The Use of Machine Learning for the Interpretation of Wellbore Data

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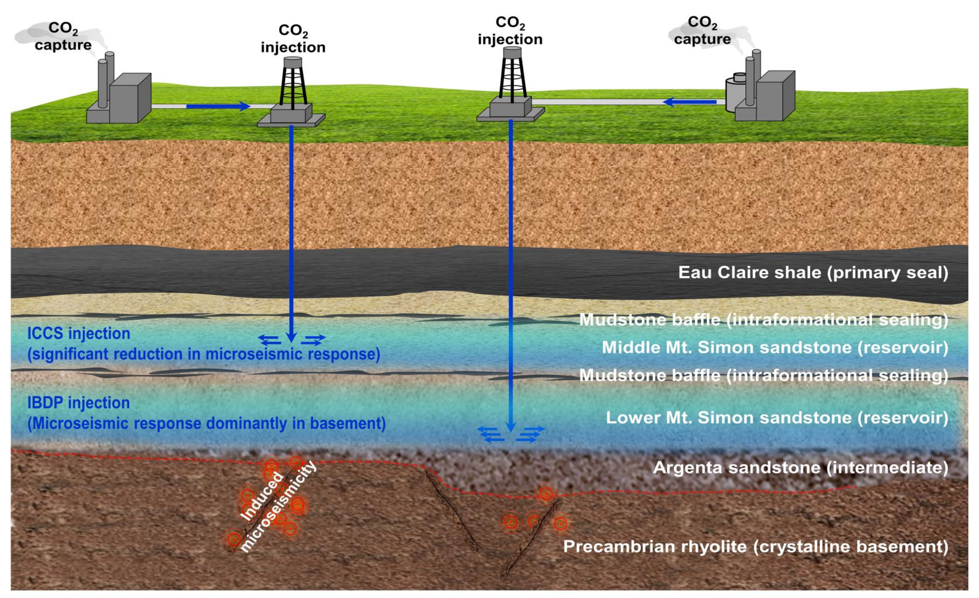
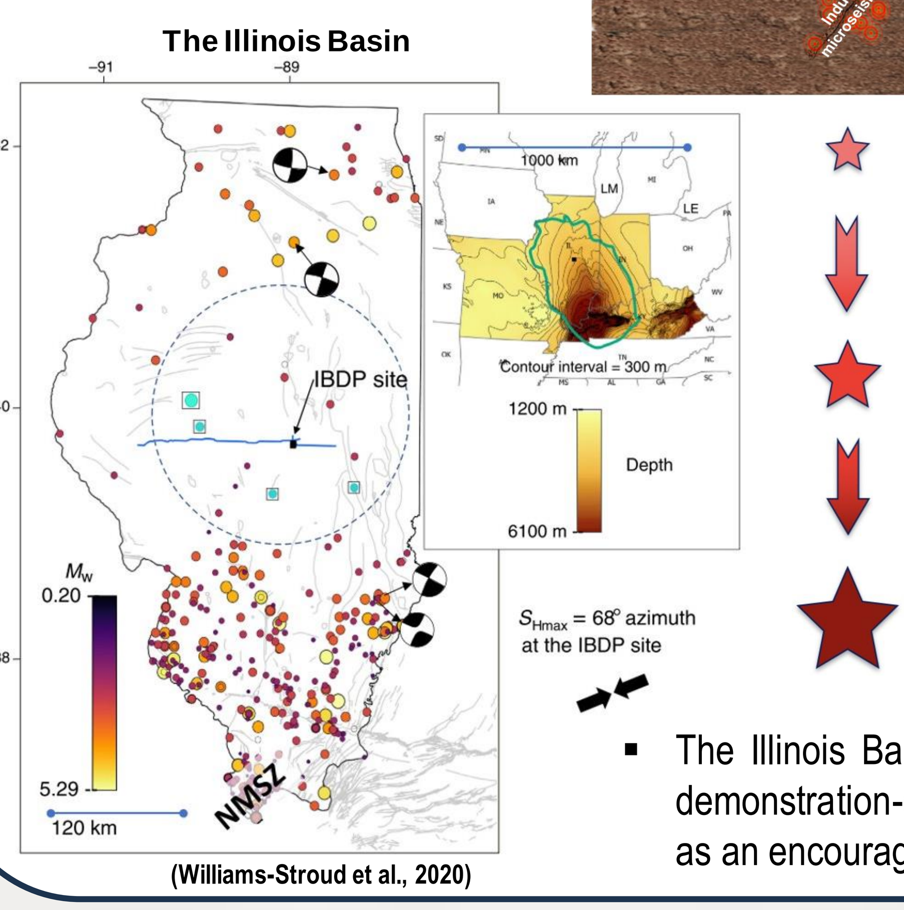
Motivation

