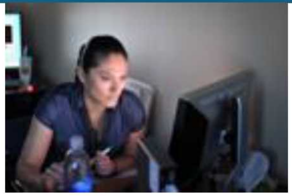
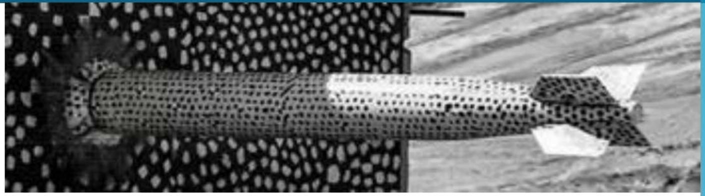
SAND2019-12072PE

Integrated Geomechanics and Geophysics in Induced Seismicity: Experiments of Geo-architectured samples and machine learning applications





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Acknowledgments

- Laboratory Directed Research and Development program at Sandia National Laboratories

- U.S. DOE, Office of Fossil Energy, Fossil Energy Research and Development Program

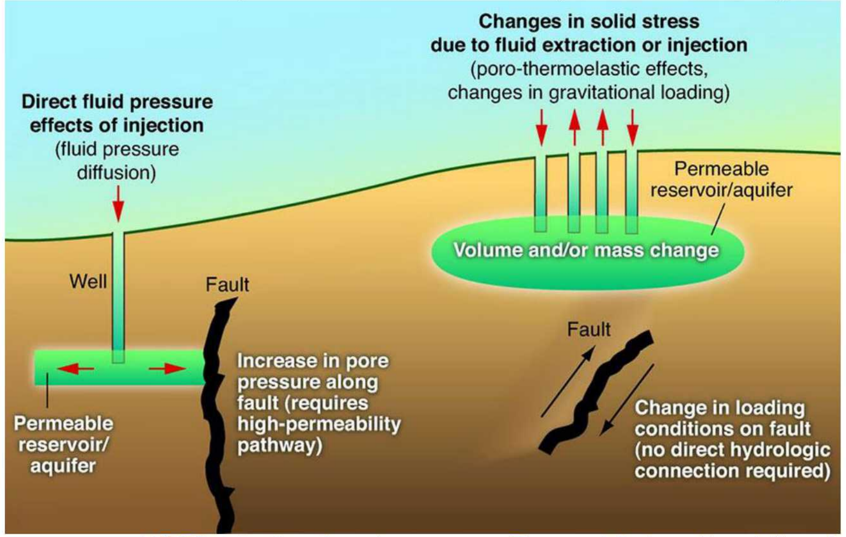
- **Motivations**
- Mechanical testing of Geo-architected rocks
- Machine learning applications at laboratory scale
- Machine learning applications at field scale

Background & Motivations

♦ Motivations

- Fluid injection or withdrawal causes changes in pore pressure, resulting in induced seismicity during subsurface energy activities
- Reduce risks of induced seismicity and improve subsurface energy activities (unconventional resource recovery, geological carbon storage, geothermal energy recovery)

Induced (human-caused) seismicity



USGS: http://earthquake.usgs.gov/Research/induced/modeling.php

♦ Goals

(1) Delineate fracture and failure mechanisms using well-controlled experiments

(2) Determine poro-elastic coupling mechanisms that lead to induced seismicity during fluid injection into subsurface (Chang et al., 2018; Chang and Yoon (2018))

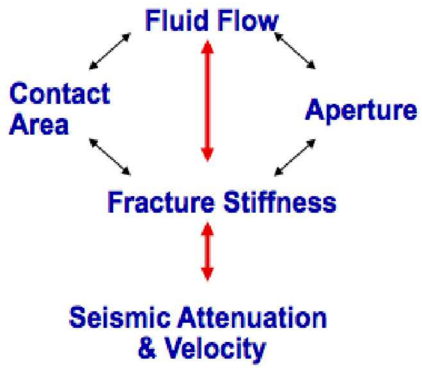
(3) Develop/apply machine-learning techniques for seismic wave data analysis and event detection

♦ Approaches

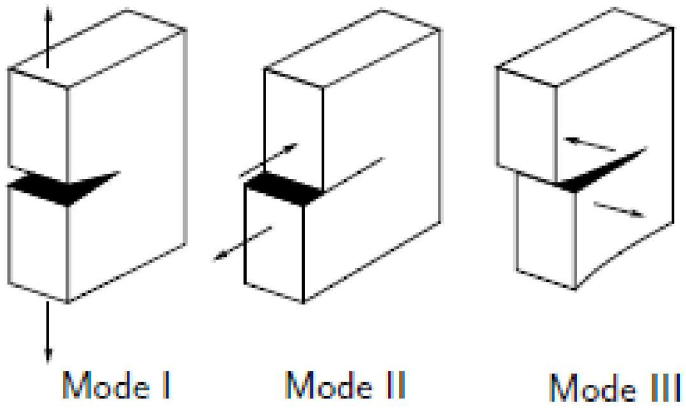
An ambitious integration of controlled mechanical failure experiments coupled with micro-CT imaging, acoustic sensing, modeling of fracture initiation and propagation, and machine learning for event detections and waveform characterization

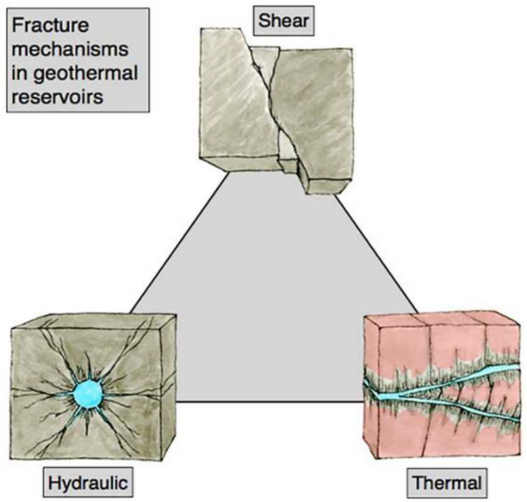
Linkage between geomechanical and geophysical processes in mechanical discontinuities

- Precursor(s) to the induced seismicity from existing fault/fracture systems is key
- Changes in the spectral contents of waveforms are likely due to wave propagation + faulting processes - initiation, propagation and coalescence of pre-existing discontinuities loaded in mixed mode I-II-III (**Damage Mechanics Challenge, AGU 2019 session**)



Courtesy from Pyrak-Nolte





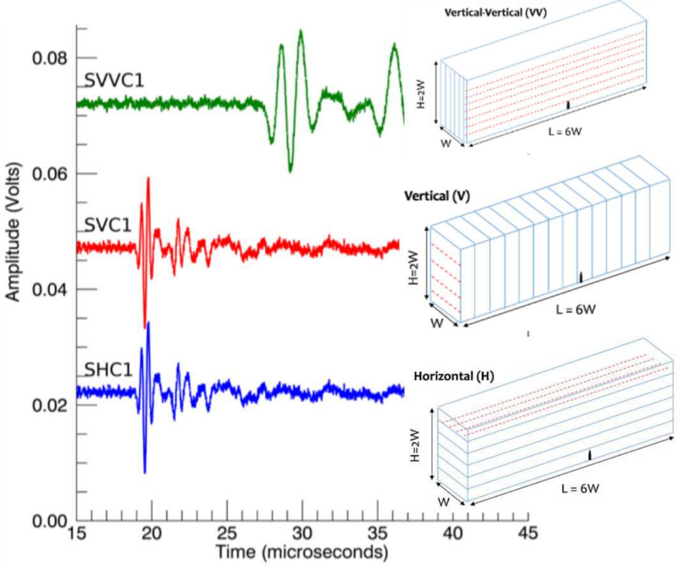
Holtzman et al. Sci Adv 2018

- Motivations
- **Mechanical testing of Geo-architected rocks**
- Machine learning applications at laboratory scale
- Machine learning applications at field scale

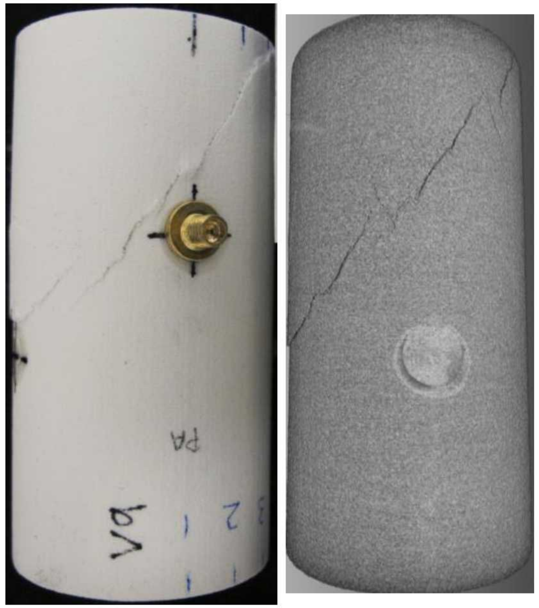
Integrated approach for geomechanical and geophysical measurements

Geo-architected Rock

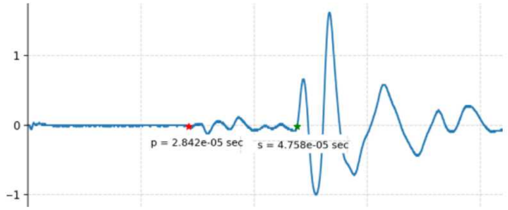
Mechanical testing (3PB) & Signals Prior to Failure



