Application of Tectonic Tremor Classifier to Continuous Data

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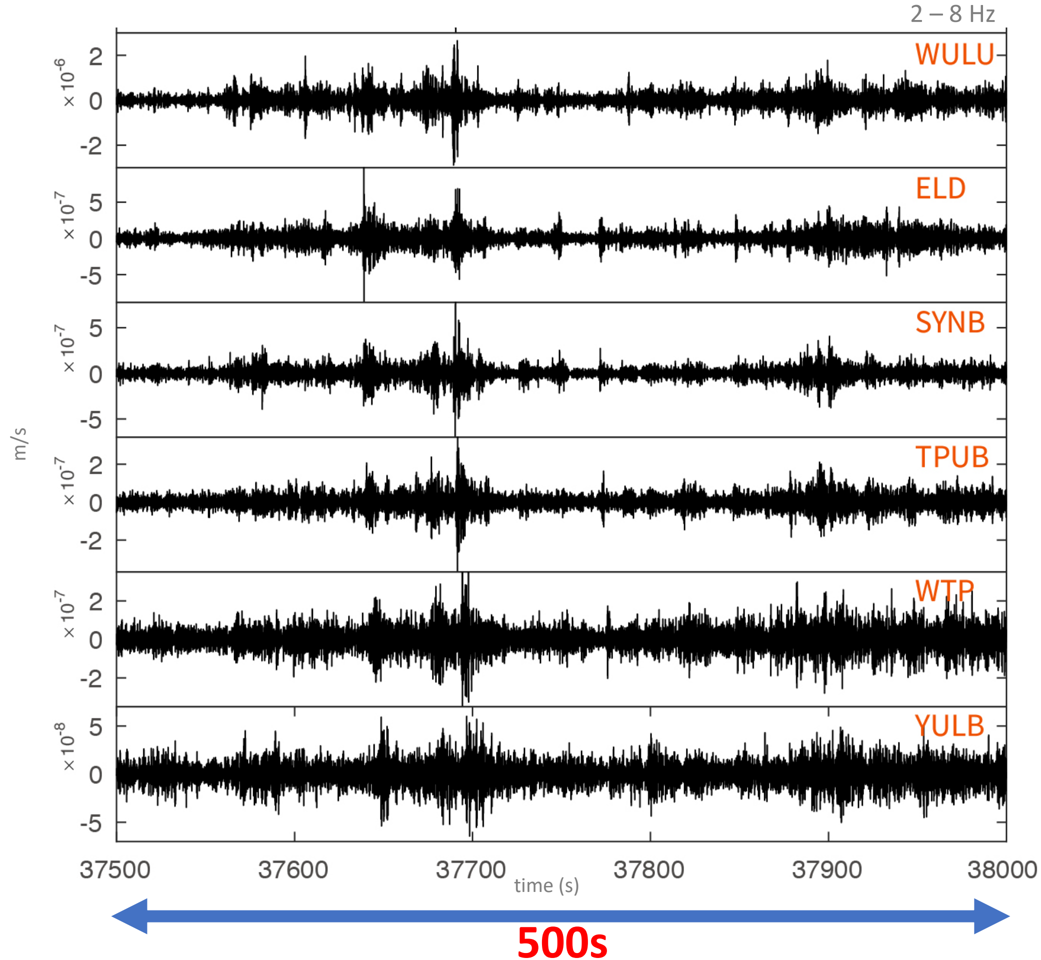
What is tremor and why it is important?

- Tectonic tremor is long-lasted, noise-like signals that represents the slow slip process at depth.
- It is usually identified with consistent arrivals of weak energy at several stations.

