Monitoring for Faults at a Critical State of Stress

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Research Team

- LANL
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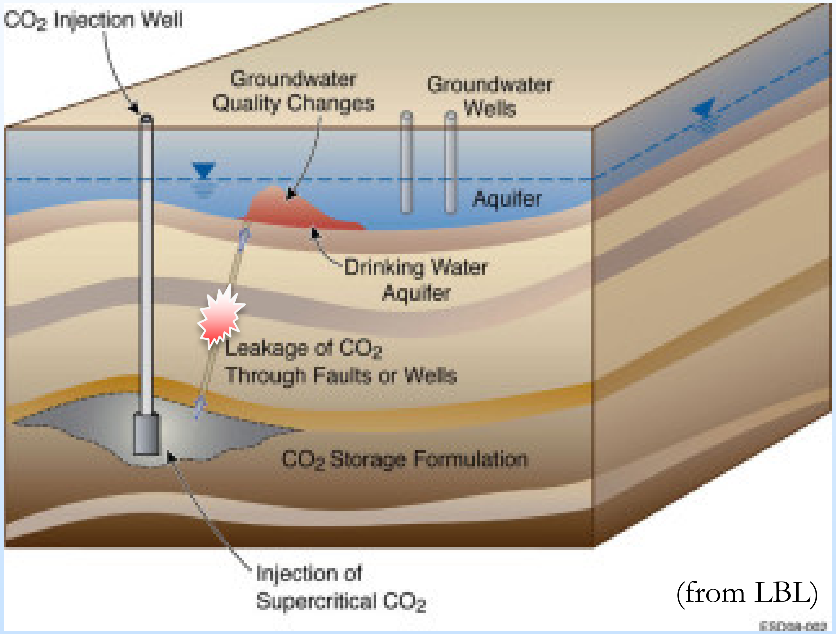
- External partners (leveraging with)
  - U. Alberta, U. Oklahoma, U. Rochester

Objectives

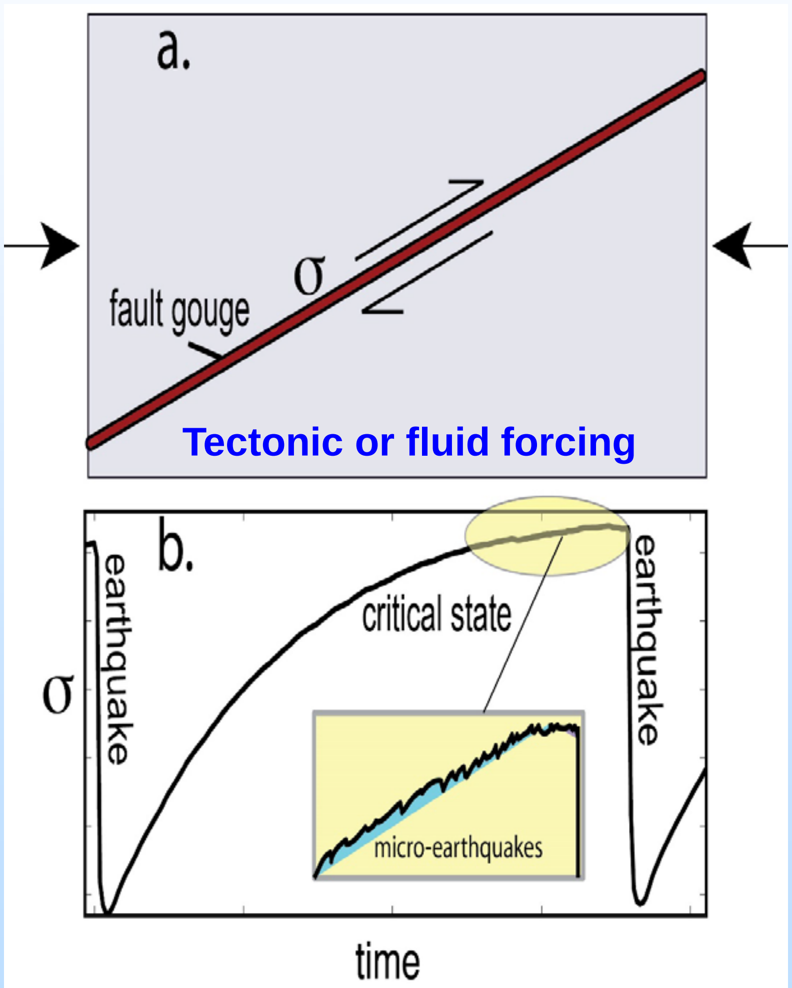
Improve the risk assessment of induced seismicity in carbon sequestration through monitoring of critical state of stress

- Pre-injection characterization
  - Identify faults of concern in the region
- During-injection monitoring
  - Avoid large induced seismicity

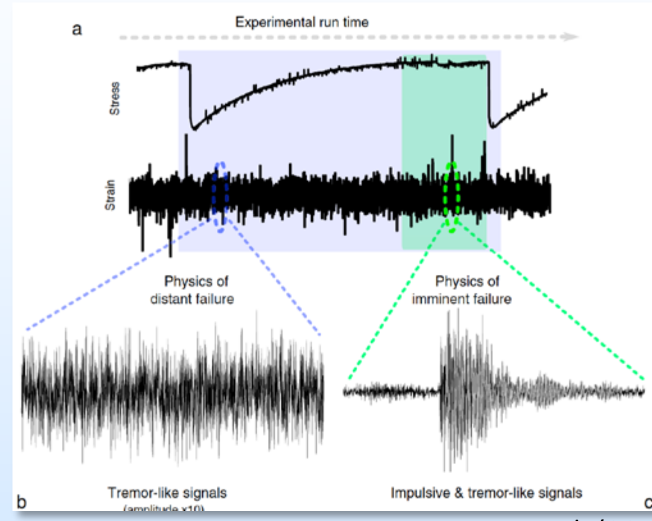


(from LBL)

Critical State of Stress

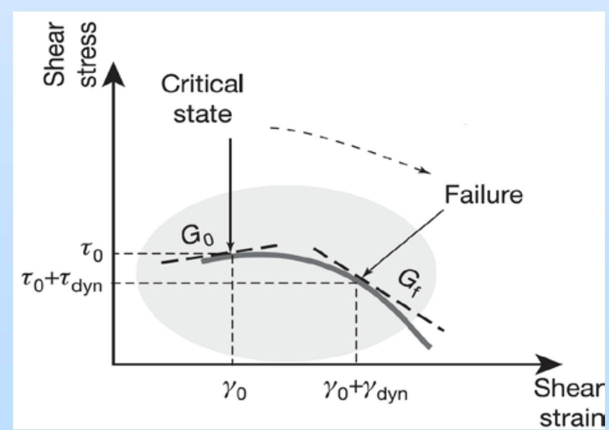


"Precursor" events occur prior to major slip events



Rouet-LeDuc et al. (2017)