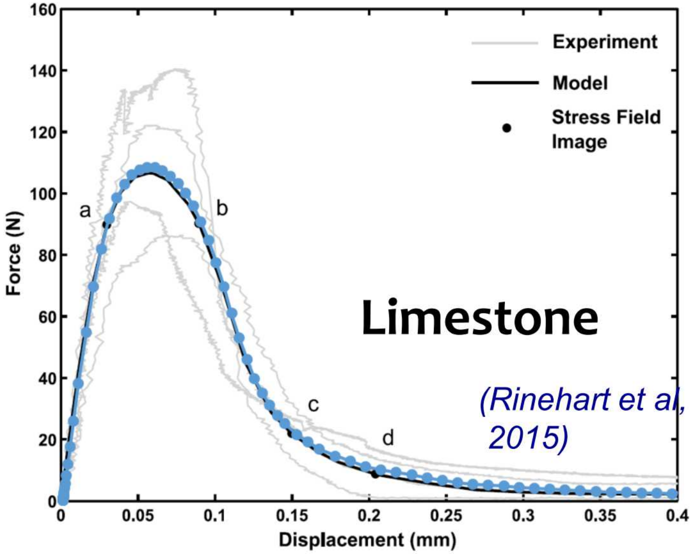
MicroCT imaging

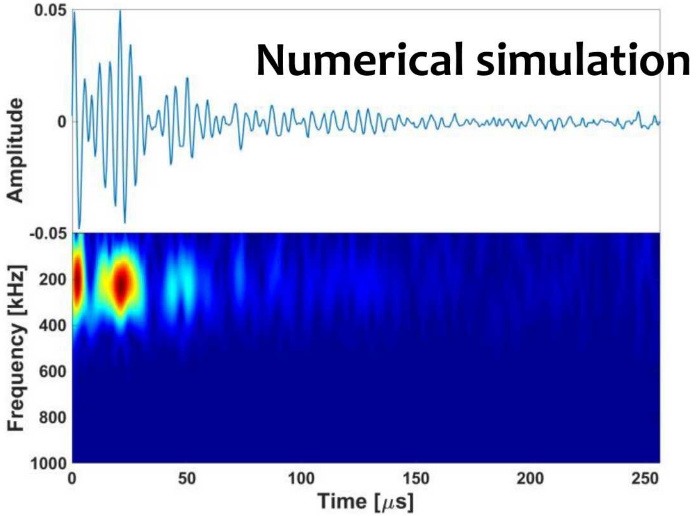


Waveform data analysis



3PB experiments and simulations

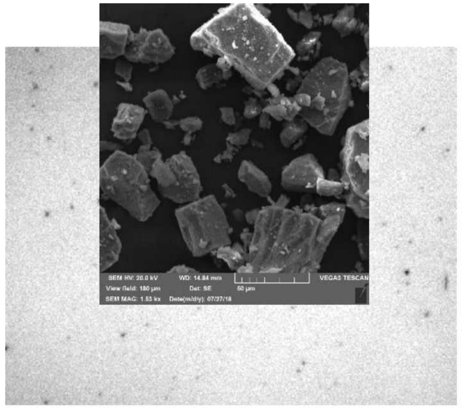




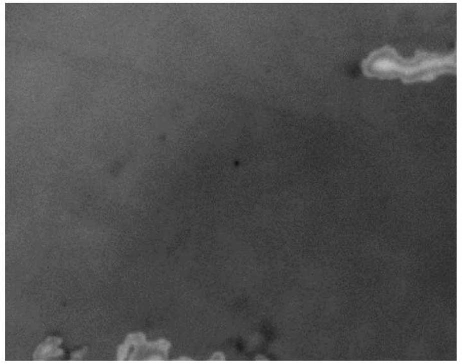
Powder Based 3D Printing Process

$$CaSO_4 \cdot 0.5H_2O + 1.5H_2O = CaSO_4 \cdot 2H_2O$$

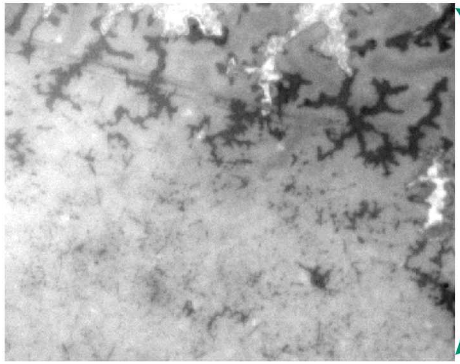
Powders (basanite) Binder Gypsum



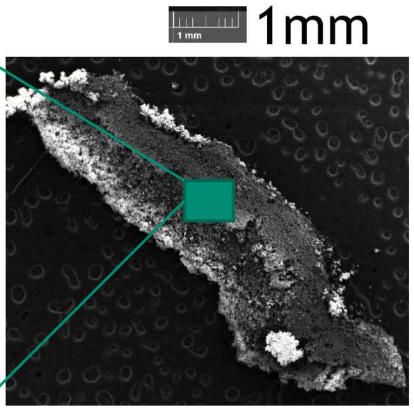
powders

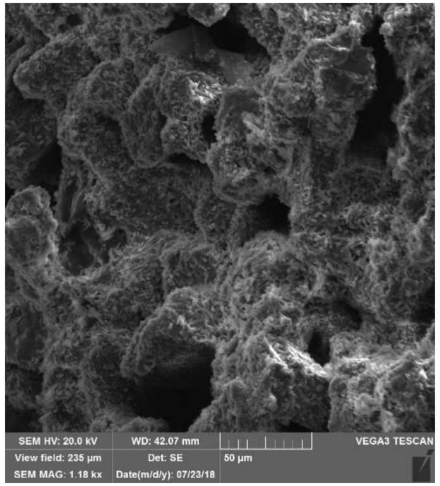


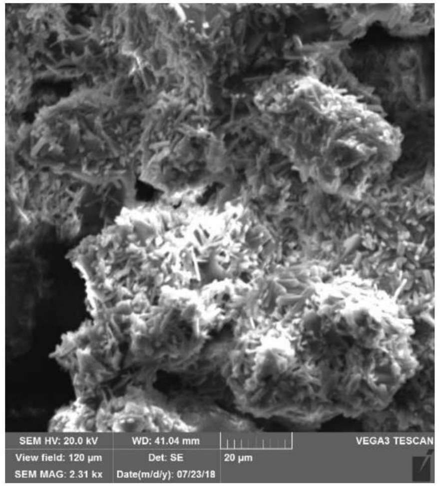
Binder dropped

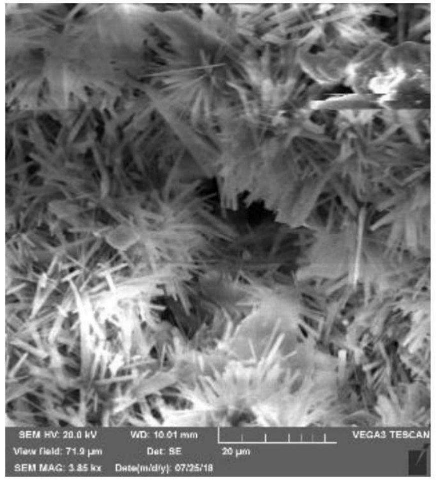


Reaction products









Geo-architected Rock

A geo-architected rock is a rock analog that is fabricated and structured using conventional or unconventional methods to develop controlled features in specimens that promote repeatable experimental behavior.

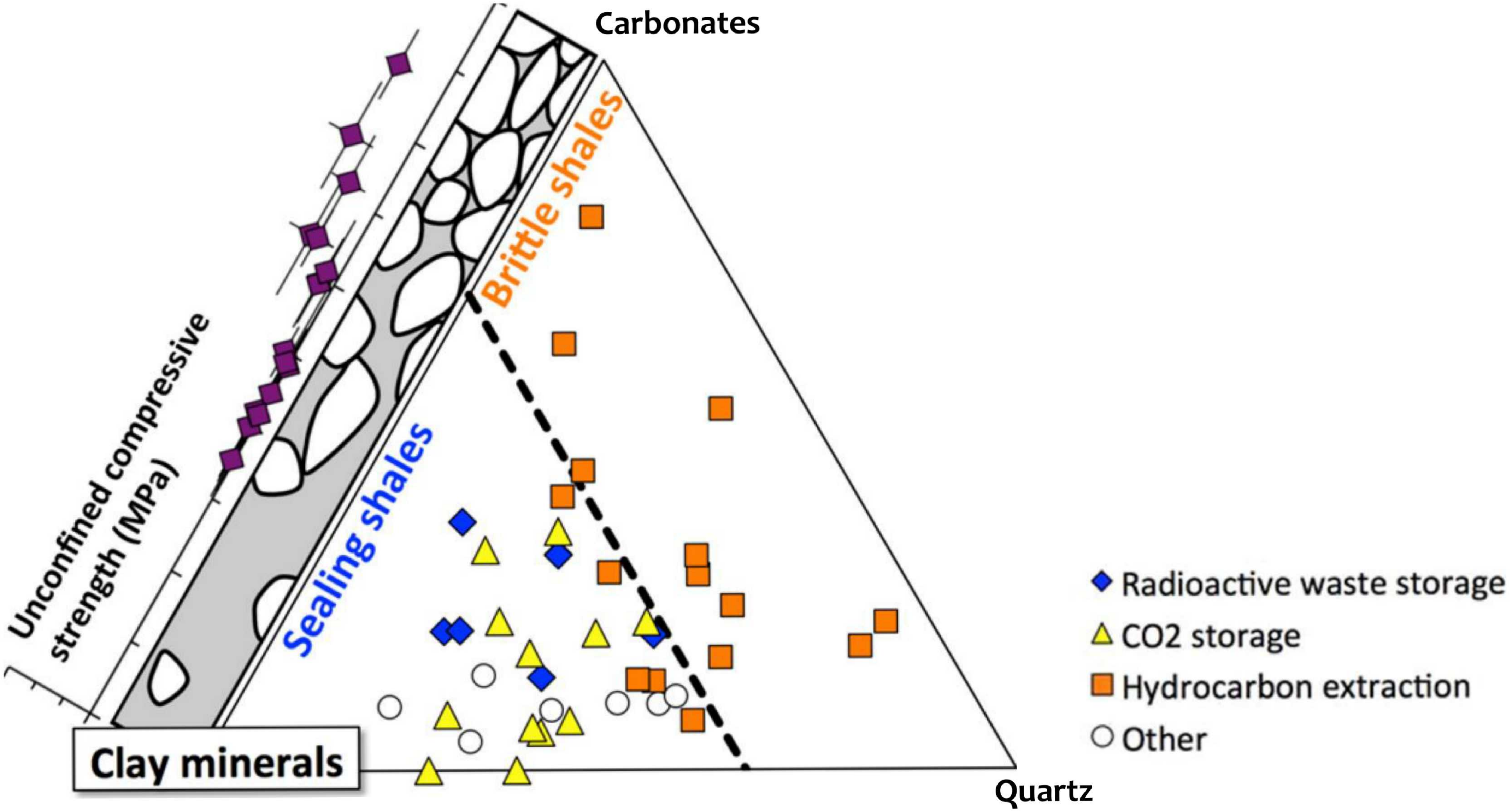
**Material Properties*

**Unconfined Compressive Strength Test*

**Ultrasonic Compressional & Shear Wave Measurements*

**Tensile Failure of Geo-Architected Rock (three point bending test)*

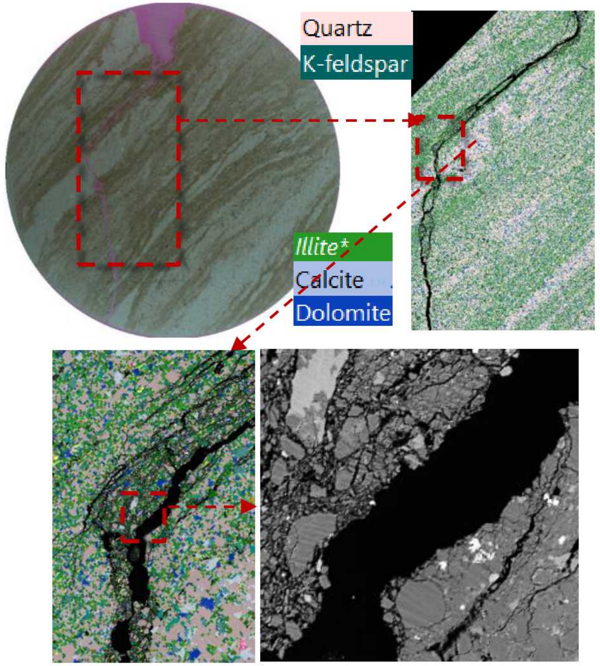
Rock Variability: "Shale"



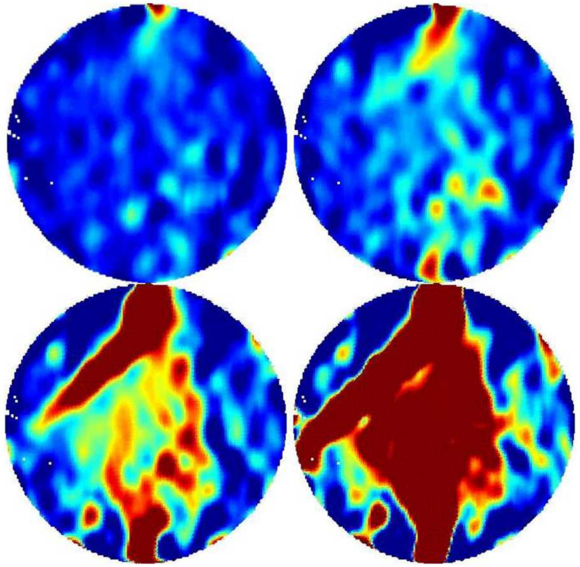
(Bourg et al., 2015)