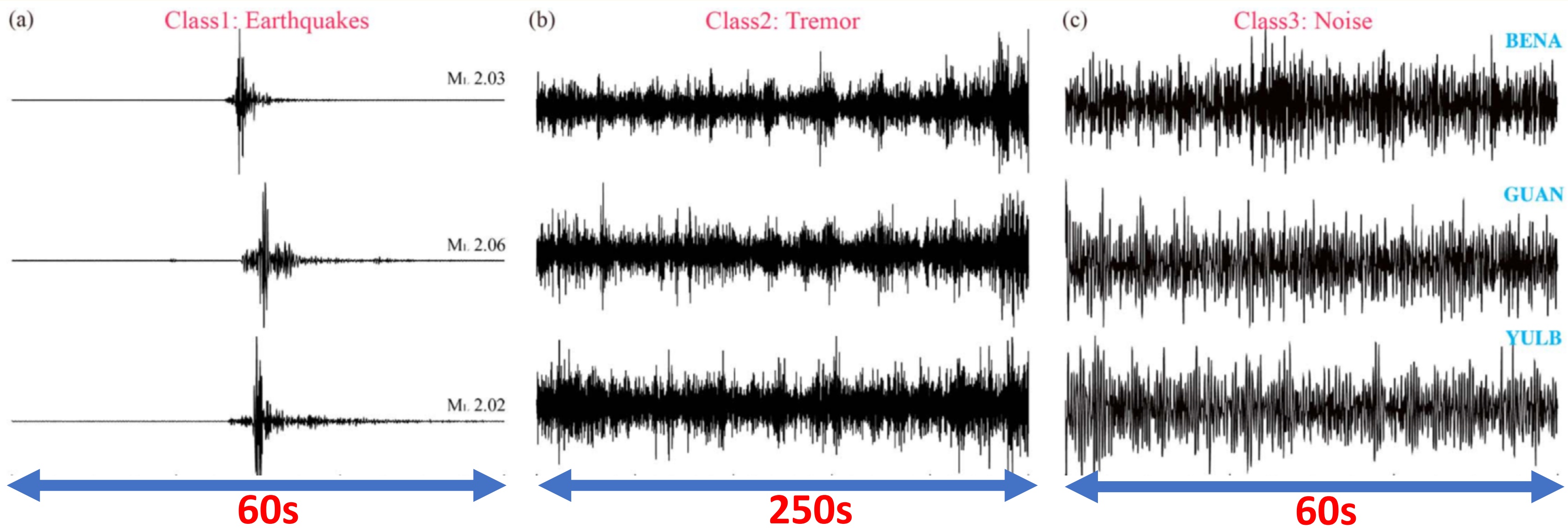


Questions

- Can we detect tremor by using a single station?

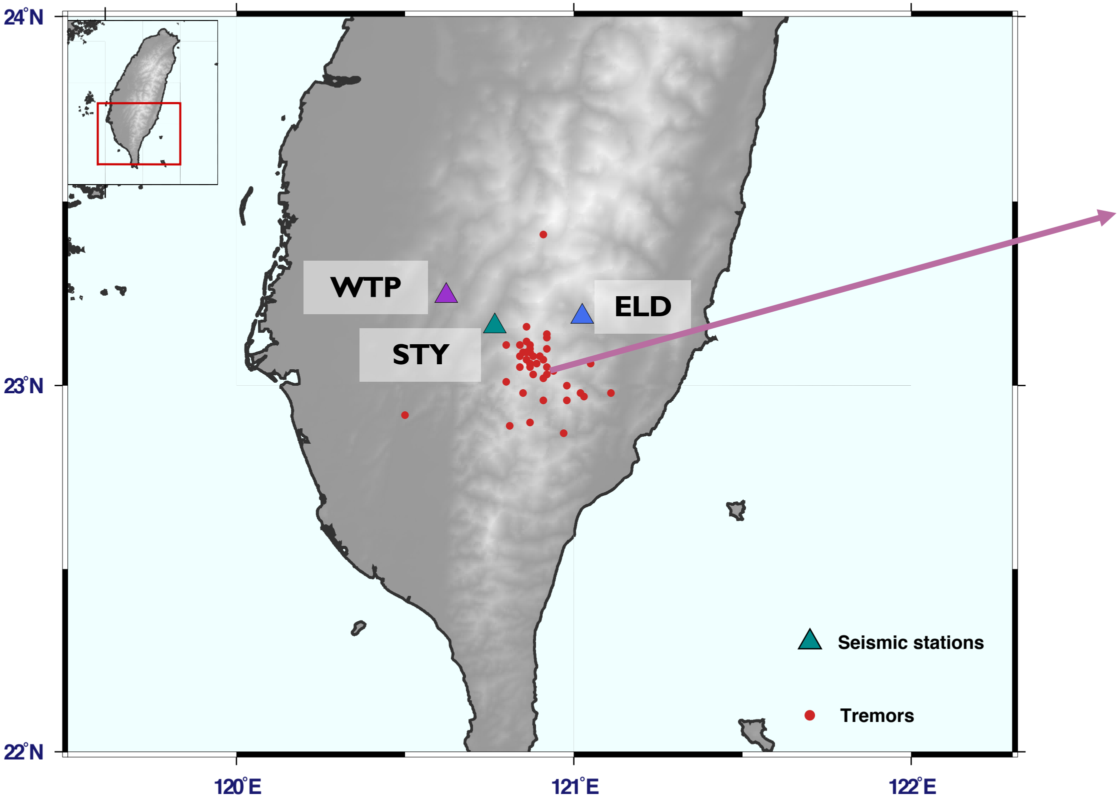
  → **machine learning approach to classify tremor from noise and local earthquake (Liu et al., 2019).**

- Can this technique be applied to continuous data?
- How the single-station classification method can be scaled to larger data sets in continuous data?

