MIT EARTH RESOURCES LABORATORY
ANNUAL FOUNDING MEMBERS MEETING 2018

Earth Resources Laboratory

Deep learning applied to induced seismicity – Earthquake detection, location and forecasting

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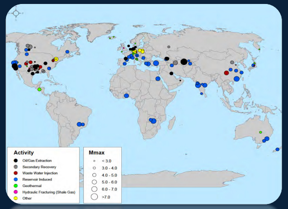
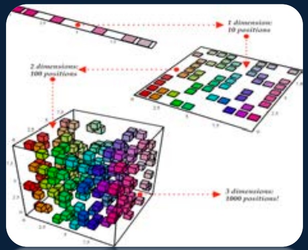
In collaboration with M. Nafi Toksöz, Youssef M. Marzouk, Saied Mighani, and J. Brian Evans

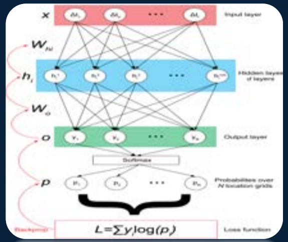
Overview



- Induced Seismicity Increases: Observations and Complexities

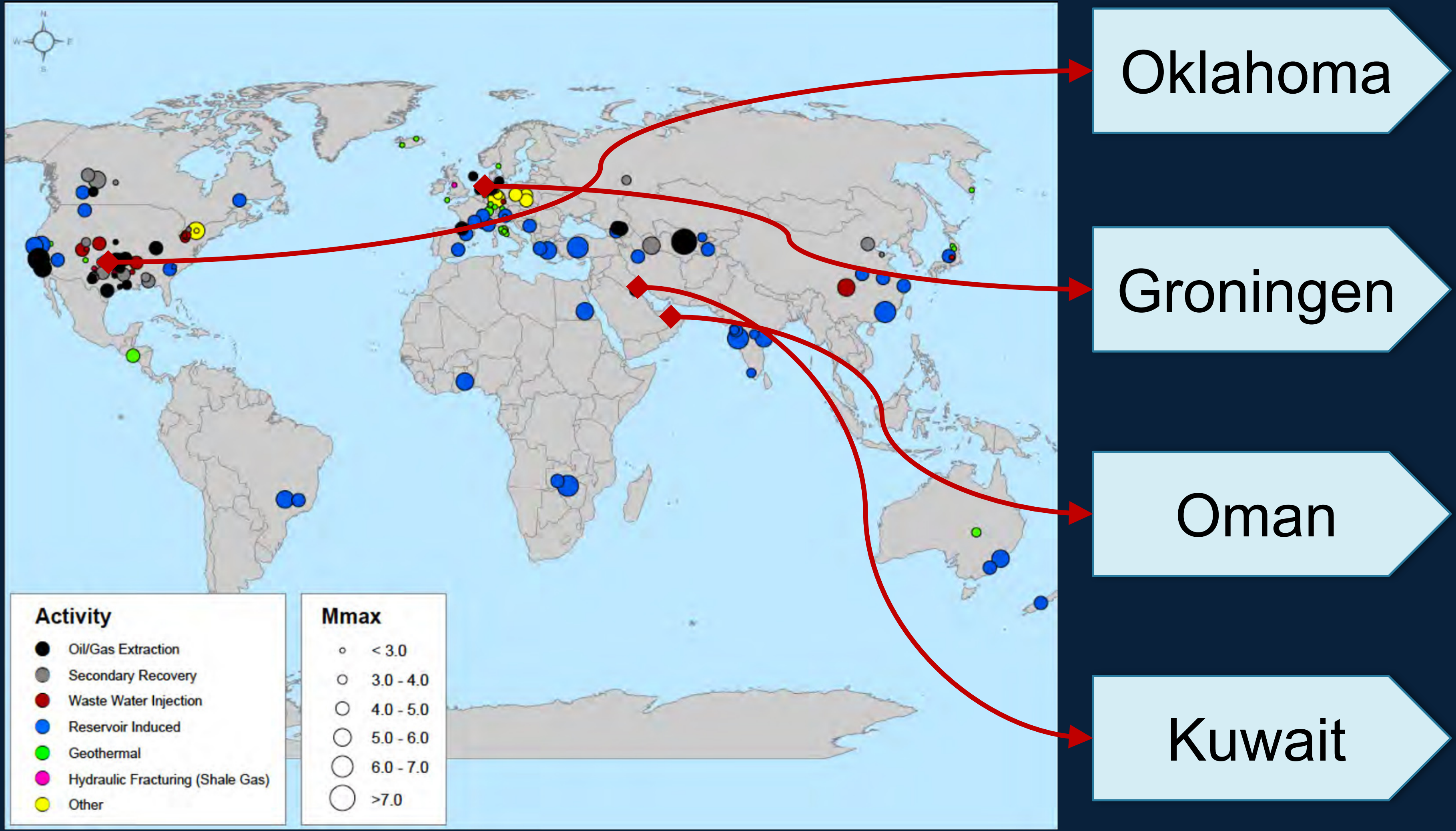


- Seismic Data Interpretation and Prediction: Uncertainty and Efficiency Challenge



