The FAST Method for Earthquake Detection: Application to Seismicity During the Initial Stages of the Guy-Greenbrier, Arkansas, Earthquake Sequence

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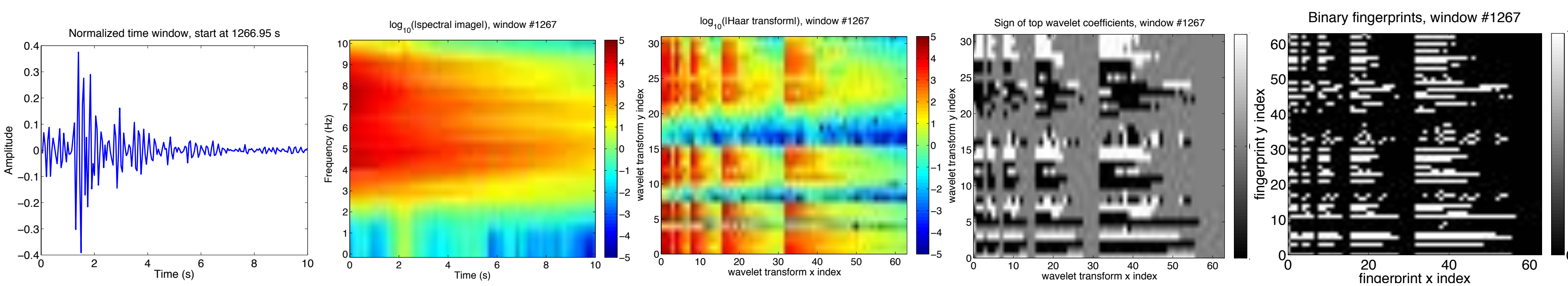
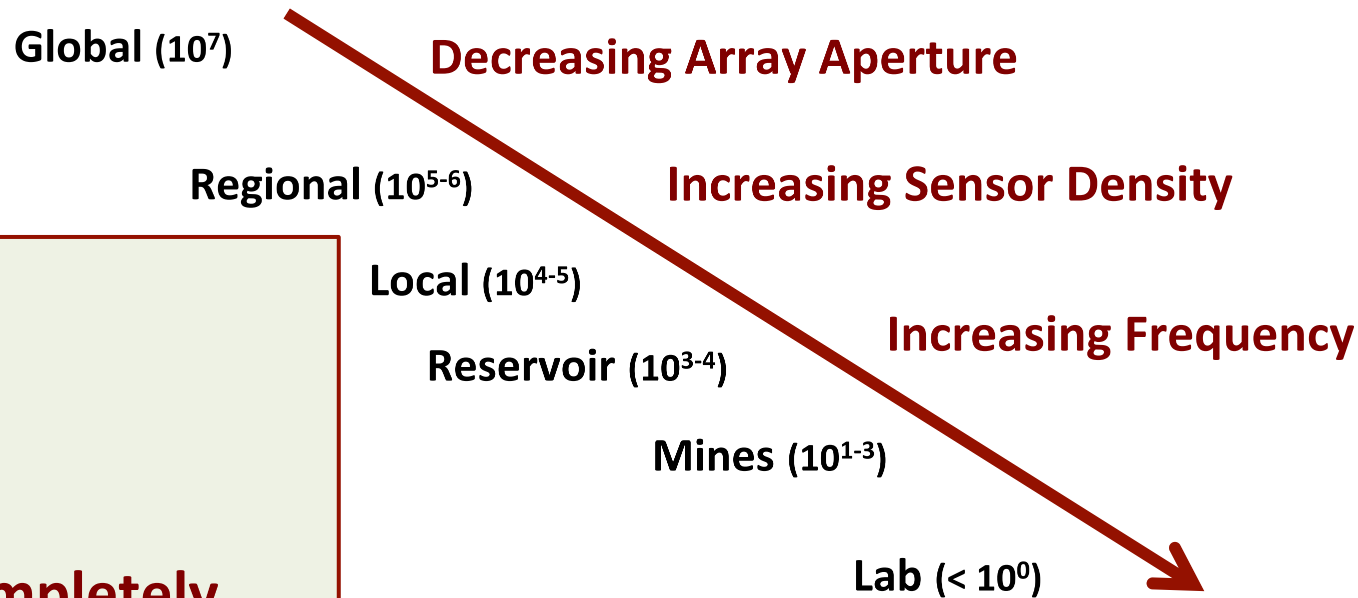
Yihe Huang (University of Michigan)

Earthquakes: Nucleation, Triggering, Rupture, and Relationships to Aseismic Processes

October 3, 2017, Cargese



Earthquake Monitoring Across Scales (meters)

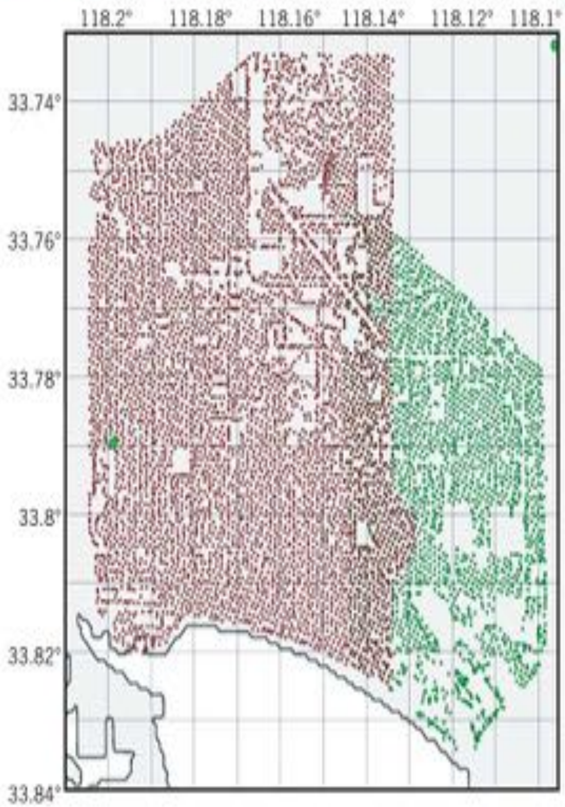


Common Goal:

- **detect**
- **locate**
- **characterize**

earthquakes as completely and as accurately as possible.

Seismology has lots of data…



Big Networks (Large-N)

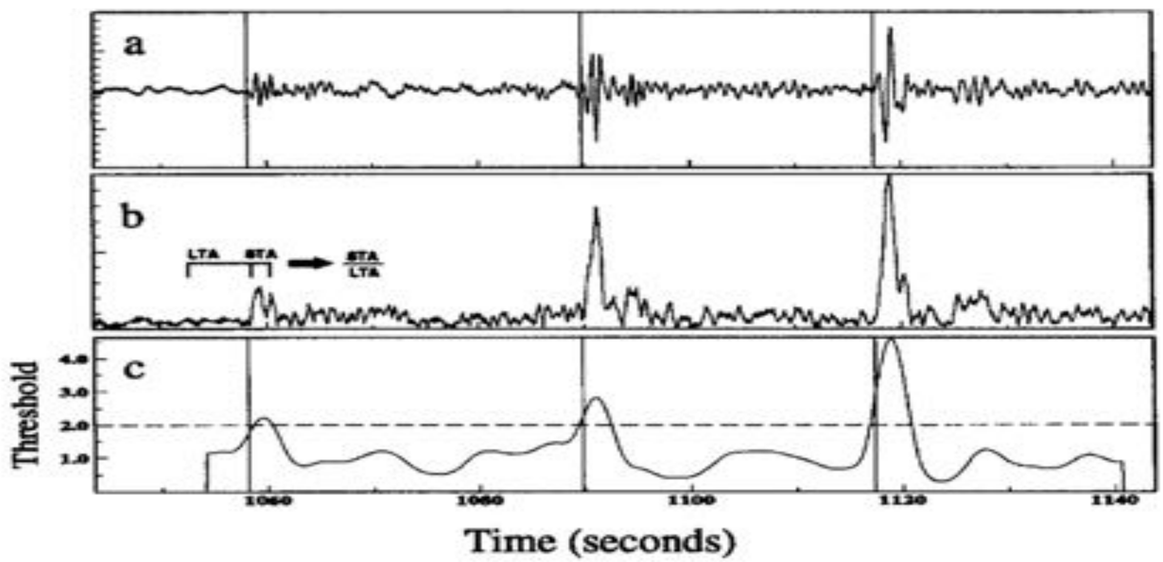
1000s of sensors

Long Duration (Large-T)

Years of continuous waveforms

We need scalable algorithms to extract useful information from these massive data volumes

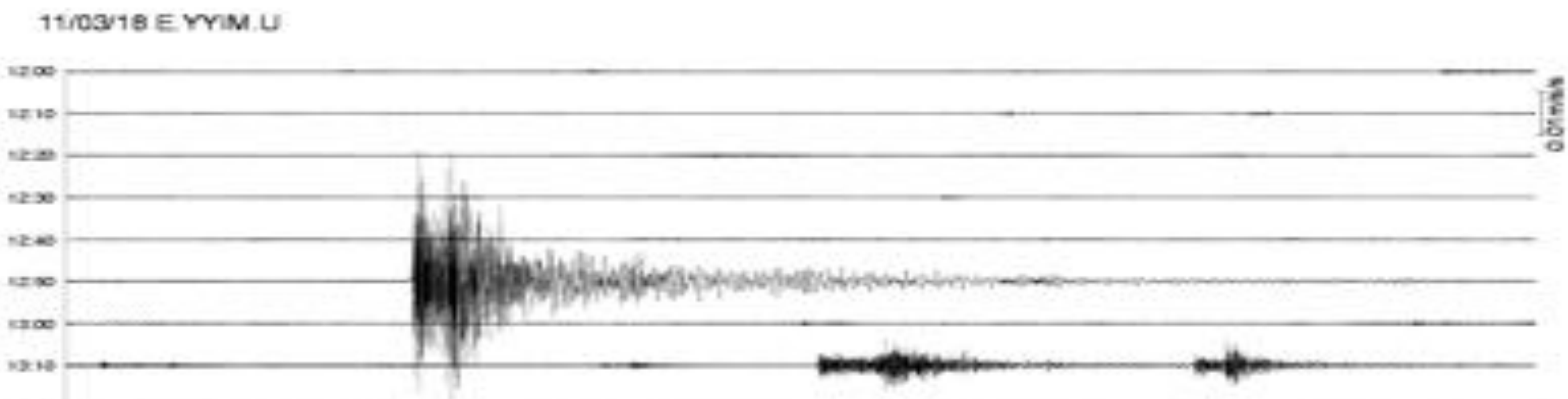
Standard Approach to Detection/Location



Earle and Shearer [1994]

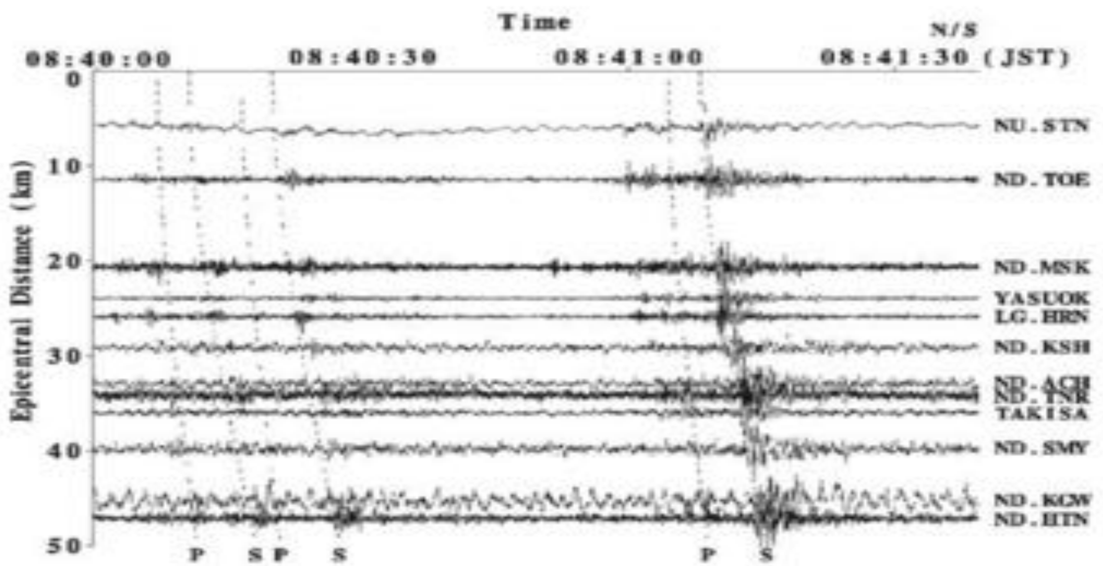
(1) Detection (STA/LTA)
(2) Association
(3) Location
(4) Characterization

Standard approach works well when…



Events are recorded at > 3 stations
Events are impulsive
Events don't overlap

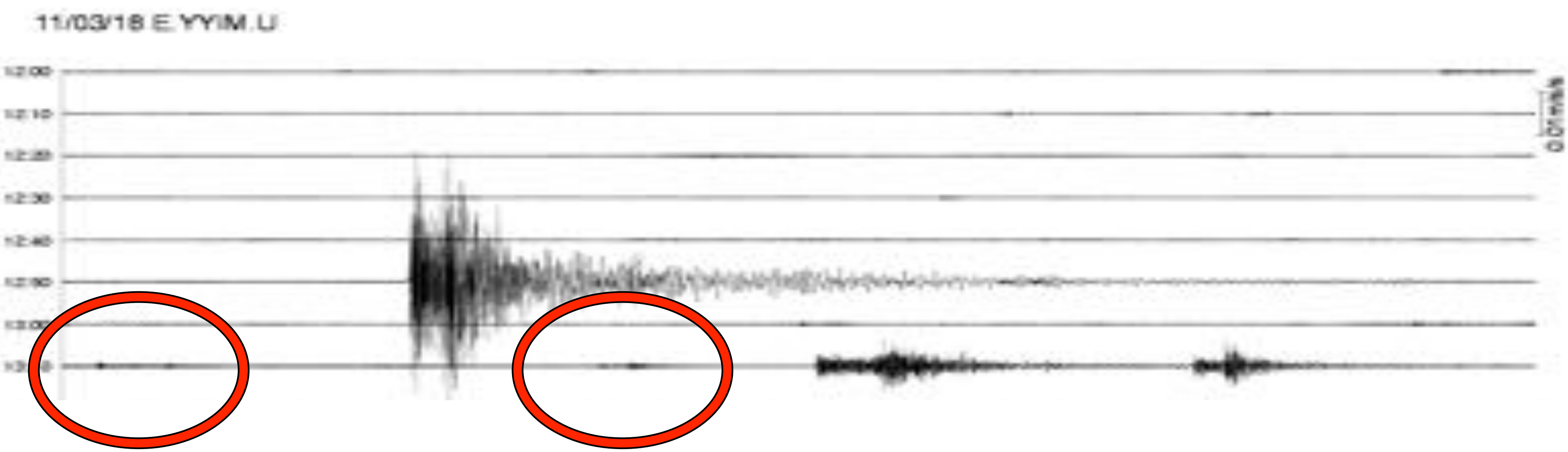
Standard approach works less well for …



…weak events with emergent arrivals (like LFEs)

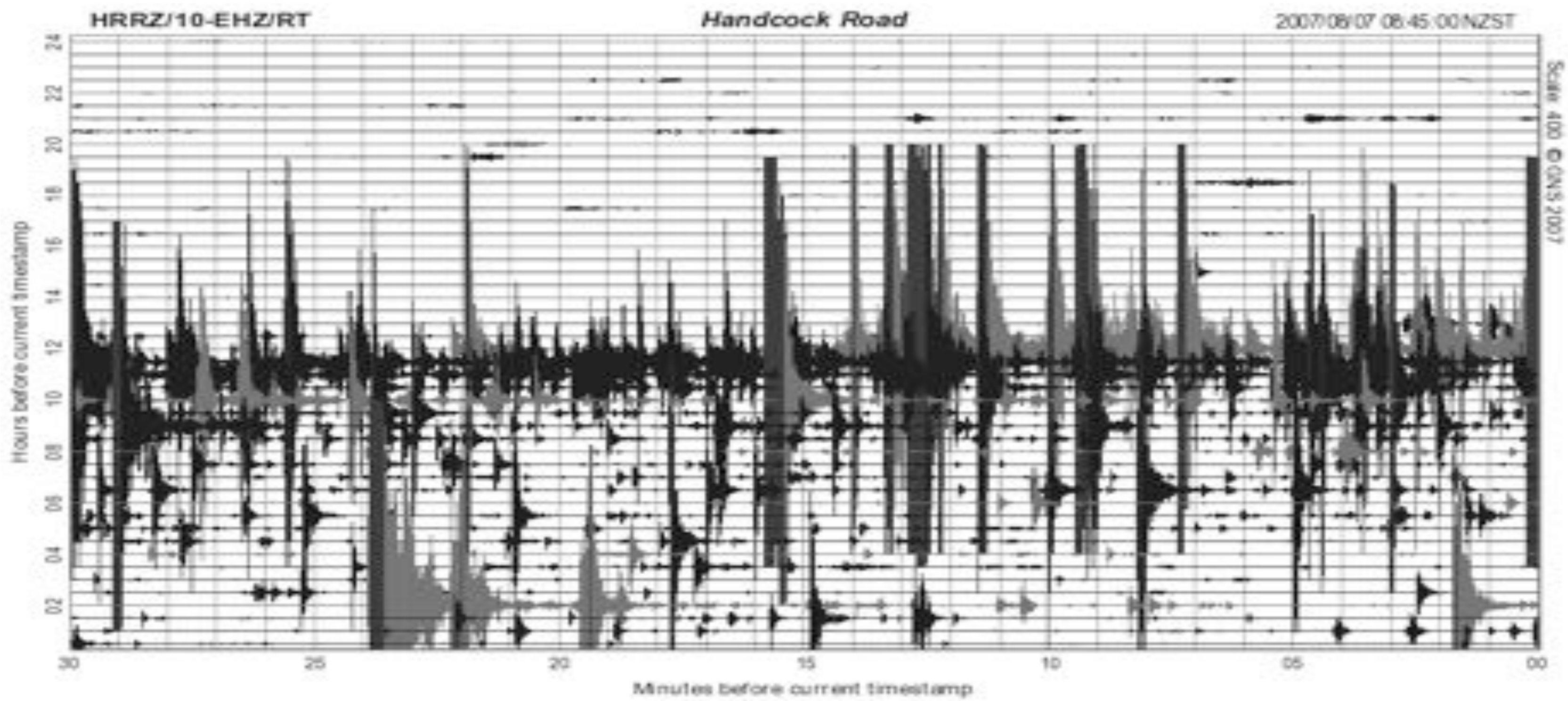
Katsumata and Kamaya [2003]

Standard approach works less well for …

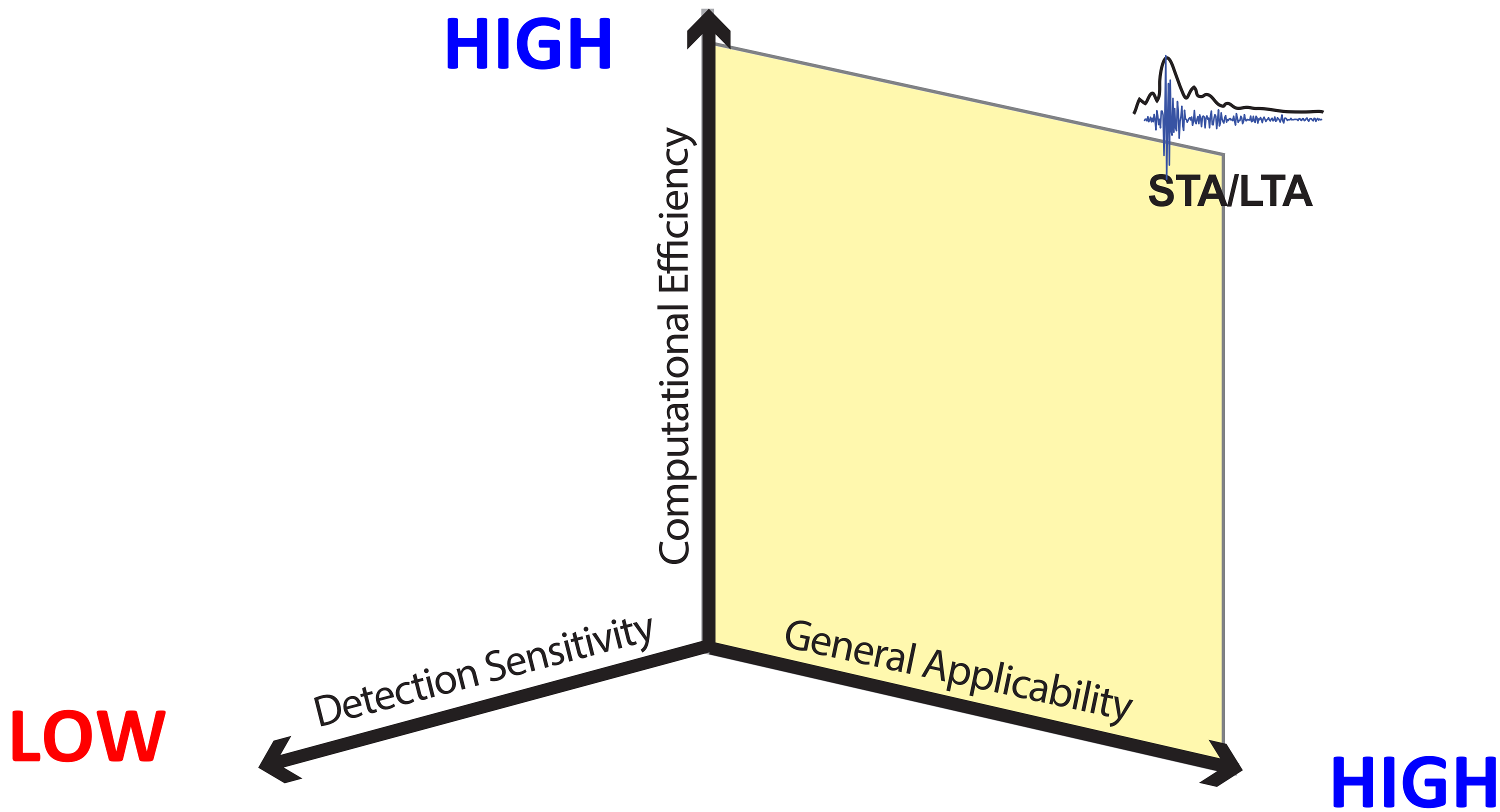


…small events with too few arrivals to locate

Standard approach works less well for …



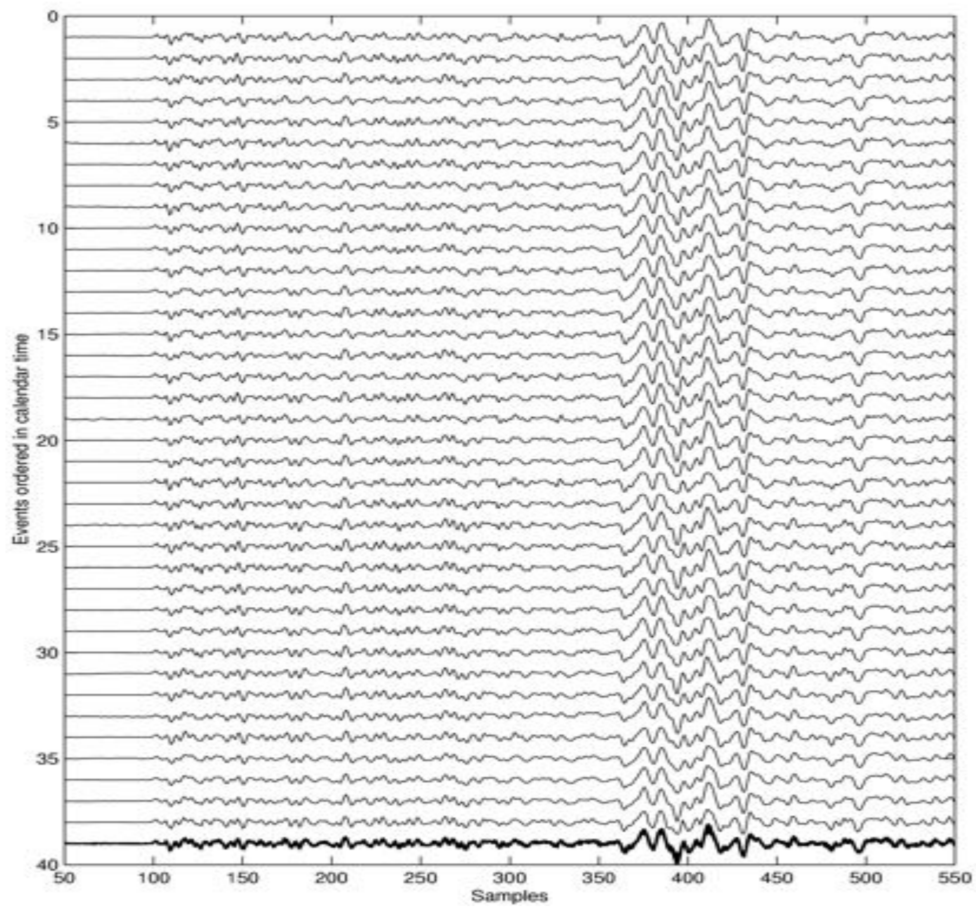
…Overlapping Events during intense activity



