

Classifying earthquakes and mining activity with deep neural networks

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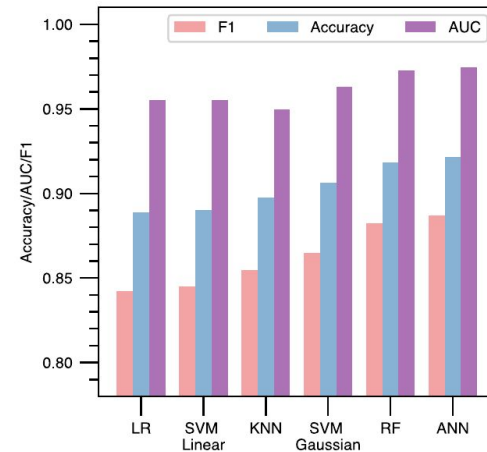
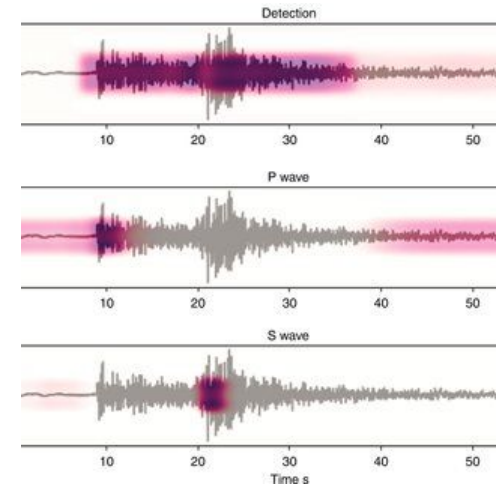
Application in seismology

There are existing solutions for earthquake detection:

- manual labour (tedious)
- classical methods (not too accurate)
- machine learning (depends heavily on the dataset)

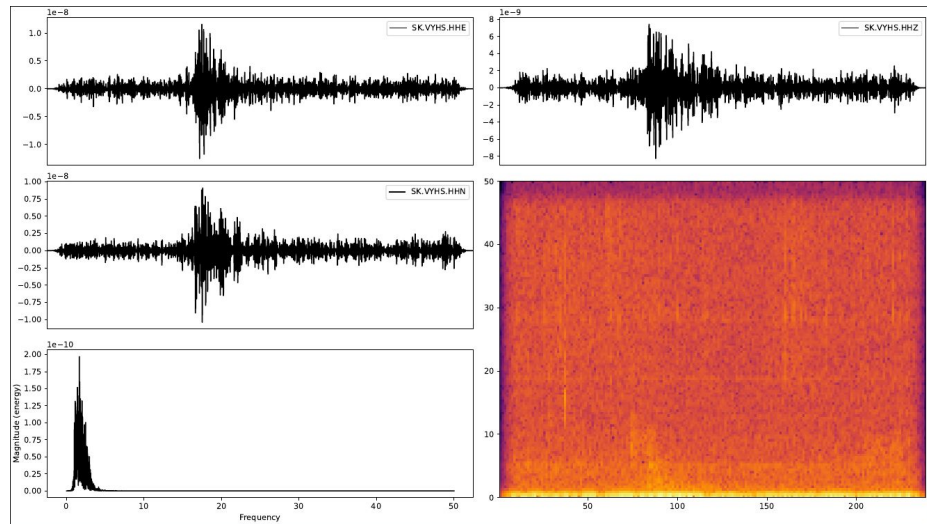
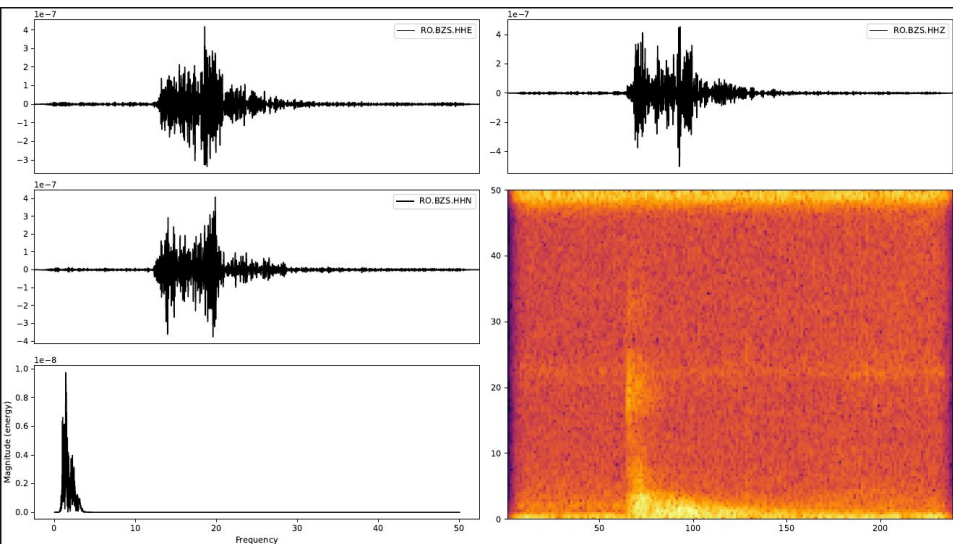
Chai, C et al. Automatic waveform quality control for surface waves using machine learning. Seismological Society of America (2022)