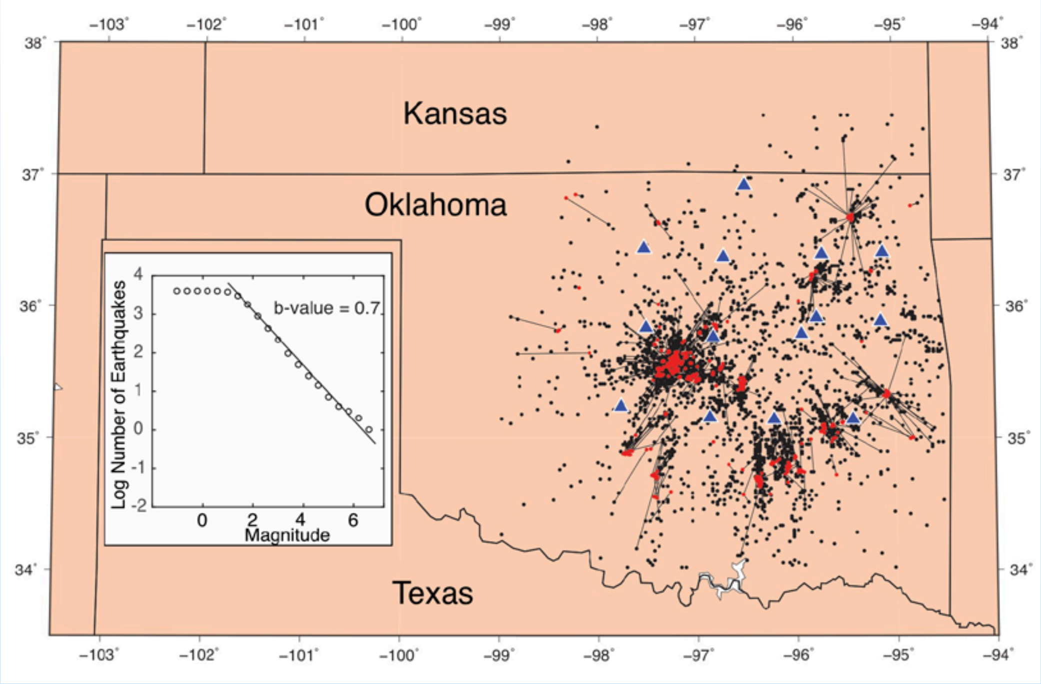
Triggering by stress perturbation

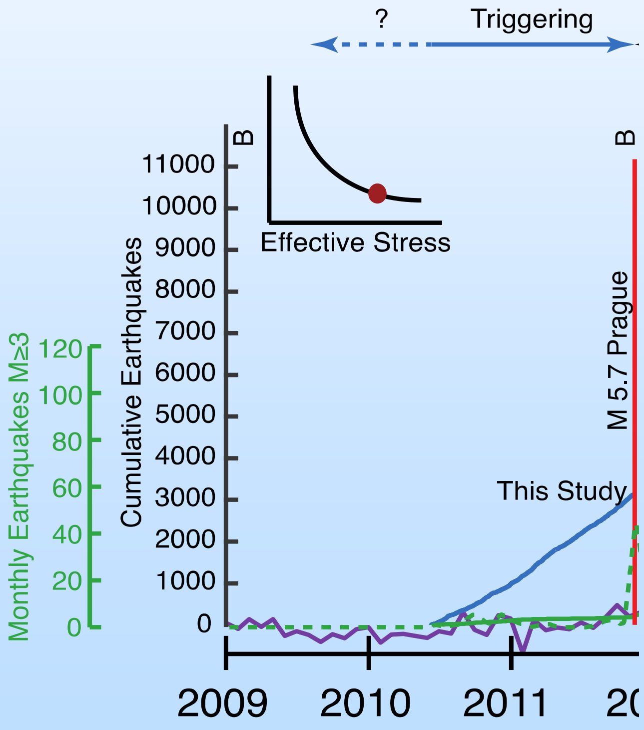


(Johnson & Xia, 2005)

Small Signals Reveal Fault State

With comprehensive new catalog (include many more small events), tidal triggering was detected before the M5.7 Prague earthquake, indicating a potential critical state





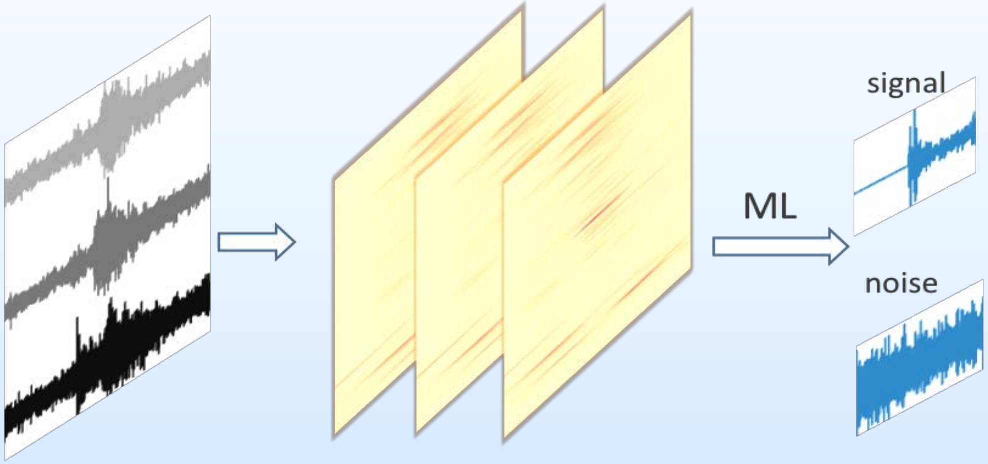
Delorey et al. (submitted)

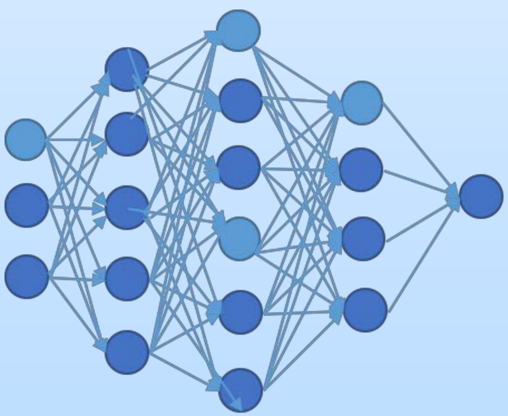
Extract Small Signals for Fault State

- Manual
  - Least false positive, but may miss small signals
  - High cost: takes hours for 1 well-trained person to process 1-day data from a 1C station
- Traditional algorithm
  - e.g., STA/LTA
  - High false positive (requires extra manual inspection); may miss small signals
- Cross-correlation based
  - Automatic
  - Can detect smaller signals
  - Computationally expensive
- Machine learning
  - Accurate (reduce the detection threshold)
  - Low cost (automatic, fast)
  - Flexible: 1C or 3C; single or multiple stations