- Deep Learning Applications: Detection, Location and Forecasting

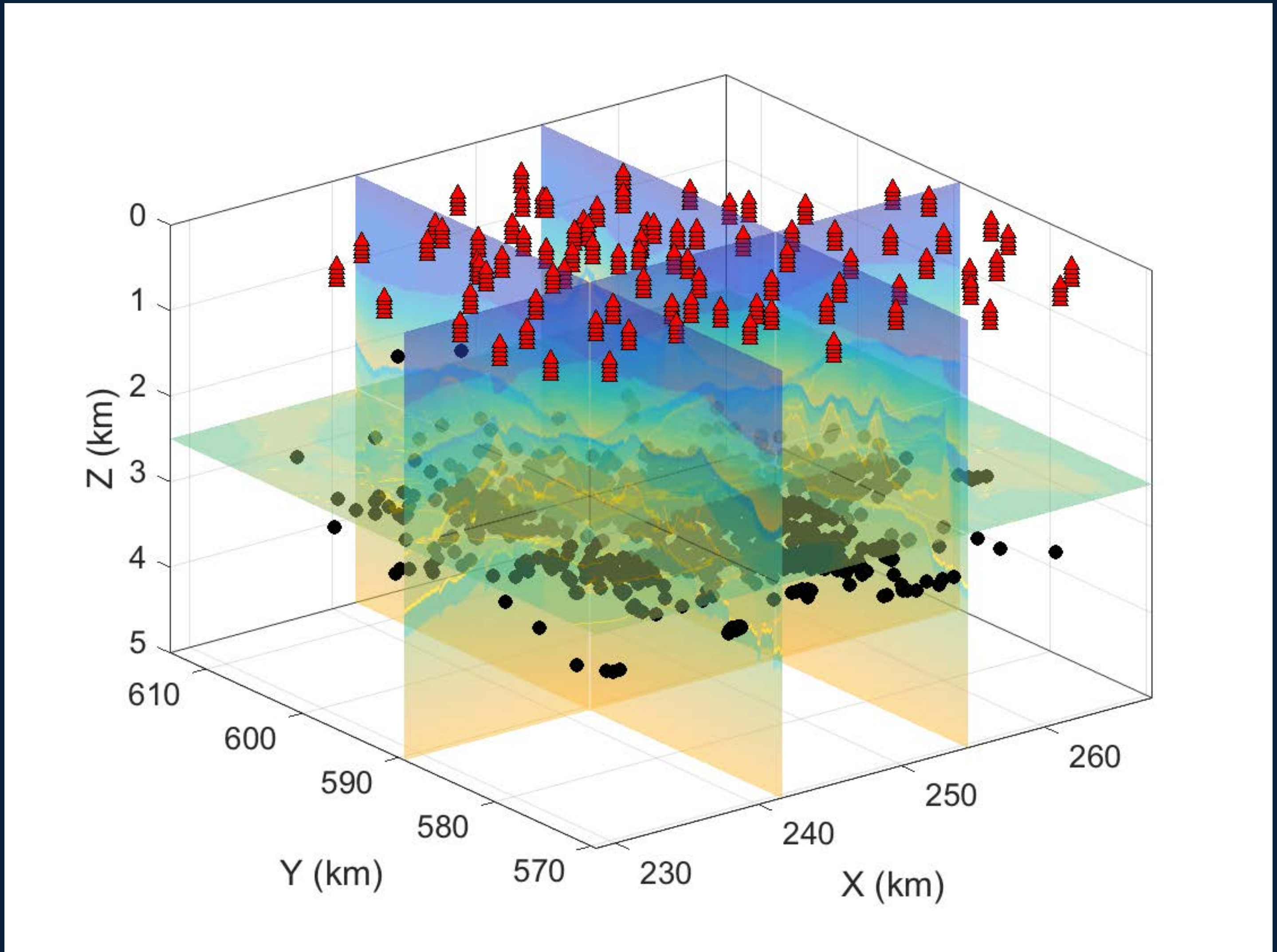
Induced Seismicity in the World



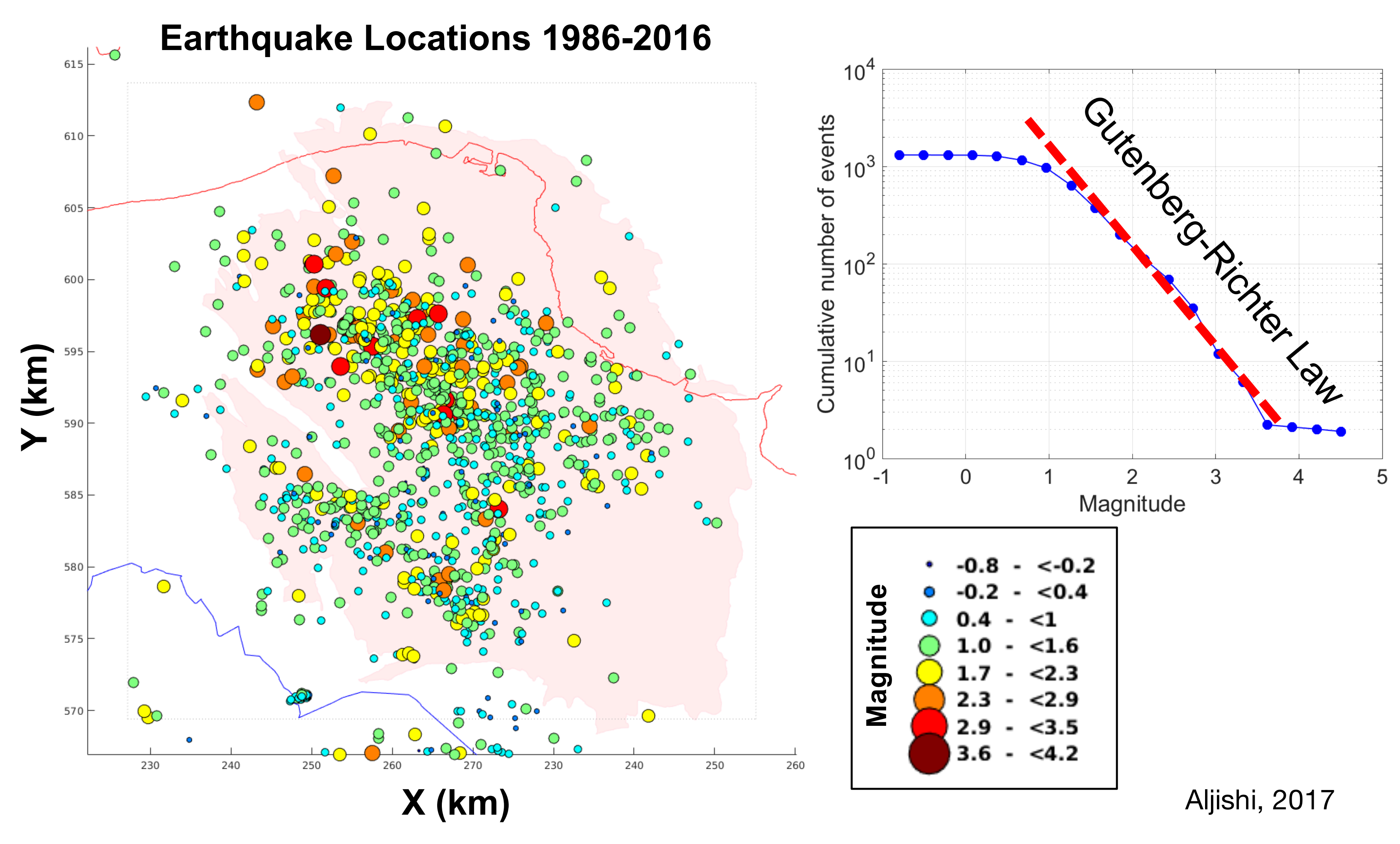
http://www.nofrackingway.us/2013/12/25/frackquakes-seismic-guidelines-for-frackland-buildings/

Induced Seismicity in Groningen

- 68 boreholes
- 1478 located events since 1986



Induced Seismicity in Groningen



Aljishi, 2017

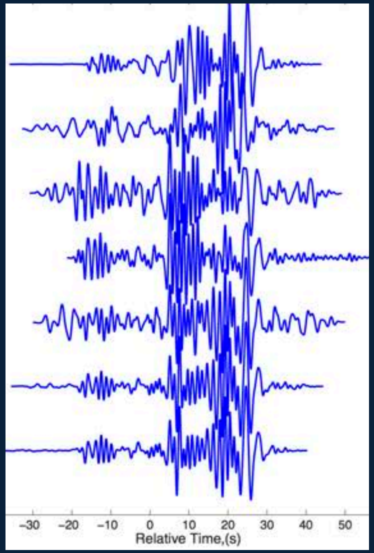
Overview of Classical Seismic Inversion

Computational Power →

Input	Traveltime	Amplitude and Phase	Migration Image (L^Td)	Full Waveform
Forward	Traveltime Integral	Lippmann-Schwinger Equation	Migration Green's Function	Wave Equation
Backward	Traveltime Location/ Tomography	Waveform Inversion	Migration Velocity Analysis	Full-Waveform Inversion

