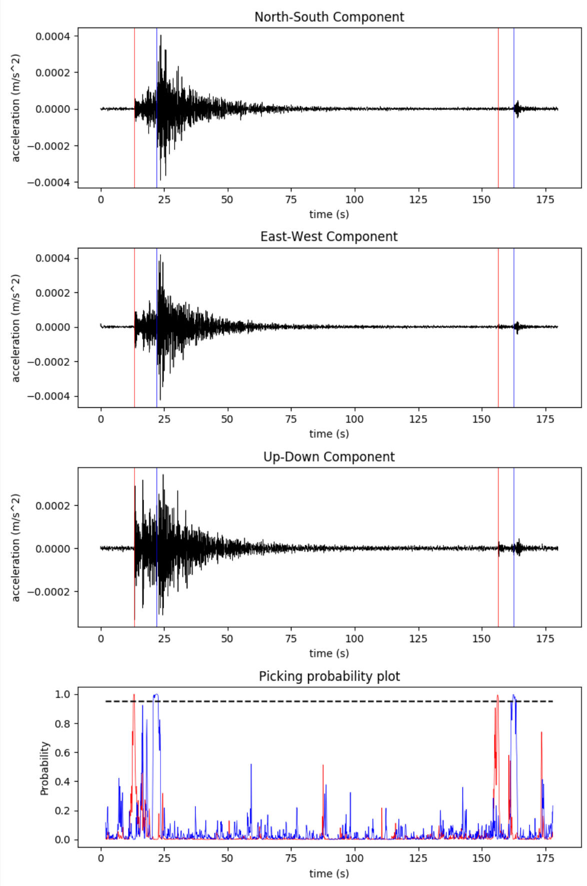

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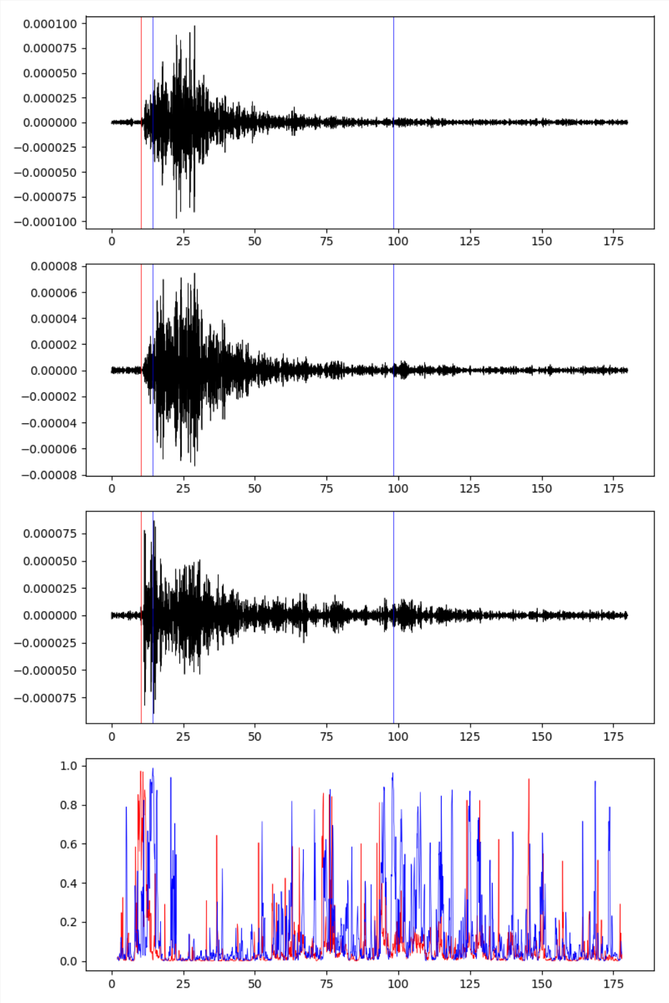
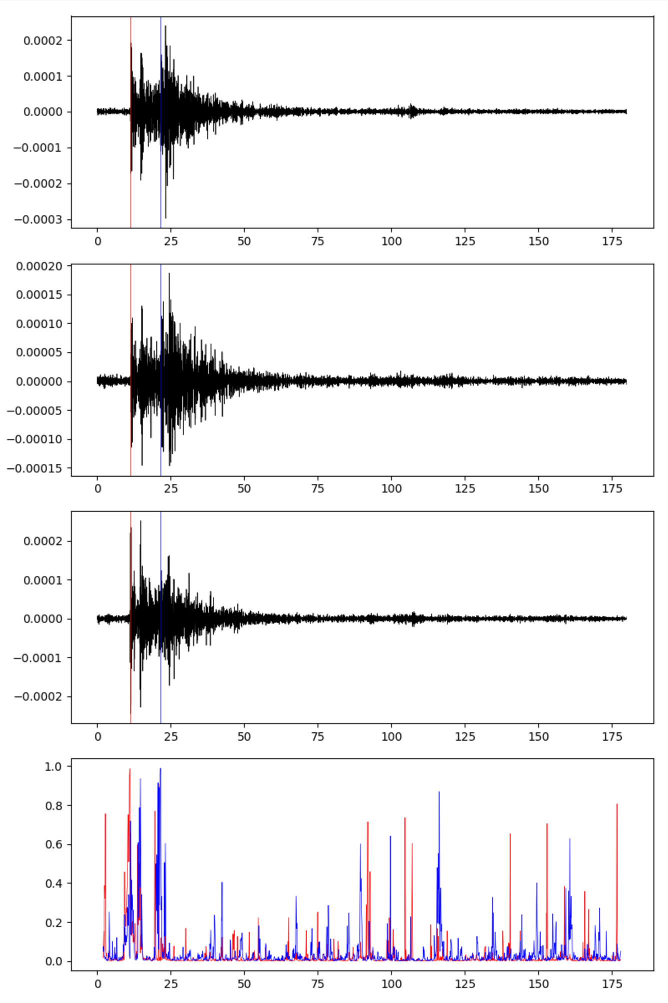
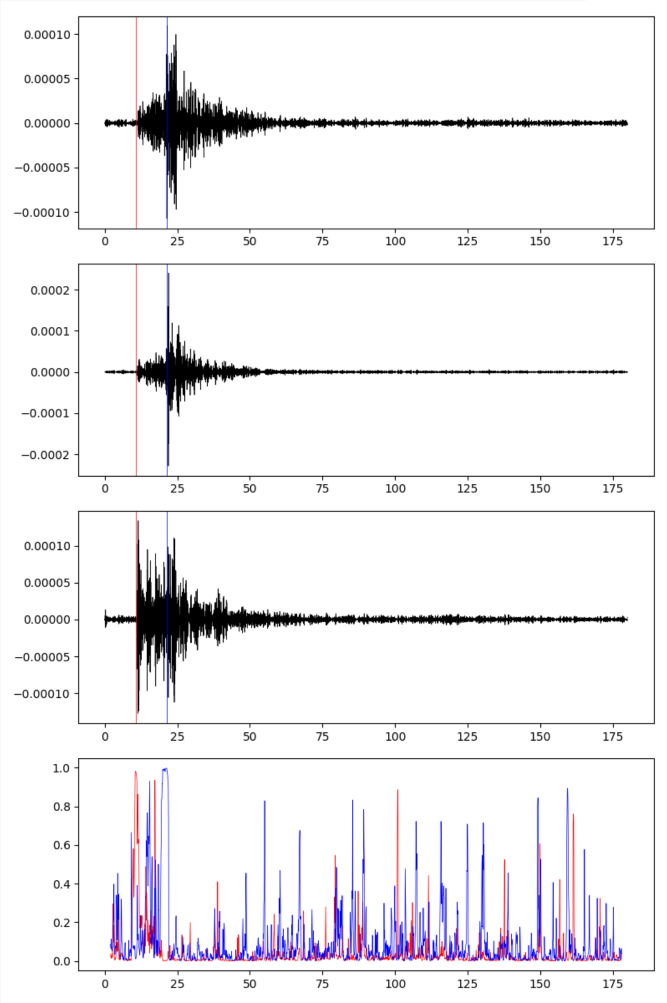
First S	22.16	22
Second P	-	156.3
Second S	-	162.5

