SMART-CS Initiative

Science-informed **M**achine Learning to **A**ccelerate **R**eal **T**ime (SMART) Decisions in Subsurface Applications

ML-Based Fracture and Fault Identification

WP 2C.2 Leads: David Alumbaugh (LBNL) and Joe Morris (LLNL)

Youzuo Lin (Formerly Affiliated with LANL)
School of Data Science and Society
University of North Carolina at Chapel Hill

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Task Objectives, Preliminary Study, and Challenges

Objectives:

1. To improve the imaging description of fractures & faults at IBDP
2. To obtain a site-agnostic ML-assisted toolset and workflow
3. To demonstrate the benefits of using ML methods

Significance:

- Provide fast fluid pathway and flow barrier (input for update reservoir model in task 5)
- Indicate and monitor potential induced seismicity (input for ORION in task 6)

Study Site & Preliminary Study:

- Study Site: IBDP
- Preliminary Study: Dando et al., (2021) deployed a modified double-difference method to identify microseismicity, and further delineated linear clustering of events with uncertainty.

Challenges:

- Expensive computational cost
- Limited imaging resolution
- Lack of training dataset

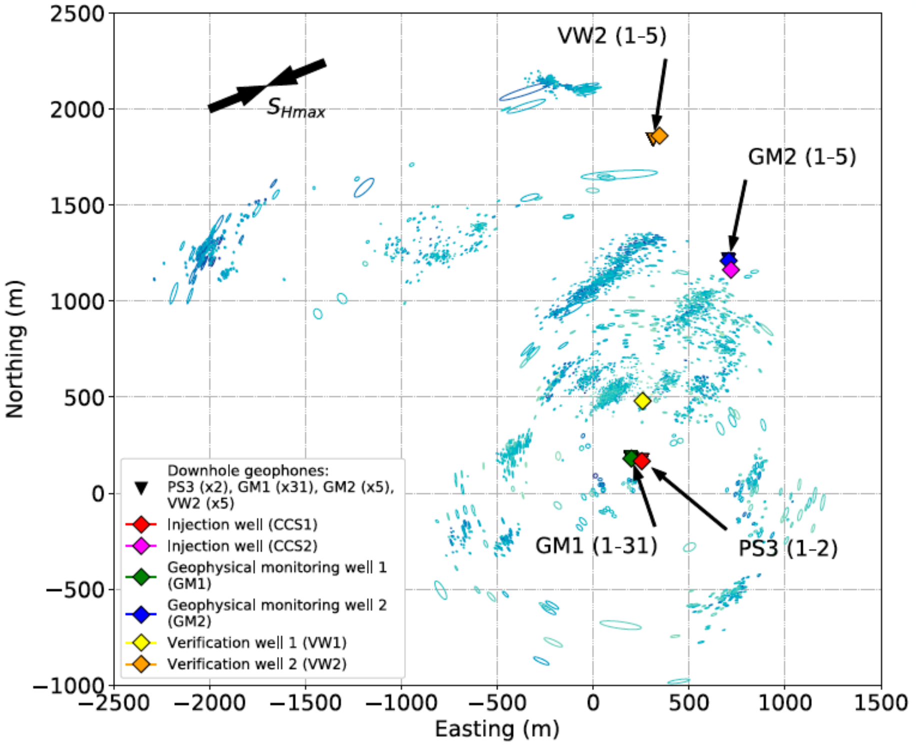
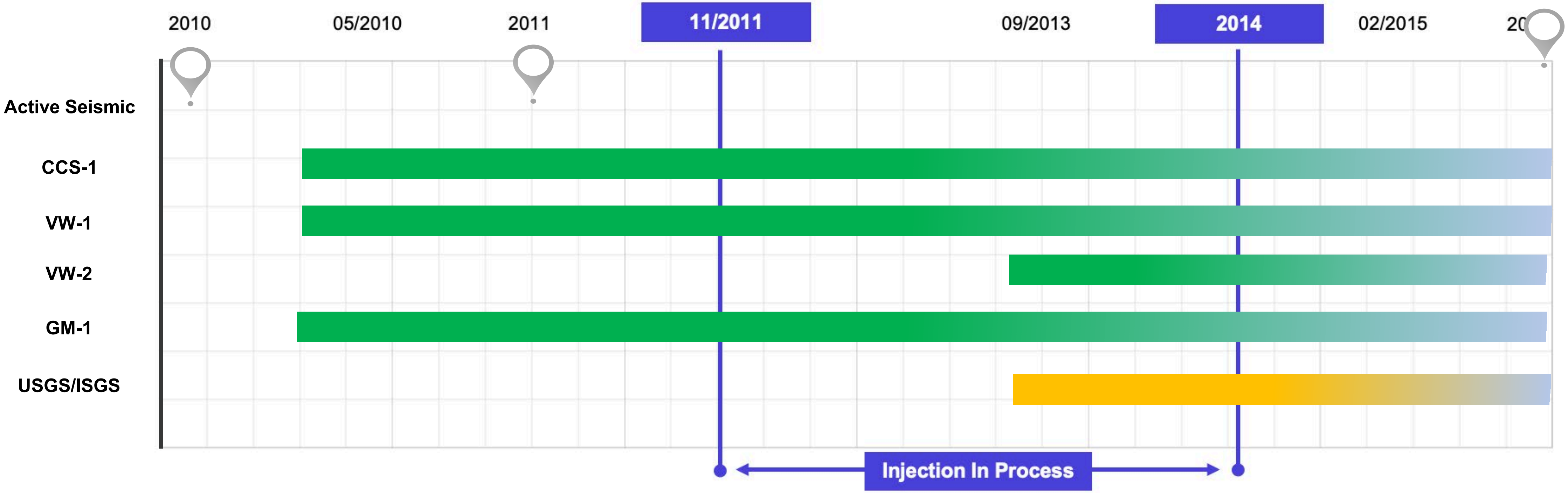