An Example of Bayesian Inference

Input



Gu et al, *GJI*, 2018

Simplest Bayesian Formulation

Location Sampling

Velocity Model Sampling

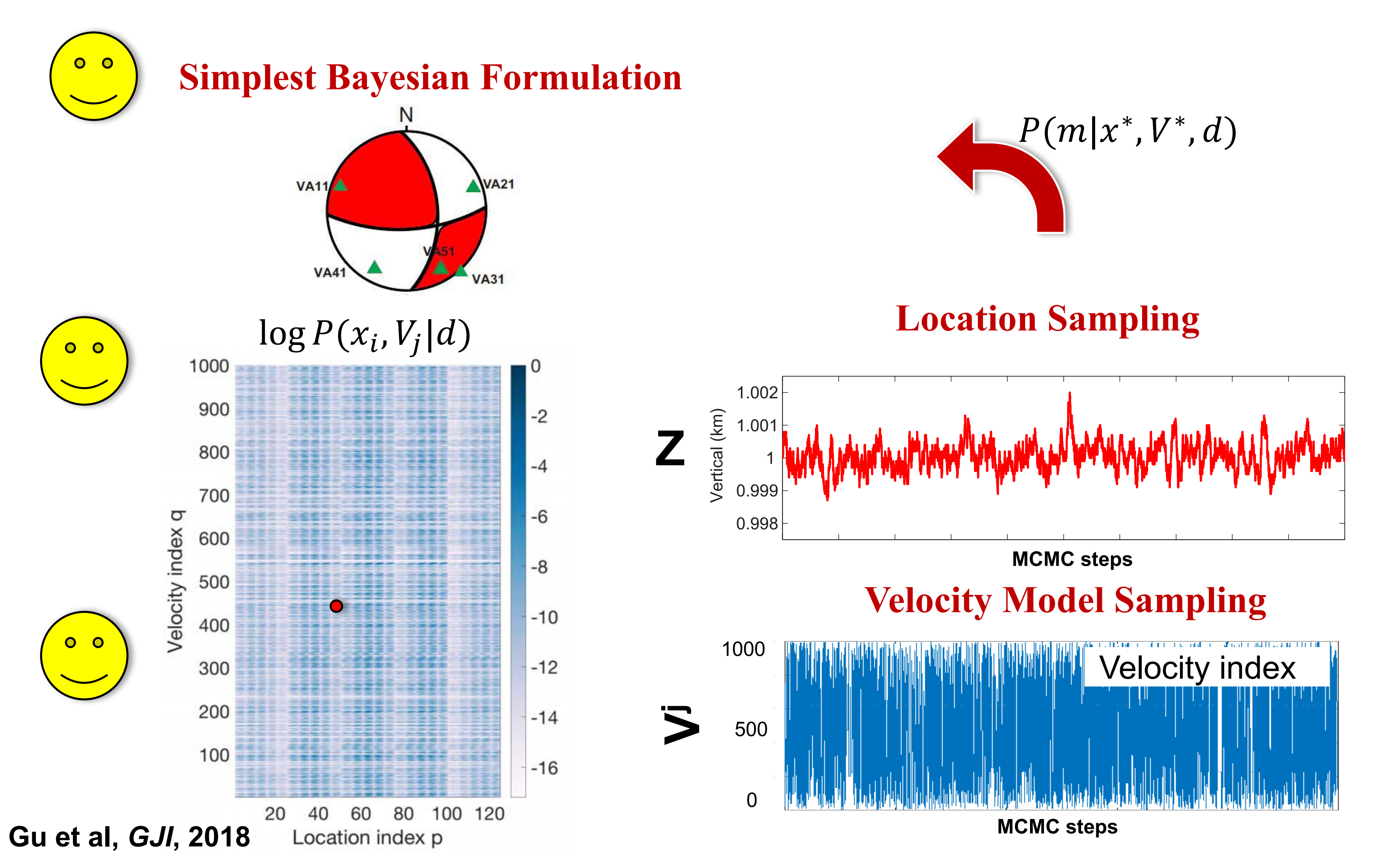
$$\begin{bmatrix} M_{11} \\ M_{22} \\ M_{33} \\ M_{12} \\ M_{23} \\ M_{13} \end{bmatrix}$$