Insensitive to weak and/or non-impulsive signals, need multiple stations

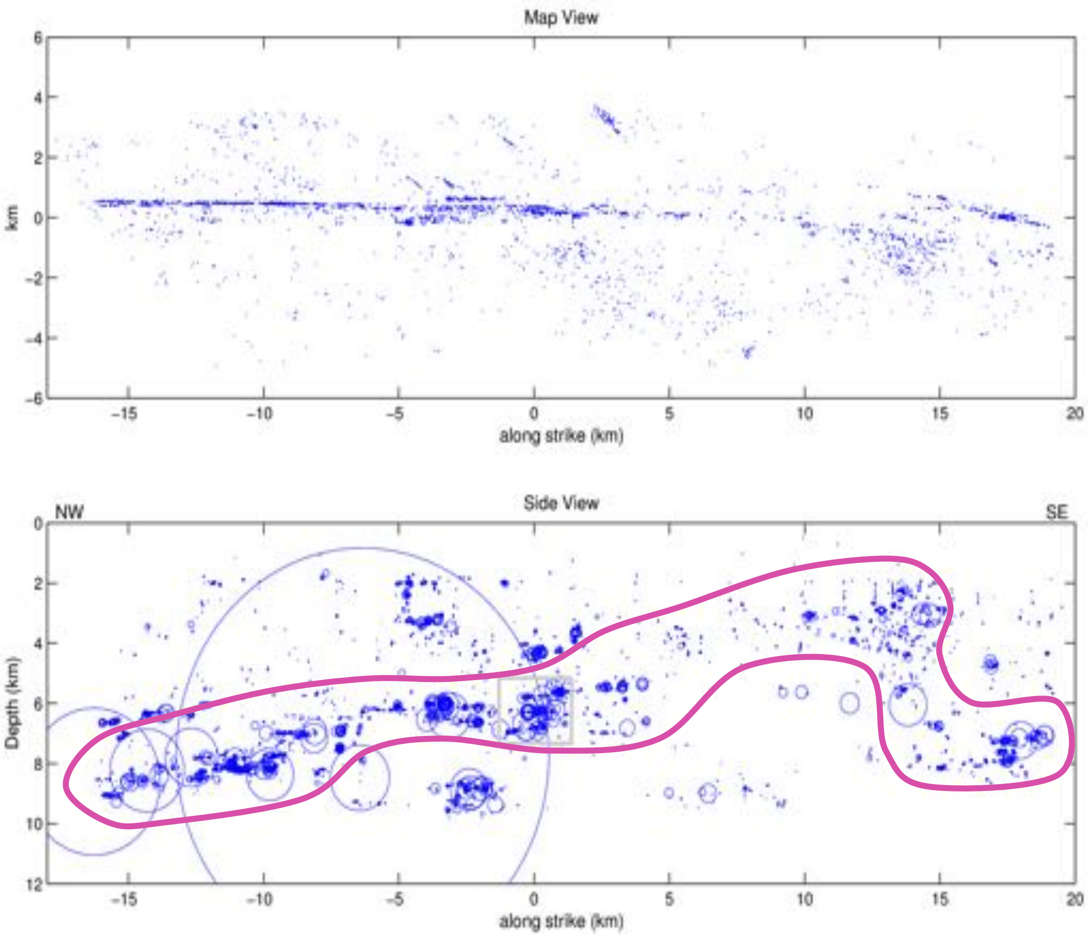
38 Repeats of Earthquake on the Calaveras Fault

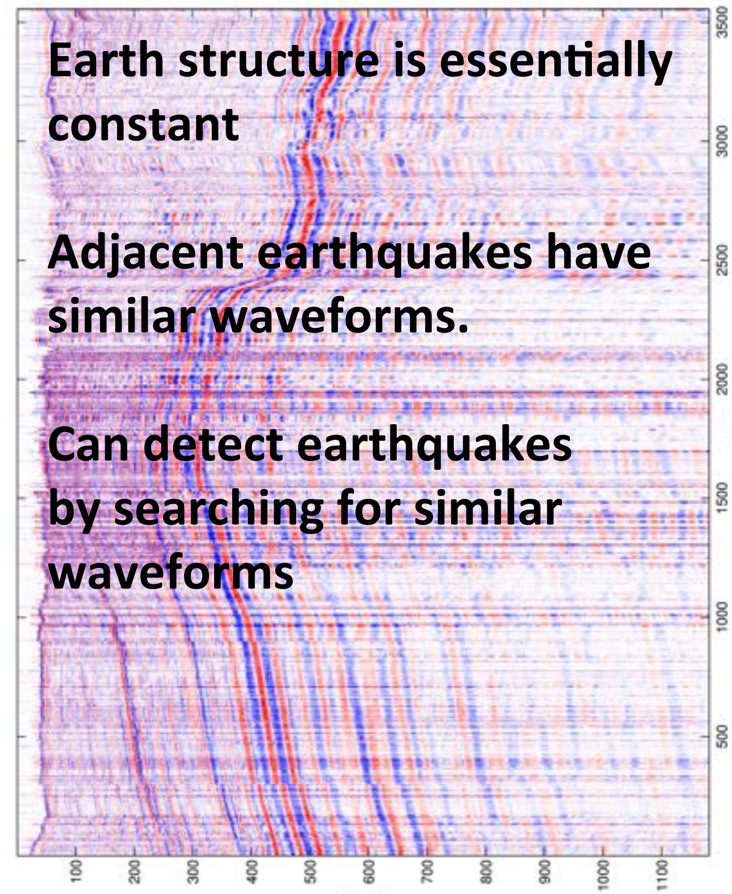
Slip occurring at different times in the same place, generates identical seismograms.



We can look for a repeating signal from a repeating source, but most sources don't exactly repeat.

Adjacent Earthquakes on the Calaveras Fault



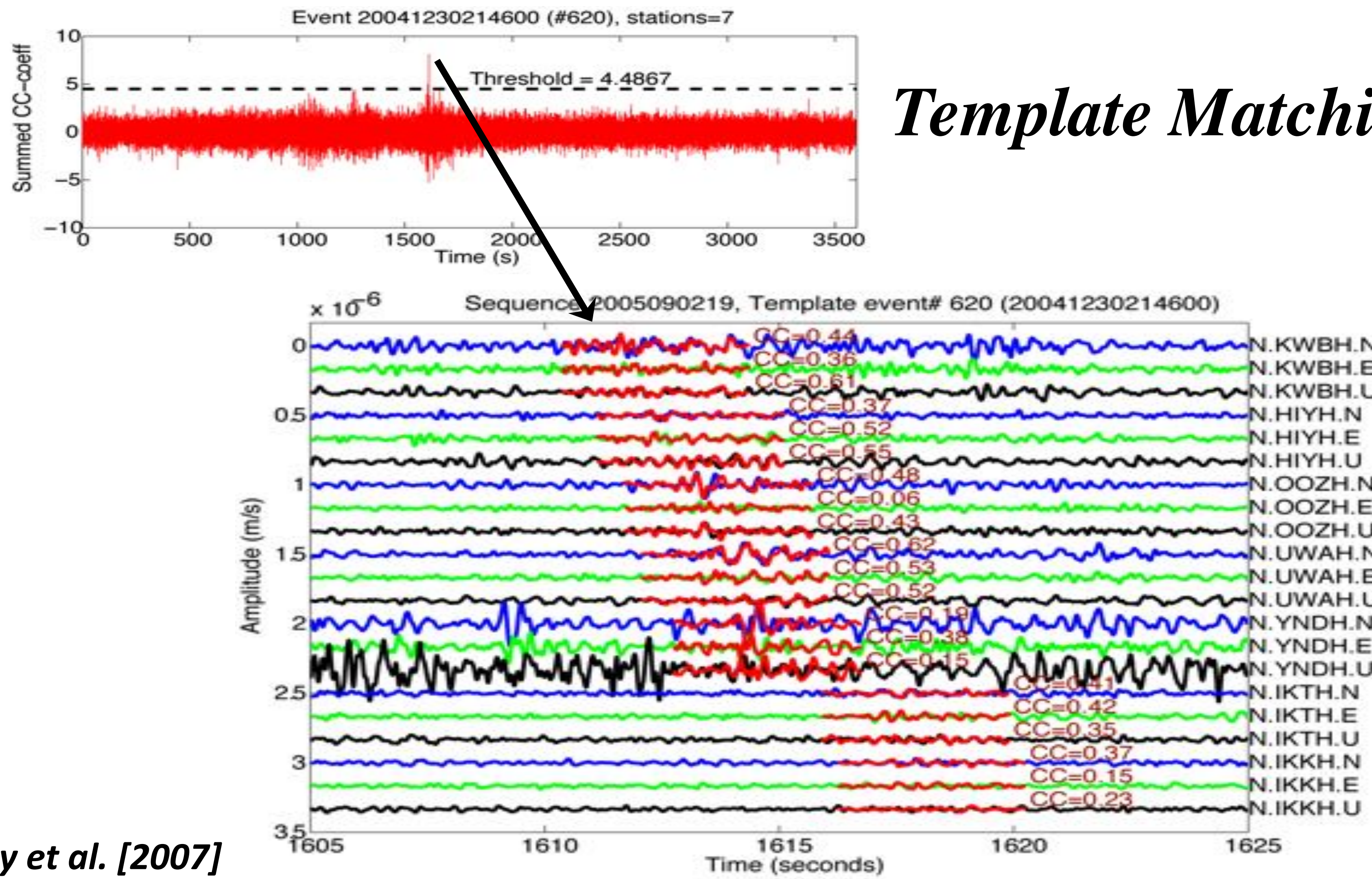


Earth structure is essentially constant

Adjacent earthquakes have similar waveforms.

Can detect earthquakes by searching for similar waveforms

Template Matching



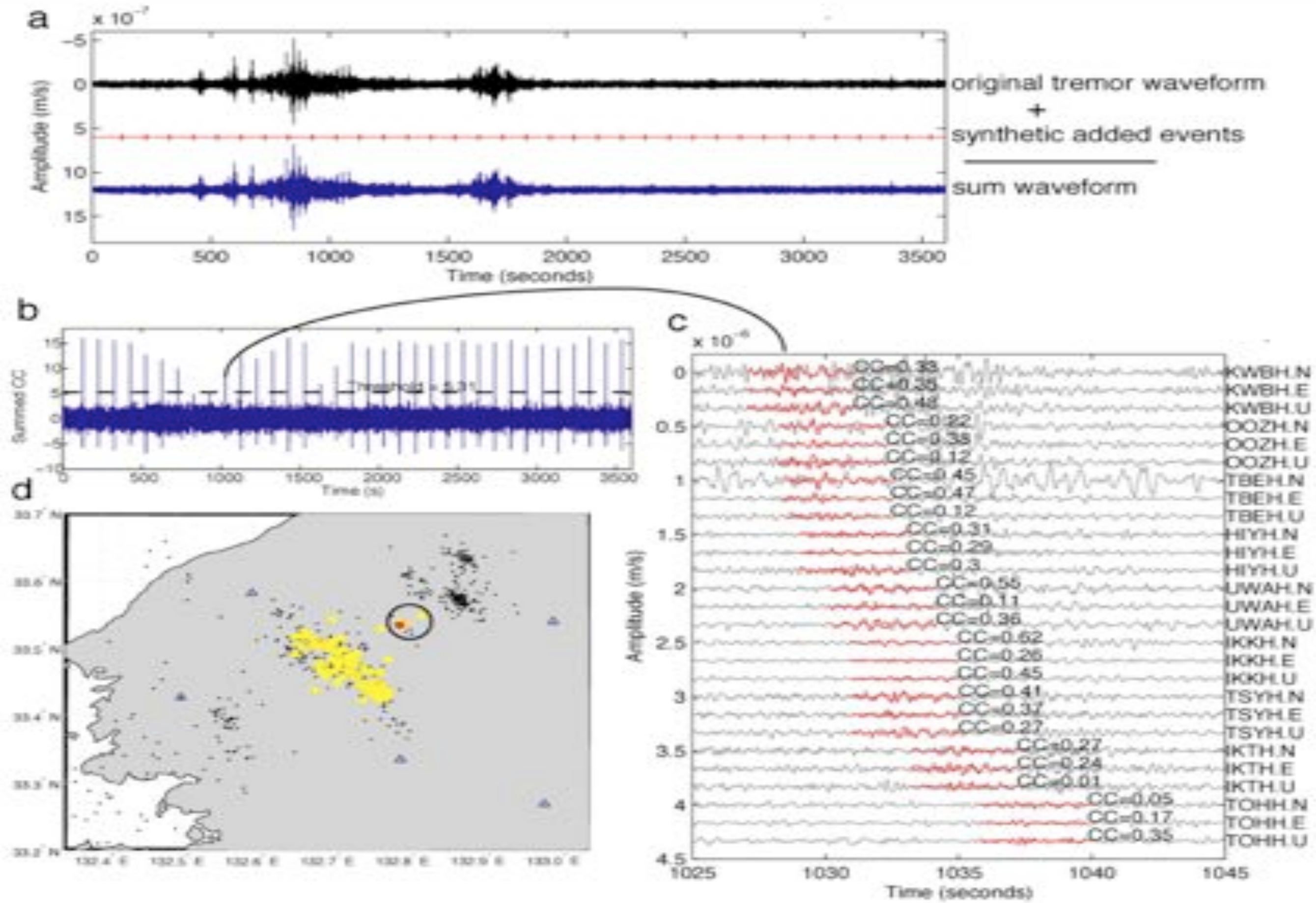
Shelly et al. [2007]

Template-based detection is powerful (few Type II errors)

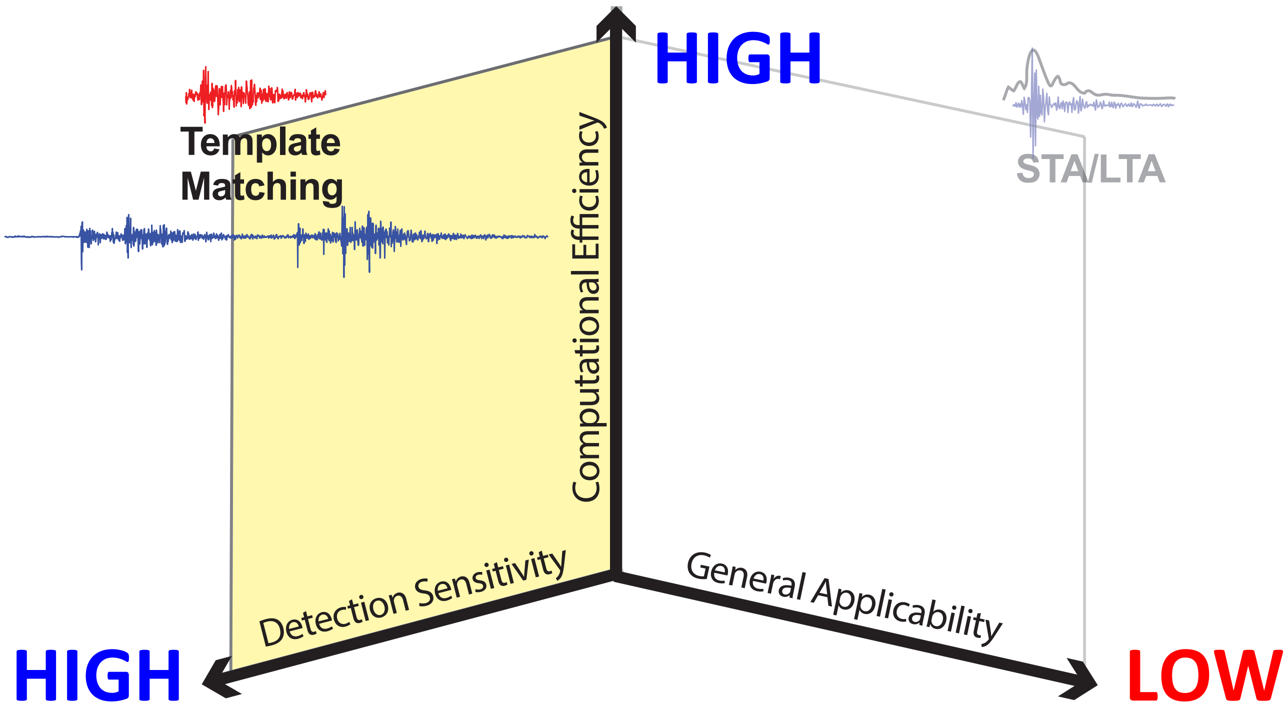
LFEs planted in real data at snr of 0.1

34/36 are detected

Shelly et al. [2007]



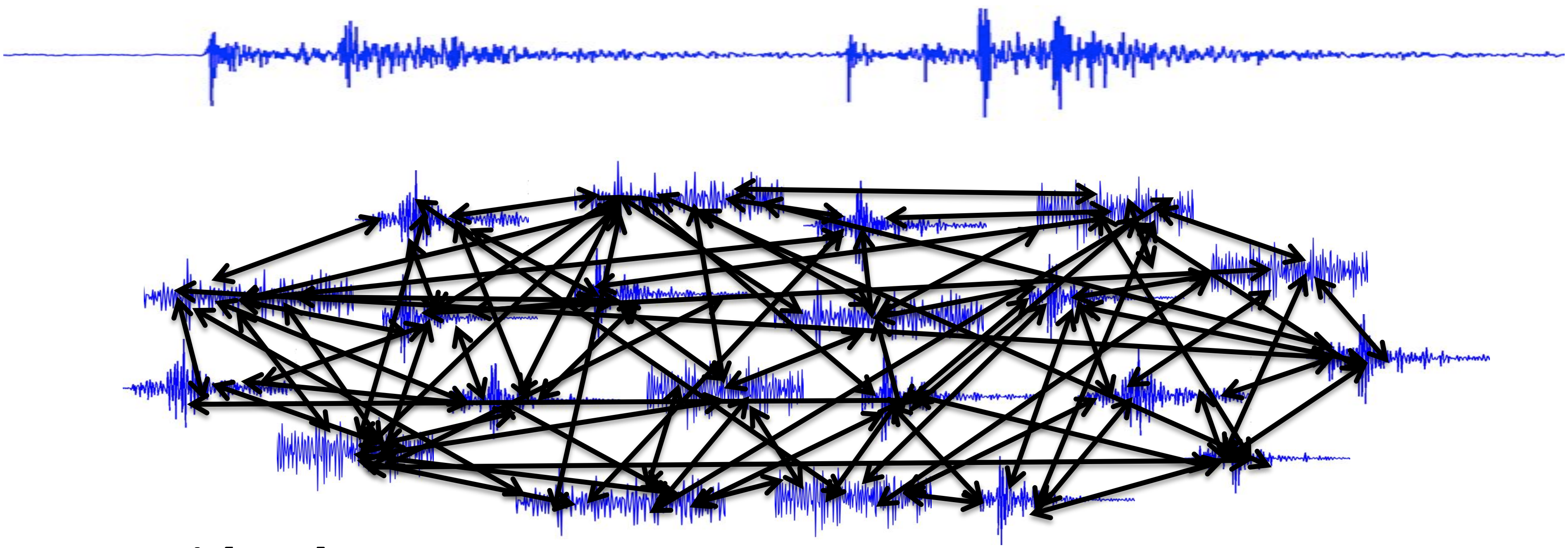
Informed Similarity Search



Need template waveform *a priori*

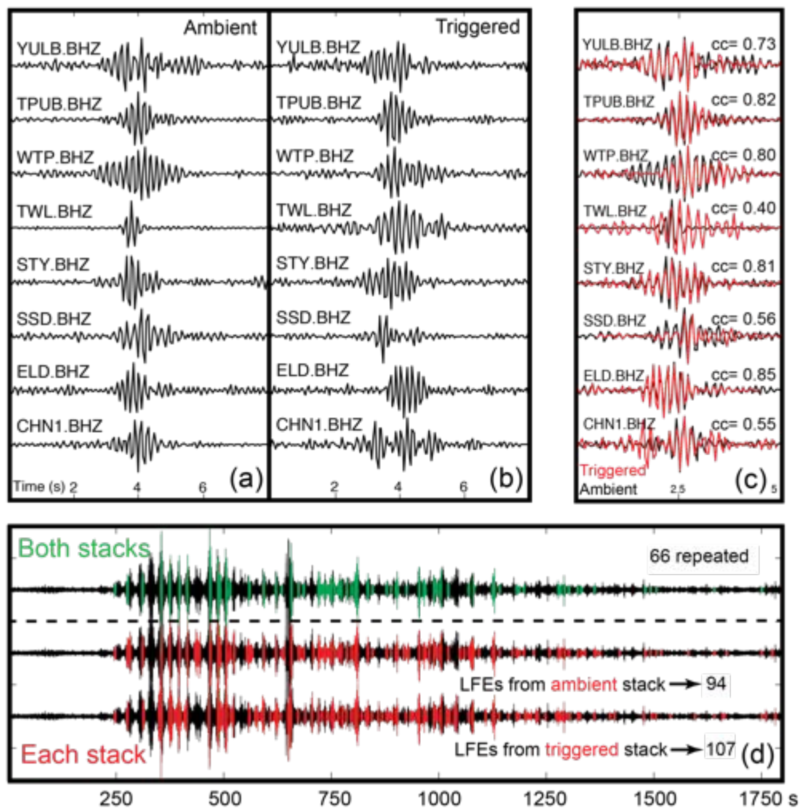
Exhaustive Search for Similar Waveforms

"Autocorrelation" - Uninformed search for similar signal – detect events by cross correlating all window pairs.

