Automatic rock classification and scaling from core data to well log: Accelerating potential CO2 storage site characterization using machine learning

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Summary

We propose a framework for automatic rock classification at the well log scale from core data using machine learning and physics-based methods. To accelerate the petrophysical interpretation of well logs using core data, we propose an automatic classification framework to estimate rock classes along a well using core data. The proposed framework compares the estimated rock classes from four different unsupervised machine learning methods and three different conventional physics-based methods. The benefit of this approach is its ability to rapidly estimate rock classes at the log scale from core data without the need for manual interpretation. We validate with data from 2434 wells in the Gulf of Mexico. The framework can be used to estimate the spatial distribution of rock classes at the basin scale to identify potential sites for CO2 storage.

Introduction

Rock classification is a common practical approach to enhance reservoir description, evaluation, modeling, and simulation. Rock classification is also critically important to characterize potential CO2 storage sites and identify sweet spots based on permeable units bounded by impermeable seals (Bachu et al., 2007). The definition of rock type highly depends on the objective of the characterization. Geological rock typing is based on depositional environments or lithofacies; petrophysical rock typing aims to describe units of petrographic facies or grain and pore types; reservoir and production rock typing aims to identify rock types as flow units. In a reservoir with negligible diagenesis, it is more likely for the rock types of different definitions to match each other (Ali-Nandalal and Gunter, 2003; Acosta et al., 2005). However, when dealing with highly heterogeneous reservoirs, it is common that geological facies, petrophysical rock types, and flow units significantly differ (Rushing et al., 2008; Xu and Torres-Verdin, 2013). In either case, rock classification has been proved to be a valid and effective strategy in characterizing complex subsurface environments.

Rock type can be wholly defined as a group of rock bodies that has acceptable petrophysical regression within each group and can be spatially traceable in line with the geological framework (Neo et al., 1998). Rock classification based on routine and special core analysis has been extensively studied in the literature. Pittman (1992) implements a rock classification method based on Winland’s metric of pore throat radius distribution. Amaefule et al. (1993) implement the concept of hydraulic flow units based on the Hagen-Poiseuille equation and derive a flow zone index to characterize heterogeneous reservoirs. For rock classification at a reservoir or basin scale, Gunter et al. (1997) implement the Stratigraphic Modified Lorenz coefficient for characterizing reservoir flow units. Other methods based on mercury injection capillary pressure (MICP) data, pore throat size distribution, and thin sections have also been studied (Al-Aruri et al., 1998; Neo et al., 1998; Clerke et al., 2008).

However, rock classification based on core measurements need to be propagated to the uncored zones along the well, to other wells in the reservoir without core data, or to a basin scale by spatially correlating the interpreted wells. For the case of uncored wells, rock classification can be based on well logs or as a spatial distribution of cored wells. Once a meaningful classification of rock types is established along a well or spatially along a reservoir or basin, petrophysicists can infer rock properties for a complete characterization of the formation (Bennis and Torres-Verdin, 2019; Raheem et al., 2023).

We propose a framework for automatic rock classification based on machine learning and physics-based methods to rapidly scale from core measurements to well log scale and detect potential CO2 storage sites in the Gulf of Mexico. The framework serves as a quick tool for automatic rock classification and comparison of different methods with minimal user intervention. We validate the framework on a field dataset with over 2434 cored wells in the Gulf of Mexico.

Method

We propose a framework for automatic rock classification based on machine learning and physics-based methods to rapidly scale from core measurements to well log scale and detect potential CO2 storage sites in the Gulf of Mexico. The framework serves as a quick tool for automatic rock classification and comparison of different methods with minimal user intervention. We validate the framework on a field dataset with over 2434 cored wells in the Gulf of Mexico.

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Results

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Conclusions

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