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

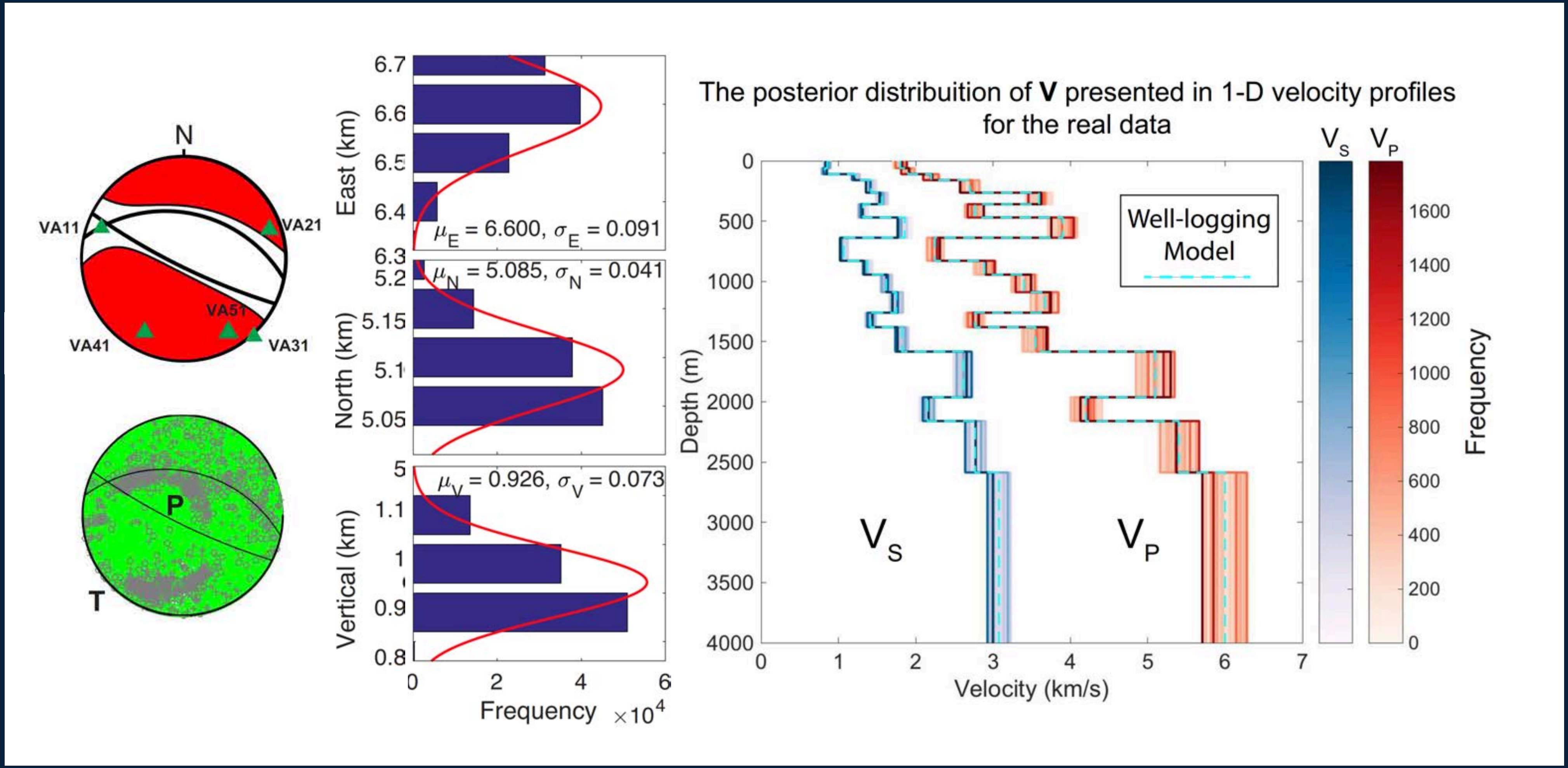
$$V$$

Output

Bayesian Machine – Mode III

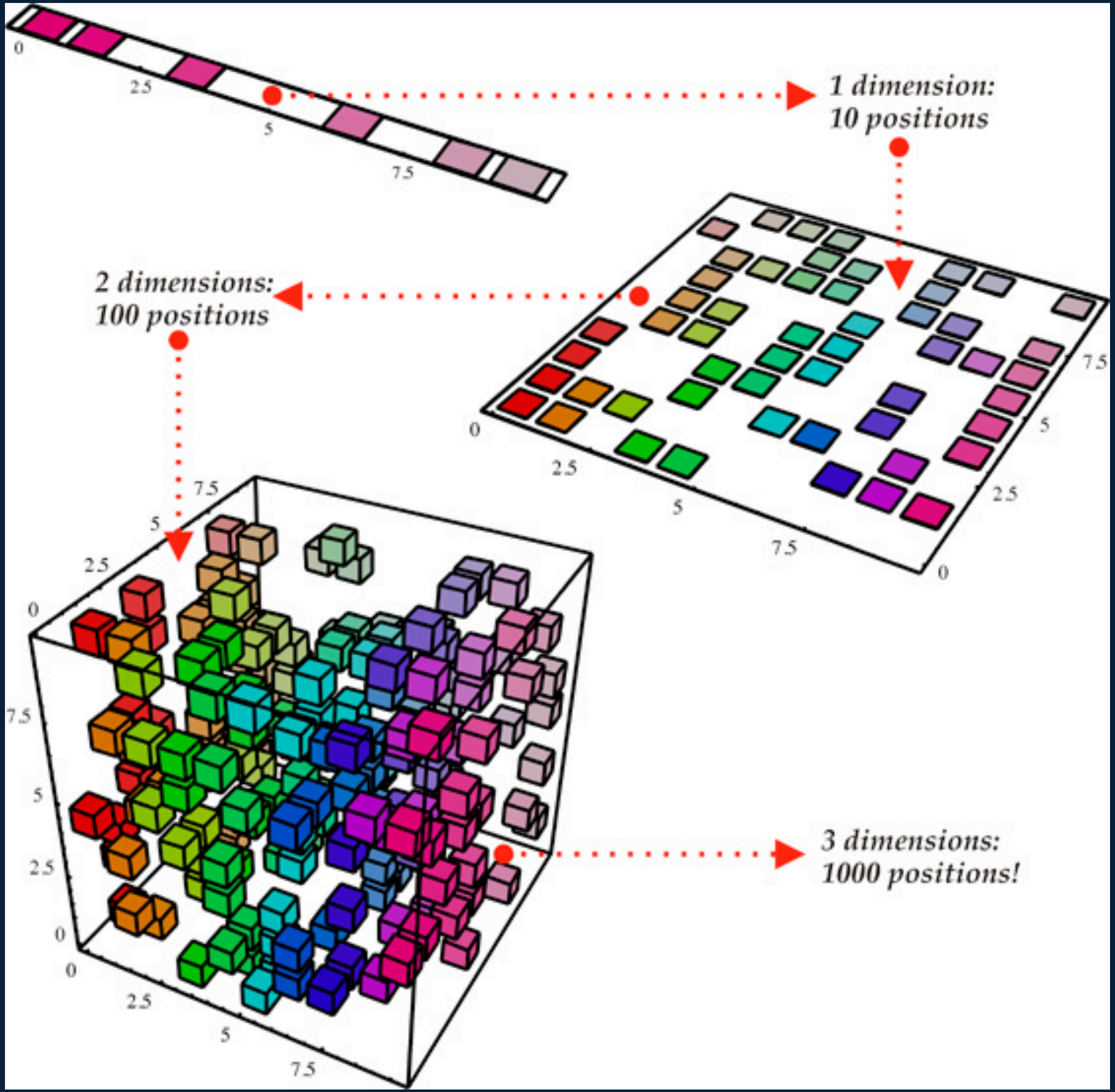


Bayesian Machine Output



Gu et al, *GJI*, 2018

Curse of Dimensionality



https://haifengl.wordpress.com/2016/02/29/there-is-no-big-data-in-machine-learning/

