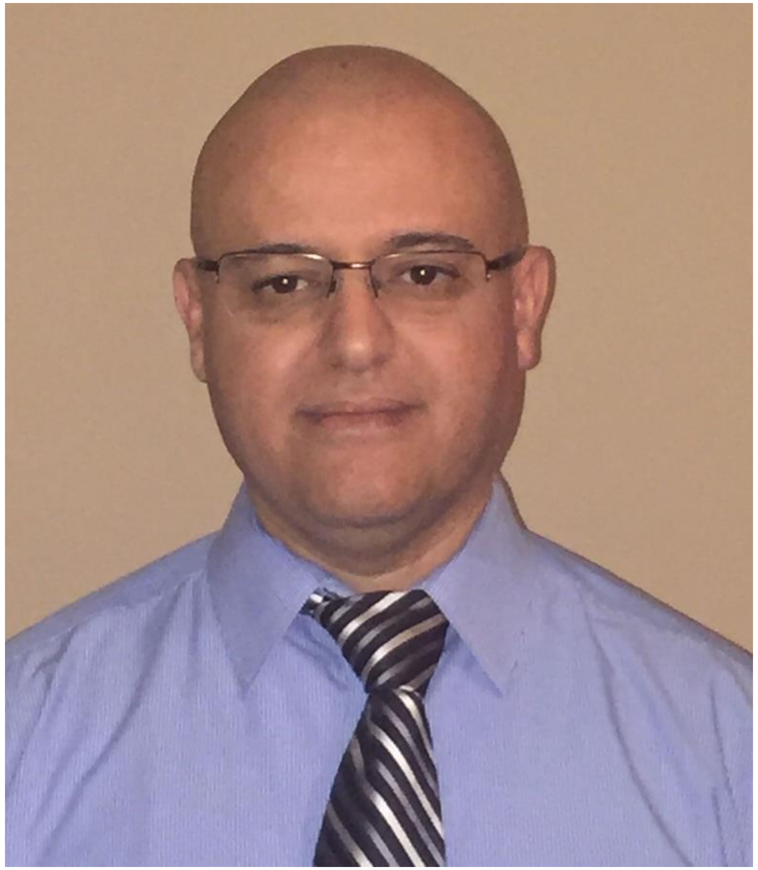
The Use of Machine Learning to Enhance Faults and Fractures Detection in seismic data

Hesham Refayee, dGB Earth Sciences

Hesham Refayee, Geoscientist works with dGB Earth Sciences since 2013. He started his career as a Well-site geologist for Veba Oil Operation and as an exploration geologist for NOC-Libya. He also worked with JOGMEC and ExxonMobil as an intern in Japan and in USA. Mr. Refayee's experience is in seismic interpretation, attribute analysis, and machine learning. He holds Bachelor degree in geology from Tripoli University and PhD in geology and geophysics program from Missouri University of Science and Technology.



Applied Geoscience Conference

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Hesham Refayee, Ph.D.

March 6, 2019

Outline

- Motivation
- Machine Learning Introduction
- Machine Learning Workflow
- Case Study 1, Utica Shale, USA
- Case Study 2, Kupe Field, New Zealand
- Conclusions

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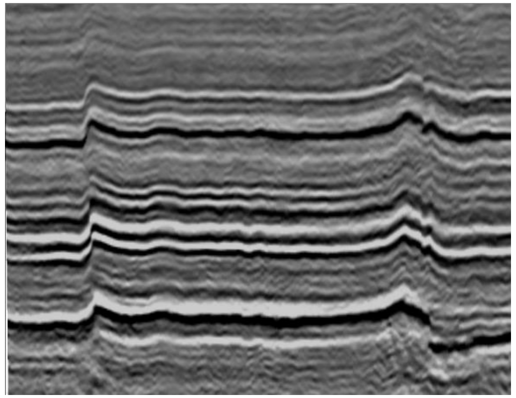
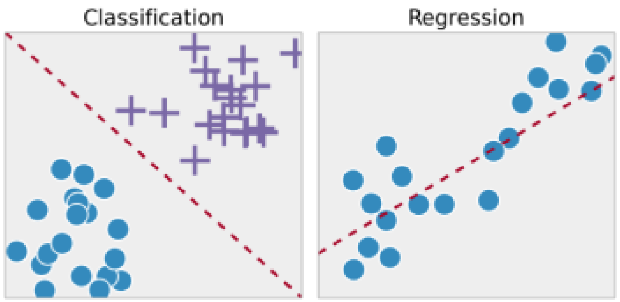
Motivation

- Data is getting bigger and we need to process data automatically and efficiently.
- Establish simple workflow using machine learning to accelerate fault interpretation.
- Apply machine learning in conventional and unconventional 3D seismic data.

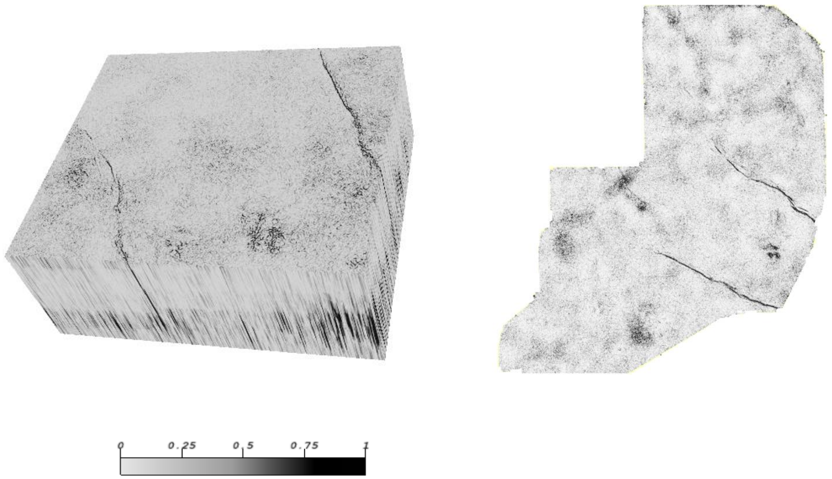
Input Data



Relationship



Output Data



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What is Machine Learning?

- **Machine learning** is a field of computer science that uses statistical techniques to give computer systems the ability to "learn" (i.e., progressively improve performance on a specific task) with data, without being explicitly programmed.

- Machine Learning is sub-field of **Artificial Intelligence**, which is defined as a branch of computer science dealing with the simulation of intelligent behavior in computers

Why Machine Learning?

Finding complex relationships and structures in data sets from different sources with widely varying accuracies and scales (e.g. satellite images, seismic data, well logs, core measurements, descriptive observations at outcrops and microscopic levels etc.)

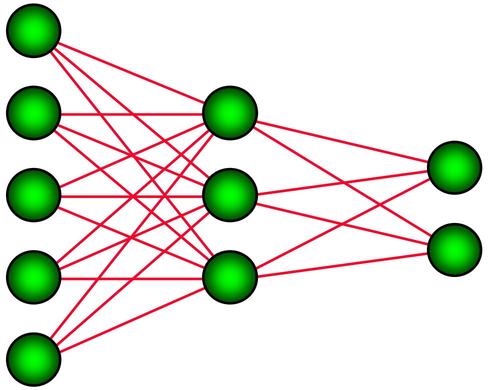
Examples:

- General Sciences: image processing, computer vision, playing chess, driving cars, robotics, …
- Earth Sciences: seismic facies clustering, finding anomalies, chimney cubes, rock property predictions, …

Neural Networks

- **Neural Networks :**are systems for information processing inspired by biological nervous systems like brains.

- **Shallow Networks :** are networks with typically 3 layers (input-hidden-output). Examples: MLP (Multi Layer Perceptrons), UVQ (Unsupervised Vector Quantizer).



- **Deep Networks :** are very large networks with typically up to 12 layers (sometimes even up to Thousands of layers). Examples: CNN (Convolutional Neural Networks), RNN (Recurrent Neural Networks), LSTM (Long Term Short Term Memory), GAN (Generative Adversarial Networks).

