Accelerating the Seismic Interpretation Workflow using Machine Learning

Introduction

Machine learning (ML) assisted seismic interpretation marks a fundamental shift to the means of extracting value from seismic data and has the potential to transform the role of geoscientists. Seismic fault and horizon interpretation form a critical part of the subsurface evaluation workflow, better informing our understanding of structural trends and the region’s tectonic history. Fault frameworks and horizon surfaces act as a direct input for a multitude of upstream workflows, with machine learning providing the next step on the path to automation. Seismic interpretation still poses a major operational challenge in the subsurface evaluation workflow, as the conventional approach requires the geoscientist to manually interpret faults and horizons line by line or use semi-automated tools which demand expertise and extensive parameterisation to carry out. This approach is not only inefficient, but frequently yields inconsistent results due to the subjective nature of identifying seismic reflector terminations and changes in seismic character due to varying signal to noise ratio.

In this contribution we will demonstrate how the application of a geoscientist driven machine learning workflow, in conjunction with elastic cloud compute technology, has the tremendous potential to significantly improve interpretation efficiency and provide enhanced geological insights. We will explore how geoscientists can input a few labelled seismic intersections to guide and fine tune the ML fault prediction and demonstrate the application of the workflow to a broadband seismic dataset from the Loppa High area in the Barents Sea (Lie et al., 2018). Using innovative new tools, the planarity and azimuth of the faults were evaluated, prior to the definition of fault extraction and segmentation to create a 3D fault framework. To complete the ML assisted seismic interpretation workflow, a handful of ‘seed’ points were input to a ML horizon model to predict horizon interpretations across the dataset. Finally, the acceleration of seismic interpretation through machine learning enables geoscientists to build multiple credible structural framework scenarios, benefitting wider subsurface modelling workflows by better capturing uncertainty and aiding geoscientists to make more informed decisions.

Methodology

Seismic fault prediction was performed using deep convolutional neural networks (CNNs) using a supervised machine learning approach (Waldeland, 2018), requiring geoscientists to create data specific training labels. In the current study, just 5 inlines and 5 crosslines were labelled, representing 0.1% of the seismic data. The density, complexity and scale of the labels are vital in training the ML ‘brain’, which predicts fault probability on a voxel by voxel basis throughout the seismic volume (Fig 1).

![Figure 1a](image1a.png) **Figure 1a** Intersection with seismic amplitude data blended with a fault prediction volume. Fault training labels (green). Fault validation labels (blue) act as a quality control for the prediction. **b** Fault prediction volume rendered in 3D displaying a continuous and consistent fault prediction.
Another key step of the ML workflow is the extraction and segmentation of faults from the fault prediction cube. Two attributes, planarity and azimuth, were generated from the fault prediction cube using geometric analysis of the eigen values and eigen vectors through principal component analysis. The planarity attribute was used to determine where two distinct fault planes intersect, assigning a value between 0 (no flatness within the search radius) and 1 (completely flat within the search radius). The azimuth attribute provides further opportunity to distinguish between fault planes and understand the orientation of the faults.

The extraction of fault planes from the planarity and azimuth volumes is a crucial stage of the workflow, enabling geoscientists to control the nature of, and relationship between faults using a series of extraction parameters. A planarity threshold was applied to the fault points to determine an acceptable level of variability within a fault plane before being extracted as two separate faults (Fig 2). Azimuthal sectoring was utilised to align the extracted fault planes to the stress regime of the Loppa High area.

![Figure 2a Fault prediction time slice. b Planarity attribute time slice, values 0-1. A planarity threshold (0.55) was applied to produce distinct fault planes.](image)

The potential for multiple sets of fault prediction training labels and customisable fault extraction parameters leads to multiple fault framework outcomes (Fig 3), contributing to the evaluation of structural uncertainty.

![Figure 3 Intersection with seismic amplitude data blended with a fault prediction volume. The extracted faults are geologically consistent with valid truncations.](image)
Machine learning was used to generate horizon interpretations, complementing the ML fault framework and completing the automation of the seismic interpretation workflow. Radial basis functions were used alongside neural network models (Tschannen, 2020) to minimise the amount of input data required to train the ML brain. Using two seismic intersections, several seed data points were labelled within key fault blocks to generate Horizon 1 (Fig 4a). A horizon confidence volume (Fig 4b) was created to guide the tracking of seed points across the seismic dataset (Fig 5), while also acting as a quality control for further interpretations.

**Figure 4a** Seismic amplitude intersection blended with fault prediction. Seed points (purple) and Horizon 1 interpretation prediction (light blue). **b** Confidence intersection blended with fault prediction. Seed points (purple) and Horizon 1 interpretation prediction (dashed light blue).

**Figure 5a** Topographical view of Horizon 1. Horizon 1 was one of several ML horizon surfaces which served as inputs to the structural model. The ML fault framework (orange) was used to segment the tracking algorithm, reducing pick uncertainty at seismic discontinuities.
Figure 6 displays the final gridded subsurface model generated from the extracted ML fault interpretation (Fig 3) and ML horizon interpretation (Fig 5).

*Figure 6* Structural model incorporating the ML generated faults and horizons. Zone 3 (white-blue) and Zone 4 (white-purple) with 10 layers each.

**Conclusions**

This contribution presents the basis for the transition to machine learning for interpreting faults and horizons on seismic data. The new workflow aims to liberate geoscientists from a repetitive manual approach, which binds the user to a limited range of subjective seismic interpretations. The application of convolutional neural networks to predict fault frameworks reduced interpretation time from months to days, while a radial basis function model required a minimal number of seed data points to track horizons across the seismic dataset.

The automation of interpretation tasks through machine learning also shifts the focus of geoscientists from producing a single best-case scenario to a range of objective model outcomes, which capture structural uncertainty and lead to better informed decisions. Machine learning, combined with innovative new tools and parameterisation, can revolutionise our industry, empowering geoscientists to gain faster and improved geological insights.

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**References**


Tschannen, V. et al. 2020 Extracting horizon surfaces from 3D seismic data using deep learning. GEOPHYSICS, 85(3):N17