Machine Learning-enhanced Realistic Framework for Real-time Seismic Monitoring - The Winning Solution of the 2017 International Aftershock Detection Contest

Dazhong Shen\textsuperscript{1,+,}\textsuperscript{1}, Qi Zhang\textsuperscript{1,+}\textsuperscript{1}, Tong Xu\textsuperscript{1,+,*}\textsuperscript{1}, Hengshu Zhu\textsuperscript{2,+,*}\textsuperscript{1}, Wenjia Zhao\textsuperscript{3}, Tikai Yin\textsuperscript{1}, Peilun Zhou\textsuperscript{1}, Lihua Fang\textsuperscript{4}, Enhong Chen\textsuperscript{1,\textbullet}\textsuperscript{1}, and Hui Xiong\textsuperscript{5,\textbullet}\textsuperscript{1}

\textsuperscript{1}University of Science and Technology of China, Hefei, Anhui, 230027, P.R. China
\textsuperscript{2}Baidu Inc., Beijing, 100085, P.R. China
\textsuperscript{3}Institute of Geology, China Earthquake Administration, Beijing, 100029, P.R. China
\textsuperscript{4}Institute of Geophysics, China Earthquake Administration, Beijing, 100081, China
\textsuperscript{5}Rutgers, the State University of New Jersey, Newark, NJ 07102, U.S.A
\textsuperscript{+}These authors contributed equally to this work.
\textsuperscript{*}The corresponding authors (zhuhengshu@gmail.com, tongxu@ustc.edu.cn, cheneh@ustc.edu.cn, xionghui@gmail.com).

ABSTRACT

Identifying the arrival times of seismic P-phases plays a significant role in real-time seismic monitoring, which provides critical guidance for emergency response activities. While considerable research has been conducted on this topic, efficiently capturing the arrival times of seismic P-phases hidden within intensively distributed and noisy seismic waves, such as those generated by the aftershocks of destructive earthquakes, remains a real challenge since existing methods rely on laborious expert supervision. To this end, in this paper, we present a machine learning-enhanced framework, ML-Picker, for the automatic identification of seismic P-phase arrivals on continuous and massive waveforms. More specifically, ML-Picker consists of three modules, namely, Trigger, Classifier, and Refiner, and an ensemble learning strategy is exploited to integrate several machine learning classifiers. An evaluation of the aftershocks following the $M_{S}0$ Wenchuan earthquake demonstrates that ML-Picker can not only achieve the best identification performance but also identify 120\% more seismic P-phase arrivals as complementary data. Meanwhile, experimental results also reveal both the applicability of different machine learning models for waveforms collected from different seismic stations and the regularities of seismic P-phase arrivals that might be neglected during manual inspection. These findings clearly validate the effectiveness, efficiency, flexibility and stability of ML-Picker. In particular, with the preliminary version of ML-Picker, we won the championship in the First Season and were the runner-up in the Finals of the 2017 International Aftershock Detection Contest hosted by the China Earthquake Administration, in which 1,143 teams participated from around the world.

Considerable research has been conducted on real-time seismic monitoring over the past few decades to mitigate earthquake damage. In this respect, one of the most important and relevant tasks is the identification of seismic P-phase arrivals, that is, to determine the exact arrival times of nondestructive primary earthquake waves, which travel more quickly through the Earth's crust than do the more destructive shear and surface waves. If such information could be determined in real time, emergency activities, such as the activation of early warning systems and the initiation of evacuation and rescue protocols, could be conducted in a more timely manner; as a result, the damage caused by earthquakes could be largely alleviated. Although this topic has received substantial attention from seismologists, it is still very challenging to effectively identify seismic P-phases hidden within intensively distributed and noisy seismic waves, such as those generated by the aftershocks of destructive earthquakes, which are often uniquely characterized by waves with a high frequency, weak signal regularity, large magnitude range, and various natural or artificial interference factors. A variety of methods, such as autocorrelation\textsuperscript{1,2}, template matching\textsuperscript{3–5}, similarity searching\textsuperscript{6} and higher-order statistics\textsuperscript{7–9}, have been developed in the literature for identifying seismic P-phase arrivals. Nevertheless, the most widely used methods are based on a comparison between the short-term average (STA) of a characteristic function (CF) of a waveform and the long-term average (LTA) of the CF\textsuperscript{10}; this approach is usually known as the STA/LTA algorithm or an energy ratio criteria-based algorithm\textsuperscript{11}. However, because the implementation of these traditional approaches is generally simple, their identification performance is usually limited, either due to the trade-off between false and missing alarms\textsuperscript{12} or due to the trade-off between the computational cost and time sensitivity\textsuperscript{6,8}. As a result, laborious and time-consuming human supervision is still needed in real-world seismic monitoring applications.

Recently, machine learning has been introduced into seismology and has provided unparalleled opportunities for seismologists to better understand seismic waveforms from a data-driven machine learning-assisted perspective. Machine learning
An overview of the ML-Picker framework, where the machine learning-assisted parts are highlighted with red lines. ML-Picker consists of three interactive function modules, namely, Trigger, Classifier, and Refiner. (a) With the continuous real-time waveform signals from individual stations as inputs, the Trigger module detects potential seismic P-phase arrival candidates with traditional methods, such as STA/LTA algorithms. (b) The Classifier module tries to introduce an effective discriminant model to evaluate the confidence level of each triggered P-phase candidate. With the features extracted from the waveforms near the potential arrivals, a number of distinct machine learning models are implemented to generate base model predictions. Then, a meta-model is used to integrate all these base predictions with an ensemble strategy and then output the final confidence level. (c) The Refiner module identifies the most accurate arrival times from among the highly confident seismic P-phase arrival candidates and rejects obvious outliers based on the Akaike information criterion (AIC) and the results from other stations. (d) A schematic diagram of the overall workflow in ML-Picker, where the blue and red bars indicate the thresholds of the confidence levels in the different modules and the width of the downward arrow indicates the number of identified arrivals.

Technologies, such as support vector machines (SVMs), hidden Markov models (HMMs) and neural networks (NNs), have been proven to achieve a competitive accuracy in pattern recognition applications and have been successfully applied in many fields of seismology, including earthquake detection, classification, and seismic phase arrival picking. Although the abovementioned machine learning-assisted methods can largely reduce labour costs, the accuracy, efficiency and stability of machine learning models cannot be fully guaranteed on continuous and massive waveforms, which restricts the application of machine learning technologies in real-time seismic P-phase arrival identification. More specifically, state-of-the-art studies in the literature focus on either identifying the time windows that contain earthquakes, or the capacity to determine the accurate arrival time of a seismic P-phase within a given time window. Indeed, most of these investigations were based on a sliding window strategy, whereas few considered how to select the most appropriate time windows from real-time, continuous seismic waveform data as candidates for machine learning models. Unfortunately, the sliding window strategy requires extensive computational resources, preventing the deployment of sophisticated machine learning models on real-time seismic monitoring systems.

