



Identification of repeating seismic events using diffusion maps

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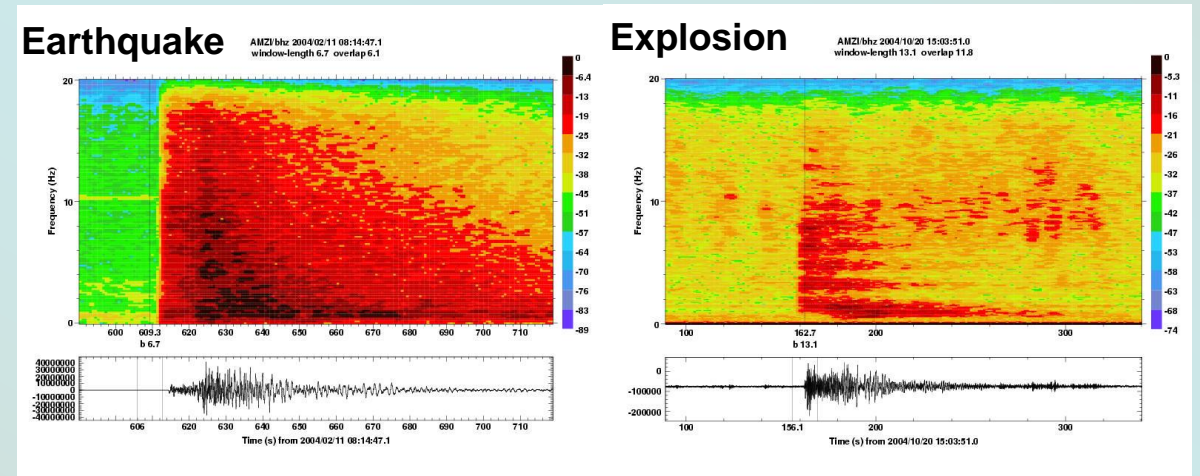
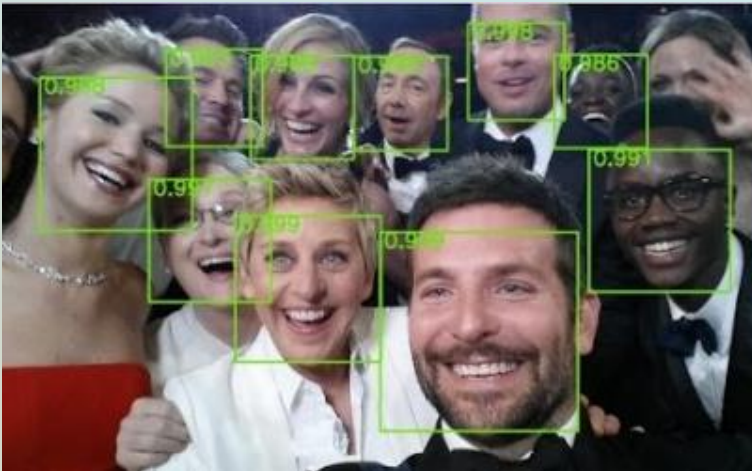
Outline

1. Motivation and Algorithm overview.
2. Aftershock identification at local distances.
3. Verification of waveform correlation detections.
4. Aftershock identification at regional distances.
5. Identification of quarry explosions.
6. Summary.

