Maximizing field development through rock physics informed hi-res ML seismic estimates of reservoir properties

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Summary

The integration of machine learning with seismic methods results in high-resolution predictions of reservoir properties as well as accurate uncertainty estimates. In addition, Explainable AI methods enable detailed and quantitative understanding of these predictions. The overall workflow allows a better communication between the various teams involved in drilling decisions and building static and dynamic models.

Method

We present a machine learning workflow previously developed internally to predict various reservoir properties (Muller and Perez, 2023). A Random Forest method is used to predict continuous (e.g. gamma ray, resistivity, density, porosity, volume of shale, etc) and categorical (facies) properties through regression and classification, respectively. The input data include various seismic data, attributes, inversion results, rock physics transforms and hundreds of wells to train the predictions. We then explain how uncertainty is estimated in the workflow for both regression and classification. The next step consists of using Explainable AI (Lundberg and Lee, 2017; Lubo-Robles *et al.*, 2022) to quantitatively understand the impact of the input features on the predictions, confirming known relationships between the data but also bringing new insight and understanding. This important step is now a key part of our workflows to not only QC the results, but also to easily communicate learnings and uncertainty with other teams. To improve our understanding of the predictions, we move away from standard machine learning metrics towards more meaningful geophysical metrics. We also explain how the workflow was further extended to predict surfaces that are challenging to identify using seismic only.
The workflow is illustrated on a real dataset from the Llanos Basin, Colombia, where the availability of seismic data and abundance of wells makes it a perfect candidate.

Observations

Machine learning is undeniably becoming increasingly important in our workflows. It allows us not only to work faster, but also to process vast amounts of seismic data much faster than traditional methods, enabling quicker decision-making. It is more capable of identifying hidden patterns and anomalies in seismic data that might be too complex for humans, leading to more accurate interpretations. It can efficiently handle and analyze massive datasets, making it possible to draw insights that would otherwise be missed by traditional methods. Additionally, it will continuously improve as more data is fed into the model.

Figure 1 illustrates how Explainable AI can be applied to log prediction. Not only does it show qualitatively which features are more important to the prediction, it also shows quantitatively by how much each feature is increasing or decreasing the prediction. It is also interesting to note how low frequency features (e.g. seismic attributes, trends, …) can be combined to produce higher frequency predictions.

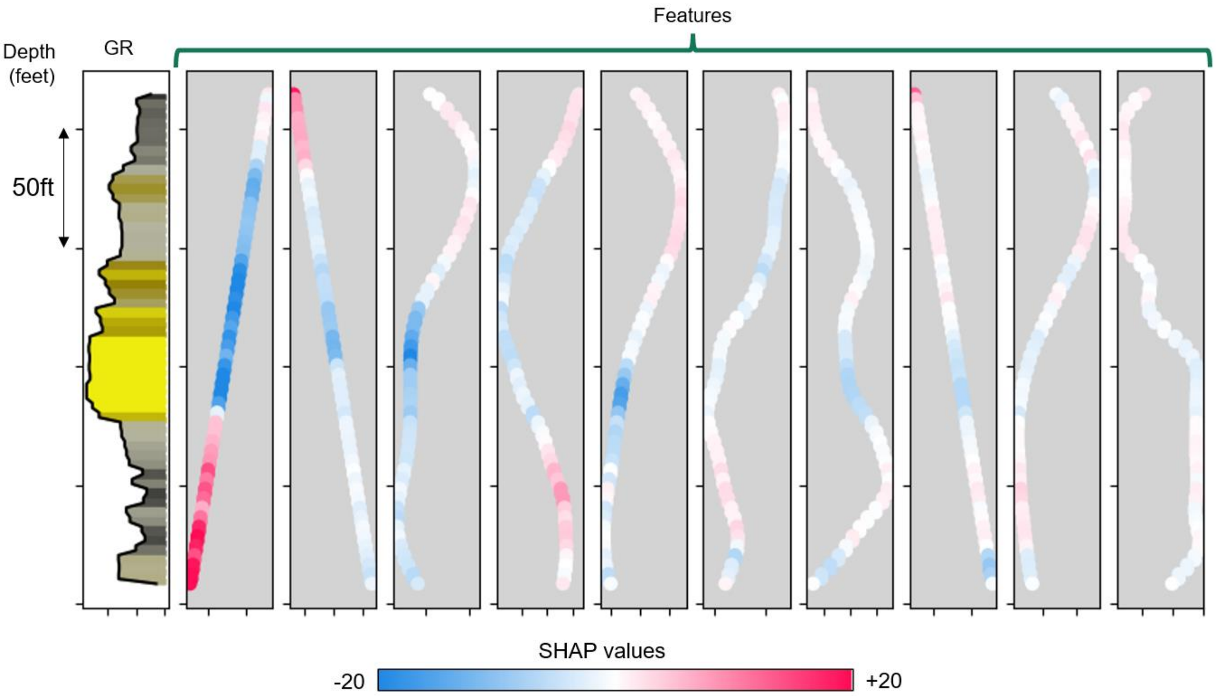

Figure 1: Explainable AI (SHAP) applied to Gamma Ray log prediction.