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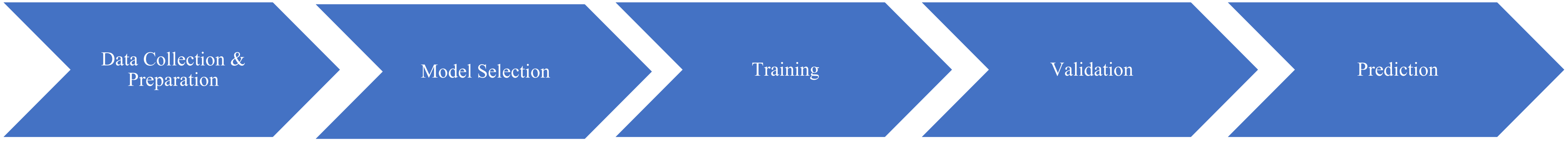
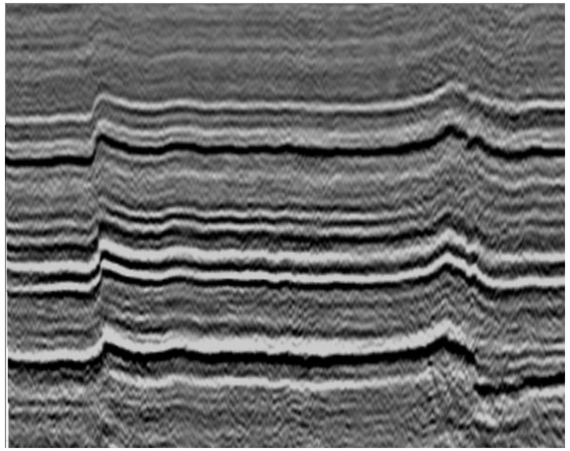
Machine Learning Workflow

"Machine learning is all about using the right feature, to create the right model, to achieve the right tasks " Peter Flach

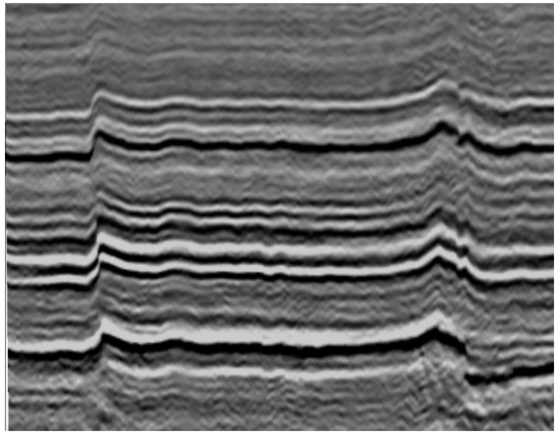


Data Collection and Preparation



- Machine learning is useful, learns by experience, however their performance is dependent on quantity and quality of the data.

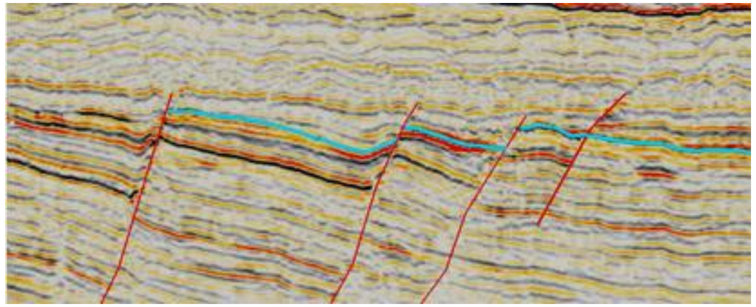
- Machine learning requires consistency in content and formatting.



- Noise in the data weakens machine learning predictive capabilities.

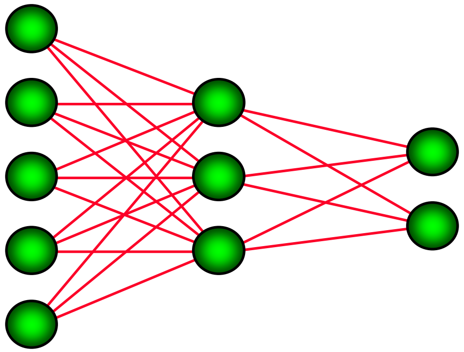
Model Selection

Fault Interpretation Methods



- Manual/auto approach

➢ Many interpretation platforms



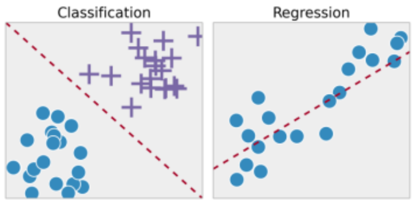
- Data Science approach

➢ Machine learning

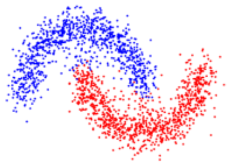
Machine Learning Algorithms

Data Collection & Preparation → **Model Selection** → Training → Validation → Prediction

- Supervised learning



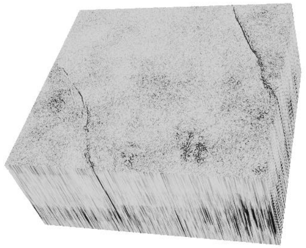
- Unsupervised learning



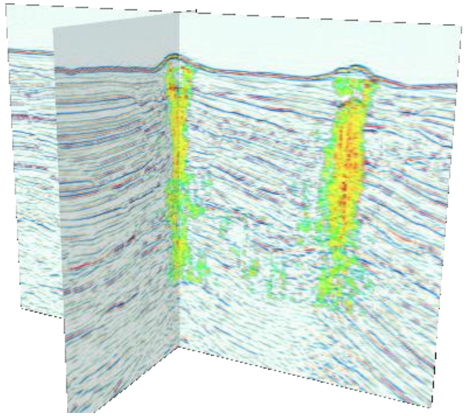
- Reinforcement learning

Supervised Neural Network

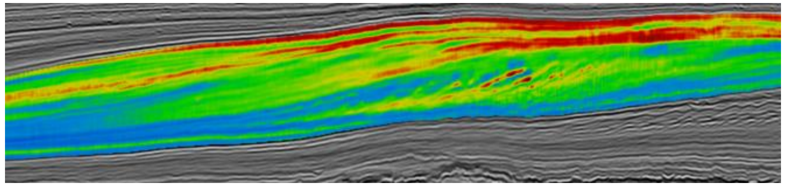
Data Collection & Preparation → **Model Selection** → Training → Validation → Prediction



- Classification: organize data in groups that represent a specific property; Supervised learning approach.



- Quantification: predict a specific property from the data; Supervised learning approach

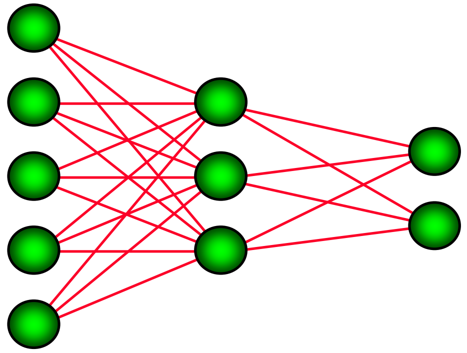


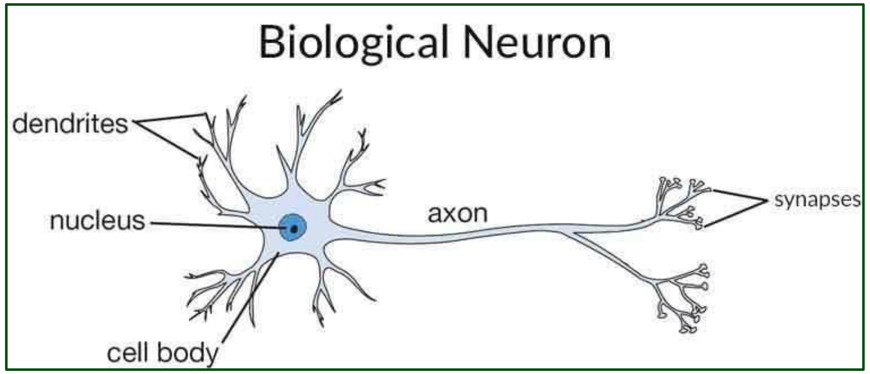
Multi-Layer-Perceptrons (MLP)

- Multi-Layerd Perceptrons are artificial neural networks employing supervised learning methods inspired by the structure of the neurons in the brain.