Figure Courtesy of Dando et al., 2021

Dando et al., "Relocating microseismicity from downhole monitoring of the Decatur CCS site using a modified double-difference algorithm" GJI , 2021.

Data Availability – A Case Study at IBDP

- Passive Seismic Acquisition
  - IBDP Installation
    - Borehole arrays located at **CCS-1**, **VW-1**, **VW-2**, **GM-1**
    - Total: 31 stations (z-component: 2/4 CCS-1 + 29/31 GM-1)
  - USGS/ISGS Installation
    - 20 surface seismometers (15 **USGS** + 5 **ISGS**)



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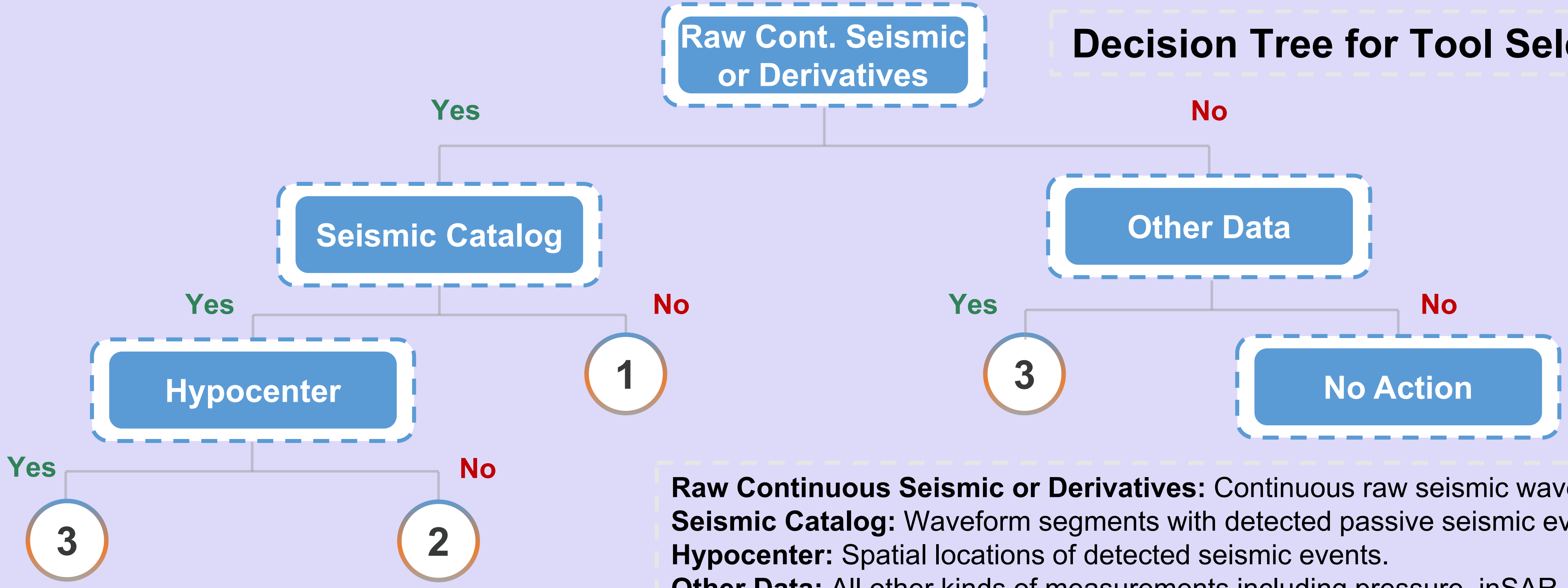
Proposed Fracture Imaging Workflow – An Overview