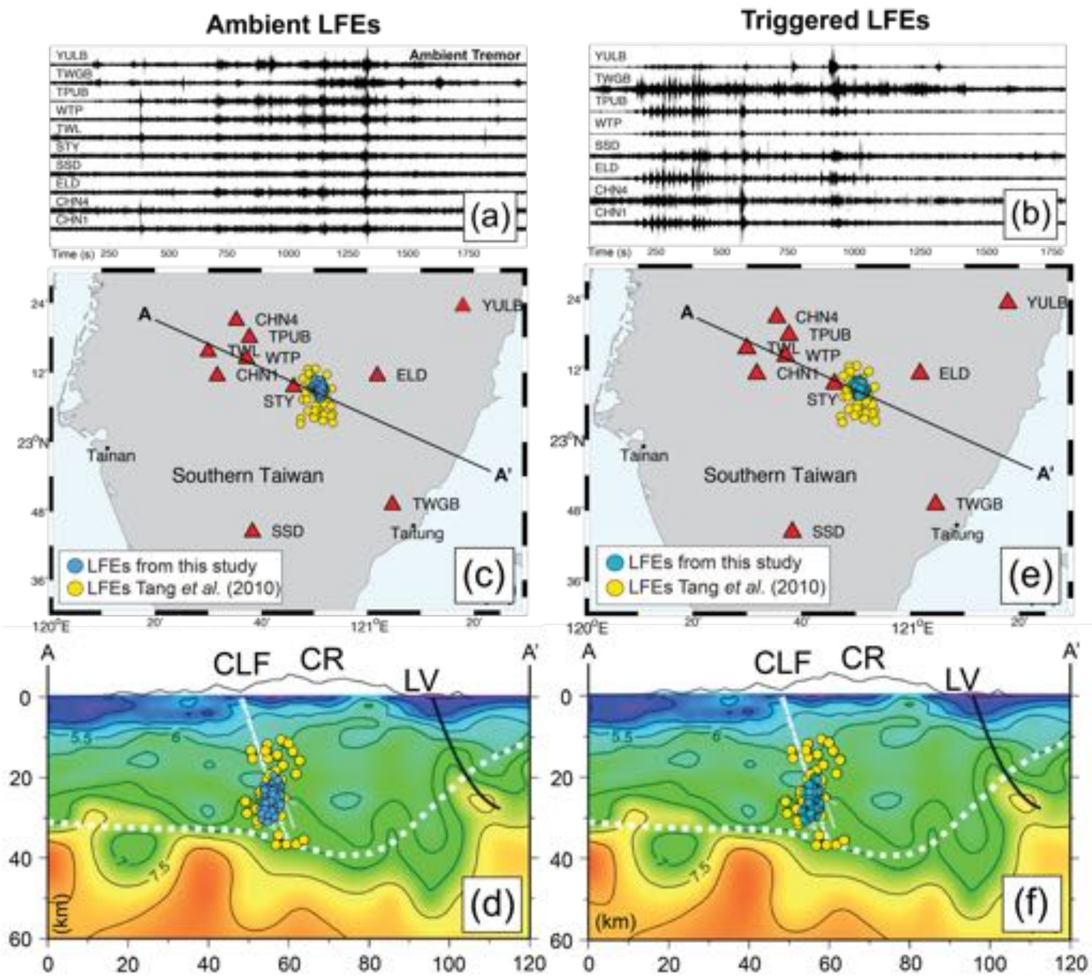


Brown et al. [2008]

Autocorrelation for LFE Detection

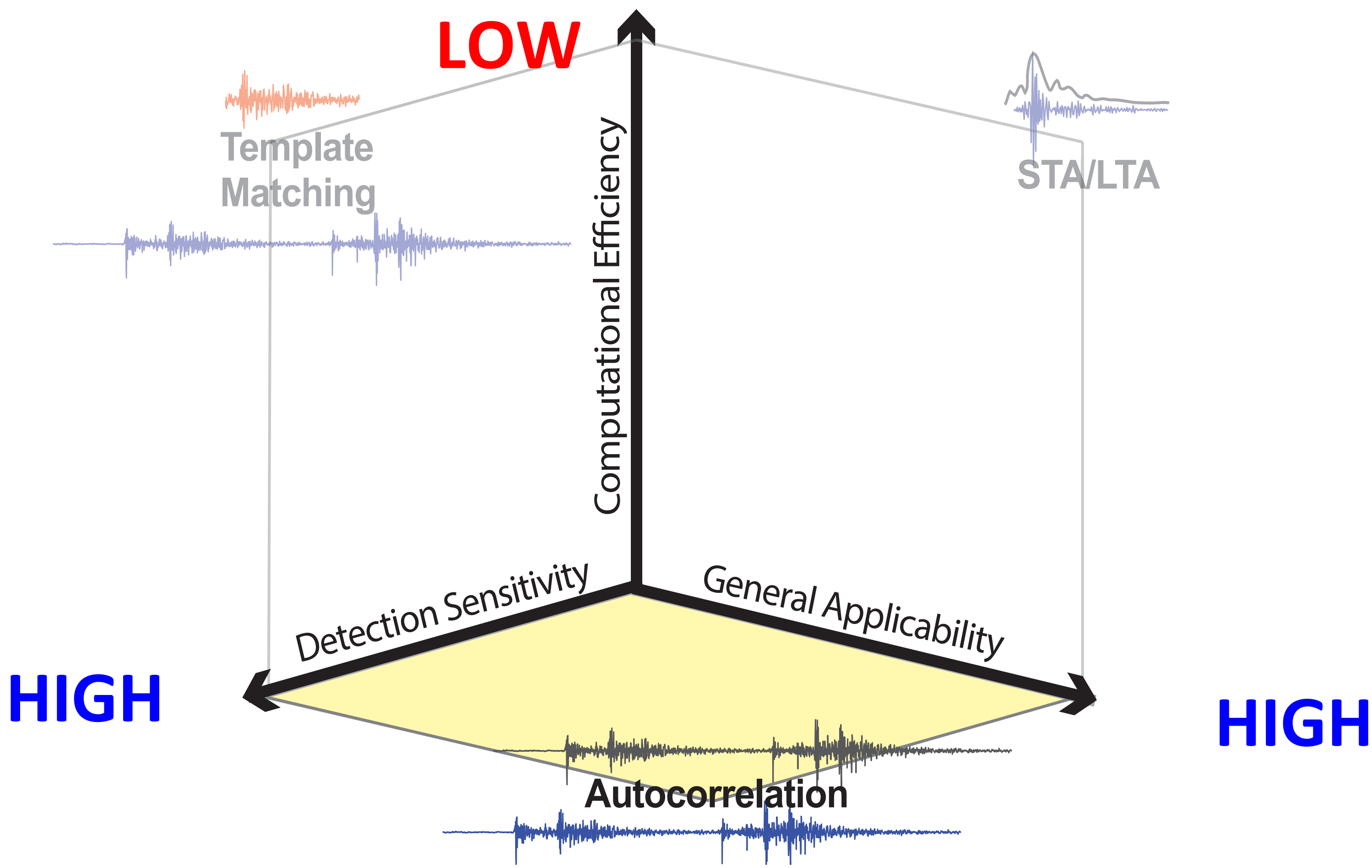


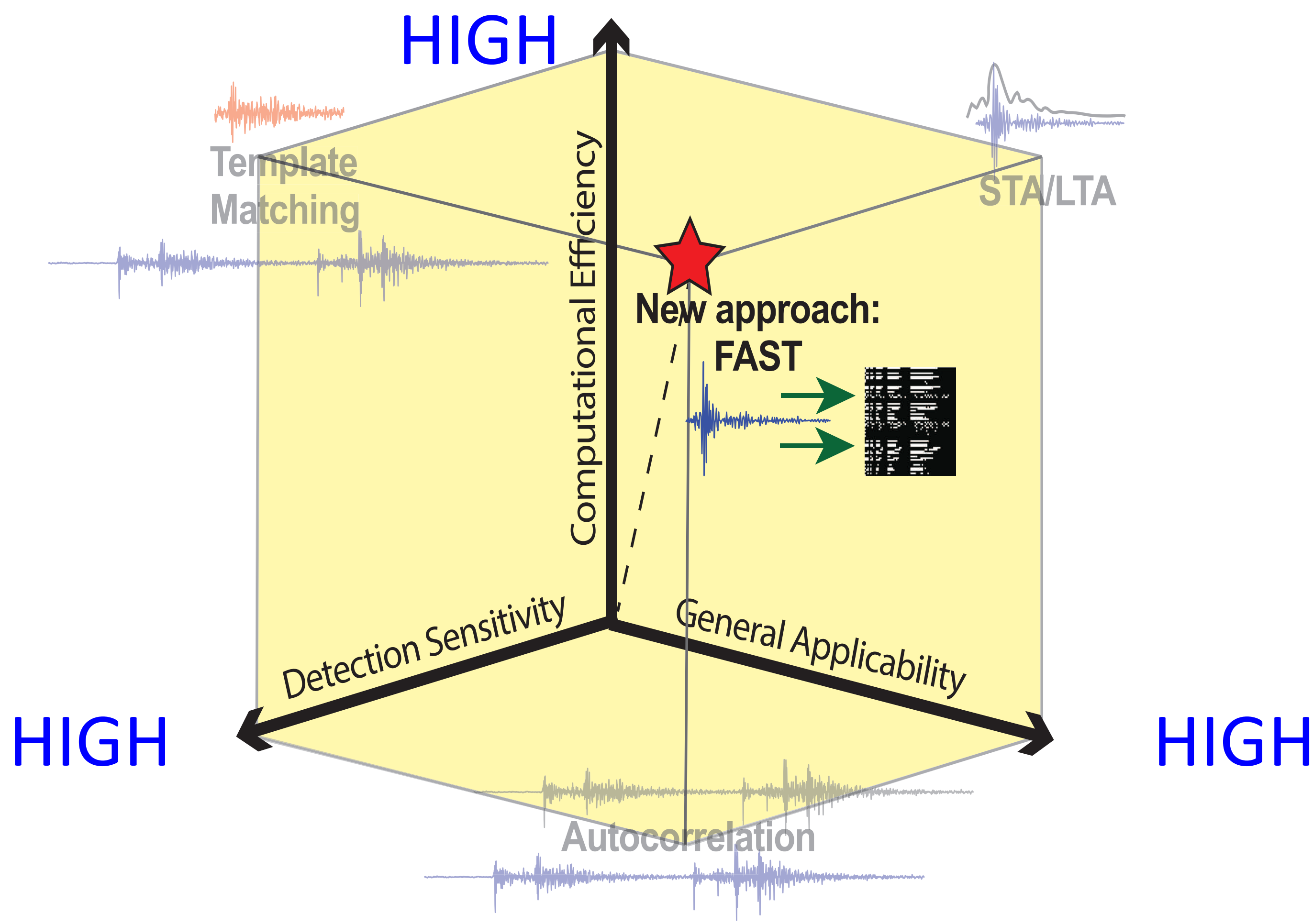
Aguiar et al. [2017]



Aguiar et al. [2017]

Naïve Uninformed Similarity Search





HIGH
Computational Efficiency
Template
Matching
STA/LTA
New approach:
FAST
Detection Sensitivity
General Applicability
HIGH
HIGH
Autocorrelation

Some Big Data Technologies for Similarity Search

Shazam – identify songs from a sample of recording.

Soundhound – identify songs from singing (seriously).

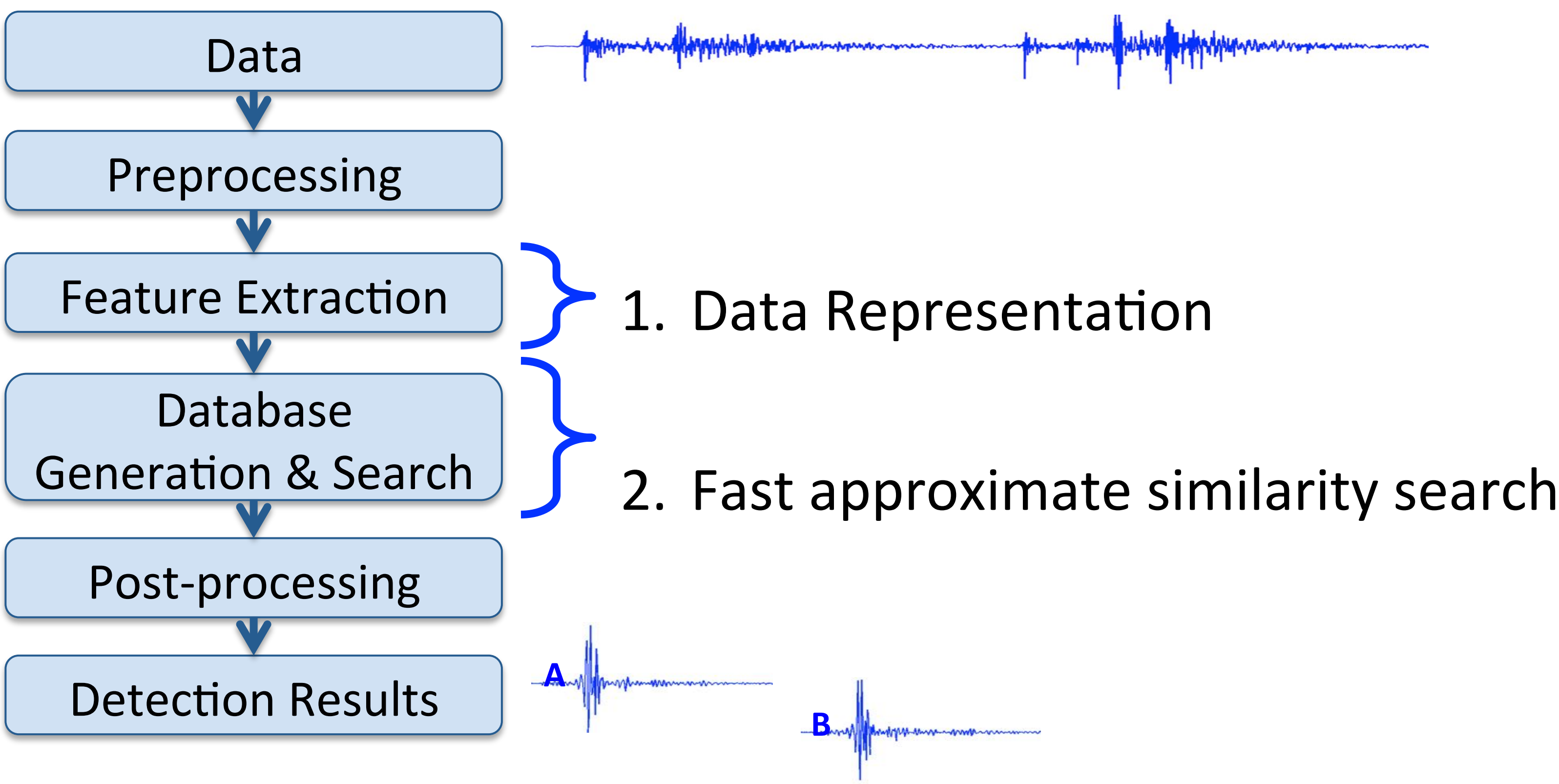
TinEye – Search the web for the source of a known image.

YouTube – detect copyright infringement

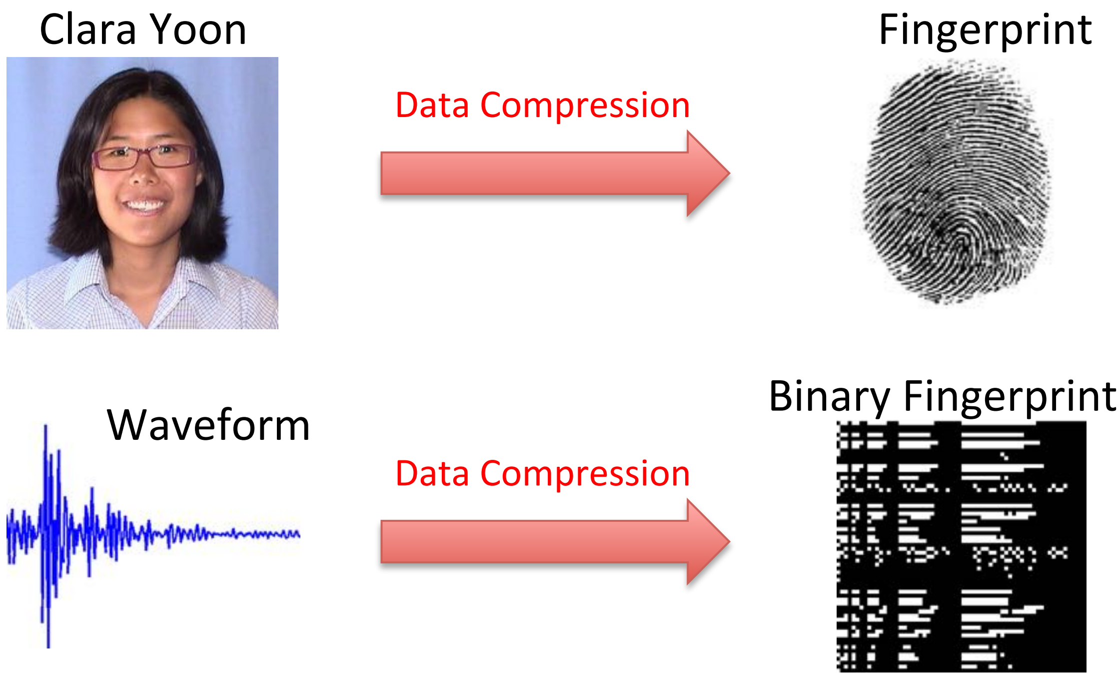
CopyLeaks – detect plagiarism

Altavista – remove duplicate web pages from search results

FAST (Fingerprinting And Similarity Thresholding)

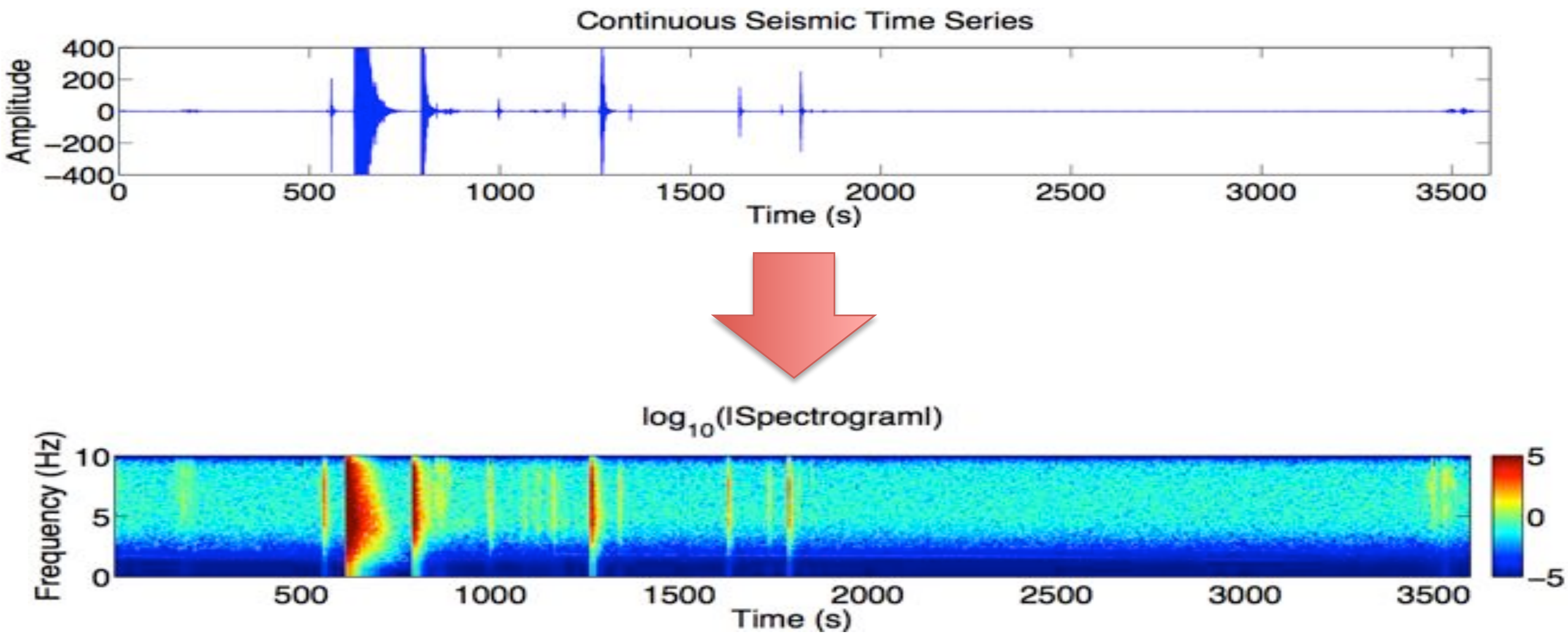


Fingerprinting



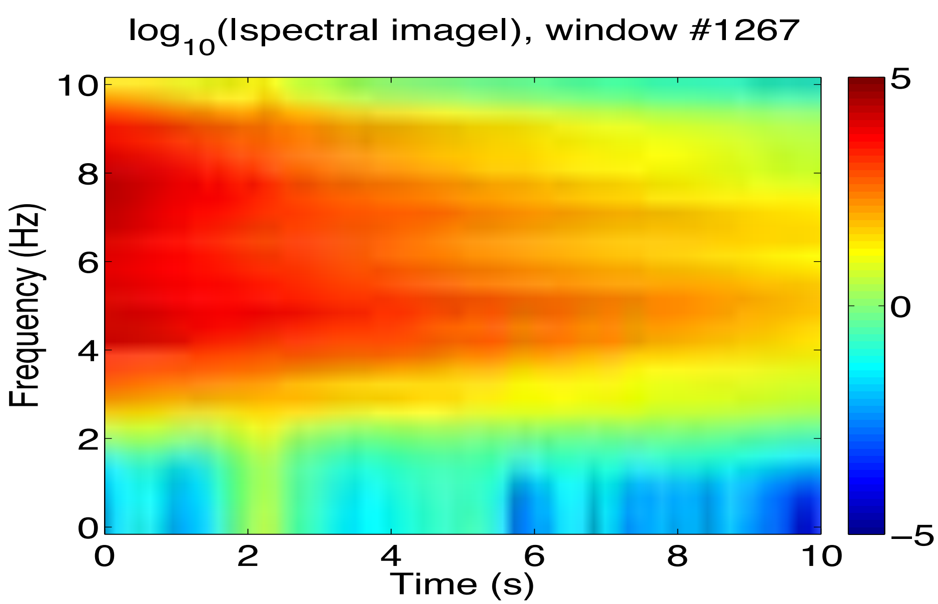
- **"Fingerprint" waveform with sparse, diagnostic description**
- **Store fingerprints in database and search it efficiently**

