

Revealing Insights in Evaluating Tight Carbonate Reservoirs: Significant Discoveries via Statistical Modeling. An In-Depth Analysis Using Integrated Machine Learning Strategies

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Abstract

More than 65% of the world's hydrocarbon reserves are contained within carbonate reservoirs. From a geological perspective, the majority of carbonate reservoirs exhibit tight characteristics, resulting in a similar resistivity response. However, the differentiating factor lies in the presence or absence of primary and secondary porosity. Given their tight nature, these carbonate reservoirs typically exhibit lower porosity compared to conventionally produced carbonate reservoirs. The main goal of this research is to construct a workflow to evaluate Carbonate reservoir potentials, outlining methodologies for identifying facies, reservoir quality, and fractures. The characterization of heterogeneity through borehole image logs is highlighted, providing detailed information on porosity, permeability, and fracture distribution.

The prediction of carbonate reservoir potentiality traditionally relies on conventional petro-physical analysis. Yet, a more sophisticated alternative emerges by leveraging machine-learning models to cluster wells according to their similarities. Then advanced approach facilitates the classification of these clusters into two categories: those that have demonstrated economic oil rates, representing successful outcomes, and those that have exhibited water or mist flow, characterizing unsuccessful cases. Clustering methods, which group elements based on similarities, offer an improved set of tests over time, enhancing the prediction of potentiality. Typically unsupervised, clustering problems lack a target for model training or direct cluster evaluation. Our developed methodology utilizes a decision tree regression for creating clusters. Tree methods effectively divide data into groups, enabling predictions based on these groups. Widely applied in petroleum-related issues, tree-based models include decision trees, assembly-based models like random forest, and gradient boost-based models such as XGBoost, LightGBM, and CatBoost. While assembly and gradient boost methods enhance prediction power.

Despite decision tree methods often exhibiting inferior performance, their advantage lies in the ability to comprehend how the model divides variables and creates cuts. This transparency can offer valuable insights into the actual problem. Utilizing these cuts, we create clusters based on different conventional log features and then classify them depending on the actual results, deviating from traditional unsupervised methods that solely rely on variables. The advantage of the hybrid approach, integrating both supervised and unsupervised methods, in constructing clusters and predicting the potentiality of A5 carbonate formation, lies in the comprehensive utilization of both labeled and unlabeled data. This combined methodology harnesses the benefits of guided learning from labeled examples while also exploring patterns and structures within the data that may not be evident through explicit supervision, thereby enhancing the accuracy and robustness of potentiality predictions.