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Aftershock Detection with Multi-Scale Description based Neural Network

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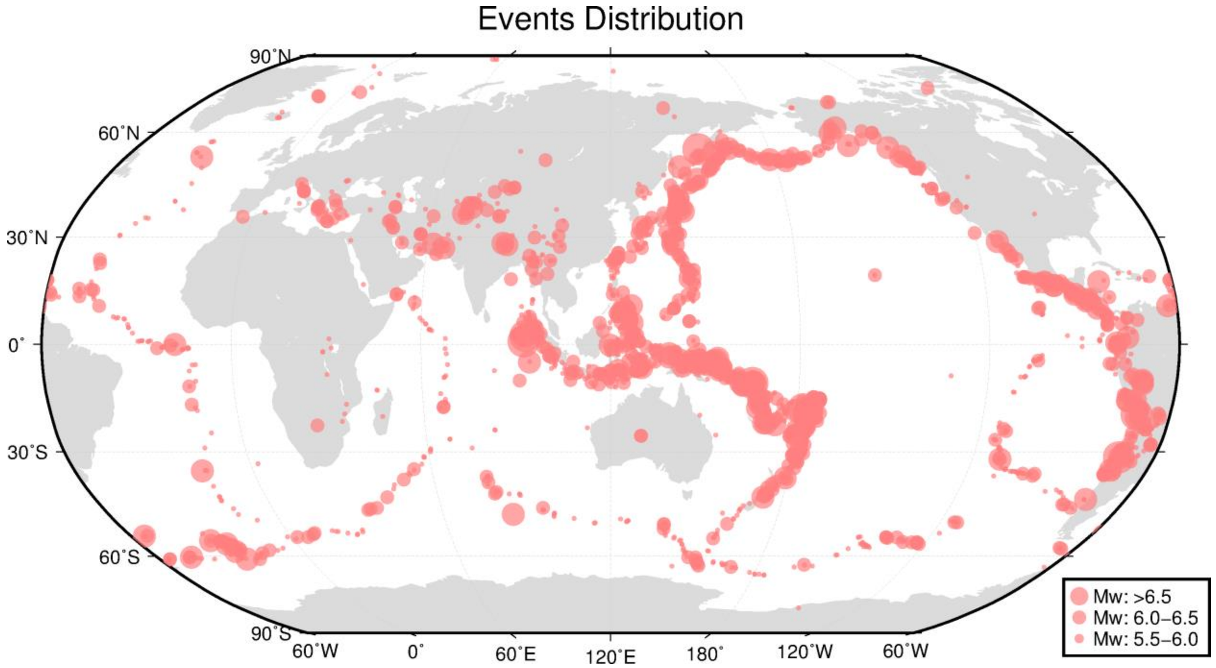
[3]Business Intelligence Lab, Baidu Research

Background

◆ Earthquake Events

Earthquake is one kind of worst nature disasters which may cause injury and loss of life and collapse of buildings.



Earthquake events distribution all over the world in 2018

Nature Disaster: Earthquake

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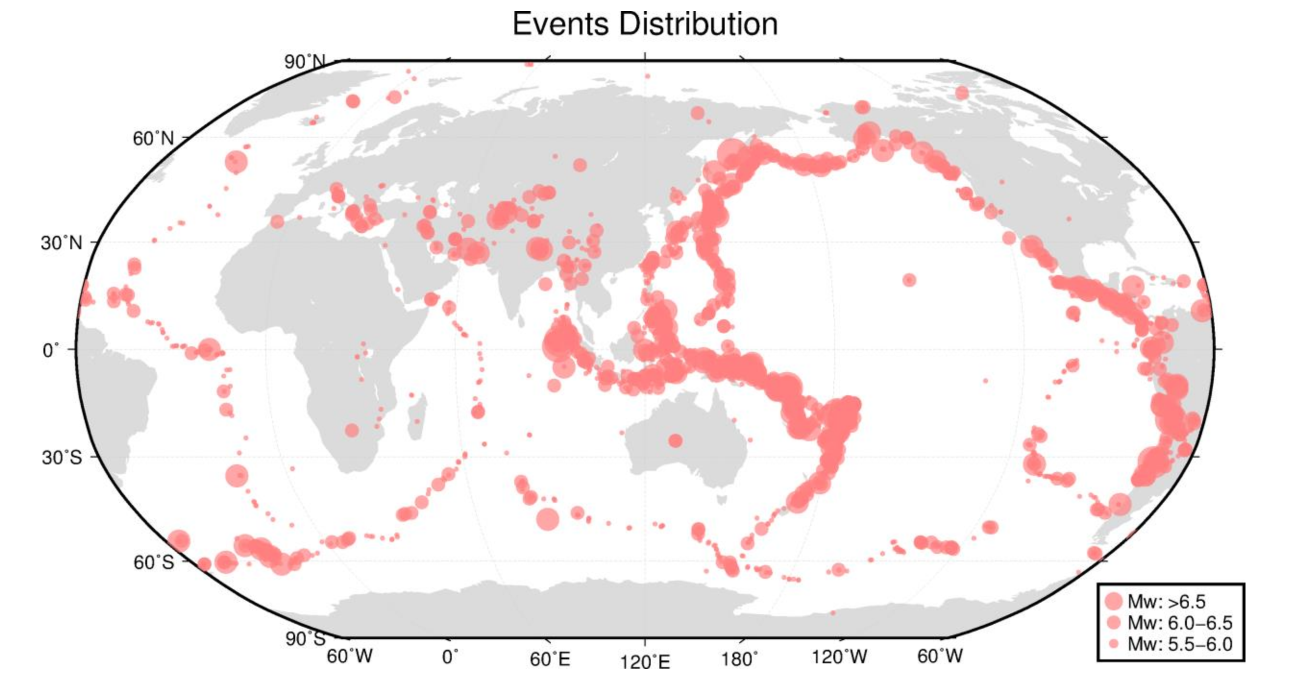

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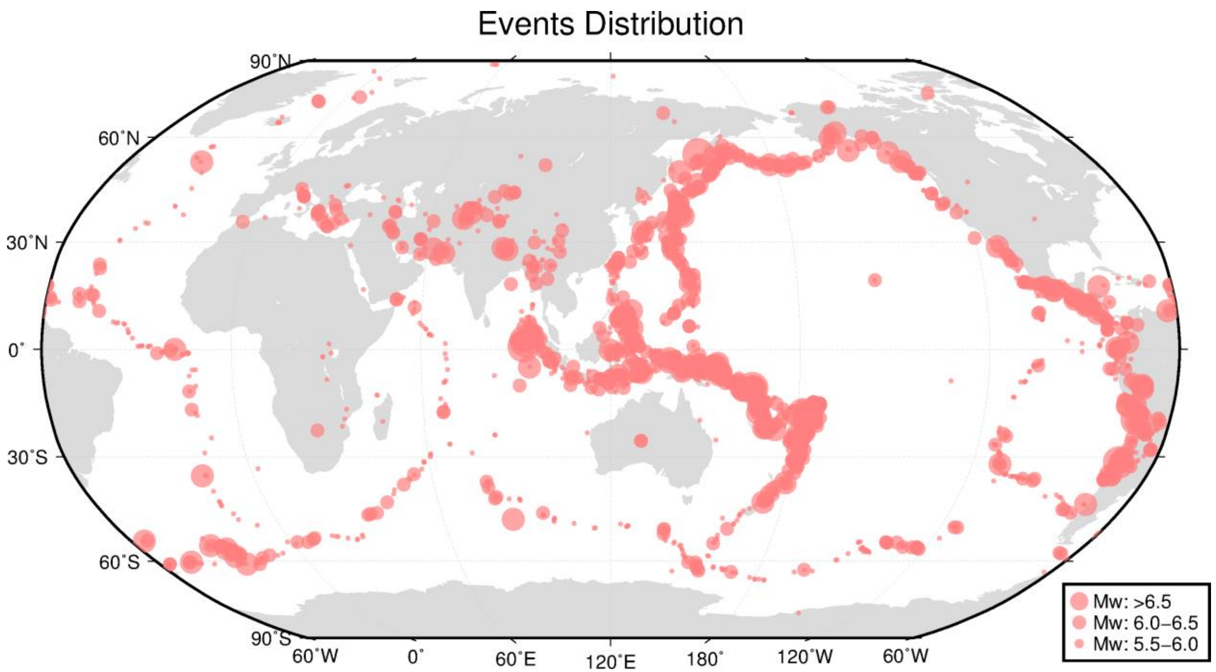

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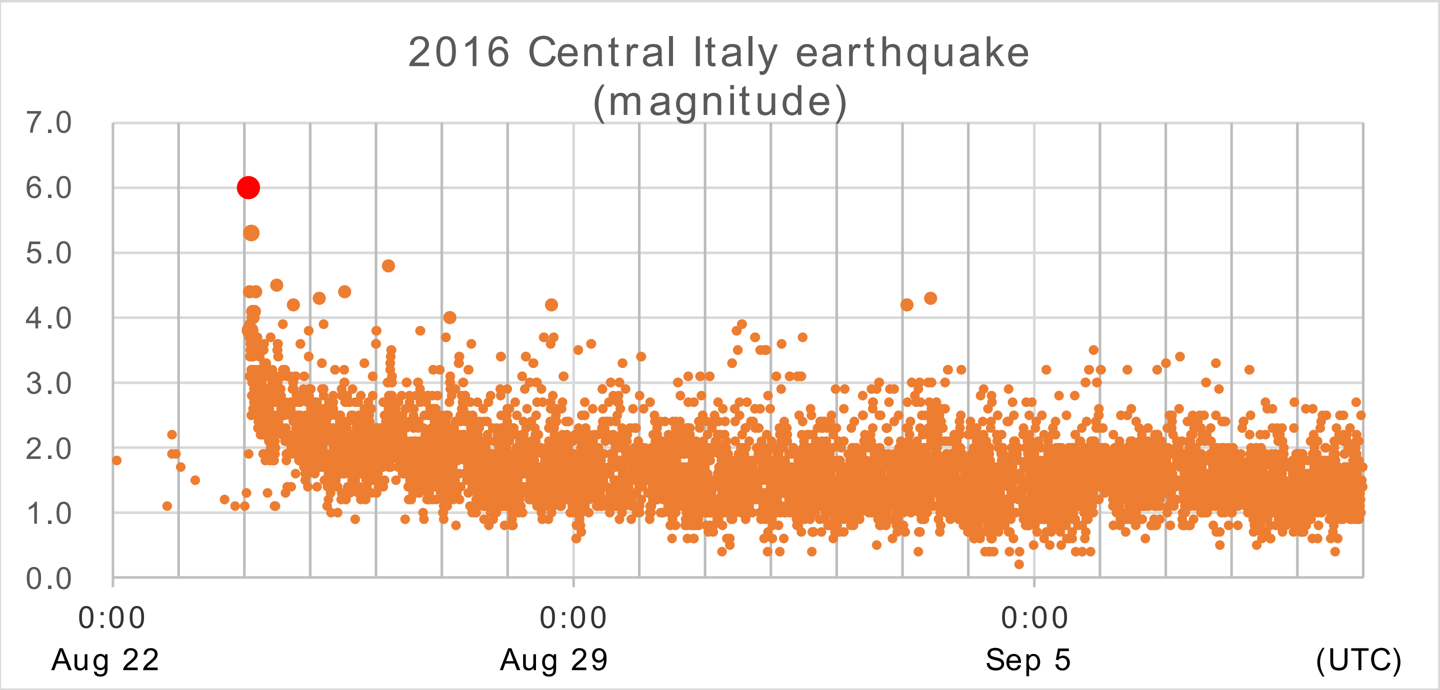
Aftershocks refer to the smaller earthquakes that occur following large earthquakes, in the same area of the main shock.

- Difficult to detect.
- Collapse buildings that are damaged from the main shock.



