



Motivations

Rock deformation is often observed to depend on temporal and spatial scales associated with deformation mechanisms and evolving microstructures that control macroscopic responses such as failure and micro-seismicity. A combination of well controlled lab and simulated data will enhance machine learning (ML) analysis of waveform data to detect different wave properties.

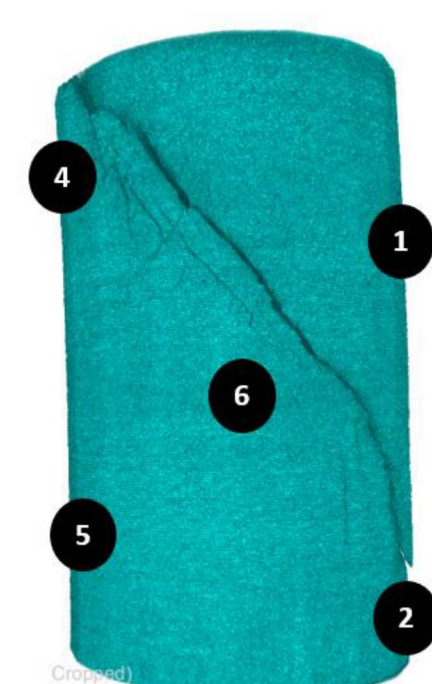
Objectives

- Identify fingerprint of waveforms at different stages of mechanical deformation
- Develop and apply a machine learning approach for automatic identification of feature sets and interpretation of waveform that can be used to infer the features of fracture initiation and propagation

UCS Experiments

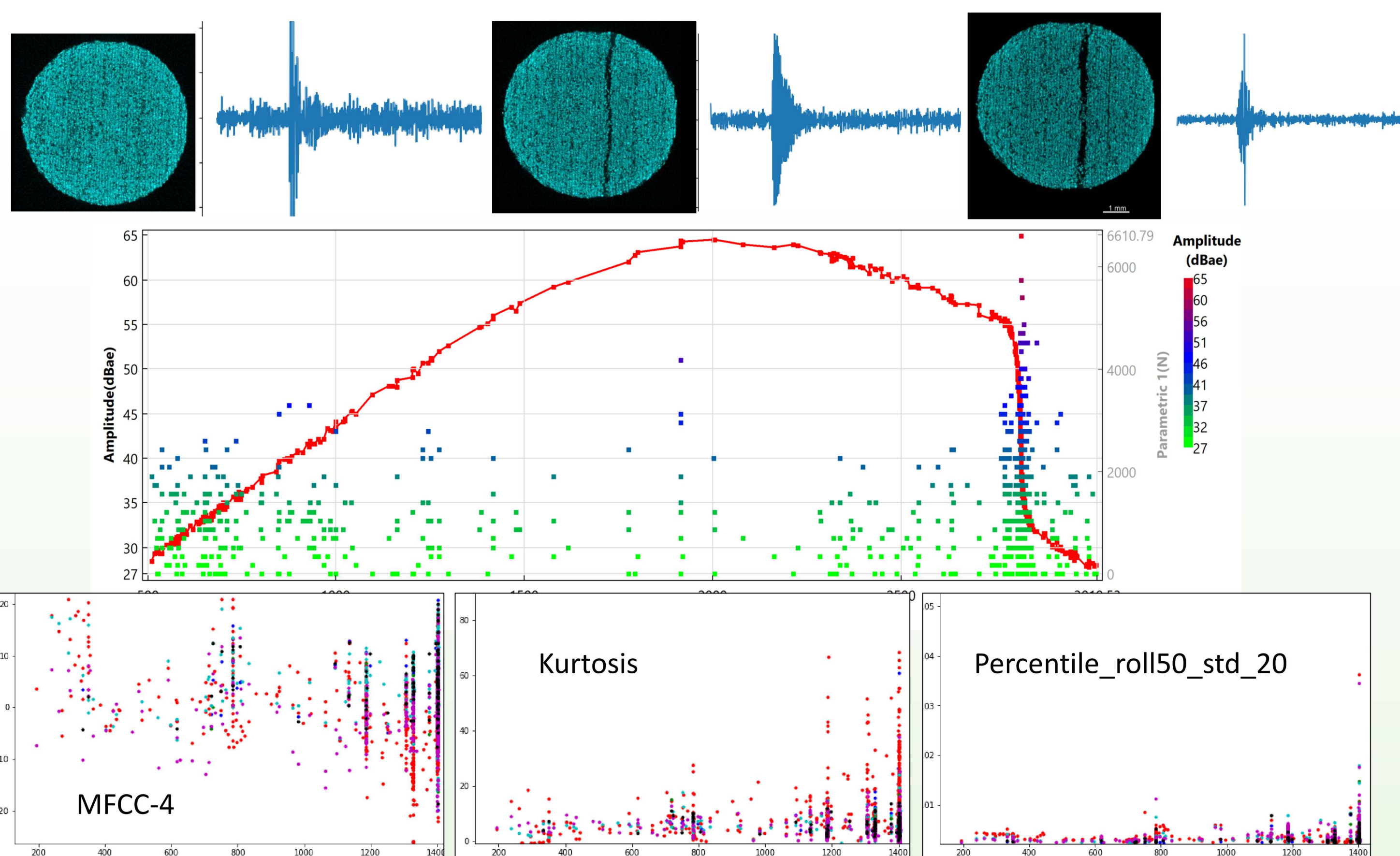
- Powder based 3D printed samples- Unconfined Compressive Strength (UCS) test
- Six sensors & 200-400 kHz filter to get rid of noise
- Feature evaluation on sample signals
- Key features: Kurtosis, Skewness, and Mel-frequency cepstral coefficient (MFCC)