To this end, in this study, we present a machine learning-enhanced framework known as ML-Picker for identifying seismic P-phase arrivals in a more automatic and real-time manner. The basic idea is to first use traditional approaches, e.g., STA/LTA, which require fewer computational resources, to filter out most of the noise; then, machine learning models are used to identify seismic P-phase arrivals in the remaining time windows. We validated the proposed framework based on the aftershocks following the M8.0 Wenchuan earthquake by simulating a real-time seismic monitoring scenario with the continuous waveforms recorded at multiple seismic stations. The experimental results clearly demonstrate the effectiveness, efficiency, flexibility and stability of ML-Picker, as well as some interesting observations. In particular, with the preliminary version of ML-Picker, we won the championship in the First Season and were the runner-up in the Finals of the 2017 International Aftershock Detection Contest hosted by the China Earthquake Administration, in which 1,143 teams participated from around the world.

Framework

The proposed framework ML-Picker is designed in a modular manner and consists of three components, namely, the Trigger, Classifier, and Refiner modules, as shown in Figure 1. More specifically, the Trigger module is designed to detect potential

---

1In the contest, we assembled only 5 unique machine learning models in ML-Picker.
seismic P-phase arrival candidates and then filter out most noise with traditional methods, while the Classifier module introduces an effective machine learning model to evaluate the confidence level of each triggered P-phase candidate, and the Refiner module identifies the most accurate arrival time from among the highly confident seismic P-phase candidates and rejects obvious outliers. Indeed, these three function modules are interactive and can be implemented in parallel for real-time seismic monitoring.

To guarantee a suitable identification efficiency, in the Trigger module, we propose to leverage traditional methods by implementing a variant of the STA/LTA algorithm (e.g., the FilterPicker\textsuperscript{11} algorithm) on the CFs of real-time waveform signals from individual stations. For every change in a CF that is beyond a pre-defined threshold, a potential seismic P-phase arrival candidate will be selected. Note that to capture as many seismic P-phase arrivals as possible, the threshold of the change in the CF should be relatively small.

However, in this situation, the number of false alarms will be relatively high. Therefore, we must further filter out positively labelled false candidates and identify seismic P-phase arrivals with a high confidence and reliability. In other words, once a potential arrival has been triggered, a time window of the waveforms near the arrival time will be conveyed to the Classifier module, which will effectively distinguish seismic P-phases from other signals (e.g., noise and seismic S-phases) with the features extracted within. In particular, to guarantee robustness, the Classifier module is also designed in a modular manner with ensemble learning\textsuperscript{23}; that is, a number of distinct base models (nine were used in our experiments) are implemented and integrated as a meta-model, which is also known as the stacking strategy\textsuperscript{24}. Here, a greater number of seismic P-phase arrivals would obtain a higher score from the meta-model as the confidence level. The fundamental idea of ensemble learning is to construct a predictive model by integrating multiple machine learning models, thereby improving the prediction performance\textsuperscript{23}.

In the Classifier module, each base model (e.g., an SVM\textsuperscript{25,26}) can be regarded as a theory for predicting the probability that one candidate is the true seismic P-phase arrival. However, in most cases, each individual theory contains certain biases that cause prediction errors; for example, SVMs with a linear kernel cannot process nonlinear feature components\textsuperscript{26}. Therefore, the stacking strategy used in ML-Picker tries to minimize this error by reducing these biases with respect to the provided learning set. The central concept is that we can do better than simply list many “theories”, which are consistent with the learning set, by constructing an optimal “theorist” that combines all those “theories”\textsuperscript{24}. Specifically, in ML-Picker, for each candidate sample, the meta-model integrates the predictions from all base models by using a linear model (logistic regression\textsuperscript{27}) was employed in our experiments), which can weigh each base model with linear coefficients. Accordingly, the base models can be improved through independent adjustments, and the Classifier module itself can boast a better performance through the selection of preferred base models.

Although the above mentioned modules can identify seismic P-phase arrivals with a high confidence level, some avenues remain with which to improve the results. For example, STA/LTA algorithms are usually not sufficiently sensitive to identify exact arrival times. Moreover, while a seismic event could be intuitively monitored by utilizing multiple adjacent stations, other modules take advantage of waveform signals from only individual stations, and thus, some misleading results might be obtained. Therefore, in the final step, we introduce the Refiner module to filter out the outliers and select the most accurate seismic P-phase arrivals as outputs. Specifically, in this study, we first propose to use the Akaike information criterion (AIC)\textsuperscript{28} to refine the arrival time of each candidate within a small time window near the original time point of each P-phase arrival. Then, for each identified seismic P-phase arrival, all other seismic stations that have also monitored the P-phase arrival are regarded as indicators with which to measure the multi-station-based confidence level. For example, we can reject the P-phase arrivals that are monitored by only one seismic station.

**Results**

Indeed, the proposed ML-Picker framework has achieved competitive performance with extensive experiments on a real-world aftershock data set, namely, the aftershocks of the M8.0 Wenchuan earthquake that occurred in Sichuan, China, on May 12, 2008; these data were provided by the Data Management Centre of the China National Seismic Network at the Institute of Geophysics, China Earthquake Administration (CEA). More specifically, 12,696 P-phase arrivals were manually picked by experts over a period of 28 days in August 2008 from waveforms recorded by 12 monitoring stations.

To comprehensively and intuitively evaluate the performance of ML-Picker, we applied the typical 4-fold cross-validation\textsuperscript{30} procedure to the Wenchuan data set. More specifically, we employed the data in each week as the test data, while the data in the other three weeks were utilized as the training data in four rounds of testing. For each moment within the seismic sequence to be judged, a short time window is cut to extract features for subsequent machine learning-assisted classification. Additionally, the length of the cut window is adjustable according to the desired accuracy; for example, as shown in Figure 2, we have a 5-second pre-window before the potential arrival as well as a 20-second post-window.