01	• **Event Detection**	Extract useful microseicmic events from continuous waveform measurements
02	• **Velocity Inversion**	Produce 3D velocity model from active/passive seismic data (SubTask 4.4.1)
03	**Hypocenter Locating**	Obtain microseismic source parameters (location, moment tensors, amplitude, etc)
04	• **Fracture Estimation**	Deploy spatio-temporal clustering analysis to obtain fracture lines
05	• **Uncertainty Quantification**	Analyze the uncertainty of the fracture and fault zones
06	• **Fracture Visualization**	Display final fault/fracture representation to field operators

Decision Tree for Tool Selections

Data Availability



Raw Continuous Seismic or Derivatives: Continuous raw seismic waveform data.
Seismic Catalog: Waveform segments with detected passive seismic events.
Hypocenter: Spatial locations of detected seismic events.
Other Data: All other kinds of measurements including pressure, inSAR, EM, etc.).

Decision

1 Events Detection

1. Traveltime: SNL/ORNL
2. Waveform: ISGS/UIC

2 Hypocenter Locating

1. Traveltime: SNL/ORNL
2. Waveform: LANL
3. Waveform: ISGS/UIC

3 Joint Interpretation

1. Seismic Pressure: NETL
2. Seismic, Well logs: ISGS/UIC
3. Seismic: LBL/LLNL
4. Seismic: FACT

4 Fracture Estimation

1. K-Mean: LANL
2. NMF: SNL
3. Clustering: NETL
4. HypoDD+Focal Mech: ISGS/UIC
5. OpenDtect: FACT

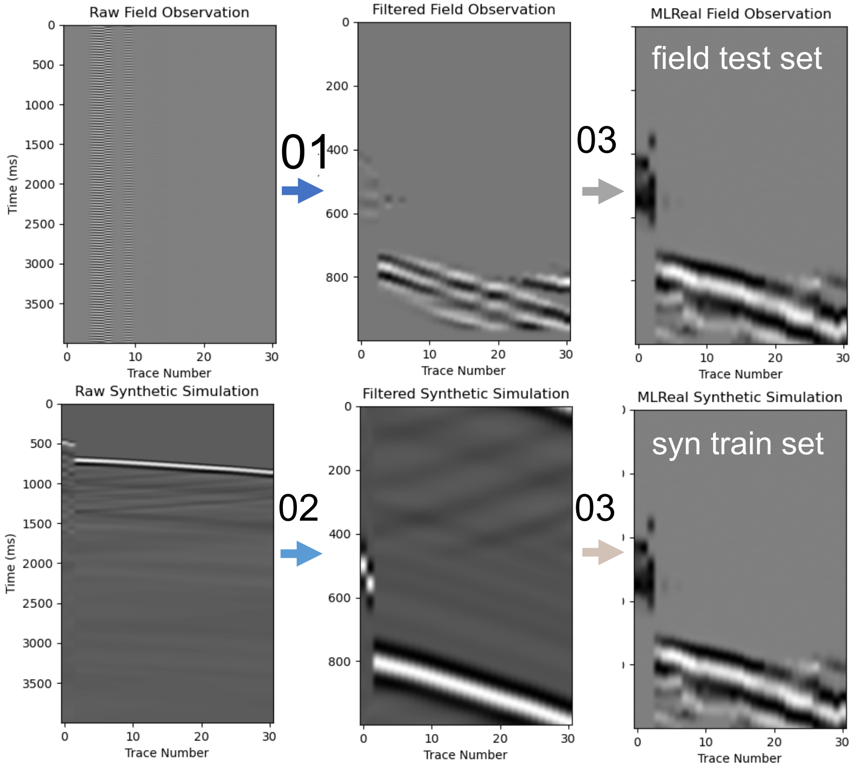
5 Fracture Visualization

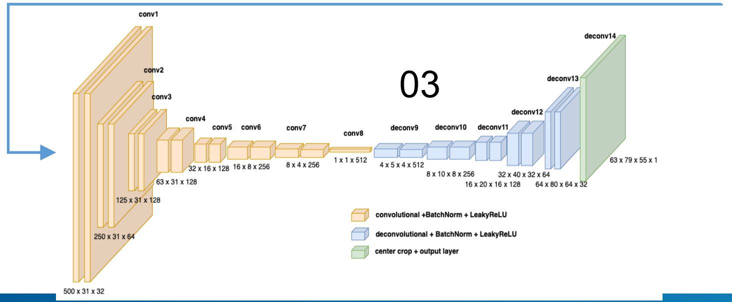
1. Petrel: EERC

Technique

Org	Data	Key Technique Descriptions	Event Detection	Hypocenter Locating	Joint Interpretation	Fracture Estimation	Fracture Visualization
NETL	Catalog, Pressure	**1.** Spatial-temporal analysis on MS **2.** Deploy five clustering methods to characterize fault & fracture.			●	●	
ORNL SNL	Raw Seismic	**1.** Detect events (raw seismic data) **2.** Leverage traveltime information to invert source location.	●	●		●	