3D printed sample with 6 sensors



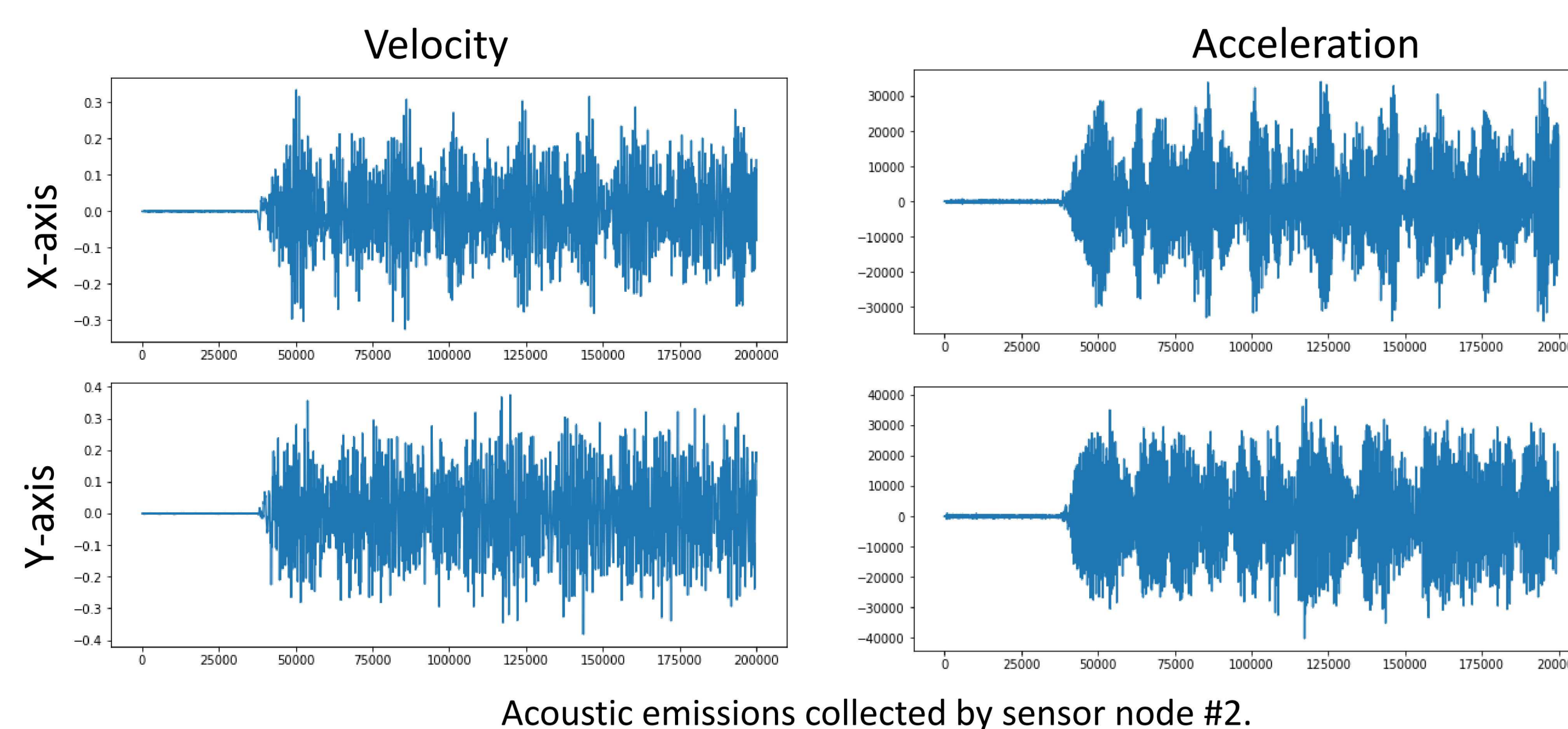
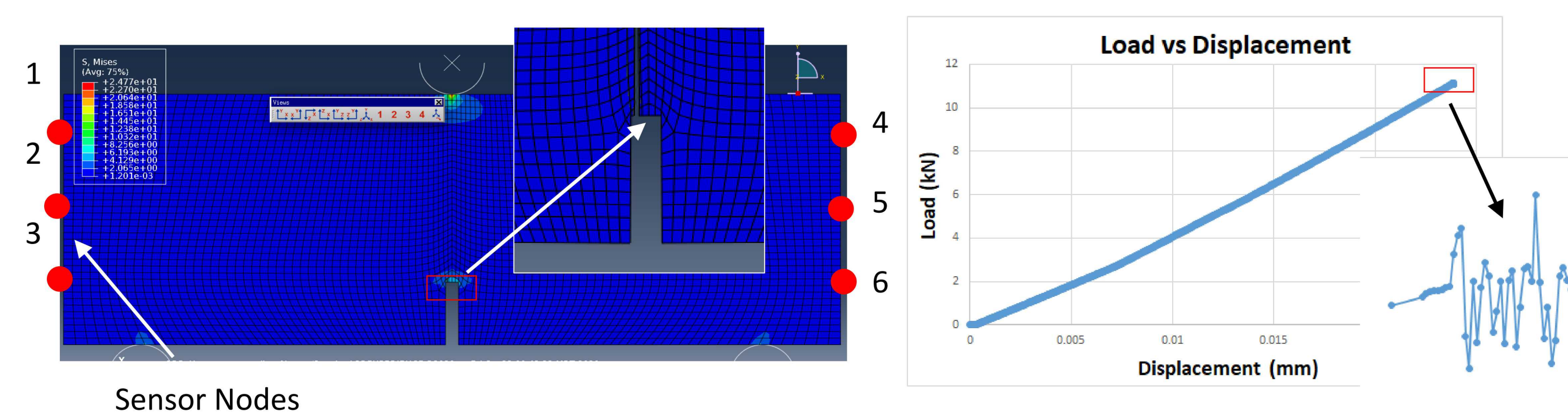
UCS test