Observations of Fracture Resistance in Layered Geological Media

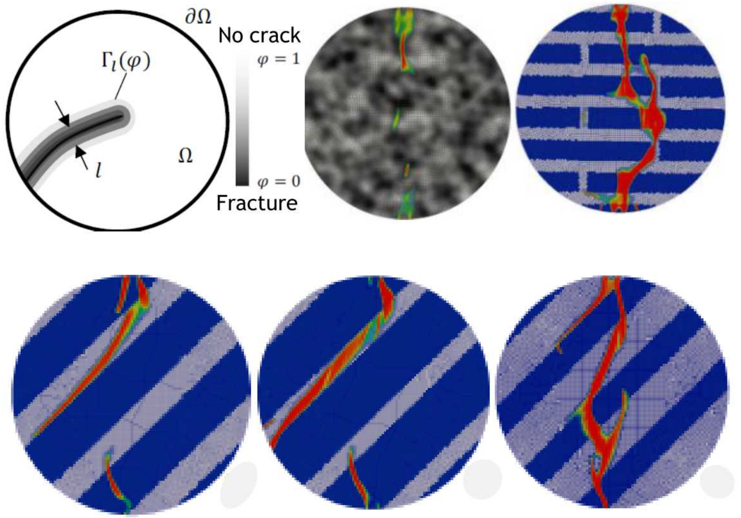
A. A thin section of Mancos shale after Indirect tensile testing



B. Lateral strain based on digital image correlation measurements

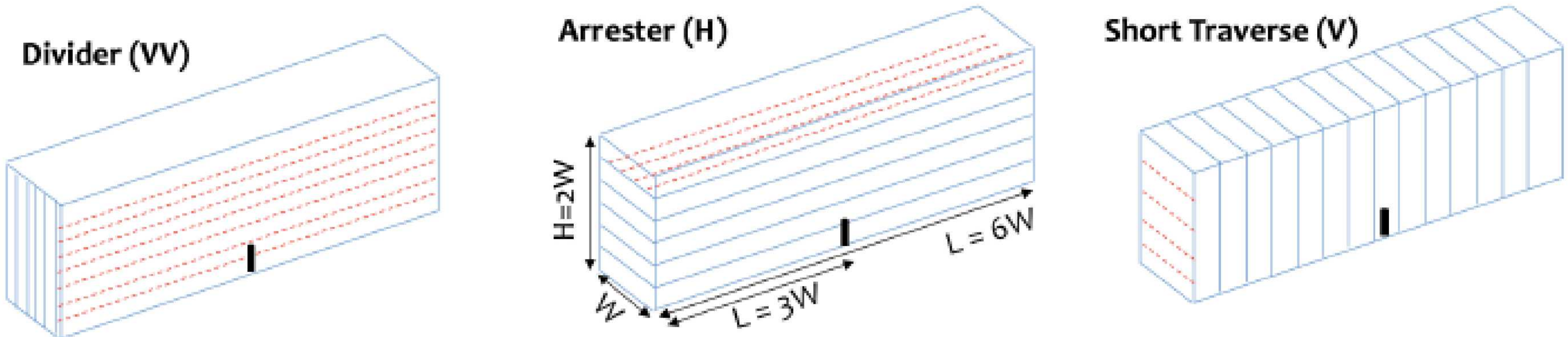


C. Phase field modeling results (crack initiation & propagation)

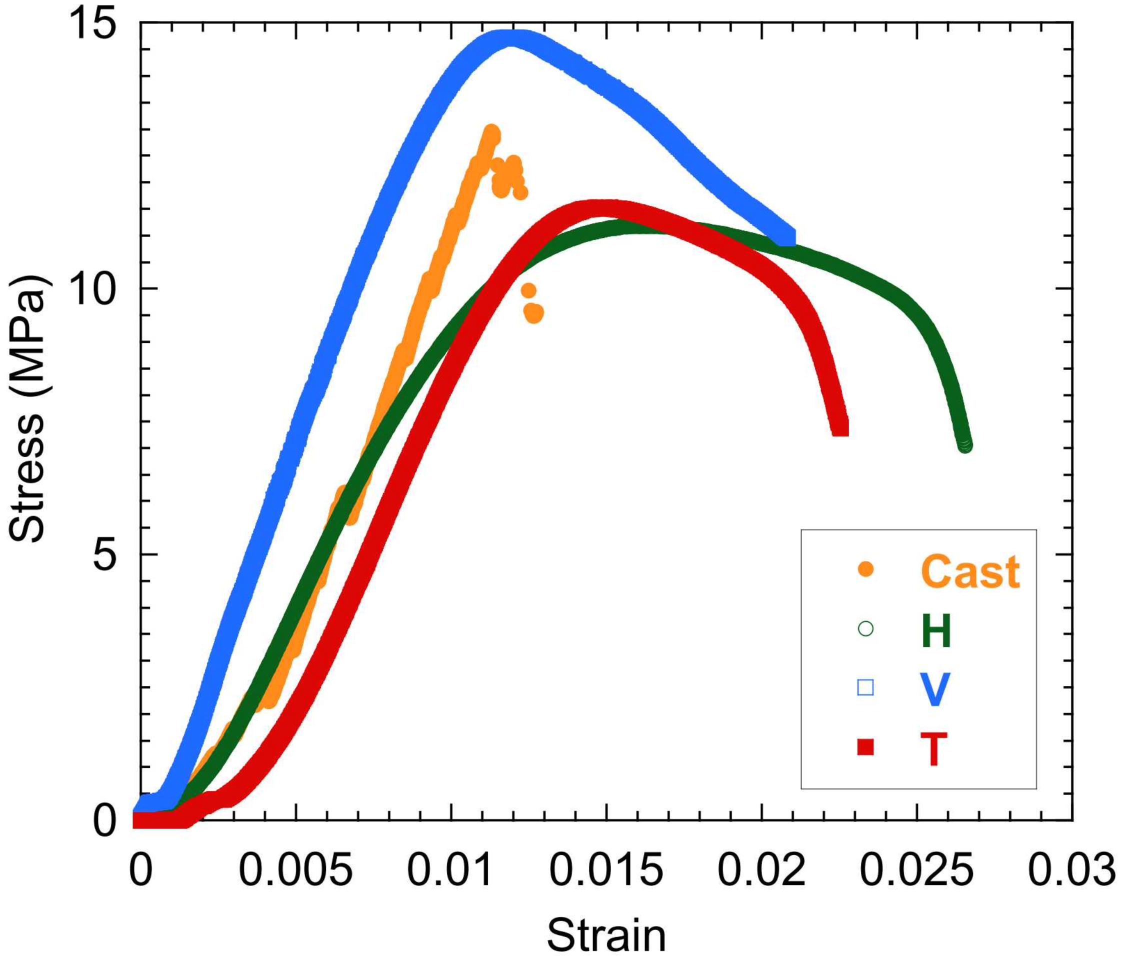


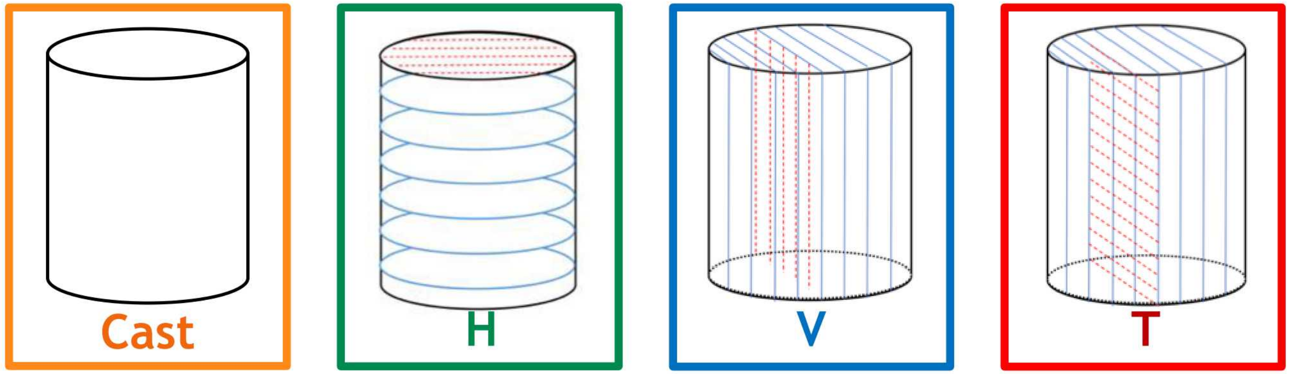
Na et al. (2017, JGR); Yoon et al. (2019, AAPG Memoir 102)

Geo-architected Rock



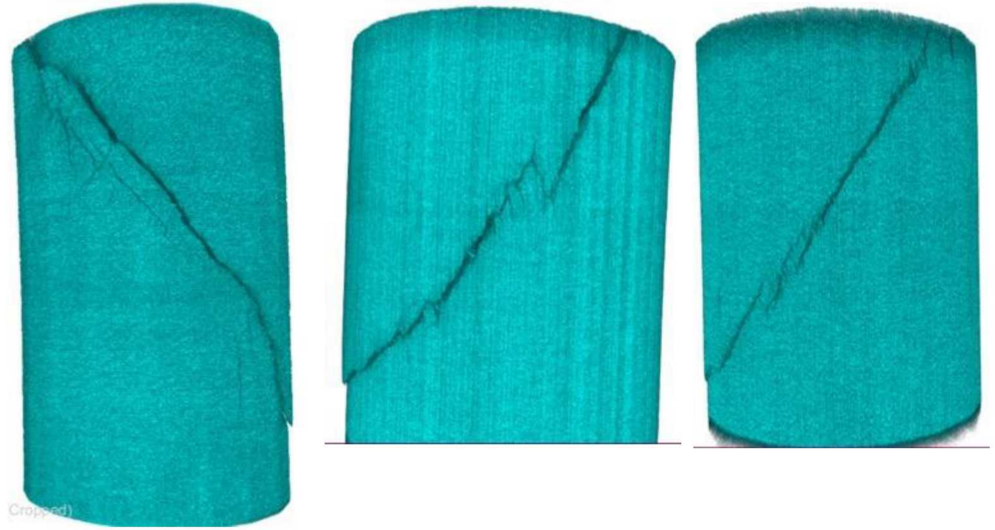
Material Properties: Unconfined Compressive Strength Tests