LANL	Catalog	**1.** Use borehole seismic waveform. **2.** Deploy full-waveform inversion to invert the source location.		●		●	
ISGS UIC	Catalog, Well logs	**1.** Infer location (PhaseNet,HypoDD) **2.** Obtain focal mech using ANN **3.** Infer fault (location & focal mech)	●	●	●	●	
LBNL LLNL	Catalog	**1.** Infer fault location using microseismicty **2.** Deploy aCNN method			●	●	
FACT	Catalog	**1.** Use OpenDtect to interpret seismic data 2. Identify useful seismic features			●	●	
EERC		**1.** Use Petrel for visualizing fault & fracture maps.					●

LANL – DeFault: Deep-learning-based Fault Delineation (POC: Y. Lin)





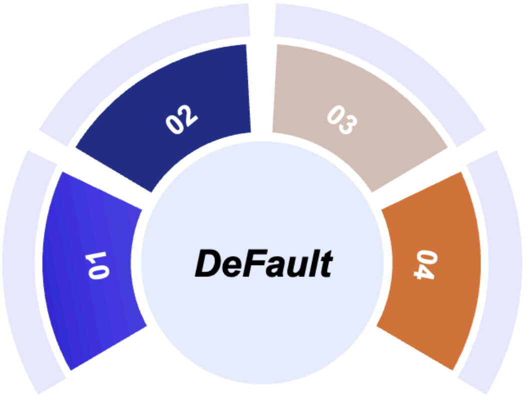
01 – Data Pre-Processing on Raw Seismic Waveform

Enhance waveform data by carrying out bandpass filters, amplitude normalization, F-k dipping filter, time-domain noise removal, averaged F-k envelop filter

02 – Full-waveform data synthesis to build high-fidelity traning set

Leverage 3D velocity model and acoustic wave equation to generate full-physics training data

Gaussian heatmaps centering at true source locations – spatial distribution



DeFault [Wang et al., 2024]

03 – ML-based Full-Waveform Inversion to Relocate Source Parameters

MLReal data domain adaptation, deploy encoder-decoder full-waveform inversion to obtain microseismic event location heatmaps
Heatmap upsampling to remove griding effect, interpolation of first and second maximum values to get coordinates predictions

04 – Employ Spatio-temporal clustering analysis to delinate Fracture imaging

Temporal period selection, K-means spatial clustering, outlier removal, least squared distance fault plane estimation

Hanchen Wang, et al, “DeFault: Deep-learning-based Delineation Using Domain Adaptation Training and Automatic Clustering”, ESS 2024 (Under Review).

