Machine Learning in Petroleum Geoscience: Constructing EarthNET

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Underutilization of data due to a lack of time, and insufficient calibration of geophysical methods are just two of the causes behind the disappointing exploration results on the NCS during the last 5-6 years. Our failure to utilise and integrate available data is partly a result of the inefficiency of traditional methods of data analysis, which typically require large amounts of human and financial resources to be spent, and the deployment of costly analytical techniques. The as-yet untapped potential of efficient analytical techniques that utilize all relevant data encourages us to further develop novel data analysis methods.

Our approach to developing more efficient and precise analytical techniques is based on artificial intelligence (AI) and machine learning (ML) technology; i.e. algorithms that can learn and make predictions directly from data. One key advantage of ML in science is the technology's ability to efficiently handle very large volumes of multidimensional data, thus saving time and cost and, therefore, allowing human resources to be deployed to other, perhaps more creative, tasks. Another advantage is ML's ability to detect complex, multidimensional patterns that are not readily visible to humans.

We aim to solve the data under-utilization problem described above by implementing ML techniques in petroleum geoscience. By doing so, we aim to provide more reliable and efficient methods for data analytics, and ultimately reduce the number of costly, unsuccessful wells.

Previous studies of the application of ML to petroleum geoscience problems have typically focused on a single task using limited data types. For example, ML-based studies using borehole data has allowed us to predict sedimentary facies, porosity, permeability and fluid saturation, whereas those using seismic data has permitted identification and prediction of reservoir architecture by automatic labelling of geological features observed in seismic attributes. More recently, the as-yet-unrealized potential of ML to help analyse integrated subsurface datasets has been illustrated (e.g. prediction of petrophysical properties, such as resistivity, from a combination of wells and seismic attributes).

We are developing machine-learning technology that can learn from, and make predictions based on, a combination of wireline log data and lab-derived measurements. These algorithms are used to predict rock- and fluid properties that are not directly measured by the wireline logging tools, in wells (or parts of wells) from which lab data are not available. More specifically, we are researching methods for prediction of property data related to; i) source rocks (e.g. TOC, HI, and vitrinite reflectance), ii) reservoir rocks (e.g. porosity, permeability, and fluid saturation), and iii) seal rocks (e.g. fracture pressure and capillary properties). We also focus on predicting electrical properties (e.g. conductivity, horizontal and vertical resistivity), and acoustic properties (e.g. shear velocity, and elastic parameters), which is used as input to ML-assisted geophysical predictions.

The geophysical part of our project is focused on relationships between well data and remote sensing (seismic and CSEM) data. We investigate how algorithms trained on different combinations of various seismic attributes and well data affect the accuracy of rock- and fluid property prediction. We explore how algorithms can be trained on a combination of seismic, CSEM, well data, rock- and fluid properties in relatively data-rich 'reference' areas, in order to predict rock- and fluid properties based on both seismic and CSEM data where data are sparse. By integrating ML methods with current methods of direct lithology and fluid prediction from geophysical data (e.g. seismic AVO and seismic and CSEM inversion), we aim to mitigate the non-uniqueness problem inherent to each individual geophysical technique. Our ML-approach will provide calibration data for geophysical methods, by making large-scale *a priori* rock- and fluid-property data accessible.

We strongly believe that, by researching, developing and deploying this technology, we will provide more efficient and accurate analytical methods that can ultimately transform petroleum geoscience into a much more data-driven science.