Mousavi et al. Earthquake transformer—an attentive deep-learning model for simultaneous earthquake detection and phase picking. Nature communications (2020)



Manual identification

Classification using only the waveforms is a complex task even for an expert



Application in seismology

Machine learning based solutions (especially deep neural networks) provide the best performance

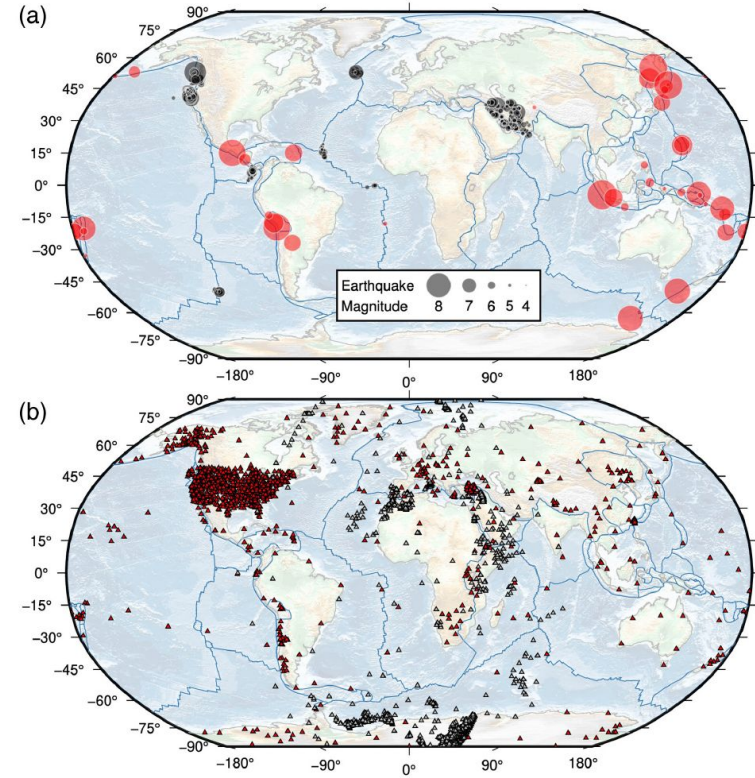
These methods are trained on datasets containing „earthquakes” and „no activity” classes

They provide poor performance in case of other activities:

Typically mining activity can easily fool them
(**98%** of the investigated samples have fooled EQ-transformer)

Not all mines report activities

Small amplitude signals → easily confused with other activities



Our Dataset

Created from the Hungarian Seismology Bulletin (1995-2020)

Input: Preprocessed temporal data

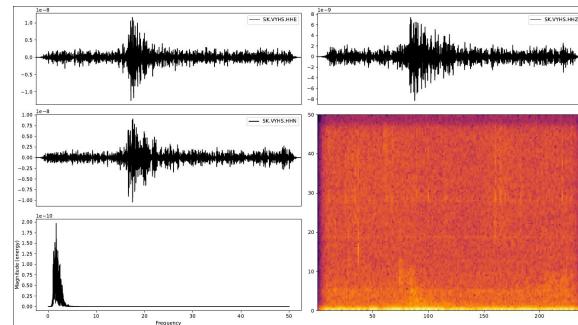
North, East, Z components
100 Hz sampling frequency

5 minute long timeseries which contains activity for all samples

Two classes:

A, Seismic activity

B, Mining activity



Event HU20131018105830		Czech and Slovak Republics																	
Date	Time	Err	RMS	Latitude	Longitude	Smaj	Smin	Az	Depth	Err	Ndef	Nsta	Gap	mdist	Mdist	Qual	Author	OrigID	Rep
2013/10/18	10:58:30.56	1.38	0.51	49.3393	19.8547	6.0	5.3	56	0.05	8	4	186	0.42	0.85	m	kx	BUD	14092899	lLoc
2013/10/18	10:58:30.88f		0.52	49.3466	19.8590f				0.05	8	105	0.43	0.85	m	kx	BUD_GT	14114118	BUD	DPdep
(#PRIME)																			
(locality : Velke Dravce)																			
[GT info : GT2 explosion]																			
Magnitude Err Nsta Author OrigID																			
ML	1.8																		
BUD 14114118																			
Sta	Dist	EvAz	Phase	Time	TRes	Azim	AzRes	Slow	SRes	Def	SNR	Amp	Per	Qual	Magnitude	ArrID	Agy	Deploy	Ln
PSZ	0.43	176.8	Pg	10:58:40.000	-0.3					T						14114120	FDSN	IR	--
PSZ	0.43	176.8	Lg	10:58:47.000	-0.4					T						14114121	FDSN	IR	--
KECS	0.44	71.6	Pg	10:58:39.500	-0.3					T						14114122	FDSN	IR	--
KECS	0.44	71.6	Lg	10:58:46.000	-0.5					T						14114123	FDSN	IR	--
VVHS	0.70	282.6	Pg	10:58:44.600	-0.3					T						14114124	FDSN	IR	--
VVHS	0.70	282.6	Lg	10:58:54.200	-1.0					T						14114125	FDSN	IR	--
LANs	0.85	342.3	Pg	10:58:48.000	0.5					T						14114126	FDSN	IR	--
LANs	0.85	342.3	Lg	10:58:59.500	-0.4					T						14114127	FDSN	IR	--