THIRD EVENT: 11-09-04 20:28:16

Left to right: IIDM, TACM, TK2M







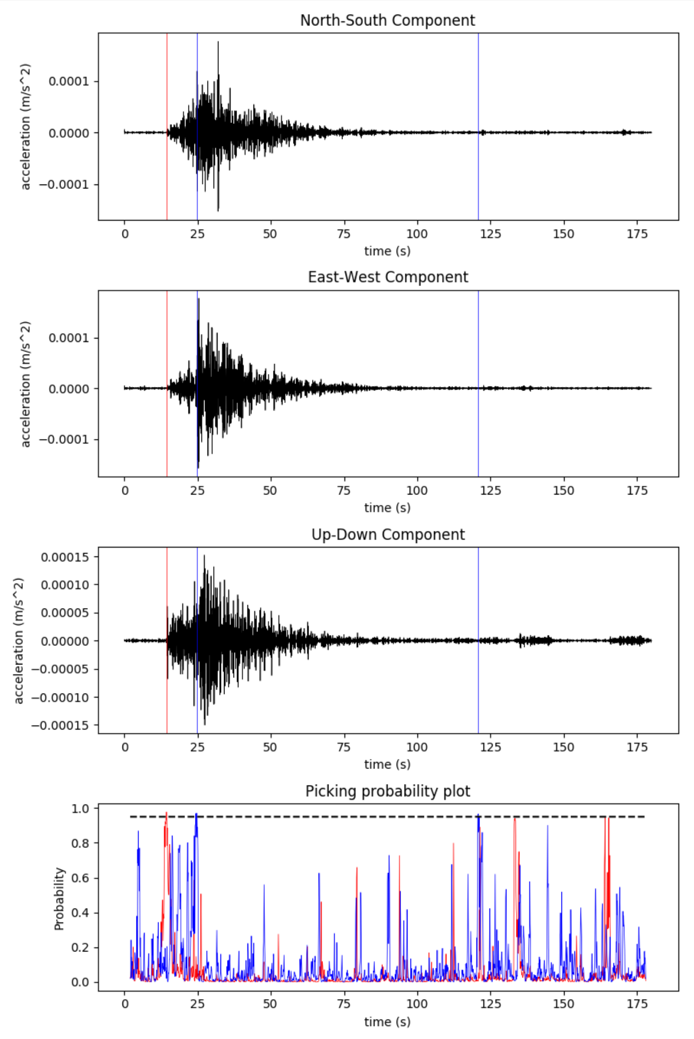
	Manual picking time (s)	CNN picking time (s)
First P	11.4	10.2
First S	20.8	14.4

	Manual picking time (s)	CNN picking time (s)
First P	11	11.2
First S	21.2	21.5

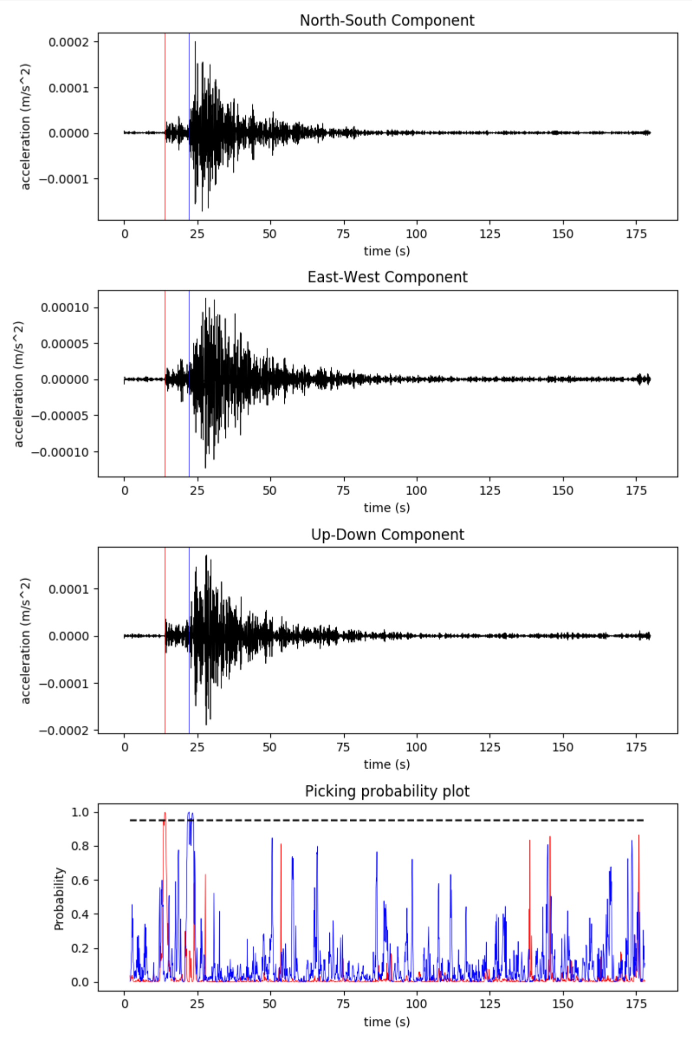
	Manual picking time (s)	CNN picking time (s)
First P	11	10.7
First S	20	21.3