In the first set of validations, we attempted to evaluate the individual performance of the Classifier module in ML-Picker. To that end, we treated the aftershocks that were manually captured by experts as positive samples. Correspondingly, five times more negative samples were manually selected from the seismic sequences. The performances of the Classifier module
are summarized in the top half of Table 1, where the cross-validation results corresponding to different numbers of folds are illustrated separately. To produce a baseline with the same experimental settings for comparison, we also implemented another state-of-the-art machine learning-assisted approach, namely, ConvNetQuake\textsuperscript{13}, which is a highly scalable and effective convolutional NN (CNN) for earthquake detection applications. The results clearly reveal that the Classifier module can achieve a competitive performance in distinguishing between the true and false samples of P-phase arrivals within the cut time windows and consistently outperforms ConvNetQuake in terms of the precision, recall and F-score, which comprehensively considers the precision and recall through their harmonic average. Indeed, with ensemble learning, our Classifier module can also achieve better performance than other state-of-the-art machine learning models that were selected as base models (see Table S4 in the Supplementary Information).

Furthermore, we validated the robustness of the Classifier module with respect to the length of the time window. Intuitively, a larger time window could provide more information that could improve the detection accuracy, while a shorter time window might conserve time, which is beneficial for emergency response efforts. Therefore, striking a balance between the effectiveness and the efficiency of our framework constitutes an important discussion topic. Accordingly, we repeated the above cross-validation procedure for the Classifier module with different post-window lengths, i.e., 5, 10, 15 and 20 seconds. The performances are shown in the bottom half of Table 1. Evidently, the performance of the Classifier module is relatively stable with different time window lengths, indicating that our framework is not sensitive to the length of the cut time window.

Next, we evaluated the overall performance of the complete ML-Picker framework. More specifically, the experiments were conducted on complete and continuous seismic waveforms to simulate a real-world application scenario. In particular, if the time difference between one estimated P-phase arrival and one expert-labelled arrival was shorter than 0.4 seconds, we treated the estimated arrival as “correct”. In this way, we repeated the above two cross-validation experiments within the complete

### Table 1. The precision-recall performance of the Classifier module.

Here, “CVn” indicates the n-th fold of the cross-validation procedure, and the times in the brackets indicate the different post-window lengths for the validations.

|       | ConvNetQuake | Classifier Module |
|-------|--------------|-------------------|
|       | Precision    | Recall | F-Score | Precision | Recall | F-Score |
| CV1(20s) | 0.8409 | 0.8771 | 0.8586 | 0.8708 | 0.9289 | 0.8989 |
| CV2(20s) | 0.8788 | 0.8243 | 0.8507 | 0.9016 | 0.8864 | 0.8939 |
| CV3(20s) | 0.9034 | 0.7965 | 0.8466 | 0.9223 | 0.8632 | 0.8917 |
| CV4(20s) | 0.8999 | 0.8406 | 0.8693 | 0.9160 | 0.8690 | 0.8919 |
| CV1(10s) | 0.8523 | 0.8334 | 0.8428 | 0.8718 | 0.9092 | 0.8901 |
Table 2. The precision-recall performance of the ML-Picker framework with continuous seismic waveforms. Here, we demonstrate a performance comparison between the complete framework of ML-Picker (i.e., Trigger + Classifier + Refiner) and the partial framework in which the Classifier module is hidden.

|               | Trigger + Refiner | ML-Picker |
|---------------|-------------------|-----------|
|               | Precision | Recall | F-Score | Precision | Recall | F-Score |
| CV1(20s)      | 0.0017     | 0.9005 | 0.0034 | 0.3165     | 0.7926 | 0.4524  |
| CV2(20s)      | 0.0019     | 0.9102 | 0.0039 | 0.4163     | 0.7435 | 0.5337  |
| CV3(20s)      | 0.0018     | 0.9266 | 0.0036 | 0.4349     | 0.7317 | 0.5456  |
| CV4(20s)      | 0.0017     | 0.9221 | 0.0034 | 0.4167     | 0.7338 | 0.5316  |
| CV1(15s)      | 0.0017     | 0.9005 | 0.0034 | 0.3075     | 0.7885 | 0.4425  |
| CV1(10s)      | 0.0017     | 0.9005 | 0.0034 | 0.3098     | 0.7807 | 0.4436  |
| CV1(5s)       | 0.0017     | 0.9005 | 0.0034 | 0.3067     | 0.7836 | 0.4408  |

framework of ML-Picker (i.e., Trigger + Classifier + Refiner) and with a baseline that was modified from our framework by hiding the Classifier module (i.e., Trigger + Refiner). Indeed, the baseline could be regarded as a generalized version of the most widely used traditional approaches for identifying seismic P-phase arrivals. From the results summarized in Table 2, we find that ML-Picker consistently outperforms the baseline with a significant margin (i.e., approximately 200 times) in terms of precision, although the Classifier module loses some performance in terms of recall. Indeed, by comprehensively considering the precision and recall (i.e., by considering the F-score), the effectiveness of the ML-Picker framework has been thoroughly validated.

In particular, compared with Table 1, the performance shown in Table 2 seems worse. Moreover, several arrivals were captured by the ML-Picker framework with a high confidence level but were not labelled by the experts as aftershocks. This phenomenon may have two potential explanations. First, compared with a simple classification task in which samples are picked in advance within a given time window, in the validations on continuous seismic waveforms, sometimes ML-Picker captured one potential arrival, but it was beyond the pre-defined 0.4 second threshold; in this case, the real-time monitoring of continuously seismic waveforms could be much more difficult. Second, we neglected to consider that the manually labelled data set could contain some trivial omissions, leading to misjudgement. This issue will be discussed later in this article.

Finally, we attempted to validate the sensitivity of ML-Picker to the time difference. To that end, we evaluated different time difference boundaries to discriminate among the correct arrivals in the interval of [0 s, 1 s]. The performances of ML-Picker with different settings are shown in Figure 3. Both the precision and the recall increase with increasing boundaries and tend to converge after 0.4 seconds, which means that the time differences between the identified P-phase arrivals and the expert-labelled arrivals are almost less than 0.4 seconds.

Based on the above results, both of the effectiveness and the efficiency of the ML-Picker framework have been validated.

