Quantitative QC for seismic machine learning

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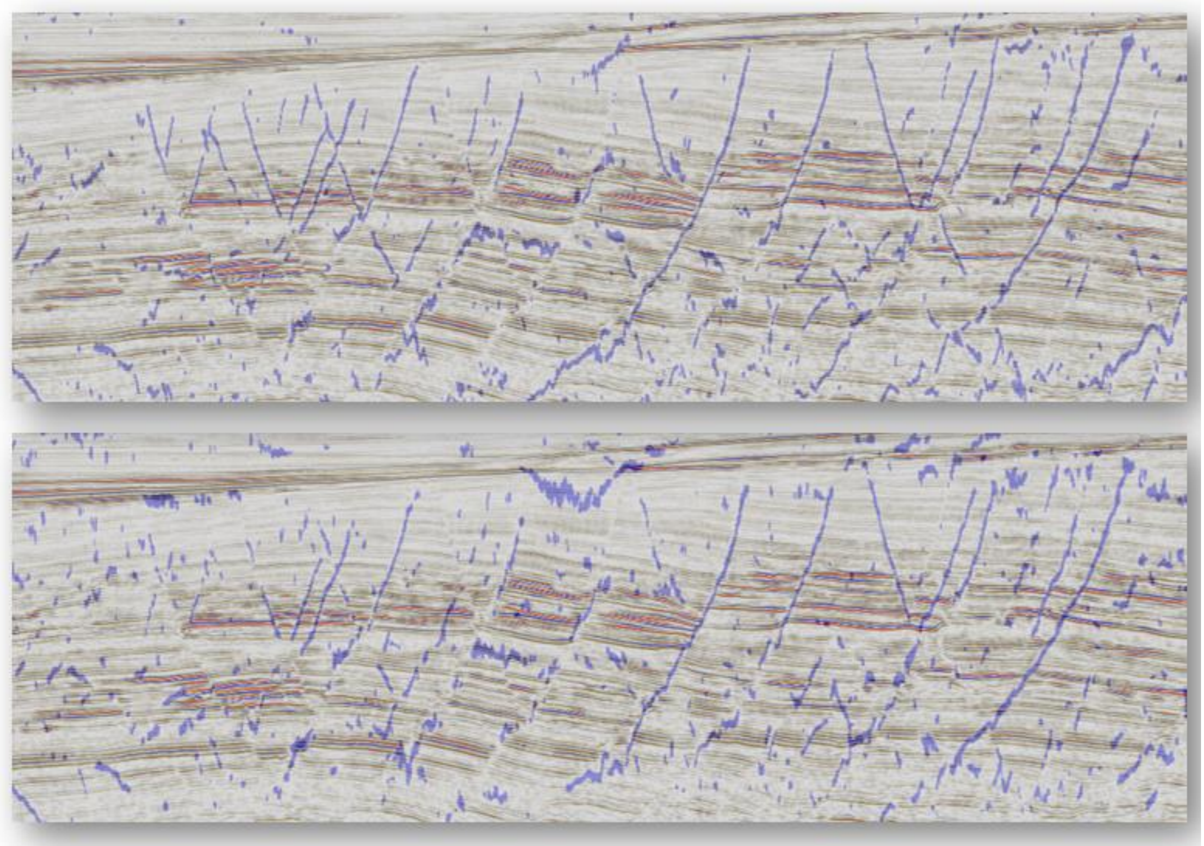
One of the biggest challenges in the oil and gas industry is how to improve efficiency and reduce the time taken to get to production of oil and gas.

An example of a task that would benefit from improved efficiency is the seismic interpretation process. Traditional seismic interpretation is a laborious and time-consuming task often taking weeks of effort for a skilled geoscientist. To speed this process up, machine learning (ML) is beginning to be used to automate some of the tasks. Automation of the process reduces the interpretation time and allows a geoscientist to focus on more important duties instead of spending most of their time manually interpreting.

The use of automated ML brings its own challenges: if 20 different ML results are available, how does a geoscientist pick which results are the best? The human visual systems are highly robust and can easily pick out the best result from a few examples; picking the best result from 20 examples starts to be difficult, and picking the best from 100 examples is almost impossible. The challenge with this project is how to provide a quantitative score for different seismic interpretation results.



Two different fault interpretation ML results: what result is better?

Based on a set of seismic machine learning results, this project aims to solve the following tasks:

1. Examine and implement a range of techniques which can be used to compare machine learning results against a geoscientist provided set of interpretations and rank the results.
2. Examine and implement a range of quantitative techniques which can be used to rank different machine learning results without user input.