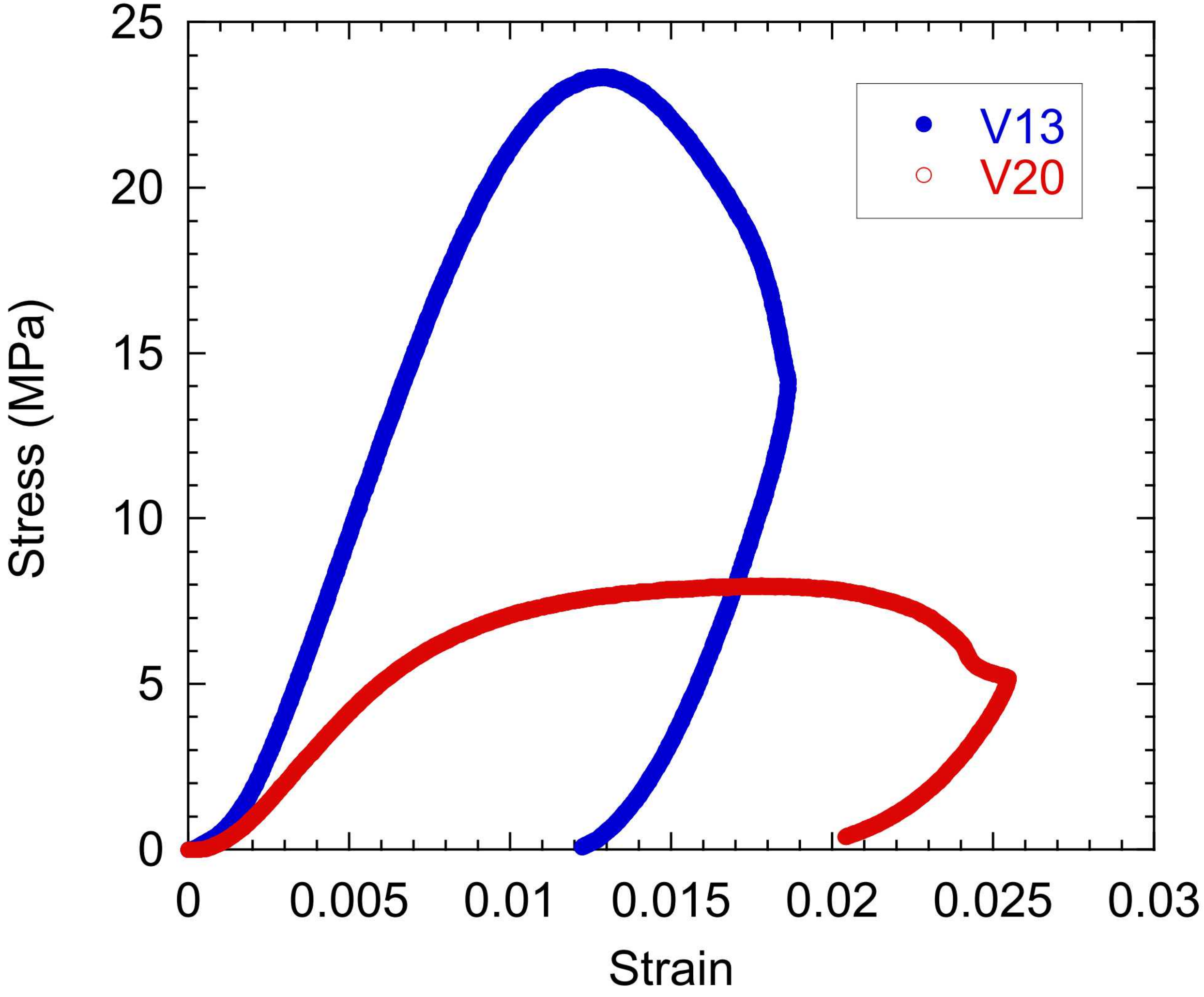
Photo

X-ray Tomographic Reconstructions

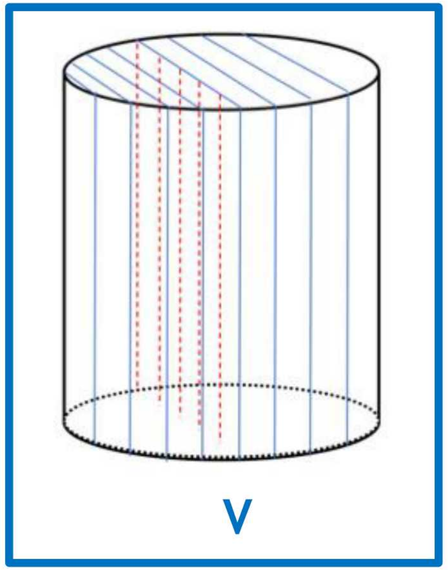


Jiang et al. (In prep for Nature Comm.)

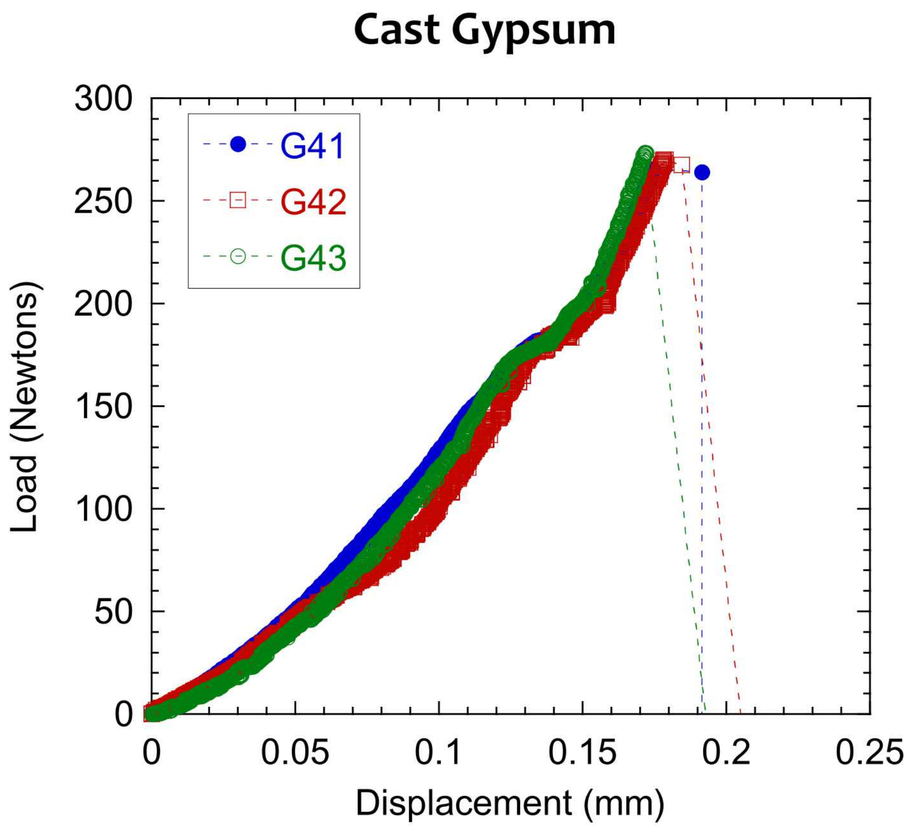
Material Properties: Unconfined Compressive Tests

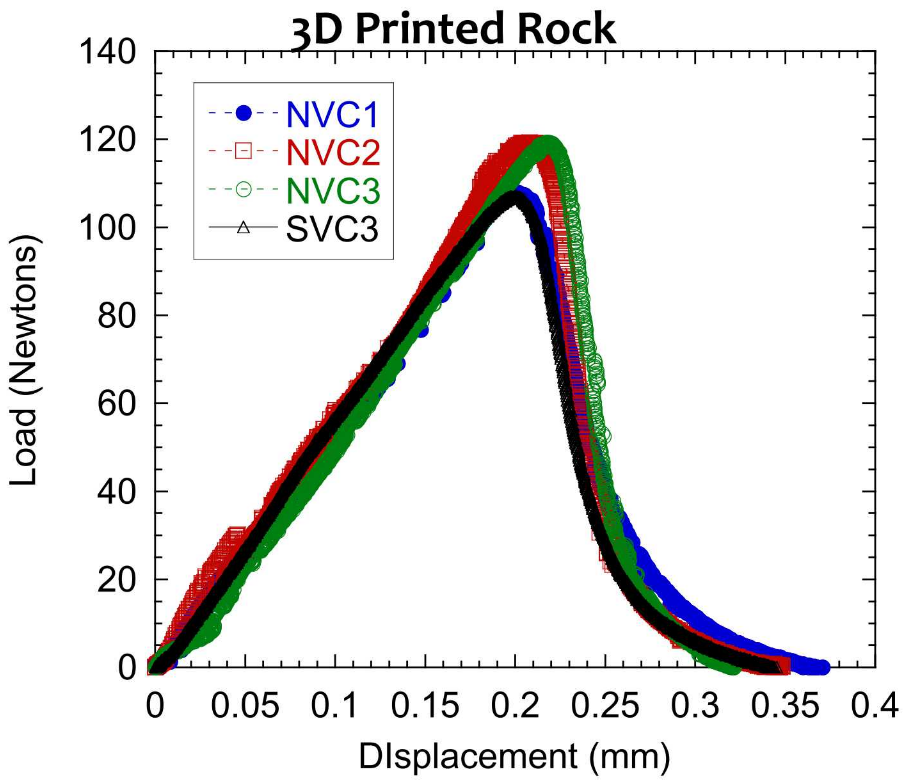


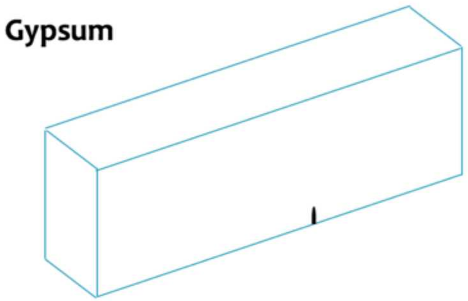
Components	V13	V20
Bassanite $2Ca_2SO_4 \bullet H_2O$	48.2	77.3
Gypsum $CaSO_4 \bullet 2H_2O$	51.8	22.7