Figure 3. The sensitivity to the time difference within the ML-Picker framework. (a) The precision (solid) and recall (dashed) curves for the validations of ML-Picker with different time difference boundaries. (b) The precision (solid) and recall (dashed) curves for the validations of ML-Picker with different time difference boundaries and different post-window lengths in the “CV1” data set.
Discussion

As we have validated the effectiveness and efficiency of ML-Picker, we now verify additional characteristics of the ML-Picker framework to further ensure its applicability in real-world scenarios. Indeed, due to the differences among various geographical environments, the seismic waveforms recorded by different stations may contain different characteristics, even for the same earthquake. Therefore, we would like to investigate whether the ML-Picker framework can be reasonably applied for various types of seismic waveforms. The Classifier module of ML-Picker is intuitively designed in a modular manner with ensemble learning to guarantee the scalability of identification compared with individual machine learning models. To that end, we designed a case study on the Wenchuan data set. More specifically, for each monitoring station in the Wenchuan data set, we separately trained the model to estimate its personalized parameters, i.e., the weight for each base model selected during the ensemble learning process. Afterwards, we clustered 12 stations based on their personalized parameters, resulting in the 4 clusters shown in Figure 4. Generally, the red cluster is located along the centre of the Longmenshan Fault, while the purple cluster is surrounded by mountains, the blue cluster lies along the edge of the mountain range and faults, and the yellow cluster is far from the faults and lies within the plain. Obviously, the clustering results as well as the personalized parameter settings are highly correlated with the geographical environment, which correspond to the different models selected in ML-Picker. For example, for the stations near the faults (i.e., the red cluster), the weights of RandomForest, SVM-linear and Adaboost are significantly higher than those of the other base models. For the stations throughout the mountains (i.e., the purple cluster and the blue cluster), RandomForest is the most prominent choice, while for the stations on the plain (i.e., the yellow cluster), the weights of the base models vary in a smaller range.

Next, we will discuss a special issue observed in the previous validations. As mentioned above, for each experiment in the second validation, several arrivals were captured by the ML-Picker framework with a high confidence level but were not labelled by the experts as aftershocks. To ensure the applicability of ML-Picker, we have to check whether the technical framework needs further refinement or if the manually labelled data set contains some trivial omissions. Correspondingly, we randomly selected 1,000 samples (arrivals) with a higher confidence than the threshold from the seismic sequences. Then, an expert from the CEA was asked to review these samples with exceptional scrutiny and caution to reduce the false alarm rate. According to the results, 907 captured P-phases among the 1,000 random samples were judged as aftershocks, further validating the effectiveness of ML-Picker. However, 125.6% more P-phases than the expert-labelled data were ignored during the first round of labelling, which raises the new challenge for explaining the ignorance during manual inspection.

We first counted the average amplitude for each arrival and its time window, including a 5-second pre-window and a 30-second post-window. As shown in the first row of Figure 5, the differences between the expert-labelled earthquakes and missing aftershocks have the potential to be dramatically significant. More specifically, among the expert-labelled earthquakes (the left figure in the first row), the waveforms exhibit violent fluctuations at approximately 15-25 seconds after the earthquakes. In contrast, at the corresponding periods in the missing aftershocks (the right figure in the first row), the waveforms are relatively stable with a lower signal-to-noise ratio (SNR). In these cases, the secondary phase arrivals, i.e., after 25 seconds, could be even more distinct, which suggests a long distance between the epicentre and monitoring stations (more examples are shown in Figure S2 in the Supplementary Information). A similar rule could also be revealed by the modelling process; we applied the recurrent attention (RA)-CNN model to the spectral waterfalls of two kinds of seismic P-phase arrivals. As shown in the
Figure 5. Case study on the statistics/model-based distinction between labelled and missing P-phases. The figures in the first row illustrate the average amplitude of each time window around the P-phase arrival for both labelled (left) and missing (right) P-phases. The figures in the second row illustrate the attention mask covering the spectral waterfall of an expert-labelled seismic P-phase arrival estimated by the RA-CNN and a magnified view of the peaks of S-phases, which should be investigated during this procedure.

According to these results, we conclude that regional earthquakes with insignificant waveforms around the peaks of S-phases can be easily ignored during manual labelling, especially when large earthquakes occur; furthermore, manual labelling can be an urgent yet laborious task for geophysical experts. Consequently, significant earthquakes may be identified first with the highest priority, while insignificant earthquakes may be ignored. This phenomenon is certainly reasonable: we always tend to finish the easiest questions in a quiz and leave the hardest questions for the end or even abandon them due to time limitations. At the same time, we also verify that ML-Picker could effectively assist experts in retrieving missing earthquakes, thereby diminishing the heavy burden of the labelling task.

In summary, with two layers of modular capabilities, i.e., the assembly of the Trigger, Classifier and Refiner modules and the design of the Classifier module with ensemble learning consisting of multiple machine learning techniques, the ML-Picker framework has been verified as a competitive solution for seismic monitoring applications due to its effectiveness and efficiency, as well as its flexibility and stability. Moreover, since ML-Picker can identify low-SNR earthquakes, the monitoring performance can be further refined with reduced manual burden.

Methods

Data Description
The data set employed for the validations consists of the aftershocks of the M8.0 Wenchuan earthquake that occurred in Sichuan, China, on May 12, 2008; all the aftershocks were recorded at 100 Hz on three channels corresponding to the three spatial dimensions, i.e., HHZ for the vertical channel, HHN for the north-south channel, and HHE for the east-west channel. We display a waveform on the HHZ channel as an example in Figure 2 (more examples are shown in Figure S1 in the Supplementary
Information). To ensure the quality of the data, all the records were automatically checked to remove some erroneous fragments, which usually contain mechanical noise or even no signal at all. Accordingly, a total of 12,696 P-phase arrivals in the Wenchuan data set were labelled over a course of 4 weeks; 3,447, 3,442, 2,997 and 2,810 P-phase arrivals were picked in each successive week. Subsequently, to train and evaluate the Classifier module, we selected five times more negative samples from potential candidates located far away from the labelled arrivals (more than 0.4 seconds) that were previously picked by the Trigger module. These negative samples included all types of waveform signals, such as noise, inaccurate seismic P-phase arrivals, and seismic S-phase arrivals.

Technical Details of ML-Picker

As mentioned above, the ML-Picker framework contains three components, namely the Trigger, Classifier and Refiner modules. In the following sections, we will separately introduce their technical details.

- The Trigger module was implemented by FilterPicker\textsuperscript{11}, a broadband phase picking algorithm that is loosely based on the short-term average/long-term average (STA/LTA) algorithm. The first step in FilterPicker is to perform multi-bandpass filtering on the signal. In the validations, we utilized three bands (2.5-5 Hz, 5-10 Hz, and 10-20 Hz) of waveform signals on channel HHZ. Then, a CF, which includes several parameters, namely, the triggering threshold $S_1$, the time width $T_{up}$ and the average threshold $S_2$, was defined to monitor each time step to check for triggers or picks. At a certain moment $t$, if the function value of $t$ exceeds $S_1$ and the average function value during the time window $T_{up}$ after $t$ exceeds $S_2$, the moment $t$ will be recorded as a potential P-phase arrival. In the validations, the thresholds were set as $S_1 = 6$, $S_2 = 2$ and $T_{up} = 0.3$ (seconds). Compared with the literature\textsuperscript{11}, we selected smaller $S_1$ and $S_2$ values to ensure high recall values for the outputs.