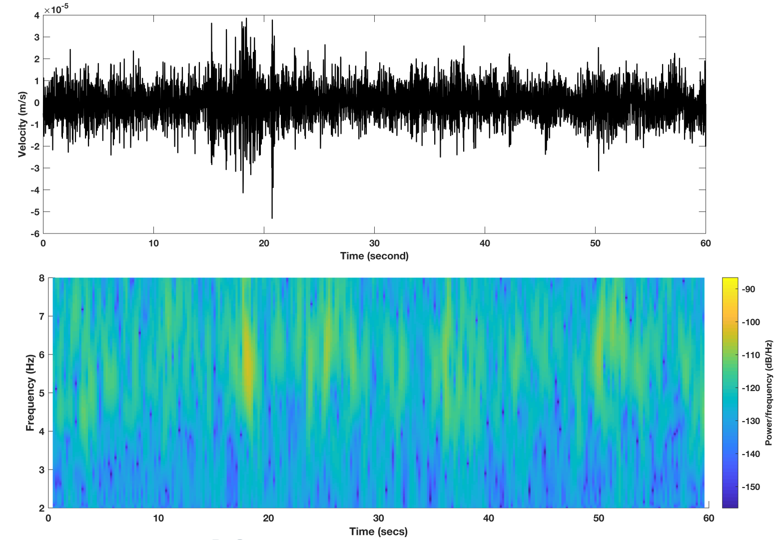


Data

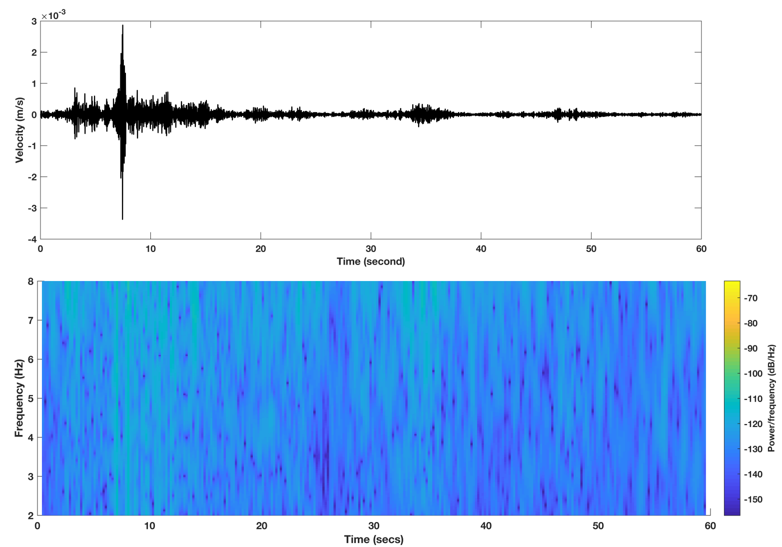
Continuous data from 3 stations :
ELD & STY & WTP



Tremor



Non-tremor



Training data for this study:

- We use 8 days data (selected from the tremor catalog during the study period of 2016/2/19~2016/9/10) to build our training data.

Station	Tremor events (number)	Non-tremor events (number)	Days	Duration (second)
ELD	489	11342	8	8598
STY	240	11424	8	4251
WTP	567	11317	8	10058

Method --Extracting 29 Seismic features

Temporal waveforms (1st family)