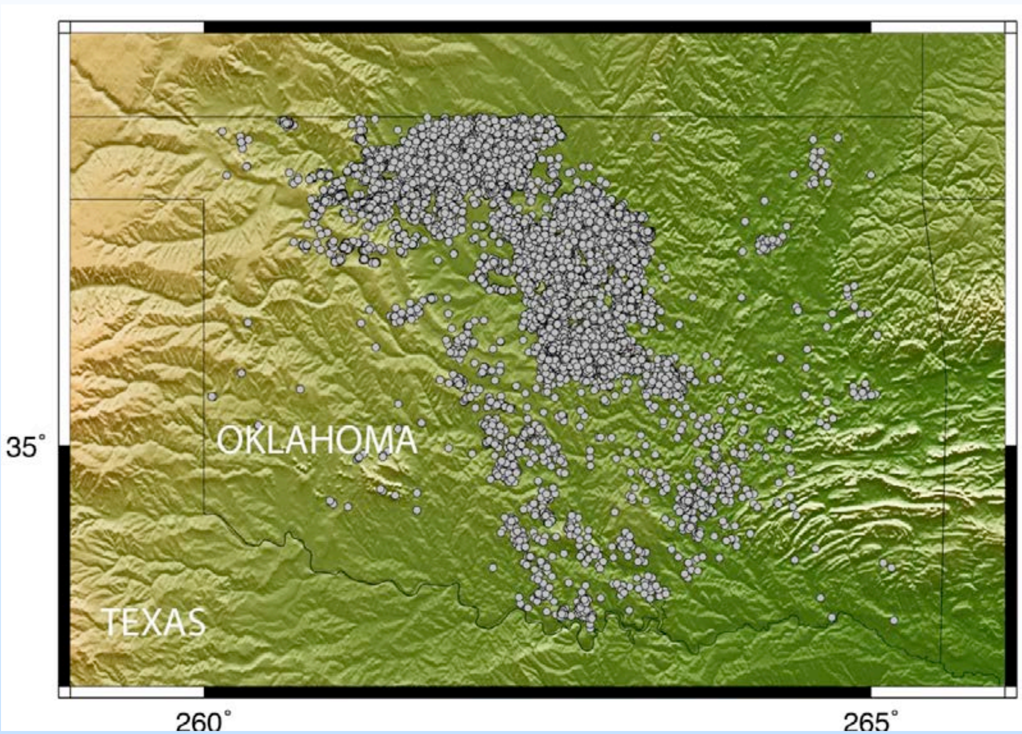
Machine Learning for Signal Detection

- Data
  - Seismic waveform
  - Single station, 1C or 3C
- Method
  - Convolutional neural network (CNN)
  - Classification
  - Spectrogram



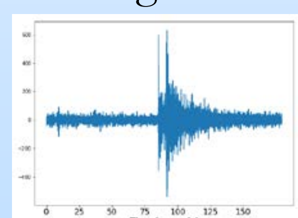


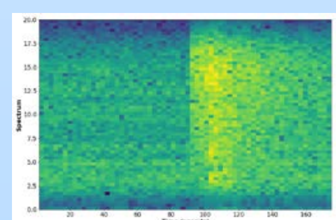
Application of ML to Field Data



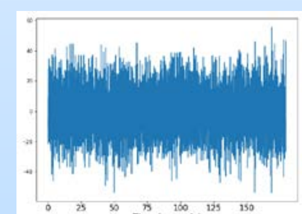
- Dataset
  - Oklahoma (water injection)
  - Broadband seismometer
  - 28737 events (2010-2018, OGS)
- Training
  - 175 stations
  - 1100980 samples (50% signal, 50% noise)