- The back propagation of error is the learning algorithm used to train this network

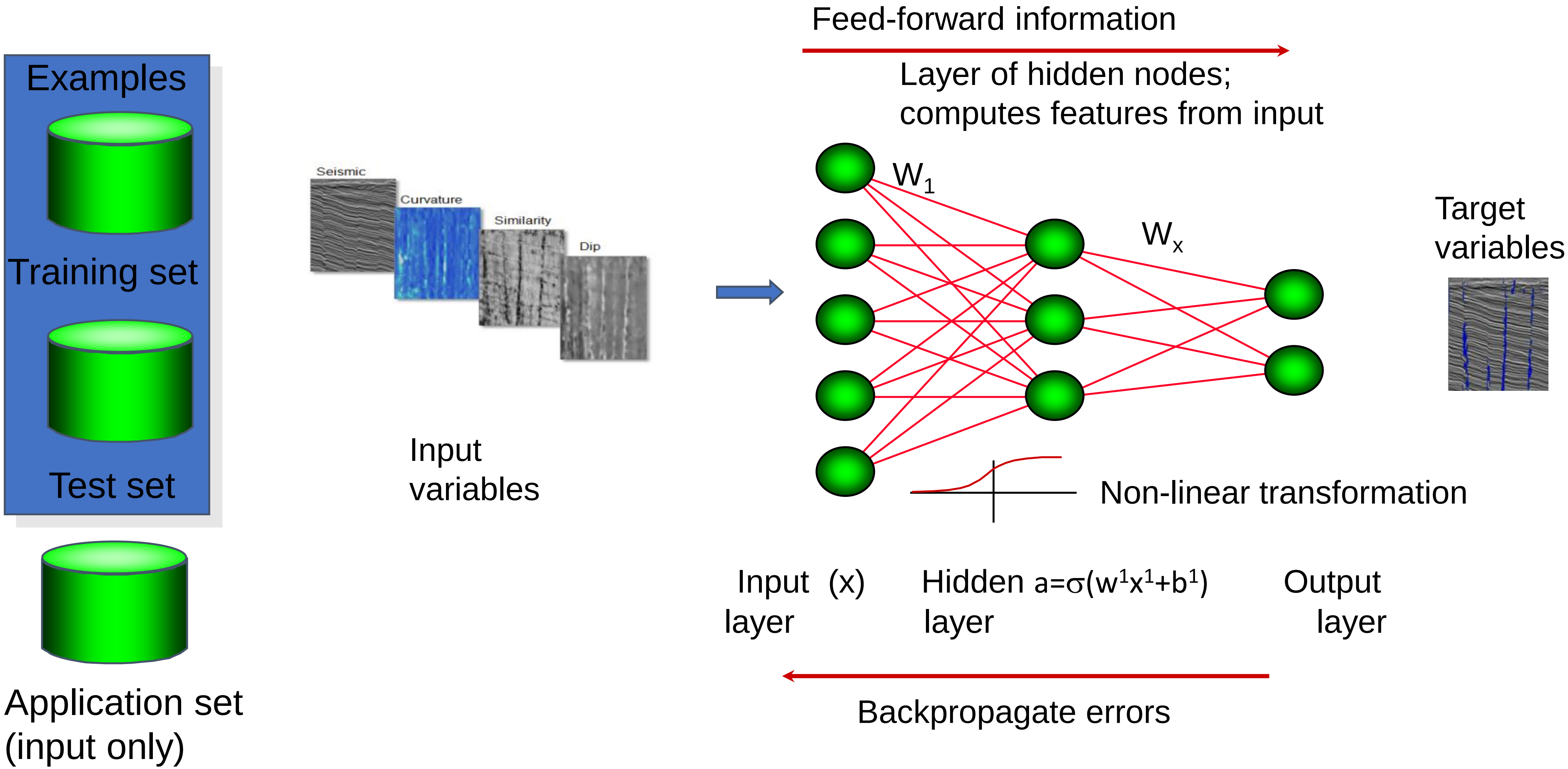
- A MLP is a classification analysis approach



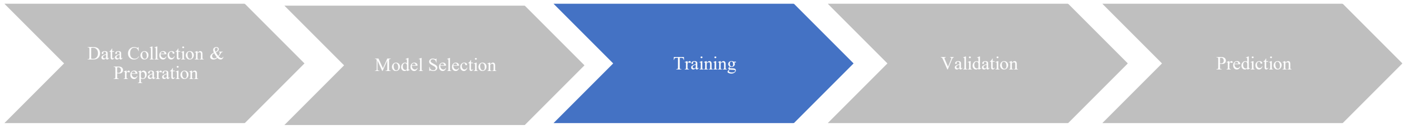


[*]https://laptrinhx.com/topic/32279/overview-of-artificial-neural-networks-and-its-applications

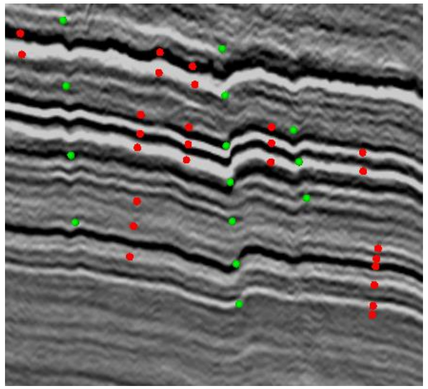
Multi-Layer-Perceptrons (MLP)

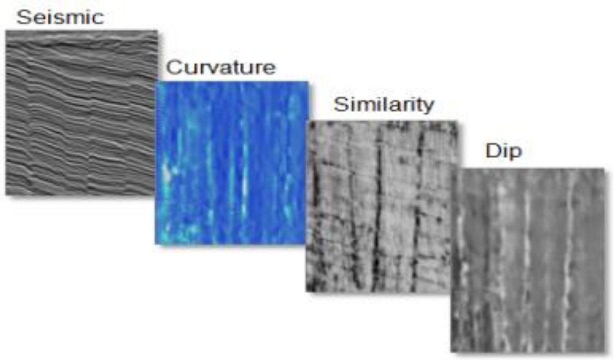


Training



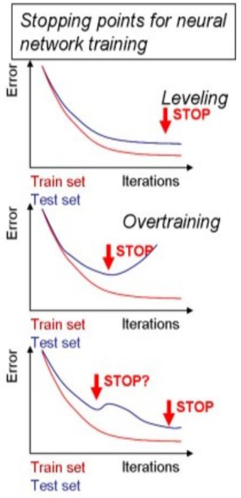
- Example picks are fed to NN



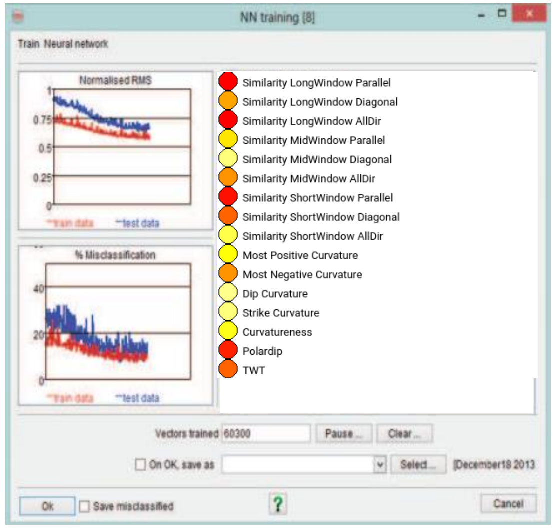


- Attributes selection

- Optimization and back propagation of error



- Proper stopping point



Validation

- Besides numerical validation using the test set, a secondary validation might be needed to correct neural network prediction.

- The outcome of neural net work should fit with the standard geological understanding.

- If neural network fails validation, neural network input can be improved by selecting more attributes or deselecting attributes that do not contribute to neural net work training