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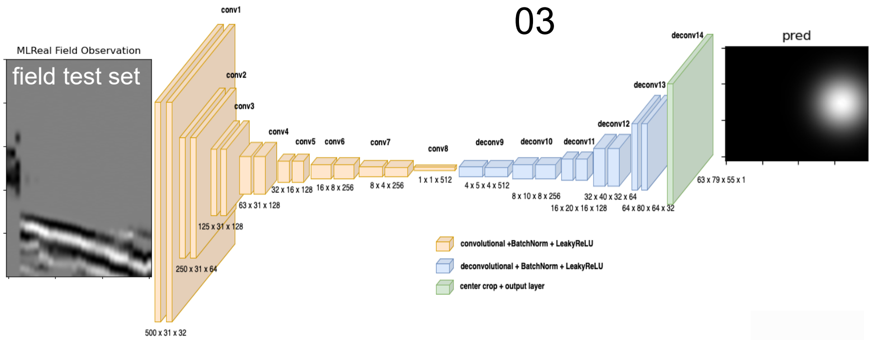
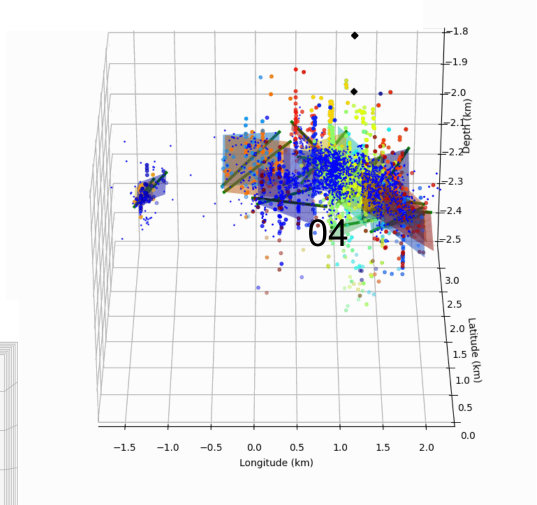
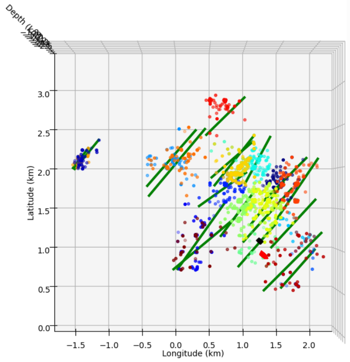
03



04





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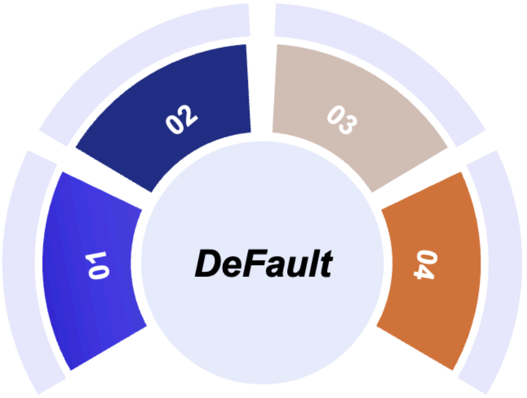

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SNL – Fault Imaging via Event Detection & Source estimation (POC: J. Harding & H. Yoon)

- Integrated ML approaches of event detection and source location estimation
- Data pre-processing of raw continuous microseismic data & event detection
- Data augmentation using WGAN (Wasserstein Generative Adversarial Network)
- PhaseNet used to downselect generated event data with high quality
- CNN model with multi-modal input for source location estimation of events

Data processing of raw waveform continuous data

- 10s raw continuous waveform data (e.g., 4 to 3 channels)

Event detection & arrival time: CNN & U-Net models

- Train a CNN model for event detection with 3 channel & energy feature as input and retrain PhaseNet for arrival time

Synthetic data generation: SeismoML (WGAN)