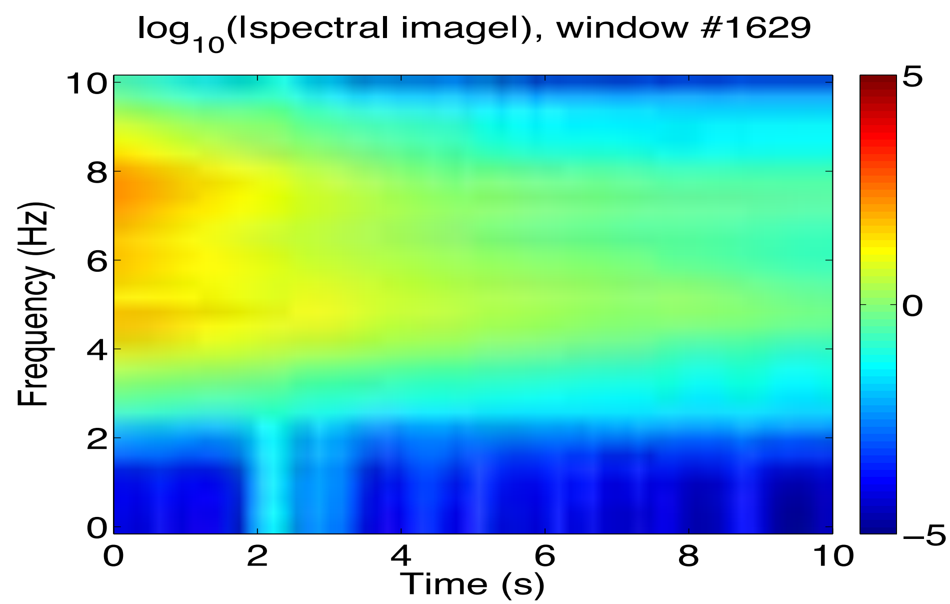
Step 1: Time Series to Spectrogram



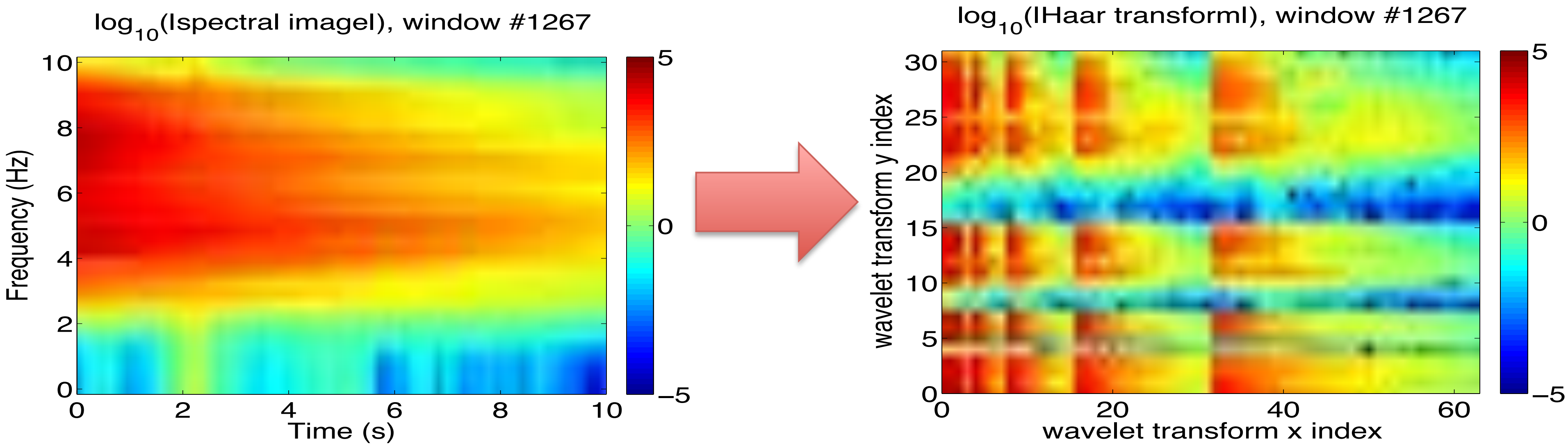
Step 2: Spectrogram to Spectral Images

To find short duration events, divide spectrogram into overlapping spectral images





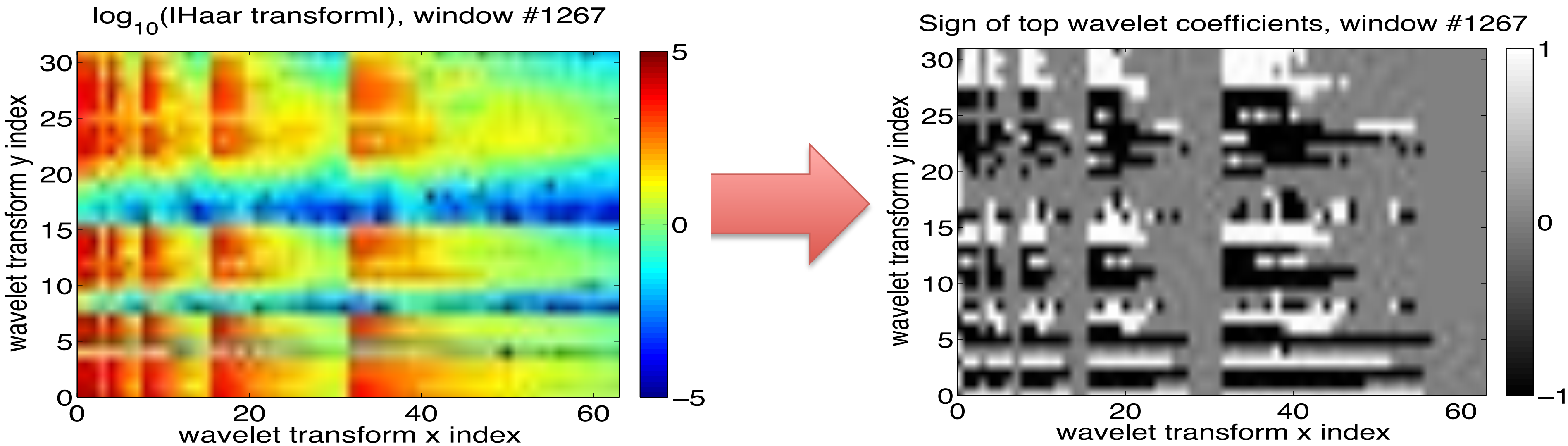
Step 3: Spectral Image to its Wavelet Transform



Goal: compress nonstationary seismic signal

– Compute 2D discrete wavelet transform (Haar basis) of spectral image to get wavelet coefficients

Step 4: Wavelet Transform to Top Coefficients

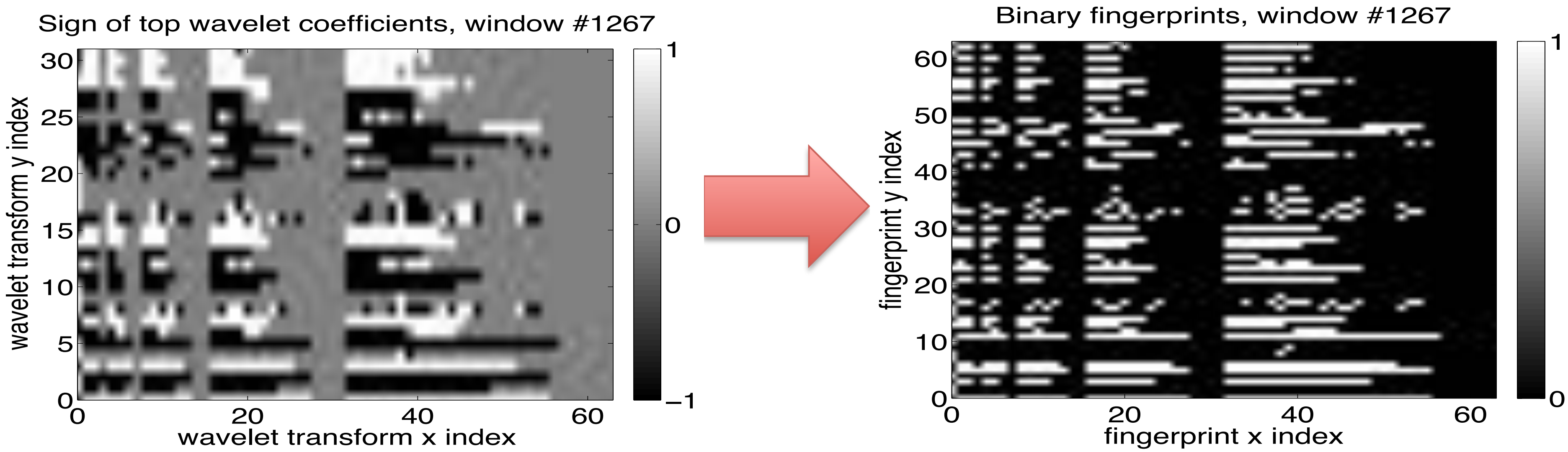


Key discriminative features are concentrated in a few wavelet coefficients with highest deviation

- Keep only sign (+ or -) of these coefficients, set rest to 0

Data compression, robust to noise

Step 5: Top Coefficients into a Binary Fingerprint



Fingerprint must be compact and sparse to store in database

Convert top coefficients to a binary sequence of 0's, 1's

- Negative: 01, Zero: 00, Positive: 10

Jaccard Similarity

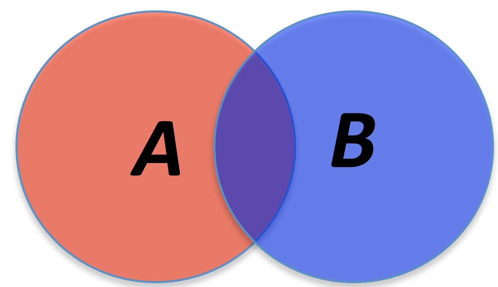
How similar are 2 binary fingerprints?

A

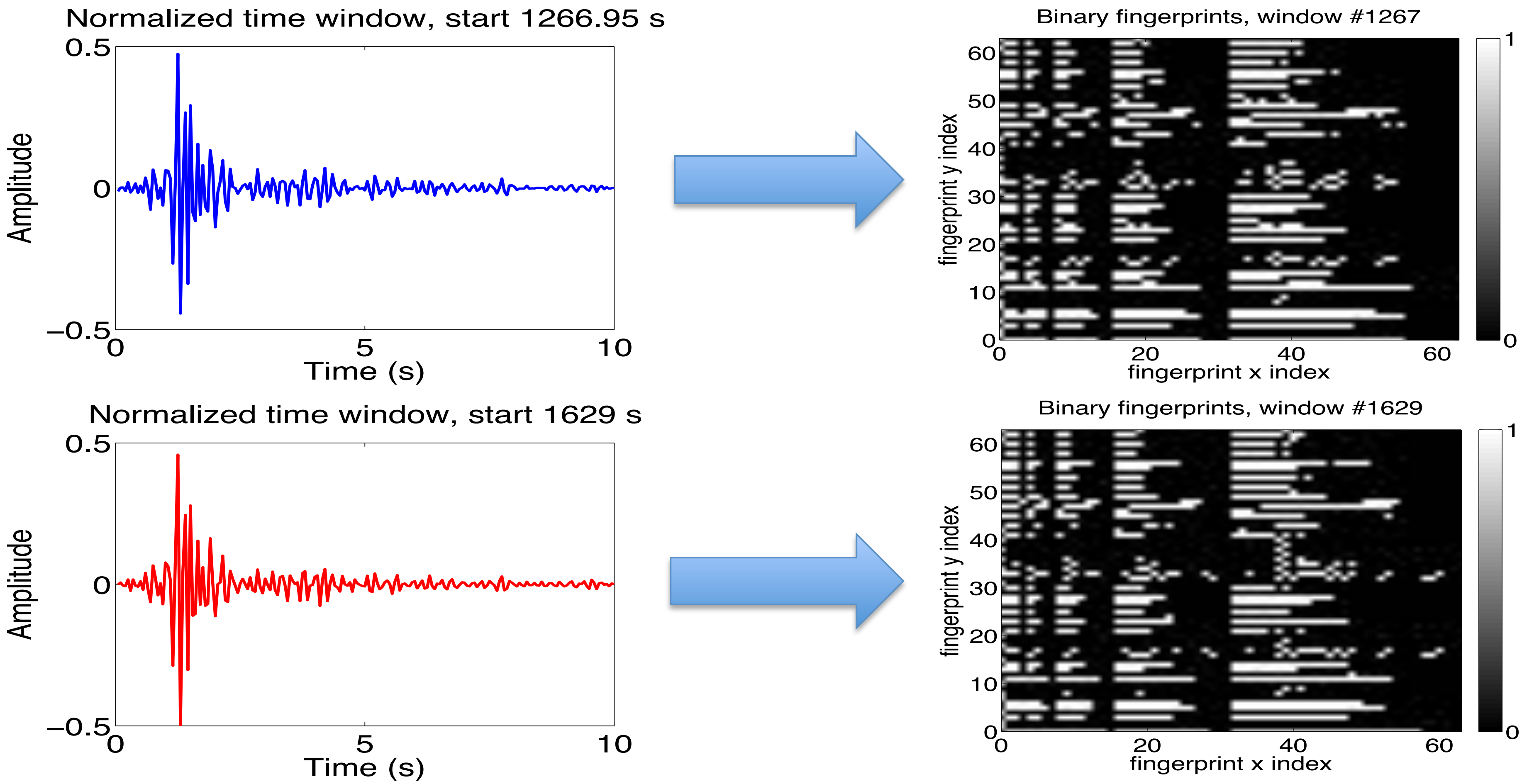
B

Jaccard similarity: "resemblance"

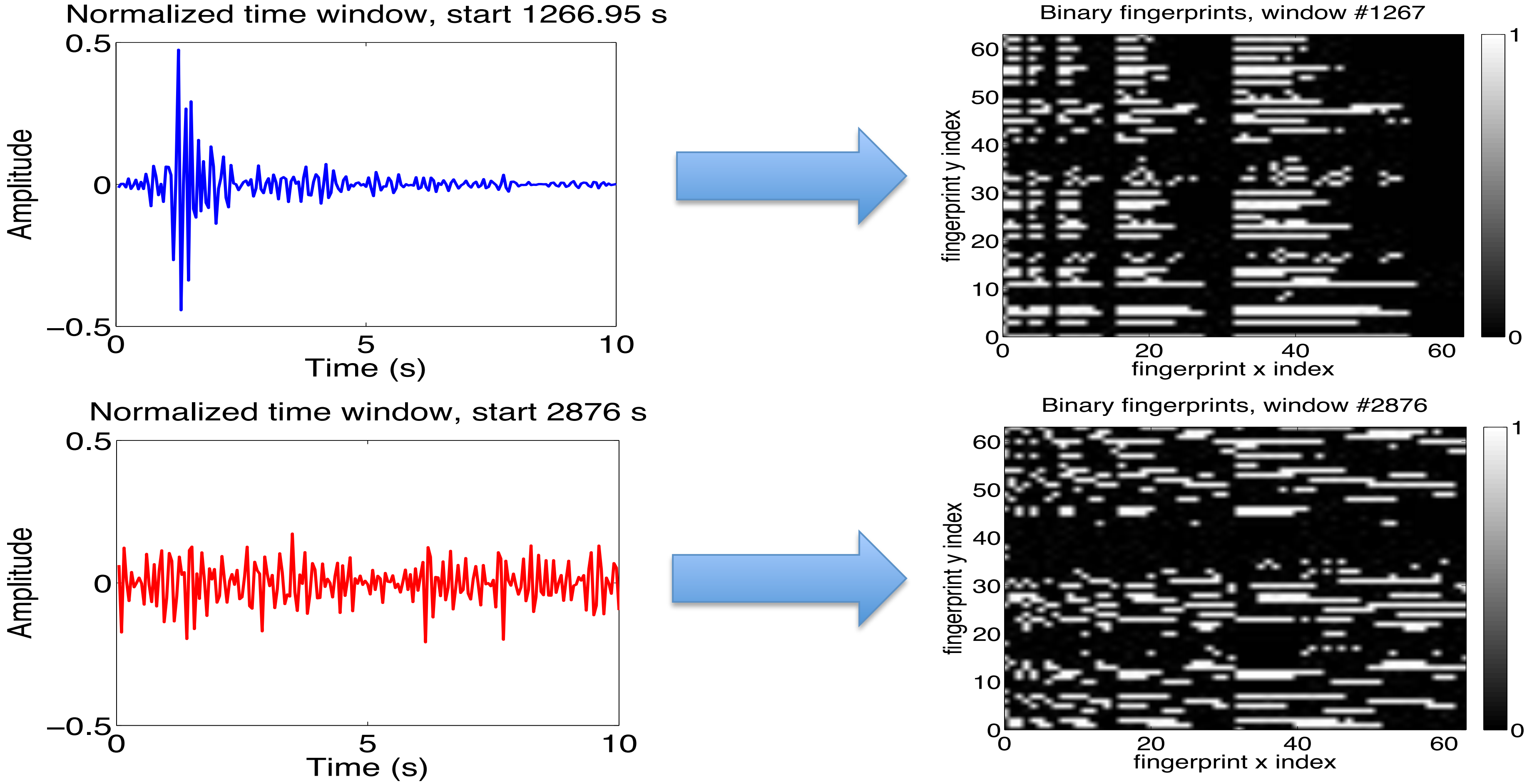
$$J(A,B) = \frac{|A \cap B|}{|A \cup B|}$$



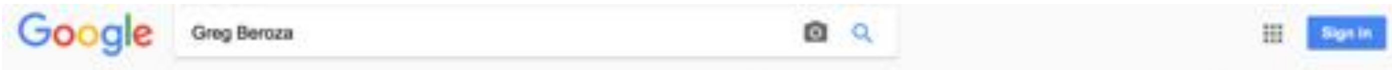
Similar Waveforms ➔ Similar Fingerprints



Fingerprints Should be Discriminative

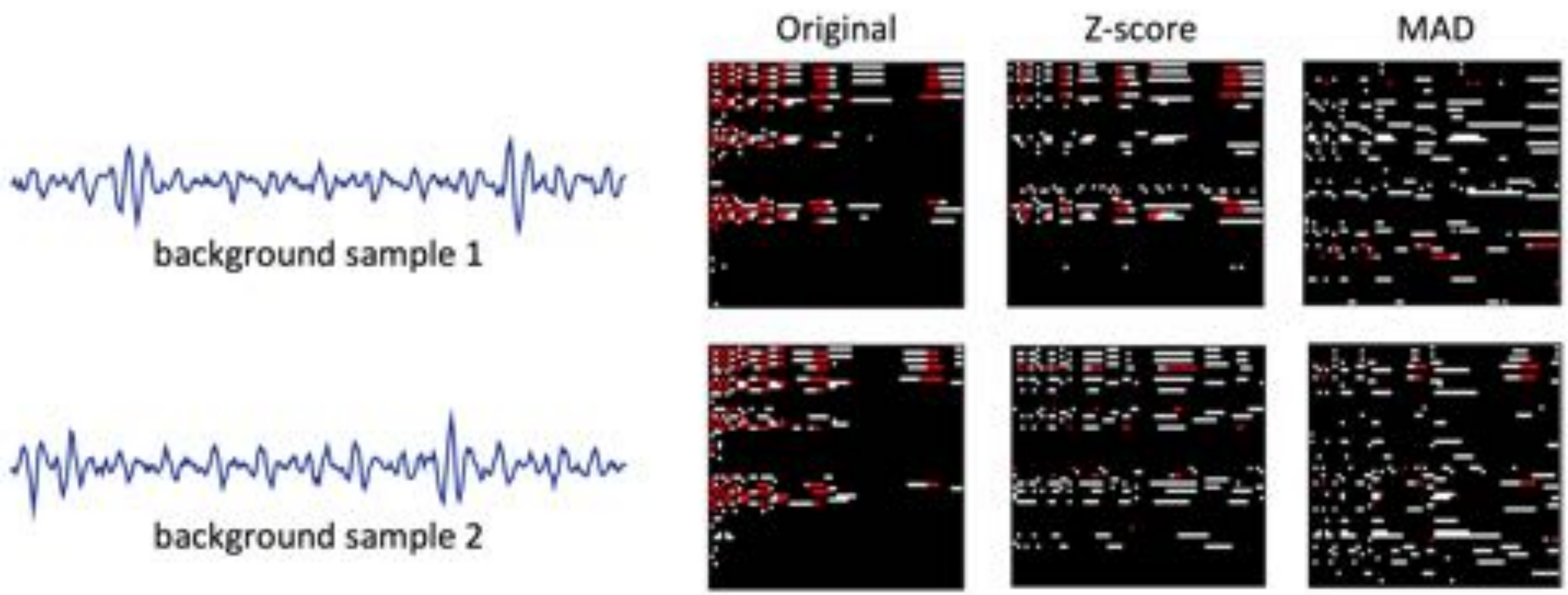


Names are a compact "Fingerprint"



Names are compact, but not discriminative.