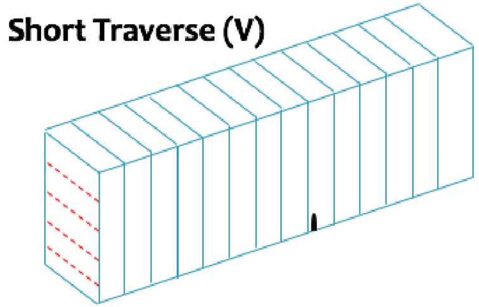


Three Point Bending Experiments: Repeatability

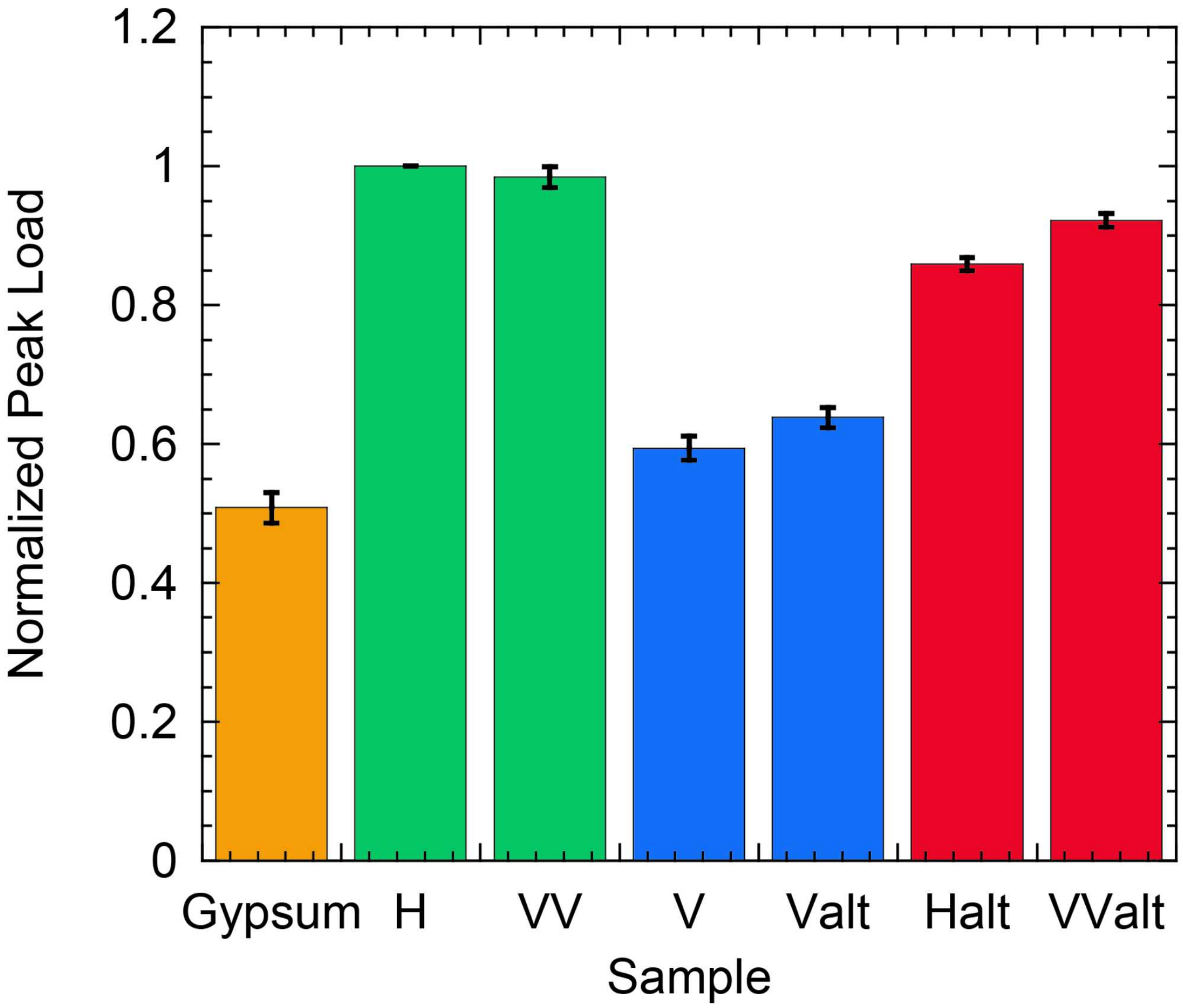


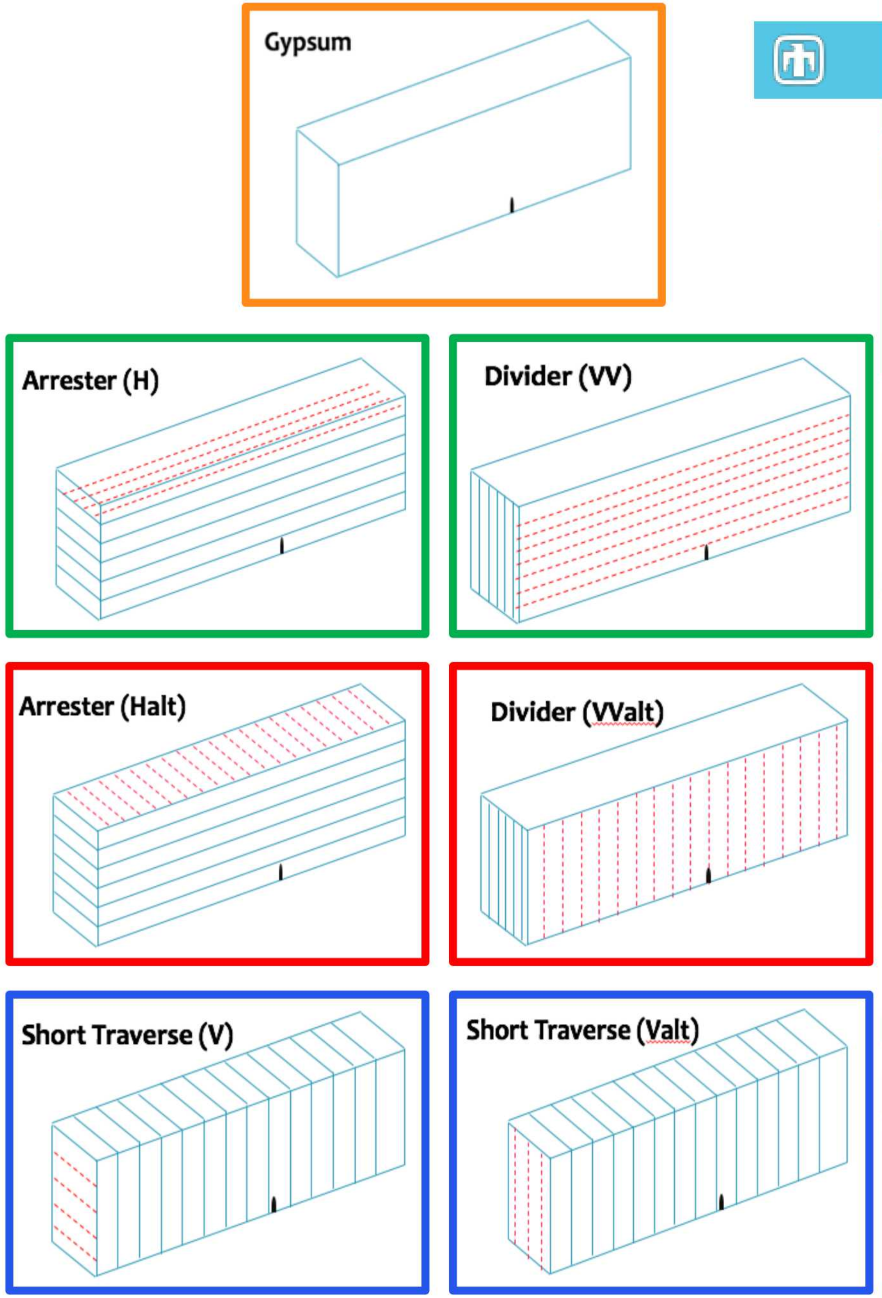






Load-Displacement Behavior



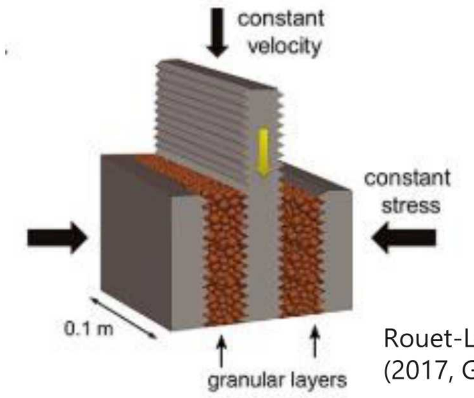


- Motivations
- Mechanical testing of Geo-architected rocks
- **Machine learning applications at laboratory scale**
- Machine learning applications at field scale

Earthquake Forecasting On Lab Scale Induced Seismic Events

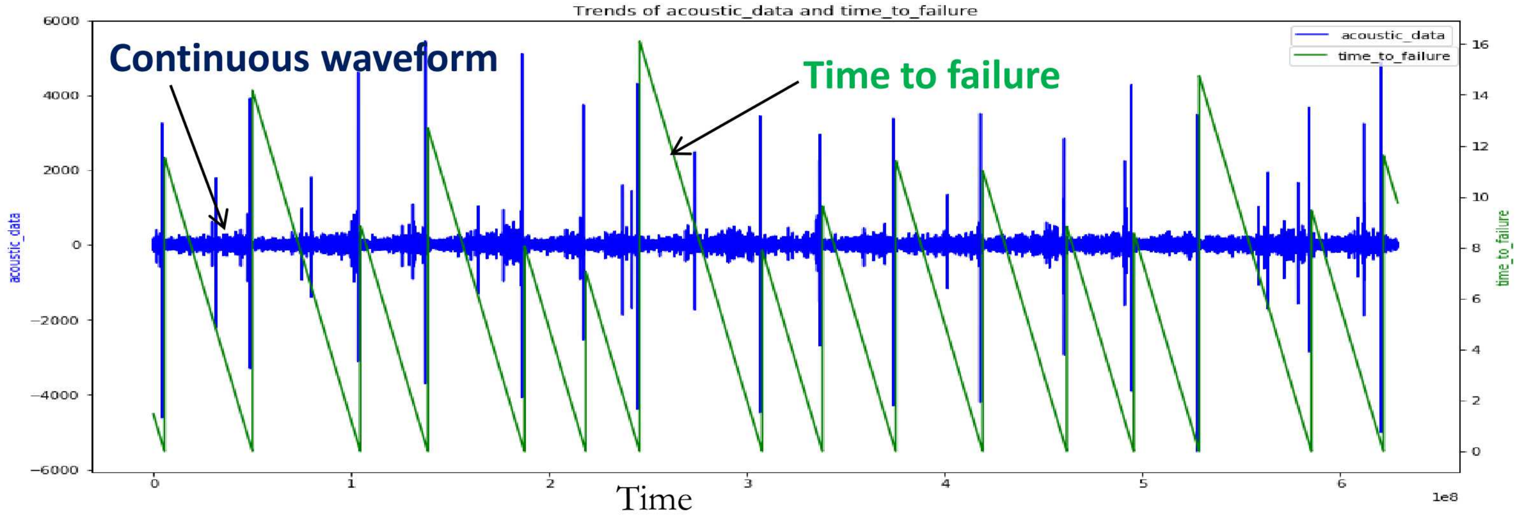
- **Kaggle: LANL Earthquake Prediction**

  Use seismic signals (acoustic emissions) to predict the time remaining for the next earthquake to happen



Rouet-Leduc et al. (2017, GRL)

  - Experimental data: Double direct shear geometry subjected to bi-axial loading
    Aperiodic cycles of stick and slip (loading & failure)
  - Training data: Continuous data containing 16 earthquakes
  - Testing data: Random earthquake cycle segments of 150,000 data-points
  - Approach: Preprocess-> Feature Extraction-> Training->Predictions



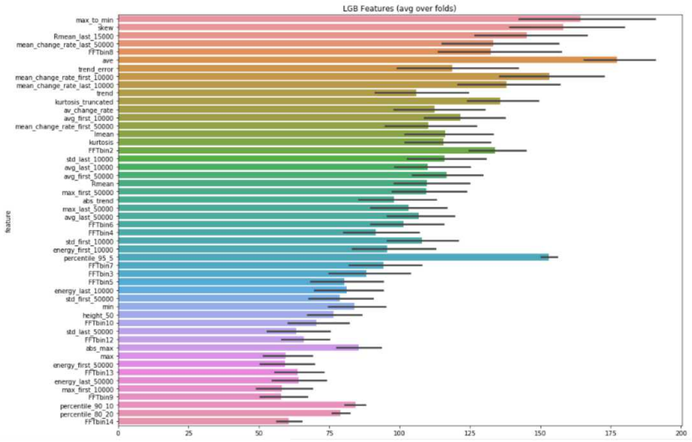
Training sample data file plotted.

Features & Prediction

- Characterize the signal through various measurements
- Features are easily comparable to other signal's features (reduce overfitting)

$\vec{F} =$

Mean	STA/LTA	Zero Crossing
Standard deviation	Correlation	Number of peaks
Change rate	Kurtosis	Medians
Percentile	Skew	Sum
Quantiles	Energy	Autocorrelation
Trend regression	Mel-frequencies	Difference
FFT	Minimum	
	Maximum	

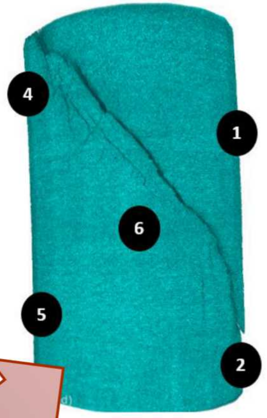


- Data analysis method in which computers learn and autonomously build models based on data patterns.
- **Decision trees**
  Random Forest, Boosting trees (LightGBM)
- **Support Vectors:**
  Support Vector Regressor (SVR)
  Kernel Ridge Regression (KRR)
- **Neural Networks**
  Artificial Neural Networks (ANN)
  Short-Long Term Memmory (LSTM)
  Convolutional Neural Network (CNN)

Submissions	CV mean	STD	Public Score	Private Score
LGB	2.0543	0.1198	1.62295	2.65173
XGB	2.0715	0.1196	1.55728	2.64105
KRR	2.0906	0.1078	1.56615	2.52527
Blend KRR XGB	——	——	1.53121	2.56981

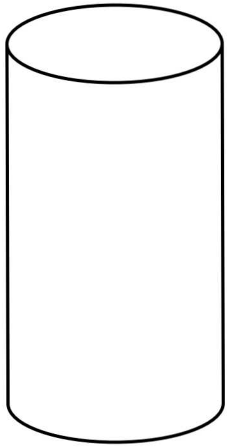
https://www.kaggle.com/c/LANL-Earthquake-Prediction/overview