- Carbon capture and storage offers a promising approach for mitigating CO_2 emissions in the atmosphere
- Fractured intervals increase the risk of induced seismic activity and CO_2 leakage, compromising the integrity of potential CCS sites





Illinois Basin Decatur Project (demonstration-scale) 1,000 tons/day CO_2 2011 - 2014

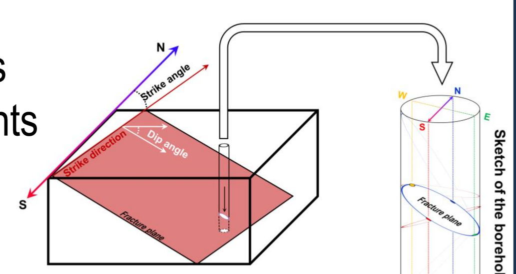
Illinois Industrial Carbon Capture and Storage (industry-scale) 3,000 tons/day CO_2 2017 - 2021

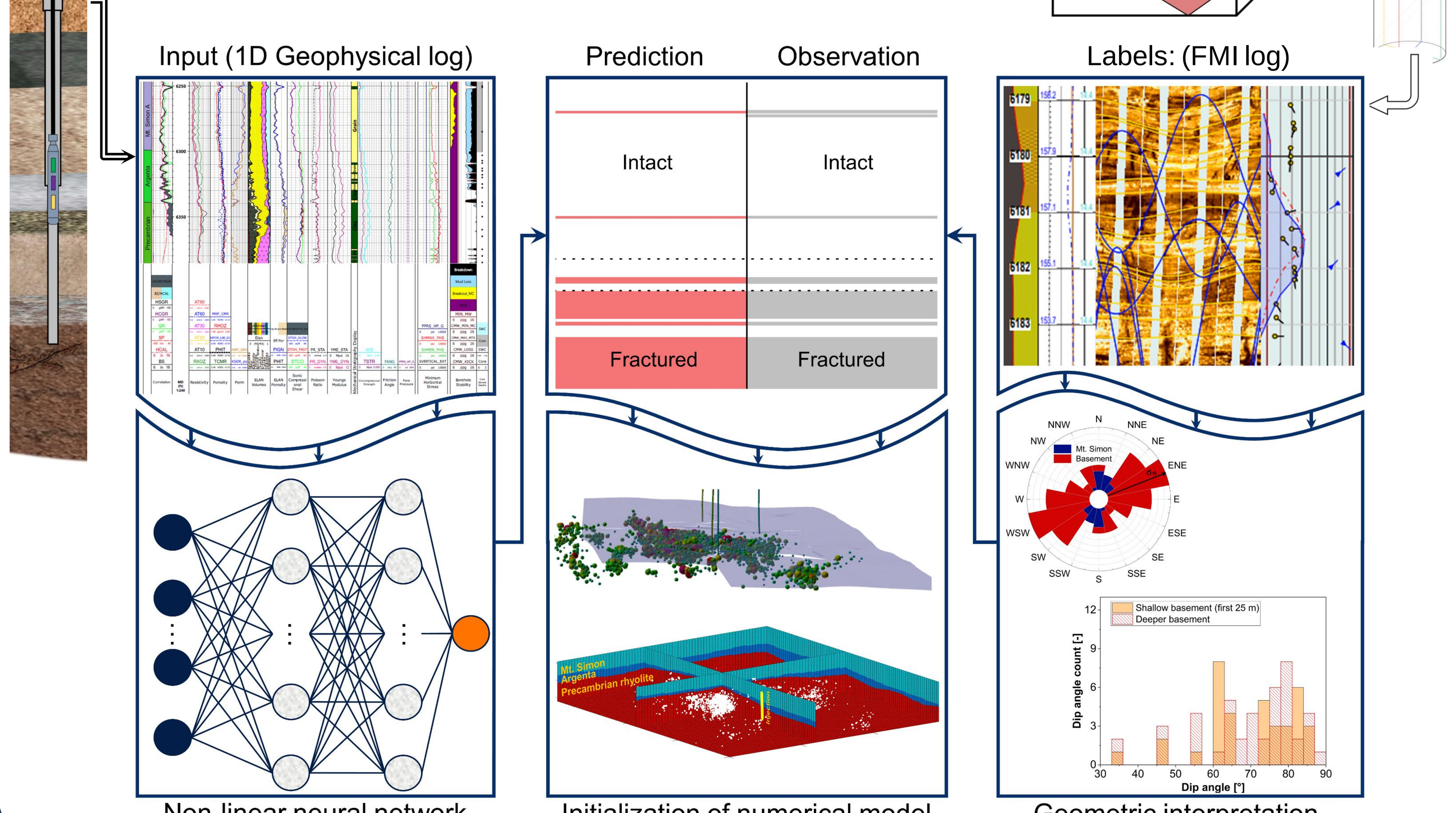
Illinois Storage Corridor (commercial-scale) 10,000 tons/day CO_2 2020-