- The Classifier module was implemented by using machine learning approaches in a modular manner with the stacking strategy. Then, 9 commonly used classifier models, namely, SVM-linear, SVM-poly\textsuperscript{12}, Tree-gini, Tree-entropy\textsuperscript{34}, K-nearest Neighbors (KNN), RandomForest\textsuperscript{31}, Adaboost\textsuperscript{32}, Logistic Regression\textsuperscript{27}, and Gaussian Naive Bayes\textsuperscript{35}, were intuitively selected as the base models. The complete training stage was designed as follows. First, all the training data were divided into 5 parts. Second, for each base model, we applied a 5-fold cross-validation procedure on all the labelled samples (including the expert-labelled positive samples and randomly selected negative samples in the first validation for the individual Classifier module, as mentioned in the Results section). Third, as each sample was assigned 9 judgements (i.e., by the 9 machine learning models mentioned above), logistic regression was performed to achieve the weights for each base model based on the judgements and corresponding labels. Finally, we trained the best solution of each base model on all the training data and then combined those solutions based on the weights achieved in the previous step. Evidently, the stacking strategy with a competitive and stable performance can benefit the Classifier module. In the validation stage, for each waveform window, the Classifier module outputs its confidence level score, and the windows with higher scores than the pre-defined threshold (set to 0.5) are regarded as potential seismic P-phase arrivals (the corresponding details for the parameter settings of each base model and the meta-model are provided in Table S1 in the Supplementary Information).

- The Refiner module contains two parts. The first part was implemented by using the Akaike information criterion (AIC)\textsuperscript{28} to refine the time of each potential seismic P-phase arrival. Specifically, with the AIC, the waveform window can be divided into two different stationary segments, and the demarcation point represents the accurate arrival time. Thus, we applied the AIC to refine the arrival time within a short window of $\pm 1$ second around each estimated P-phase arrival. The second part attempts to reveal whether some arrivals are caused by the same aftershock. To that end, for any pair of arrivals, we checked whether their time difference was shorter than the maximal P-wave propagation time approximated as $Distance/v_p$. Here, $v_p$ is set as 5.5km/s, which is less than the average P-wave velocity in Sichuan to tolerate some error. Additionally, to filter out the outliers, all P-phase arrivals that were recorded by only one monitoring station were removed.

Classification Features

Next, we summarize the features we utilized in the Classifier module. For different post-window lengths of 5-20 seconds, we extracted 679-715 different features (the details are summarized in Tables S2 and S3 in the Supplementary Information), which can be roughly divided into 4 kinds of features as follows:

- **Amplitude Fluctuation.** Considering the sharp fluctuations in the amplitudes of the P-phase arrivals, we selected 5-8 short time windows (according to post-window length) around the arrivals, and then filtered the waveforms on all the 3 channels with 2 bandwidths (2-10Hz and 10-20Hz) to compute 2 values, namely the mean value and the variance of amplitude. In summary, we contained 60-96 features for amplitude fluctuation.
- **Maximal Amplitude.** Considering that the S-phase usually follows the P-phase with a maximal amplitude, especially on the horizontal channels. Thus, we summarized the maximal amplitude on all 3 channels, resulting in 3 features. Additionally, we computed the **mean value** and **variance** of the amplitude within a window of ±1 second around the maximal amplitude, on both the HHN (north-south) and the HHE (east-west) channels; consequently, we obtained additional 4 features. Moreover, the features were extracted with 2 bandwidths (2-10Hz and 10-20Hz), which results in a total of 14 features in total.

- **Spectral Waterfall.** Considering the importance of the spectral waterfall of waveform around the P-phase arrival, we selected a short window of ±1 second around each estimated arrival, and then divided it into 10 segments. For each segment, we filtered the waveform with 9 adjacent bandwidths lower than 50Hz to compute 2 values, namely the **mean value** and the **variance** of the amplitude. The features were extracted on all the 3 channels, which results in total of 540 features in total.

- **Other Feature.** In addition, some other features, such as the polarization and envelope slope of the arrivals, were extracted to enhance the classification. In total, 65 additional features were extracted, and more details about these features will be introduced in Supplementary Information.

**Details for the Validations and Case Studies**

- **Evaluation Metrics.** To evaluate the performance, we applied **precision** and **recall** as the metrics. The **precision** indicates the ratio of “correct” arrivals among all the estimated arrivals, while the **recall** indicates the ratio of “correct” arrivals captured among all the expert-labelled arrivals. The “F-score” is another metric of the testing accuracy that considers both “precision” and “recall” and can be computed through their harmonic average.

- **Details for ConvNetQuake.** We implemented the convolutional neural network (CNN), **ConvNetQuake**, with the same network architecture and parameter settings as the guide from Perol et al.\(^\text{18}\) to trained and tested it on our data set.

- **Clustering Details.** To further discuss the flexibility and stability of **ML-Picker**, we clustered the monitoring stations based on their similar model selections for ensemble learning. For each monitoring station in the Wenchuan data set, we separately trained the model with the data from all four weeks to estimate the personalized parameters of each station as a 9-dimensional vector (the detailed personalized parameters for each station are shown in Table S5 in the Supplementary Information). Then, we divided all the 12 stations into 4 clusters by the K-means method. It should be noted that the K-means algorithm could retrieve a biased model whose output could be severely affected by the initial centre of a cluster. To address this problem, we repeated the clustering process a sufficient number of times to ensure the confidence for the clustering results, as shown in Figure 4.

- **RA-CNN Details.** For the case study, to re-inspect the P-phase arrivals, we utilized the recurrent attention (RA)-CNN model\(^\text{35}\) to train a classifier to differentiate the spectral waterfalls of expert-labelled and missing P-phase arrivals to discover their significant differences. The RA-CNN can find an attention region in the spectral waterfall to obtain better classification results than can be achieved with the full-size spectral waterfall. Compared with the original network, our RA-CNN consists of two stages. The inputs of the first stage are the full-size spectral waterfalls of the seismic waveforms, whereas the inputs of the second stage are the attention regions. More specifically, in different stages, spectral waterfalls were fed into three convolutional layers with depths of 16, 32, and 64; in the first stage, a region-based feature representation was extracted by an additional attention proposal network. Then, the results of both stages were evaluated to predict the probability scores by using one 128-unit fully connected layer and a softmax layer. The proposed RA-CNN was optimized for convergence by alternatively learning the softmax classification loss in each stage and a pairwise ranking loss across neighbouring stages. We used **L2** regularization with normalization on each layer and used the Adam optimizer to train the network.