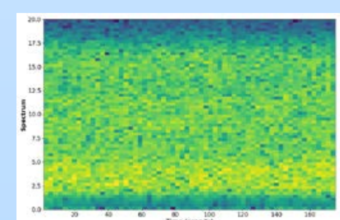
signal





noise



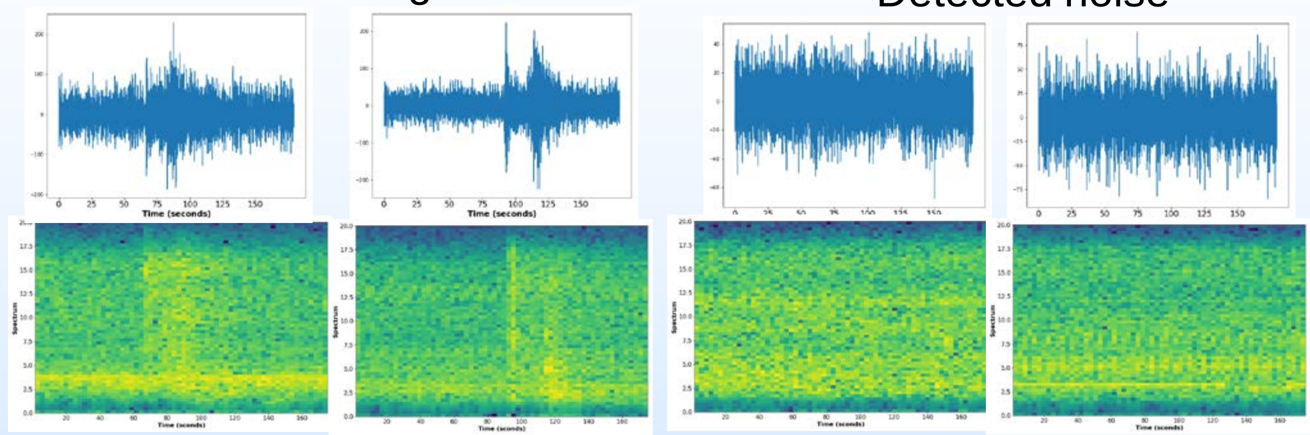


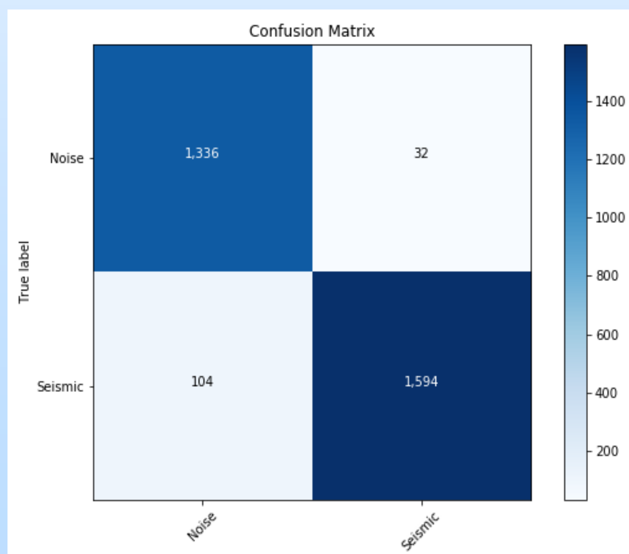
Performance of ML Signal Detection

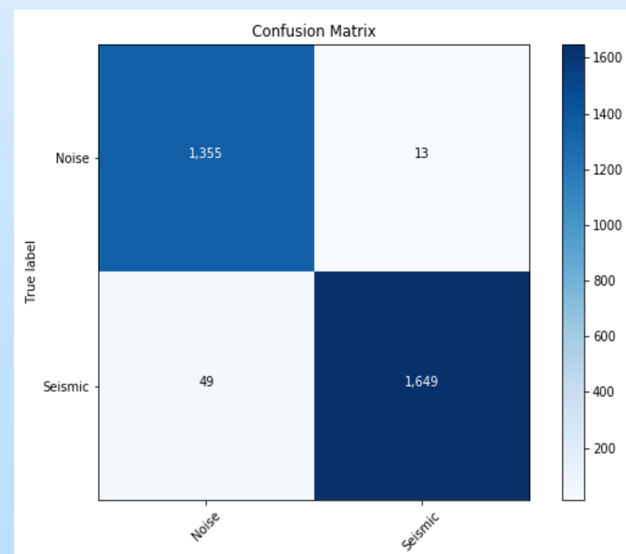
- Test
  - 10% samples
- Performance
  - Accuracy: 98% (3C)
  - Accuracy: 95% (1C)