The workflow we present is not meant to replace seismic inversion, but rather to complement it. Seismic inversion and derived properties are used as an input to the workflow to ensure the results make physical sense. However, the machine learning workflow allows greater flexibility compared to traditional seismic inversion and facilitates the integration with the static geomodel: the results are directly predicted in depth, at the geomodel vertical resolution (e.g. 2ft), with uncertainty and are calibrated to hundreds of wells.
On the other hand, traditional seismic inversion is restricted to the time domain, its vertical resolution is limited by the seismic bandwidth and can only use the wells for which sonic logs are available (less than 3% of the wells in our case).

Figure 2 shows a comparison of the volume of shale obtained from seismic inversion followed by a rock physics transform (left) and the volume from the machine learning workflow (right). A well with a log of volume of shale is also displayed to help validate the increased resolution obtained with the machine learning workflow on the right.

Seismic inversion is also restricted to the estimation of properties that can be theoretically related to the wave equation, and facies may overlap in the elastic property model space spanned by those properties. On the other hand, machine learning can explore any model space that provides higher separability between the facies.

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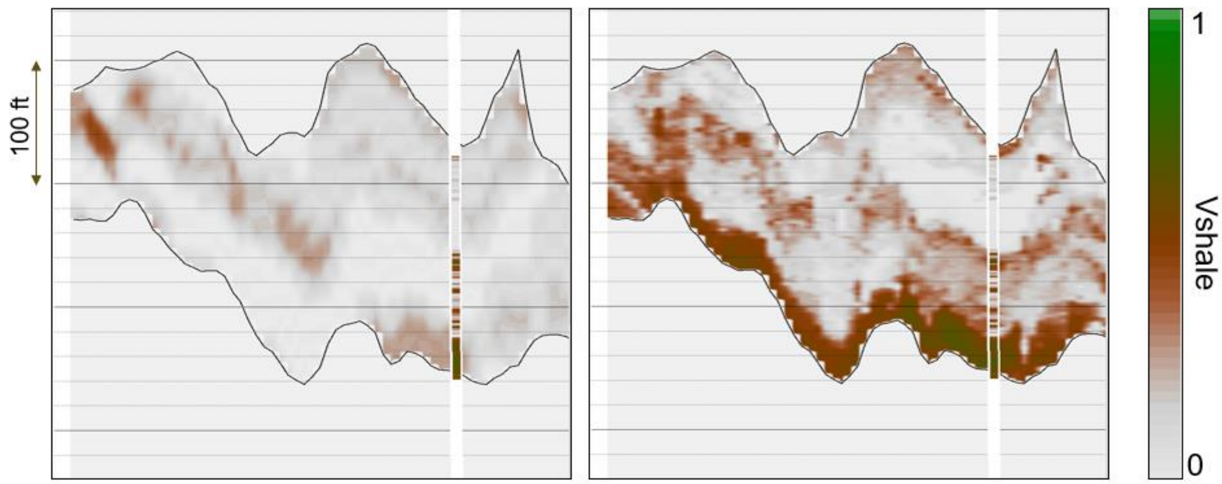

Figure 2: Comparison between volumes of shale from seismic inversion (left) and machine learning (right).

The benefits of using the machine learning generated gamma ray volume compared to seismic is illustrated on Figure 3. The sections have been flattened to the top surface of the zone of interest. The amount of details provided by the gamma ray section (left) greatly improves the interpretation compared to the seismic section (right).

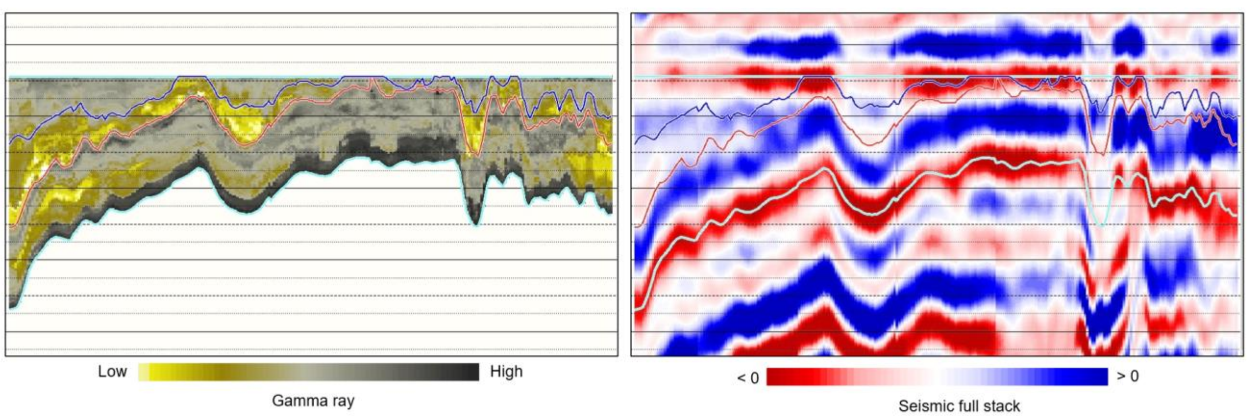

Figure 3: Comparison between flattened sections of gamma ray obtained from the machine learning workflow (left) and seismic full stack (right).

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References

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