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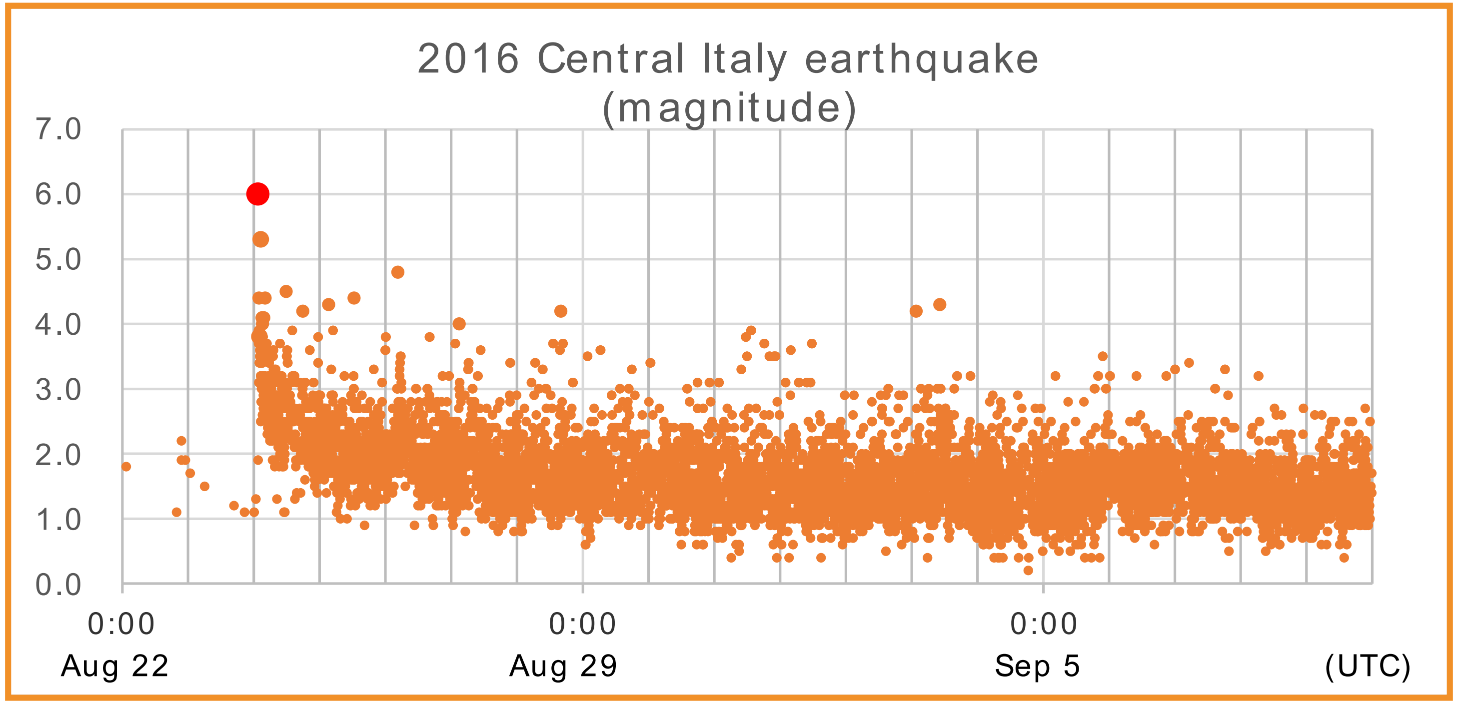

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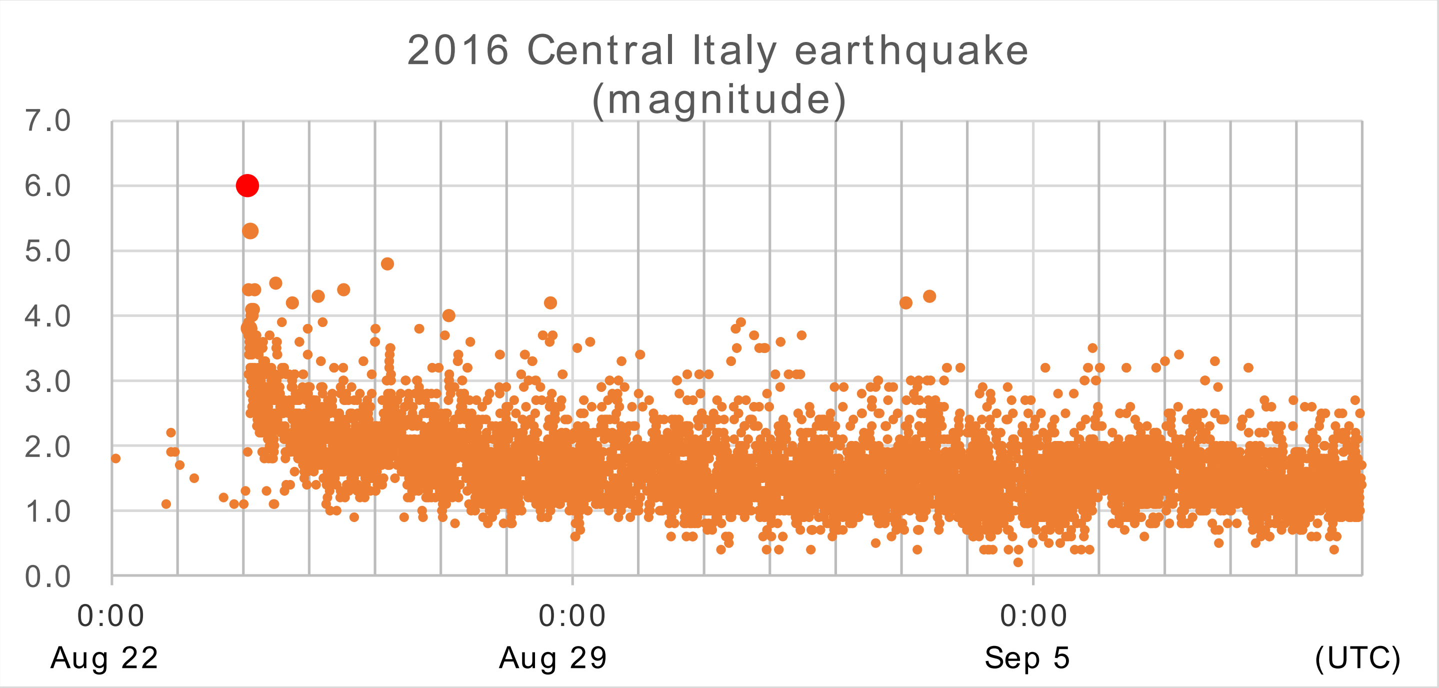

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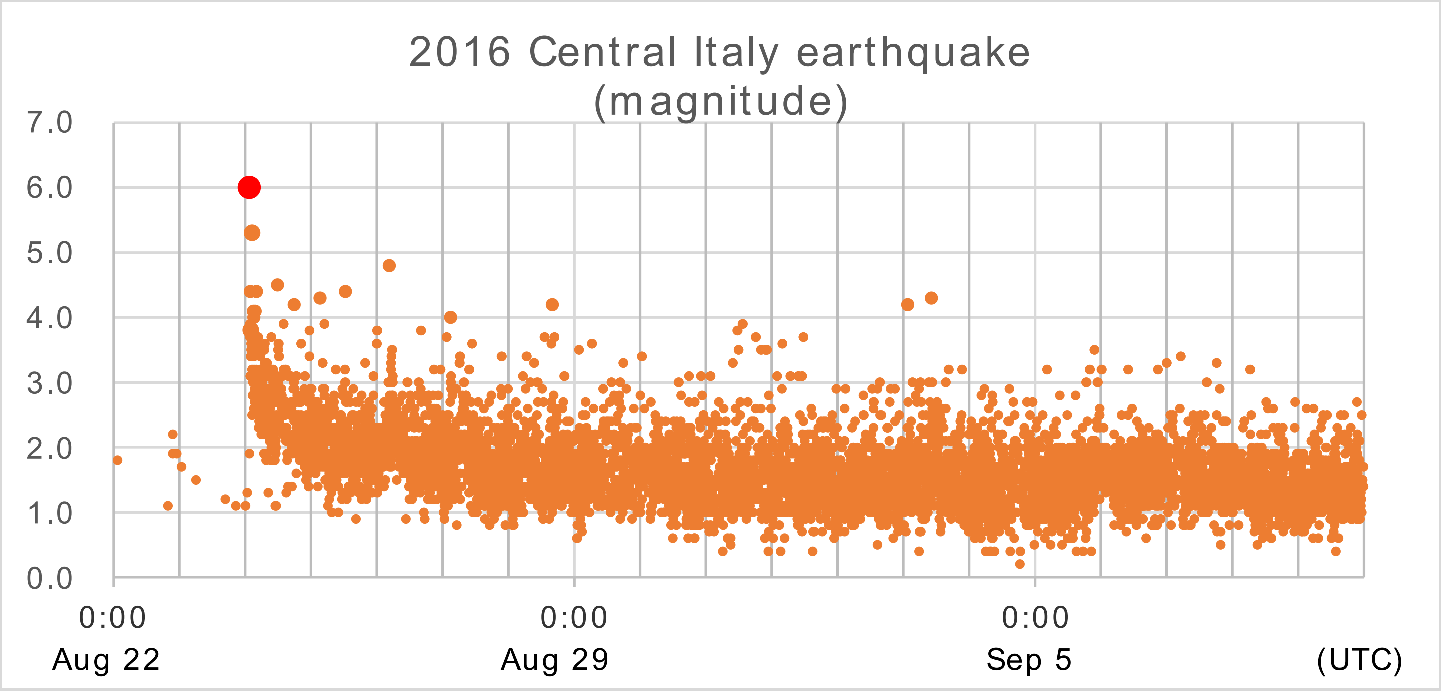

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- **Motivation**

Benefit

- Automatic aftershock detection can support emergence actions.

- Useful for the research of geological activity and seismic mechanism.

Challenges

- Highly-noise and weak signal. How to effectively detect aftershocks?
  Multi-Scale Description based Neural Network.

- Multiple monitoring stations. How to utilize this relationship?
  multi-task learning strategy .

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Problem Formulation

◆ Aftershock Detection

Definition: Machine-learning-based Aftershock Detection.

Given a set of waveform windows D, where each $d_i \in D$ has a label l_i for indicating the existence of seismic P-wave, the **objective** is to learn a predictive model M for classifying waveform windows with respect to the label y_i.

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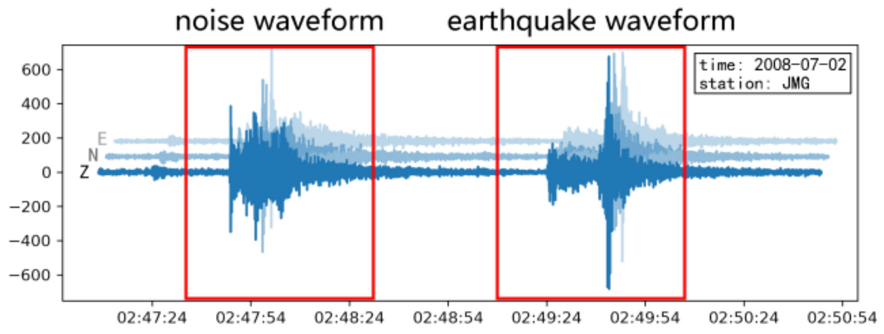
Methodology

- **Data Set Description**
  - The waveforms after the Wenchuan M8.0 Earthquake.
  - There are 2,833 aftershocks, corresponding to 9,891 pieces of seismic waveforms in short time window.
  - These waveforms were recorded in three spatial dimensions (i.e., Z for the vertical channel, N for the north-south channel, and E for the east-west channel) by 15 monitoring stations.



(a) Example for aftershock detection.

TABLE I: The number of aftershock waveforms.