**Limitation**

In this study, we focus mainly on the task of seismic P-phase arrival identification. Indeed, **ML-Picker** is a general framework for identifying seismic phase arrivals and thus is also applicable for determining the arrival times of other seismic phases (e.g., seismic S-phases) through training the phase-specific **Classifier** module.

**Programming Environment**

Our programs were implemented in a Linux operating system with the standard packages available in Python 3.4.5. Specifically, we filtered waveforms with the scipy (0.19.1) package, **ML-Picker** was implemented with the sklearn (0.19.0) package, and all other computational processes and statistical analyses were implemented with the Numpy (1.13.3) package.
Data Availability
The seismic data that support our findings in this study were provided by CEA\textsuperscript{29}, as a part of the Aftershock Detection Artificial-Intelligence Contest\textsuperscript{29}.

Code Availability
All codes of this project are available upon request.

References
1. Brown, J. R., Beroza, G. C. & Shelly, D. R. An autocorrelation method to detect low frequency earthquakes within tremor. Geophysical Research Letters \textbf{35} (2008).
2. Aguiar, A. C. & Beroza, G. C. Pagerank for earthquakes. Seismological Research Letters \textbf{85}, 344–350 (2014).
3. Shelly, D. R., Beroza, G. C. & Ide, S. Non-volcanic tremor and low-frequency earthquake swarms. Nature \textbf{446}, 305 (2007).
4. Plenkers, K., Ritter, J. R. & Schindler, M. Low signal-to-noise event detection based on waveform stacking and cross-correlation: application to a stimulation experiment. Journal of seismology \textbf{17}, 27–49 (2013).
5. Yoon, C. E., O'Reilly, O., Bergen, K. J. & Beroza, G. C. Earthquake detection through computationally efficient similarity search. Science advances \textbf{1}, e1501057 (2015).
6. Saragiotis, C. D., Hadjileontiadis, L. J. & Panas, S. M. A higher-order statistics-based phase identification of three-component seismograms in a redundant wavelet transform domain. In Higher-Order Statistics, 1999. Proceedings of the IEEE Signal Processing Workshop on, 396–399 (IEEE, 1999).
7. Riggelsen, C. & Ohrnberger, M. A machine learning approach for improving the detection capabilities at 3c seismic stations. Pure and Applied Geophysics \textbf{171}, 395–411 (2014).
22. Zhu, W. & Beroza, G. C. Phasenet: a deep-neural-network-based seismic arrival-time picking method. *Geophysical Journal International* **216**, 261–273 (2018).

23. Rokach, L. Ensemble-based classifiers. *Artificial Intelligence Review* **33**, 1–39 (2010).

24. Wolpert, D. H. Stacked generalization. *Neural networks* **5**, 241–259 (1992).

25. Cortes, C. & Vapnik, V. Support-vector networks. *Machine learning* **20**, 273–297 (1995).

26. Cristianini, N., Shawe-Taylor, J. et al. An introduction to support vector machines and other kernel-based learning methods (Cambridge university press, 2000).

27. Cox, D. R. The regression analysis of binary sequences. *Journal of the Royal Statistical Society. Series B (Methodological)* **215**–242 (1958).

28. Akaike, H. A new look at the statistical model identification. *IEEE transactions on automatic control* **19**, 716–723 (1974).

29. Fang, L., Wu, Z. & Song, K. Seismolympics. *Seismological Research Letters* **88**, 1430–1430 (2017).

30. Kohavi, R. et al. A study of cross-validation and bootstrap for accuracy estimation and model selection. In *IJcai*, vol. 14, 1137–1145 (Montreal, Canada, 1995).

31. Ho, T. K. Random decision forests. In *Document analysis and recognition, 1995., proceedings of the third international conference on*, vol. 1, 278–282 (IEEE, 1995).

32. Freund, Y. & Schapire, R. E. A decision-theoretic generalization of on-line learning and an application to boosting. *Journal of computer and system sciences* **55**, 119–139 (1997).

33. Fu, J., Zheng, H. & Mei, T. Look closer to see better: Recurrent attention convolutional neural network for fine-grained image recognition. In *CVPR*, vol. 2, 3 (2017).

34. Breiman, L. *Classification and regression trees* (Routledge, 2017).

35. Russell, S. J. & Norvig, P. *Artificial intelligence: a modern approach* (Malaysia; Pearson Education Limited, 2016).

36. Hartigan, J. A. & Wong, M. A. Algorithm as 136: A k-means clustering algorithm. *Journal of the Royal Statistical Society. Series C (Applied Statistics)* **28**, 100–108 (1979).

**Acknowledgement**

We thank Mingshuai Tang for labeling the experimental results; Chen Zhu, Chao Ma, Qi Liu, Ying Sun, Baoshan Wang and Haitao Wang for helpful discussions and advice; and the rest members of the Baidu Talent Intelligence Center for their support, ideas and encouragement.

**Author Contributions**

D.Z.S, Q.Z, T.X and H.S.Z designed and implemented the framework of *ML-Picker*. D.Z.S, Q.Z, T.X, H.S.Z and W.J.Z conceived the experiment and evaluated the results. D.Z.S, Q.Z, Z.K.Y and P.L.Z processed the data and implemented the feature extraction of *ML-Picker*. W.J.Z and L.H.F advised on the literature review, data process and technical design of *ML-Picker*. T.X, H.S.Z, H.X, and E.H.C managed and advised on the project. D.Z.S, Q.Z, T.X, H.S.Z and H.X wrote the paper.