FOURTH EVENT: 11-09-04 22:28:46

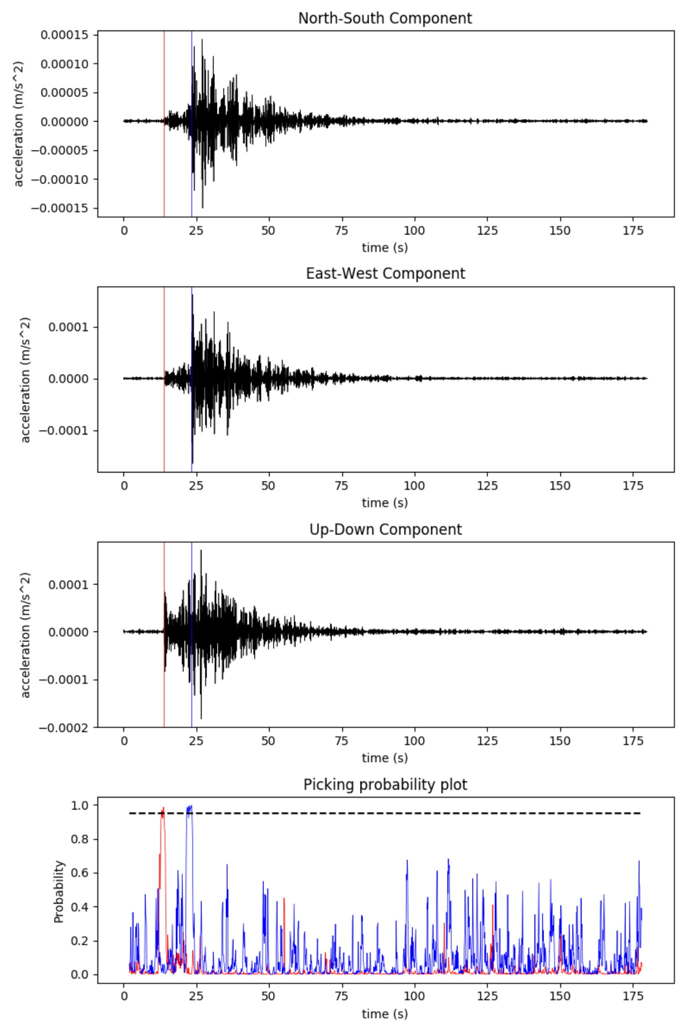
Left to right: IIDM, TACM, TK2M



	Manual picking time (s)	CNN picking time (s)
First P	14.6	14.4
First S	24.3	24.7



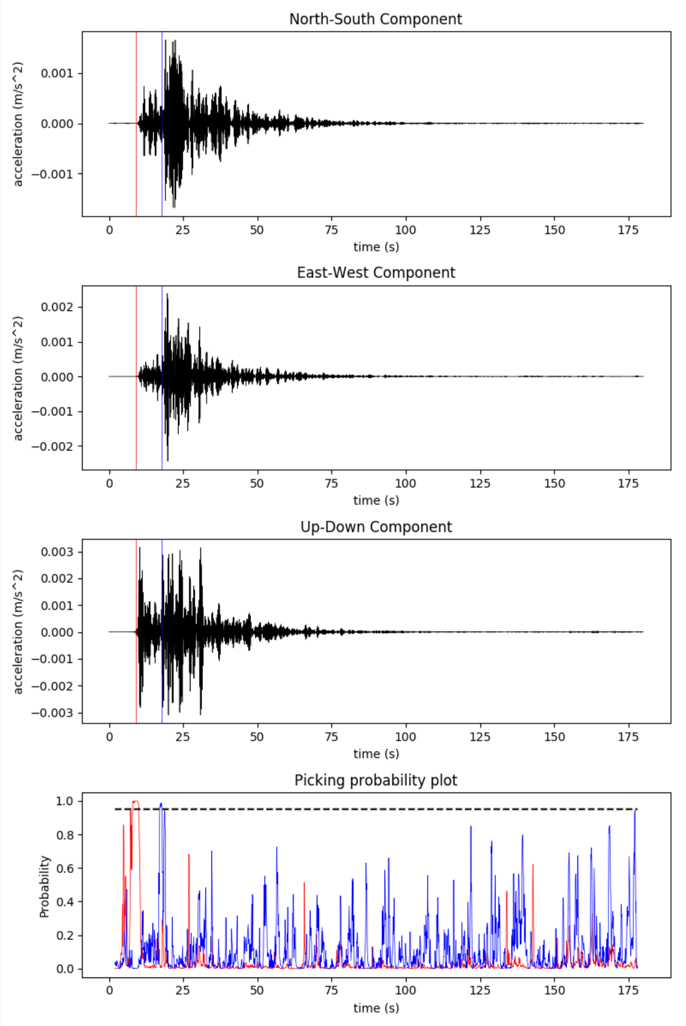
	Manual picking time (s)	CNN picking time (s)
First P	14.2	13.9
First S	23.8	22.2



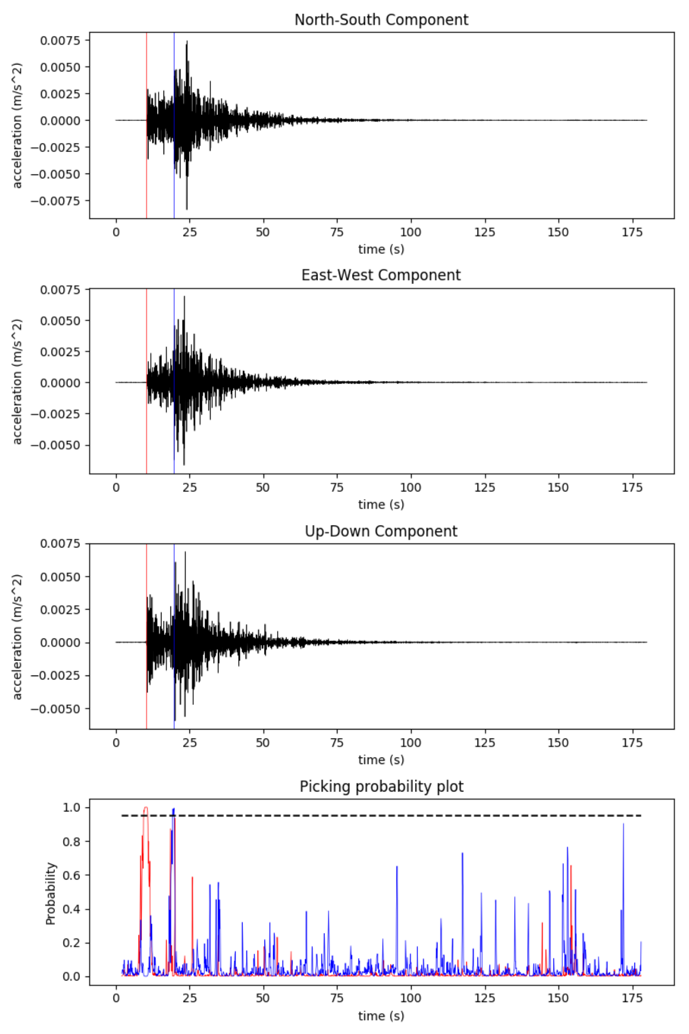
	Manual picking time (s)	CNN picking time (s)
First P	14	13.8
First S	23.4	23.3

FIFTH EVENT: 11-09-05 17:04:25

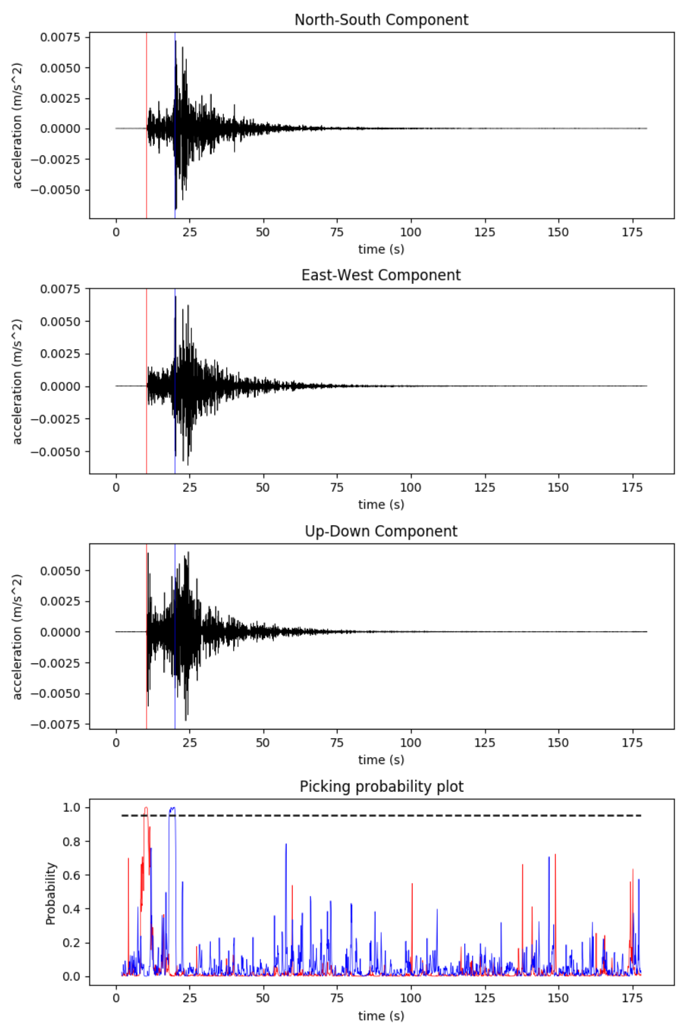
Left to right: IIDM, TACM, TK2M



	Manual picking time (s)	CNN picking time (s)
First P	10.31	9.1
First S	18.58	17.7



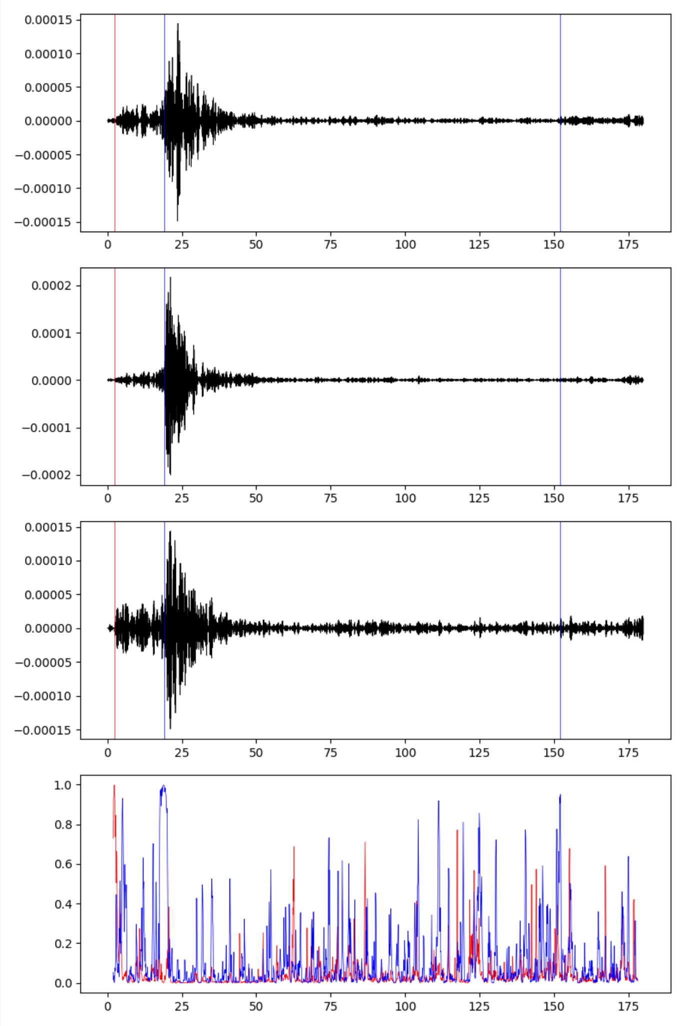
	Manual picking time (s)	CNN picking time (s)
First P	10.6	10.2
First S	19.63	19.7

