# Machine Learning Enriches the Data Available to Seismic Interpreters

The interpretation of seismic data poses significant challenges as to the information we can reliably extract using the seismic method. Data quality, data complexity, and resolution can limit the value of seismic data in prospecting and field development. Are we at the point where machine learning can play a significant role in enhancing the seismic interpretation process with these limitations? And are we closer to using machine learning as a component of the core interpretation process?

Geoscientists regularly face limitations in the interpretation process: Many of the tasks associated with interpretation are repetitive and time-consuming, requiring the dedication of a skilled geoscientist to ensure that the final interpretation is geologically-consistent. As the interpretation is dependent on data quality and on the capacity of the stacked seismic data to image and fully represent the subsurface, the interpretation can become more subjective and carry a higher degree of uncertainty. Adding auxiliary seismic data (e.g. seismic attributes, VSP data) and non-seismic data (e.g. electromagnetic, completions, engineering, well log data) can improve the interpretation process and reduce interpretational uncertainty; however, the integration of these data types into the processing and imaging sequence can be quite time-consuming.

Increases in computational power, expanded access to that power on the Cloud, and the availability of a wealth of Open Source machine learning engines have empowered developers to create new applications to automate, integrate, and transform the interpretation process. Machine learning workflows are being adapted to work through large volumes of seismic data in shorter periods of time, to transform seismic data to other value-added attributes that better describe the depositional and stratigraphic processes of the subsurface, and to recognize patterns in the data image volume corresponding to specific subsurface features (low energy faults, small faults, edges, discontinuities, reefs, salts, diffractions, channels, etc.).

Machine learning is not new to Emerson. With a twenty-five-year history of applying Machine Learning to improve different seismic processing, imaging, and interpretation technologies, we have established an base of experience that includes of the underlying physics model and appropriate data input preparation. In this article, we focus on two of emerging solutions – the use of deep learning to classify pre-stack depth image gathers to deliver more informative volumes to the interpreter, and a classification methodology which uses well data and multi-dimensional seismic data to predict facies away from the well bore.

In the last ten years, the exploration community has benefited from the acquisition of high-density and rich-azimuth seismic data surveys. These data-rich surface acquisitions sample the subsurface, resulting in different wavefields associated with different subsurface features. These wavefields carry signatures related to fractures, faults, edges, points, and other structural discontinuities. When isolated, these wavefields can be used to produce feature-targeted images of the subsurface.

Unfortunately, traditional seismic processing and imaging procedures impose many averaging operations before the final interpreted image is generated, preventing the isolation and recovery of the wavefields. Consequently, seismic interpreters routinely work with "composite" wavefield images of the subsurface of high signal-to-noise quality, but low seismic image resolution.

Concurrently, a new generation of machine learning methods has become available, enabling geophysicists to develop applications that better automate, classify, transform, analyze, and identify features in high-density seismic datasets. Deep learning is a specific type of machine learning technology used to classify features or objects. It is carried out with a convolutional neural network, a network consisting of many layers, neurons and connectors, where each layer of the neural network detects a certain characteristic of the input data that permits a comprehensive classification. To become efficient at seismic feature classification, thousands of data records (or models) are required to train the network.

However, for the reasons referenced above, the separation of the wavefields associated with all the subsurface and near surface features cannot be solved with deep learning methods alone. A sophisticated data preparation process must be run to allow the image capture of wavefields prior to the generation and application of deep learning filters. This problem is solved by using a full azimuth prestack depth imaging procedure carried out in the local angle domain (Emerson's EarthStudy 360™) where full-azimuth directional angle gathers are created. Each directional angle gather consists of thousands of traces (directions) illuminating each subsurface point from a rich spectrum of angles. This makes it possible to isolate and extract targeted wavefield energy associated with subsurface features, such as faults, stratigraphic edges, channels, and reefs. The separation of continuous (specular) energy associated with dominant reflectors and discontinuous (diffraction) energy creates the opportunity to generate feature-targeted images using wavefield separation.