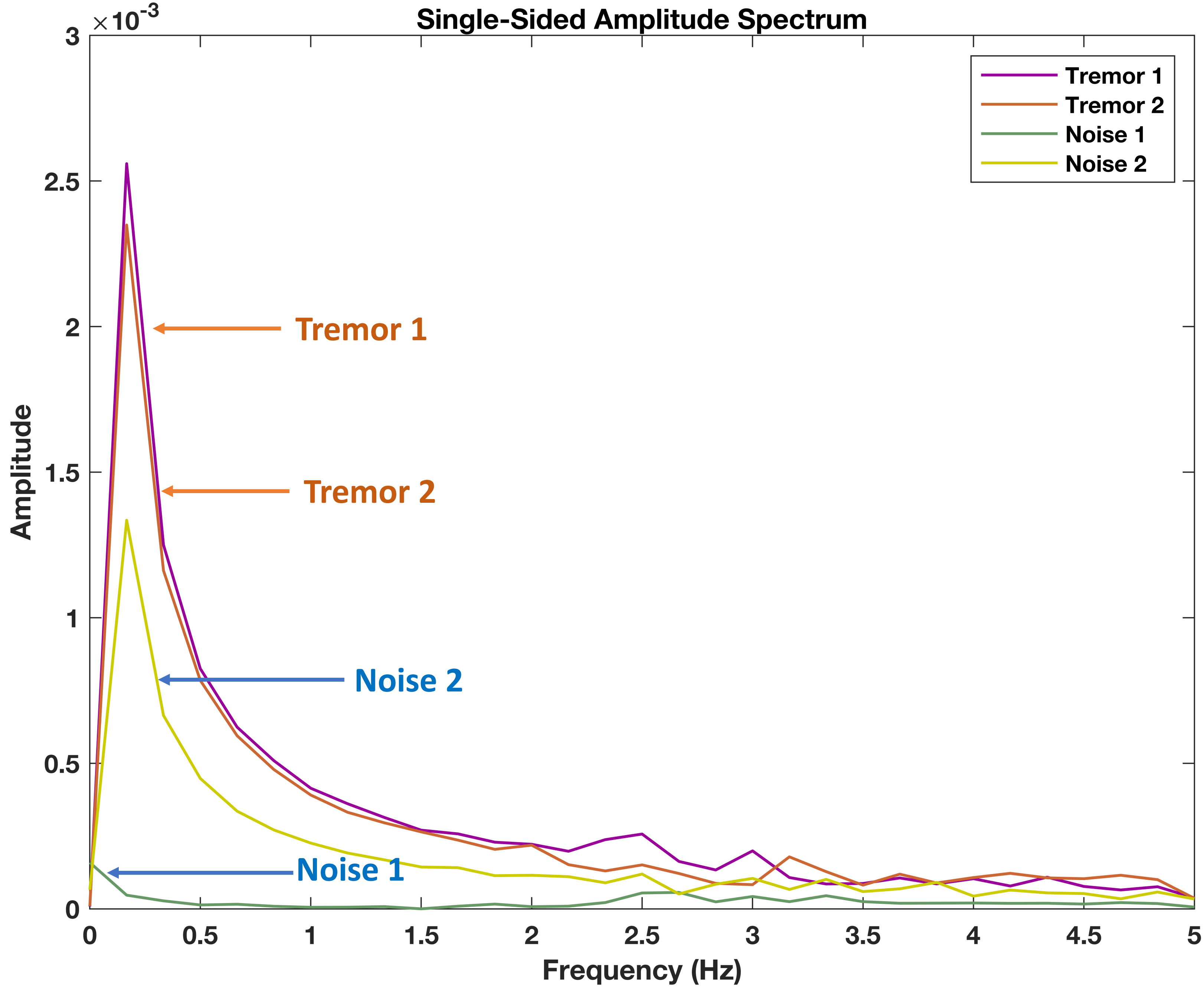
Example:
- Maximum envelope amplitude
- Kurtosis of the envelope
- Skewness of the envelope

Spectral content (2nd family)

Example:
- Energy in the first third part of the autocorrelation function
- maximum amplitude of 2-8 Hz

Energy concentration in frequency and time (3rd family)