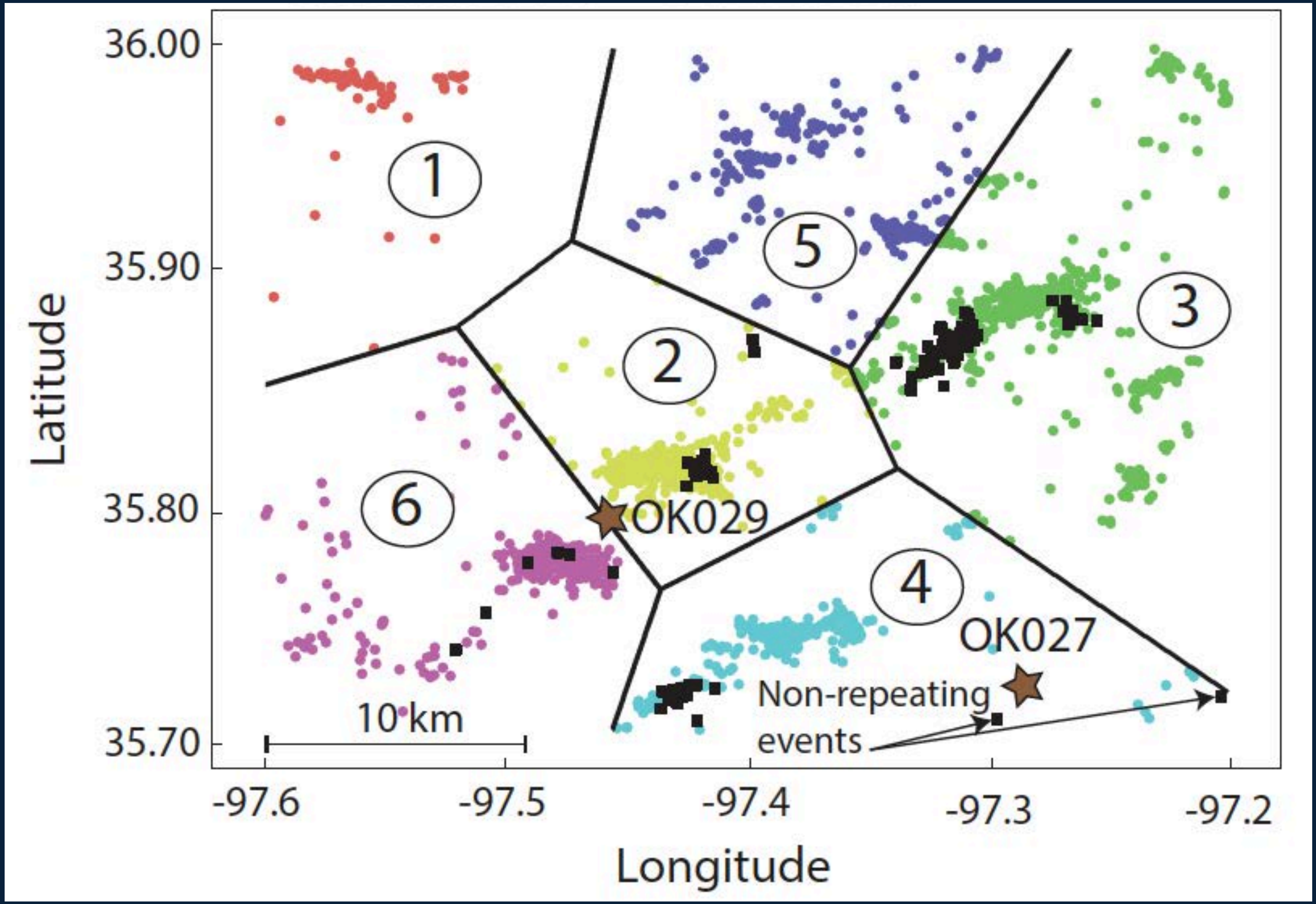
Deep Learning Possibilities

Seismic Sources
- Detection
- Location
- Source Mechanism

Shallow Structure
- Velocity Model
- 3D Fault Map
- Attenuation

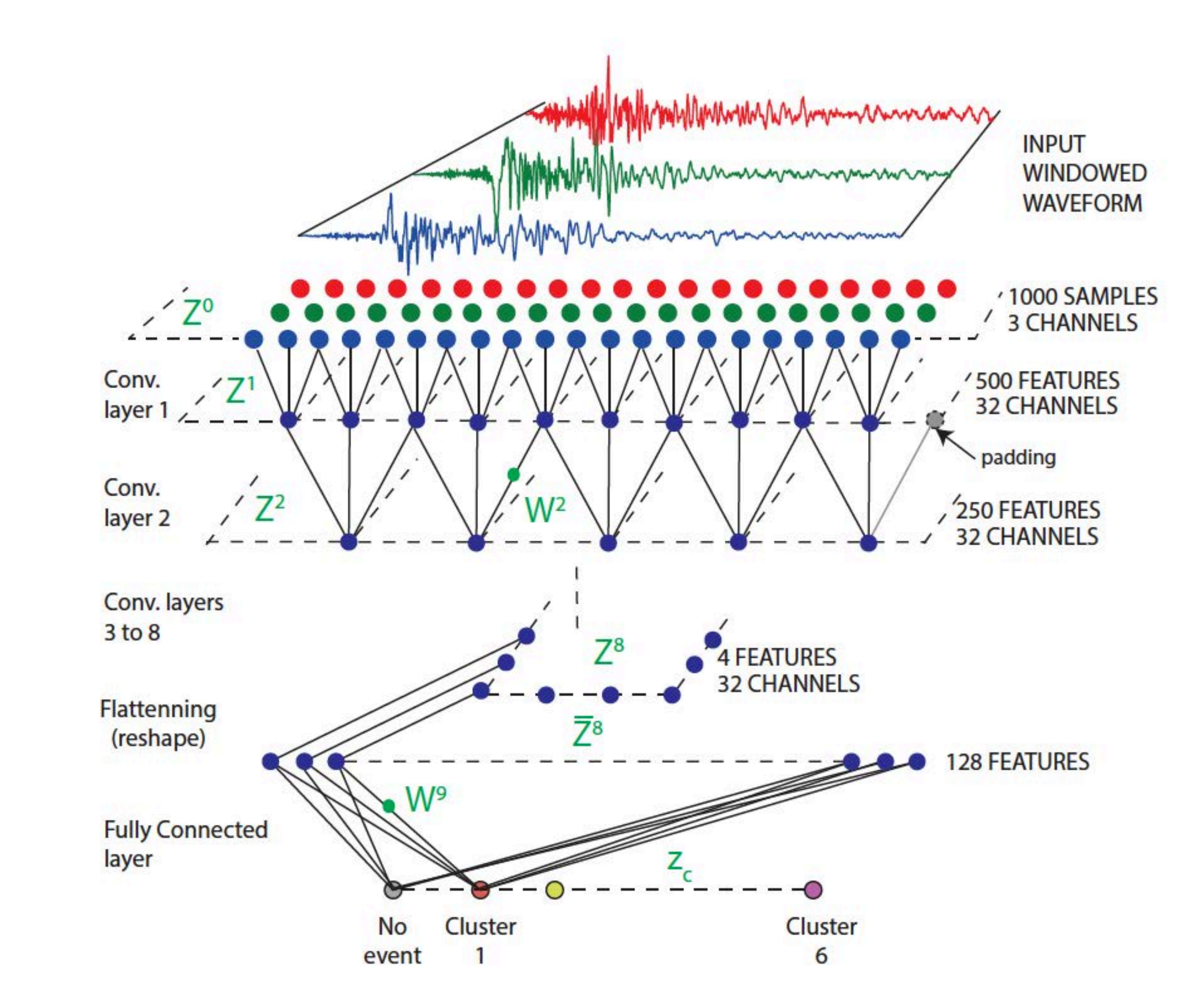
Earthquake Forecasting
- Next Earthquake
- Temporal-Spatial Distribution