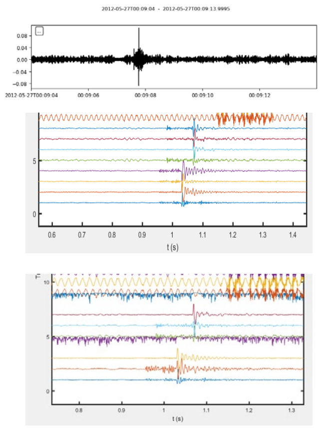
- WGAN model Input: source locations and distance of ~400 events from catalog and output of waveform
- Apply trained seismoML model to generate synthetic waveforms of each channel (H1,H2,V)
- Screen generated waveform data by phase arrival times (PhaseNet)

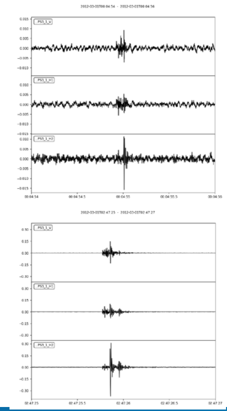
Multi modal CNN for source locations of newly detected events

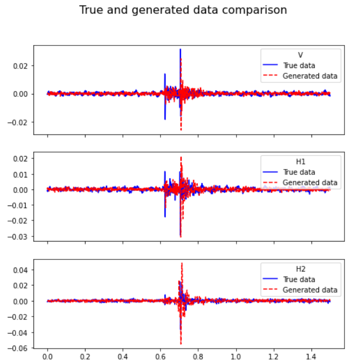
- Construct synthetic waveform data over a range of source locations & distance
- Train a multi modal CNN with spectrograms and P&S arrival (binary) of each channel data

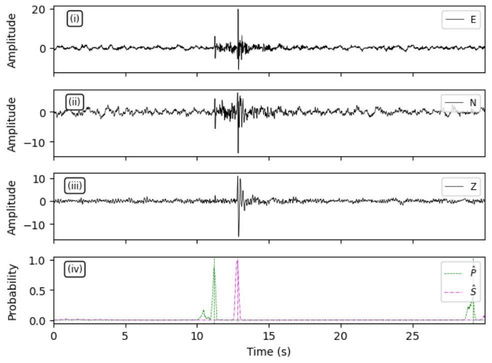
Event clustering & construct faults

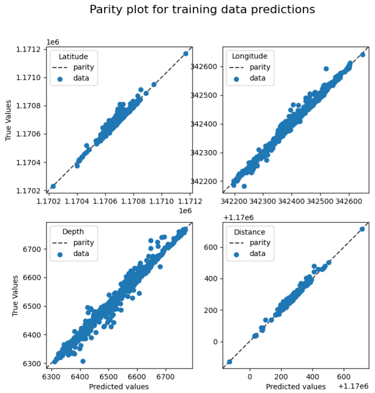
- Event clustering using NMF-HMM (Non-negative matrix factorization Hidden Markov Model) to construct planar faults