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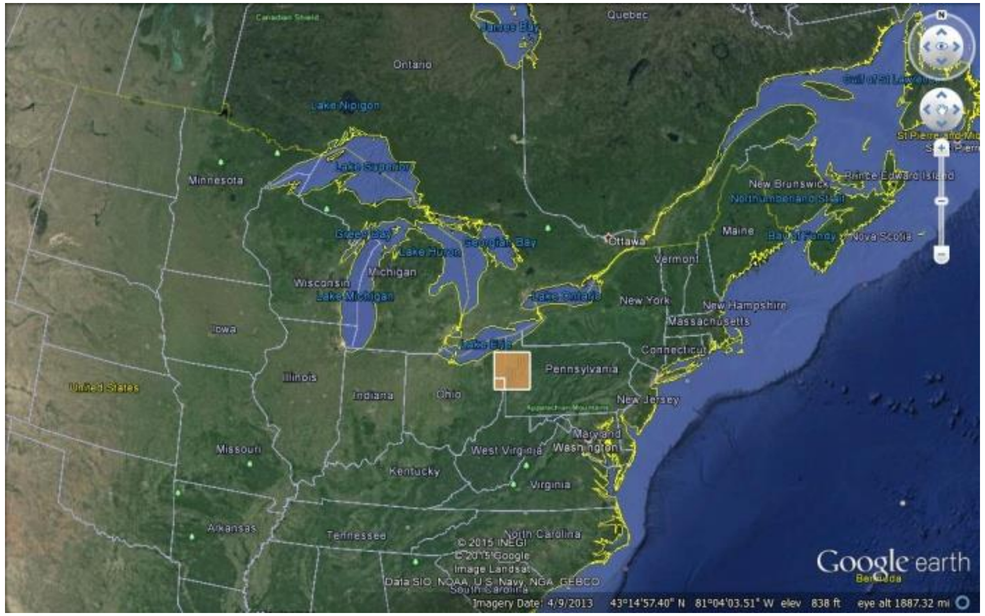
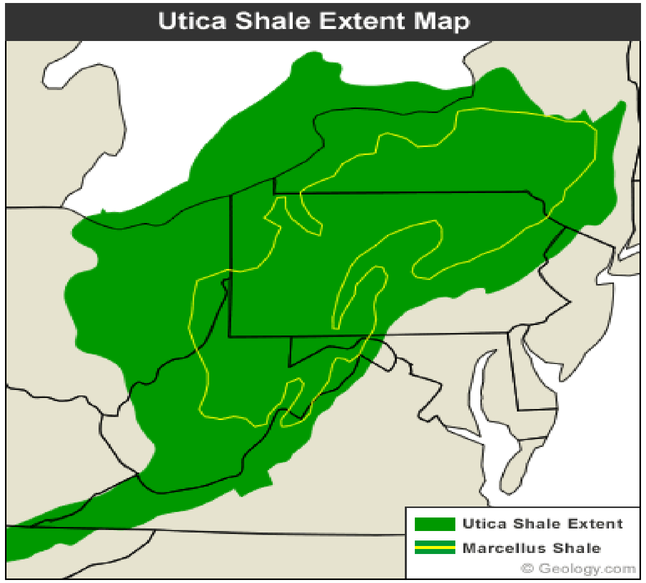
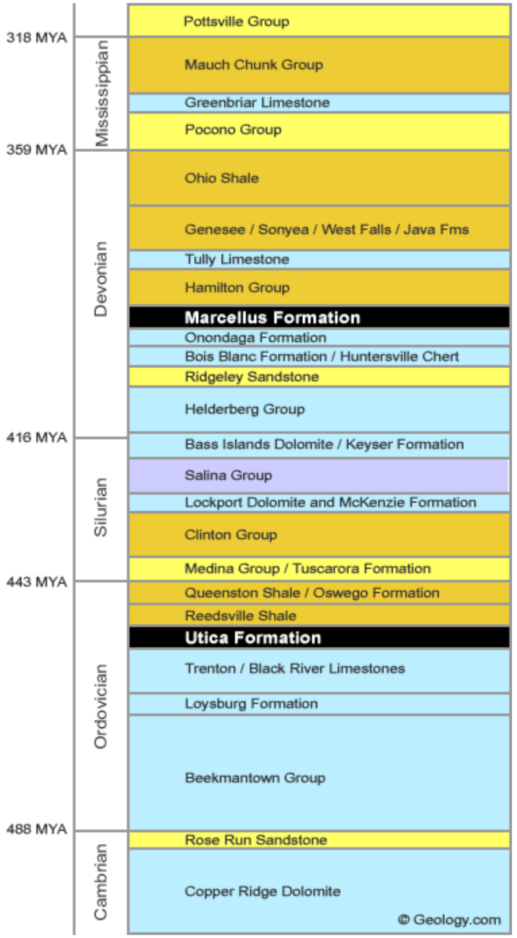
Case Study 1: Utica Shale

Location

- Appalachian Basin, Ohio
- One of the most prolific unconventional play in US.
- Very large geographic extent, few thousands feet below Marcellus (3000-7000ft).
- Large amount of natural gas

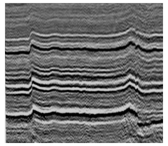


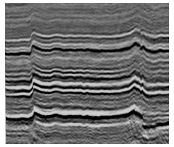




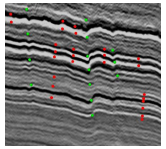
Workflow

Raw Data



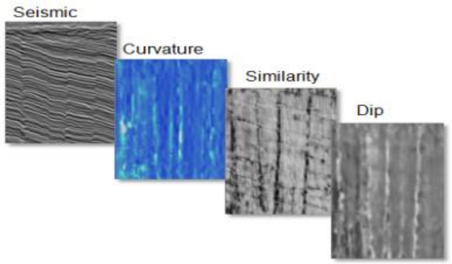


Enhanced Data

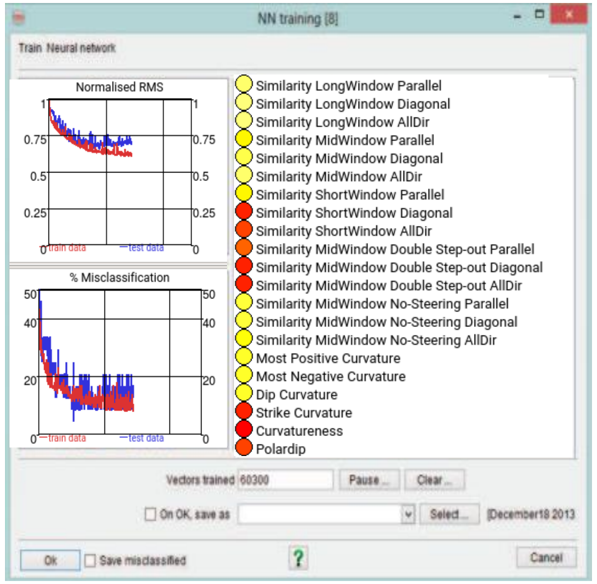


Picks example

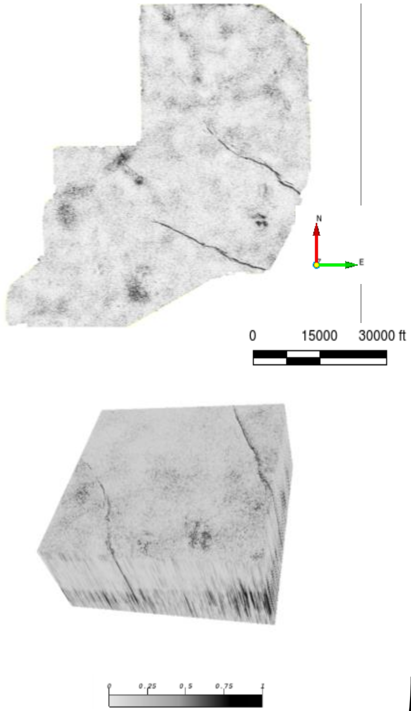
Attributes



Training



NN Results



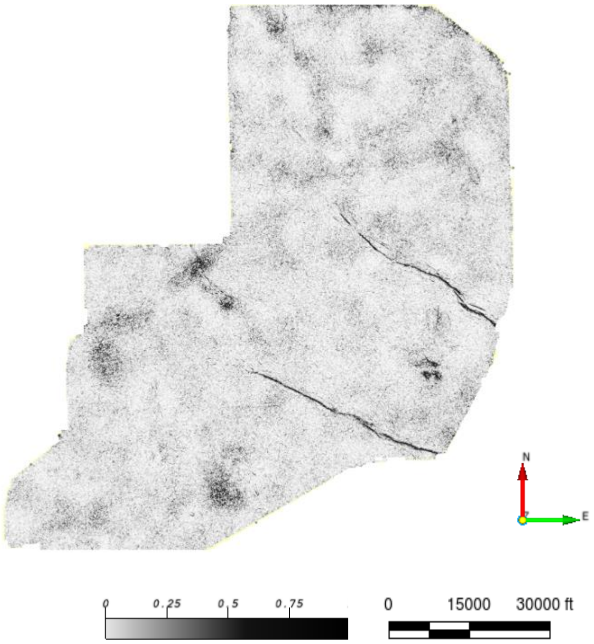
Input

Output

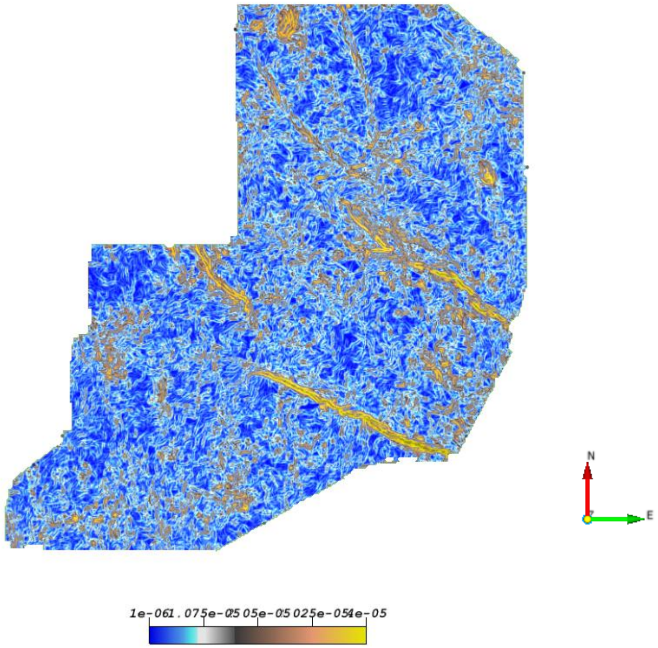
Neural Network Prediction

- It highlights main geological features
- Maps out fracture network
- Robust solutions to many problems (mapping out faults & fractures) compared with one single attribute