Detected signal

Detected noise

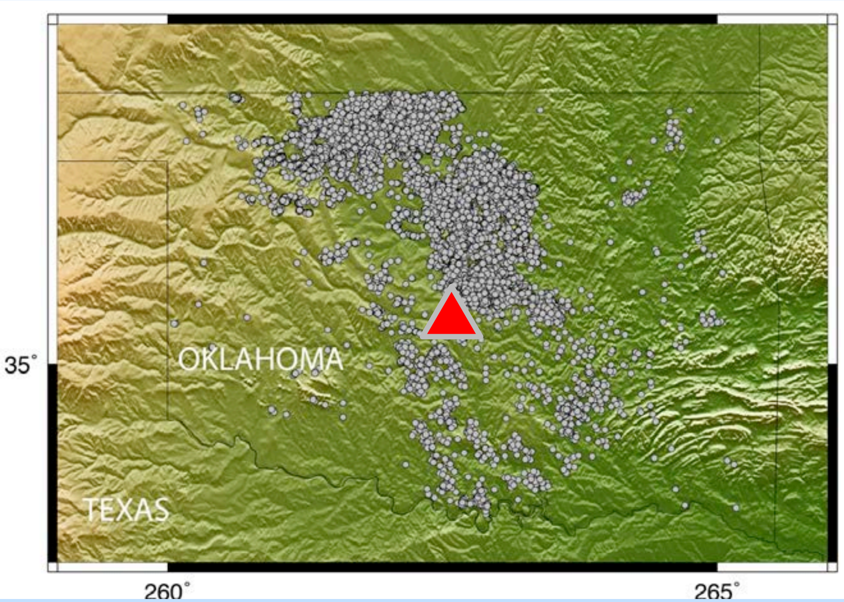


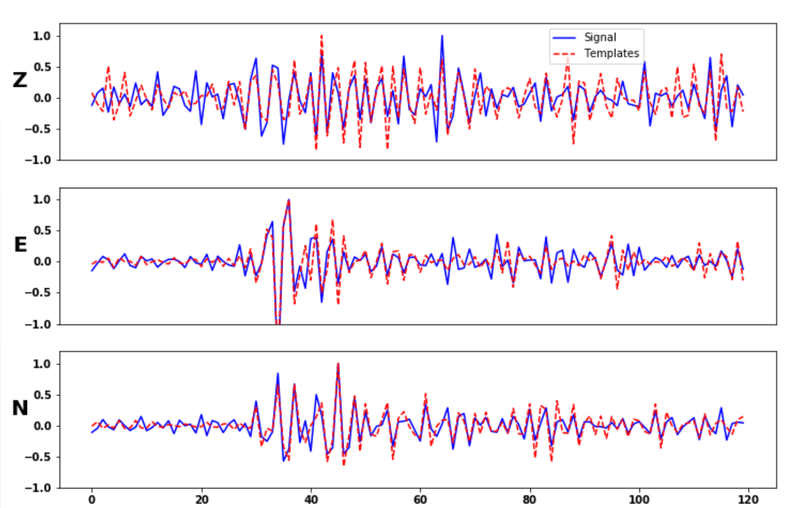


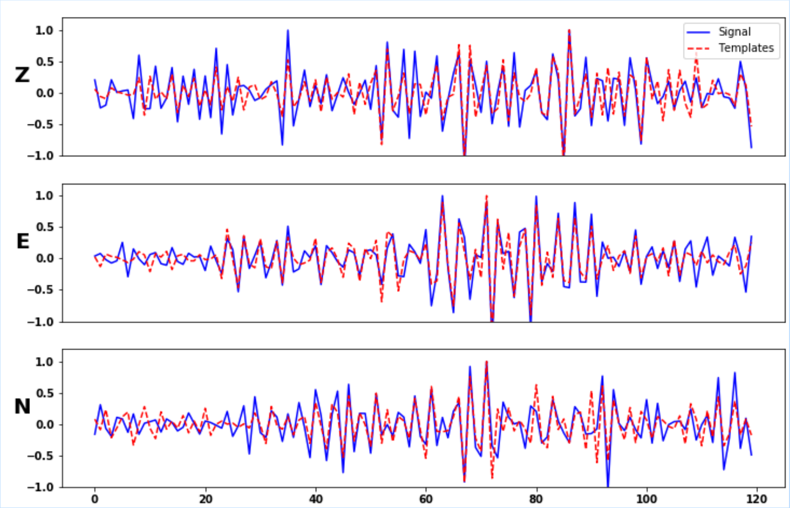


Performance of ML Signal Detection

- Apply
  - OKCFA
  - 2-day continuous data
  - 128 detected events







Performance of ML Signal Detection

- Apply
  - OKCFA
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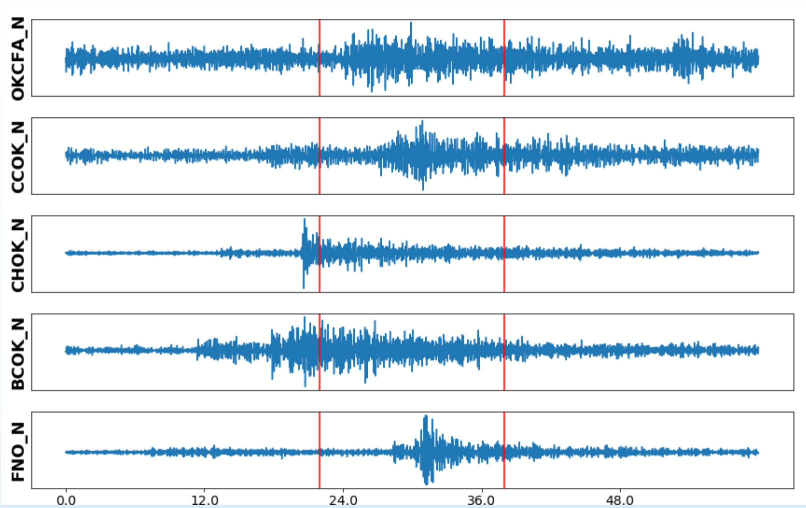
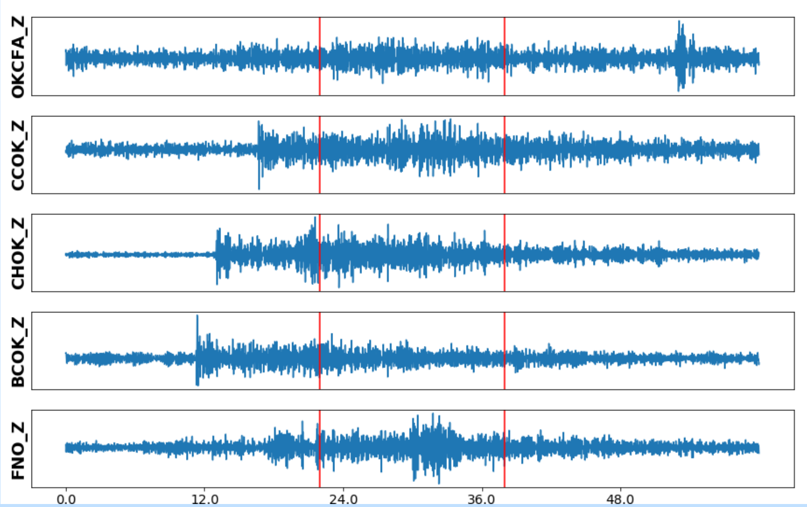
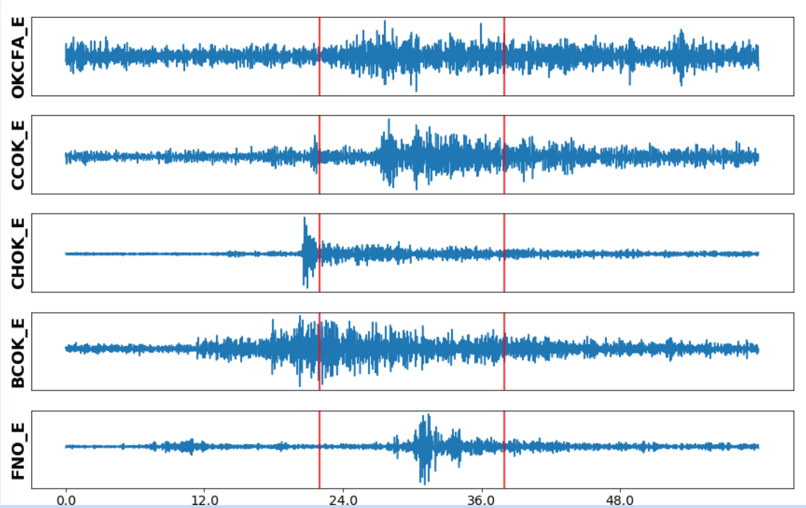
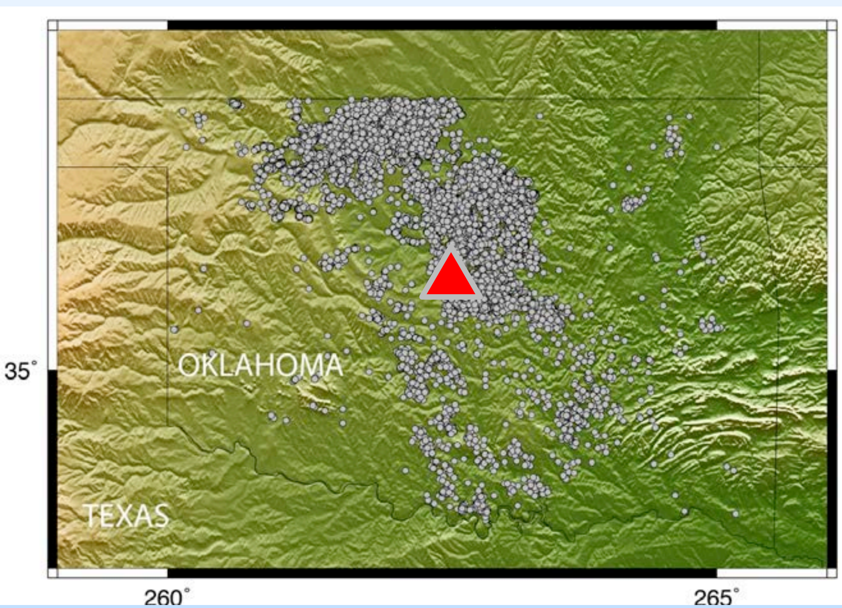






Performance of ML Signal Detection

- Apply
  - OK029
  - 1-month continuous data
  - 4720 detected events



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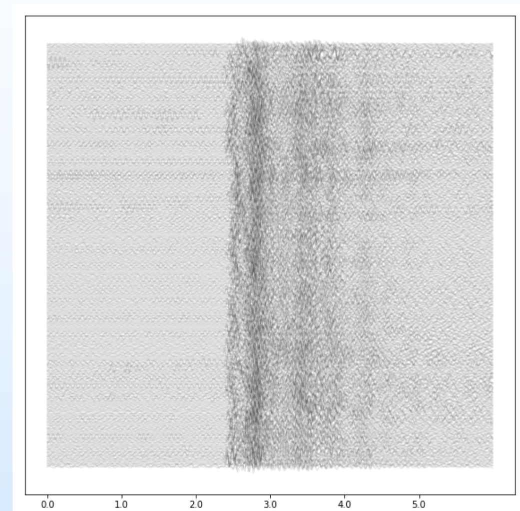

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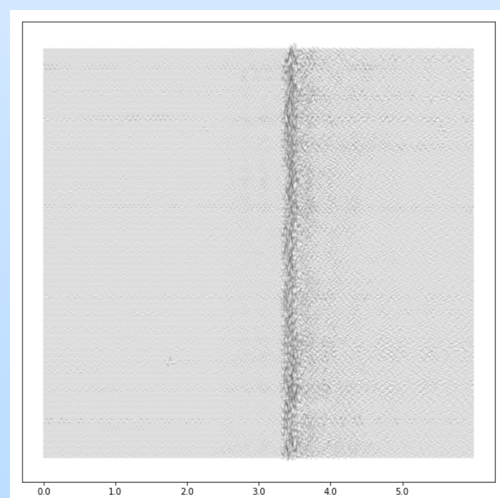