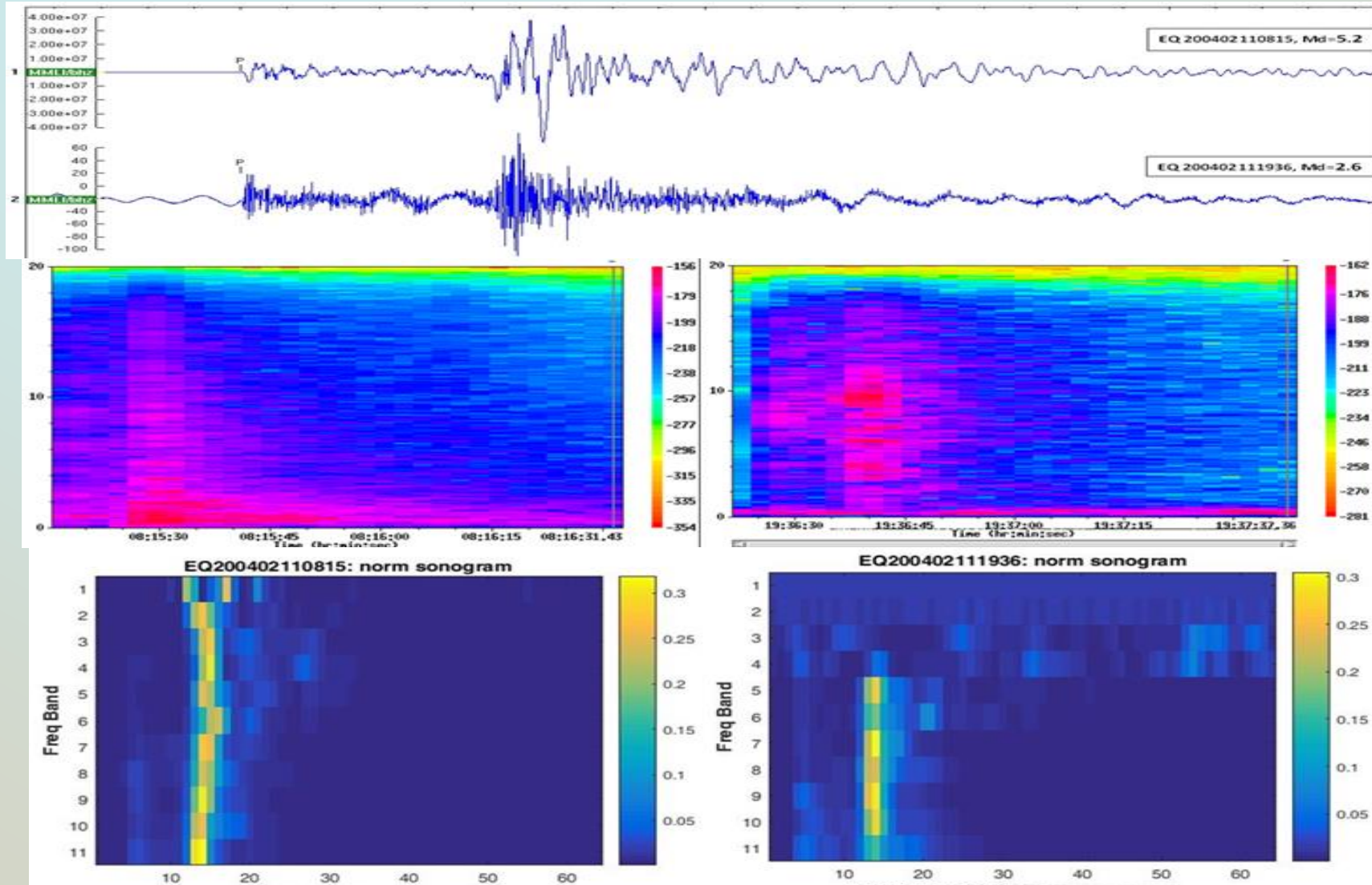
Motivation:

Automatic identification of repeating seismic event clusters such as an aftershock sequence which will help to lighten the analysts' burden and to allow for timely production of reviewed bulletins.

We consider the seismic event identification as a machine learning classification problem similar to face recognition.

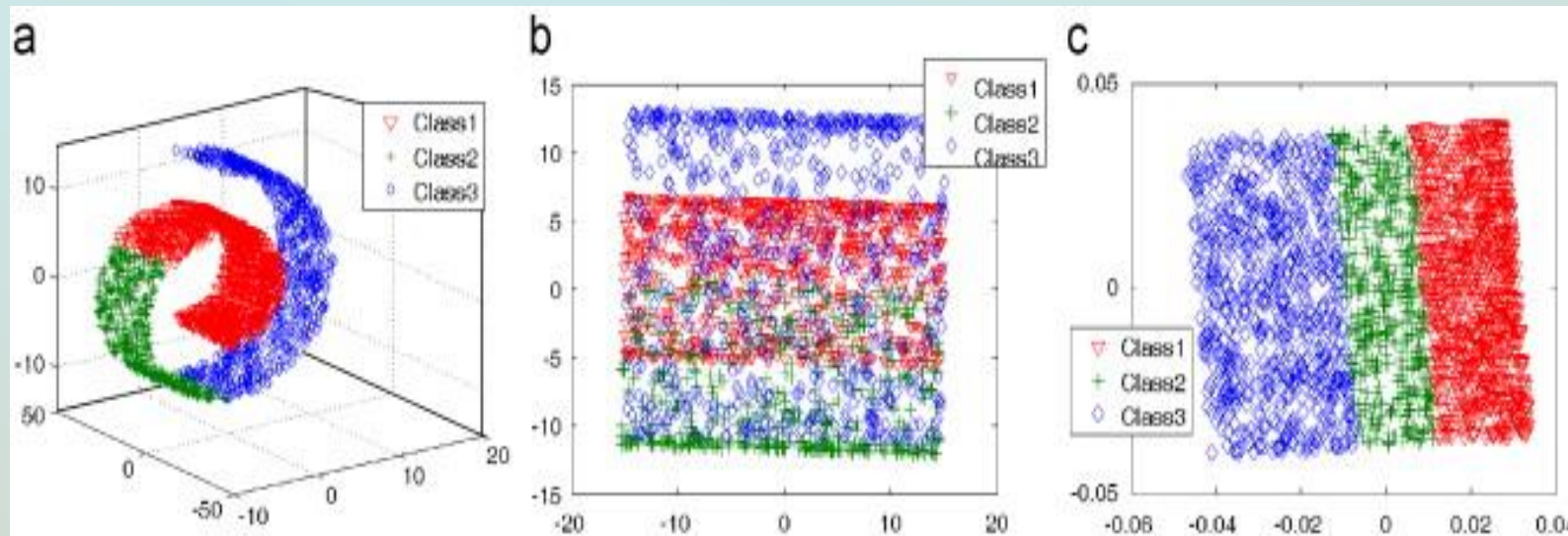


Normalized sonograms



Diffusion maps: a nonlinear dimensionality reduction technique

When the data has a nonlinear structure, linear methods like Principal Component Analysis (PCA) fail