MicroCT image, waveform, load & amplitude vs. time data



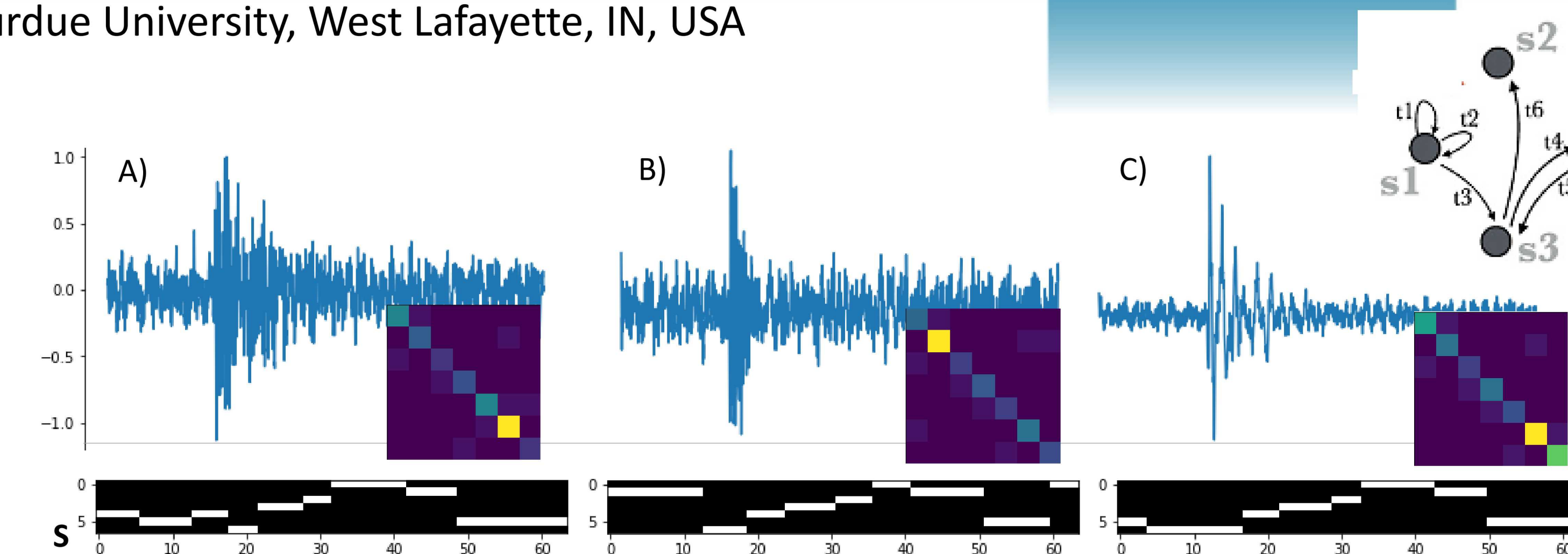