Station	Number	Homology Number	Percent
JMG	1,208	1,208	100%
YZP	1,072	1,015	94.7%
QCH	894	890	99.6%
PUW	1,350	1,338	99.1%
WXT	839	838	99.9%
SPA	574	574	100%
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YGD	166	166	100%
JJS	908	903	99.4%
MXI	1,215	1,196	98.4%
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WDT	6	6	100%
MIAX	1	1	100%
SUM	9,891	9,791	99.0%

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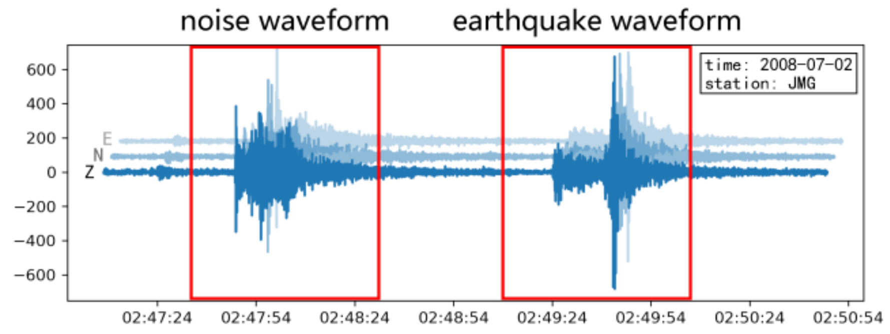

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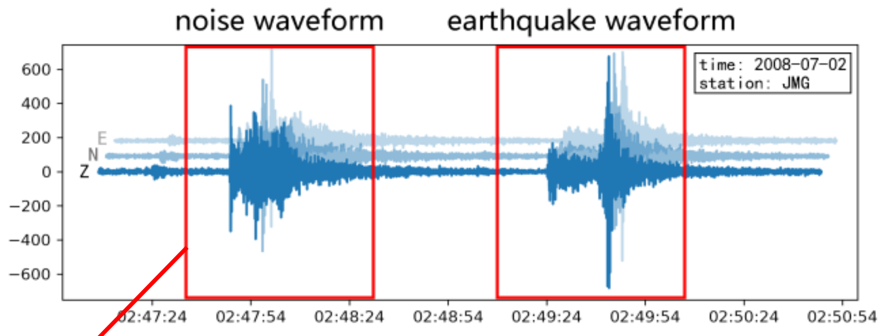

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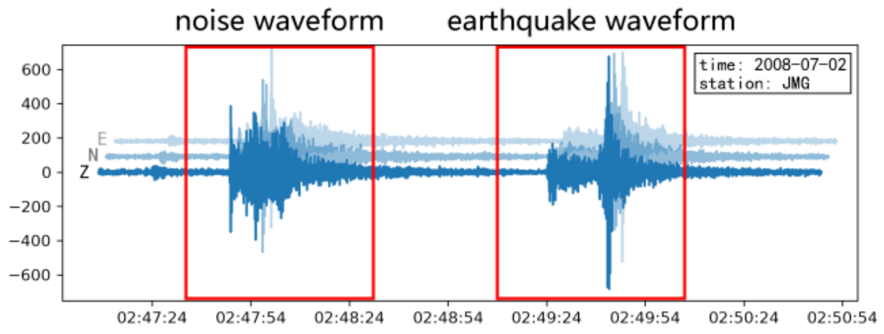

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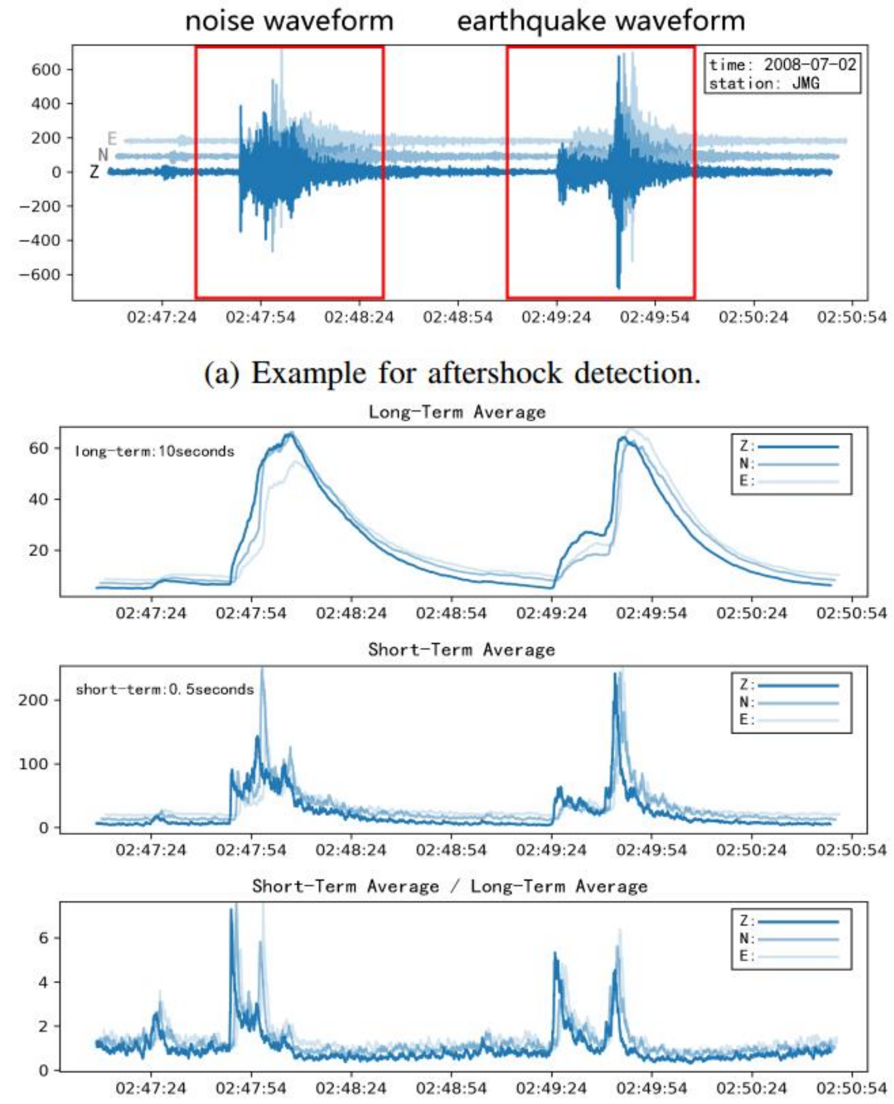
  - STA/LTA(Short-Term Average/Long-Term Average) is the most widely-used earthquake detection approach.

  - The different scale-aware descriptions reflect different characteristics of seismic waveform.



(a) Example for aftershock detection.

(b) Example of classical multi-scale description.

Fig. 2: Some motivating examples of our multi-scale description based aftershock detection approach.

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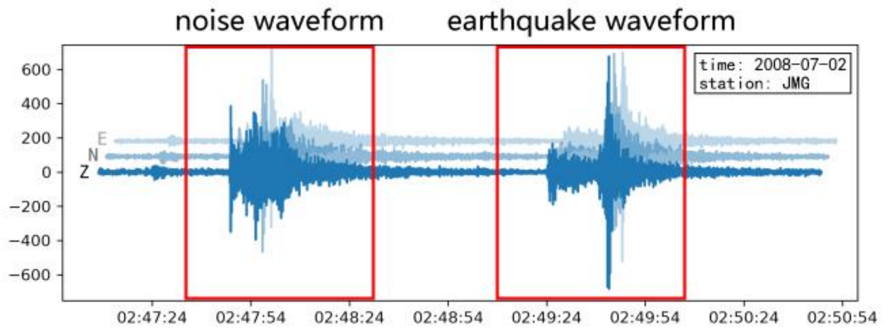

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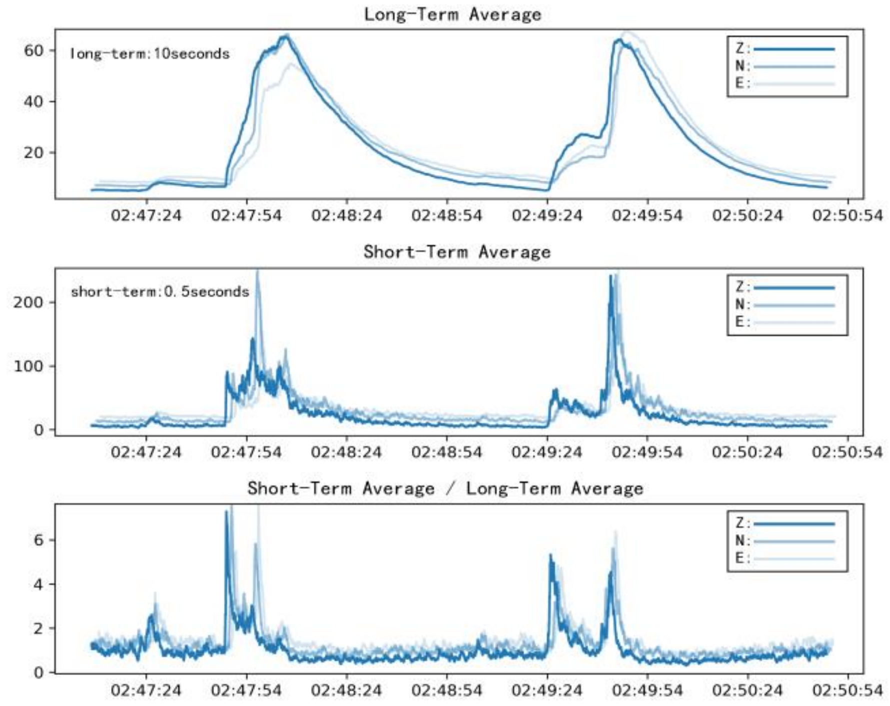

(b) Example of classical multi-scale description.

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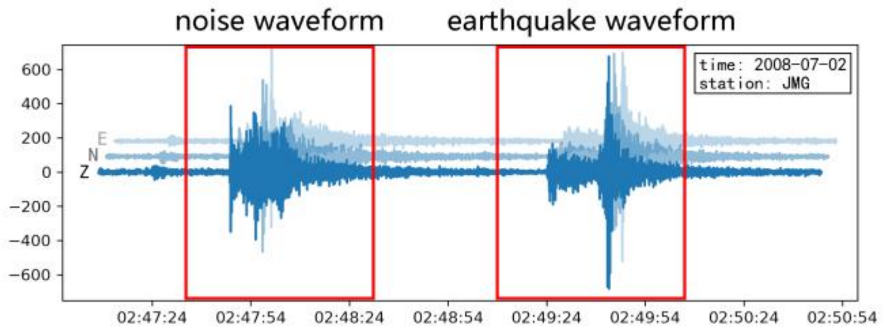
We design a **Multi-Scale Description Based Neural Network** to extract appropriate features for improving the performance of aftershock detection.



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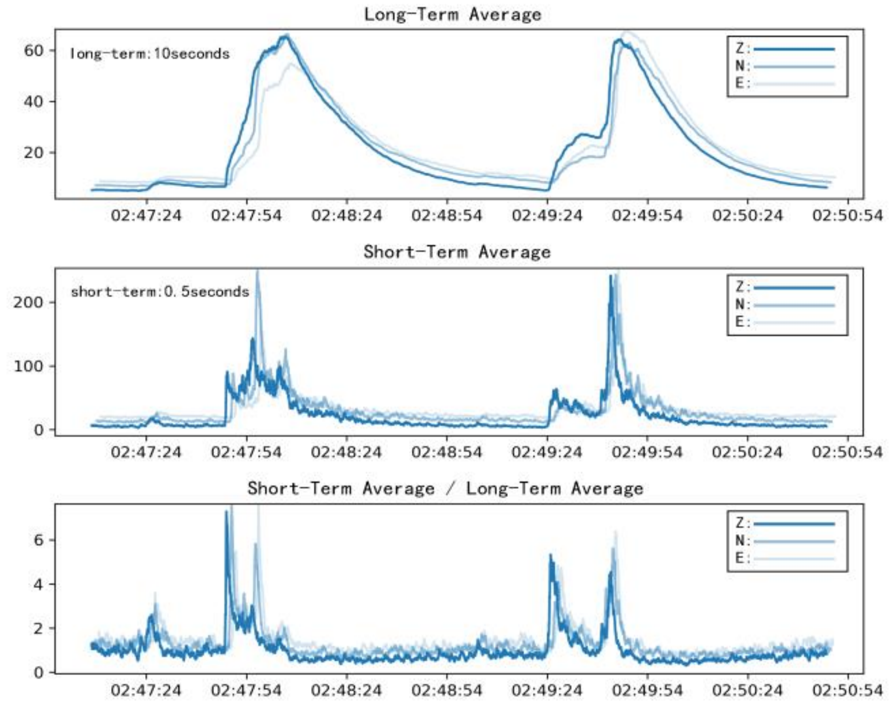