Experimental Setup

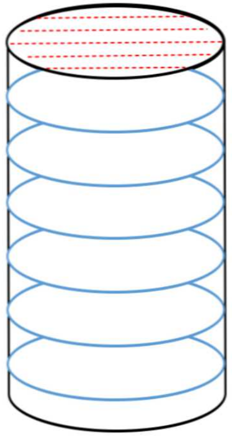


- Six sensors (Channels)
- 200-400 kHz filter to get rid of noise

Cast Sample
C22, C33, & C23

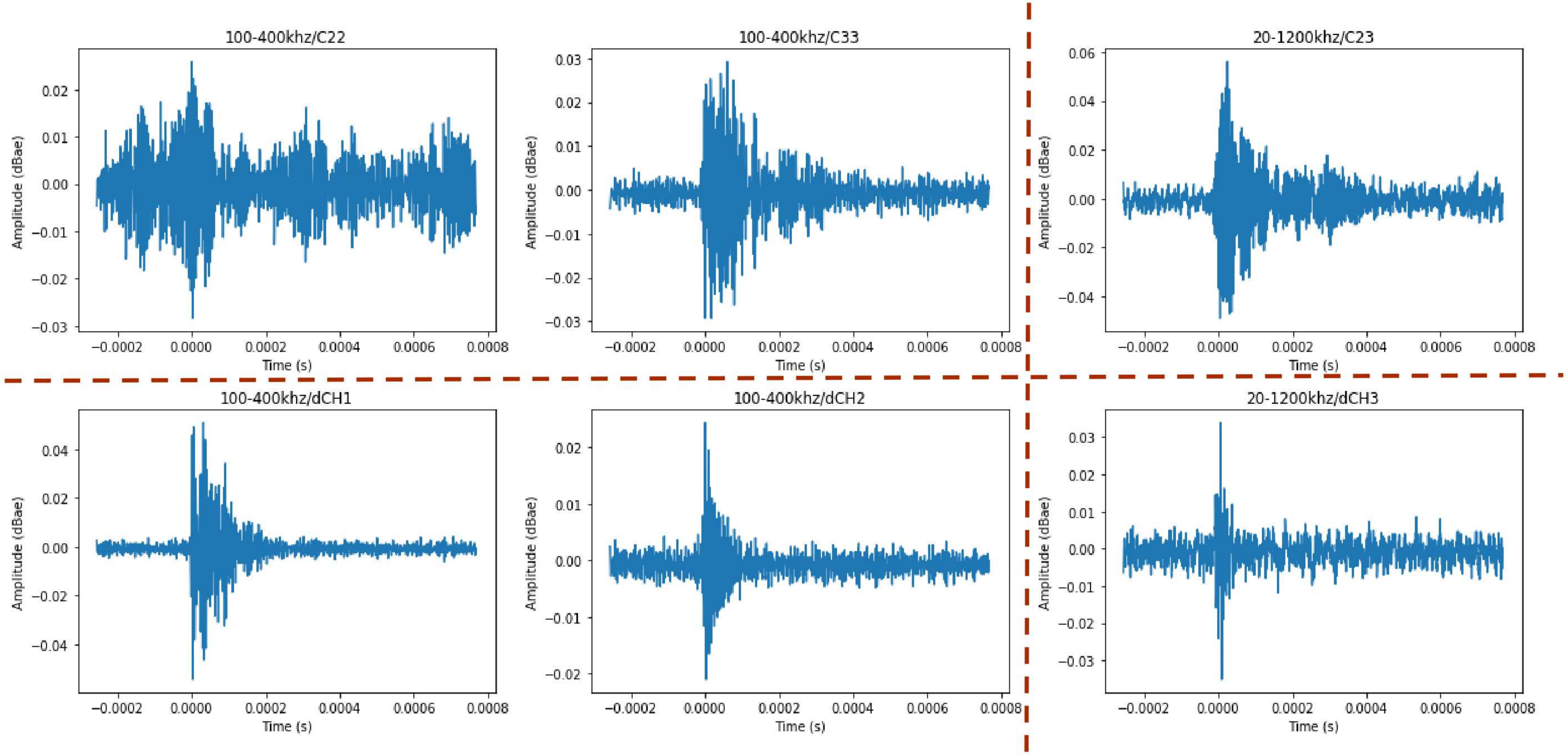


H Sample
dCH1, dCH2, & dCH3



Acoustic Data

6 Samples → 2 Types of Samples → 6 Acoustic Channels Per Sample → 2 Different Frequency Ranges



Feature Extraction

We apply different machine learning features to find patterns or precursors to predict failure.

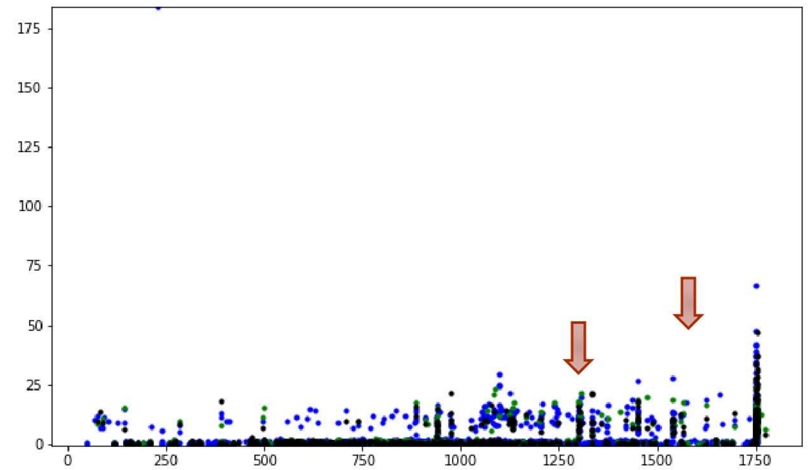
1.
- Load one set of data.
- Assign each sensor a different color.

2.
- Apply and analyze basic features.
- Ave, Std, Skew, Kurtosis, & Energy.

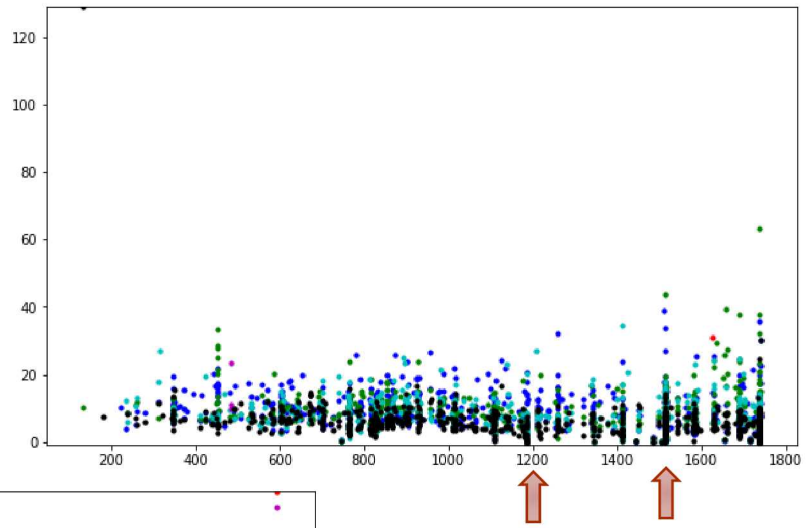
3.
- Apply and analyze complex features.
- mfcc_mean4, mfcc_mean18, percentile_roll50_std_20, & trend_error

Feature Analysis -- Kurtosis

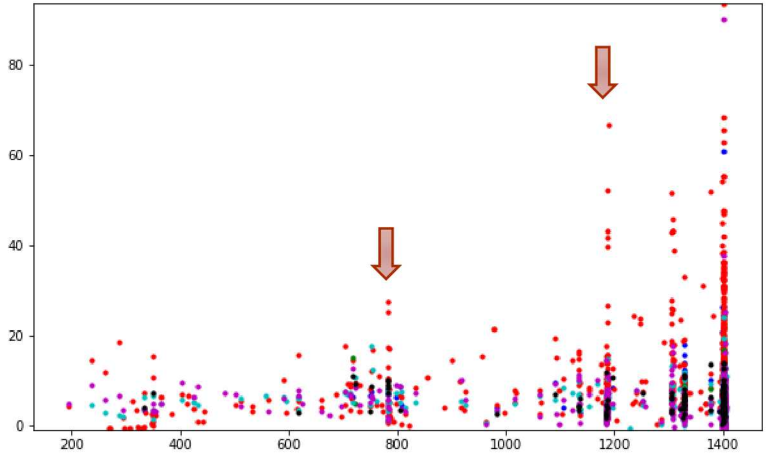
100-400khz/C22



100-400khz/C33



20-1200khz/C23



There is an upward trend present in all samples meaning as we approach failure there is an increase in peaks so more events are recorded. Again there are outliers present in C22 and C23. The behaviors between Kurtosis and Skew seem to be similar.

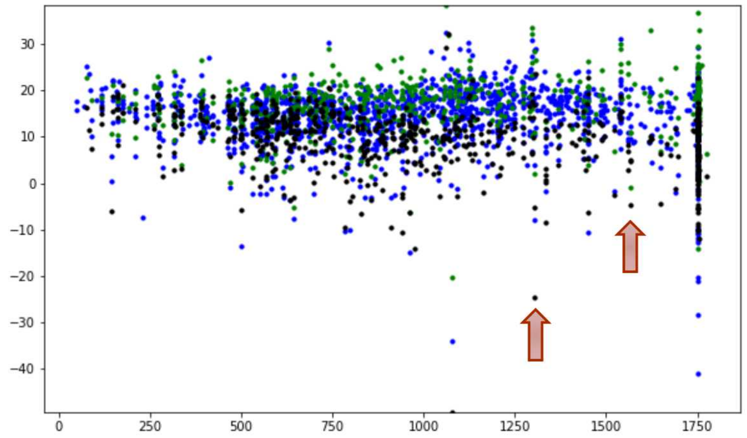
Feature Analysis

We can conclude the following from our analysis of the common machine learning features:

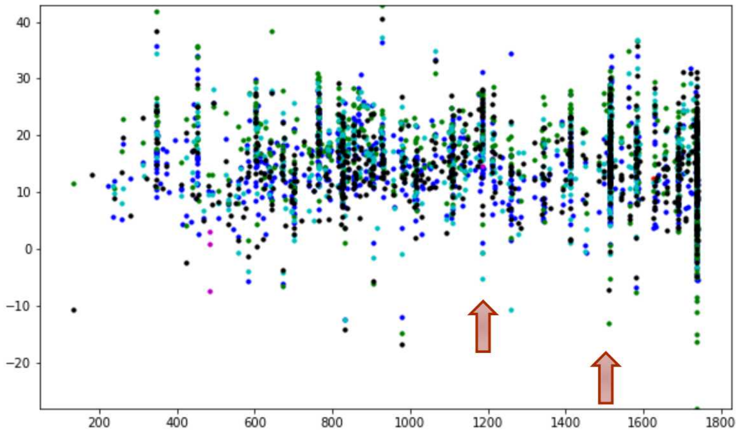
- Several significant outliers, need to filter.
- Skew and kurtosis have a similar behaviors.
- Possible significant events:
  C22 1300 s & 1600 s;
  C33 1200 s & 1500 s ;C23 1200 s.
- Best performing features: skew & kurtosis.