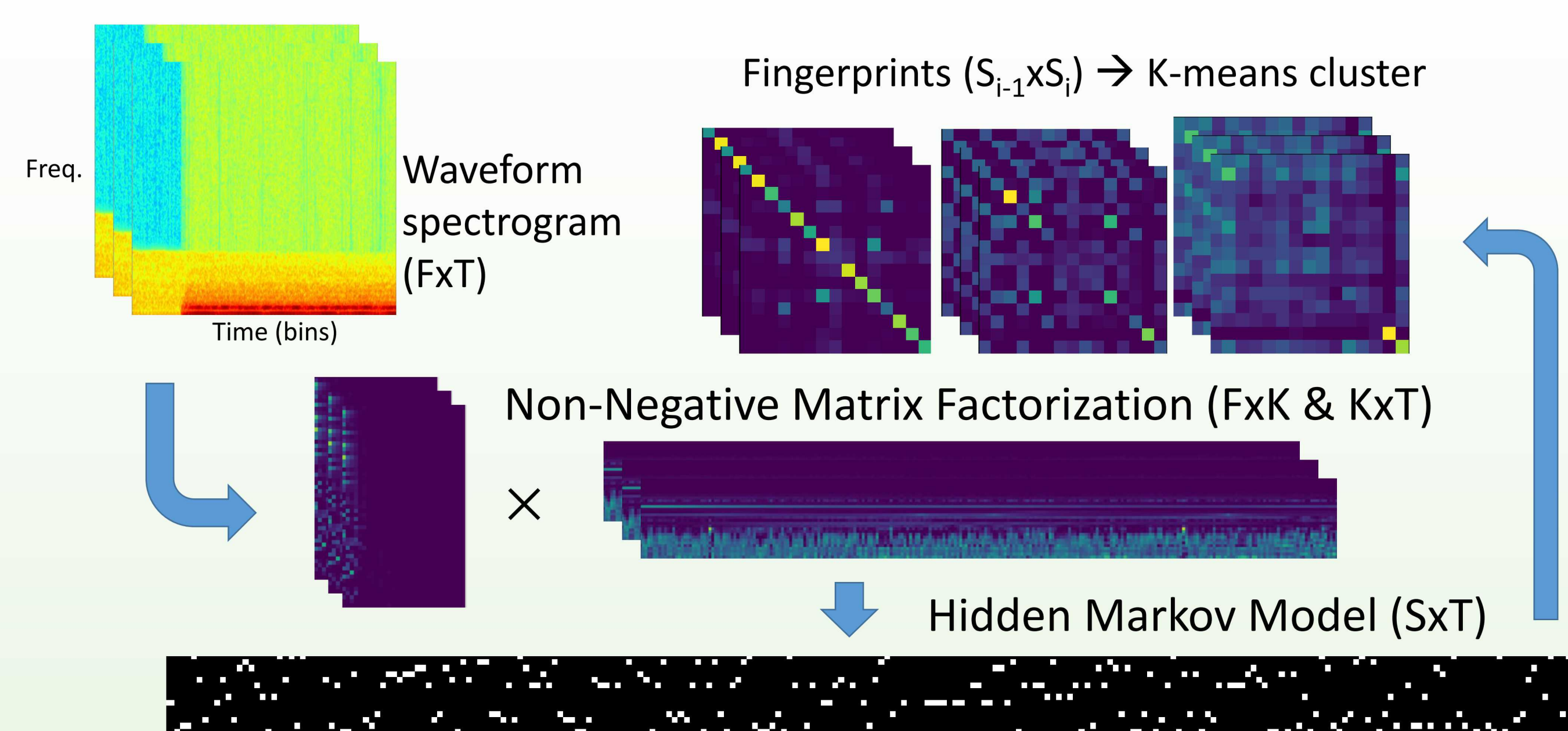
Simulations of crack initiation and acoustic emission