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Methodology

◆ MSD-cell: Generating Multi-Scale Description

the module needs to implement two key functions

First function: extract multi-scale description

- The first function can remember prior features on different scales and add new scale feature.
- Implemented by a 1x3x32/1 convolutions

Second function: mix multi-scale description

- the second function can compare and mix these two kinds of features.
- Implemented by a 1x1x32/1 convolutions

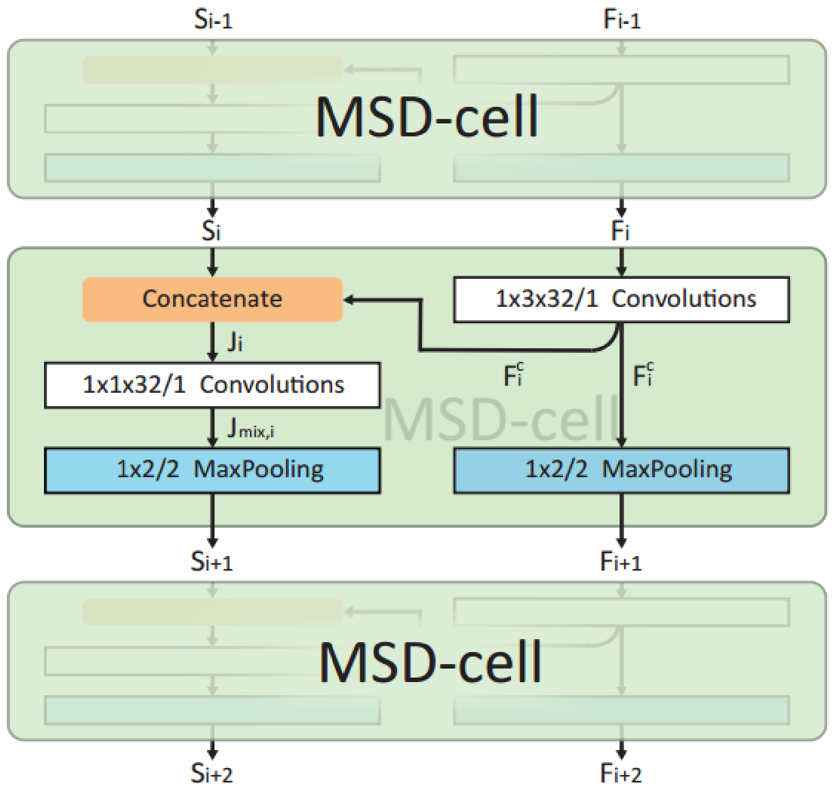

Fig. 3: The detailed structure of MSD-cell, which can be expanded easily.

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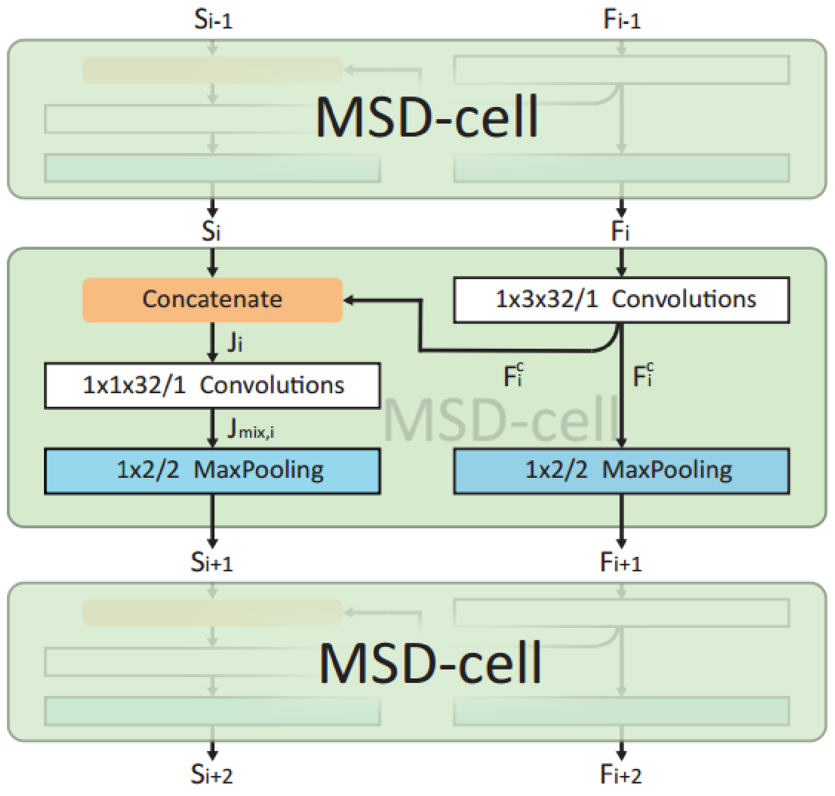

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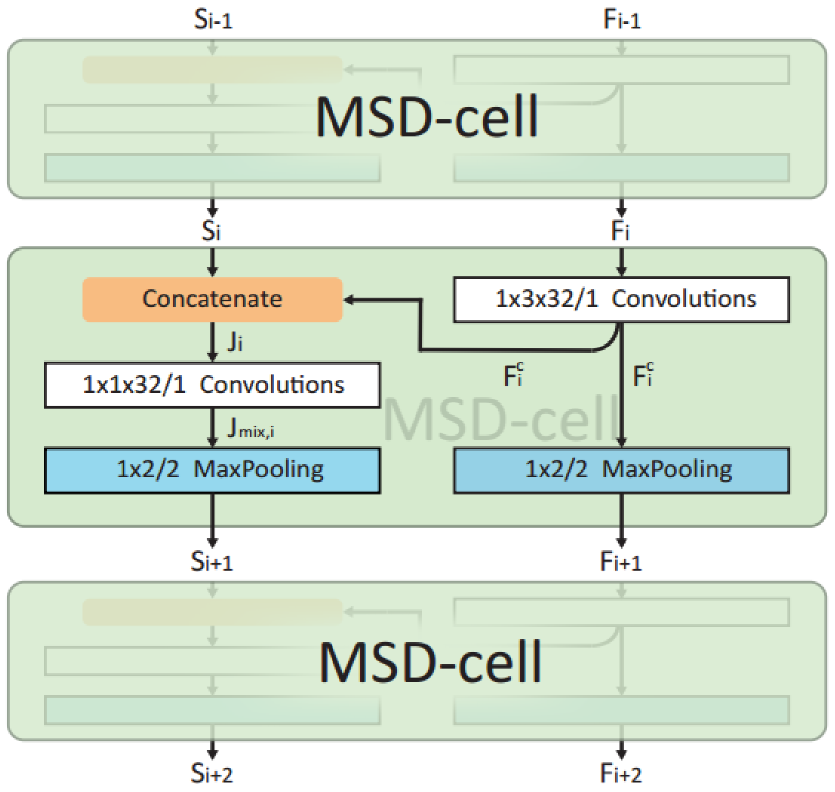

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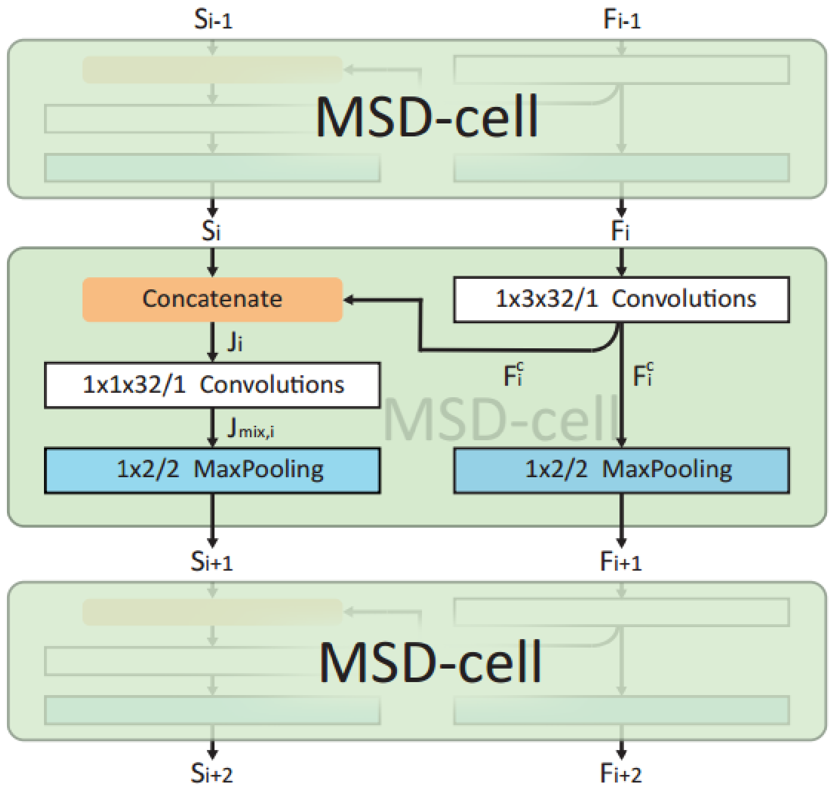

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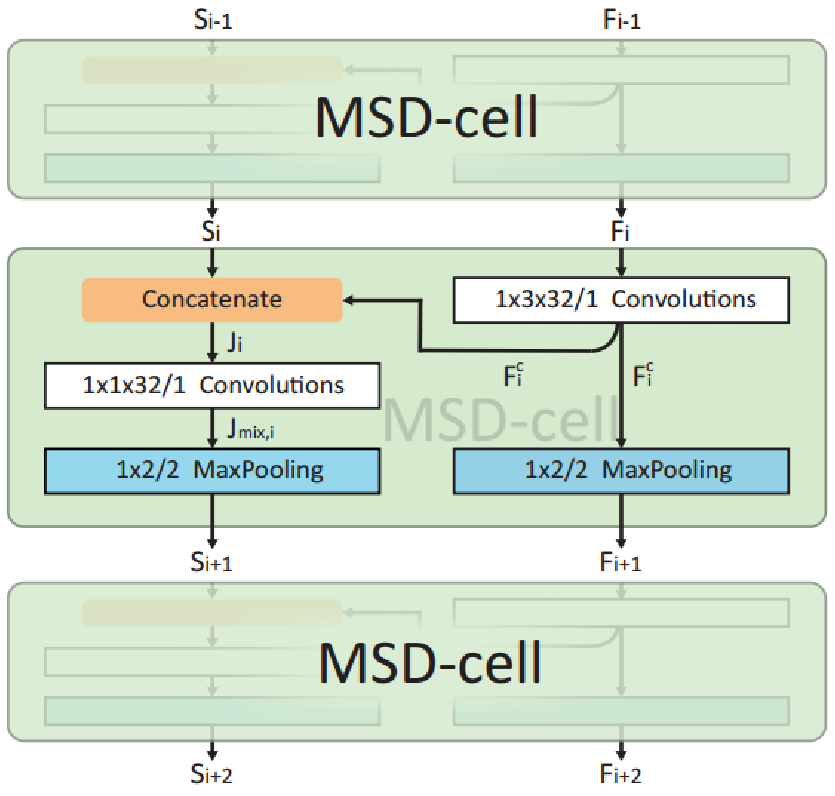