For example, the diffraction energy from a fault spreads throughout all dips but keeps a specific orientation, the azimuth of the interface between the fault and the reflectors. The diffraction energy is usually only 1-10% of the strength of the reflections. This makes diffractions hard to see in a post-stack image, as they are masked by the more dominant reflection energy. That is why it's important that this wavefield separation be performed in the pre-stack domain. If we create small sub-volumes in the pre-stack domain, we can create 'images' which can be passed to neural network technology to automate the recognition and classification process.

Deep learning is an advanced methodology within the broader machine learning portfolio. It adopts a more sophisticated approach involving multiple layers of neural networks which learn to solve problems of higher complexity. In the deep learning classification workflow, we use a Convolutional Neural Network consisting of 18 layers. Each layer applies a convolutional operation to the input, passing the result to the next layer, with the layers gradually detecting more and more complex features and structures. The training of the neural network is carried out with many overlapping images or tiles constructed from the principle directivities of the directional angle gather derived from Principle Component Analysis.

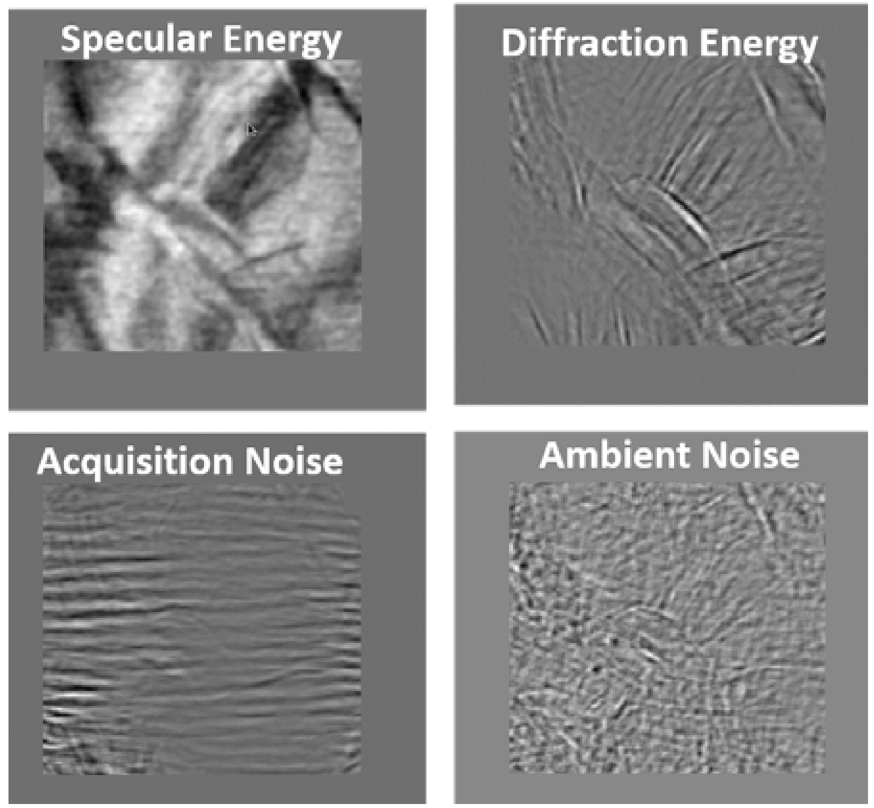


*Figure 1. Deep learning applied to full-azimuth gathers to isolate signal and noise patterns.*