How to select "discriminative" coefficients?



0.266 **0.117** **0.040**

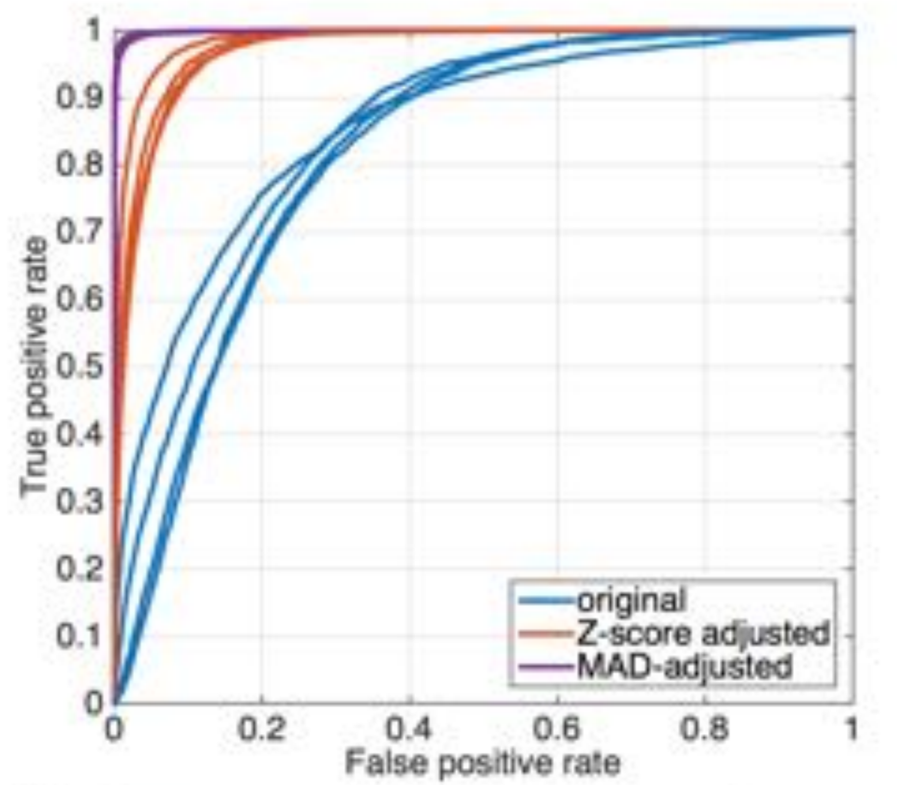
Red represents intersection of fingerprints for samples 1 and 2.

True Detections vs. False Positives

Don't choose largest coefficients, choose those on the tails of a distribution.

Suppresses false detections of persistent noise, but maintains high accuracy for relatively rare earthquake signals.

Trade-off Curves



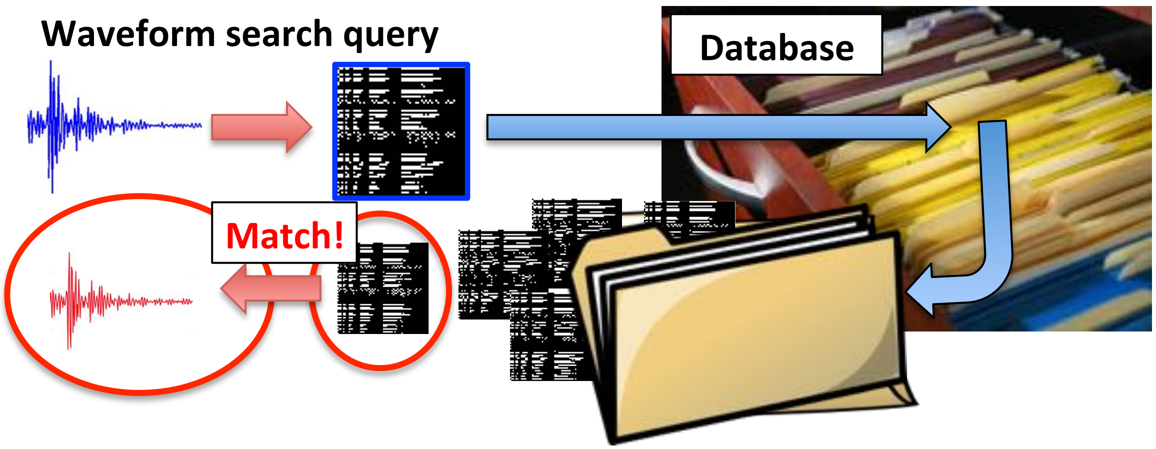
FAST Workflow

Min-Hash uses multiple random hash functions to map a binary fingerprint to a single integer.

The probability of two fingerprints A and B mapping to the same integer is equal to their Jaccard similarity.

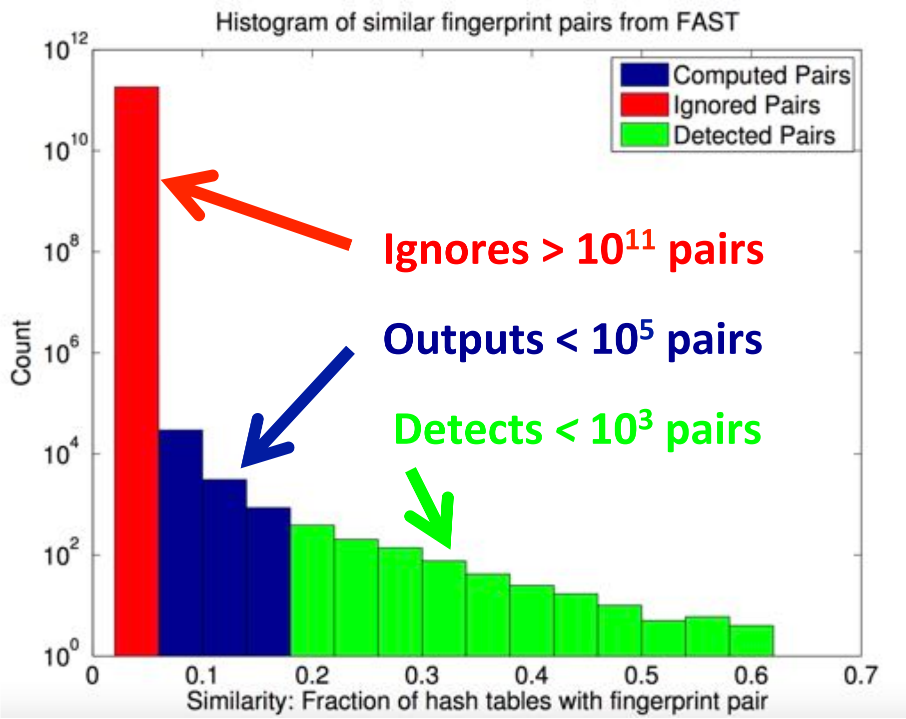
Min-Hash reduces dimensionality while preserving the similarity between A and B in a probabilistic manner.

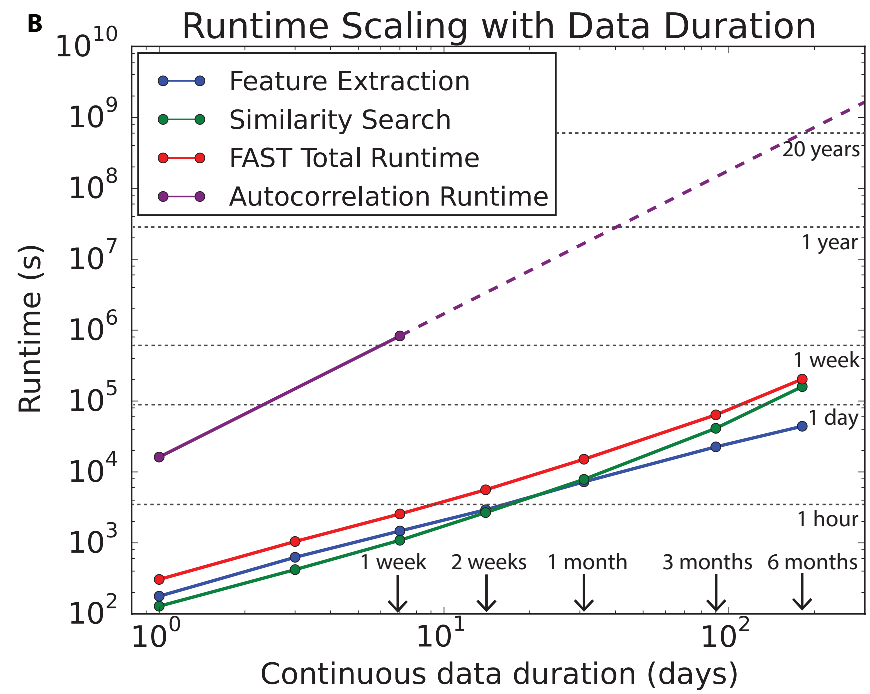
Locality Sensitive Hashing groups similar fingerprints drawn from a high-dimensional space with high probability



Yoon et al. (2015)

Why is FAST Fast for Large T?





Yoon et al. **(2015)**

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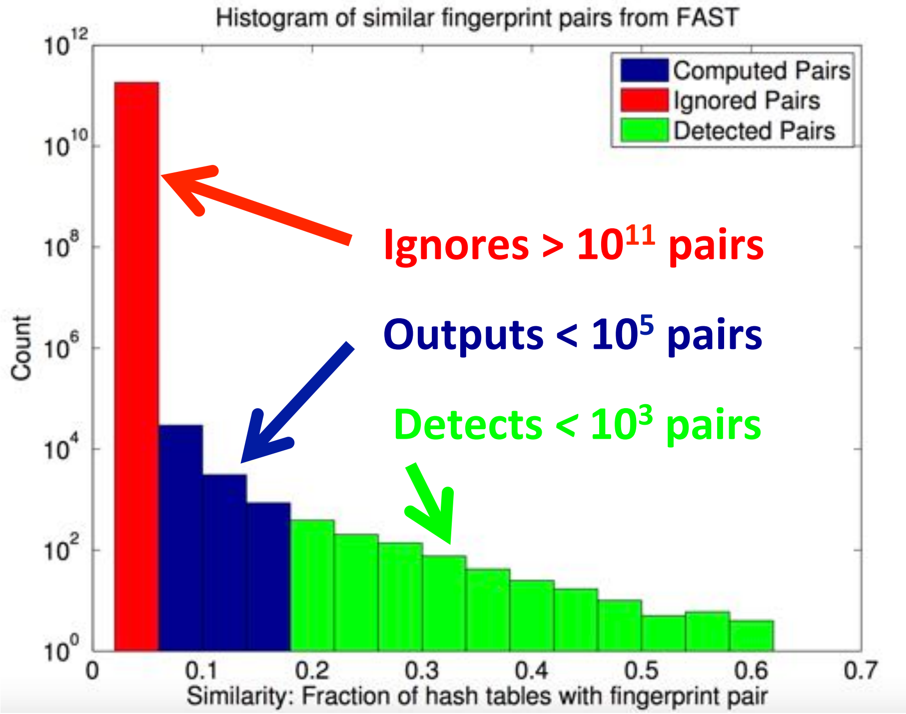
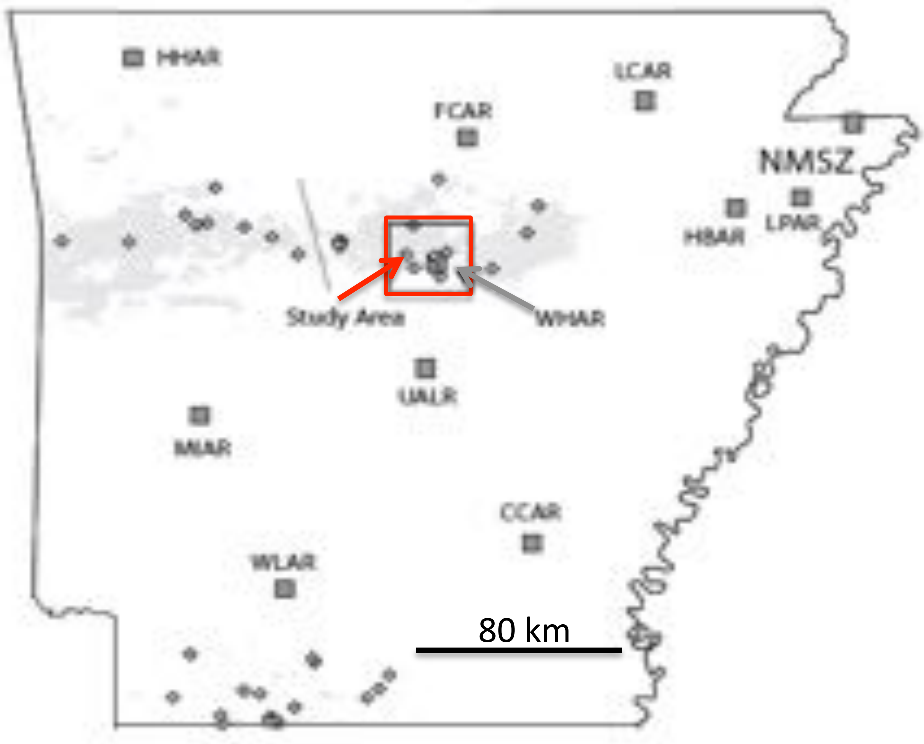
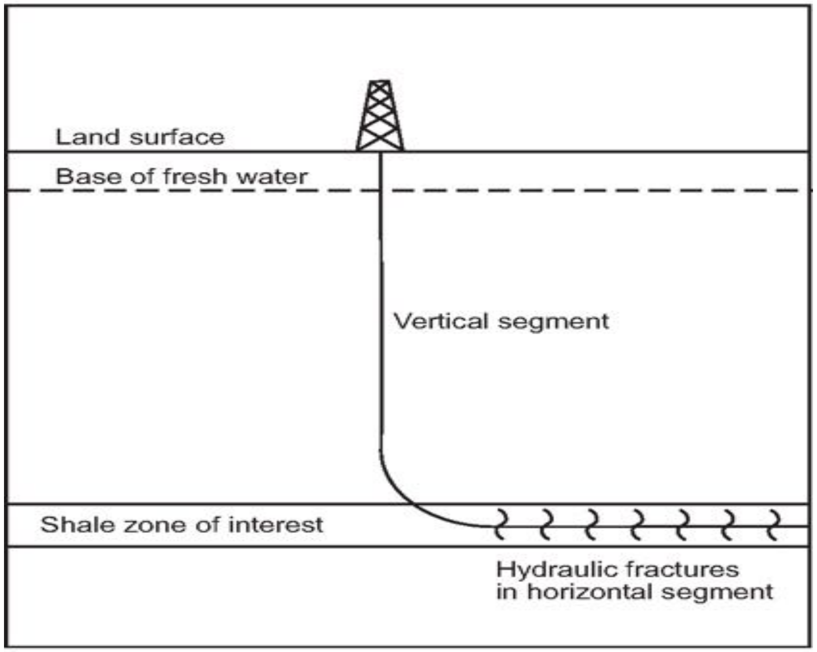


Yoon et al. (2015)

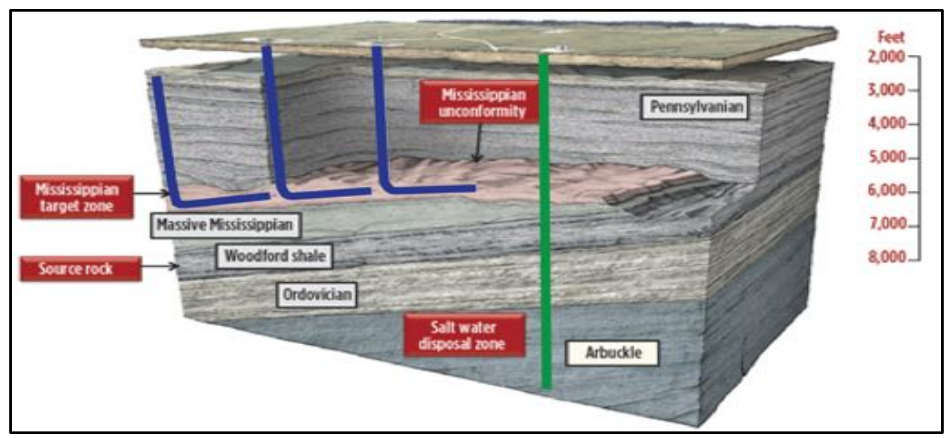
Guy-Greenbrier Sequence in Arkansas



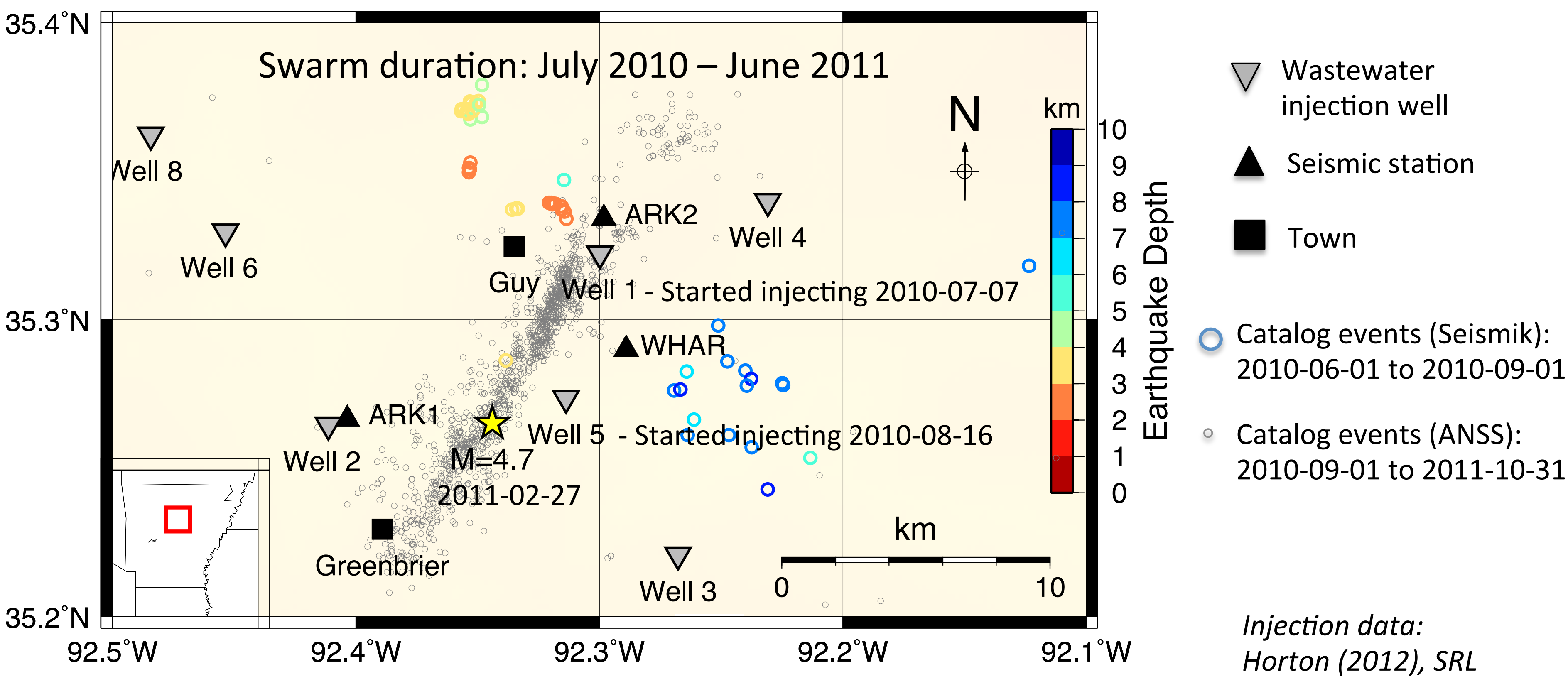


Hydraulic Stimulation (Fracking) wells use a staged injection of fluid to increase permeability and access hydrocarbons.

Deep disposal wells inject produced water, or fracking flowback water, to get rid of it.