The Swiss roll

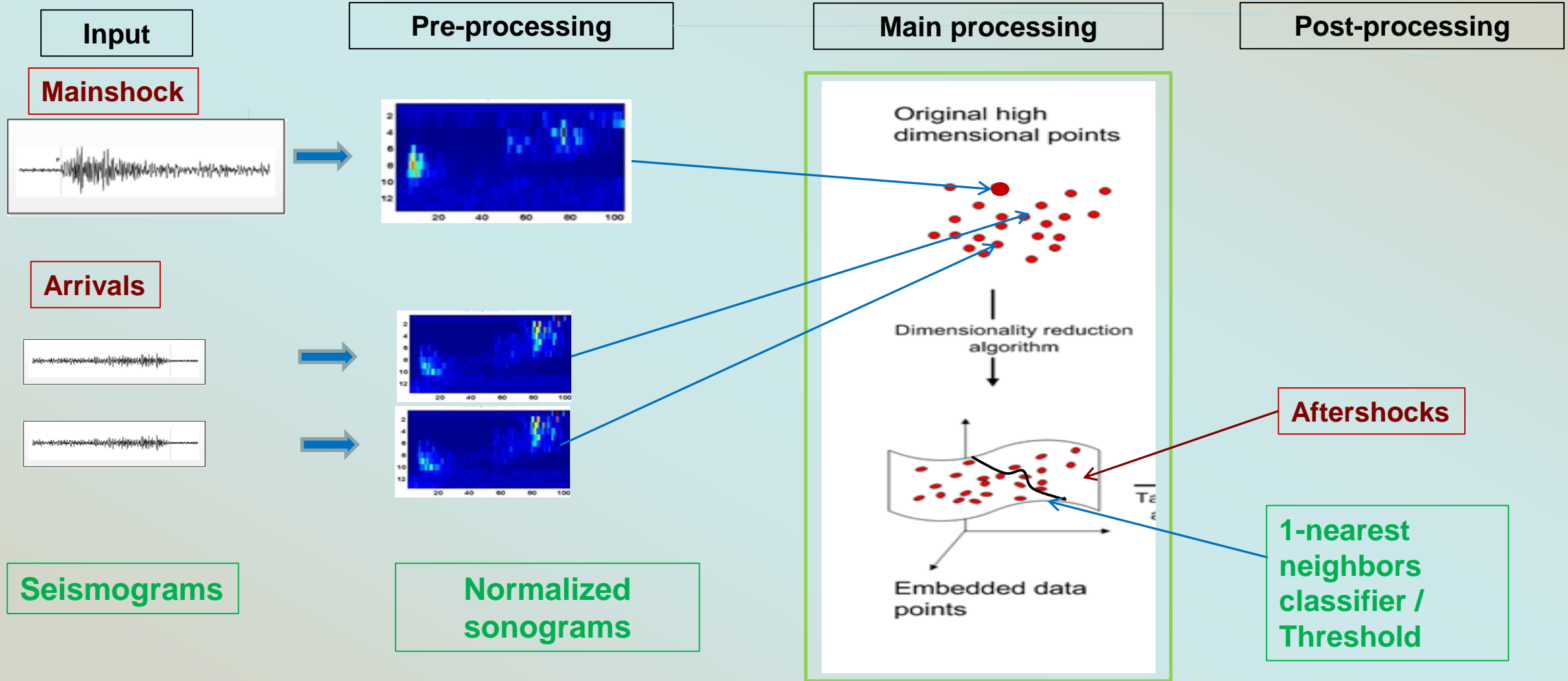
PCA (linear)

Nonlinear

Diffusion maps

- ❖ An unsupervised technique, does not use the data labels
- ❖ Constructs a global description of the dataset from local similarities
- ❖ Uses the eigenfunctions of a Markov matrix
- ❖ Preserves the distances of the original data by defining a diffusion metric.
- ❖ Close points in the original space remain close in the embedded space.