- The Illinois Basin has an excellent history of pilot and demonstration-scale CO_2 injection projects, positioning it as an encouraging potential hub for CCS

Input Data and Labels

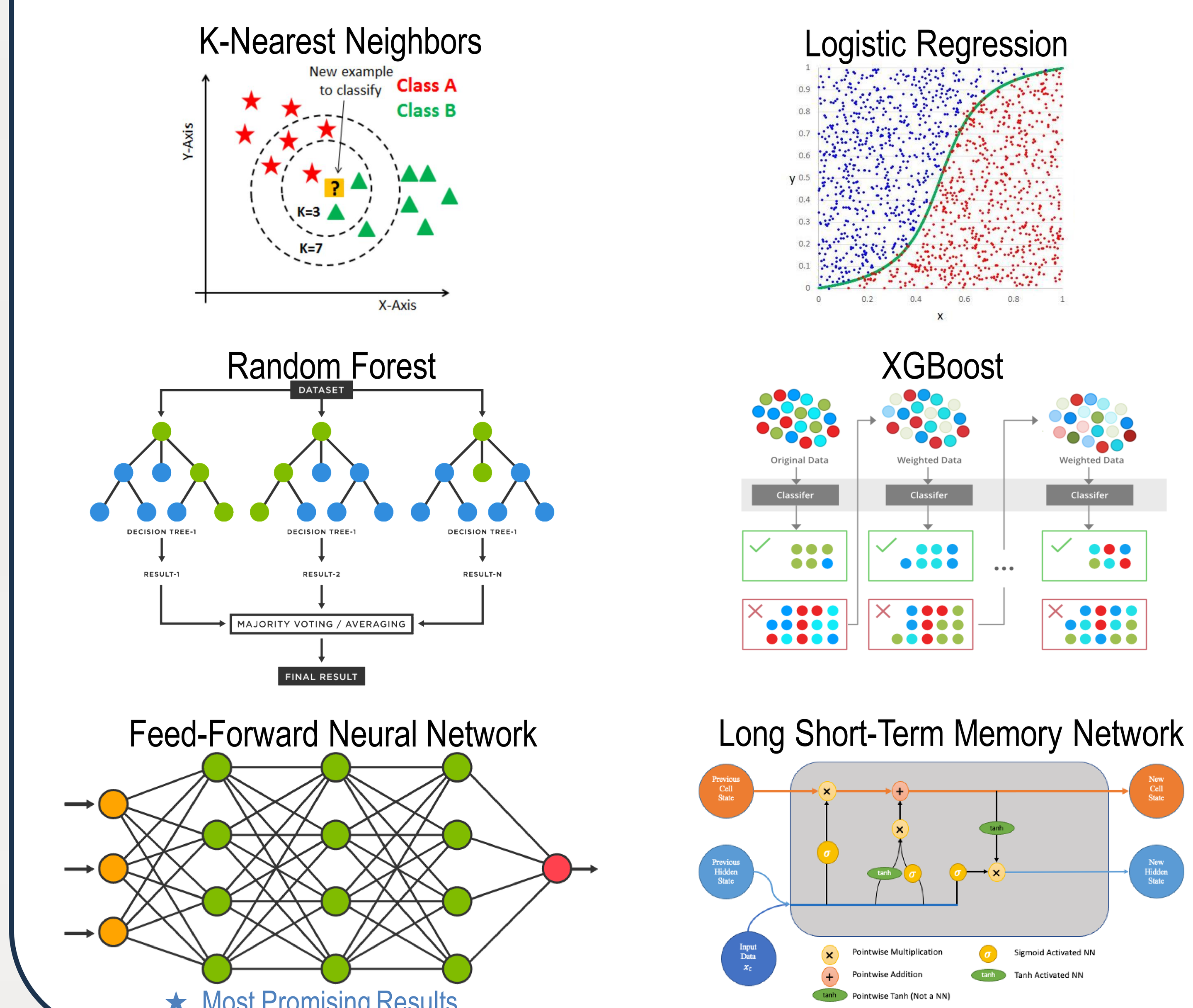
- Geophysical measurements are recorded every 0.5 ft from roughly 5,000 – 7,000 ft below the surface for 4 deep wells at IBDP site
- Considered 26 mineralogical + petrophysical input features
- FMI Logs generated from electrical resistivity measurements along the wellbore