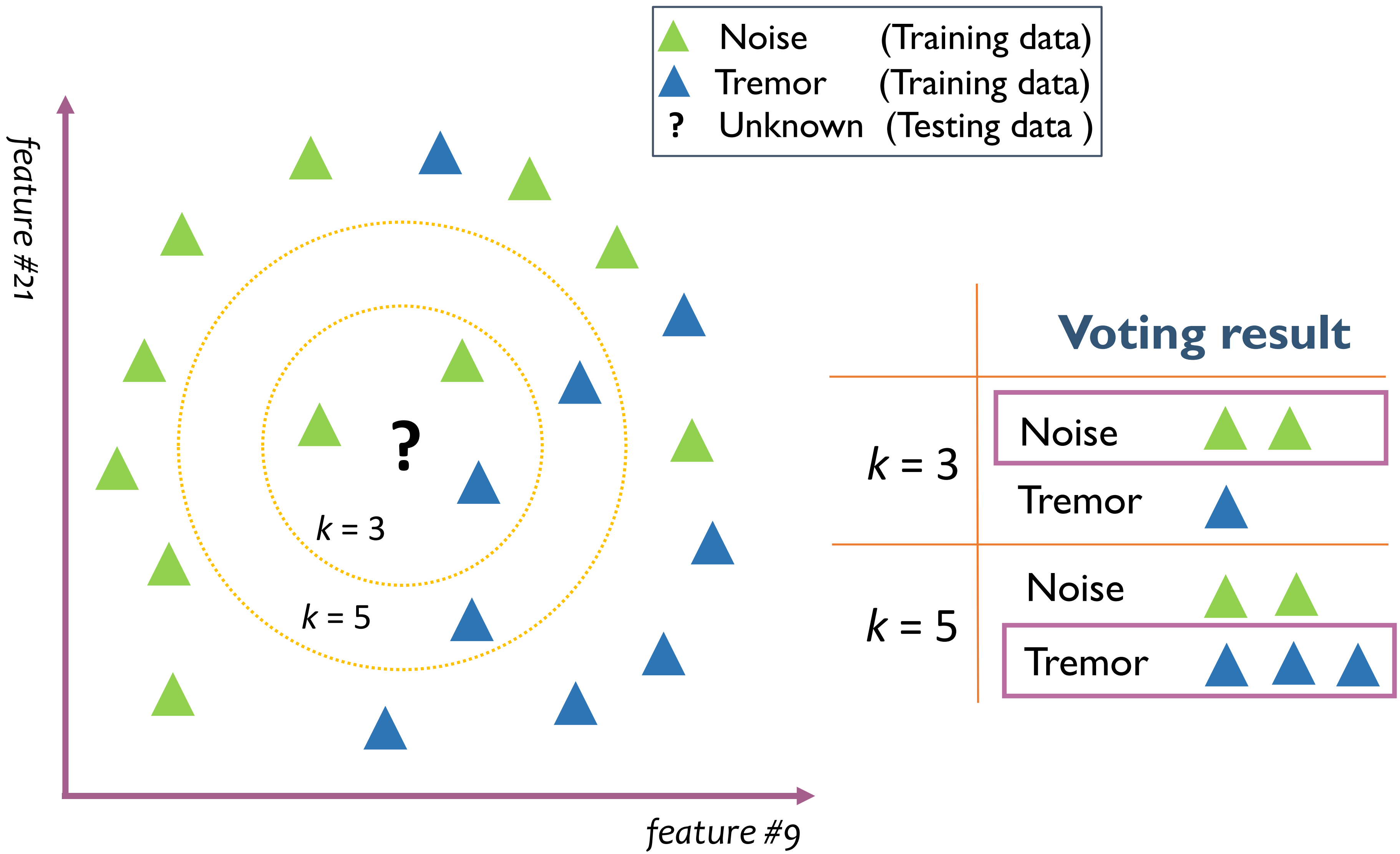
Example:
- Number of peaks in the curve showing the temporal evolution of the DFTs maximum
- Number of peaks in the curve showing the temporal evolution of the DFTs mean
- Ratio between sum of energy in 2-8Hz and sum of energy in 5-20Hz



Single-Sided Amplitude Spectrum
×10^-3
3
2.5
2
1.5
1
0.5
0
Amplitude
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
Frequency (Hz)
Tremor 1
Tremor 2
Noise 1
Noise 2
Tremor 1
Tremor 2
Noise 2
Noise 1

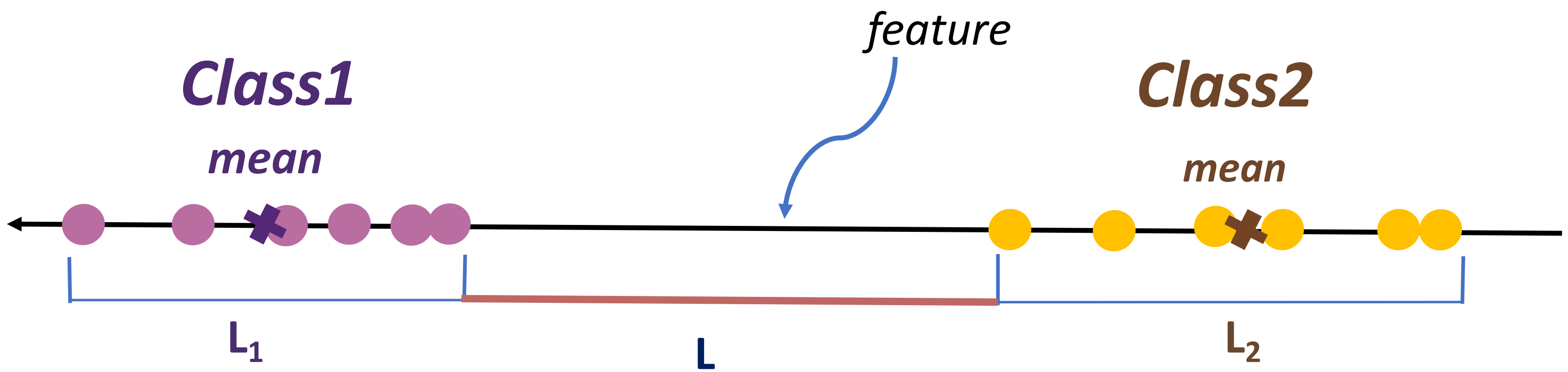
Method --Building training model

- *k*-Nearest Neighbor Classification (Cover and Hart, 1967)