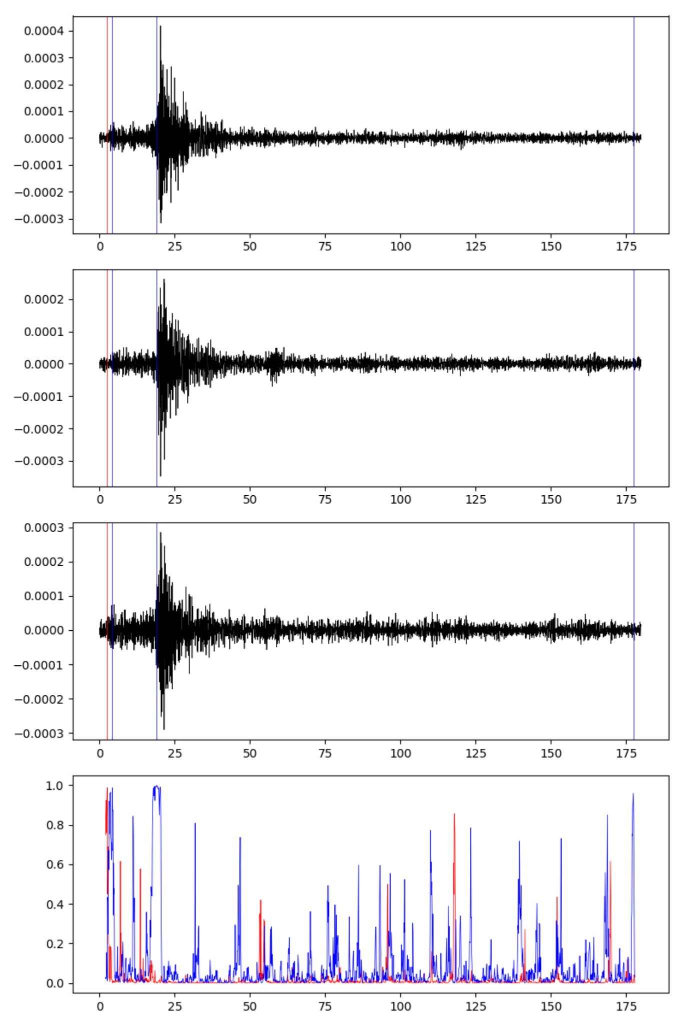


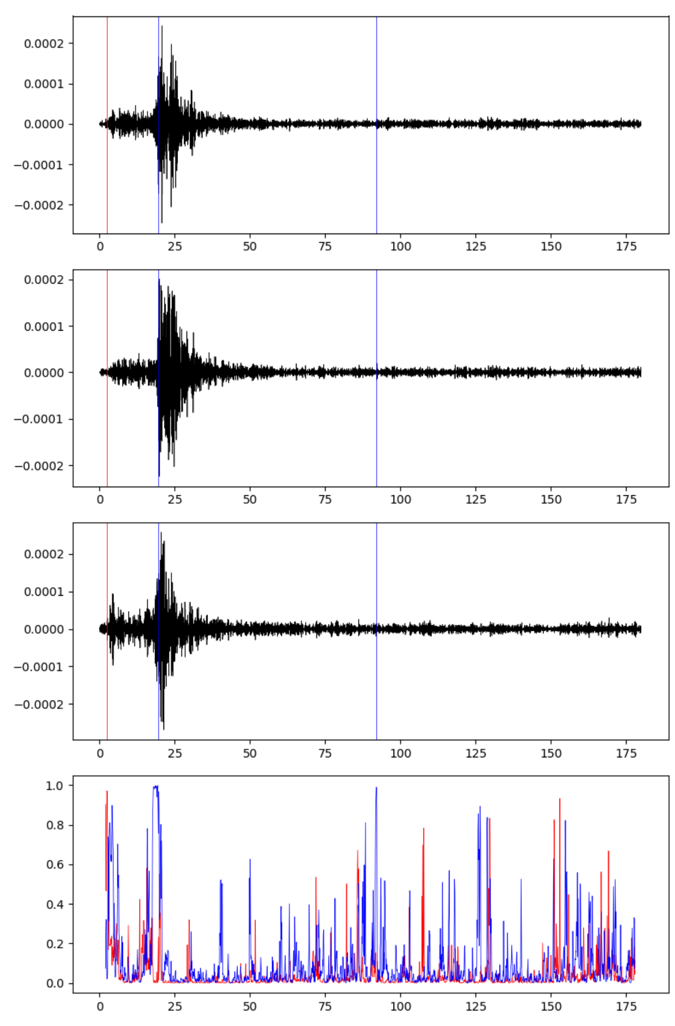
	Manual picking time (s)	CNN picking time (s)
First P	10.77	10.3
First S	19.79	19.9

SIXTH EVENT: 11-09-06 18:06:51

Left to right: IIDM, TACM, TK2M







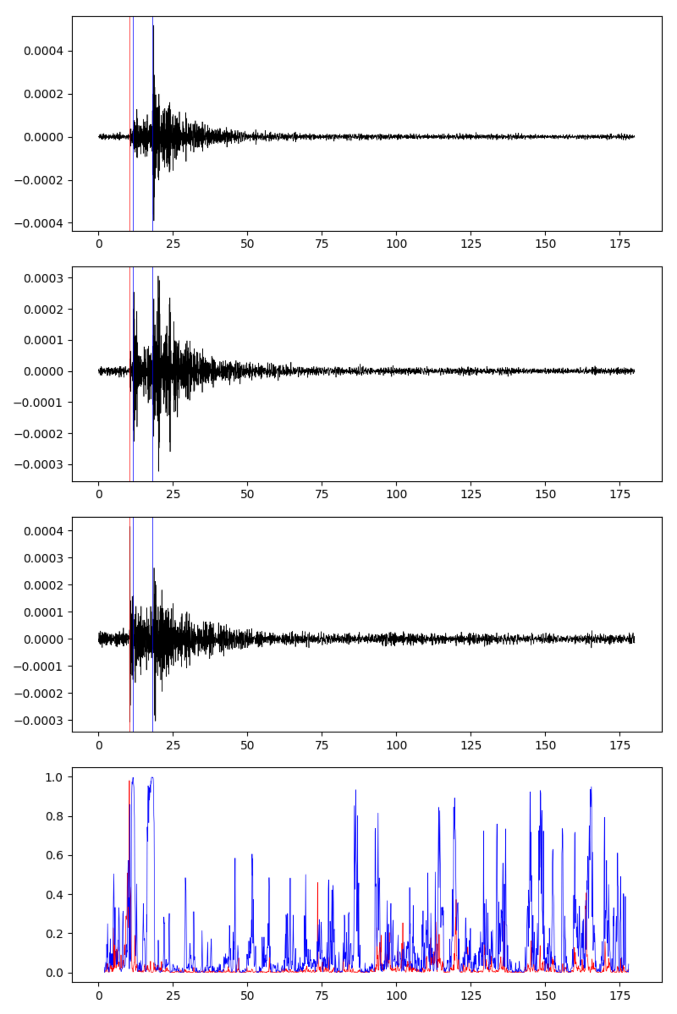
	Manual picking time (s)	CNN picking time (s)
First P	2.1	2.4
First S	19.3	19