Basic processing framework



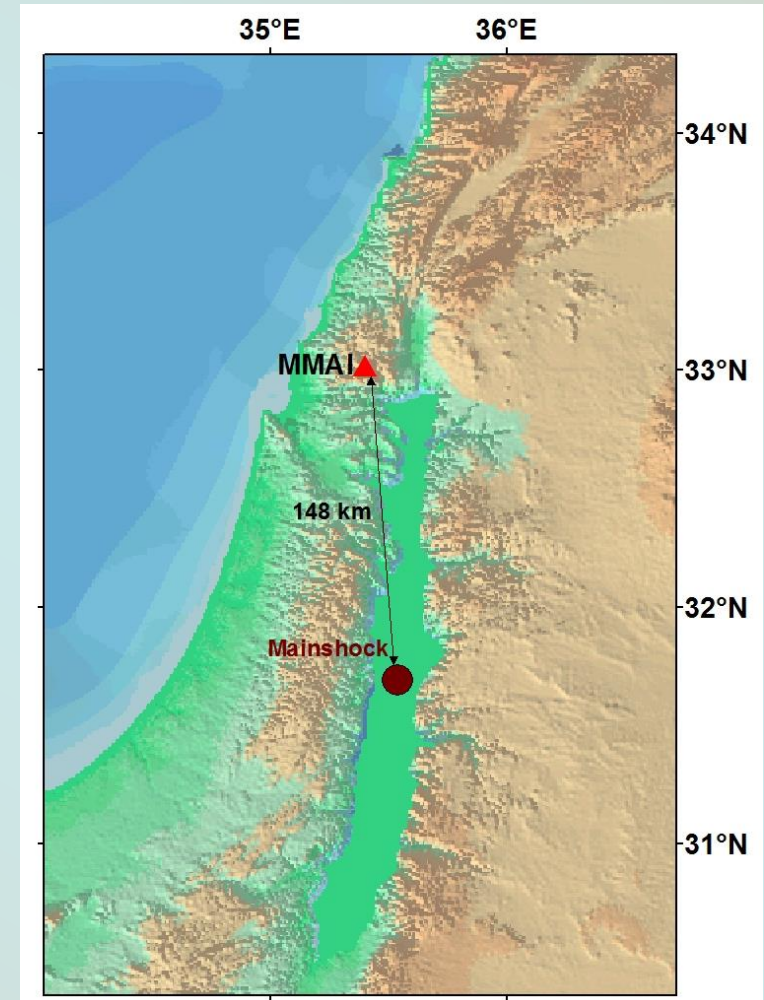
Aftershock identification method

- ❖ No templates, only the mainshock needs to be identified in advance.
- ❖ Input: arrivals at a single station (detected by STA/LTA, cross-correlation etc.).
- ❖ Processing: normalized sonograms and diffusion maps.
- ❖ Output: a list of identified aftershock arrivals with an associated score.

Aftershock identification of 2004 Dead Sea earthquake with $m_b=5.2$

Data:

Feb 11-17, 2004 waveforms
of vertical channel MMA0 of
MMAI IMS array

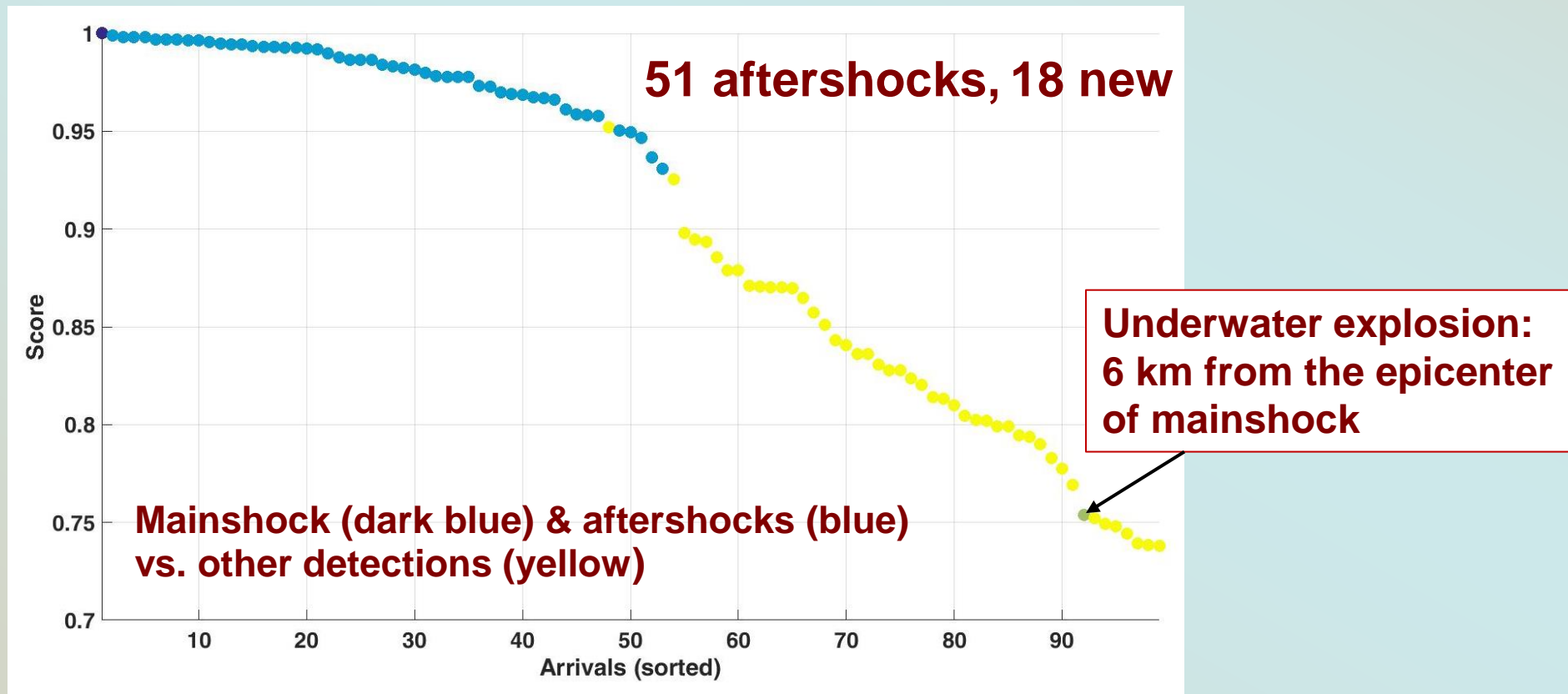


2004 Dead Sea earthquake (cont.):

MMA0 continuous waveforms: Feb 11-17, 2004

Detector: BW(3,1,5)>>STA/LTA(1,25), threshold=3.5

Detections: 98



Verification of correlation detections

Template: 2008/04/11 19:36 aftershock, Md=2.6;

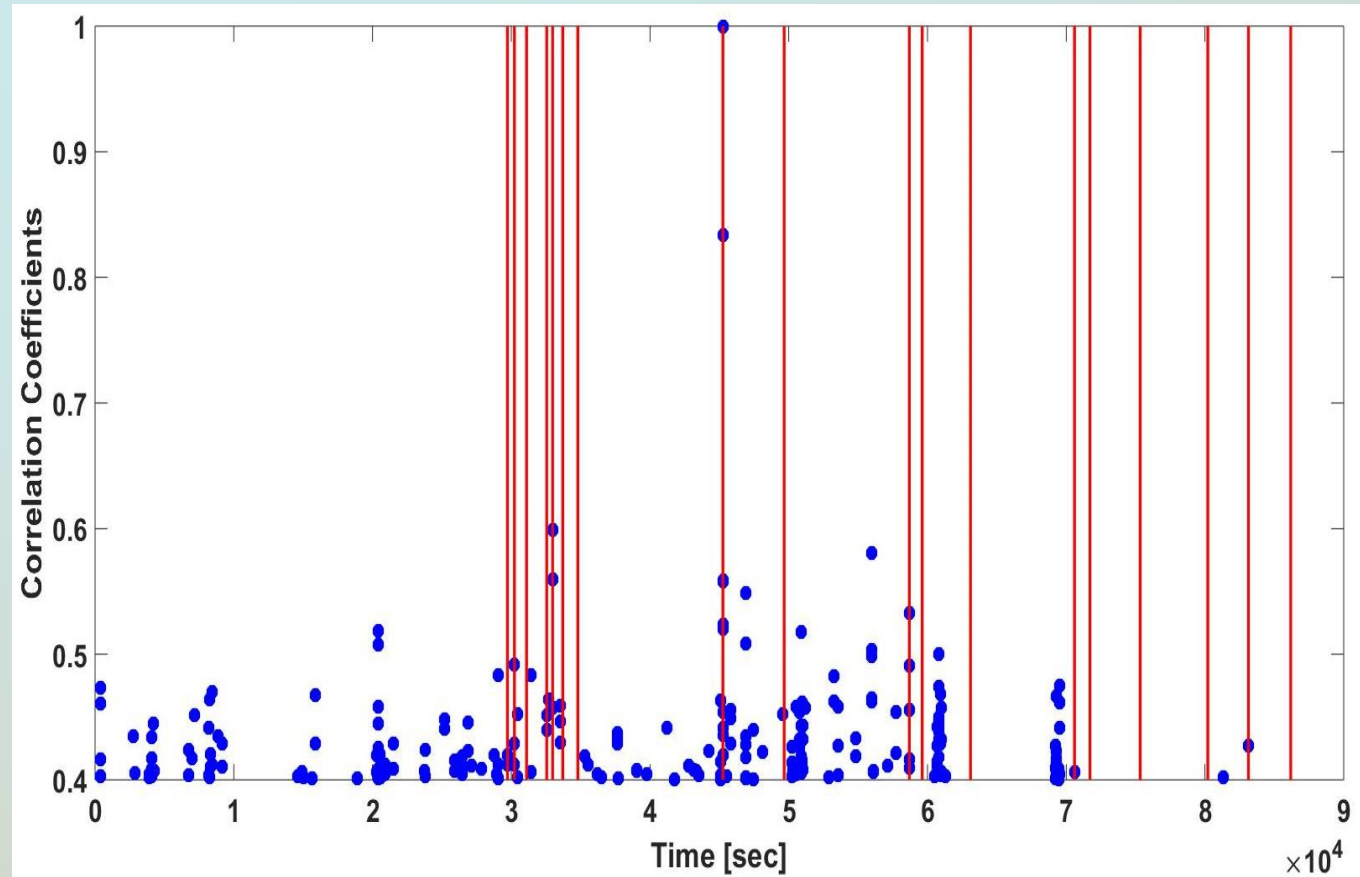
15 sec long segment filtered with BW(3,2,4).