Deep Learning Detection and Location



Perol et al., *Sci. Adv.*, 2018

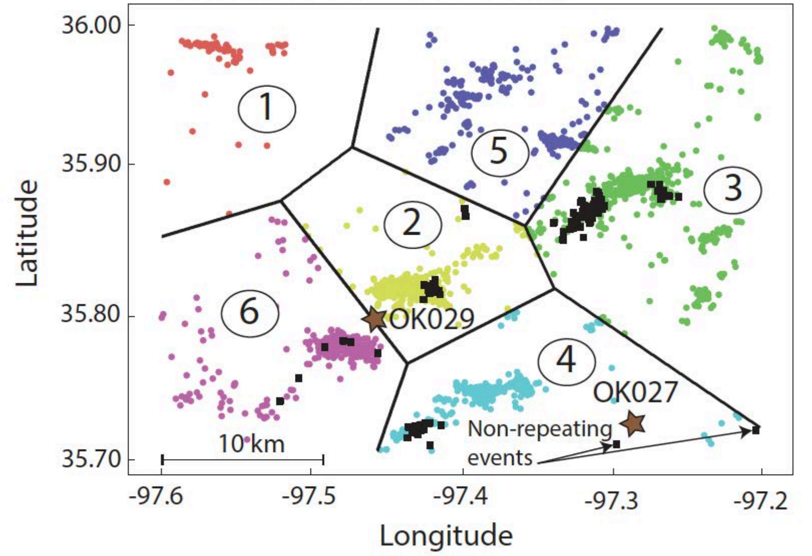
Deep Learning Detection and Location



Perol et al., *Sci. Adv.*, 2018

Deep Learning Detection and Location

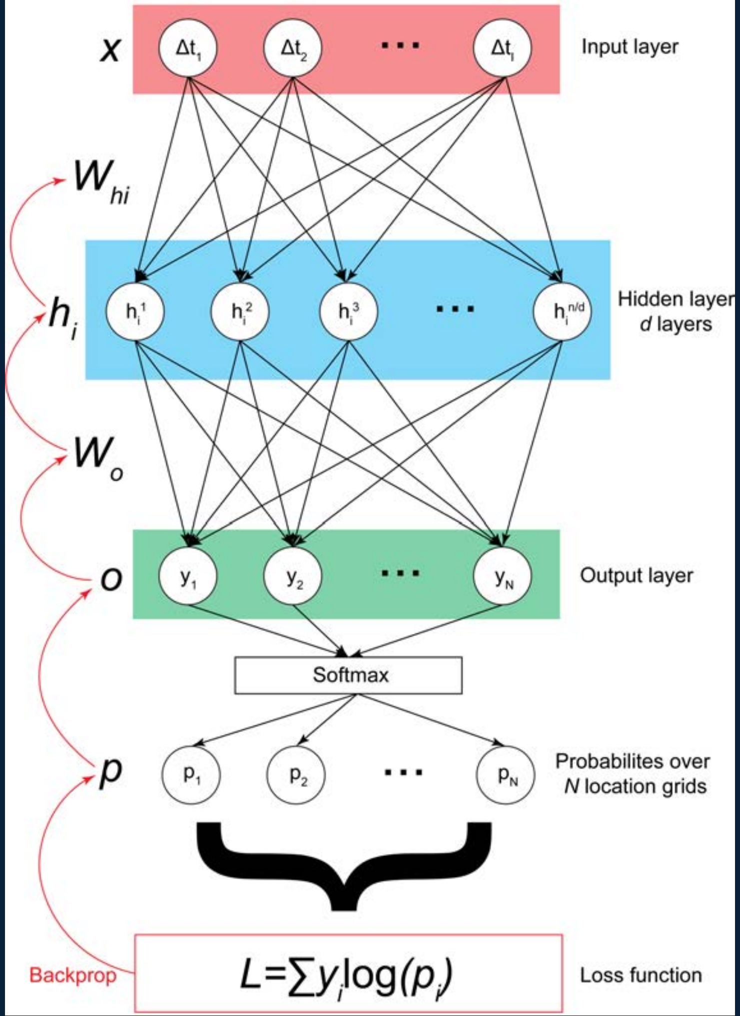
	Autocorrelation	FAST	ConvNetQuake (ours)
Noise detection accuracy	100 %	≈ 100 %	99.9 %
Event detection accuracy	100 %	87.5 %	100 %
Event location accuracy	N/A	N/A	74.6 %
Runtime	9 days 13 hours	48 min	1 min 1 sec

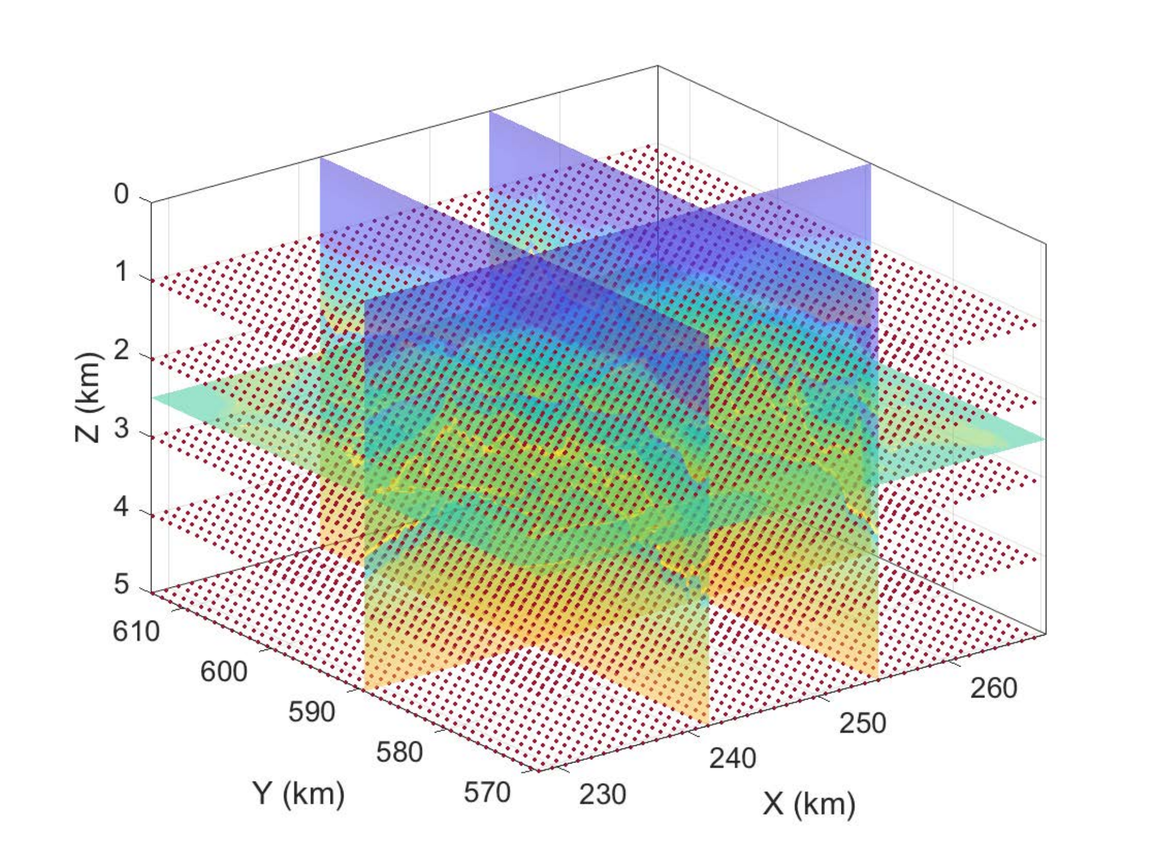


What we can improve:
1. Location resolution.
2. Use multi-station data.