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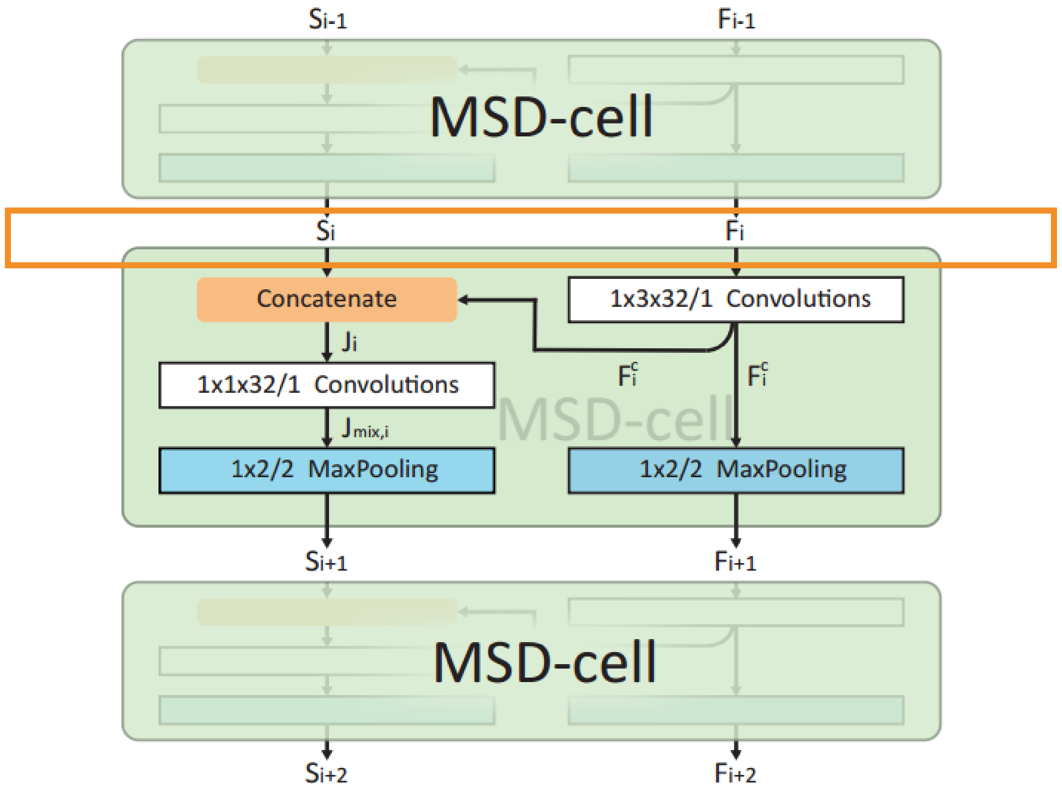

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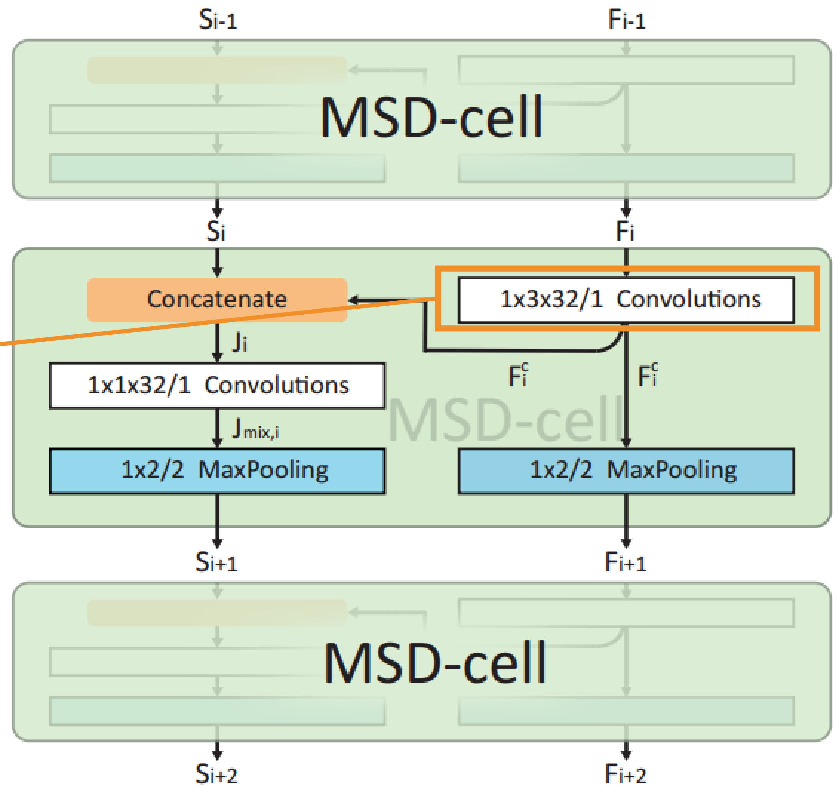

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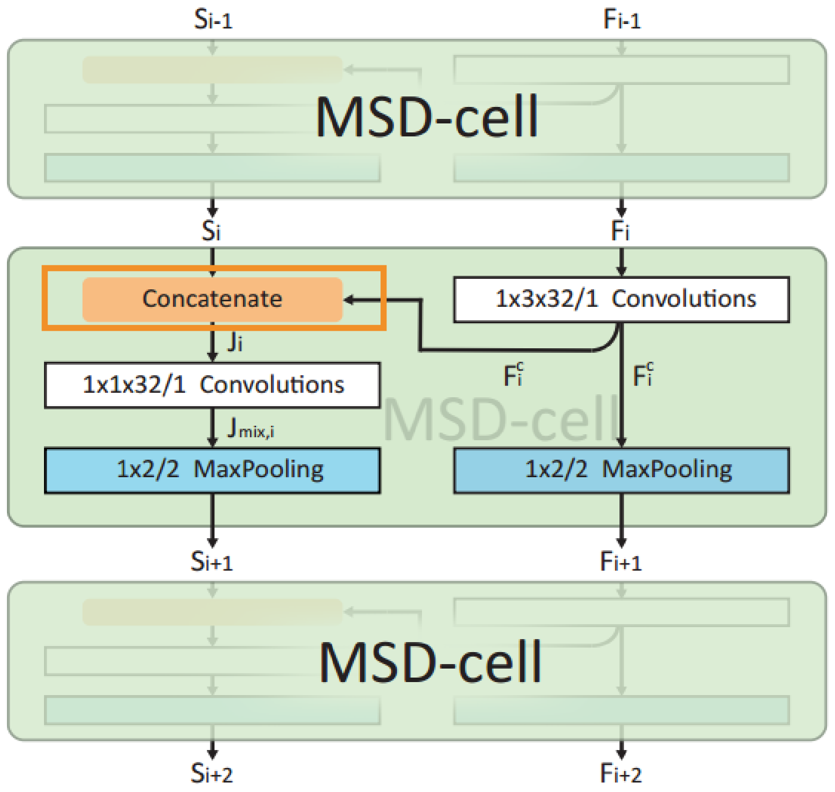

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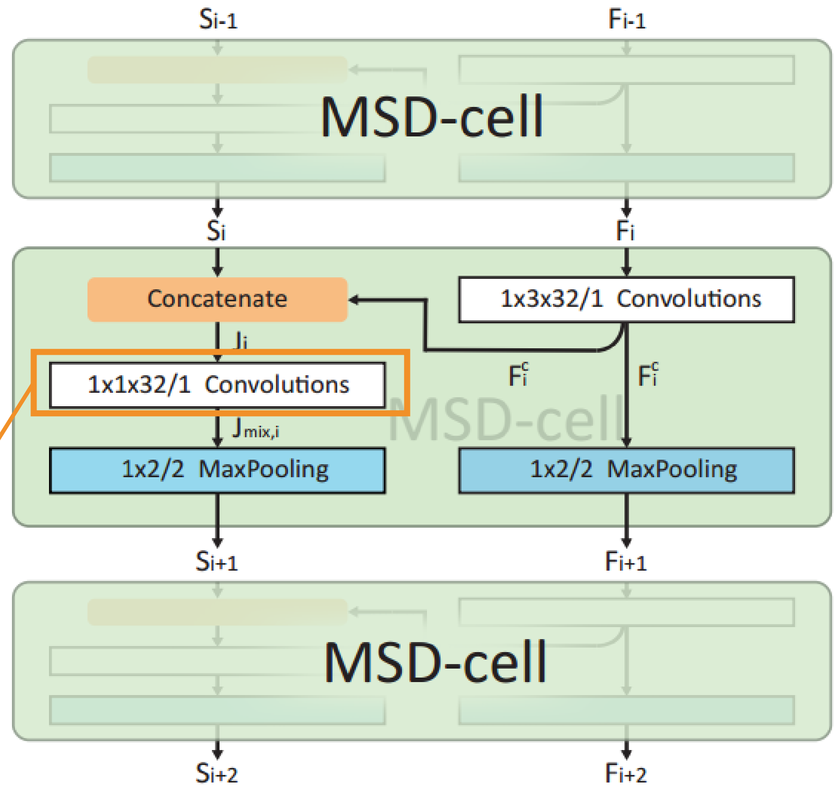

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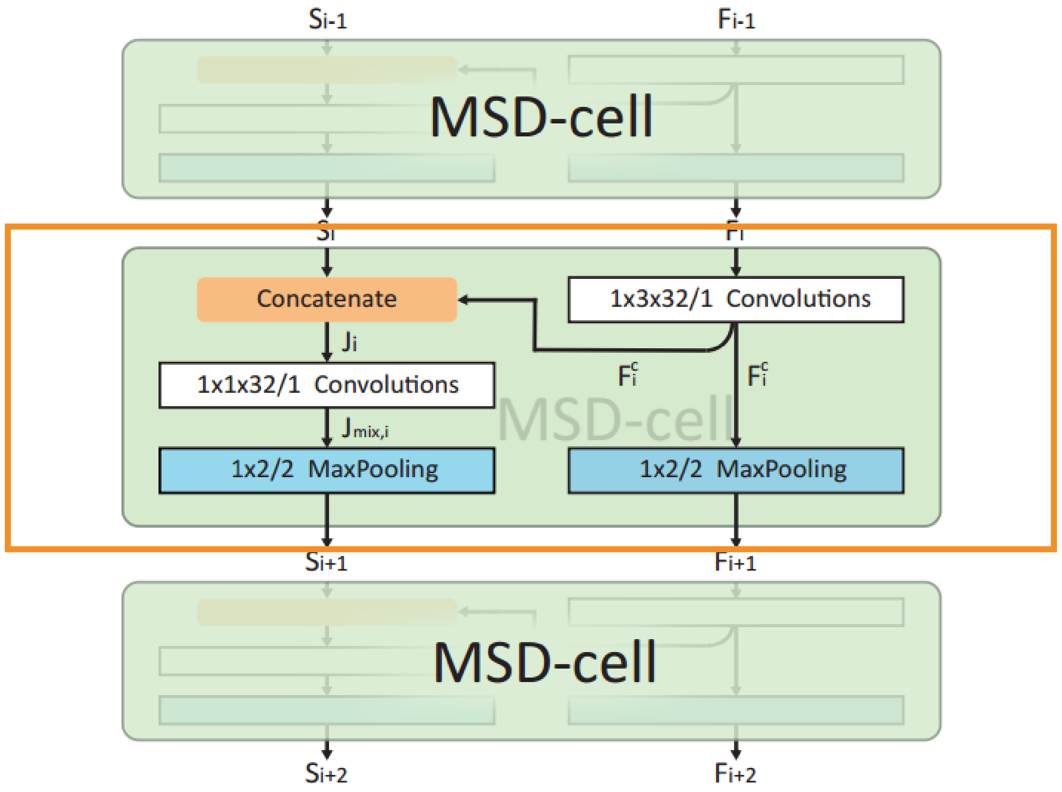