Continuous waveforms: Feb 11-12, 2004

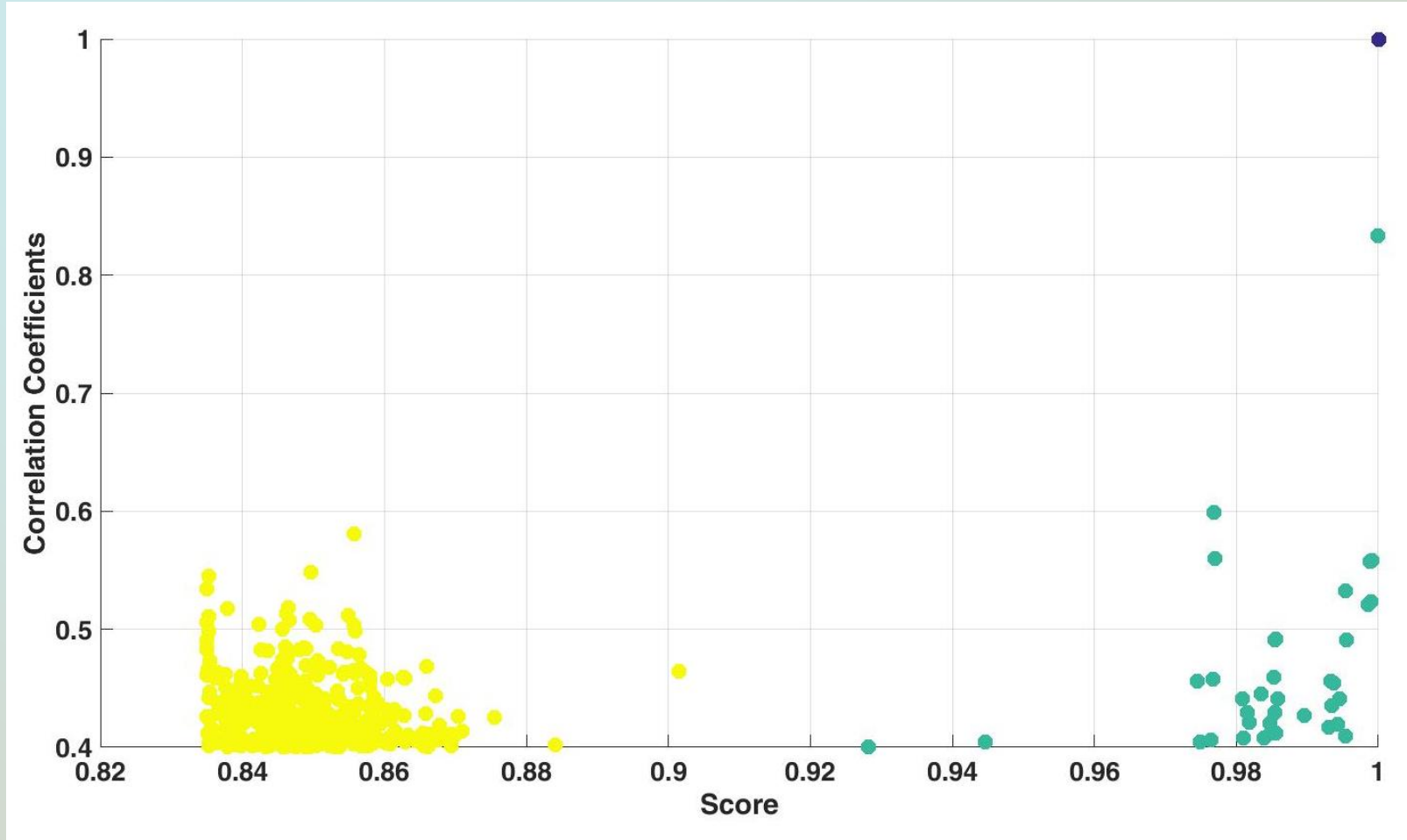
Threshold: 0.4

Detections: 442

Detections (blue)
& arrival times of
aftershocks (red)



Verification of correlation detections(cont.)

