Machine Learning for Lithofacies Prediction – A Fast, High-Resolution, and Economic Alternative to Seismic Inversion

Alvaro Chaveste[1], Rocky Roden[2], Tom Smith[1]

[1]Geophysical Insights
[2]Rocky Ridge Resources

Abstract

Objectives:
A methodology for lithofacies prediction is presented. It is based on computing Self Organized Maps (SOM), an unsupervised form of Machine Learning (ML), and cross-referencing the results to lithofacies from petrophysical logs. The methodology defines the lithofacies of interest with improved resolution and significant time savings when compared to inversion-based reservoir characterization.

Procedures
Inversion-based reservoir characterization computes rock properties (i.e., P- and S-wave Impedance and density) through seismic inversion. The sought for reservoir properties (porosity, lithology, and fluids) are obtained through petrophysical inversion that relates rock properties to reservoir properties through rock physics models. The proposed alternative approach, unlike seismic and petrophysical inversions, is not deterministic. It computes SOM from a User defined number of seismic attributes. The process' multi-dimensionality (each attribute is a dimension) reduces the non-uniqueness associated with seismic and petrophysical inversions. SOM classifies several attributes sample by sample (same sample for all attributes) and assigns a cluster (neuron) to each time/depth sample. This results in interpretable data below the wavelet's limit of resolution.
The assignment of geologically meaningful labels to SOM neurons is done by cross-referencing neurons from seismic to lithofacies computed from the wells' petrophysical evaluation. By matching neurons to lithofacies at the same depth, the process assigns a label to each neuron that indicates the most likely rock type. This way, we can use the SOM neurons to map the distribution and variation of the lithofacies in the subsurface.
The methodology does not require wavelet estimation or a low frequency model; thus, easing processing and interpretation requirements.

Results
ML Lithofacies Prediction is illustrated with a case study in the Niobrara formation of the Delaware-Julesburg Basin in Colorado, USA. The petrophysical evaluations in five wells are used to create four lithofacies computed using K-Means. These are cross-referenced with a 64 neuron SOM in which eight seismic attributes are input to the calculation. The result is a 3D volume of lithofacies that matches the analysis wells, has aerial continuity, and shows reliable data at a fraction of the wavelet's limit of resolution.

Conclusions
The methodology presented results in lithofacies computed from seismic data. It has the following characteristics:

Process is not deterministic – does not require data to match physical models.
No requirement to estimate the wavelet or compute a low-frequency model, which are non-trivial.
- Employs ML seismic clustering that identifies natural patterns in the data relating to lithology.
- Works on thin and thick beds as ML clustering is done at the seismic sample interval - below the wavelet's limit of resolution.
- Neurons generated by ML have some of the characteristics of inverted data, including mapping intervals, not interfaces.

It results in reliable high resolution lithofacies prediction that can be executed in a fraction of the time of inversion-based processes.