Perol et al., *Sci. Adv.*, 2018

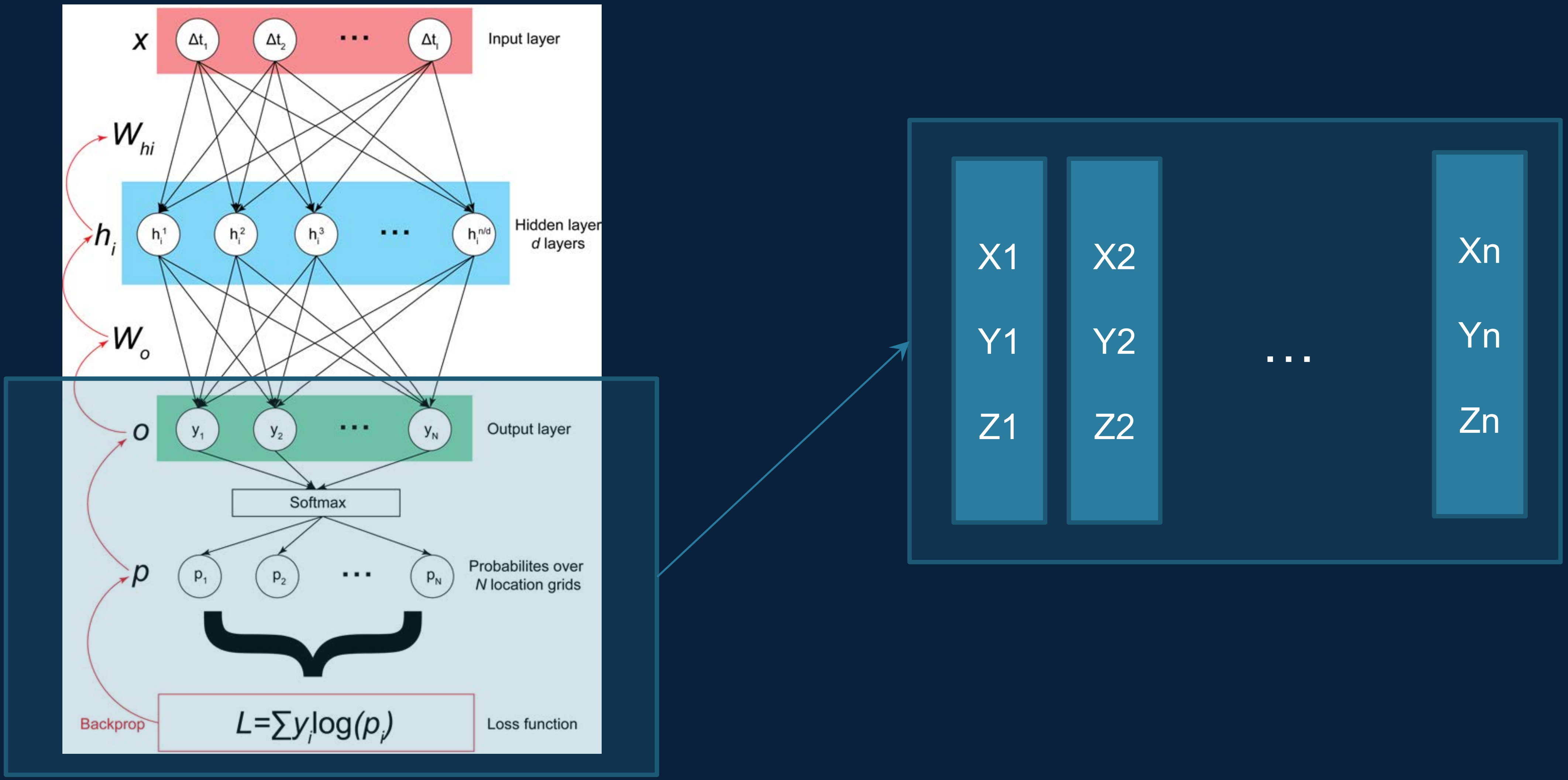
Upgraded 3-D Location in Groningen





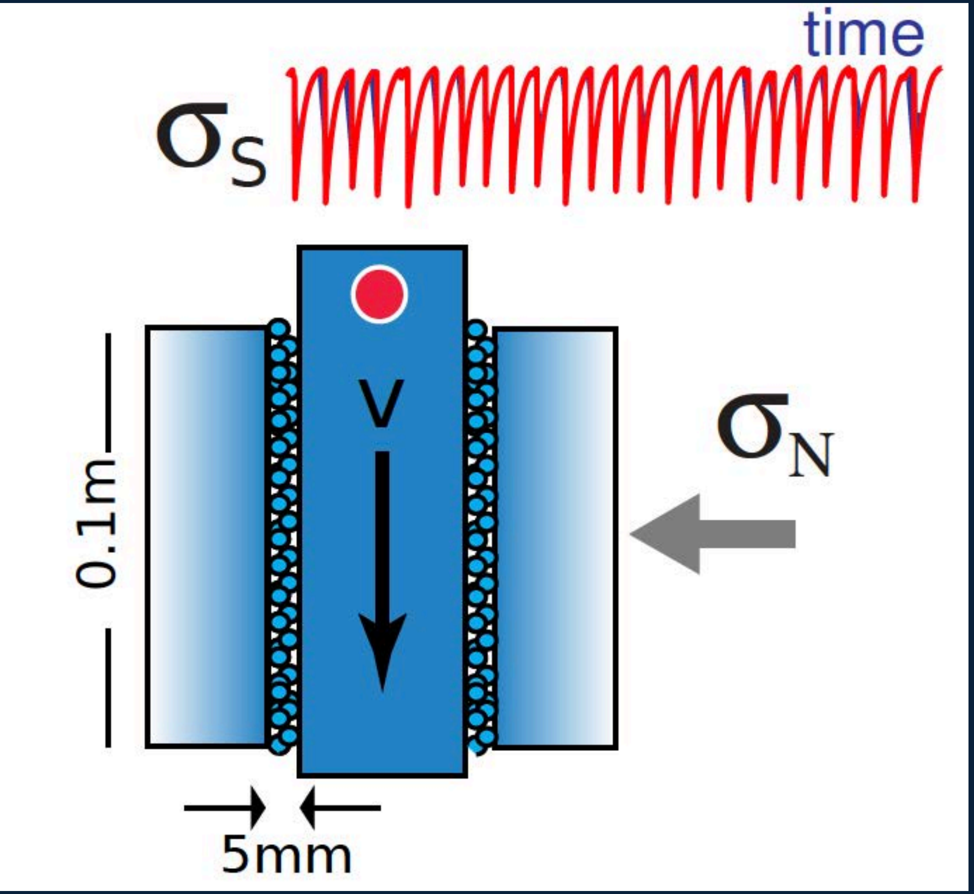
Gu et al., SEG expanded abstract, 2018

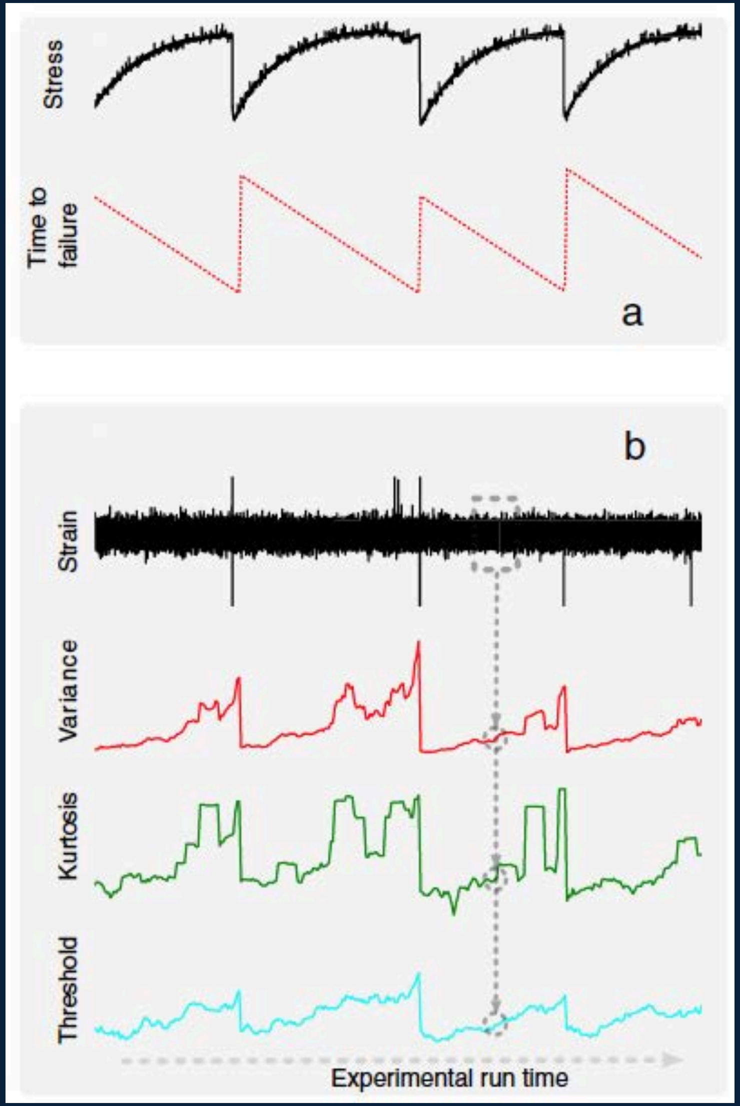
Beyond Classification



Earthquake Prediction

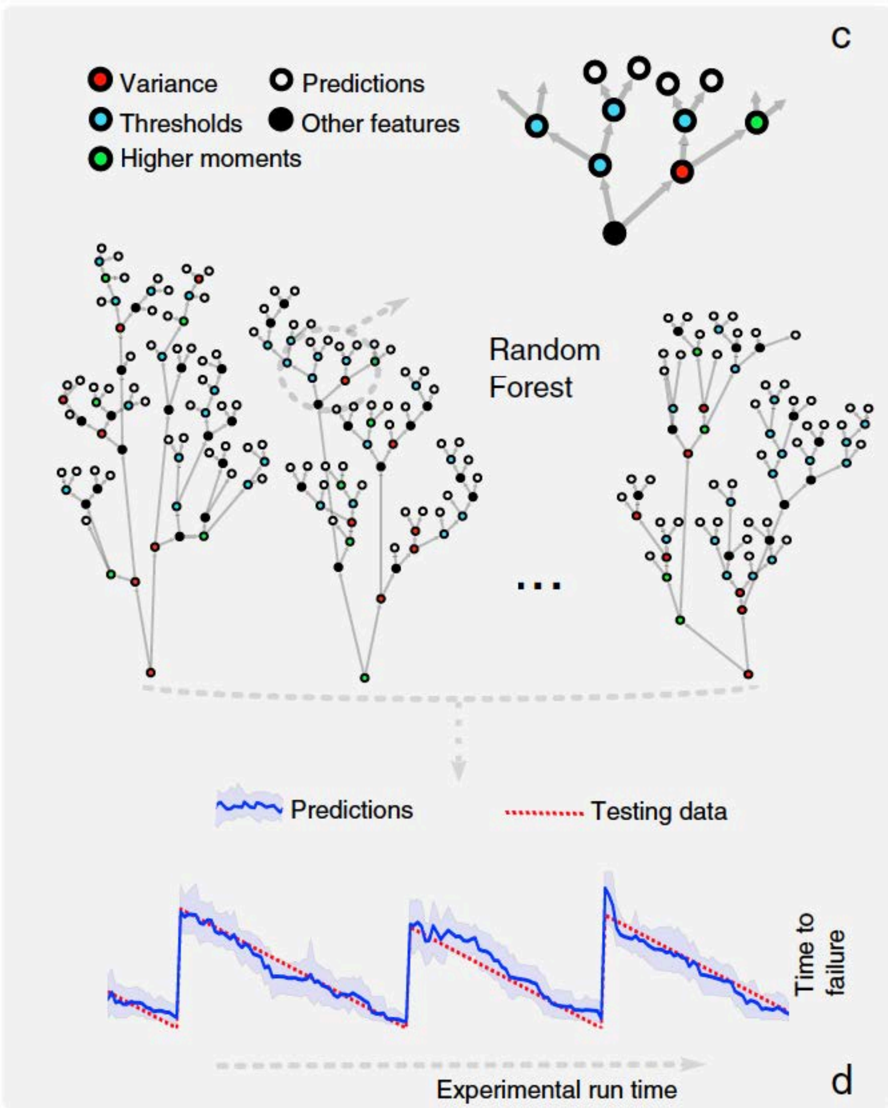
Bi-axial Stick-Slip Experiment





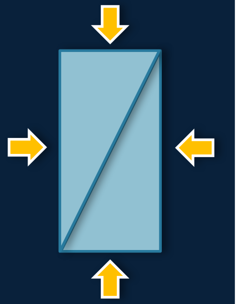
Rouet-Leduc et al., 2017

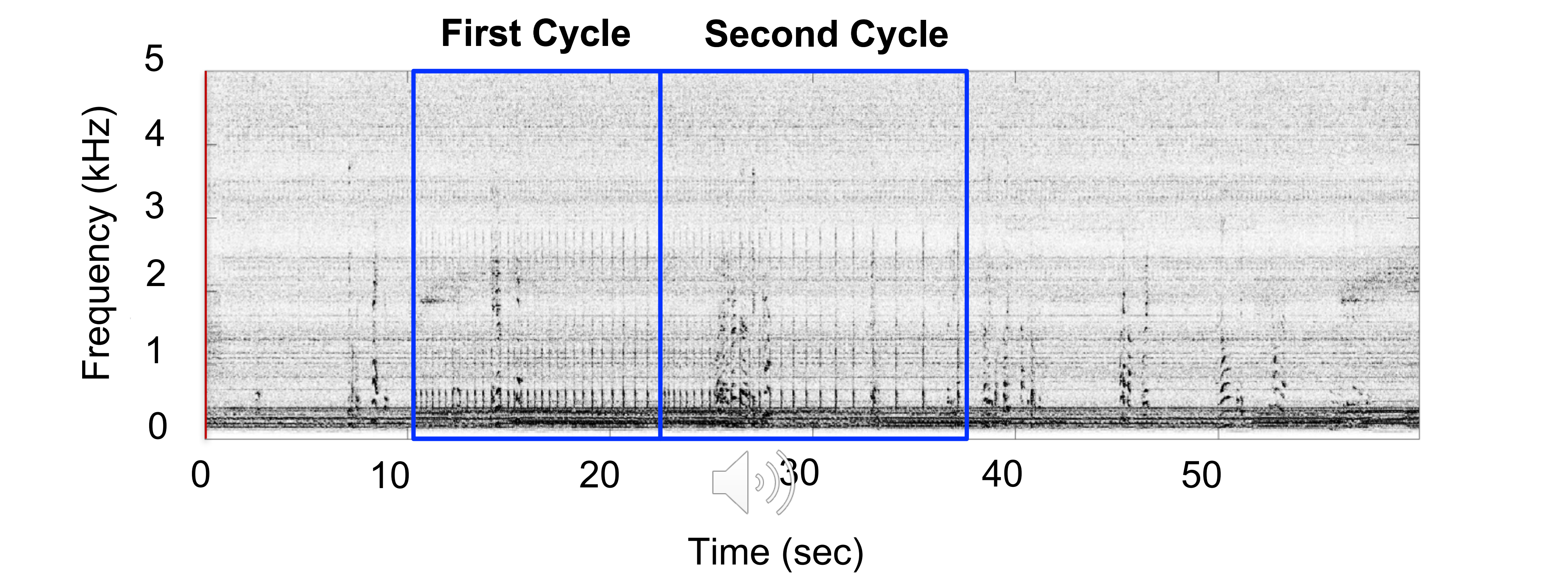
Earthquake Prediction



Rouet-Leduc et al., 2017

Earthquake Forecasting





This Experiment is conducted by Saied Mighani at the rock physics lab.

Conclusion

- The traditional geophysical algorithm becomes costly and impractical with the huge increase of data, both in oil/gas fields and laboratories.
- The big volume of labeled micro-seismic and pico-seismic (laboratory) data makes it possible to apply deep learning to earthquake detection, location and forecasting problems more efficiently and smartly.

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Thank you!

Conclusion

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