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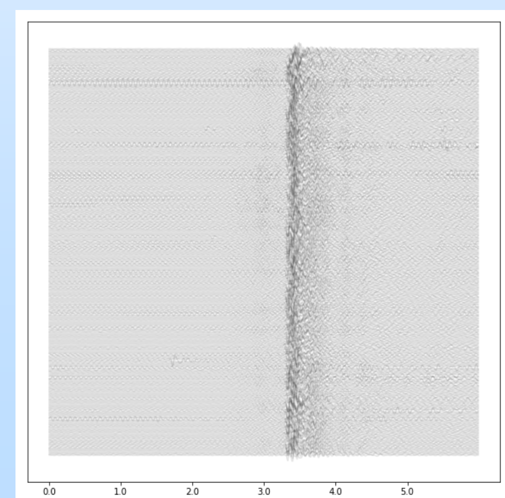
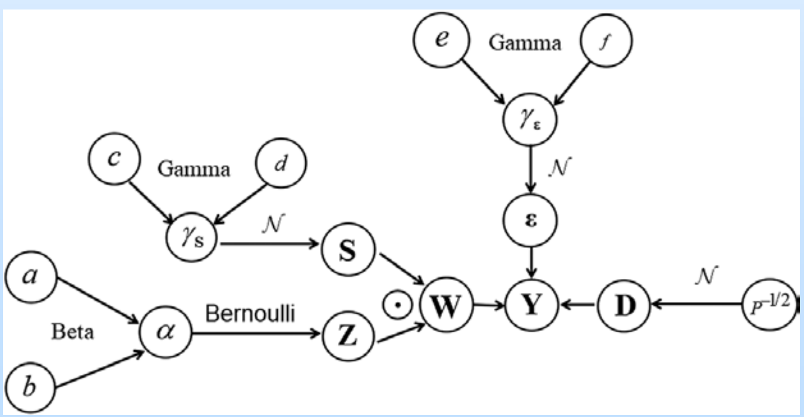


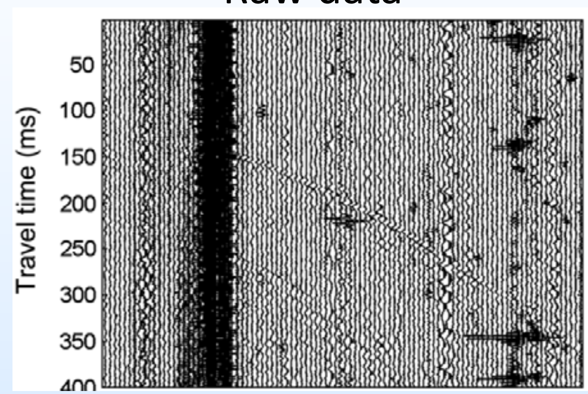
Seismic Signals Enhancement

- Enhance SNR to help detect small events on seismic arrays (data from Oklahoma)
- Unsupervised dictionary learning (Bayesian nonparametric model)

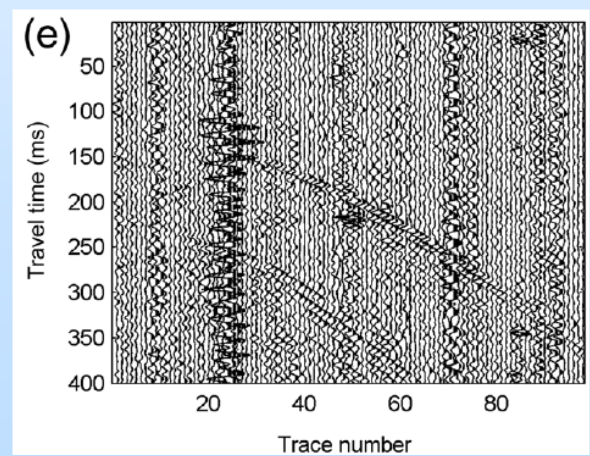
$$\mathbf{y}_i = \mathbf{D}\mathbf{w}_i + \boldsymbol{\varepsilon}_i,$$



Raw data



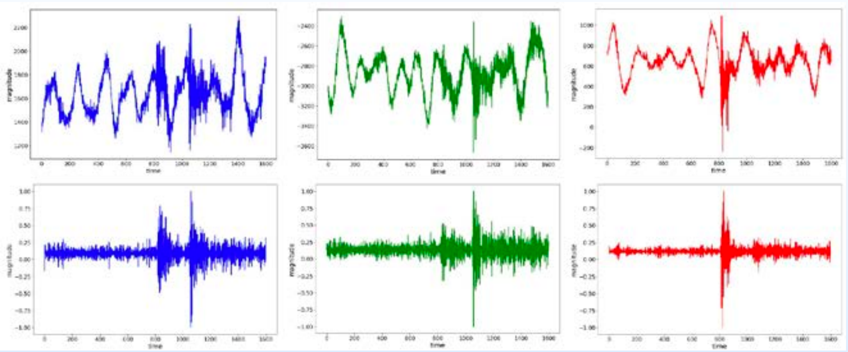
Enhanced data

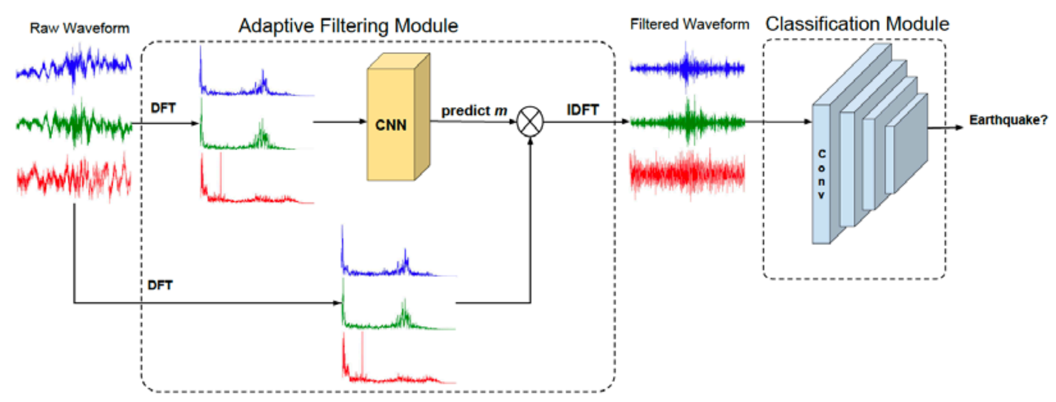


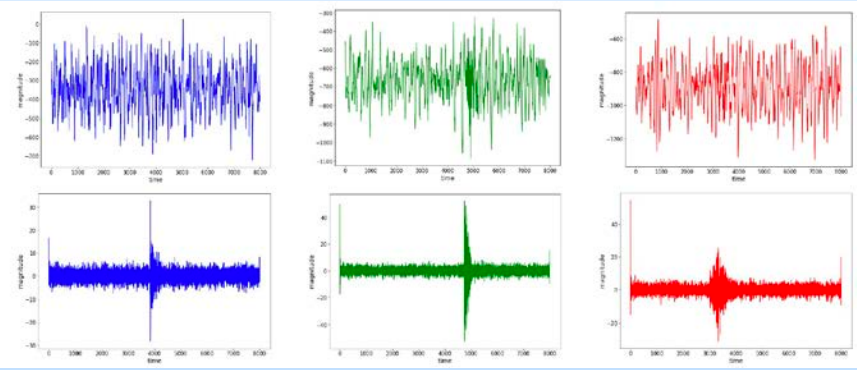
Zhang et al. (2018)