Feature Analysis
mfcc_mean4

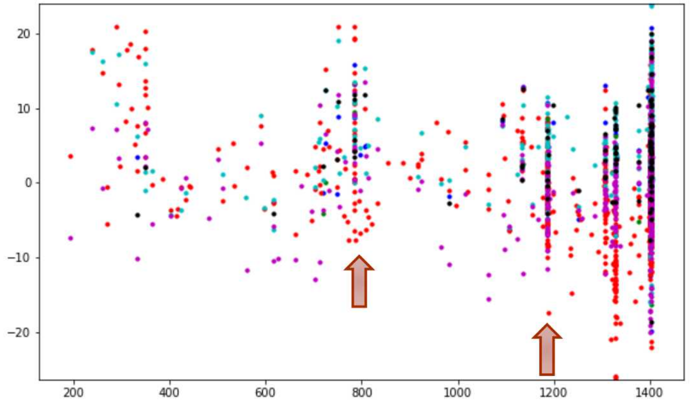
100-400khz/C22



100-400khz/C33



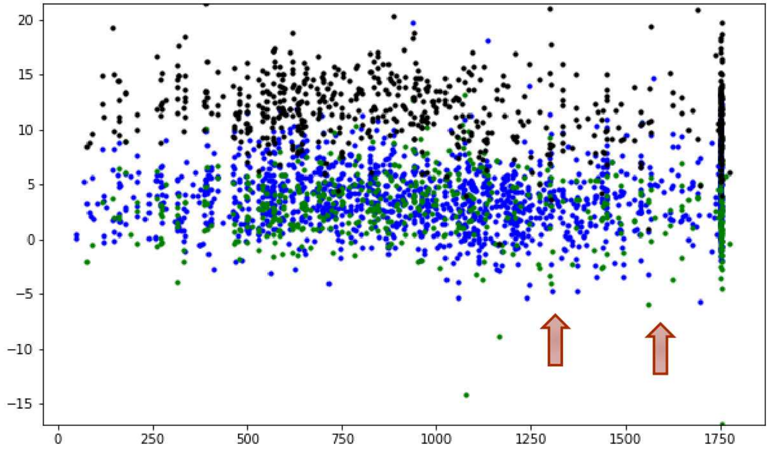
20-1200khz/C23



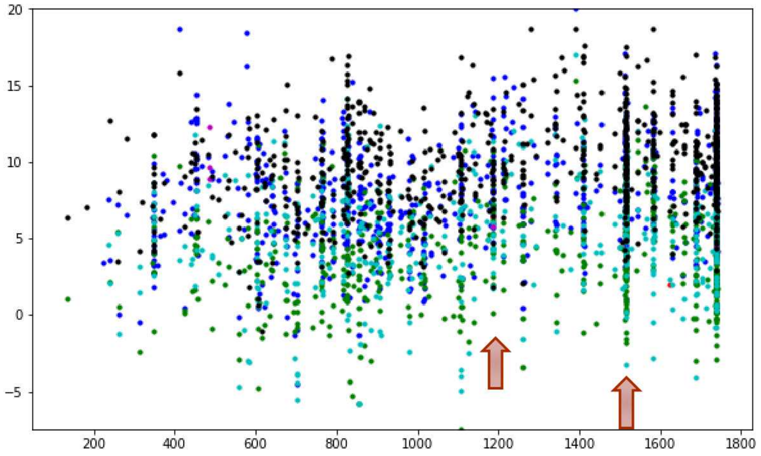
Mfcc represents filterbanks for energies and frequencies. This is targeting low frequencies. When a significant event occurs the data points either jump above or below the mean.

Machine Learning Analysis mfcc_mean18

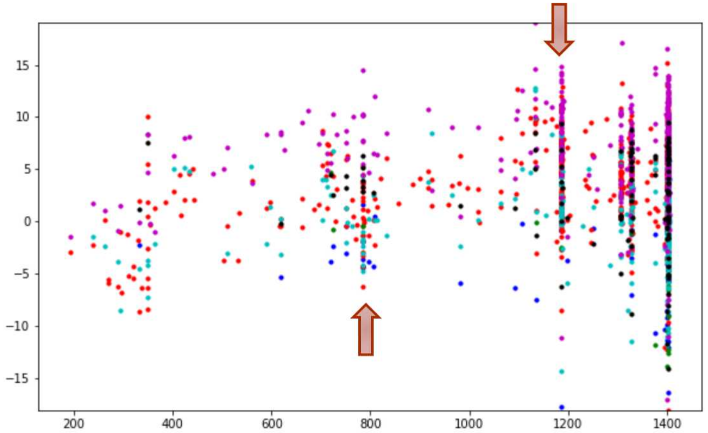
100-400khz/C22



100-400khz/C33



20-1200khz/C23



In this mfcc we are targeting higher frequencies and it appears to be less stable than the lower frequency mfcc. This could be due to the large amount of noise present in the data and acoustic propagations.

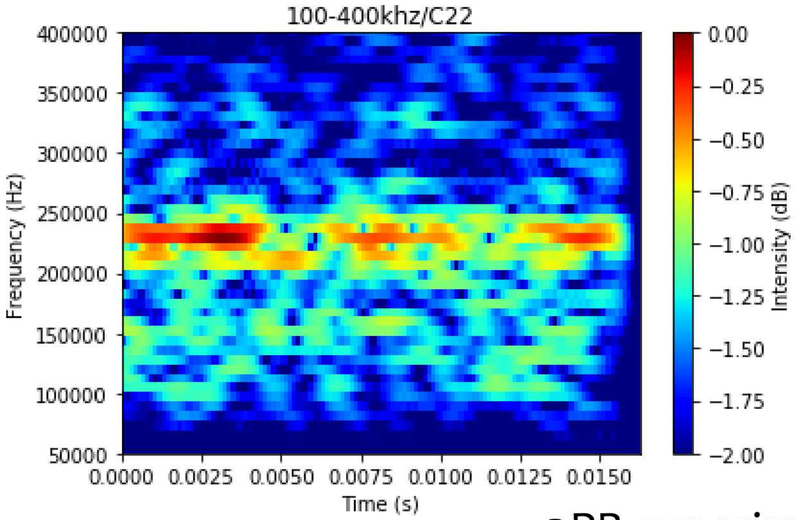
Feature Analysis

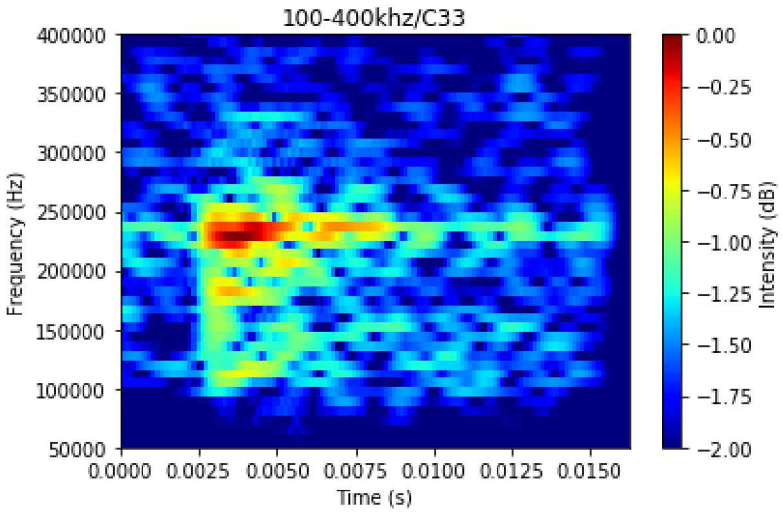
We can conclude the following from our analysis of the complex machine learning features:

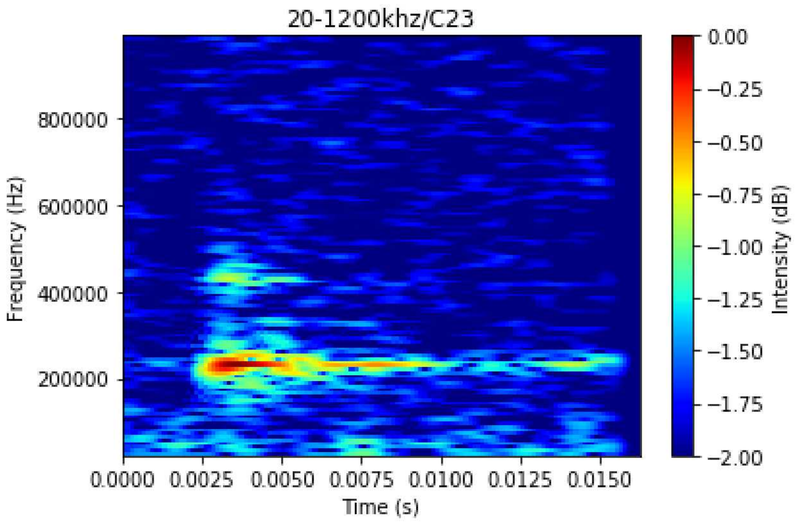
- Several significant outliers.
- mfcc_mean4 has a more stable distribution that mfcc_mean18.
- Possible significant events:
  C22 1300 s & 1600 s;
  C33 1200 s & 1500 s; C23 1200 s.
- Best performing features: mfcc_mean4 & mfcc_mean18.

Waveform Analysis for Machine Learning Applications

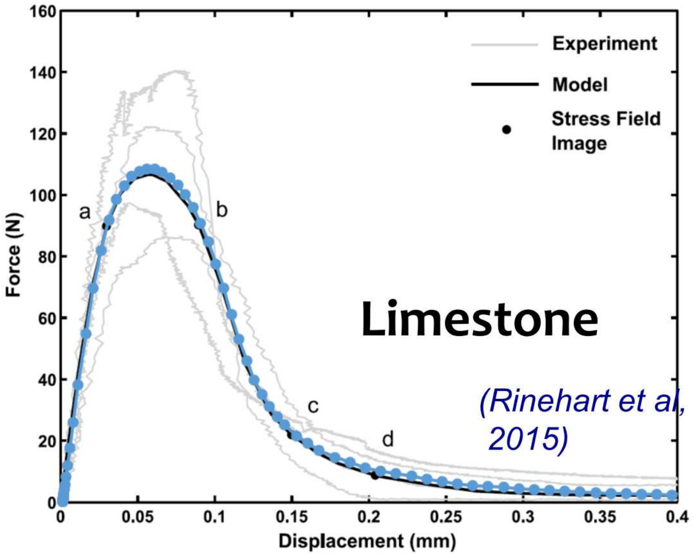
Waveform data is converted into a frequency domain (Spectrogram)



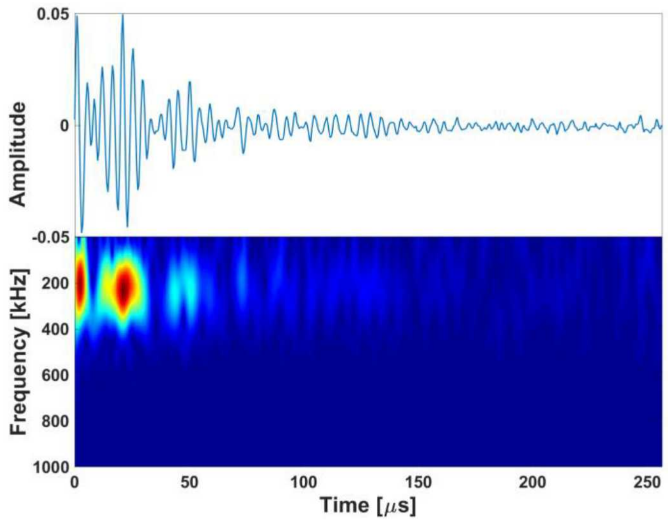




3PB experiments and simulations



Numerical simulation



- Motivations
- Mechanical testing of Geo-architected rocks
- Machine learning applications at laboratory scale
- **Machine learning applications at field scale**

Machine Learning for EQ detection

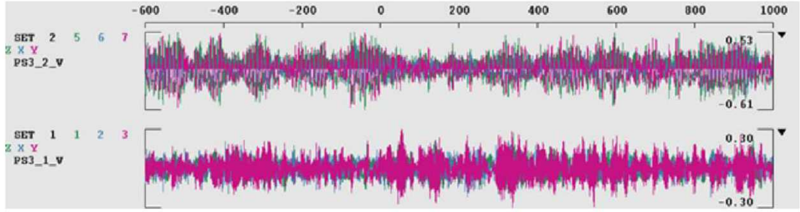
- Recent developments

- Massive seismic data driven by
  - Big sensor networks and new data stream with new sensing methods
  - Long duration continuous waveform data
- New ML algorithms and models (e.g., CNN, LSTM)
- Improvements in computational efficiency
  - GPU Computing (e.g., NVIDIA)
  - Open source ML tools (Tensorflow, Keras, PyTorch)
  - Open source EQ detection and characterization models (e.g., Github)

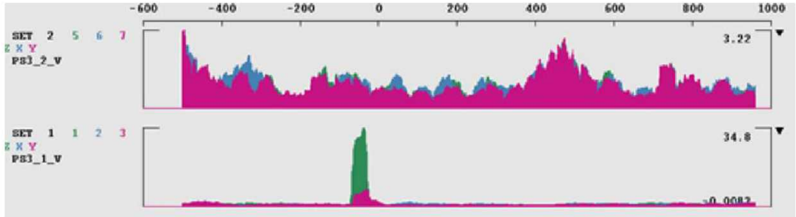
Microseismic Data at Illinois Basin Decator Project