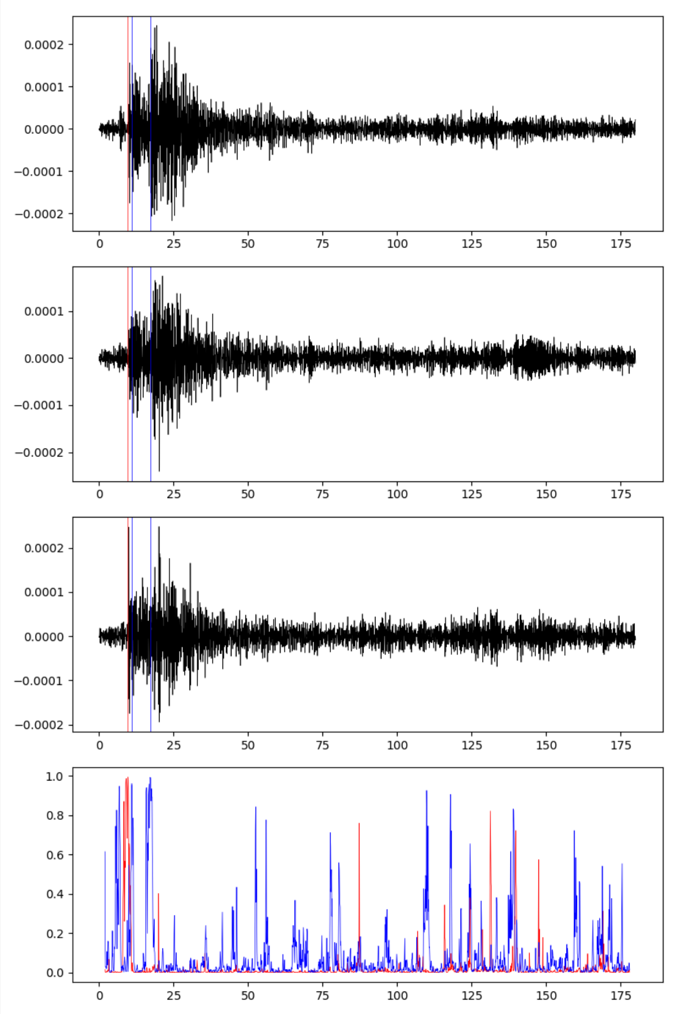
	Manual picking time (s)	CNN picking time (s)
First P	1.8	2.6
First S	18.2	4.2

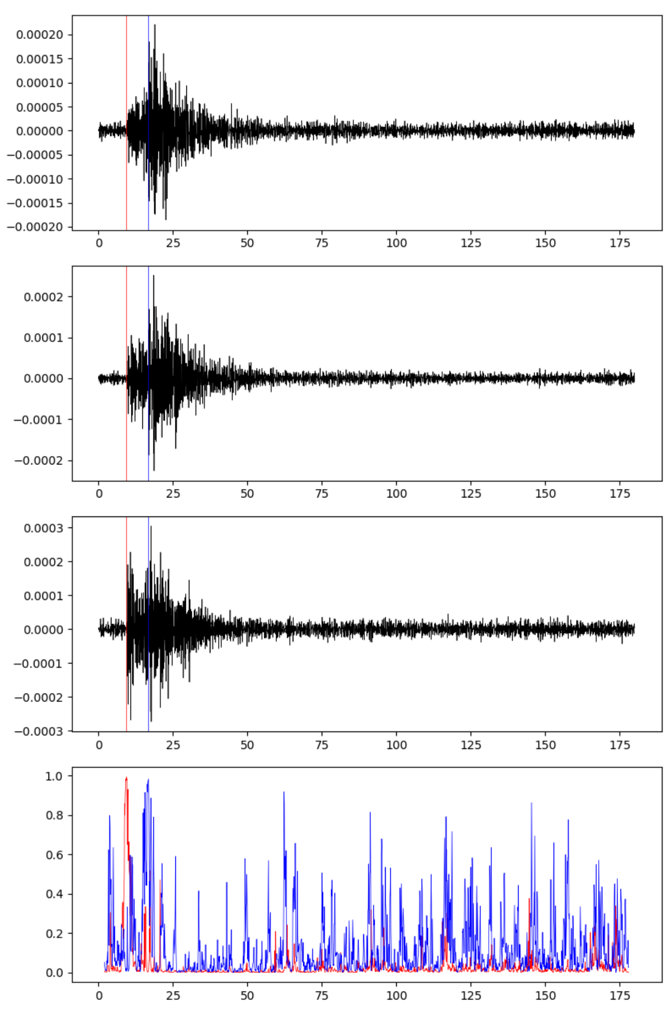
	Manual picking time (s)	CNN picking time (s)
First P	2.2	13.2
First S	18.6	22

SEVENTH EVENT: 11-09-07 17:08:46

Left to right: IIDM, TACM, TK2M







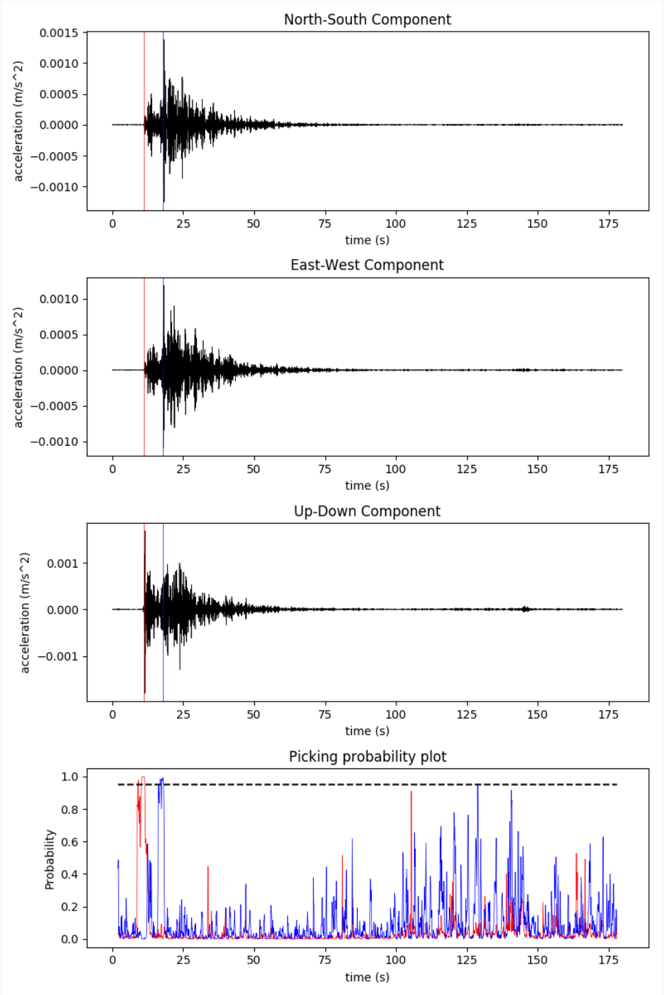
	Manual picking time (s)	CNN picking time (s)
First P	10.4	10.4
First S	18.21	12.7

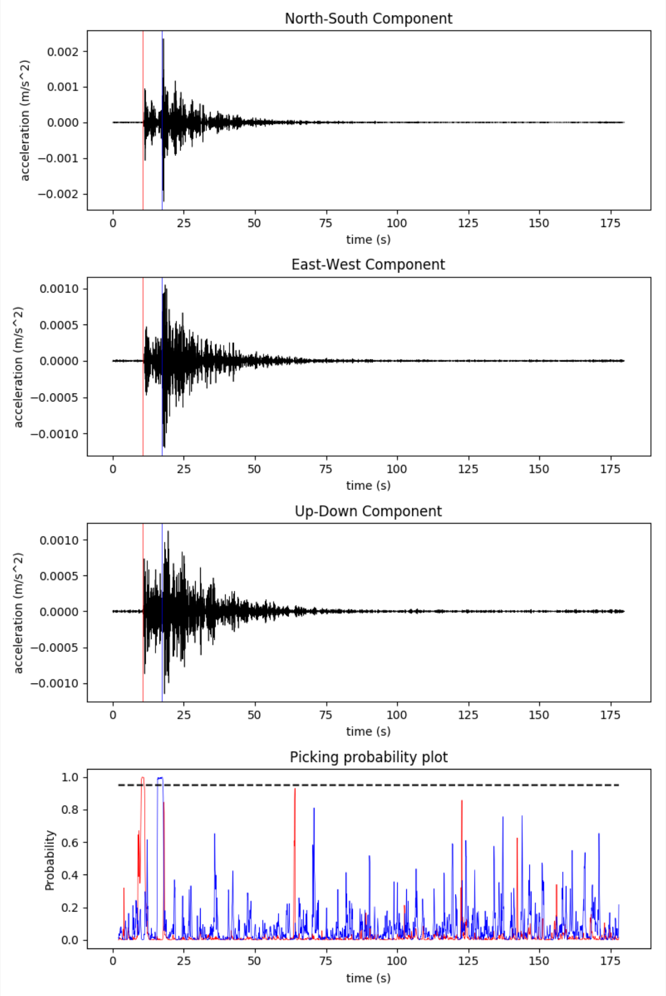
	Manual picking time (s)	CNN picking time (s)
First P	9.8	9.7
First S	17.68	11