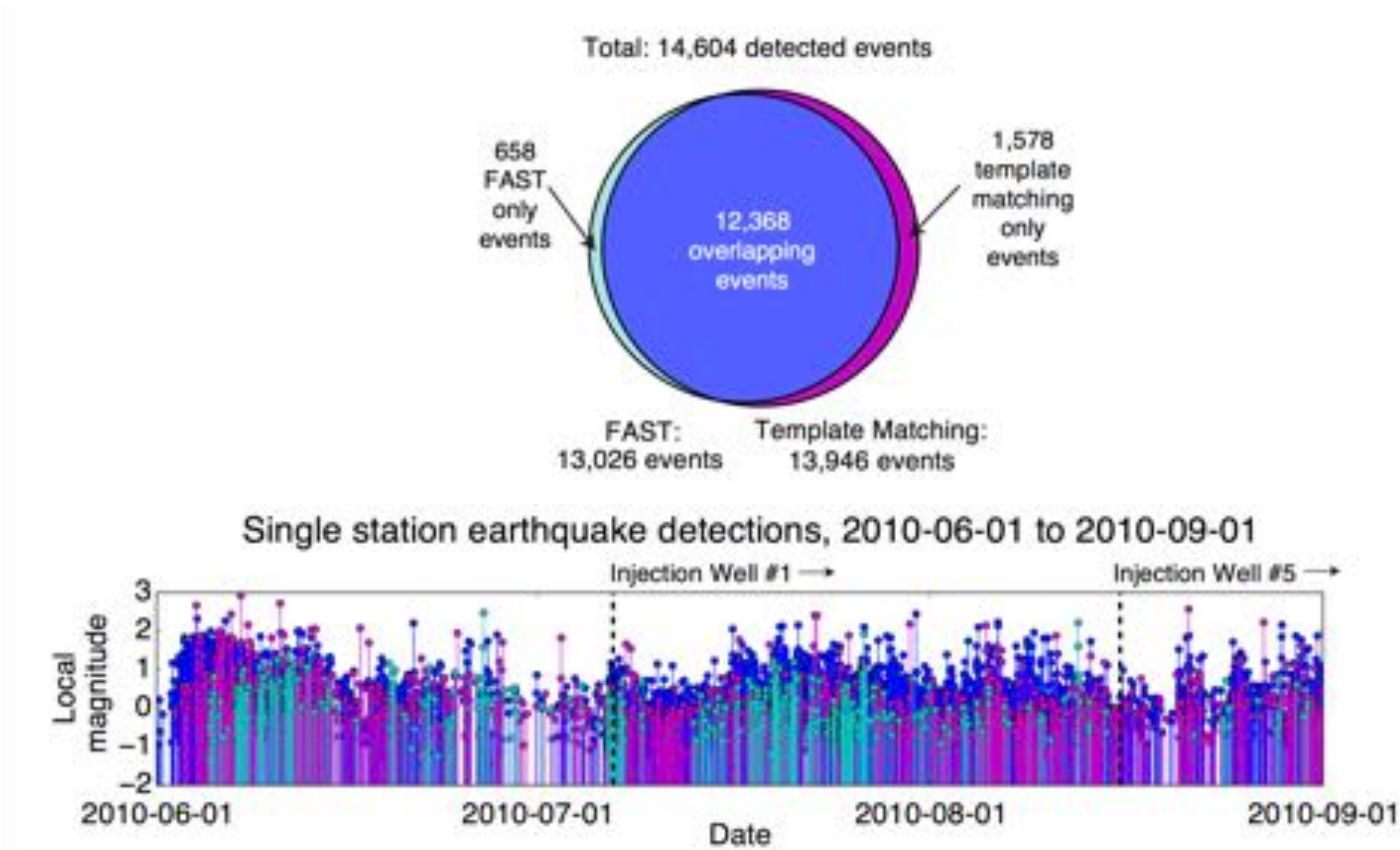


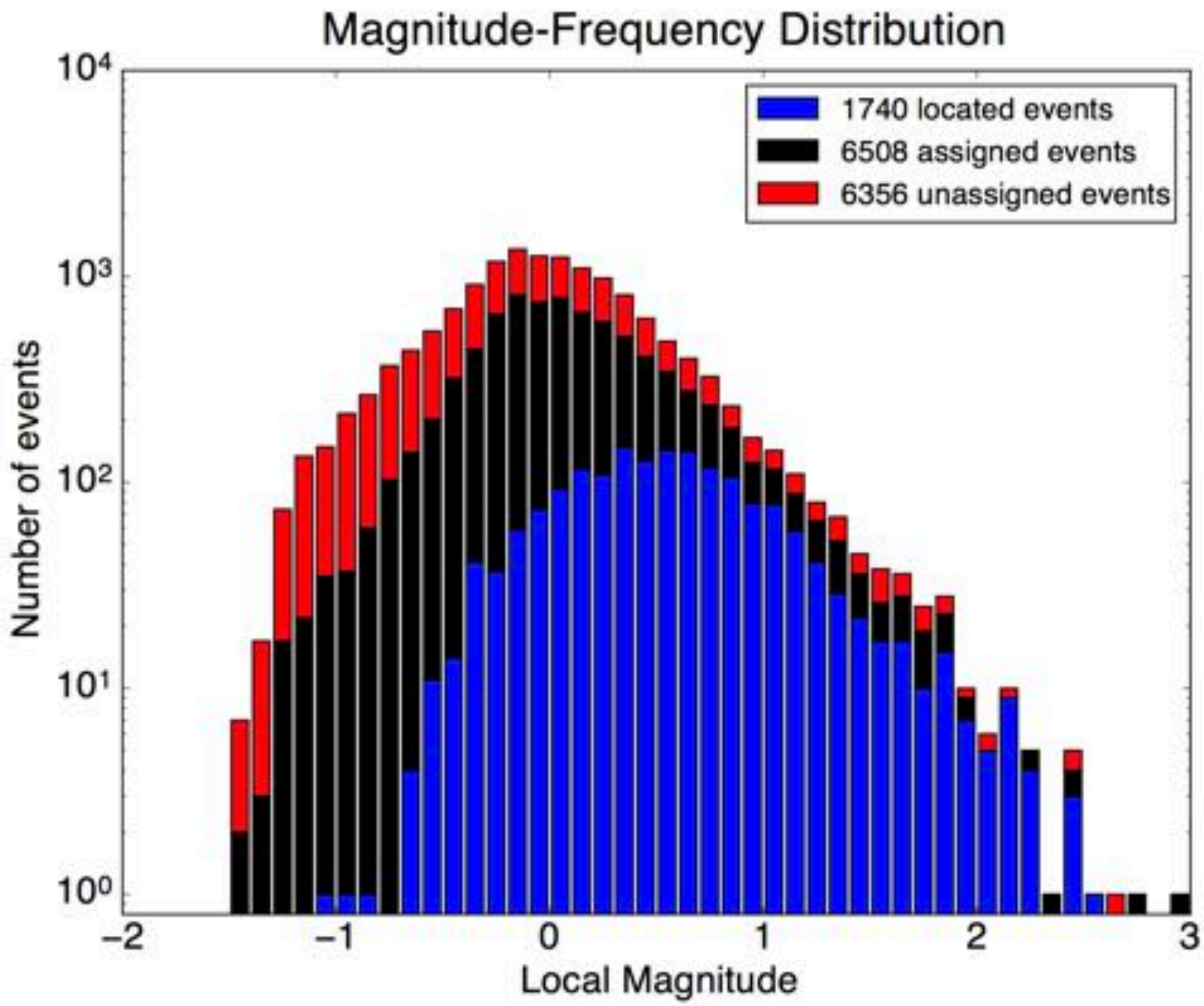
Guy-Greenbrier, Arkansas Sequence



Injection data: Horton (2012), SRL

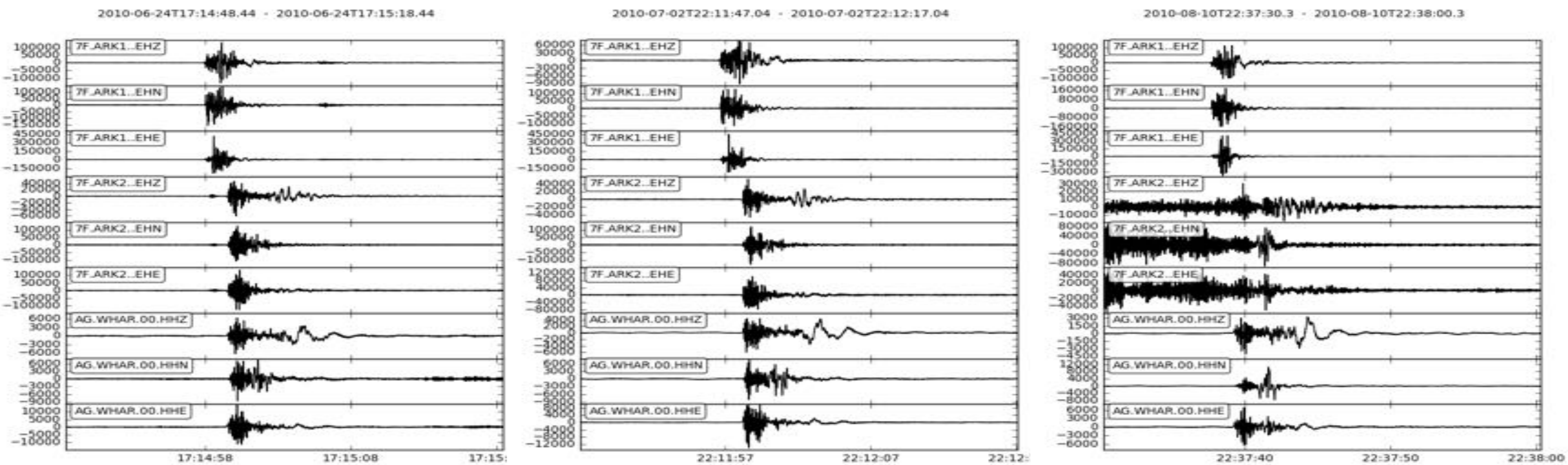
3 Months Guy-Greenbrier Induced Seismicity





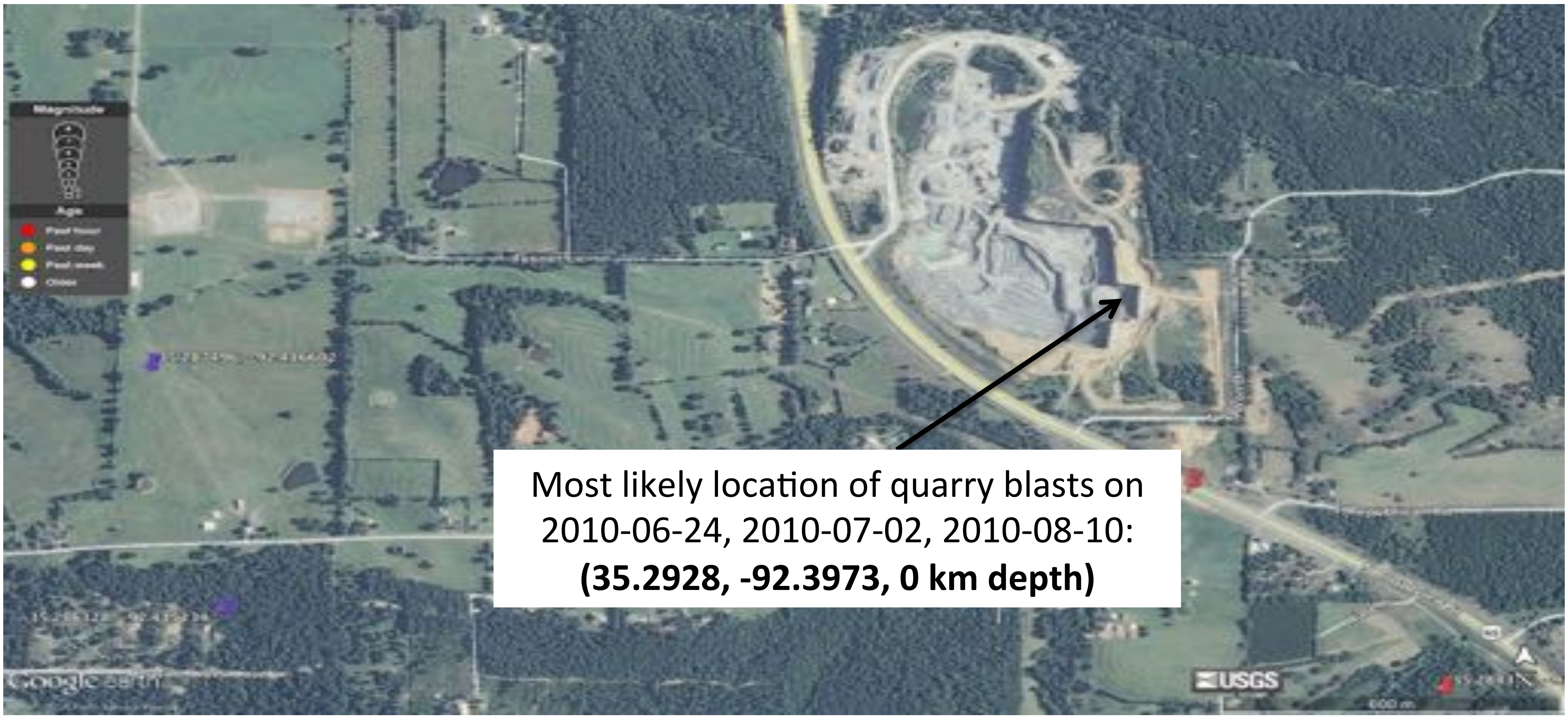
Magnitude-Frequency Distribution
1740 located events
6508 assigned events
6356 unassigned events
Number of events
Local Magnitude

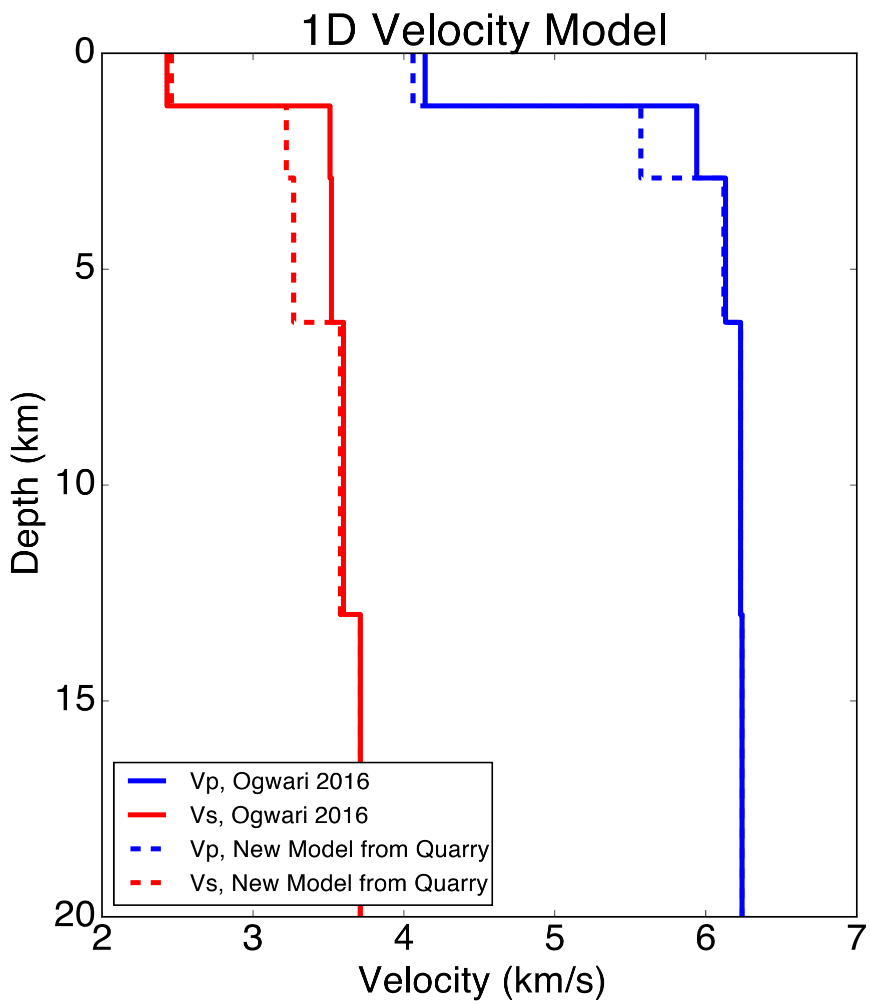
3 Quarry Blasts



Quarry Image, 2009-07-23

Quarry Image, 2010-09-15



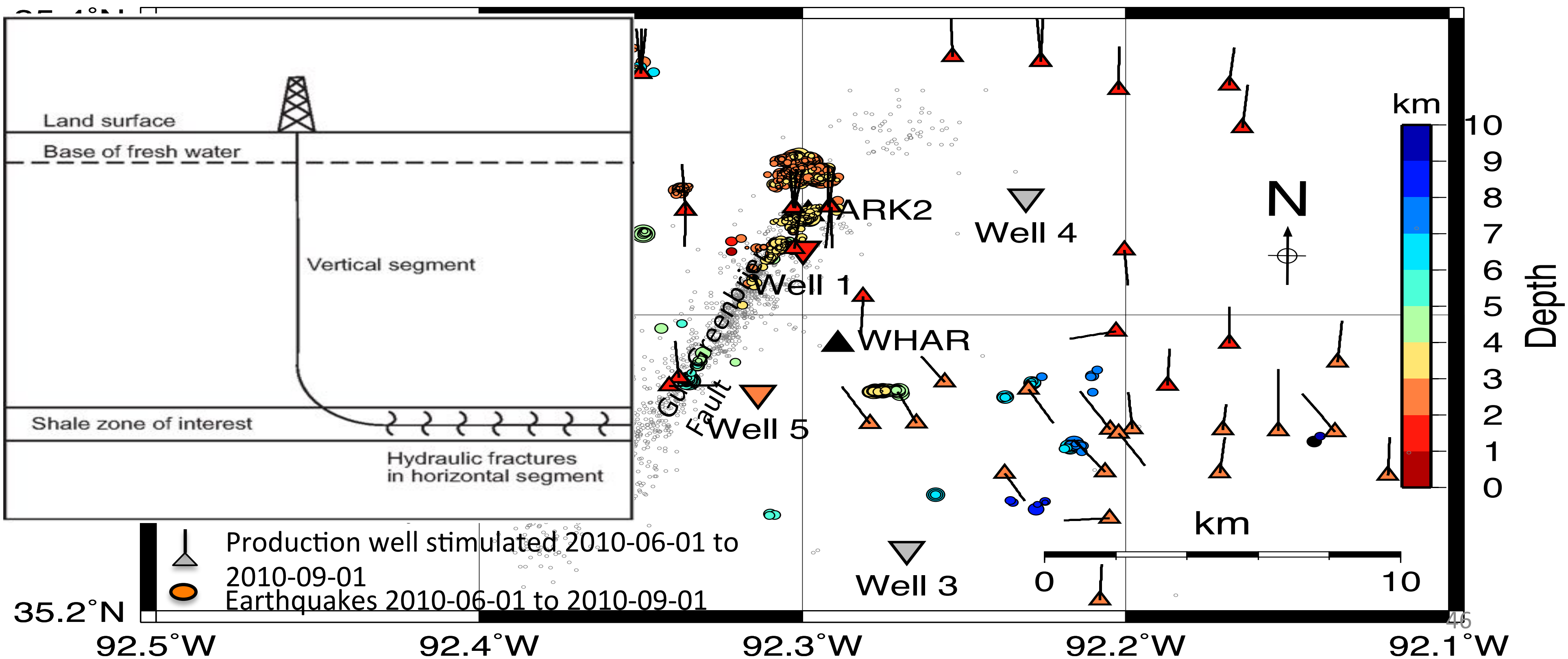


Improved *P* and *S*-wave velocity structure based on known quarry blasts using Velest.

Sparse network – (3) 3-component stations hypo-DD using *P* and *S*

700 m *a posteriori* adjustment.

Group Earthquakes into Clusters (-1.1 < M < 1.8)