Machine Learning Models

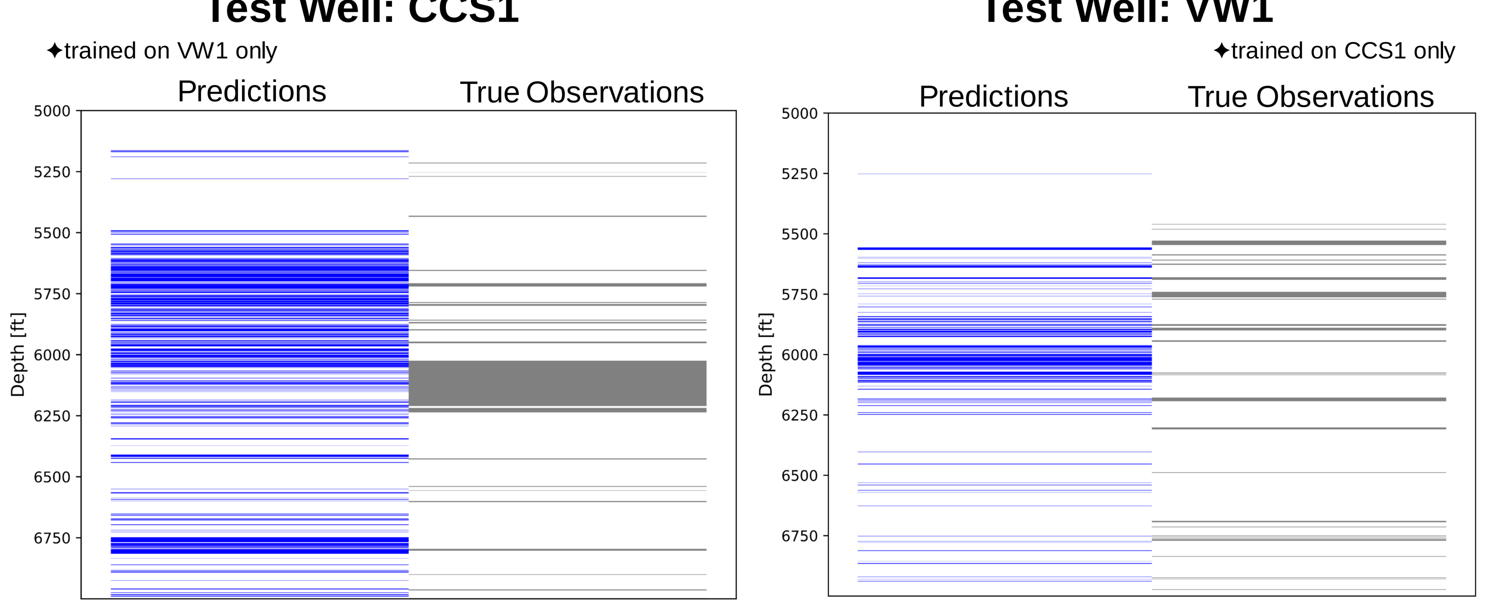
- Machine learning models designed to infer the presence of fractures based on geophysical wellbore data