- 3 point bending (3PB) with a central notch (2D simulation, ABAQUS)
- Crack propagation and acoustic emission (XFEM)
- 6 sensor nodes sampling at 8 MHz
- 1-3 for training, 4-6 for testing
- Limestone material properties (isotropic homogeneous)



ML: fingerprint and K-means cluster (Holtzman et al. 2018)

- Clustering: acoustic state & mechanical state
- Spectrogram
- Short Time Fourier Transform
- Non-negative Matrix Factorization
 - Bayesian and Standard (K rank)
- Hidden Markov Model (S states)
- K-means cluster



Mechanical state clustering by comparing waveform evolution in the UCS test. Waveforms correspond to 3 stages in the loading curve, namely A) initial loading slope, B) max load region, C) post-failure region. Figure includes information of the waveform, along with its hidden state sequence and corresponding fingerprint.

Discussion

- Fingerprint method based on HMM and clustering was applied for waveform data generated using numerical simulation of 3PB testing, demonstrating that distinct fingerprints can be extracted and clustered corresponding to pre-trigger, p-wave arrival, and post-arrival stages.
- Fingerprint method was also applied for waveform data obtained from the UCS test, showing the distinct patterns at different crack initiation and propagation stage.
- Our additional analysis indicates that sensor location with respect to the acoustic emission source affects the quality of the waveforms
- Due to not enough training data, trained ML model does not have a good classification performance. A large number of training data may help improve the testing accuracy
- Other fingerprint and detection algorithms will be tested and compared with the current method.

Conclusion and Future work

- Waveforms reflect feature patterns specific to the sequence of fracture initiation and propagation. Preliminary experimental results show high possibility of discerning between crack initiation stages (during, pre, and post).
- Our ML captures unique variations between datasets for acoustic emissions.
- Physics-informed ML approach needs to be more developed to leverage from prior knowledge or constraints of deformation mechanisms for predictive modeling.

References

- Cuadra, 2015, A Computational Modeling Approach of Fracture-Induced Acoustic Emission, PhD thesis, Drexel University
- B. K. Holtzman, A. Paté, J. Paisley, F. Waldhauser, D. Repetto, Machine learning reveals cyclic changes in seismic source spectra in Geysers geothermal field. Sci. Adv. 4, eaao2929 (2018). 10.1126/sciadv.aao2929pmid:29806015