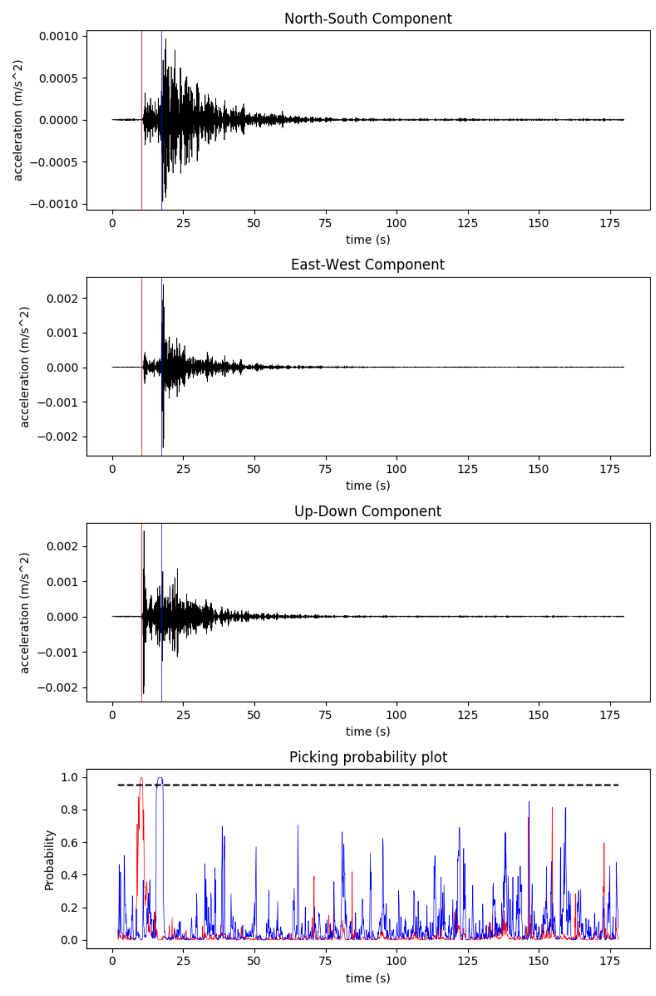
	Manual picking time (s)	CNN picking time (s)
First P	-	9.4
First S	-	16.8

EIGHTH EVENT: 11-09-08 17:22:37

Left to right: IIDM, TACM, TK2M







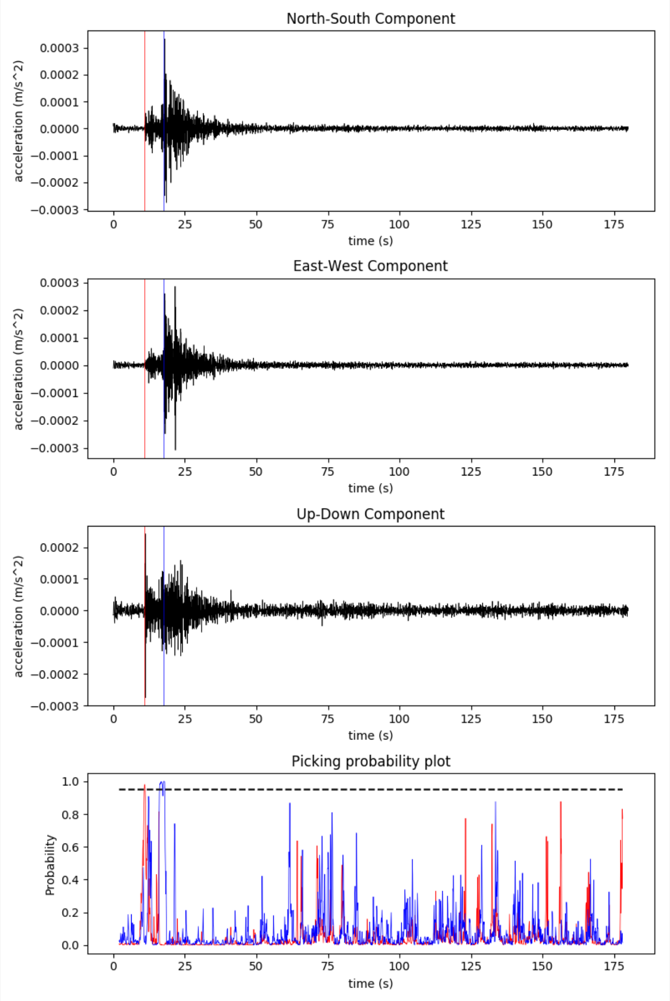
	Manual picking time (s)	CNN picking time (s)
First P	11.2	11.1
First S	17.95	17.8

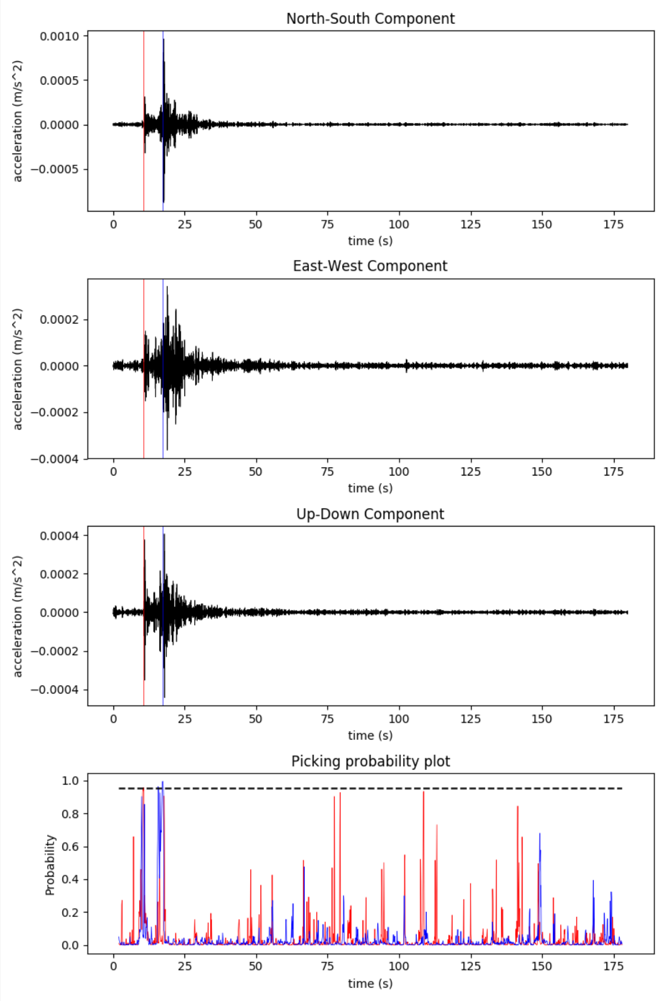
	Manual picking time (s)	CNN picking time (s)
First P	11	10.5
First S	17.63	17.4