FFNN Model Findings

- The current model's performance is inadequate for practical fracture detection

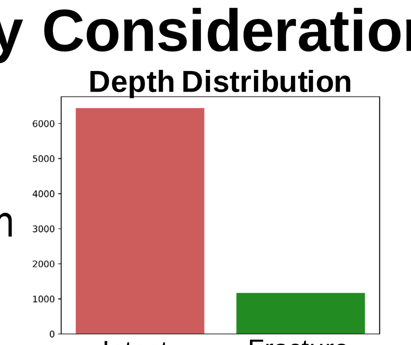
★blue line indicates that the probability of fracture at given depth >= 20%

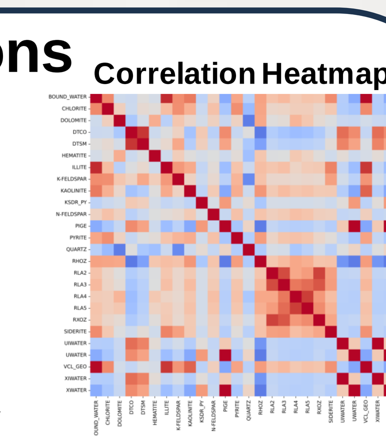


Test Well: CCS1				Test Well: VW1			
Train Accuracy	= 97.6%	Test Accuracy	= 79.1%	Train Accuracy	= 96.1%	Test Accuracy	= 74.8%
Train F1	= 95.0%	Test F1	= 54.0%	Train F1	= 92.0%	Test F1	= 50.1%

Preliminary Considerations

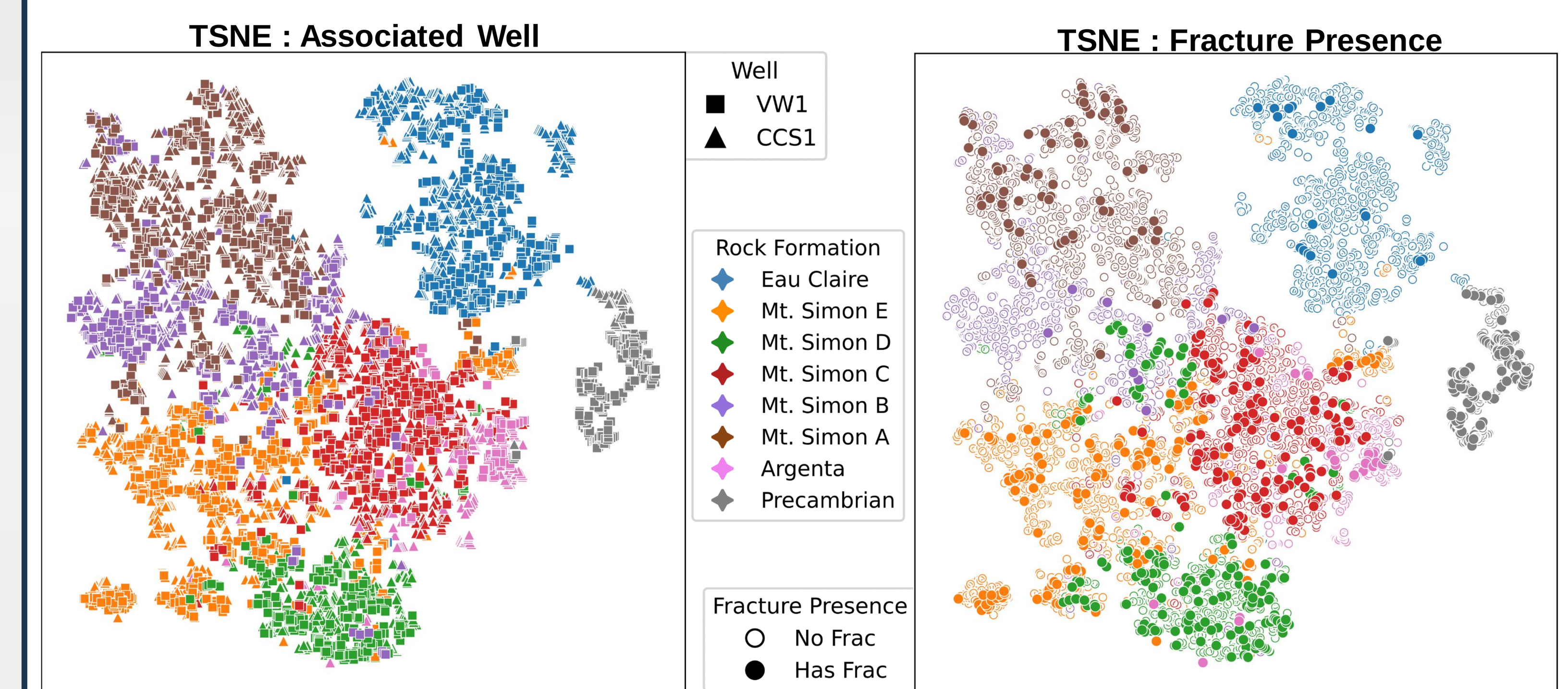
- Limited Number of Wells
- Unbalanced Dataset ~10% of recorded depths contain fractures
- Certain features are correlated
- Data originating from different wells can vary significantly