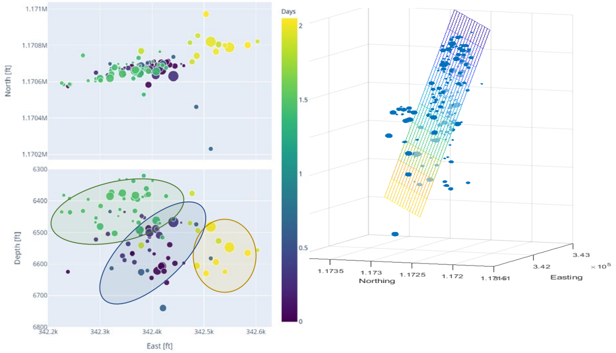












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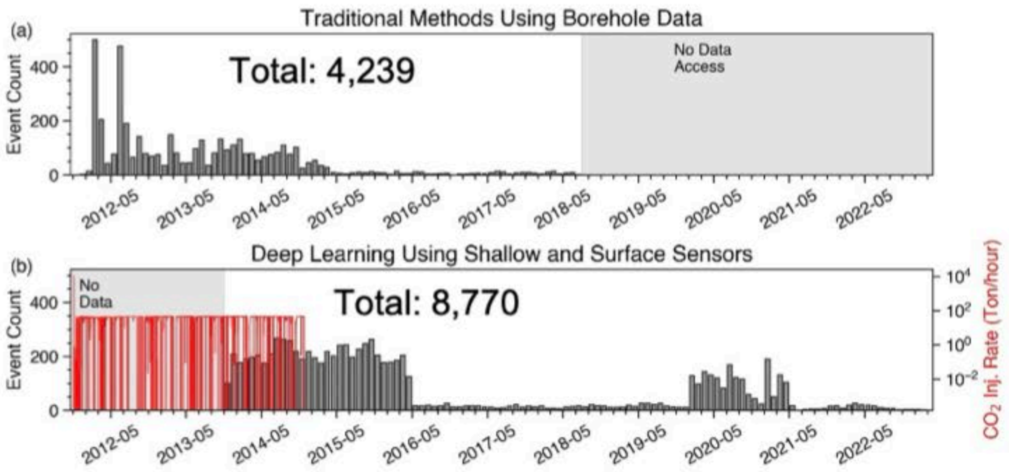
ORNL – Fault & Fracture Identification (POC: C. Chai & M. Maceira)

USGS Dataset (surface)

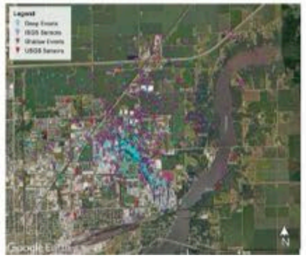
ML Picker → ML Models

Continuous Seismic Data → Signal Arrival Times → Seismic Event Catalog

Physics-based Algorithm



We detected and located 8,770 seismic events using 10 years of continuous seismic data from 17 USGS seismic stations.

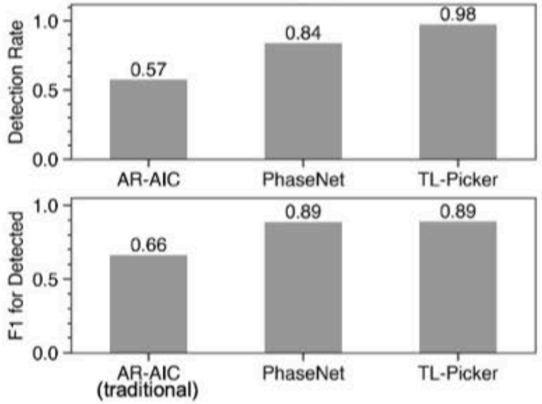


IBDP Dataset (borehole)

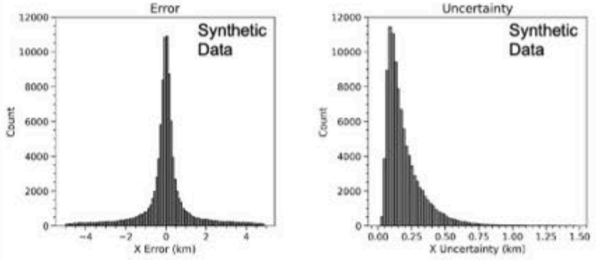
TL-Picker → DL-TT-Locator → ML-Fault-Mapper

Passive Seismic Data → Signal Arrival Times → Seismic Event Catalog → Fault & Fracture

