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Method Guides Development Decisions

By Bruno de Ribet

AUSTIN, TX.–A variety of new tools for interpreting the subsurface at different resolutions has become available to geoscientists in recent years. At the same time, geoscientists have access to a multitude of local and global measurements of the subsurface–much more data than one person can process and consume simultaneously.

While using statistical tools to help extract information from vast amounts of raw data is not new, technological advancements have allowed this methodology to quickly surpass anything imaginable only a few years ago. Big data analytical tools enable users to handle huge amounts of data at unprecedented speed, and predictive analytics are being used as forecasting tools in many fields to ramp asset performance and accelerate exploration, field development and production decision making cycles.

Several innovative predictive methods are applicable to the challenges of oil and gas exploration and production. These include deep learning and other machine learning-based methods for enriching subsurface models. As demonstrated in an application in the Permian Basin Wolfcamp play, machine learning has been integral to developing a new approach to resolving reservoir facies heterogeneities in seismic data. In the Permian case study, the primary challenge encountered by the oil and gas operator was a thin and laterally discontinuous reservoir (oil-filled packstone).

Despite having collected a high-resolution, state-of-the-art 3-D seismic survey with usable frequencies up to 138 Hertz, and even after generating seismic attribute volumes to aid with the interpretation, the operator was not able to manually generate an interpretation that matched the rock-type interpretation at the wells. Therefore, the decision was made to supplement human interpretation with the machine learning methodology.

To evaluate the quality of a reservoir and gain a more realistic measure of its behavior, geoscientists try to achieve accurate facies distribution mapping. Predicting rock-type quality distribution enables geoscience professionals to better understand depositional processes in order to help them optimize the drilling decision making process.

A standard approach to understanding reservoir quality is to perform seismic inversion to predict elastic properties. However, this solution may suffer from a "nonuniqueness" problem and it may be difficult to separate different facies, since reservoir quality is not linearly correlated with seismic data, which needs the introduction of uncertainty measurements. The true integration of well and seismic data always has been a challenge because of their different responses and resolutions.

Machine Learning Method

To resolve these ambiguities, new machine learning methods change the applicability of seismic data from exploration to becoming a valuable prospect development tool. While automatic unsupervised classification methods enable a valid geologic interpretation embedded in the seismic data for exploration or infill development well positioning, this new supervised approach delivers the most probable facies and probability associated with each. The strength of this method is based on the system's ability to integrate different types of data (core, wireline and seismic).

The developed technique assumes the existence of a relationship between a seismic response at a given point and the rock-type distribution around that point. However, no model has been established yet, and the mathematical formulation of such an operator is complex. Its determination would imply a long empirical process to evaluate the consequence of rock-type distribution on seismic response. Estimating the number of parameters is challenging and is a function of the geological context, measurement constraints and experimental design. Therefore, the workflow creates an operator using learning techniques.

As with any learning method, the democratic neural network association (DNNA) technique utilized needs a representative dataset to build a robust operator. Unfortunately, rock type is not available as a volume and must be approximated by the lithofacies distribution defined within vertical windows along the borehole.

The initial phase in this method is to use facies logs constructed from well data as the main source for describing the quality of the reservoir in terms of lithology, hydrocarbon saturation or rock type. In this sequence, another machine learning method, called multiresolution graphic clustering, is used. This method defines clusters of different resolutions, helping to differentiate between homogeneous and laminated geologic contexts.

The goal is to generate a probabilistic facies model from the seismic data. An association of naïve neural networks, each with a different learning strategy, is