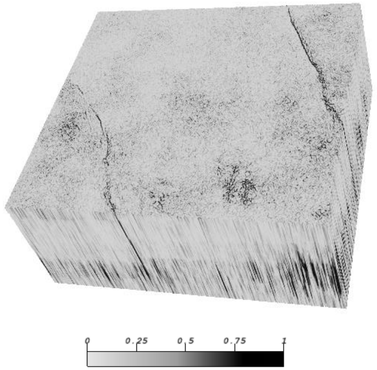
NN faults prediction



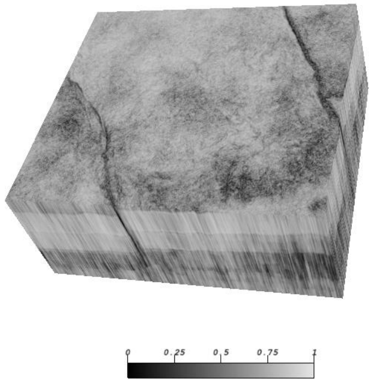
Curvature Attribute



NN faults prediction



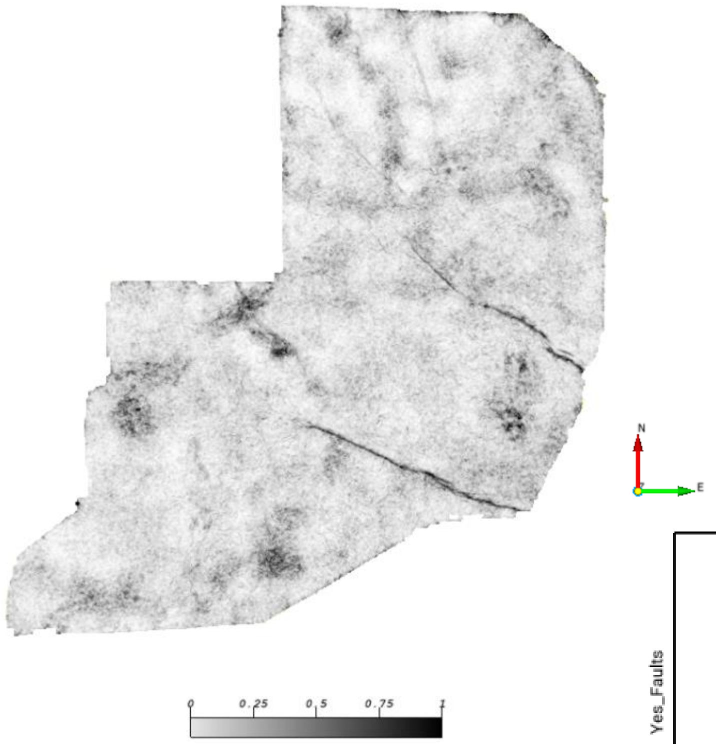
Similarity (coherency volume)



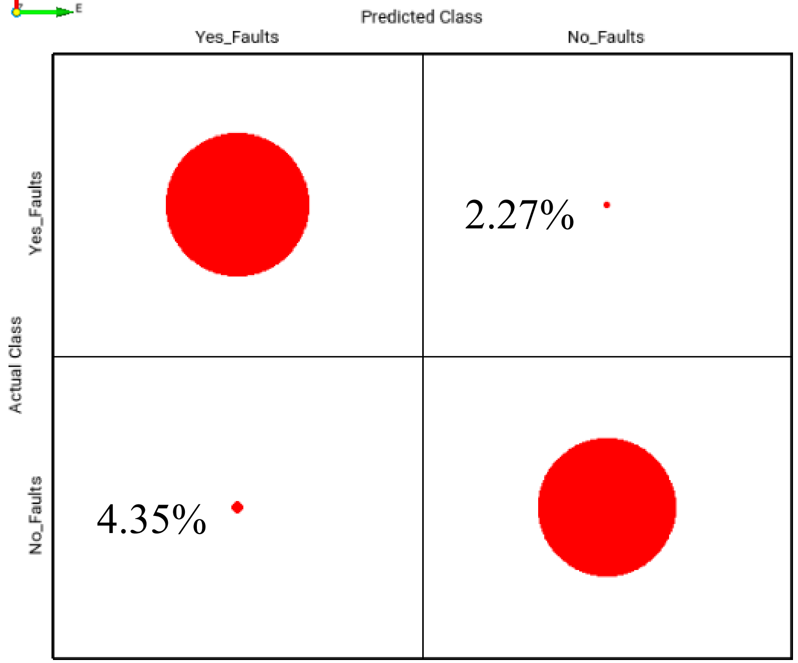
Neural Network Prediction

- Success Rate: 93%.
- Misclassification Rate: 7%

NN faults prediction

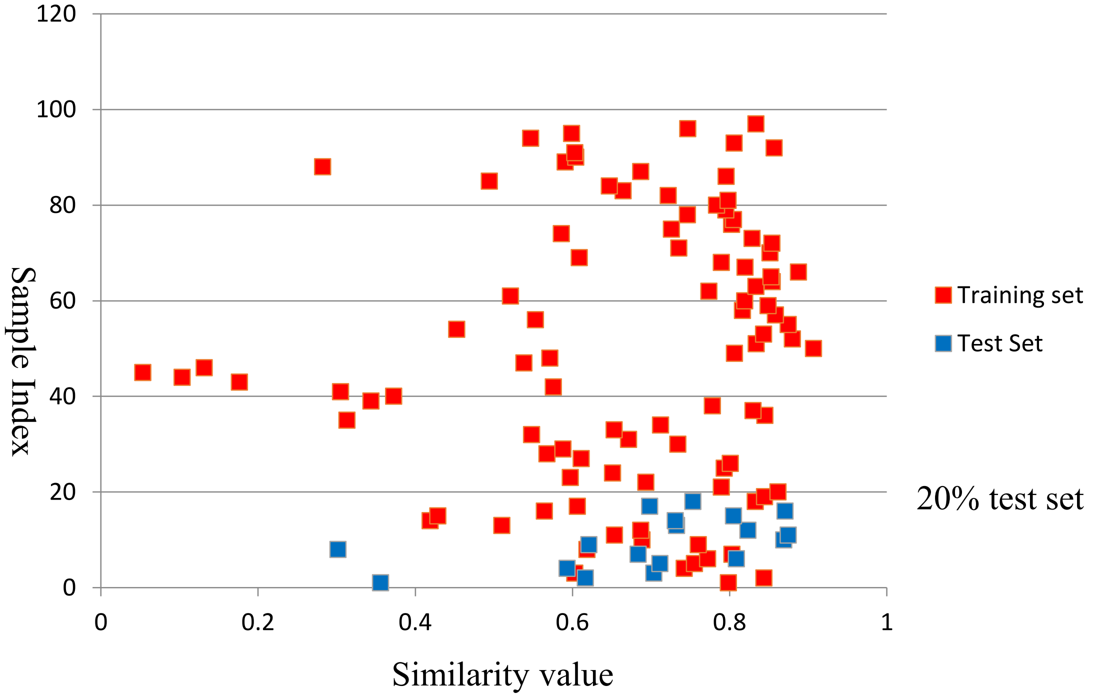


Confusion Plot

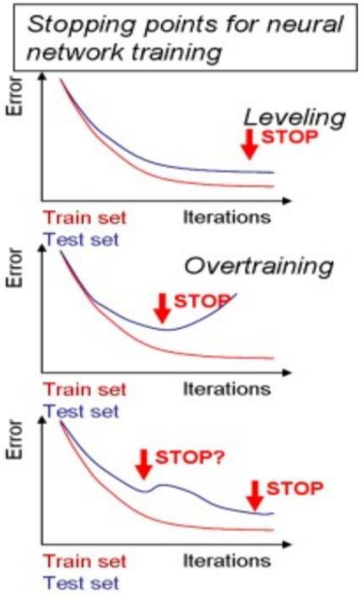


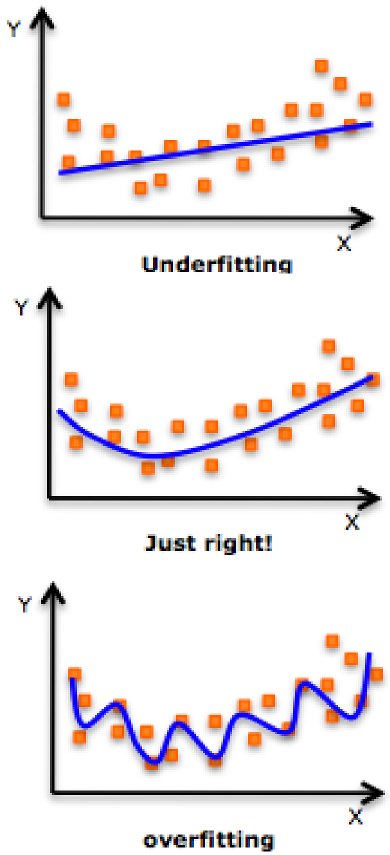
Pitfalls with Neural Networks

- Training (and test) sets may not be representative for the problem
- Training time