Method --Analysis

- **We use Fisher Scores to analyze the classification result.**



$$F_i \equiv \frac{\left(\bar{x}_i^{(+)} - \bar{x}_i\right)^2 + \left(\bar{x}_i^{(-)} - \bar{x}_i\right)^2}{\frac{1}{n^{(+)}-1}\sum_{k=1}^{n^{(+)}}\left(x_{k,i}^{(+)} - \bar{x}_i^{(+)}\right)^2 + \frac{1}{n^{(-)}-1}\sum_{k=1}^{n^{(-)}}\left(x_{k,i}^{(-)} - \bar{x}_i^{(-)}\right)^2}$$

Fisher score : $\frac{L}{L_1+L_2}$

The closer the data get and the wider the blank between two class of events is, the higher the Fisher Scores will be, which is related to better classification result.

Results

Confusion matrix of each station :

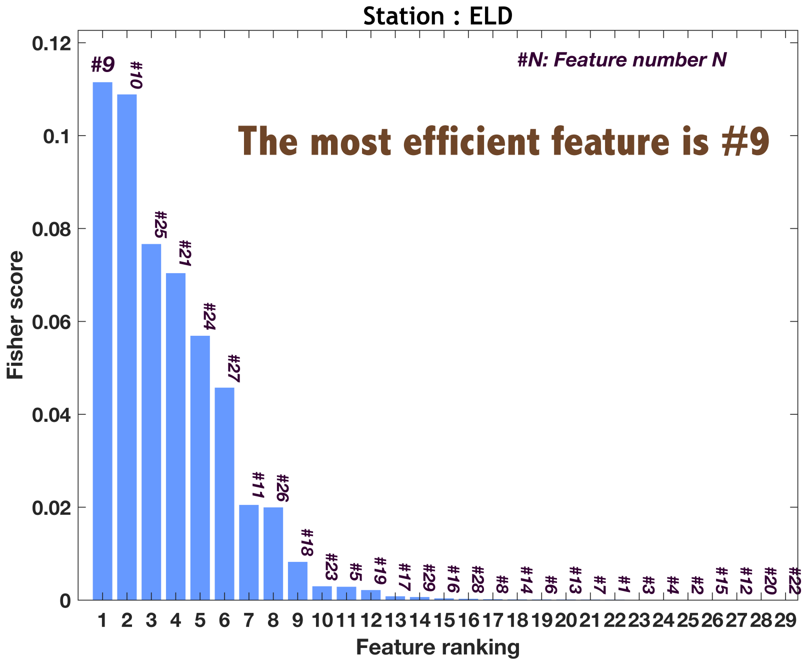
Station	ELD		STY		WTP	
Predicted / Actual	Tremor	Non-tremor	Tremor	Non-tremor	Tremor	Non-tremor
Tremor	284	11547	112	11552	313	11571
Non-tremor	679	11152	344	11320	787	11097
TPR	58.1		46.7		55.2	
CR	96.7		98.0		96.0	

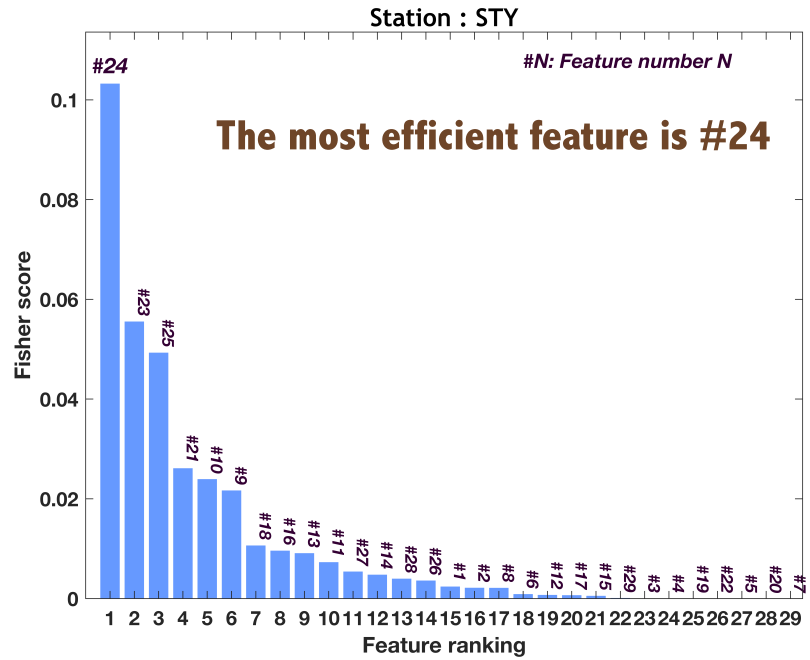
True Positive rate (TPR)