Seismic Signals Enhancement

- Enhance SNR to help detect small events on single seismic station (data from Oklahoma, Decatur)
- Adaptive filtering



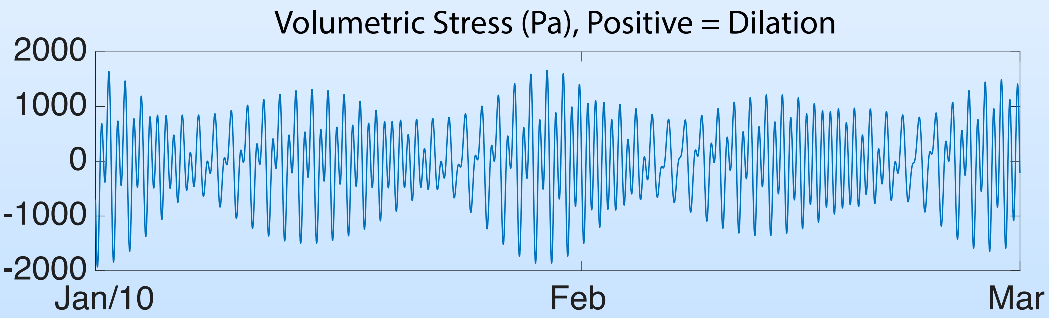


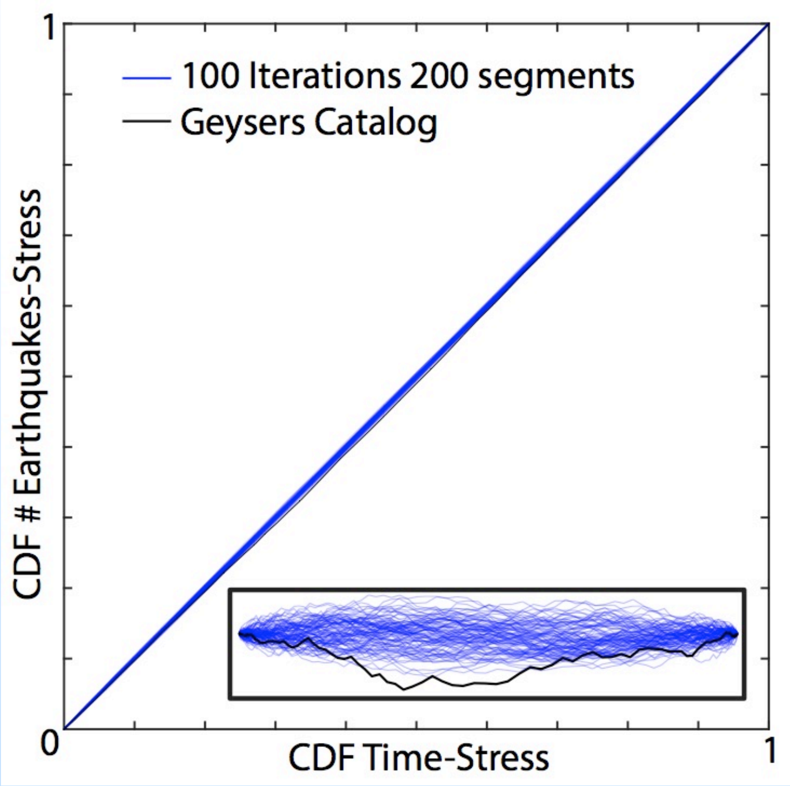


Zhang et al. (2019)

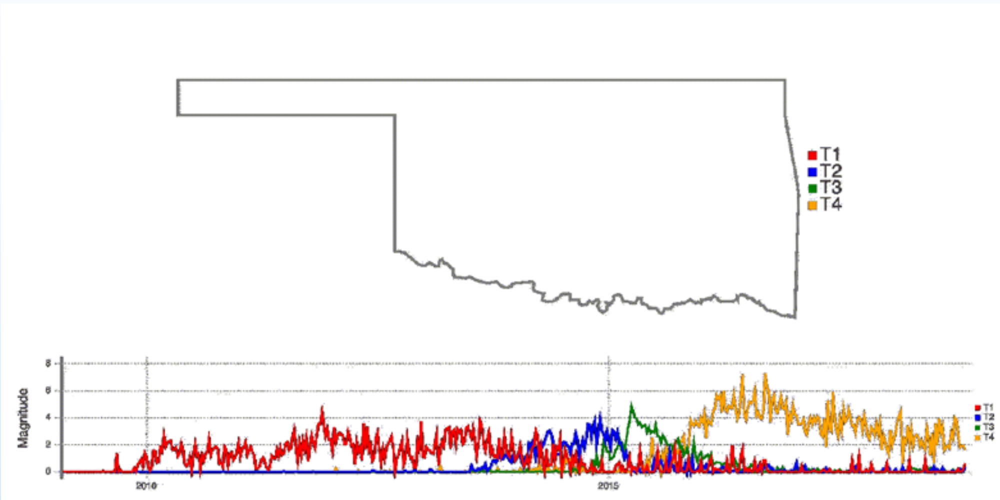
Extract Signatures from Seismic Catalog

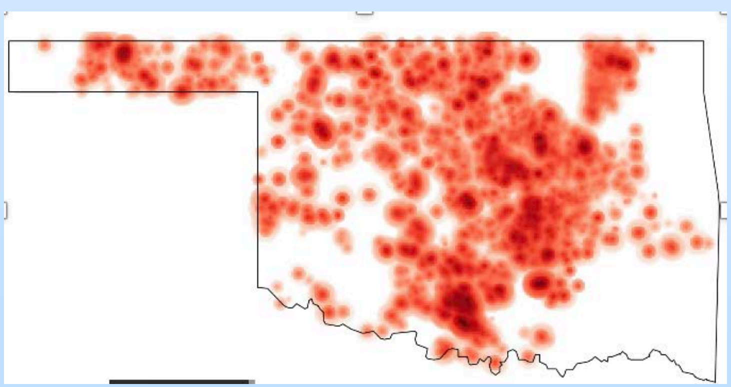
- Geysers, CA (geothermal field)
- Earthquake Catalog:
  - ~400,000 (2003-2017)
  - -0.6 < M < 4.7





Extract Signatures from Seismic Catalog





- Catalog
  - ~ 32,000 events (2009-2018, $0 < M < 5.8$)
- Method
  - unsupervised learning based on nonnegative matrix/tensor factorization (NMF/NTF)
- Investigation
  - Physical relevance of the signals, e.g., correlation with injection? System resetting after large event?