- Raw & processed data (e.g. Will et al., IJGGC 2016)
  - Data acquisition at Injection, monitoring, and verification wells
  - Data analysis for event detection and location
    - Various filters, STL/LTA, and spectral analysis applied
  - Velocity model and MS clustering

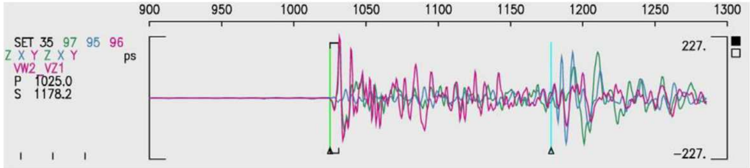
Raw data from multichannel acquisition

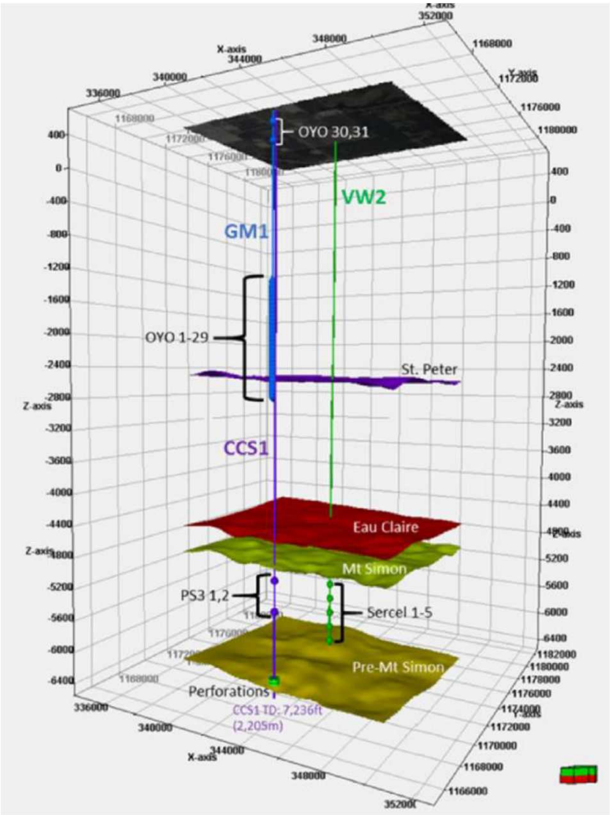


Short/long term average function



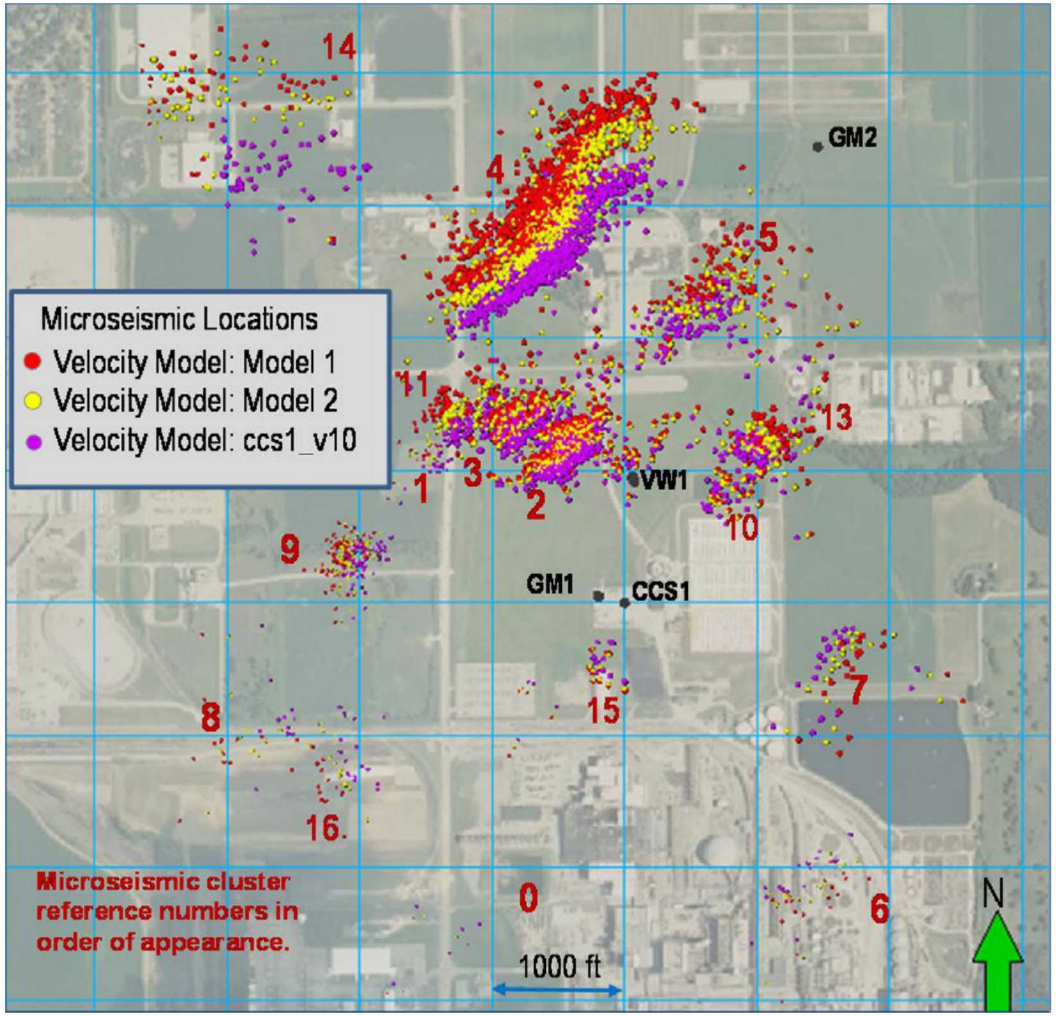
Event waveform

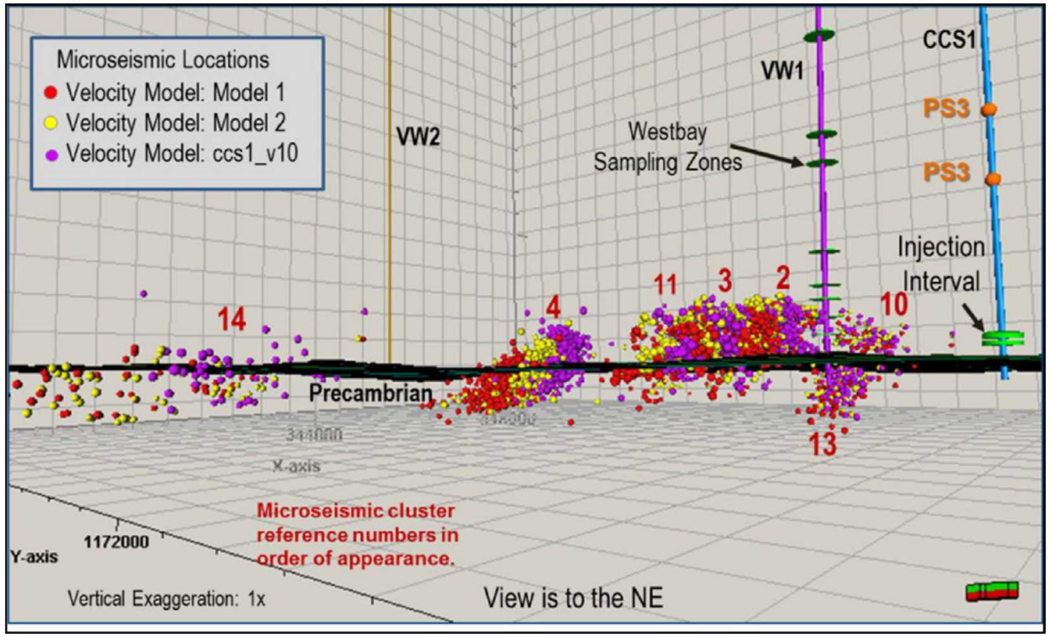




Will et al., IJGGC 2016

Microseismic Data at Illinois Basin Decator Project

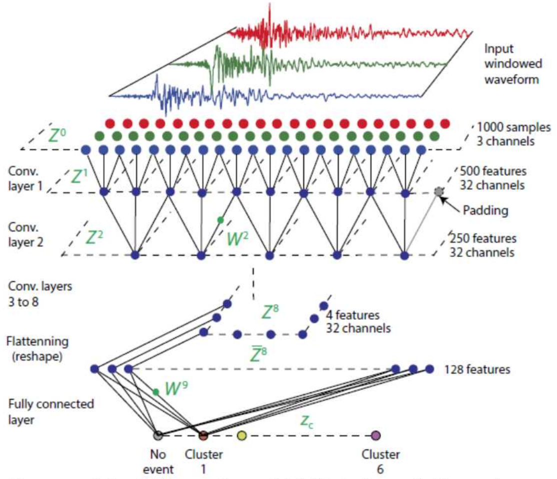




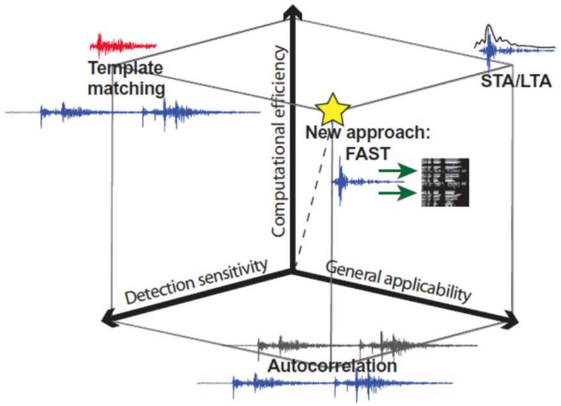
Will et al., IJGGC 2016

ML Approaches

- Supervised ML: Convolutional neural network (CNN) for event detection and location
  - Open source ConvNetQuake (Perol et al., 2018)
    - Processed data from ISGS will be used to train models
    - Trained model will be used to validate again the remaining dataset to develop real-time recognition of events and locations
- Unsupervised ML: Waveform similarity-based event detection methods
  - Fingerprint and Similarity Thresholding (FAST, Stanford FAST group)
    - FAST shows the increase in event detection of low magnitude seismicity by > a factor of 10
    - High efficiency in big data processing time
- Characterization of Microseismic events
  - Spectral clustering and regression-based machine learning analysis (e.g. random forest)
    - Identify seismic phases from successive slip or fracturing stage events and their constitutive wave patterns
    - Extract the salient features present in the data set, such as individual wave types, spectral content, p-s converted waves, and local energy decay
    - Link microseismic data to other measured/simulated quantities (e.g., injection, pressure and stress field)



ConvNetQuake CNN Architecture
Perol et al. (2018, SciAdv 2018)



Earthquake detection methods from
C.E. Yoon et al. (SciAdv 2015)

Summary

► Through additive manufacturing (3D printing), we have produced bassanite-gypsum rock samples with repeatable physical, geochemical and structural properties. With these "geo-architected" rock, we provide the first demonstration of the role of mineral texture orientation on fracture surface roughness. This unique correspondence between the fracture geometry and the relative orientation of layers and mineral texture in rock opens the door to accurate prediction of fluid flow anisotropy.

► Integration of multiphysics (geomechanical and geophysical approaches) and multiple tools (controlled experiments, simulations, machine learning) for sensing, analyzing, and broad geoscience topics

► Advances achieved in this study will impact a wide range of geoscience applications with important societal impact, including the sustainability of geothermal systems, contaminant remediation, long-term subsurface storage of anthropogenic waste (CO2, radioactive waste) and subsurface recovery and storage of energy fluids (oil & gas).