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- **MSDNN**

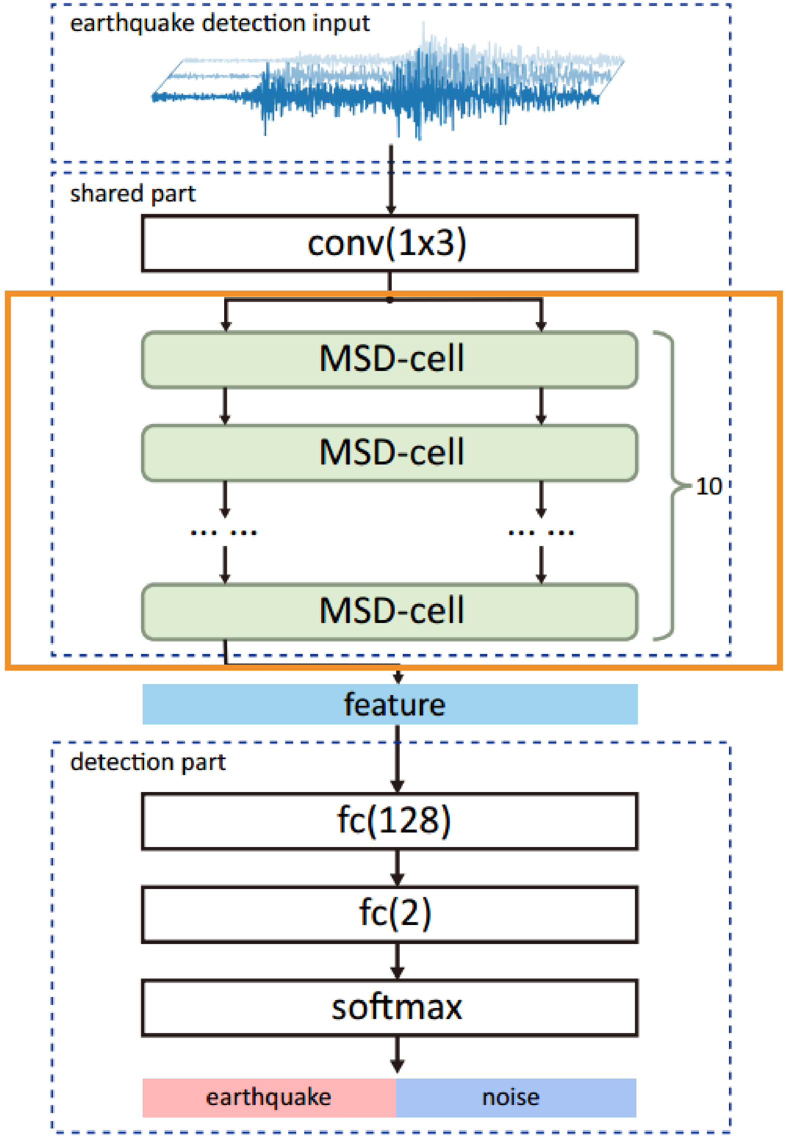
Multi-Scale Description based Neural Network

Shared part

- The shared part can extract multi-scale description feature from seismic waveforms with three spatial dimensions.
- Implemented by 1 conv(1x3) and 10 MSD-cell

Detection part

- the Detection part can distinguish multi-scale description features for earthquake detection.
- Implemented by fc(128), fc(2) and softmax



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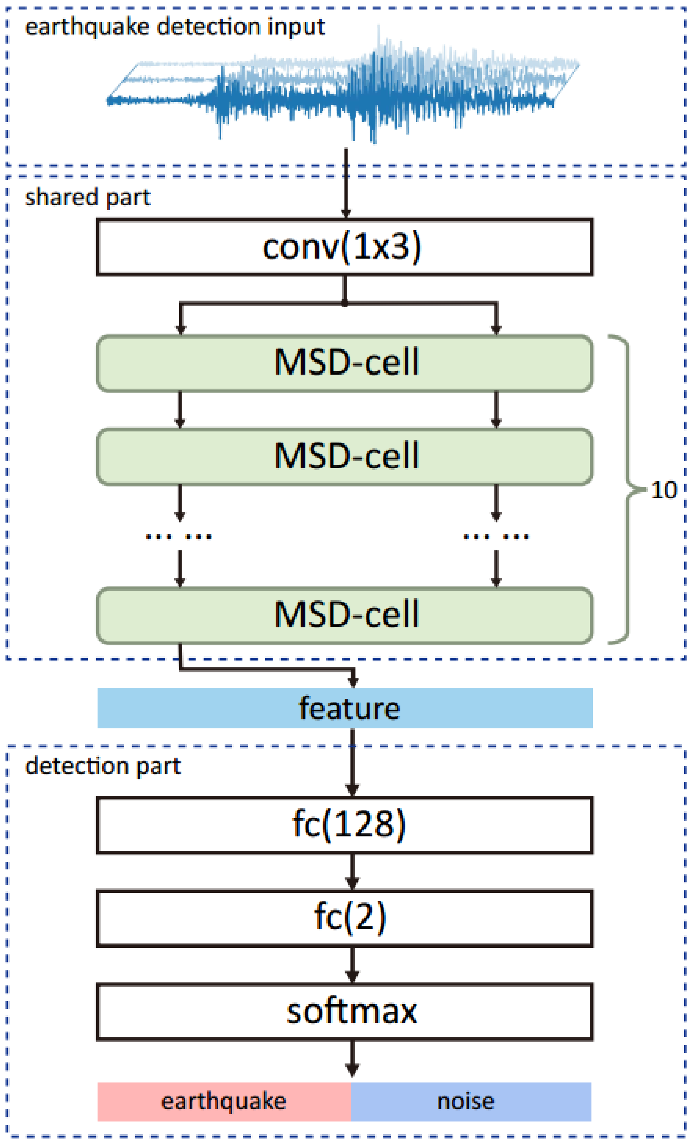

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Homologous Earthquake Waveforms

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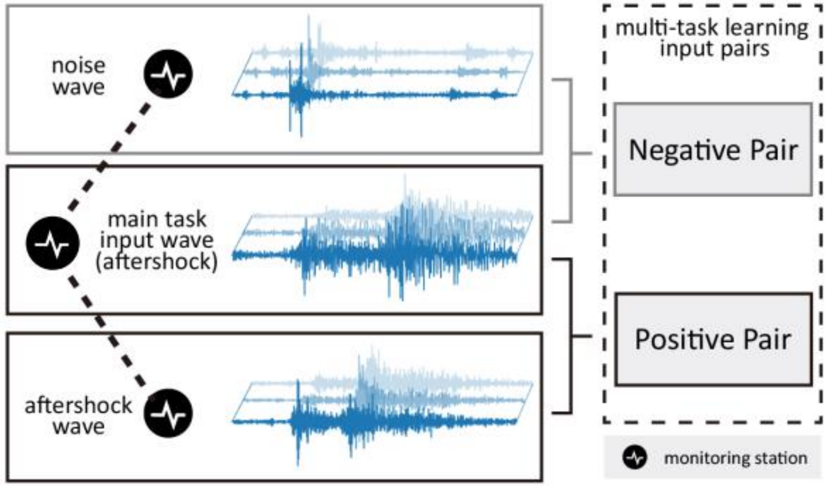
- Each pair of waveforms can be label as positive pair (means homology) or negative pair (means non-homology)



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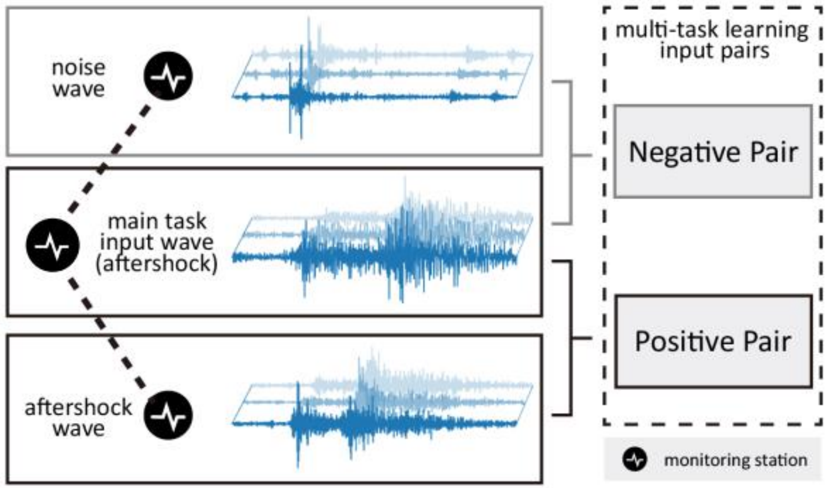

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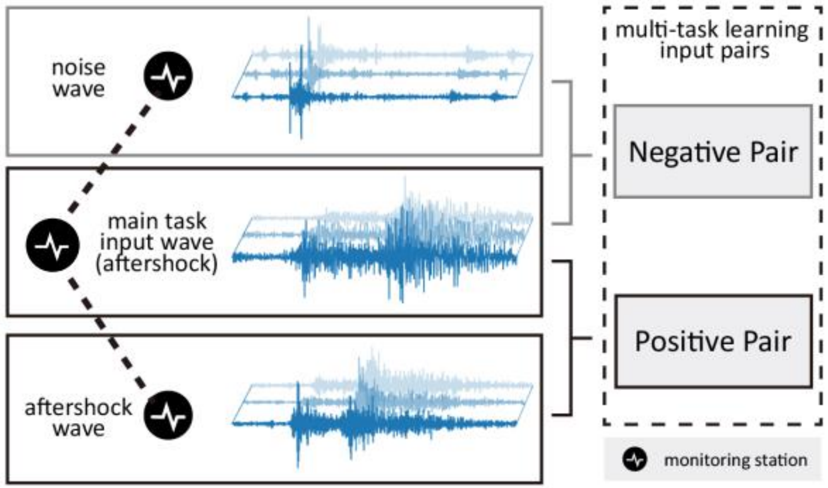

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Methodology

- **Multi-Task Learning Strategy**

  - **Auxiliary task** : homologous earthquake detection task.

  - **Main task**: aftershock detection task.

  - Auxiliary task can optimize the multi-scale description feature

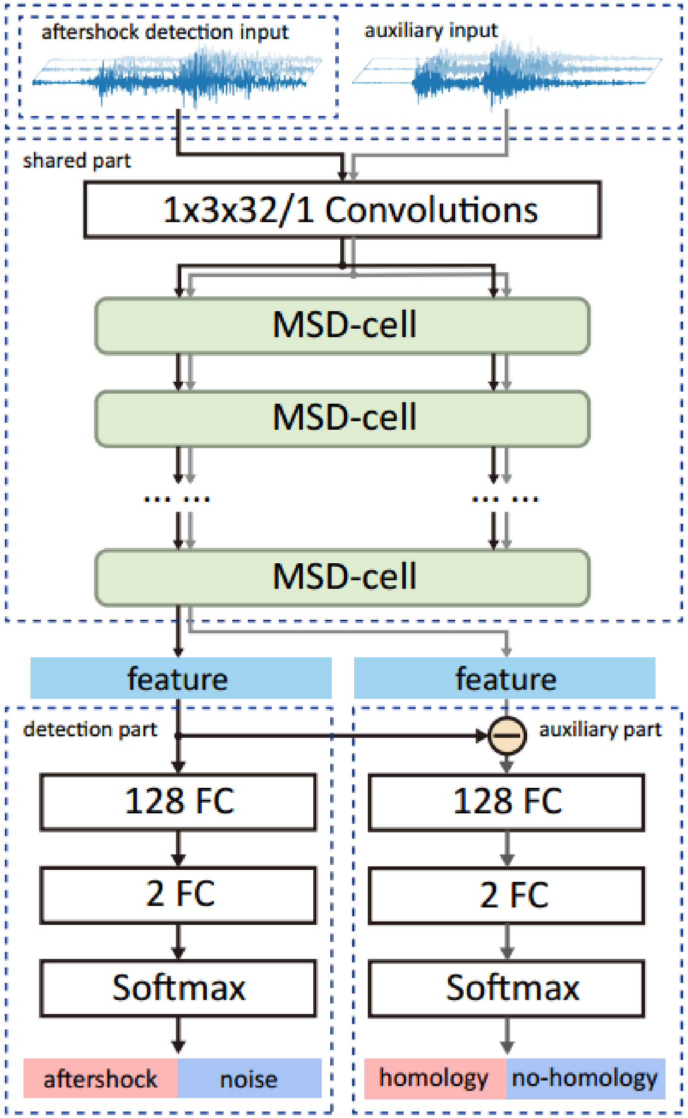

Fig. 4: The framework of MSDNN and multi-task learning, which is divided into shared, detection and auxiliary part.

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- **Multi-Task Learning Strategy**

  - **Auxiliary task** : homologous earthquake detection task.

  - **Main task**: aftershock detection task.