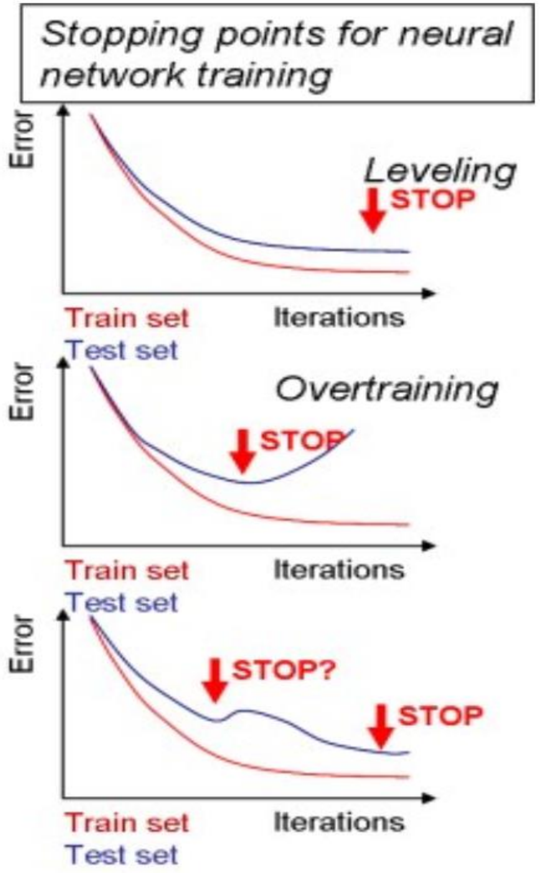


20% test set

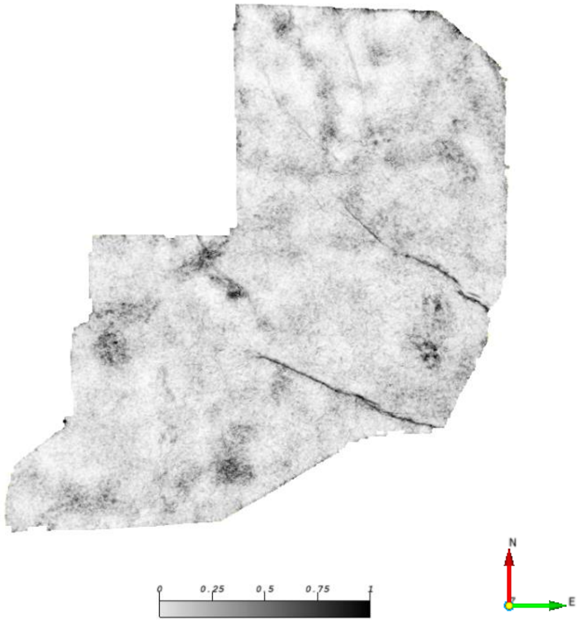




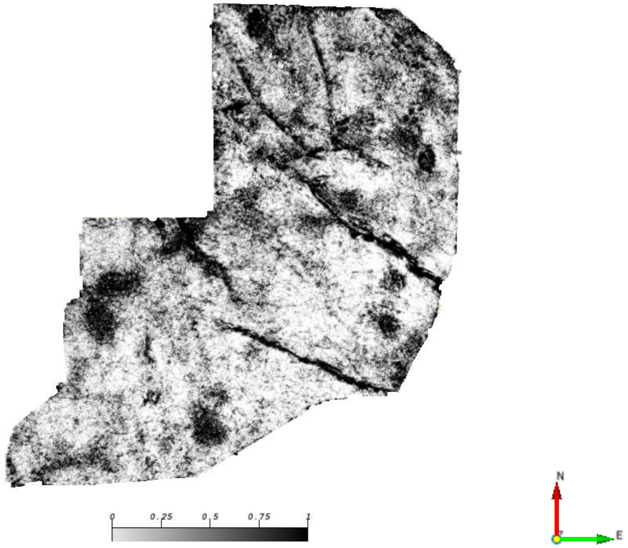
Pitfalls with Neural Networks

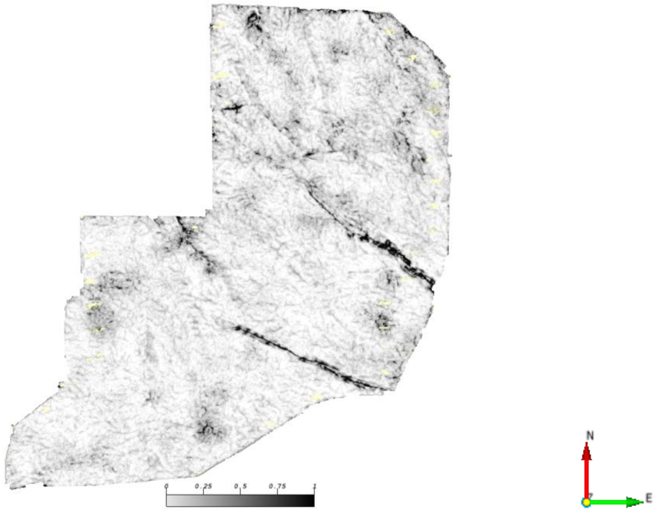


Sufficient training
SR: 93%



Insufficient training (long)
SR: 78%





Insufficient training (short)
SR: 89%

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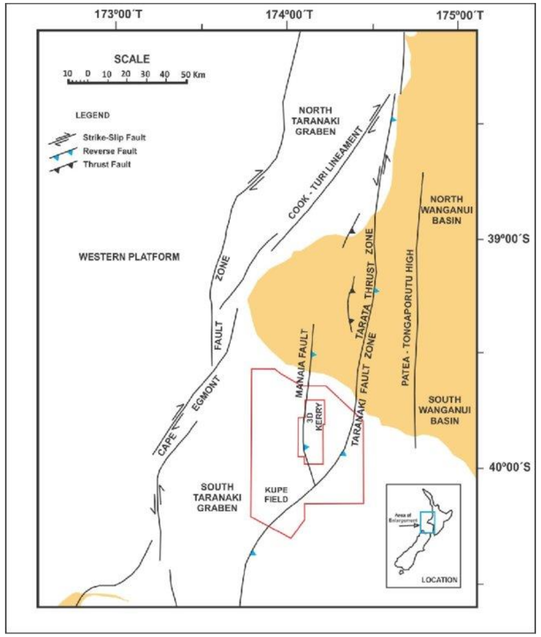
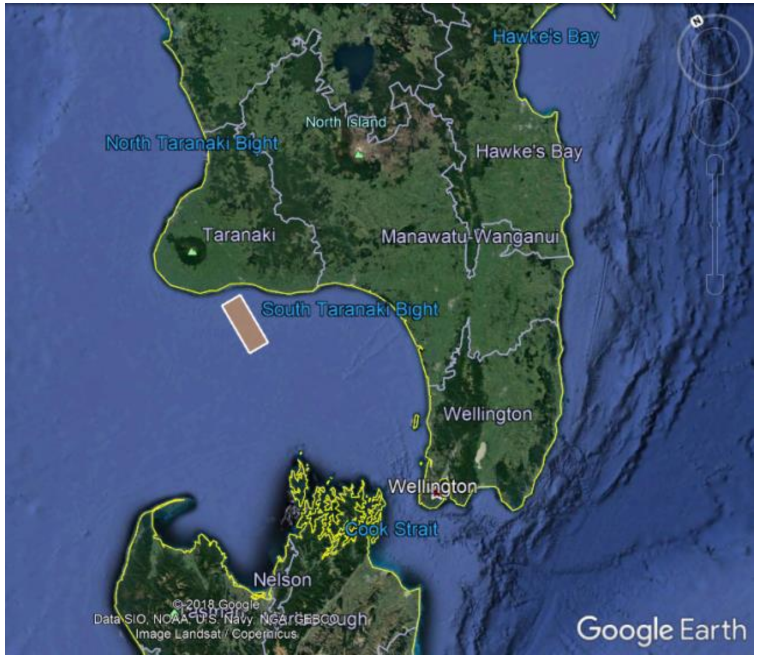
Case Study 2: Kupe Field, Taranaki Basin, NZ