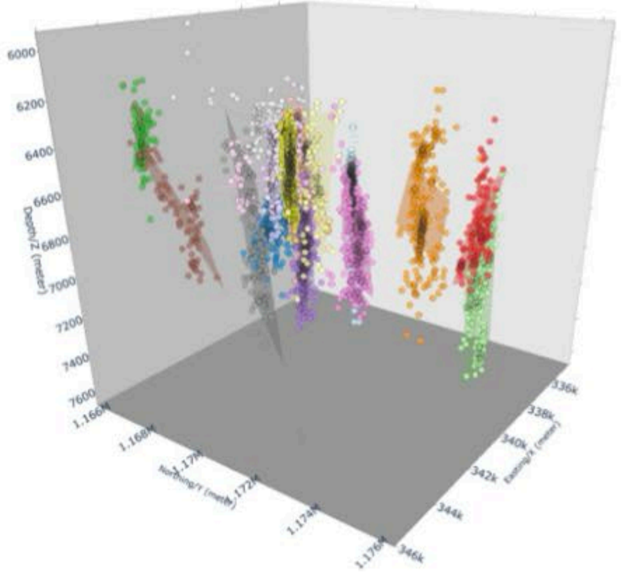
TL-Picker



DL-TT-Locator

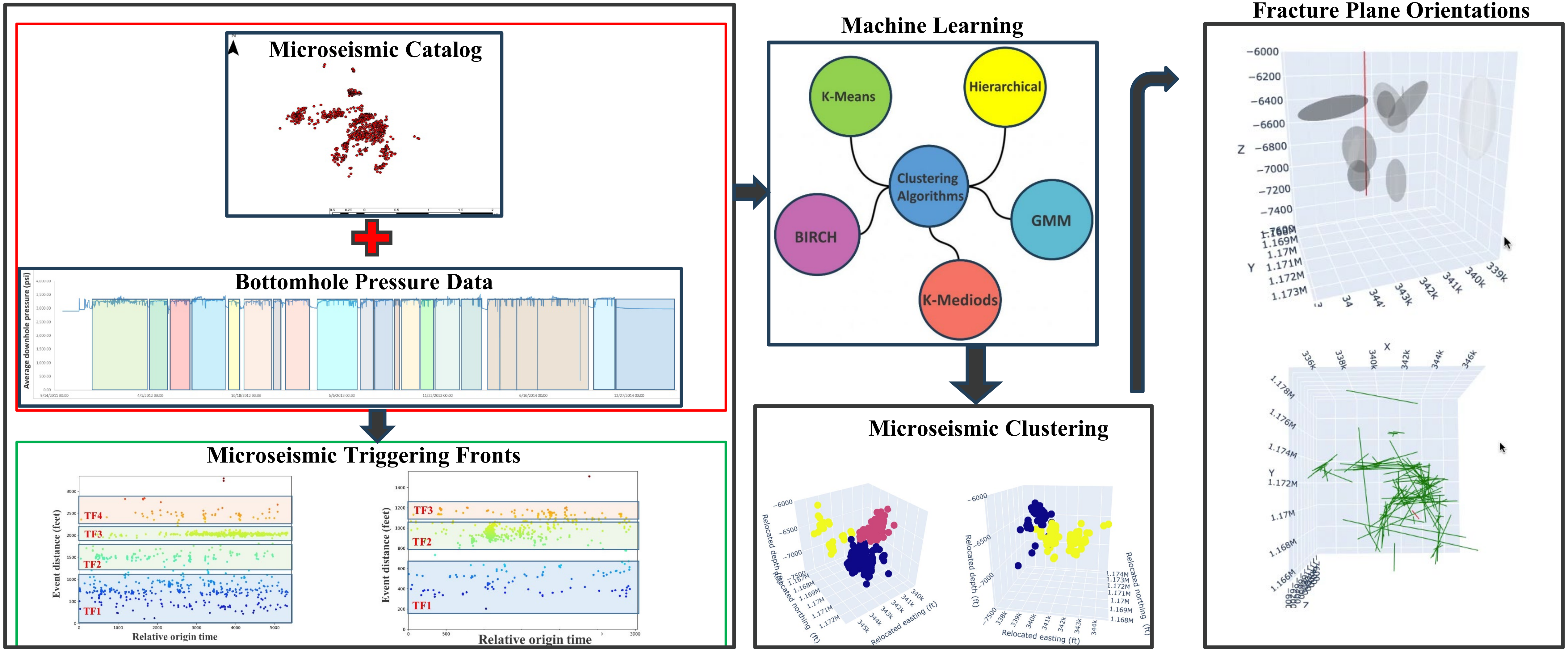


ML-Fault-Mapper



Three ML modules have been developed to process passive seismic data precisely and efficiently.

NETL – ML-Based Fracture Network Quantification (POC: A. Kumar)



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EERC		**1.** Use Petrel for visualizing fault & fracture maps.					●

Fracture Imaging Workflow – Lessons Learned

		Accuracy	Efficiency	Generalization	Data Demanding
01	Event Detection				
02	Velocity Inversion	SubTask 4.4.1 (LBL/LANL)			
03	Source Inversion				
04	Fracture Analysis				
05	Uncertainty Quantification				
06	Visualization				

Physics Wins

Pure ML Wins

Fracture Imaging Workflow – Lessons Learned

- Pure ML methods suffers from **weak generalization ability**, **high training cost**, and **require a large volume of training data**
- One solution is to incorporate underlying physics, geology knowledge – **Physics-guided ML**

Questions?