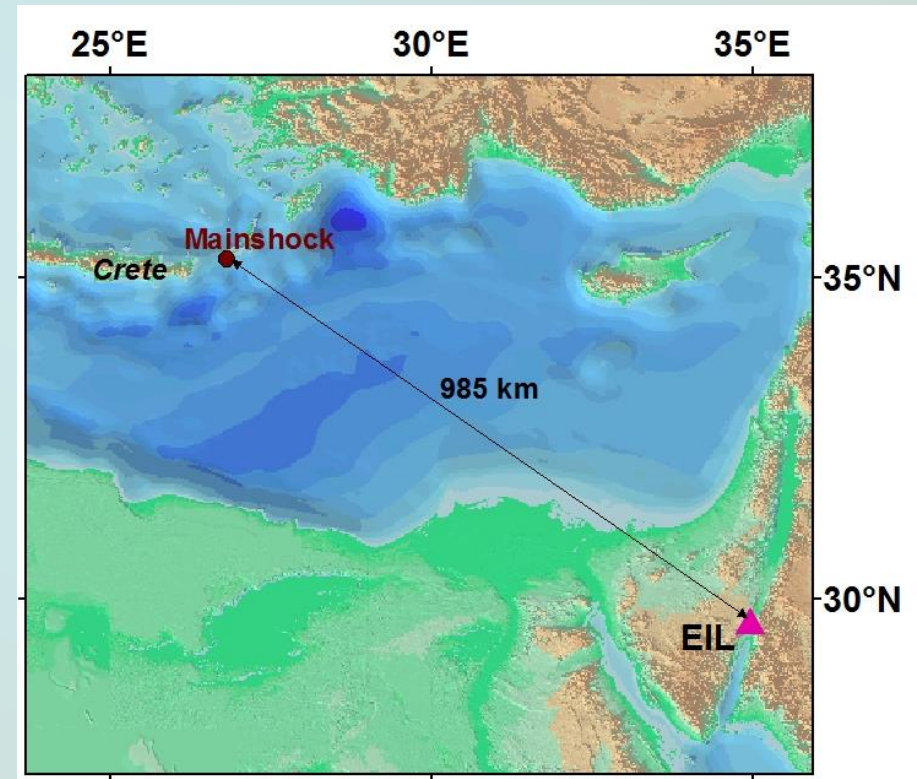


Template (dark blue) & aftershocks (blue) vs. false detections (yellow)

Example: Aftershocks identifications of Crete earthquake on Apr 16, 2015 with $m_b=5.6$

Data: vertical waveforms of IMS station EIL on Apr 16-17, 2015.

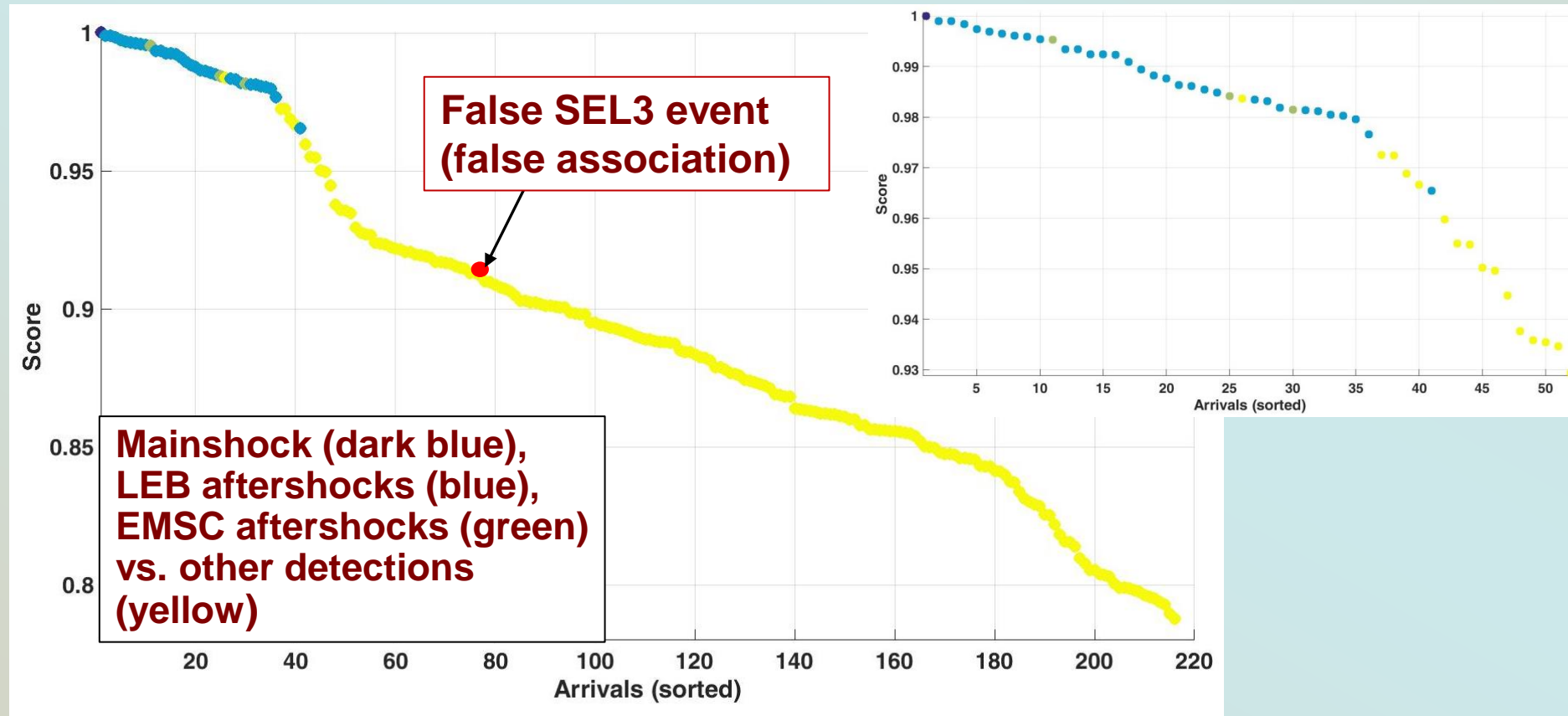
LEB: 33 aftershocks with EIL arrivals.