FIGURE 1

Lithofacies with Definition And Extracted Seismic Traces along Borehole

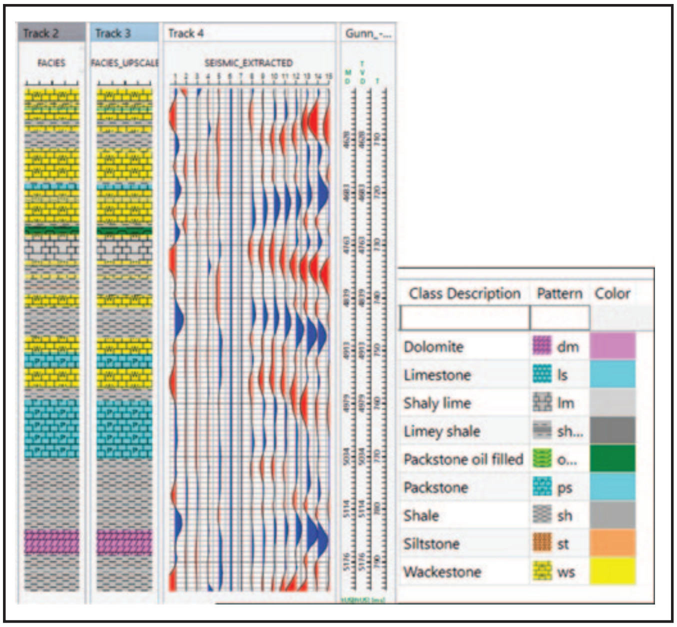
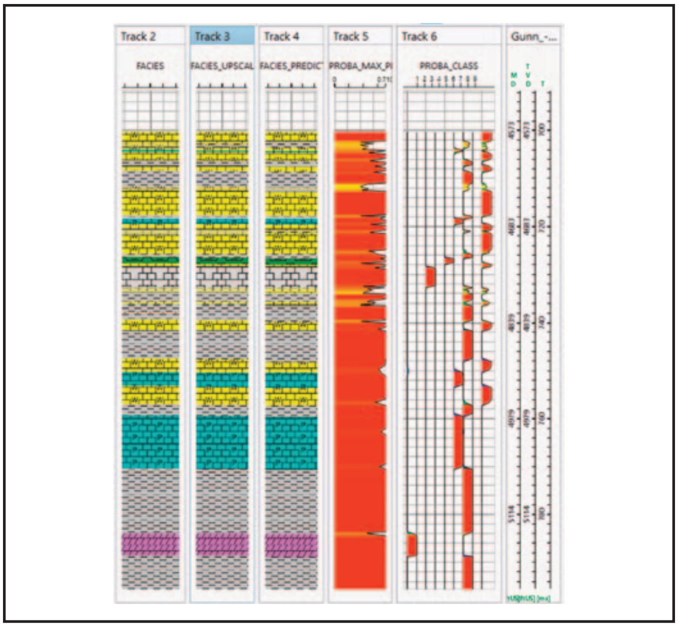


FIGURE 2

Facies Reconstruction Results From DNNA Process



run simultaneously to predict facies and avoid biasing any of the neural network architectures. To train the neural networks, facies at the well and seismic data extracted along the wellbore in the interval of interest are used as input data (the hard training dataset). A major benefit of this technology is its ability to combine the full dimensionality of the prestack data, which carries more information, with any type of seismic attributes.

A second phase introduces seismic data away from the borehole (soft data). The neural networks "vote" on their integration to enrich the initial training dataset in order to update the model. Adding the soft data avoids overlearning from a limited dataset.

The last step is to propagate the final neural network model on the full seismic dataset to generate probabilistic facies models composed of three different volumes: most probable facies, maximum probability for all facies, and probability for each. Analysis of the facies and associated probability distribution provides valuable insights into prospect uncertainties and seismic data reliability for prediction.

East Soldier Mount Area

The East Soldier Mount study area is located about 125 miles northeast of Midland, in the Eastern Shelf of the Permian Basin. The packstones were formed at the time of deposition during Lower Permian/Wolfcamp/Unayzah time (295 million years ago) when the area was shallow marine, and organisms were inhabiting the mounds and subtidal zones. The study area contains thin and laterally discontinuous oil-filled packstones in both the Upper and Lower Wolfcamp intervals.

Bioturbation and oolitic shoals caused the initial porosity, but much of the porosity was occluded by cementation after burial. The porosity was enhanced by fracturing that occurred after burial due to differential compaction beneath and tectonic faulting in the deeper formations.

Oil migrated into the packstones many millions of years after burial from some 20 miles away. The northeastern end of the Horseshoe Atoll features a large reef 20 miles west-southwest of the study area. Oil leaked out of this reef into the Tannehill sand (Middle Wolfcamp) detrital, then migrated up the detrital zone into the delta, which is located only 1.25 miles west of the East Soldier Mount area. The oil then migrated out of the delta and into the study area itself.

The total drilled depth for the three vertical wells available for the project is about 4,900 feet. Each successful well produces 3 million-4 million barrels of reserves. These wells flow naturally, without the need for hydraulic fracturing.

Data And Results

To carry out the rock-type classification procedure, several different data objects must be considered, including:

- Well data (accurate well-to-seismic tie and lithofacies logs);
- Top and base of the interval of interest;
- Post-stack seismic attributes such as high-resolution, time-migrated stack, P-impedance from seismic inversion, instantaneous frequency, instantaneous Q factor, and dominant frequency; and
- Prestack seismic data in the form of partial angle stacks.

The lithofacies and seismic data at the well location represent the training dataset used as input to the DNNA process (Figure 1). On the left is a lithofacies log, and then another that may be a duplicate or upscaled to eliminate thin layers to give more homogeneity to the vertical distribution of the facies. The third track corresponds to the seismic traces, each associated with a different attribute, extracted along the wellbore.