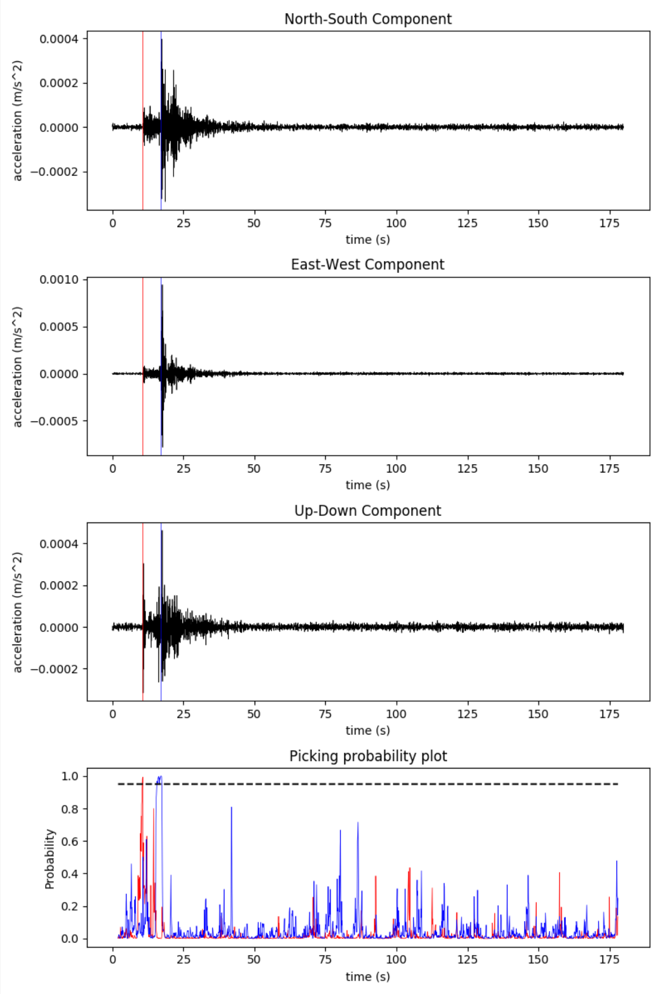
	Manual picking time (s)	CNN picking time (s)
First P	10.8	10.3
First S	17.42	17.3

NINTH EVENT: 11-09-08 18:13:46

Left to right: IIDM, TACM, TK2M







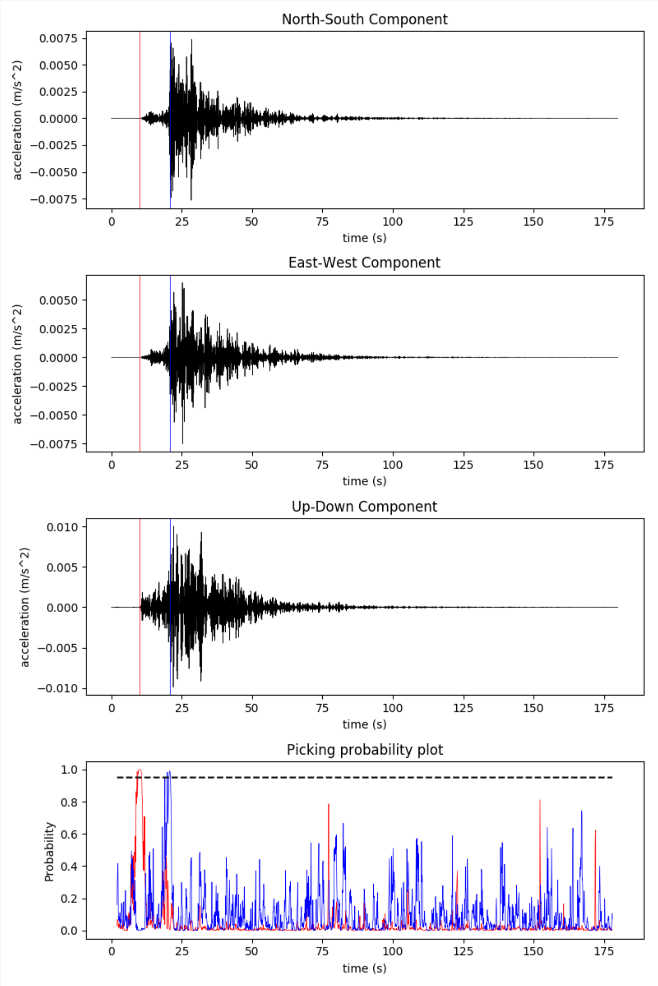
	Manual picking time (s)	CNN picking time (s)
First P	11	10.9
First S	17.84	17.7

	Manual picking time (s)	CNN picking time (s)
First P	10.8	10.6
First S	17.37	17.4

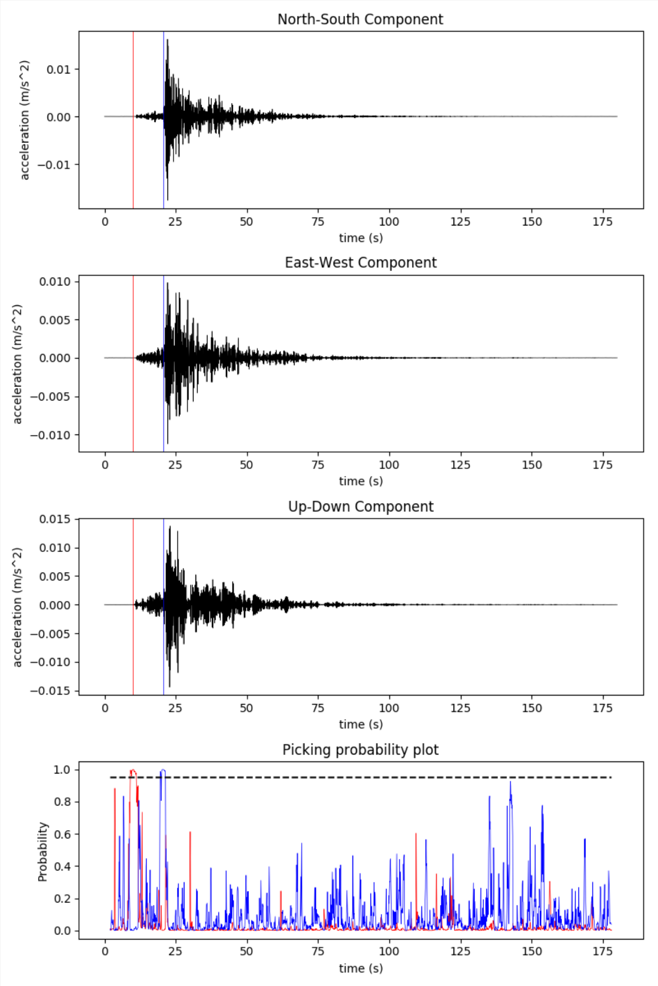
	Manual picking time (s)	CNN picking time (s)
First P	10.6	10.7
First S	17.16	17.1