2015 Crete earthquake (cont.):

Input:

- ❖ EIL.BHZ continuous waveforms from Apr 16-17, 2015.



Identification of quarries by classifying explosions

Data:

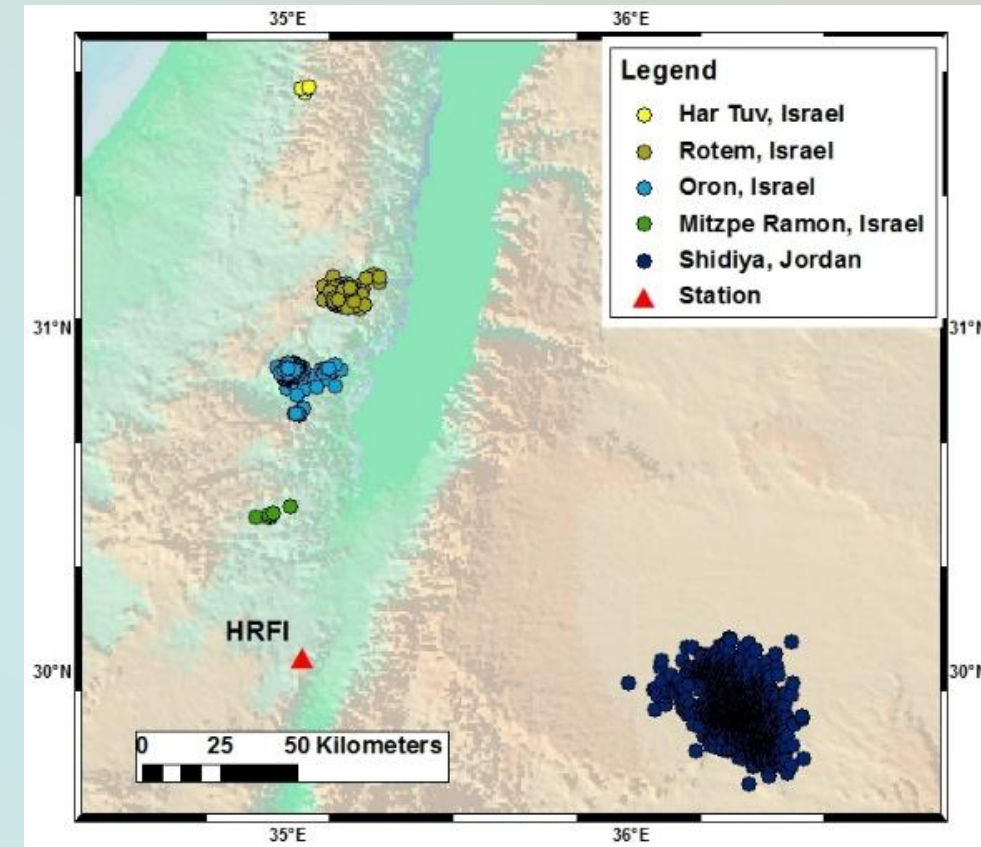
3-component waveforms of station HRFI of 602 explosions from 5 quarries in Israel and Jordan.

Task:

Classify the explosions to the known quarries.

Results:

85% correct classification rate



Summary

- ❖ We have introduced a new, diffusion maps based, method for automatic identification of repeating seismic event.
- ❖ The method was successfully applied to aftershock identification at local and regional distances.
- ❖ The method performs satisfactory for identifying quarry explosions
- ❖ The method can be used as a validation tool for waveform cross-correlation to exclude the false correlation detections.

Publications:

- 1. Rabin N., Bregman Y., Lindenbaum O., Ben-Horin Y., Averbuch A., Earthquake-Explosion Discrimination Using Diffusion Maps, Geophysical Journal International, 2016, v.207, p.1484–1492.**
- 2. Lindenbaum O., Bregman Y., Rabin N., Averbuch A., Multiview Kernels for Low-Dimensional Modeling of Seismic Events, IEEE Transactions on Geoscience and Remote Sensing, 2018, v.56, p.3300–3310.**
- 3. Bregman Y., Rabin N., Seismic event identification using diffusion maps, Seismological Research Letters, Special Issue in Machine Learning, 2019, v.90, p.539-545.**

Thank you