**Competing Interests and Author Information**

Reprints and permissions information is available at www.nature.com/reprints. The authors declare no competing financial interests. Correspondence and requests for materials should be addressed to T.X (tongxu@ustc.edu.cn), H.S.Z (zhuhengshu@gmail.com), E.H.C (cheneh@ustc.edu.cn) or H.X (xionghui@gmail.com).
## Supplementary Information

**Table S1. Parameter settings for all base models and the meta-model in the Classifier module.** The *Classifier* module was implemented by sklearn package in python 3.4.5.

| base-models | Functions in Python | Parameter settings |
|-------------|----------------------|--------------------|
| SVM-linear  | sklearn.svm.SVC      | kernel='linear', gamma=0.1, C=1.0 |
| SVM-poly    | sklearn.svm.SVC      | kernel='poly', gamma=0.1, C=1.0 |
| Gaussian Naive Bayes | sklearn.naive_bayes.GaussianNB | default |
| KNN         | sklearn.neighbors.KNeighborsClassifier | algorithm='ball.tree' |
| Logistic Regression | sklearn.linear_model.LogisticRegression | penalty='l2',C=1.0 |
| RandomForest | sklearn.ensemble.RandomForestClassifier | n_estimators=1000,max_depth=10 |
| Adaboost    | sklearn.ensemble.AdaBoostClassifier | n_estimators=1000 |
| Tree-gini   | sklearn.tree.DecisionTreeClassifier | criterion='gini' |
| Tree-entropy| sklearn.tree.DecisionTreeClassifier | criterion='entropy' |

| meta-model | Functions in Python | Parameter settings |
|------------|----------------------|--------------------|
| Logistic Regression | sklearn.linear_model.LogisticRegression | penalty='l2',C=10.0 |
Table S2. Detail Computation of Some Features Functions. Specifically, functions mean(x), max(x) var(x) aim to compute the average, maximum and variance of the amplitudes (absolute value) in time window x. Function sum(y) sums each element in vector y. Function x.index(a) aims to find the position of value a in time window x. Function cov(v) outputs the covariance matrix of vector v. Function eign(mv) tries to compute the all eigenvalues of matrix mv.

| Function                              | Input for functions                                                                 |
|---------------------------------------|-------------------------------------------------------------------------------------|
| Normalization(x)                      | Input: time window x  
Output: \(x - \text{mean}(x)\) \(\sqrt{\text{var}(x)}\) |
| Root Mean Square(RMS) Amplitude Ratio(x,y) | input: two time windows x, y  
Output: \(\sum[t^2 \text{ for } t \text{ in } x]\) \(\sum[t^2 \text{ for } t \text{ in } y]\) |
| Mean Difference(x, y)                 | Input: two time windows x, y  
Output mean(x) − mean(y) |
| Envelope Slope(x)                     | Input: time window x with range (-5, 5)  
a = max(x[-5, -1.5])  
ta = x[-5, -1.5].index(a)  
b = max(x[1.5 : 5])  
tb = x[1.5 : 5].index(b)  
c = max(x[-0.5 : 0.5])  
tc = x[-0.5 : 0.5].index(c)  
Output: \(\frac{c-a}{100(tc-ta)}\), \(\frac{c-b}{100(tc-tb)}\) |
| Polarization Slope(a,b,c)             | Input: the amplitudes of the arrival in three channels, a, b, c  
v = vector(a,b,c)  
mv = covariance(v)  
a, b, c = eign(mv)  
Output: \(\frac{(a-b)^2+(a-c)^2+(b-c)^2}{2(a+b+c)^2}\) |
### Table S3. Detail Computation of Features for Classification

$AN > 5$ is the length of post-window in the windows conveyed from the *Trigger* module. The interval in the column titled by “time window”, represents the selected short time windows for computation of specific feature, where the time point of arrival is tagged by 0, the negative number means the time length before the arrival and the positive number means the time length after the arrival. And, all computation processes in the last column operate on corresponding time windows, which have been normalized by *Normalization* function in Table S2.

| Time window /second | Bandwidth /HZ | Channel | Computation process for each time window $x$ with each bandwidth in each channel | Number of features |
|---------------------|---------------|---------|---------------------------------------------------------------------------------|-------------------|
| **Amplitude Fluctuation** | (-5, 0), (0, AN), (-1, 0), (0, -1) (5(i-1), 5i) $1 \leq i \leq \text{int}(AN/5))$ | 2-10 10-20 | HHE HHN HHZ | mean($x$) var($x$) 48+ 12×int(AN/5) |
| **Maximal Amplitude** | (2, AN) | 2-10 10-20 | HHE HHN HHZ | idx=x.index(Max($x$)) mean($x[idx-1, idx+1]$) var($x[idx-1, idx+1]$) 12 |
| **Spectral Waterfall** | (-0.2, 0), (0, 0.2) (-0.4, 0), (0, 0.4) (-0.6, 0), (0, 0.6) (-0.8, 0), (0, 0.8) (-1.0, 0), (0, 1.0) | 0.5-0.833 0.833-1.389 1.389-2.314 2.314-3.858 3.858-6.430 6.430-10.717 10.717-17.816 17.816-29.768 20.768-49.615 | HHE HHN HHZ | mean($x$) var($x$) 540 |
| **Other Feature** | (-5, 5) | 1.389-2.314 2.314-3.858 3.858-6.430 6.430-10.717 10.717-17.816 | HHE HHN HHZ | RMS Amplitude Ratio($x[0, 5], x$) Mean Difference($x[0, 5], x$) Envelope Slope($x$) 60 |
| | | | | Polarization Slope($x[-5]$ in channel HHE, HHN, HHZ) for each time window with each bandwidth 5 |
Table S4. The performance for all validations on the Classifier module on Wenchuan data set. The overall performances of the Classifier module are shown in the second row, titled by “overall”. And we also display the performances of each base-model in the following rows. With respect to F-score, we can find that the overall Classifier module with Stacking strategy outperforms best in all four validations on Wenchuan data set.