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Two classes:

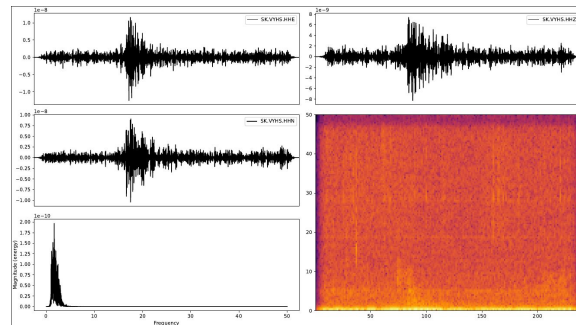
A, Seismic activity

B, Mining activity

3400 events → labeled by human experts

(knowing the event times locations etc..., not just the waveforms)

66% of them are mining activity: 2000 samples were used to train the models



Each event was recorded
by multiple stations

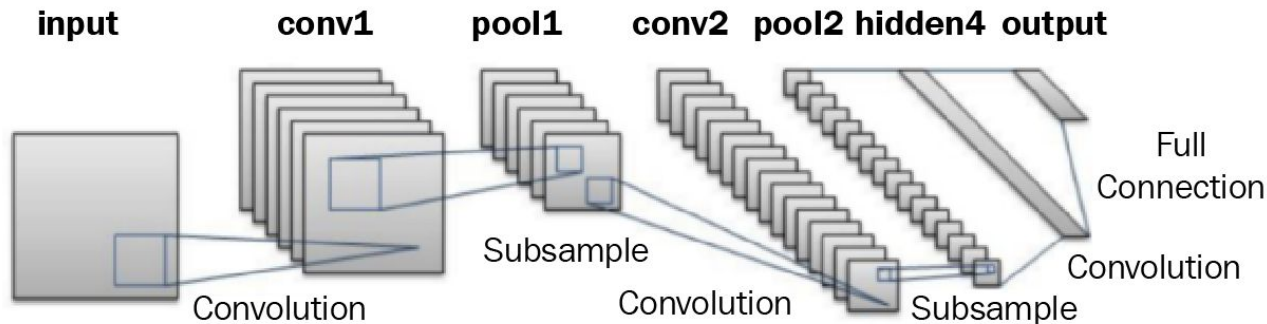
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Quantitative results

Five-fold cross validation with 80-20 split

	4 layered ConvNet	AlexNet 8 layers	4 layered Transformer
Accuracy	94.4 %	92.6%	91.3%

The decreasing accuracy could be caused by low amount of training data and increased number of parameters → overfitting



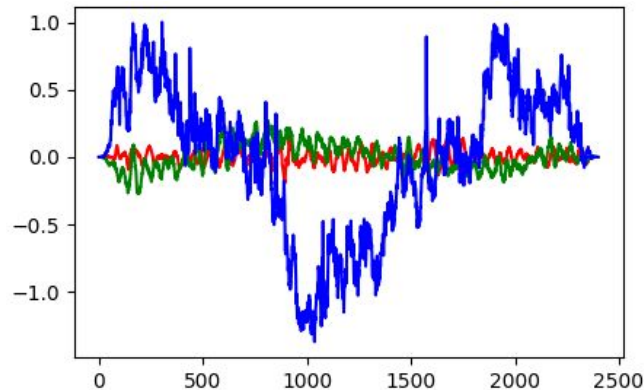
Explainable AI

Neural networks are considered black boxes

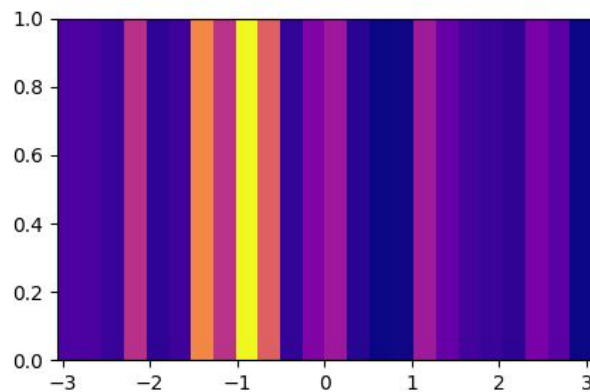
With saliency map generation approaches one can visualize the regions which were important for the network

We can ask experts about these features, whether they are meaningful or not

We can use these maps in data augmentation to preserve important regions



North, East, Z components



Importance map for the time series

Conclusions

- We collected a fairly large dataset containing seismic and mining activities, created a human baseline for this task
- Implemented data augmentation methods specially tailored for seismic activity
- We have demonstrated the the classification of seismic activities is solvable via deep neural networks

In case of any further questions please write us:

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