Location

- Taranaki Basin is an offshore basin covering an area of around 100,000 km2
- Basin structure development controlled by major structural elements

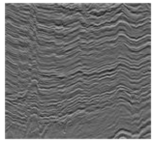


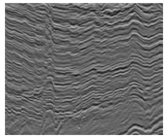


Palmer and Bulte, 1991

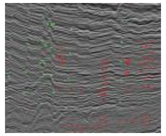
Workflow

Raw Data



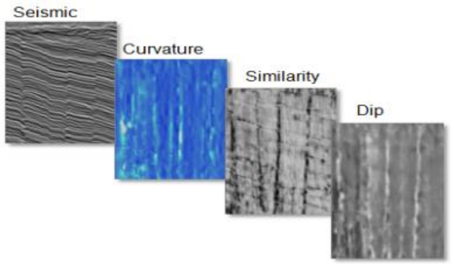


Enhanced Data



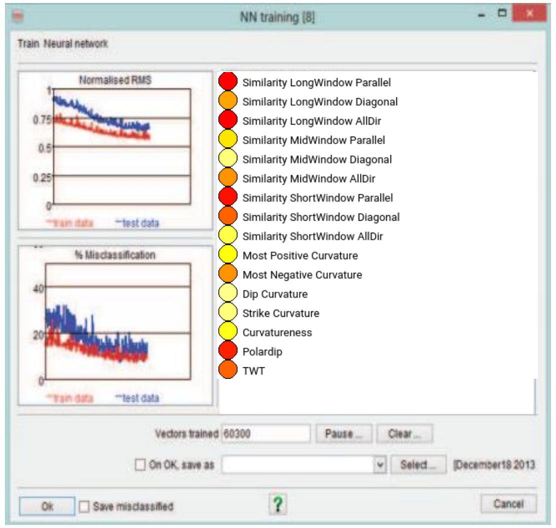
Picks example

Attributes



Input

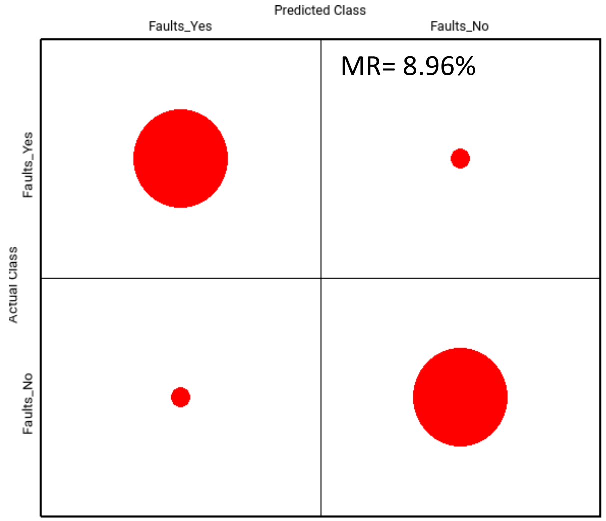
Training



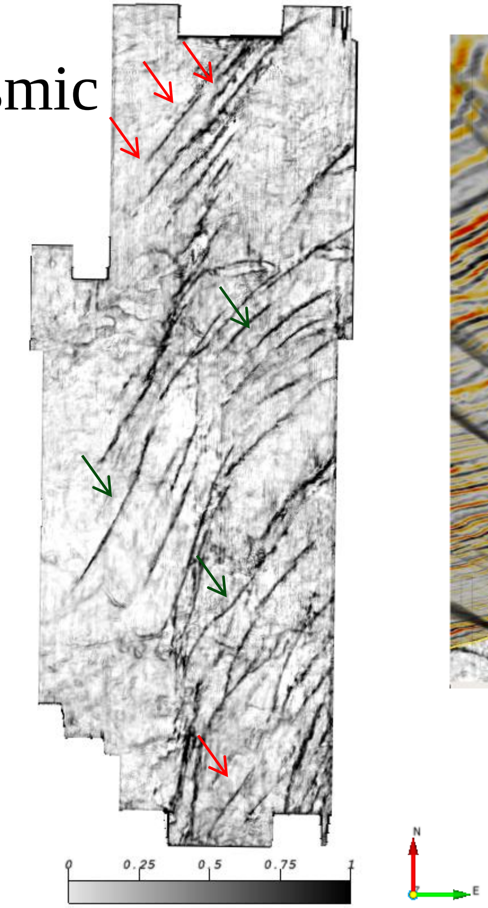
Output

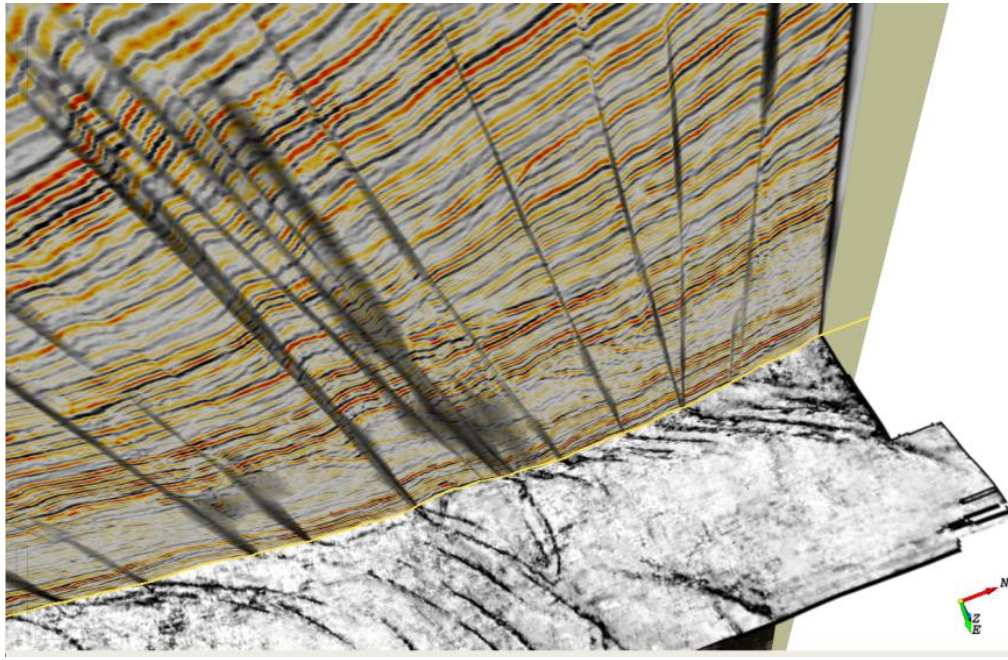
Neural Network Prediction

- Faults are clearly defined , on seismic section and time slice
- Success Rate (SR): 91%
- Misclassification Rate (MR): 9%