|                | CV1        |          |          | CV2        |          |          |
|----------------|------------|----------|----------|------------|----------|----------|
|                | Precision  | Recall   | F-score  | Precision  | Recall   | F-score  |
| overall        | 0.8708     | 0.9289   | **0.8989** | 0.9016     | 0.8864   | **0.8939** |
| SVM-linear     | 0.8517     | 0.9228   | 0.8858   | 0.8832     | 0.8940   | 0.8885   |
| SVM-poly       | 0.8396     | 0.8578   | 0.8486   | 0.8657     | 0.8016   | 0.8324   |
| GaussianNaiveBayes | 0.6431     | 0.9310   | 0.7607   | 0.7087     | 0.8696   | 0.7810   |
| KNN            | 0.7343     | 0.8314   | 0.7799   | 0.7839     | 0.7737   | 0.7788   |
| LogisticRegression | 0.8498     | 0.9257   | 0.8861   | 0.8822     | 0.8919   | 0.8870   |
| RandomForest   | 0.8455     | 0.9333   | 0.8872   | 0.8854     | 0.8867   | 0.8861   |
| Adaboost       | 0.8566     | 0.9202   | 0.8873   | 0.8830     | 0.8925   | 0.8877   |
| Tree-gini      | 0.7894     | 0.8622   | 0.8242   | 0.8229     | 0.8274   | 0.8251   |
| Tree-entropy   | 0.8052     | 0.8767   | 0.8394   | 0.8291     | 0.8260   | 0.8275   |
|                | CV3        |          |          | CV4        |          |          |
|                | Precision  | Recall   | F-score  | Precision  | Recall   | F-score  |
| overall        | 0.9223     | 0.8632   | **0.8917** | 0.9160     | 0.8690   | **0.8919** |
| SVM-linear     | 0.9026     | 0.8788   | 0.8906   | 0.8951     | 0.8772   | 0.8861   |
| SVM-poly       | 0.8922     | 0.7897   | 0.8378   | 0.8835     | 0.7911   | 0.8348   |
| GaussianNaiveBayes | 0.7176     | 0.8772   | 0.7894   | 0.7128     | 0.8726   | 0.7846   |
| KNN            | 0.8067     | 0.7634   | 0.7844   | 0.8107     | 0.7637   | 0.7865   |
| LogisticRegression | 0.9020     | 0.8815   | 0.8916   | 0.8947     | 0.8765   | 0.8855   |
| RandomForest   | 0.8997     | 0.8505   | 0.8744   | 0.8956     | 0.8605   | 0.8777   |
| Adaboost       | 0.8977     | 0.8642   | 0.8806   | 0.9069     | 0.8705   | 0.8883   |
| Tree-gini      | 0.8348     | 0.8144   | 0.8245   | 0.8477     | 0.8025   | 0.8245   |
| Tree-entropy   | 0.8533     | 0.8114   | 0.8318   | 0.8467     | 0.8135   | 0.8298   |
Table S5. The personalized parameters for each monitoring station in 4 clusters. For each station cluster, the corresponding table shows the personalized parameters for each station and the average of absolute values of those parameters, which imply the weight for each base-model selected during the ensemble processing. And, the three most preferred base-models are highlighted for each cluster.

| Stations in Cluster 1 | MXI    | PWU    | QCH    | JMG    | Average of absolute value |
|-----------------------|--------|--------|--------|--------|---------------------------|
| **RandomForest**      | 4.994197921 | 4.771802368 | 4.381485515 | 4.226648703 | **4.593533627** |
| SVM-linear            | 4.77473423 | 4.19456298 | 2.817016529 | 3.198943306 | **3.746314261** |
| Adaboost              | 4.473290274 | 4.284575073 | 2.668214752 | 3.087011523 | **3.628272906** |
| SVM-poly              | 1.548744943 | 1.561873192 | 1.72125379 | 1.796313577 | 1.657046375 |
| LogisticRegression    | -1.884746339 | -1.200216858 | -0.795337695 | -0.819698254 | 1.174999787 |
| KNN                   | 1.013739645 | 0.708891841 | 0.808629325 | 0.572242557 | 0.775875842 |
| Tree-entropy          | 0.652681866 | 0.431239555 | 0.597497281 | 0.498858242 | 0.545069236 |
| GaussianNaiveBayes    | -0.767543174 | -0.544691671 | -0.078327501 | -0.003905786 | 0.348617033 |
| Tree-gini             | 0.198163853 | 0.250015706 | 0.651904951 | 0.047937693 | 0.287005551 |

| Stations in Cluster 2 | MIAX    | LUYA    | Average of absolute value |
|-----------------------|---------|---------|---------------------------|
| **RandomForest**      | 6.97130546 | 7.42129467 | **7.196300065** |
| SVM-linear            | 3.66255261 | 3.047124024 | **3.354838317** |
| Tree-gini             | 1.358209248 | 1.135104303 | **1.246656776** |
| Adaboost              | 0.900568835 | 1.487898001 | 1.194233418 |
| KNN                   | 0.960008264 | 0.854313166 | 0.907160715 |
| SVM-poly              | -1.288486696 | -0.511126229 | 0.899806462 |
| LogisticRegression    | -0.997462716 | -0.684356731 | 0.840909724 |
| GaussianNaiveBayes    | -0.823444447 | -0.751012756 | 0.787228601 |
| Tree-entropy          | -0.648310466 | -0.453291286 | 0.550800876 |
### Stations in Cluster 3

| Algorithm    | HSH       | SPA       | WXT       | XJI       | Average of absolute value |
|--------------|-----------|-----------|-----------|-----------|---------------------------|
| RandomForest | 7.149646261 | 6.139001655 | 5.866068262 | 4.881717195 | **6.009108343**          |
| Adaboost     | 2.026267848 | 5.000261974 | 2.575846489 | 2.387665305 | **2.997510404**          |
| SVM-linear   | 0.917091342 | 2.115927751 | 2.691505864 | 2.582753177 | **2.076819534**          |
| KNN          | 1.438019752 | 1.15254235  | 0.909536474 | 1.081492308 | 1.145397721               |
| SVM-poly     | 1.060357457 | 0.802246919 | 0.224690194 | 1.057831371 | 0.786281485               |
| Tree-entropy | 0.45878909  | 0.375846428 | 0.750851189 | 1.335867291 | 0.730338499               |
| GaussianNaiveBayes | -0.767122421 | -0.527248484 | -0.366094208 | -0.221559753 | 0.470506217             |
| LogisticRegression | -0.12555884 | -0.374929023 | -0.134926637 | -0.517478493 | 0.288223248              |
| Tree-gini    | 0.129176556 | -0.097641009 | 0.366370748 | 0.131256551 | 0.181111216              |

### Stations in Cluster 4

| Algorithm    | JJS       | XCO       | Average of absolute value |
|--------------|-----------|-----------|---------------------------|
| RandomForest | 4.737440197 | 3.300031534 | **4.018735865**          |
| Adaboost     | 3.685475916 | 1.718002589 | **2.701739252**          |
| SVM-poly     | 1.304380652 | 1.272499836 | **1.288440244**          |
| KNN          | 0.871922385 | 0.837072289 | 0.854497337              |
| GaussianNaiveBayes | 0.317111293 | 1.310435512 | 0.813773402              |
| SVM-linear   | 0.684226398 | 0.503837513 | 0.594031955              |
| Tree-entropy | 0.727136098 | 0.116311568 | 0.421723833              |
| Tree-gini    | -0.067598434 | 0.509443883 | 0.288521159              |
| LogisticRegression | 0.411759282 | -0.138280932 | 0.275020107              |
Figure S1. Examples for waveform data in three channels. (a) A waveform example of a seismic phase. (b) A waveform example for one whole day.
Figure S2. Examples for expert-labeled P-phases and missing P-phases. (a) Waveform examples around expert-labeled P-phase arrivals. (b) Waveform examples around missing P-phase arrivals automatic picked by ML-picker. All P-phase arrivals are located at 5 seconds.