Data

We will provide one labeled public seismic dataset from offshore northwest Australia. The data will be delivered in either CSV or binary generic format, such that the files (input seismic data file and label file) can be easily read programmatically in any programming language:

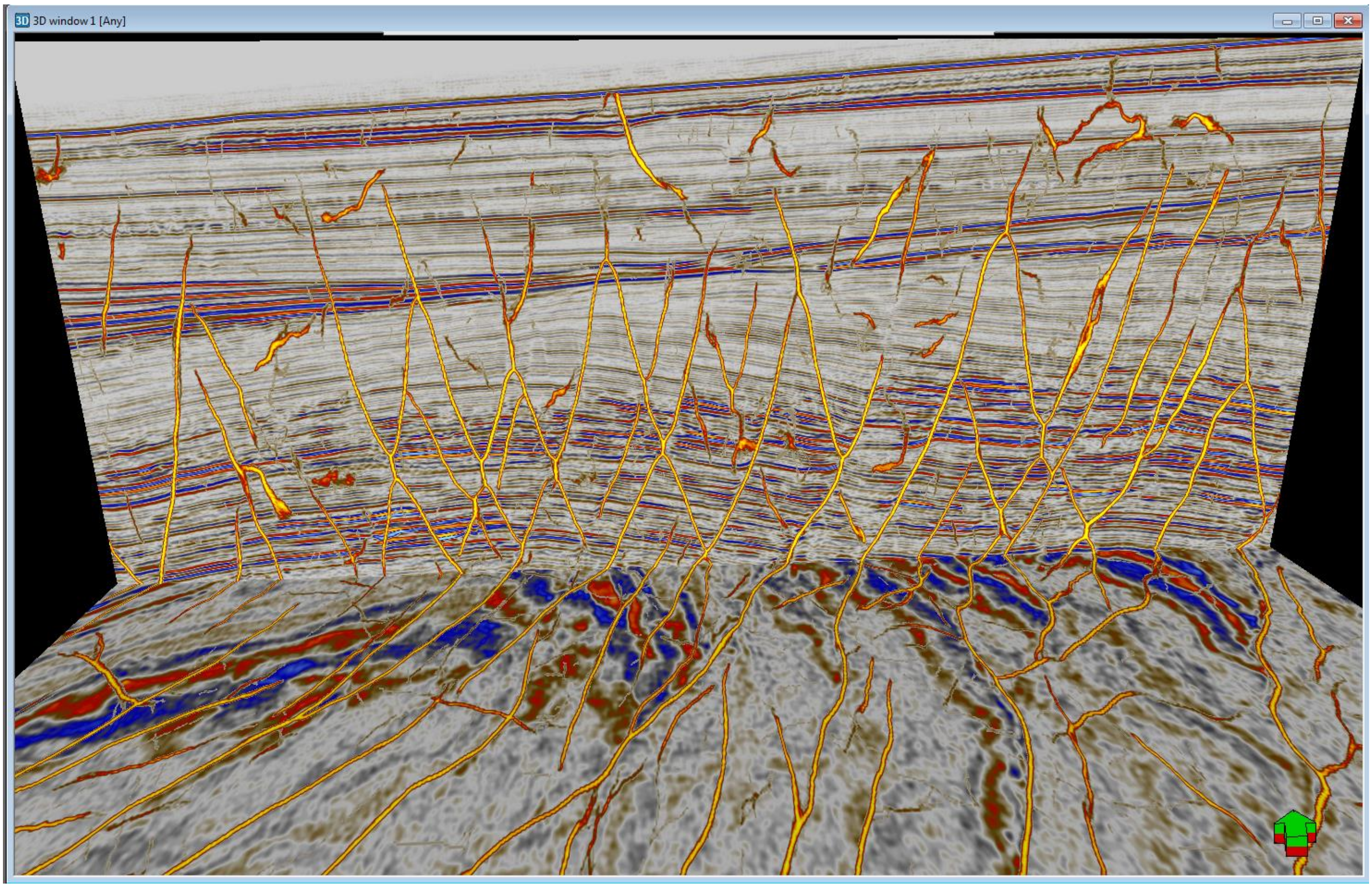


***Figure**: Input 3D image (in red-white-blue color scale), overlaid with fault labels (in yellow)*

Each 3D file will contain circa 1000 x 1000 x 1500 = 1.5 billion samples in 32-bit format (which is 6 GB each, in binary format). The data is already available on a computer at NTNU.

For the benchmarking data (a set of Machine-Learned predictions), we see two optional tracks:

a) **12-month duration track:** Use a sub-set of the provided labeled data to train a set (at a minimum three) of ML models, and use them to benchmark their quality, using your improved metrics for ML interpretation
b) **6-month duration track**: Add various types of noise to the provided labels, and then use those noisy labels as substitutes for actual ML predictions. Then measure the degradation in quality of those synthetic prediction results.

Even more datasets, with the same details, but covering images from the underground from other parts of the world, can be provided as needed.

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