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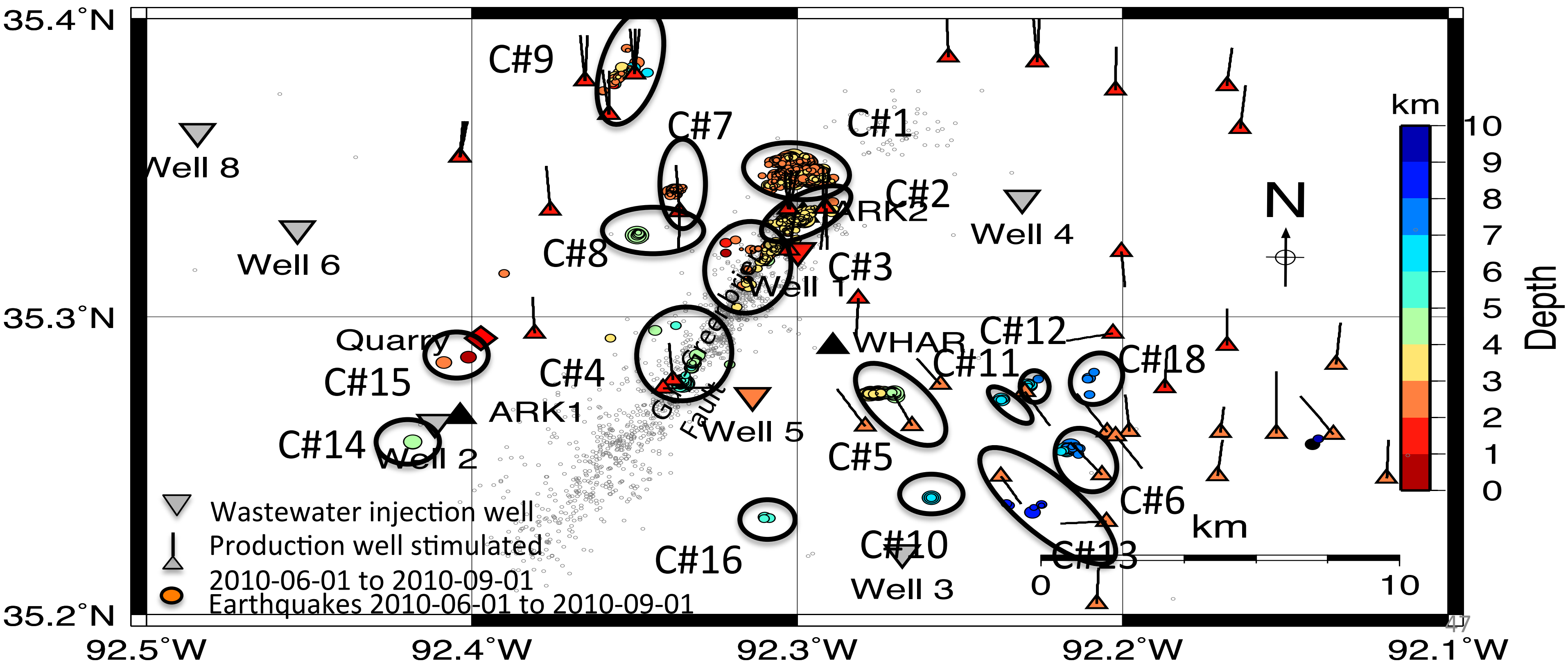
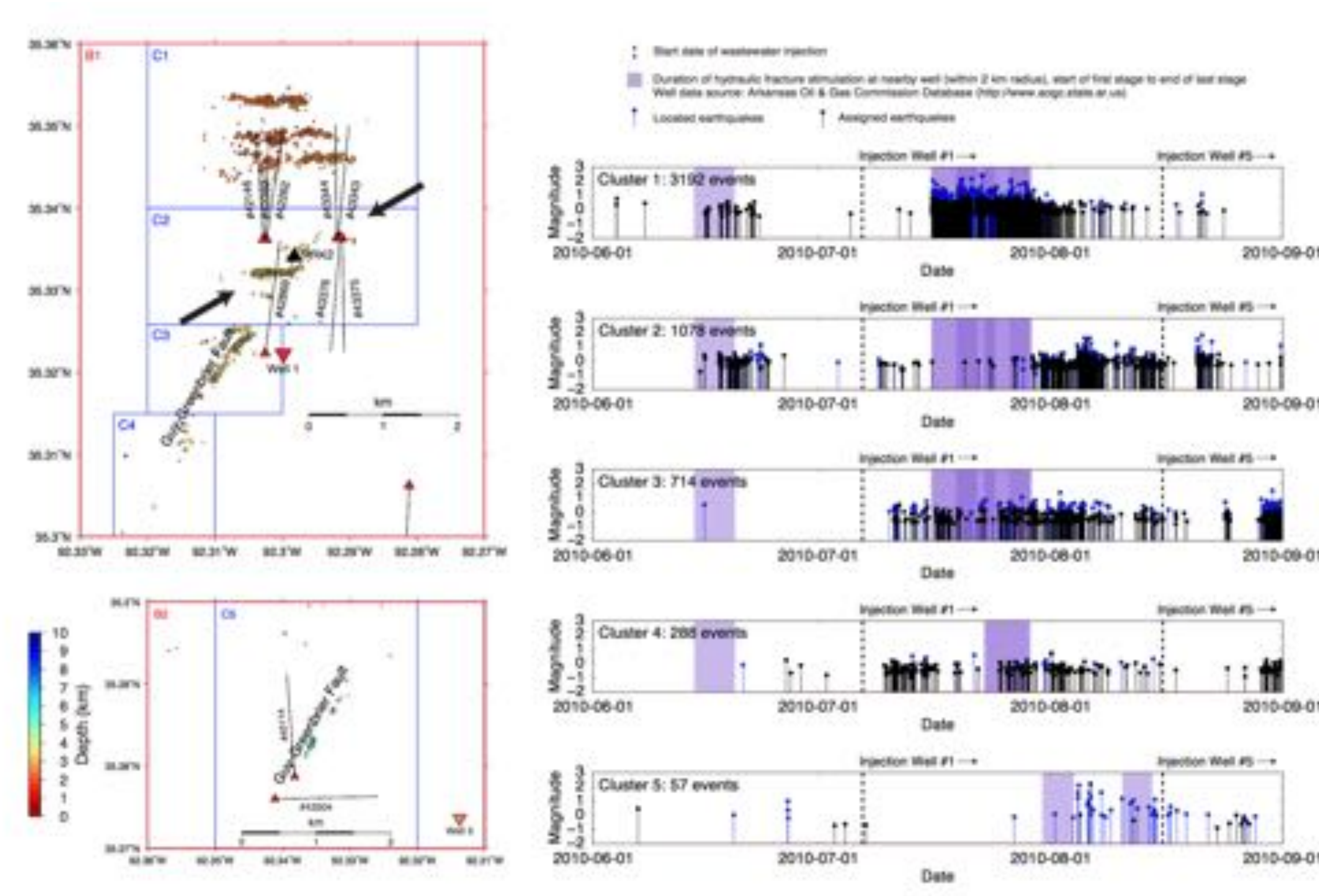
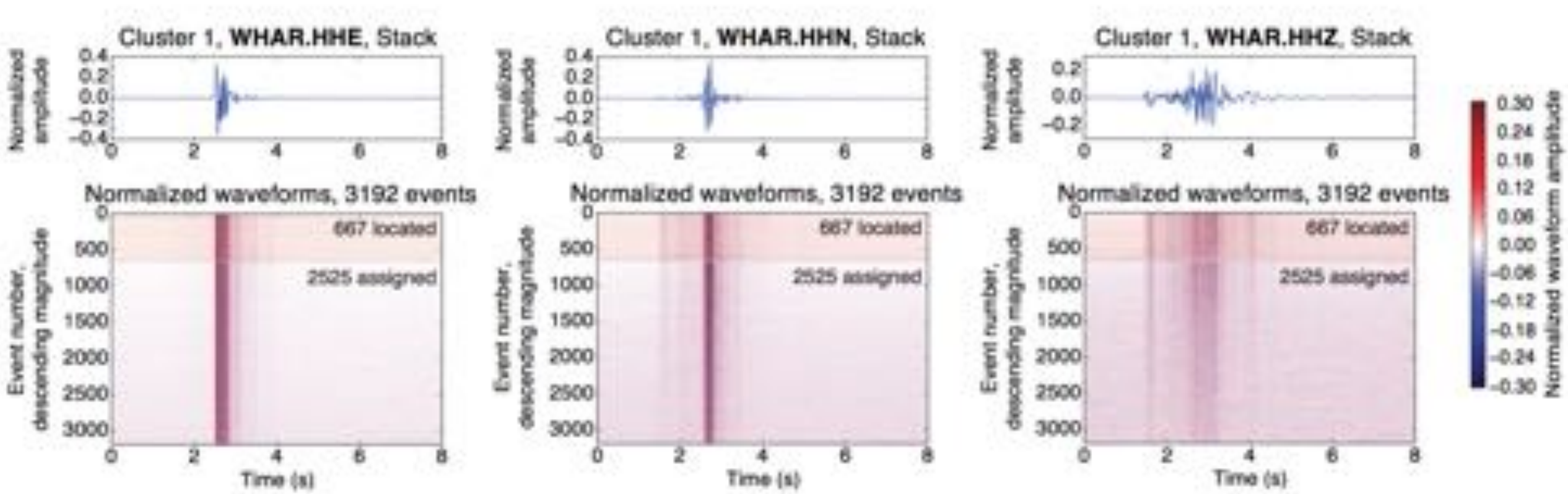


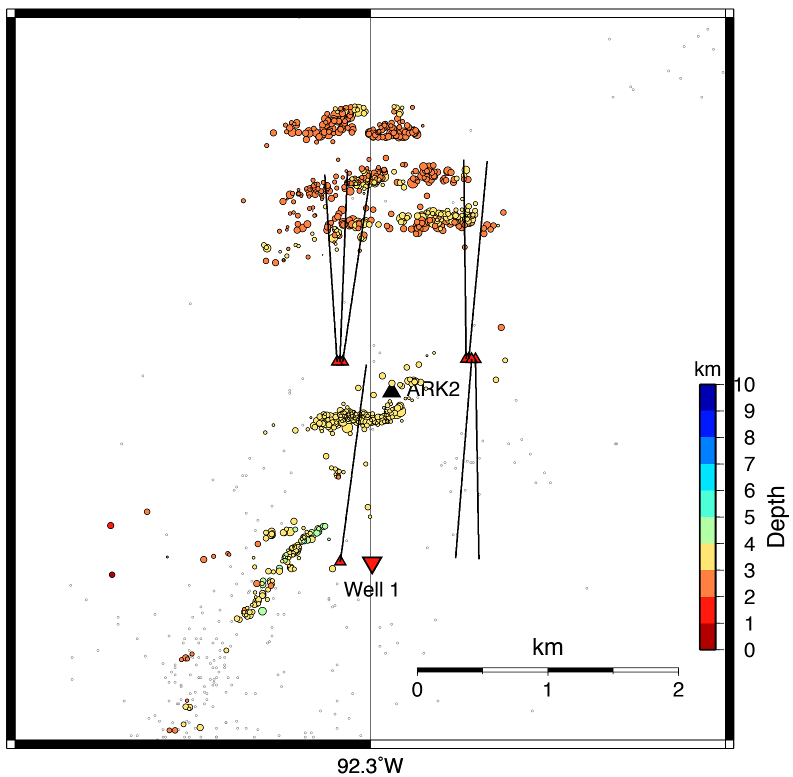


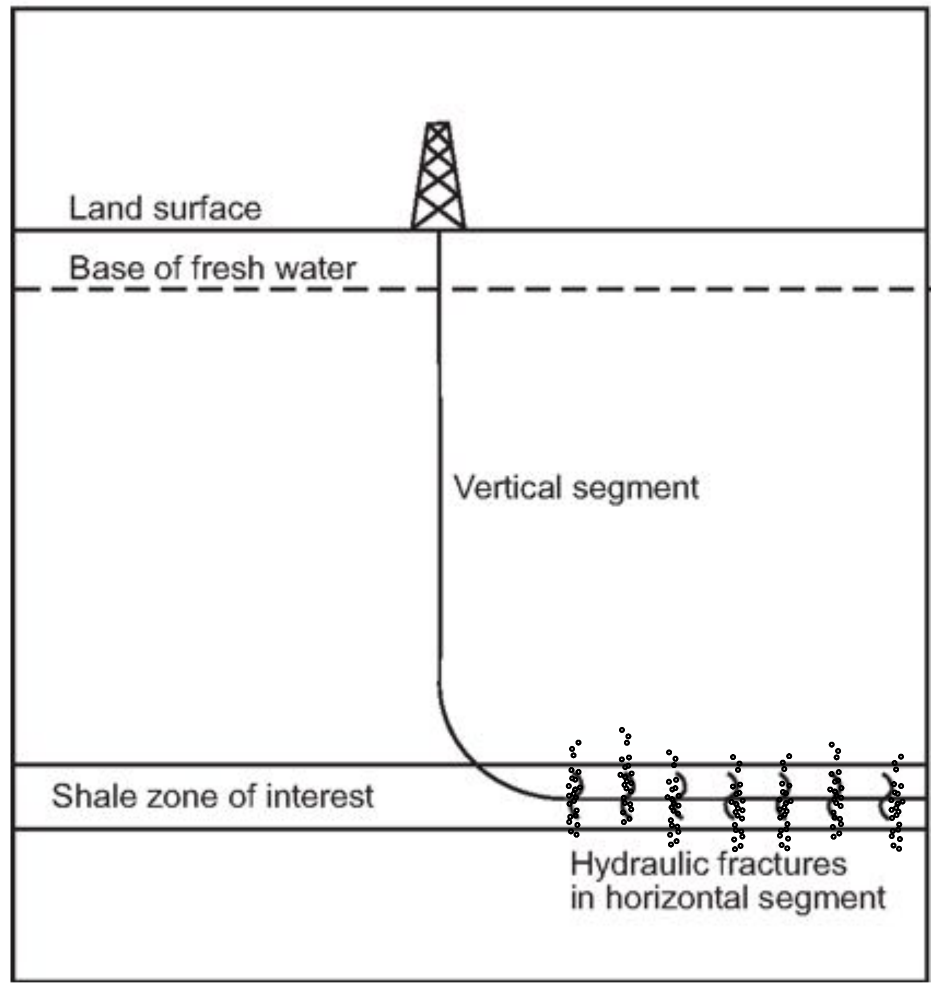
Stimulation at nearby well

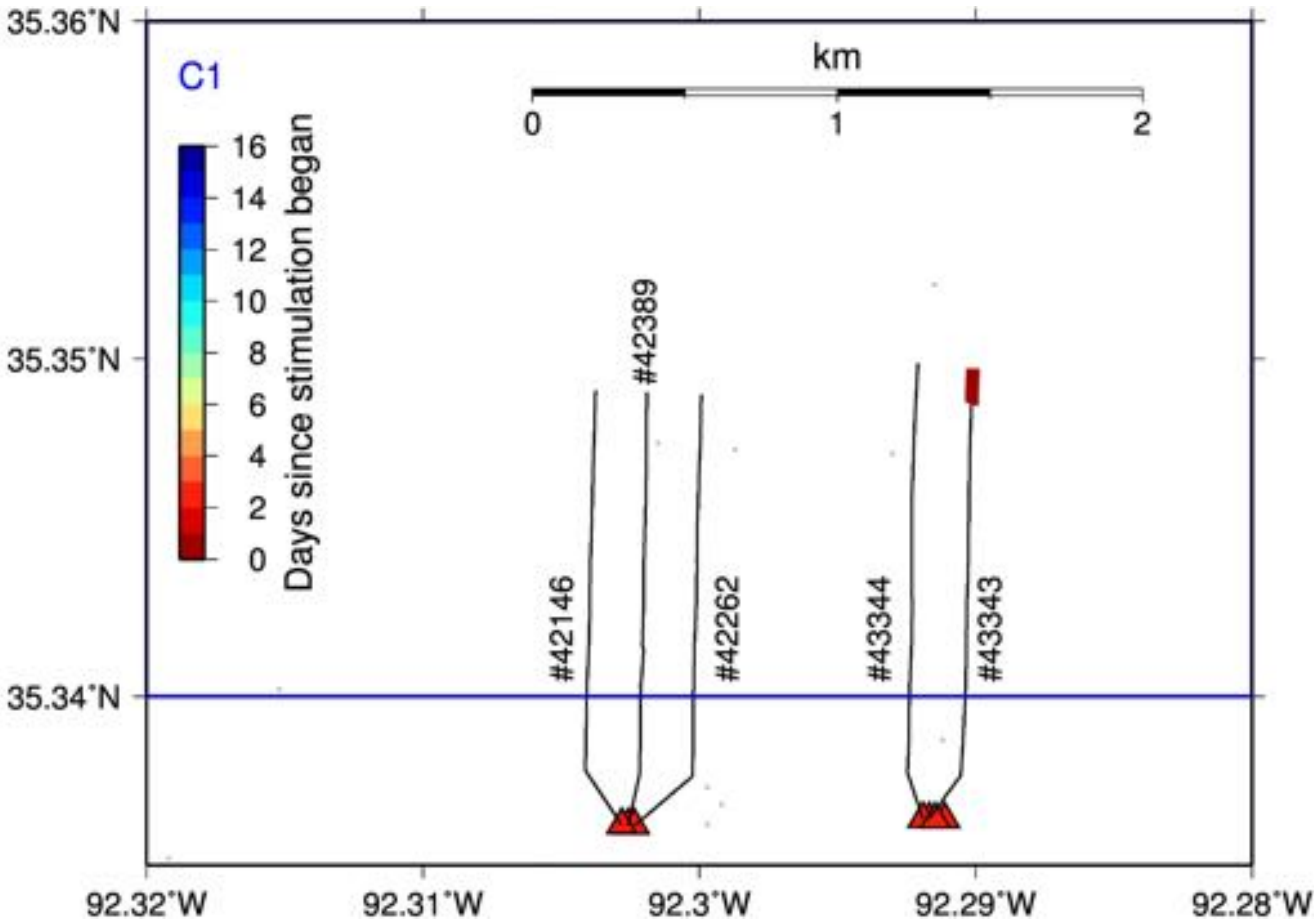
Cluster #1: 3143 events (667 located + 2525 assigned)



Further Evidence for Earthquakes Induced by Hydraulic Stimulation

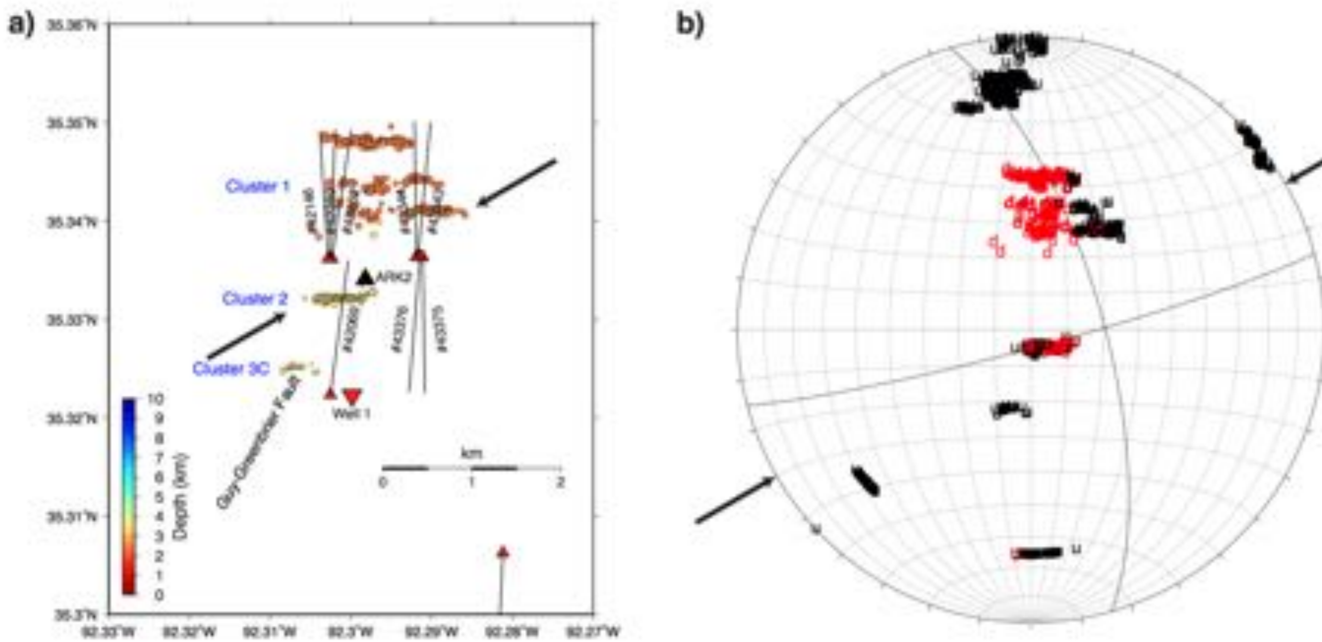






35.36˚N
35.35˚N
35.34˚N
92.32˚W
92.31˚W
92.3˚W
92.29˚W
92.28˚W
C1
km
0
1
2
16
14
12
10
8
6
4
2
0
Days since stimulation began
#42389
#42146
#42262
#43344
#43343

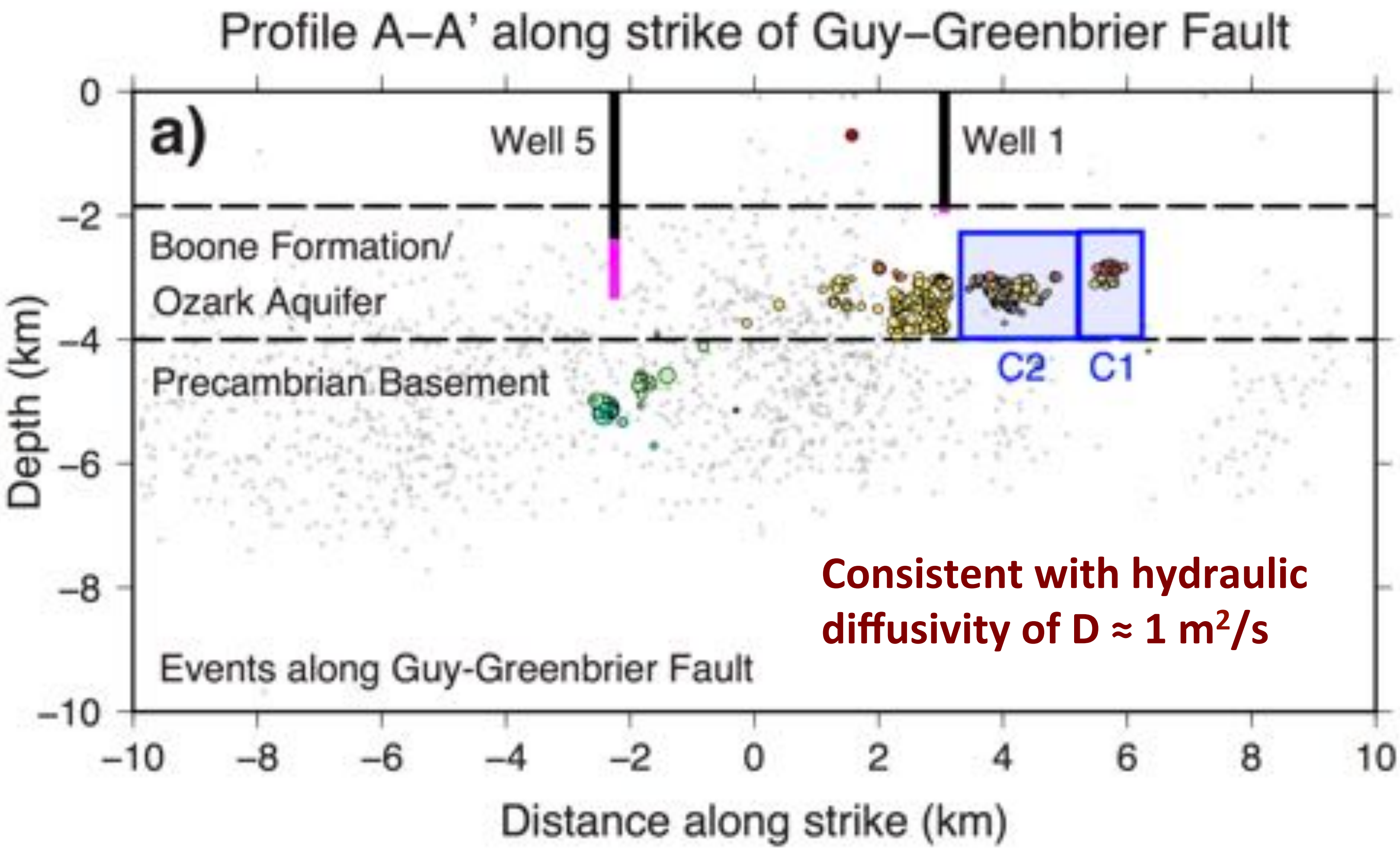
Composite Focal Mechanism



N60°E Shmax

(Hurd and Zoback, 2012]

If double-couple, plane of seismicity is right-lateral – contrary to stress. More likely that first motions reflect combined tensile & shear failure.



Consistent with hydraulic diffusivity of D ≈ 1 m^2/s

Conclusions I

Both wastewater injection and hydraulic stimulation appear to trigger earthquakes – probably some natural earthquakes as well.

It is challenging to disentangle different influences – requires good data (both seismic and injection).

Precision seismology is a powerful tool to provide a clearer picture of induced seismicity and the nucleation process to the extent it is expressed in seismicity.