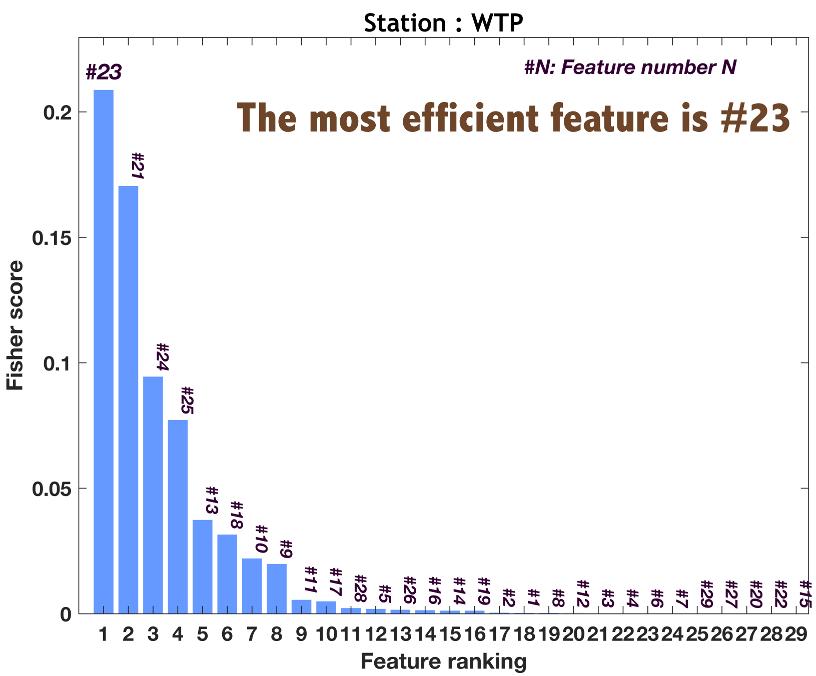
- How many of the input events are "predicted" as their actual class ?

CR (Classification Rate)

- One metric for evaluating classification models. Informally, CR is the fraction of predictions our model got right.







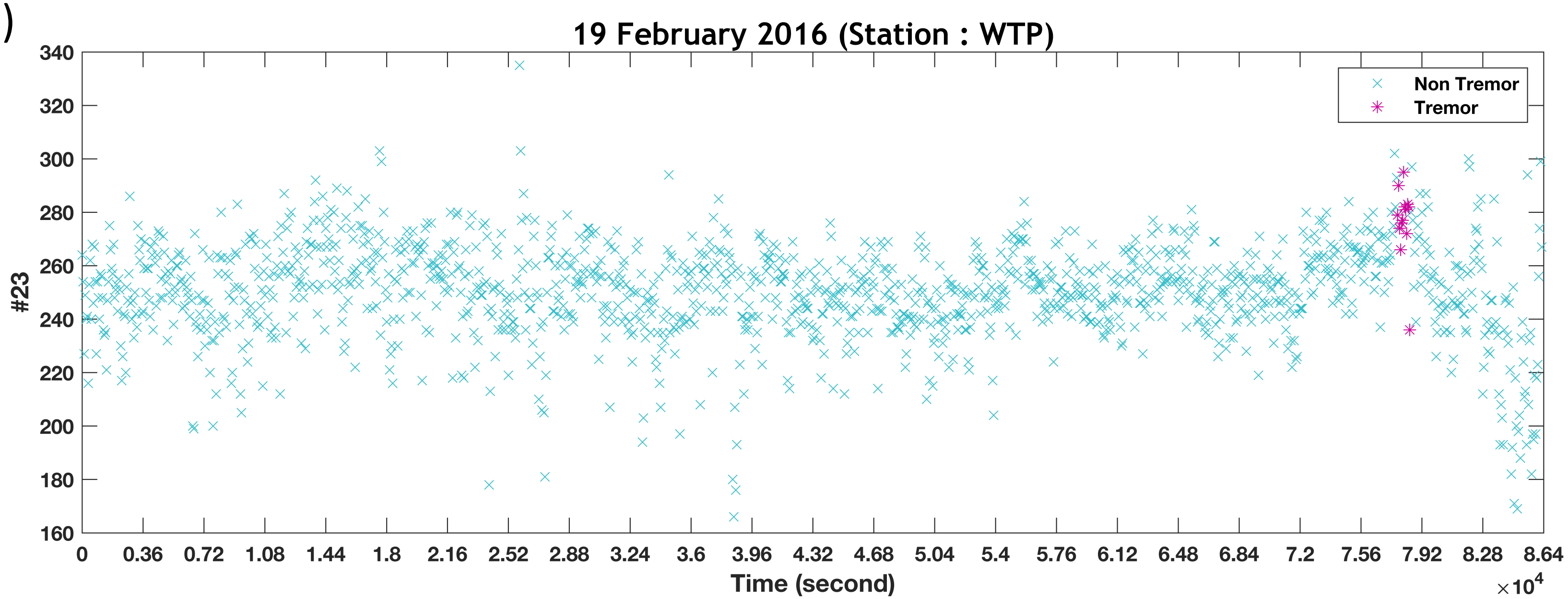
Station	#Feature	The top fisher score
ELD	#9	0.11
STY	#24	0.10
WTP	#23	0.21

