

## “Old” Big-Data Awakened to New Life with AI / ML Processing

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### Abstract:

Vintage seismic 3D data cover large areas in mature petroleum provinces. On the Norwegian shelf most of the data is part of the public domain and has on several occasions been merged into large 3D surveys (Mega-Merge). While these surveys are great tools for regional geological analysis, they also represent an enormous amount of data that can be used in big-data analysis leading to new understandings.

AGGS, PSS-Geo and Cama Geosciences are working as a consortium combining seismic big-data and well data with AI and ML processes integrated in a geological context. In a R&D project sponsored by Lime Petroleum and Innovation Norge (IN 2020\_521538), we develop methods to predict lithology and fluids from well and seismic data using Artificial Intelligence (AI) and Machine Learning (ML) techniques.

Our workflow is divided into two parts. For the first part we used an Artificial Intelligence inversion (annealing global optimization) to estimate P- velocity and density from post-stack seismic data. Further, the inverted volumes are used to compute Volume of Clay (Vcl), Porosity (Phi) and Reservoir Quality  $((1-Vcl)*Phi)$ . This method, the Rune Inversion, has been tested on Mega-Merge seismic data of Mid-Norway (60 000 km<sup>2</sup>) and proved highly successful (Fig. 1). We will discuss advantages and limitations for the interpretations of this inverted Mega-Merge data.

In the second part, we are investigating fluid detection from seismic Mega-Merge data. Since the post-stack Mega-Merge seismic does not contain S-wave related information, we are investigating possibilities of using ML techniques with well data as training input to predict fluid and specific fluid type. The basic principle of such automation is to find relationships among attributes for identifying fluid. Well-logs have been used as input for training, testing and validation. The learning process considered the following log data; registration time (T), density (DEN), acoustic p-velocity (Vp), porosity (Phi), volume of shale (Vcl), P-impedance (P-imp) synthetic seismic trace and its eleven attributes. The target parameter is water saturation (Sw). An indicator was defined as 0 for brine and 1 for hydrocarbon (HC), with a cut-off on Sw-log for more than 60% of HC.

In a first approach, we used full-stack seismic data and its eleven attributes as recognition data set; and in a second approach, inverted seismic data, DEN, Vp, Phi, Vcl and P-imp. The tests included Logistic Regression (LogReg), Gaussian Naïve Bayes classifier (GNB), Support Vector Machine (SVM) classifier, Gradient Boosting classifier (GBC) and Multi-layer Perception classifier (MPLC algorithms).

The well-to-well ML predictions of water-saturation proved to be successful, and high R-scores were archived by LogReg method. Recognition from full-stack seismic data and its eleven attributes gave low R-scores for all algorithms, GBC having the highest. Using AI inverted volumes as recognition set, however, resulted in high R-scores and accurate fluid prediction for all algorithms. We will here present examples for all investigated cases, including first results from 2D seismic sections and a small 3D test-cube.

Our ongoing research on AI and ML processing of vintage big-data 3D seismic (Mega-Merge) appears to give good results that yield new insights in the petroleum system of the Norwegian Continental Shelf.

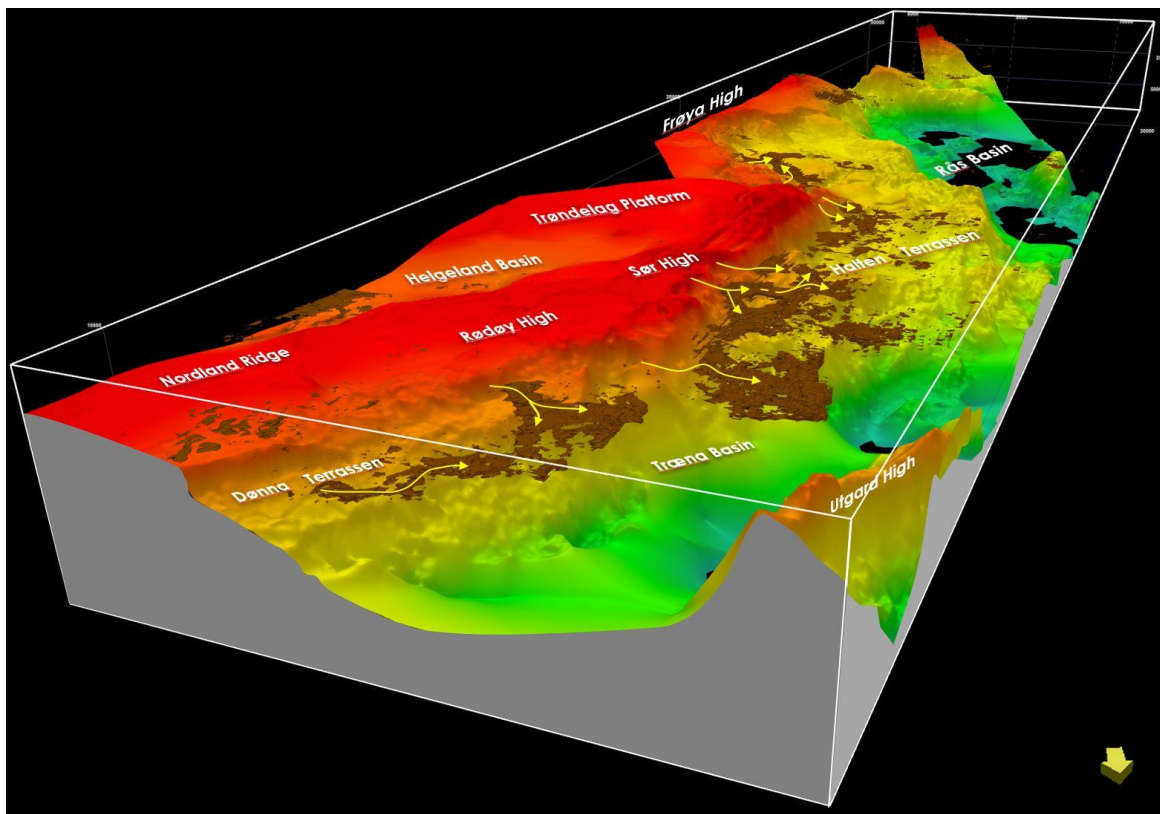


Figure 1 Volume extraction of the Reservoir Quality Attribute  $((1-V_{cl}) \cdot \Phi)$  from AI inverted post-stack seismic data of a Mid-Norway 3D-MegaMerge. The volume extraction shows the distribution of good reservoir Lysing Formation. 3D map is the Base Cretaceous Unconformity.