**Use of Neural Networks for Interpretation of Geophysical Wellbore Data**

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**Research Goals**

The goal of this research project is to develop machine learning models that can effectively analyze geophysical wellbore log data from the Illinois Basin. Specifically, these models will be utilized to infer the presence of fractured intervals in geological formations.

The first research task is the manual analysis of the geophysical wellbore log data to create a comprehensive dataset of fractured intervals in involved geological formations. The main research focus will be training machine learning models with the created dataset to predict potentially fractured intervals from the limited geophysical log data.

**Background**

Fractures play a crucial role in geoenergy projects because they enable fluids to flow through rock formations. In the context of carbon capture and storage (CCS), fractures can compromise the integrity of storage sites, acting as potential leakage pathways for CO2 (Rutqvist, 2015). Moreover, the presence of pre-existing fractures is associated with a higher risk of induced seismic activity (Kivi et al., 2023). It is challenging to detect fractures with characteristic size smaller than ten meters due to the low-resolution of seismic surveys. Since fractures of this size can still impact the processes happening in the subsurface, there is a pressing need for more advanced fracture detection and prediction techniques.

Various petrophysical and mineralogical properties of subsurface formations are interdependent and affected by the presence of fractures, though their precise relationships remain largely unknown. Machine learning algorithms provide a promising framework for analyzing these intricate relationships, as they do not rely on explicit equations to make predictions. Additionally, ML eliminates the need for subjective interpretation and allows for real-time predictions, which is advantageous for fracture analysis during the project implementation. However, one significant challenge with applying ML to wellbore logs is that it is difficult to extract a sufficiently large and representative dataset that spans a wide measurement space. To address this obstacle, a combination of various classification learning algorithms for Class-Based Machine Learning (CBML) are successfully implemented for the interpretation of wellbore data (Jain et al., 2019).

**Research Method Design**

In order to produce labels for the machine learning algorithm, Formation MicroImager (FMI) logs will be examined manually to identify and characterize fractures. FMI sensors operate by measuring the electrical resistivity of rock formations along the wellbore as a function of azimuthal angle. Since most of the fractures contain water, which lowers resistivity of rock, azimuthal resistivity measurements enable the production of high-resolution images of high water content zones. As a result, FMI logs represent highly effective sources for label extraction due to their reliable and high-quality fracture identification capabilities.

To address the main research question, a nonlinear neural network will be designed to take in geophysical data from multiple wells as input and generate a binary classification indicating whether a fracture exists at a given depth. However, as most depths do not contain fractures, a general ML model would be biased toward predicting an absence of fractures. To overcome this bias, the neural network will utilize a weight cross entropy (WCE) loss function, which assigns different weights to fractured and non-fractured intervals proportional to the inverse of their frequencies. Same datasets from at least 5-6 wells will be used for training and testing the ML model to broaden the range of fractured formations to be properly characterized. To optimize performance, hyperparameter tuning programs will be used to determine the most effective settings for the network depth, number of neurons, and learning rate. In addition, dimension reduction techniques such as principal component analysis (PCA) and T-SNE clustering will be employed to identify the dominant features within the dataset and their relative importance. The model will then only consider the n most significant features that results in the most optimal performance and suggest the most cost-effective geophysical exploration program for coming CCS projects.

**Potential Benefits**

The Illinois Basin has an excellent history of pilot and demonstration-scale CO2 injection projects, positioning it as a promising potential hub for CCS with numerous commercial-scale injection sites (Greenberg et al., 2018). Since the presence of fractures in geological formations increases the risk of an induced seismic response and CO2 leakage, it is essential that these injection sites are properly characterized before project deployment. While well-boring produces high-quality information about the ground composition, it is expensive, one-dimensional, and data interpretation can be time-consuming. Reliable fracture prediction techniques that operate quickly and at a regional-scale will therefore play an invaluable role in guaranteeing the safety of various injection site locations. This research project has the potential to advance machine learning techniques that can be leveraged to improve the quality of geophysical wellbore data interpretation for the upcoming CO2 injection projects in the Illinois Basin.

**References**

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