  - Auxiliary task can optimize the multi-scale description feature

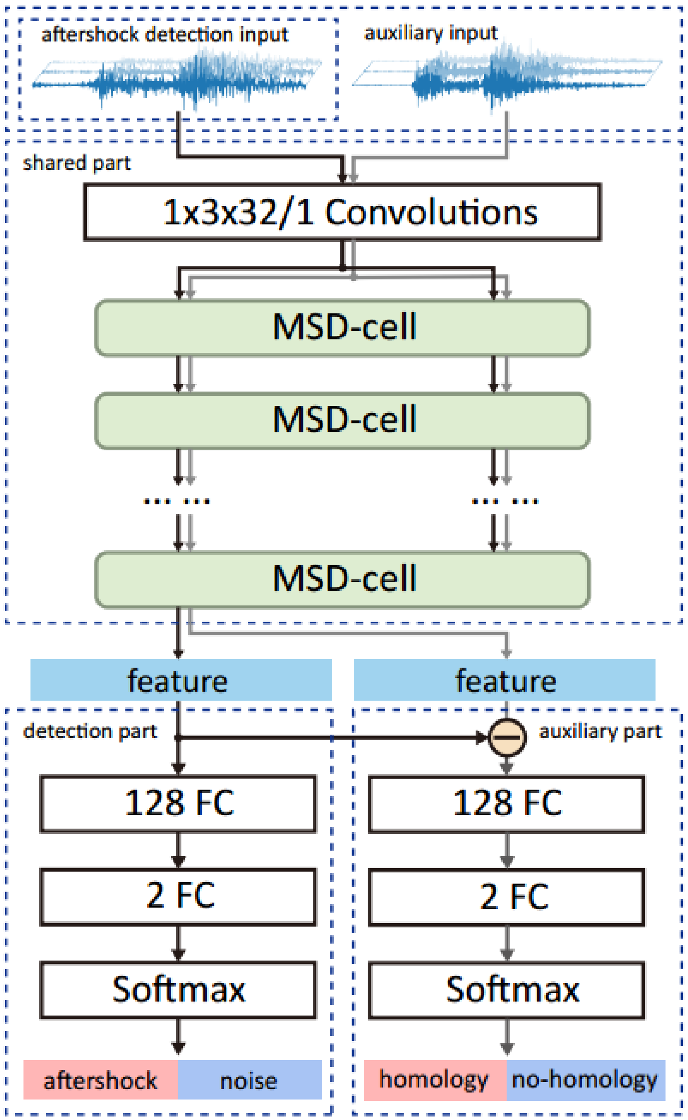

Fig. 4: The framework of MSDNN and multi-task learning, which is divided into shared, detection and auxiliary part.

Methodology

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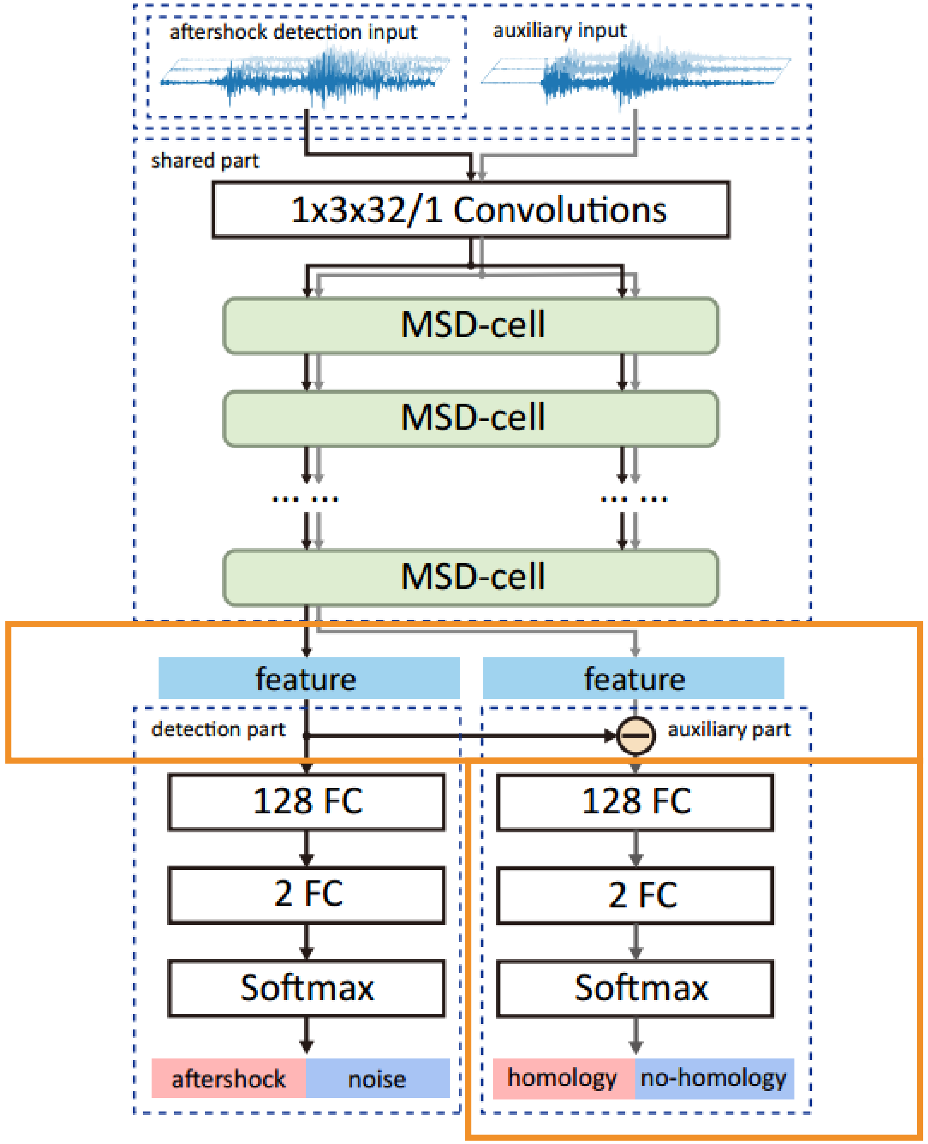

Fig. 4: The framework of MSDNN and multi-task learning, which is divided into shared, detection and auxiliary part.

Experiments

Overall Performance

- our **MSDNN** methods consistently outperform all the baselines.
- the **Multi-task Learning** can improve performance in all metrics.

TABLE III: The overall performance.

Method	Accuracy	Recall	Precision	F_1
Logistic Regression	0.505	0.520	0.080	0.130
Support Vector Machine	0.515	0.520	0.080	0.130
Random Forest [40]	0.767	0.680	0.190	0.300
XGboost [41]	0.882	0.770	0.350	0.490
ConvNetQuake [7]	0.935	0.602	0.544	0.571
Inception Net [11]	0.941	0.637	0.582	0.608
Our Solutions				
MSDNN	0.952	0.638	0.678	0.658
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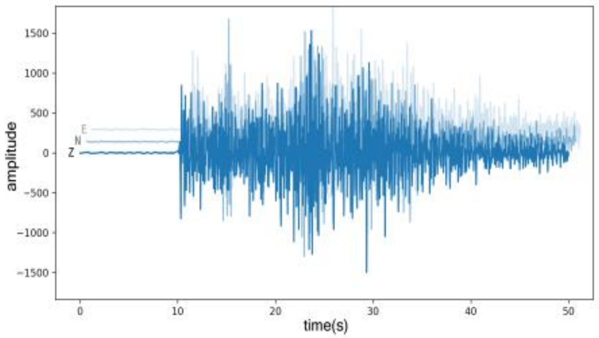
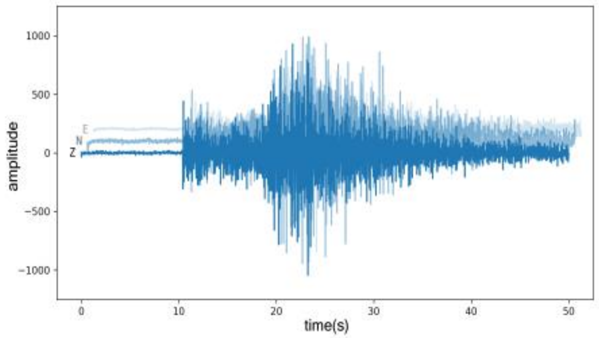
Case Studies

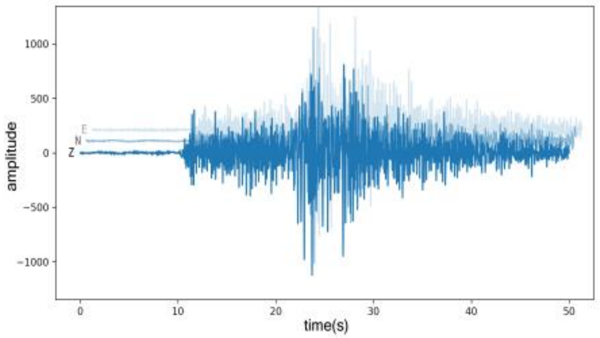
- The “False Positive” waveforms and the “True Positive” waveforms are similar.
- Several geophysical experts re-check 163 “False Positive” waveforms, and 161 waveforms of them were labeled as “Positive”. MSDNN framework can help manual checking.



(a) Average of False Positive



(b) True Positive



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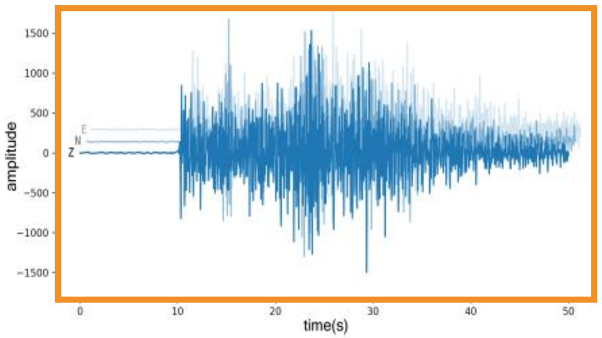

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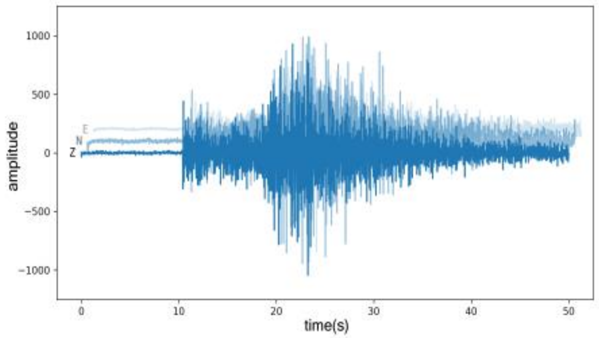

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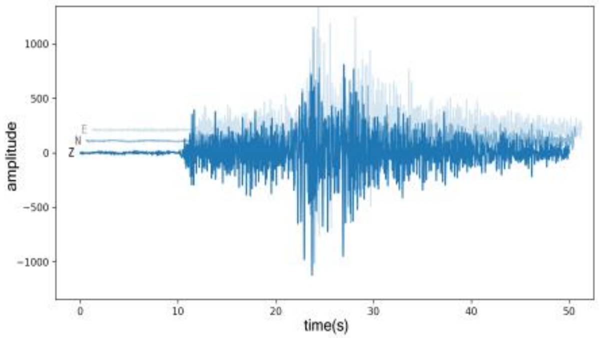

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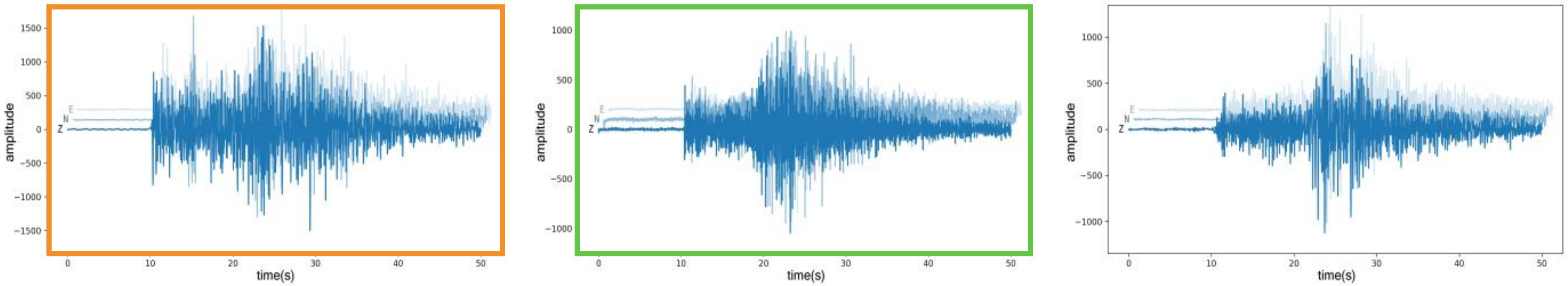