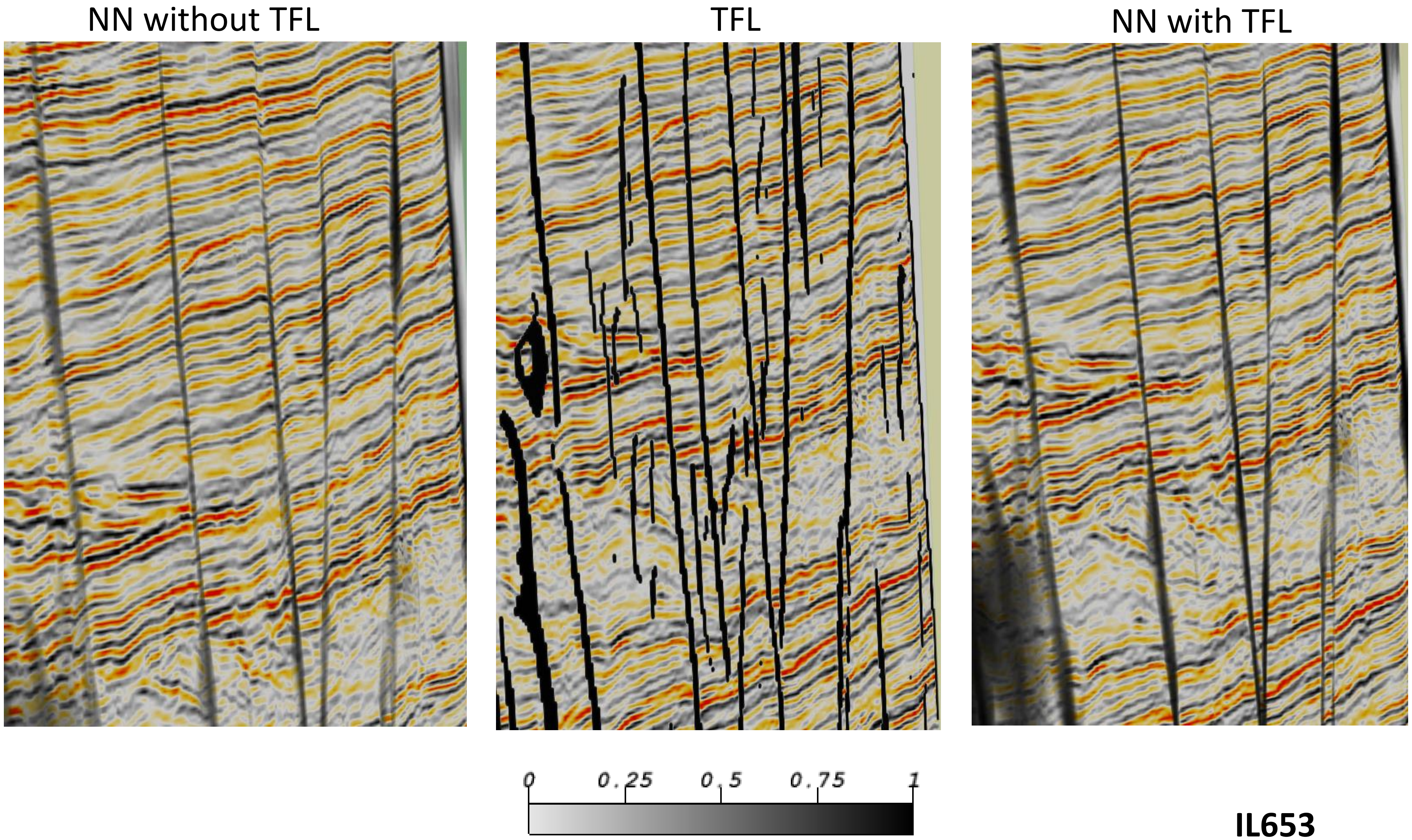


Confusion Plot





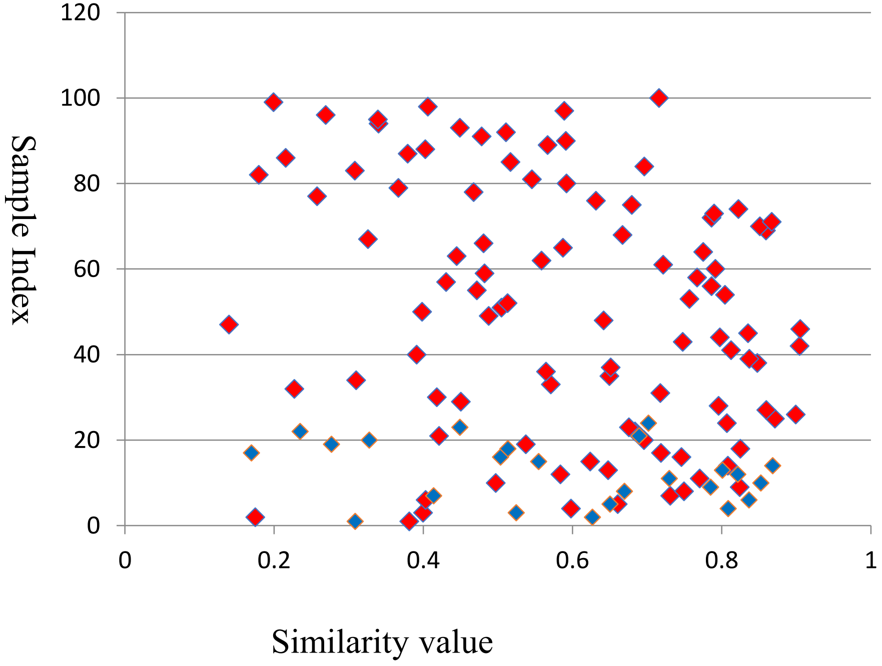
Meta-Attributes NN Results Vs. TFL

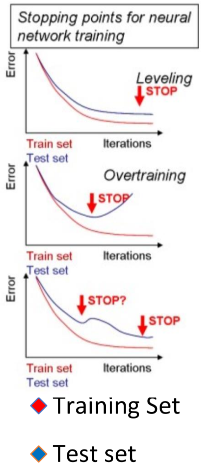


- Thinned Fault Likelihood (TFL)
- TFL used as an input to improve NN prediction
- Noise free

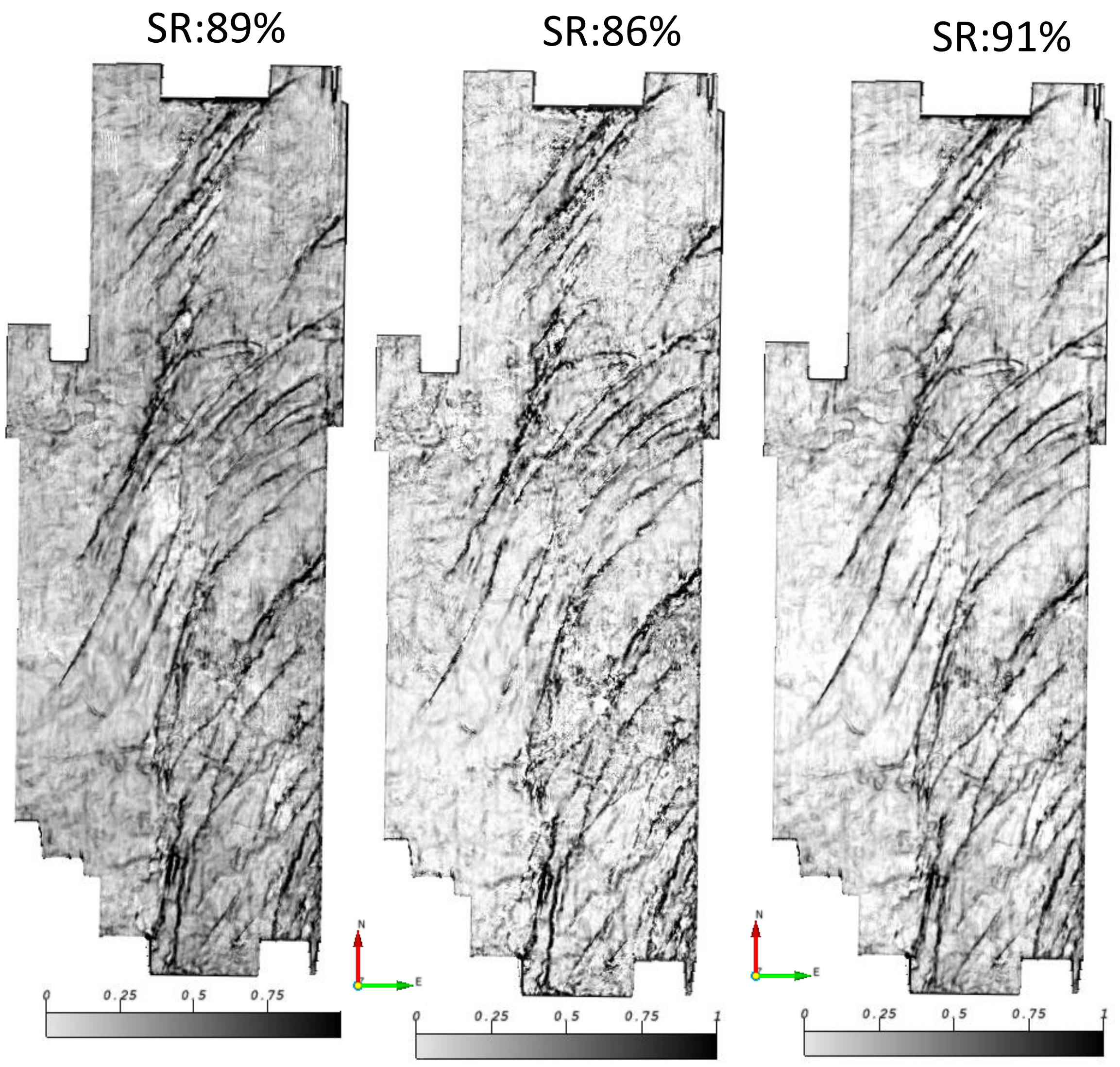
Pitfalls with Neural Network

- Insufficient training:
- Over fitting by training the NN more than it should
- Or by stopping the training too early.





% 20 test set
% 80 training set



Insufficient training (short)

Insufficient training (long)

Sufficient training

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Conclusions

- The quality and the quantity of the data, determines how good the predictive model can be.

- Demonstrated machine learning capabilities to map out a network of faults and fractures in conventional and unconventional data set.

- Using meta- attributes, machine learning enabled us to better visualize and understand the faults and fractures density in the study areas.

- The application of machine learning in seismic interpretation shows a great promise in oil and gas exploration

References

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Questions?