#9: Energy in the first third part of the autocorrelation function

#24: Number of peaks in the curve showing the temporal evolution of the DFTs mean

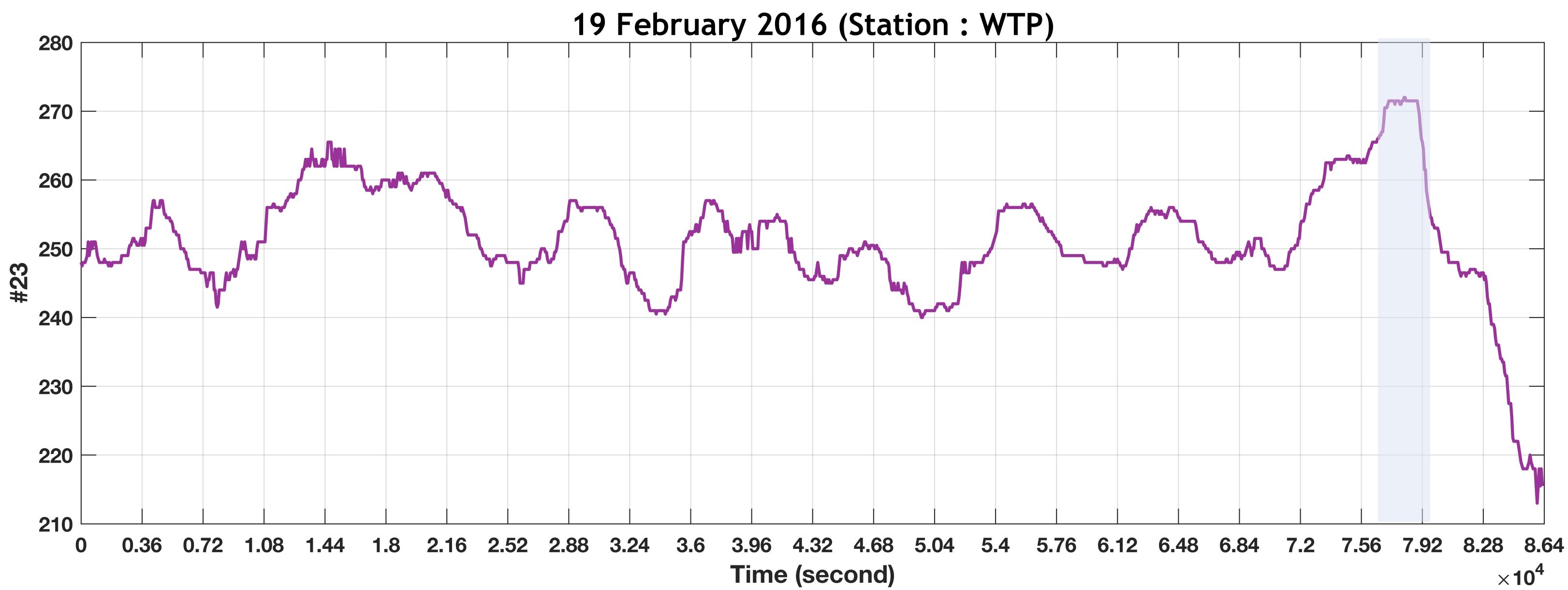
#23: Number of peaks in the curve showing the temporal evolution of the DFTs maximum

(a)



19 February 2016 (Station : WTP)
Non Tremor
Tremor
#23
Time (second)
$\times 10^4$

(b)



19 February 2016 (Station : WTP)
#23
Time (second)
$\times 10^4$

Summary

1) The k-NN based classification tool allows the discrimination between tremors and noise with **49-58% true positive rate(TPR)**. Increasing the number of tremor may improve the true positive rate.
2) The top ranked features are different between stations, suggesting strong variation of **path and site effects**.
3) To further improve the discrimination between tremor and non-tremor events, more seismic data and stations can be introduced in the training model.

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Thanks for your attention！