TENTH EVENT: 11-09-10 15:00:35

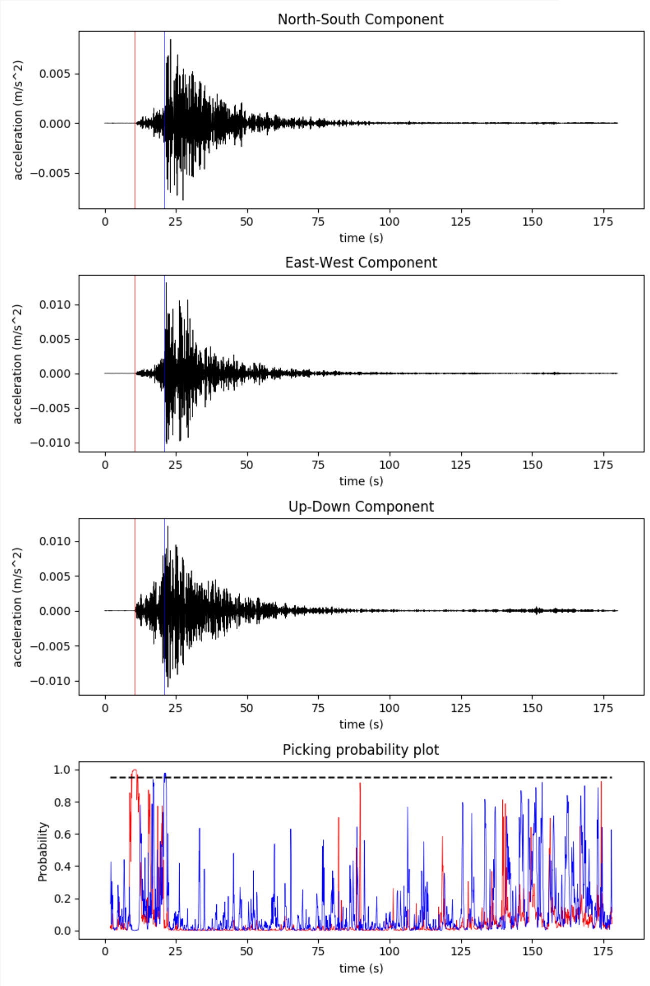
Left to right: IIDM, TACM, TK2M station



	Manual picking time (s)	CNN picking time (s)
First P	10.6	10
First S	20.95	20.7



	Manual picking time (s)	CNN picking time (s)
First P	10.8	10
First S	20.9	20.6



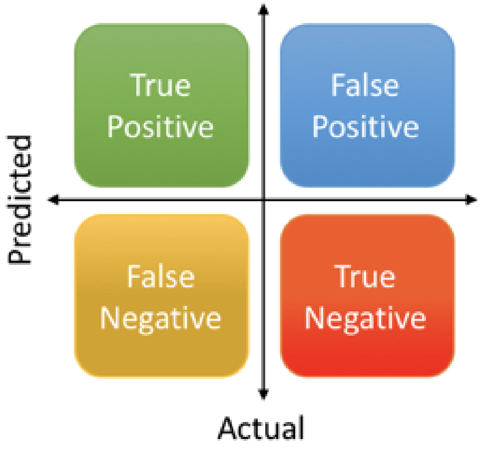
	Manual picking time (s)	CNN picking time (s)
First P	10.8	10.6
First S	21.4	21

TERMINOLOGIES FOR CONFUSION MATRIX COMPONENTS

$$\textbf{Precision} = \frac{\text{True Positive}}{\text{Actual Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive + False Positive}}$$

$$\textbf{Recall} = \frac{\text{True Positive}}{\text{Predicted Results}} \quad \text{or} \quad \frac{\text{True Positive}}{\text{True Positive + False Negative}}$$

$$\textbf{Accuracy} = \frac{\text{True Positive + True Negative}}{\text{Total}}$$



- Probability: confidence that the picked data match with the features learned
- Precision: Precision means the percentage of your results which are relevant
- Recall: the percentage of total relevant results correctly classified by your algorithm
- Accuracy: (True Positive + True Negative)/Total

CONFUSION MATRIX AND MODEL EVALUATION

The numbers are counted from the amount of picking. Used manually picked data as references for true labelling.

- **Precision P =** 32/(32+0+0) = 32/32 = 1
- **Precision S =** 31/(31+0+8) = 31/39 = **0.79**
- **Recall P =** 32/(32+0+1) = 32/33 **= 0.97**
- **Recall S =** 31/31 **= 1**

	True P	True S	True Noise
Predicted P	32	0	0
Predicted S	0	31	8
Predicted Noise	1	0	

DISCUSSION

- Major earthquakes were successfully detected with this CNN model.
- Several different filters did not eliminate false positives
- Main cause: other type of noises such as noise from traffic are not available in large quantity in the training data set.
- Because the model has not learned about the type of noise in MeSO-Net data, the model recognized the noise poorly and mislabelled it as P or S wave.
- To enhance the performance, we experimented with frequency range for bandpass filter to optimally cut out the noise as much as possible.
- Despite of this problem, the model performance is still decent, keeping in mind that the waveform source is different, and the frequency range for the filter is different from the training data.
- Recall score is high, but the precision score is moderate (can still be improved).

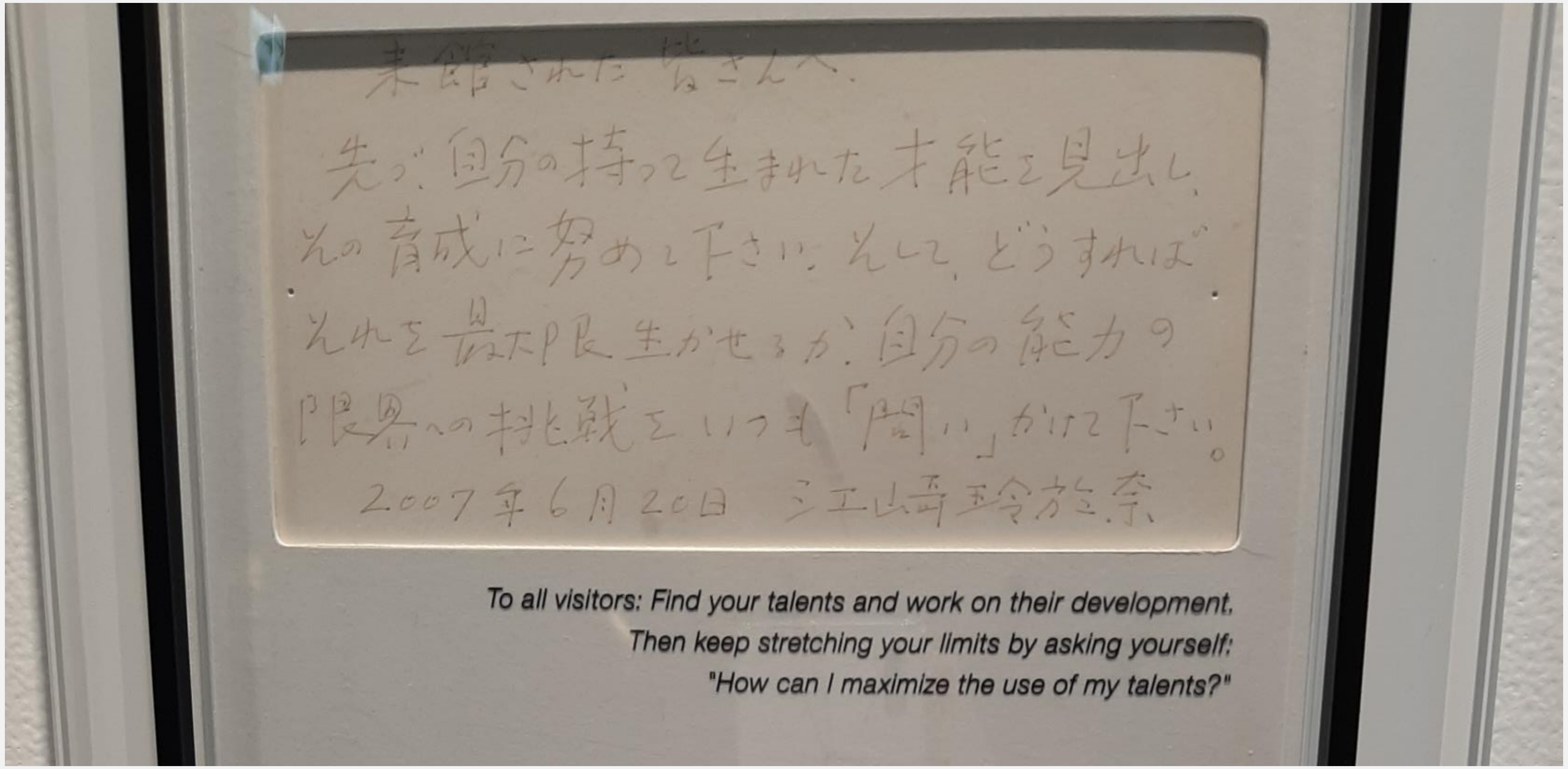
CONCLUSION

- Major earthquake events automatic detection from MeSO-net data were successfully done by the CNN.
- Signal processing, especially frequency range for the filter, is important prior to feeding the waveform to the model.
- CNN has to be trained with wide variety of noise possibility to improve its model performance.
- With its current performance and several improvements, this CNN can prove to be useful as a tool for earthquake monitoring and earthquake catalog generation.

RECOMMENDATIONS/FUTURE WORK

- Include waveforms with artificial noise to the training data so the noise can be distinguished more accurately.
- Improve the CNN model to be more efficient when used in less-sophisticated computer hardware, to democratize AI in geoscience.
- Apply CNN to automatically detect earthquakes in Indonesia (no researches about it has been done)

THANK YOU



Christopher Salim

Email: christopher.salim@brocku.ca

LinkedIn: https://www.linkedin.com/in/christophersalim/