Once that process has been run, the intermediate stage is to validate the quality of the operator by visualizing the reconstruction results at the wells (Figure 2). The third track from the left is the reconstructed lithofacies log curve. In this context, "reconstructed" is defined as the predicted lithofacies curve that results from applying the neural network

FIGURE 3

Lithofacies Classification 3-D Volume And Lithofacies Logs

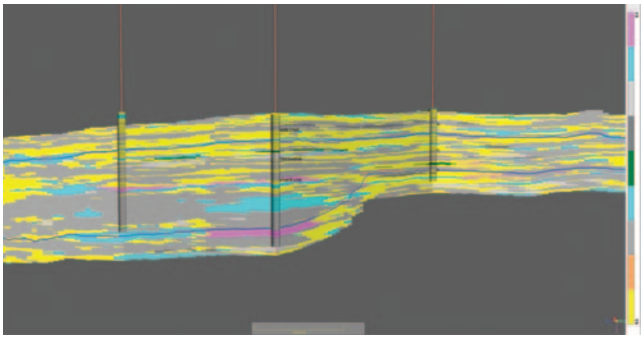
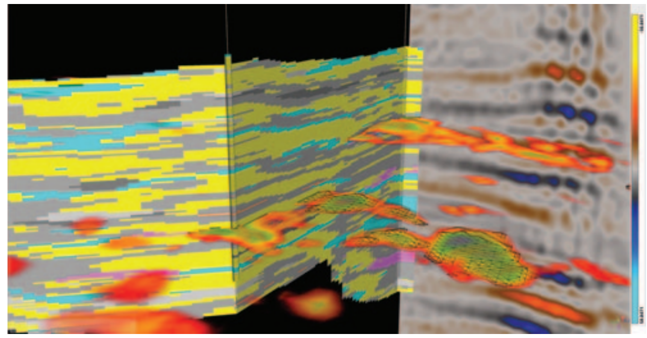


FIGURE 4

Voxel Visualization Display of Most Probable Rock-Type Volume Calibrated to Wells

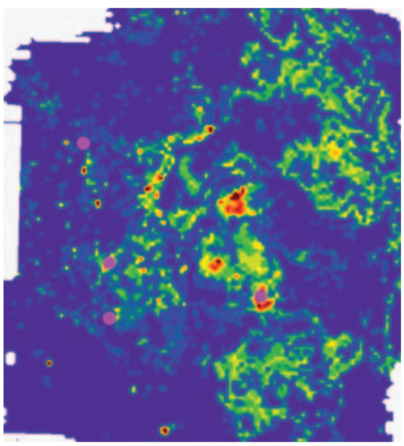


model at the well location using only seismic data as input. Therefore, it is a best-case scenario for reconstruction of lithofacies using this method. To the right of the reconstructed lithofacies curve is the maximum probability curve, which shows the probability of the most probable reconstructed lithofacies. Finally, at the far right are the individual facies probabilities for each of the created lithofacies classes.

For the three wells, some differences were observed in lithofacies prediction, and occasionally the DNNA method lost a few thin beds or they were not reconstructed with exact thickness and became the main source of prediction errors. There also were some minor differences in terms of the positioning and thickness of the lithofacies, but overall the reconstruction was excellent for the three wells that are collocated within the East Soldier Mount 3-D seismic survey. Reservoir facies groups are well reconstructed, as shown by associated probability values (tracks 3 and 4 in Figure 2).

FIGURE 5

Two-Way Time Thickness Map of Oil-Filled Packstone Pay Facies



The three-dimensional most probable facies distribution by DNNA is summarized in a "rock-type" cube in which each value at a given (X, Y and Z) position corresponds to the most likely facies distribution predicted (i.e., each facies associated with its highest probability value). Figure 3 shows the 3-D lithofacies classification volume juxtaposed against the lithofacies logs. Analyzing the results shows a higher level of lateral and vertical detail than with any conventional attribute or seismic inversion results. It can be observed that the vertical resolution of the most probable facies matches that of the lithofacies logs, with a good tie at the well locations.

The pay facies, represented by the green color, can be identified in the Upper Wolfcamp position in the middle well, and the Lower Wolfcamp position in the right-hand well. On the well to the left, the Upper Wolfcamp facies almost reaches the well, falling short by only a few meters.

Voxel visualization display allows the analyst to visualize where the pay facies may be located spatially by controlling the opacity on the corresponding probability volume before detecting the main geobodies for volumetrics and connectivity analysis. Figure 4 shows a traverse of the most probable rock-type volume calibrated to wells, jointly visualized with input prestack seismic data, opacity on probability volume, and detected geobodies associated with the net pay facies.

A two-way time thickness attribute of the oil-filled packstone pay facies can be extracted and mapped, as shown in Figure 5. This map clearly shows that there are other potential drilling opportunities in this area (red corresponds to thicker pay prediction).

In this project, the ensemble of neural networks was trained at the wells to identify a specific pay facies using lithofacies logs and a series of 3-D seismic volumes as input, then predicted from the seismic attributes onto the full volume using the final operator. At the wells, the training statistics are of high quality, and most importantly, there is no confusion about pay facies. The volumes and thickness map provide geological intelligence that helped the operator make better field development investment decisions.

The results provided a significant

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uplift from conventional seismic-driven reservoir characterization workflows. Lateral resolution also was improved. Additional drilling opportunities could be identified from the facies probability voxel clouds or the net pay facies thickness map. The study results were accurate; after moving the rig from its original position, the well found a good pay facies at correct depth, with double the pay zone thickness and increased porosity (from 10 to 17 percent). ❒

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