(a) Average of False Positive (b) True Positive (c) False Positive

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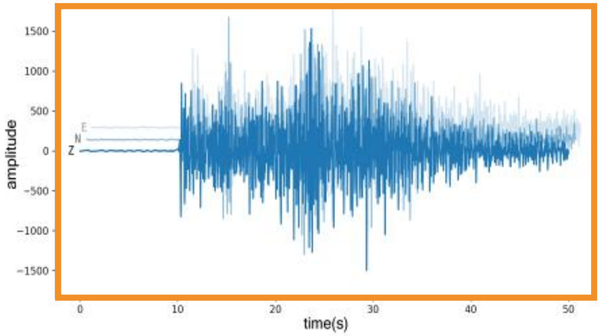

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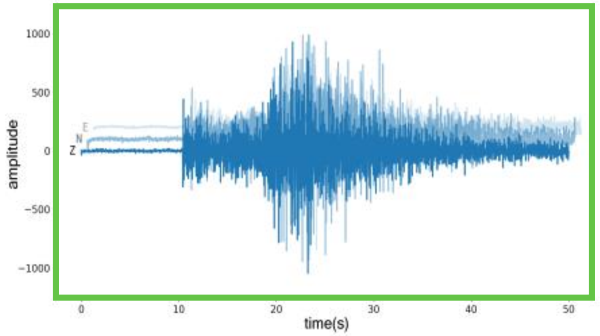
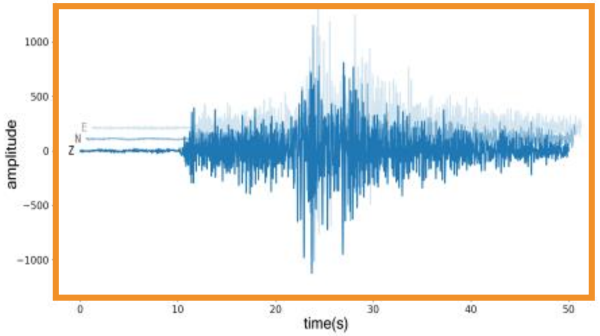


(b) True Positive



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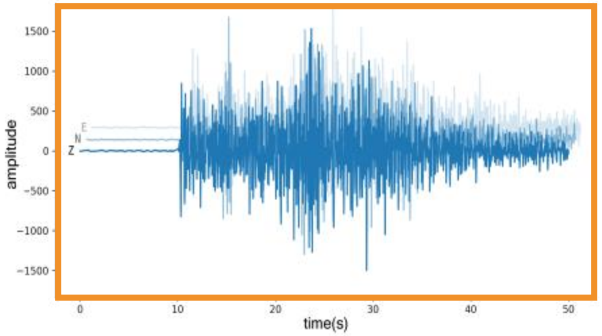

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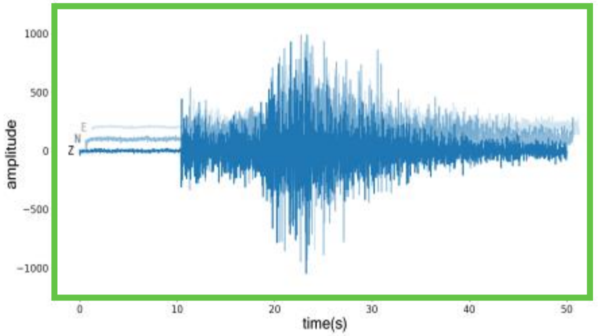
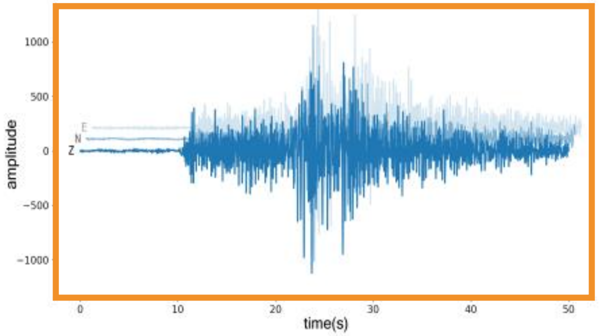


(b) True Positive



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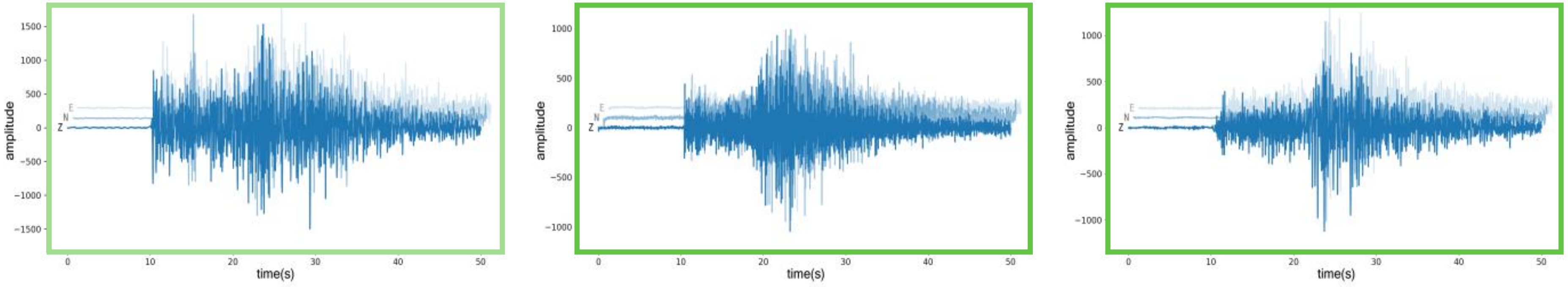
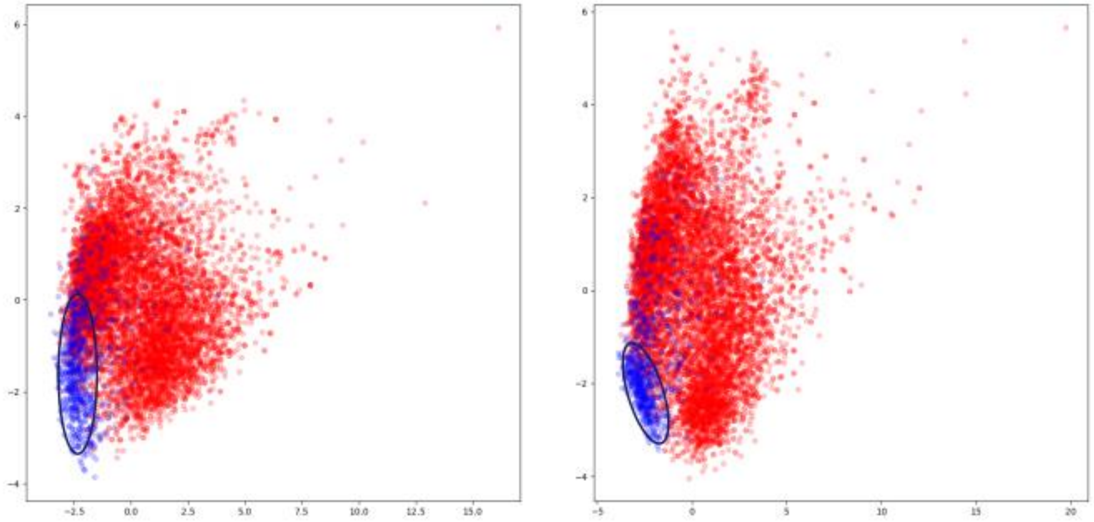


(a) Average of False Positive (b) True Positive (c) False Positive

Experiments

PCA Visualization

- Blue dots are the positive samples and the red dots are negative samples.
- The positive blue dots are close together and easily separated from the red dots when multi-task learning is deployed.



(a) MSDNN (b) MSDNN+Multi-task Learning

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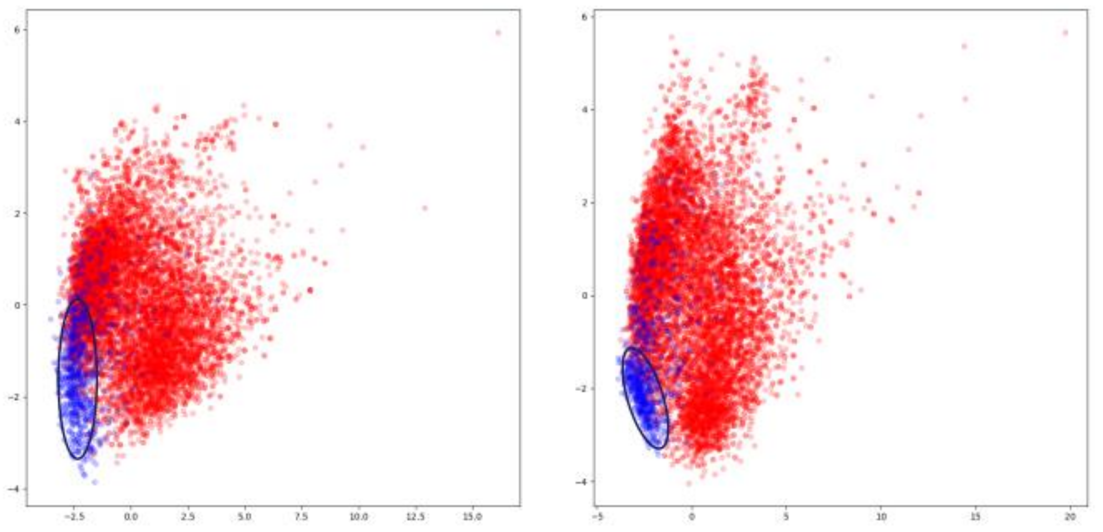

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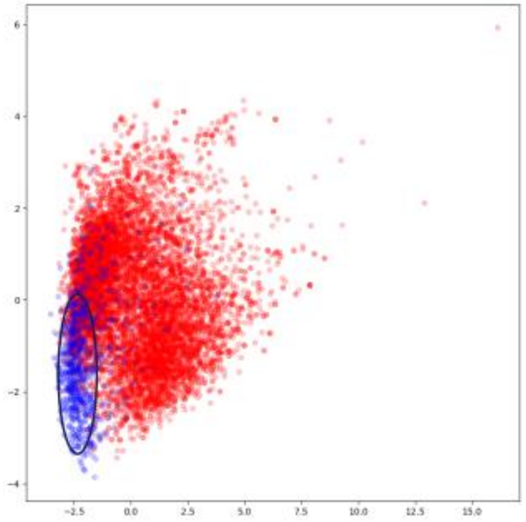

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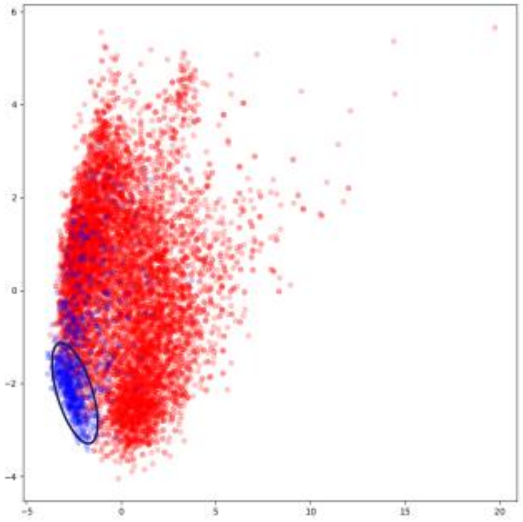

(b) MSDNN+Multi-task Learning

Conclusion

- **Contributions**
  - We propose a novel neural network based solution: **MSDNN (*Multi-Scale Description based Neural Network*)**
  - We design a **multi-task learning** strategy for utilizing the relationship between different monitoring stations.
  - We evaluate our framework on a **real-world data set** from aftershocks of the Wenchuan M8.0 Earthquake.
- **Future Work**
  - Earthquake Rapid Report and Time-series Event Detection

Thank you for listening !
Q&A

Reporter: Qi Zhang

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