Summary

– We have developed machine learning algorithms (CNN) to efficiently detect seismic events
  - One-component record from one station
  - Multi-component record from one station
  - differentiate seismic signals from noises
  - detect seismic events of different length in times

- We have demonstrated current capability of this method by applying it to field fluid-injection sites
  - Oklahoma, Decatur
  - High accuracy
  - Detected many more events than original catalog

Summary

- We have developed ML algorithms to enhance SNR
  - Array seismic data
  - Single seismic station data
- We have discovered interesting signatures related to fault state from large seismic catalogs
  - Geysers, CA
  - Oklahoma

Synergy Opportunities

- Injection projects that have seismic monitoring system to collect passive seismic data
- Validate our methodology
- Feed back with seismic characterization and inferred fault state

Appendix

Benefit to the Program

- Program goals being addressed by this project
  - Improve the risk assessment of induced seismicity in carbon sequestration.
- Project benefits
  - The research project is developing new methodology to identify and monitor faults at a critical state of stress. If successful, the proof-of-concept work will demonstrate at field scale a transformational approach for both identifying potential faults of concern during site pre-characterization and monitoring a site during injection such that induced seismicity is minimized or even avoided.

Project Overview

Goals and Objectives

- Relationship to the program goals and objectives
  - The stress state of the fault is related to risk level of induced seismicity. Monitoring faults at critical state of stress enables advanced risk assessment of induced seismicity for carbon storage.

- Success criteria
  - New methodology for monitoring the stress state of faults
  - Successful application of the methodology to CO_2 storage field

Organization Chart

- LANL
  - Ting Chen, Youzuo Lin, Andrew Delorey, Xiaofei Ma, Richard Alfaro, Yan Qin, Avipsa Roy, Alex Eddy, Yue Wu, Zhongping Zhang, Tiantong Wang, Peter Roberts, Christine Gammans, Paul. Johnson, Velimir Vesselinov, Daniel O'Malley, Rajesh Pawar, George Guthrie

- External partners (leveraging with)
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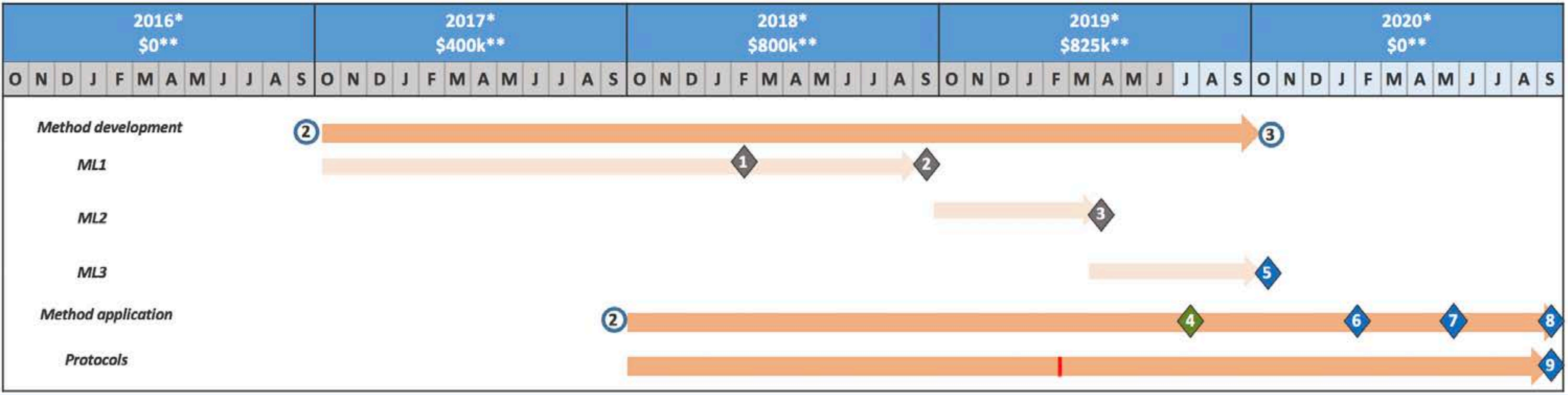
Gantt Chart



Prior work—IWC analysis of multi-station/multi-component data shows changes in small events using pre-2012 OK dataset

1. Develop/train machine-learning algorithm (ML-1) to extract events from single-component, single-station seismic data
2. Evaluate ability of ML-1 to extract small events relative to interstation waveform coherence (IWC) using pre-2012 OK dataset
3. Extend ML-1 to extract events from multi-component, single-station data (ML-2); test using pre-2012 OK dataset
4. Verification/validation with OK dataset at site scale (2009–2016)
5. Extend ML-2 to extract events from multi-component, multi-station data (ML-3); test using pre-2012 OK dataset
6. Verification/validation with OK dataset at regional scale (2009–2016)
7. Verification/validation with Illinois dataset
8. Verification/validation with Cascadia dataset
9. Protocols for use and application of ML algorithms as applied to seismic datasets at site- (ML-1; ML-2) or regional-scale (ML-3)

Bibliography

- Ma, X. and Chen T., 2019, A neural network based small seismic event detector, AGU Fall Meeting, San Francisco CA.
- Roy, Avipsa, Chen, T., and Calseton, E., 2019, Understanding the Effects of Fluid Injection on Induced Seismicity in Oklahoma using Machine Learning, AGU Fall Meeting, San Francisco CA.
- Delorey, A. and Chen, T., 2019, Triggered Earthquakes at the Geysers in Northern California, SSA annual meeting, Seattle, WA.
- Lin, Y., Zhang, Z., and Chen, T., 2019, A Neural Network Based Multi-component Earthquake Detection Method, SSA annual meeting, Seattle WA
- Zhang, Z., Lin, Y., Zhou, Z., and Chen, T., 2019, Adaptive Filtering for Event Recognition from Noisy Signal: an Application to Earthquake Detection. In ICASSP 2019 - 2019 IEEE International Conference on Acoustics, Speech and Signal Processing. IEEE.
- Zhang, C., van der Baan, M., and Chen, T., 2018, Unsupervised Dictionary Learning for Signal-to-Noise Ratio Enhancement of Array Data. Seismological Research Letters. https://doi.org/10.1785/0220180302
- Chen, T., Zhang, Z, Lin, Y., and Eddy, A., 2018, Microseismic Event Detection Methods Using Single or Multiple Stations for Monitoring CO2 Storage Sites, AGU Fall Meeting, Washington DC.
- Lin, Y., Chen, T., and Wu, Y., 2018, DeepDetect: Application of Deep Densely Connected Convolutional Neural Network to Detect Earthquake Events, IRIS workshop, Albuquerque, NM
- Wu, Y., Zhou, Z., Delorey, A., Chen, T., and Lin, Y., 2018, DeepDetect: A Deep Densely Connected Neural Network to Detect Seismic Events, Proceedings of SIAM Data Mining Conference
- Wu, Y., Zhou, Z., Chen, T., and Lin, Y., 2018, DeepDetect: Application of Deep Densely Connected Convolutional Neural Network to Earthquake Detection, SSA Annual Meeting, Miami, FL