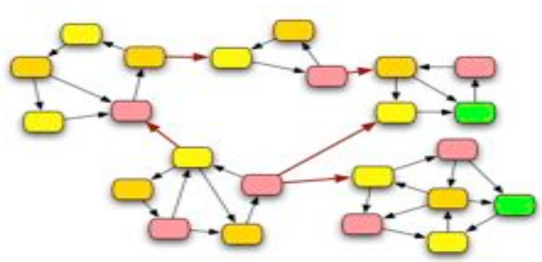
Conclusions II

Now

Seismology has:

- **Long duration data (Large-T)**
- **Big networks (Large-N)**

➔ FAST algorithm enables data-driven discovery



Need better algorithms

Future

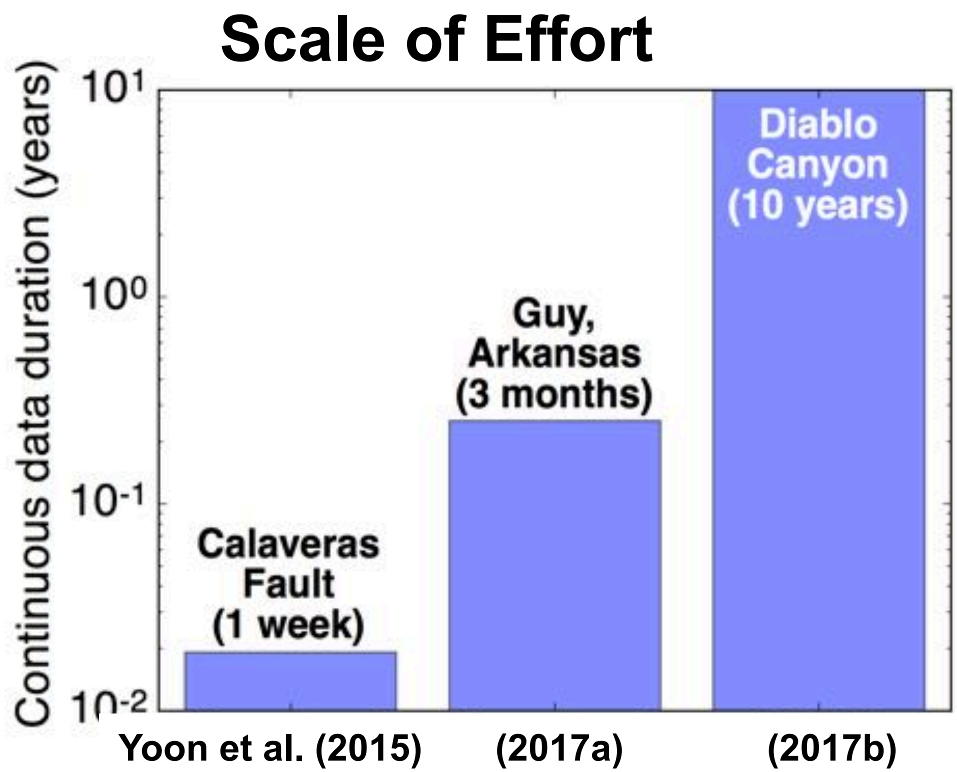
More data

More memory

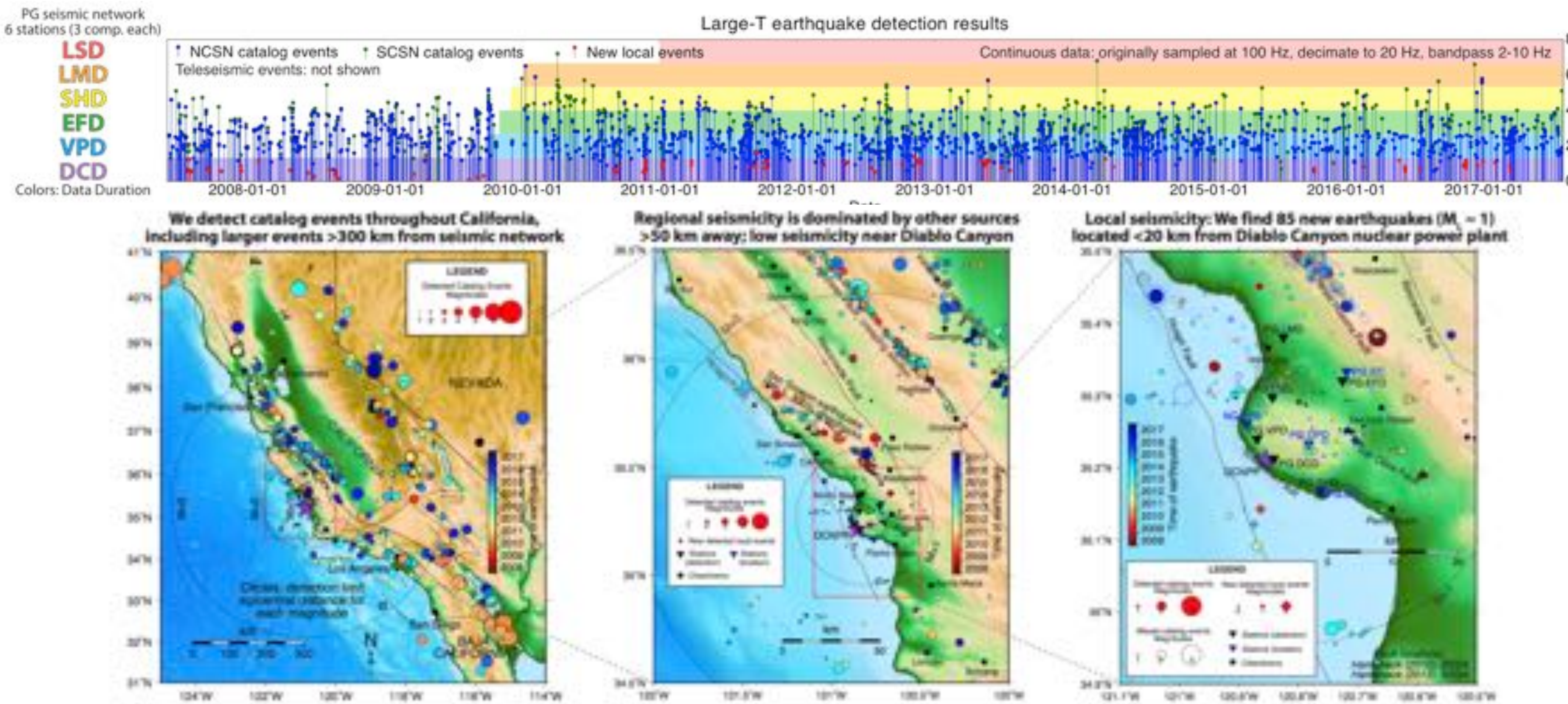
More computing power

Progress on FAST for Large-T Problems

- 140x FASTer than original.
- Reduced memory requirements.
- Reduced false detection rate.
- Improved post-processing.
- Working towards public release.



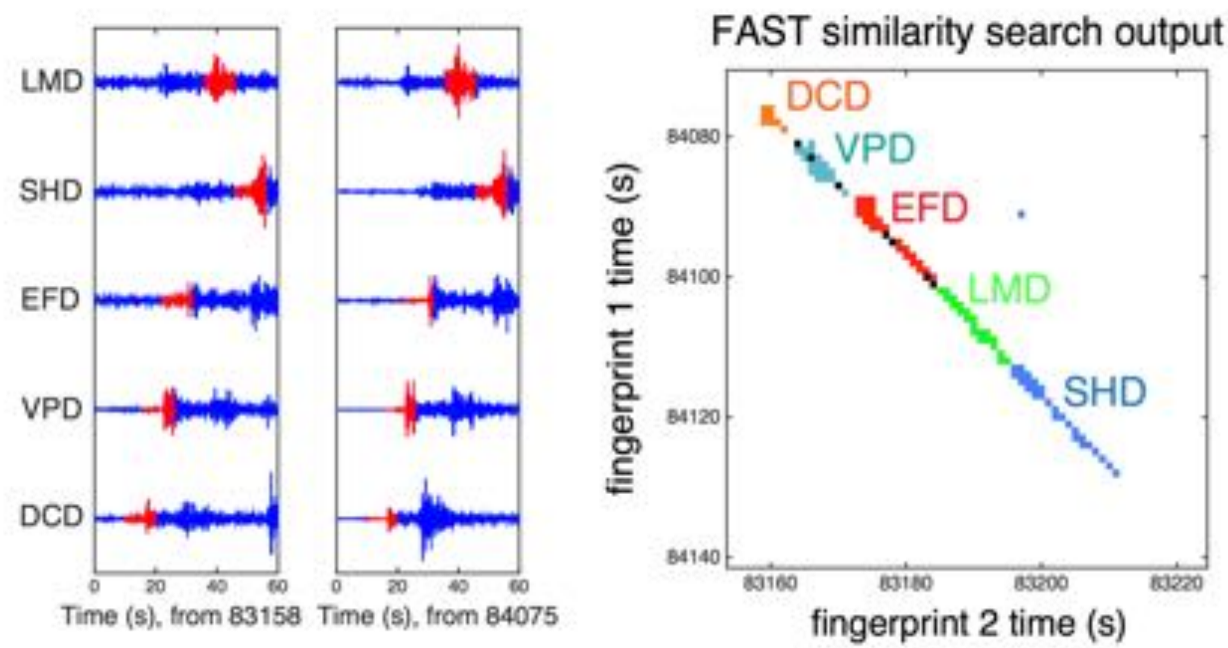
FAST for a Decade of Continuous Data



Yoon et al. (2017b)

FAST over a Network

Combine matching earthquake pairs at different stations
(consistent inter-event time intervals); reduce false detections

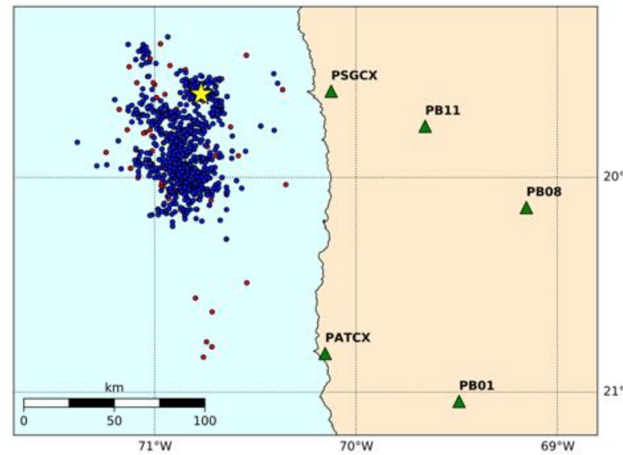


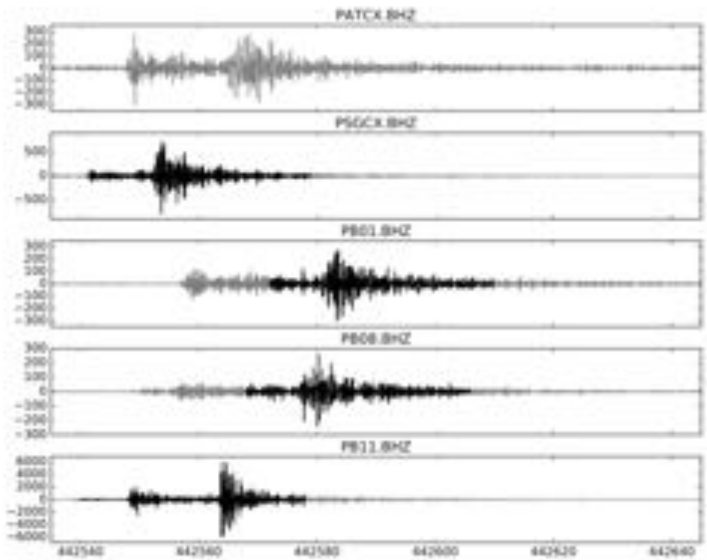
Bergen and Beroza (2017)

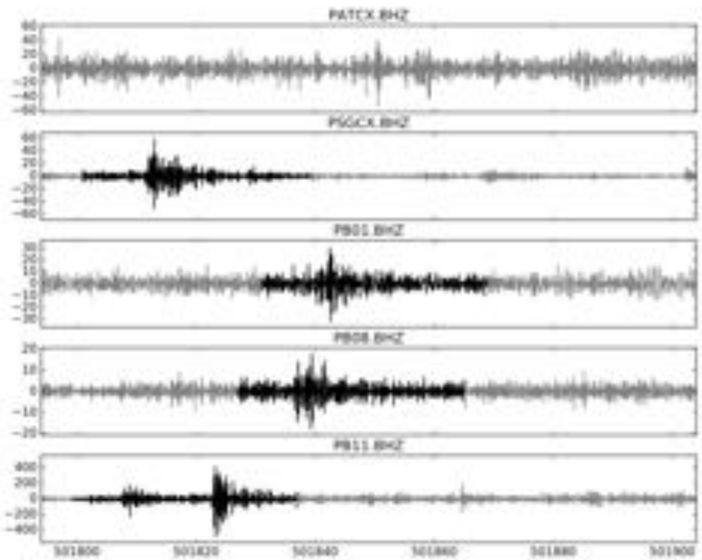
Network FAST for Iquique

~580 new detections in 17 days before the mainshock.

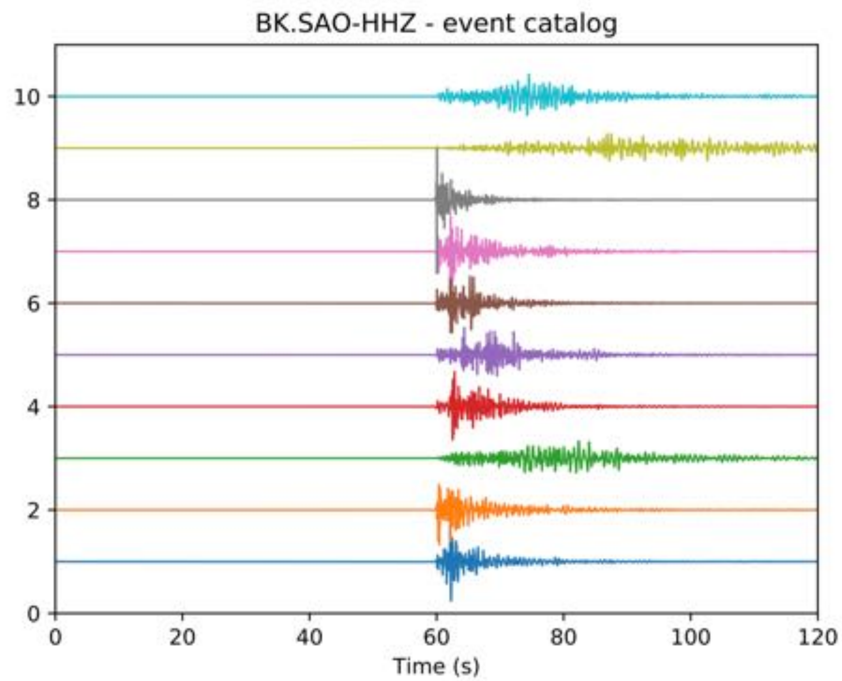
Can be used as templates to increase that number.

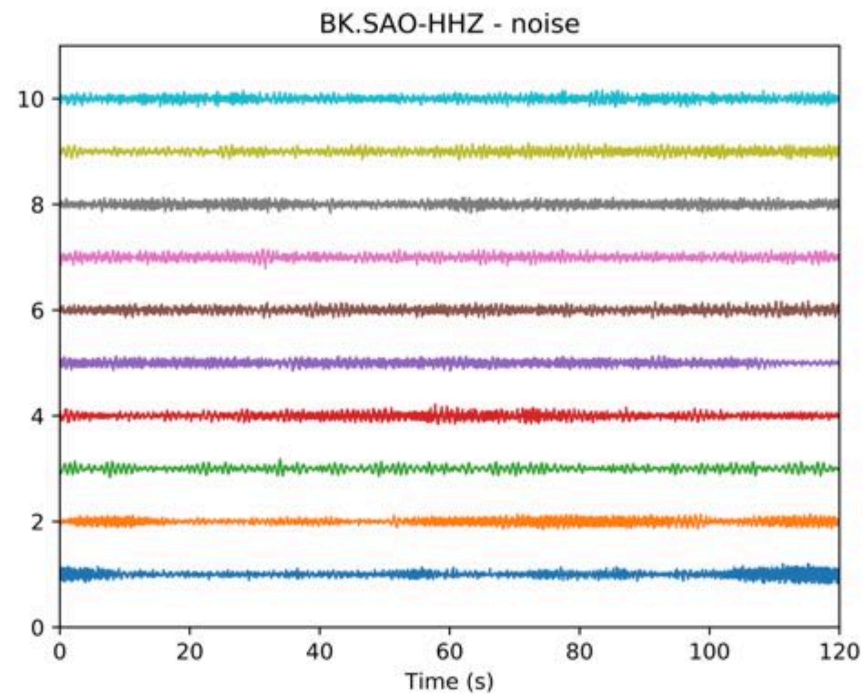






Machine Learning for Earthquake Detection

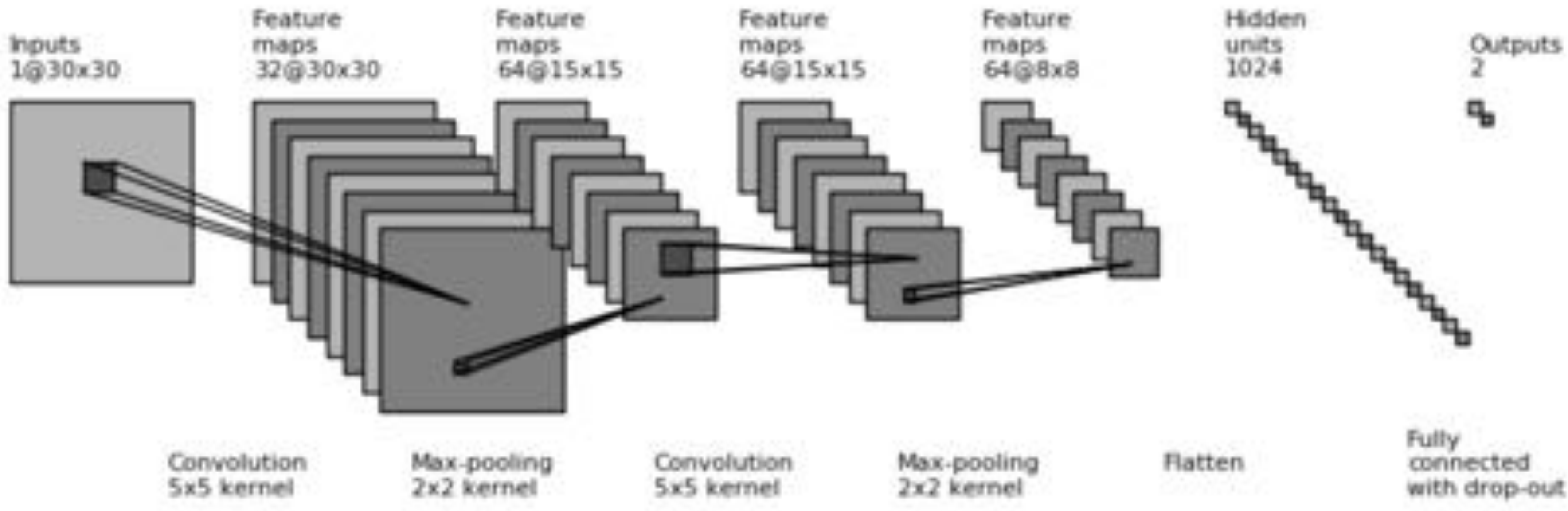




Labeled data as input to neural network (most of what we record is noise)

Huot et al. (2017)

ML for Earthquake Detection

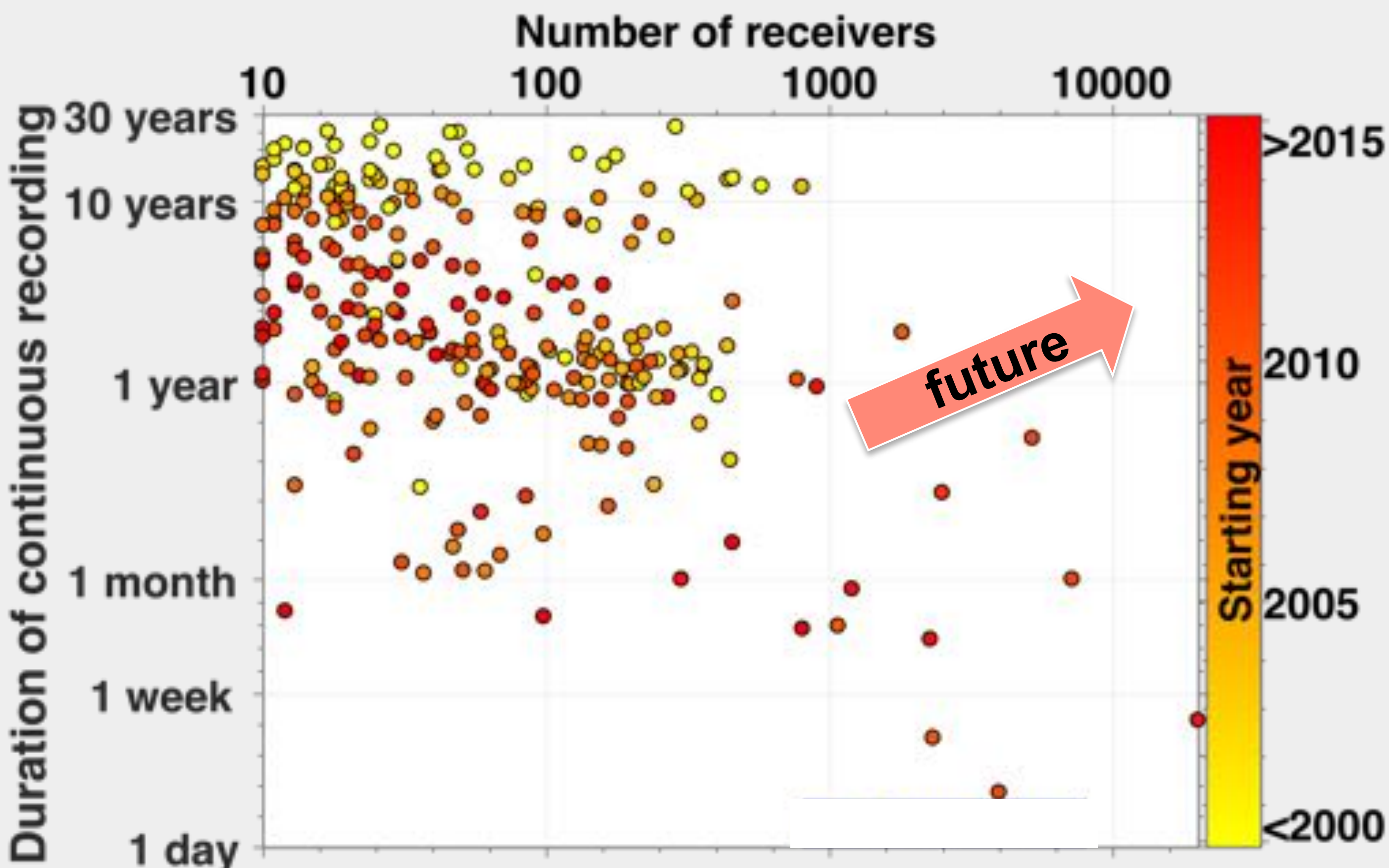


99.5% accuracy when trained, validated and tested on one station.

Accuracy drops to 98.2%, with multiple stations but with only a limited data set.

Huot et al. (2017)

Scale of Seismic Observations



Nakata (2017)

Merci