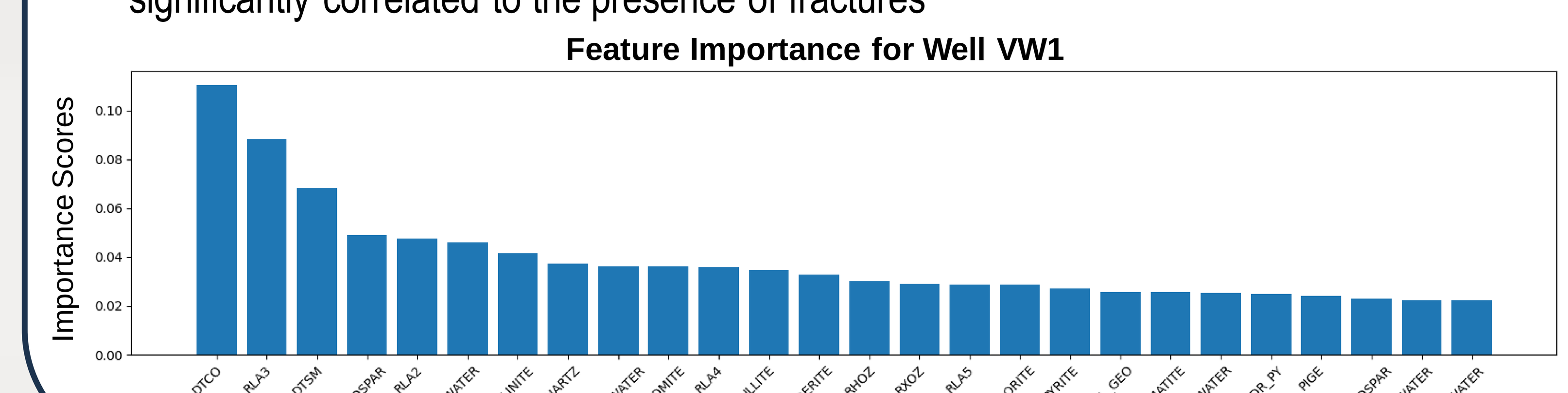


Exploration of the Dataset

- Data exhibits clustering based on rock formation type rather than the associated well or the presence of fractures



- The XGBoost model yields high importance scores for factors such as compressional/shear velocity (DTCO/DTSM) and resistivity (RLA3), which are known to be significantly correlated to the presence of fractures



Conclusions

- The dataset demonstrates a more prominent variation between rock formations than between intact and fractured intervals
- Incorporating geological context, such as rock formations, in addition to the geophysical data holds the potential to enhance fracture prediction abilities
- Although the XGBoost model successfully identified key geophysical factors, further analysis is required to define an optimal combination of input features

Acknowledgements

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- Input data is provided by Energy Data eXchange public repository

References

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