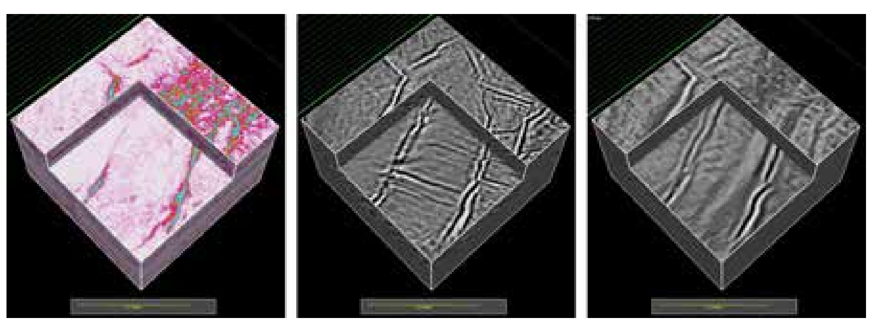

*Figure 2: Coherency, diffraction weighted stack and deep learning results*

This methodology delivers post-stack volumes in which the energy relating to each type of structural feature has been isolated. Thus, we obtain a volume containing only primary reflections, a volume containing only faults, or even a volume containing a specific source of noise, etc. (Figure 1). The separation of these features significantly enhances the resolution of each volume: In the fault volume we see faults which are missing in a conventional full stack, as they are masked by stronger energies

Techniques aimed at enhancing fault energy are not uncommon, from post-stack discontinuity methodologies to more modern diffraction imaging workflows. So how do the results of deep learning compare with more conventional approaches? Figure 2 shows a comparison between a post-stack coherency attribute, a diffraction-weighted stack image, and the deep learning result, where the fault detail and definition are clearly superior.

If we can deliver these structural features as independent volumes to the interpreter, they can respond better to other forms of automated machine learning processes for map and model creation.

The second of the emerging technologies is a tool for predicting rock type distribution in the reservoir

The Emerson Rock Type Classification methodology uses a machine learning algorithm called Democratic Neural Network Association (DNNA), an ensemble of naïve neural networks which propagate probabilities with each predicted rock type. The steps used in Rock Type Classification are conventional machine learning steps – definition of the training set, training, classification, and ultimately a validation stage before propagation of the classification (Figure 3). The deliverables are a volume of most probable facies with a volume of maximum probability, and a probability volume for each facies.

DNNA can be divided into two parts: The first is Associative Neural Networks, where several independent networks work alongside each other within a single layer. This has the effect of debiasing the result that may occur from the use of a single neural network. This step is used to train the neural network, making use of seismic data and electrofacies derived from wireline data calibrated with core data. The next stage is the 'Democratic' part – where the networks effectively vote on unlabelled data comprised of seismic data sampled away from the well bore. If all networks agree, then a label is added, enriching the training set for further learning. If they do not agree, the data is rejected.

Once the training is complete, the classification is performed. We obtain the classification volumes mentioned above by exposing the data to the neural network. Results can be validated through 3D visualization of the volumes, blind well tests, and through the use of QC diagnostics related to the separation of the classifications.

We can illustrate this methodology using a case study from North Texas, the Eastern shelf of the Permian Basin, where the study area is a mixed siliciclastic shelf. The goal was to predict rock type/fluid content distribution through the reservoir to capture lateral and vertical heterogeneities and to constrain the reservoir models away from the wells, in order to validate the drilling strategy. Time was short and longer turnaround inversion workflows could not be accommodated.

The available data consisted of a small, high-resolution, good-quality seismic survey with pre-stack data and attributes, but with only three wells within the survey area. From the electrofacies logs it is observed that the oil-filled packstone layers were thin, so the challenge was to use the limited well data and select the highest resolution and most relevant seismic data to provide the best prediction possible.

Figure 4 shows the high-resolution facies result obtained, clearly better than the individual seismic volumes used as input. This is a benefit of using multiple pre- and post-stack volumes in the input stage, as they help to enhance the resolution. As a result of this study, the well found a good pay facies at correct depth, with double the pay zone thickness and an increase in porosity from 10% to 17%.

These are just two of the ways in which Emerson continues to find innovative ways to use machine learning to deliver improved data and better results to the interpreter, in a variety of geological settings. The capacity to automate repetitive tasks to handle very large volumes of data makes these technologies a must in today's exploration and production environments. As part of our mission to deliver high-quality, innovative software and services designed to tackle the most challenging geoscience problems, we at Emerson see machine learning as an essential technology whose value will only continue to increase.

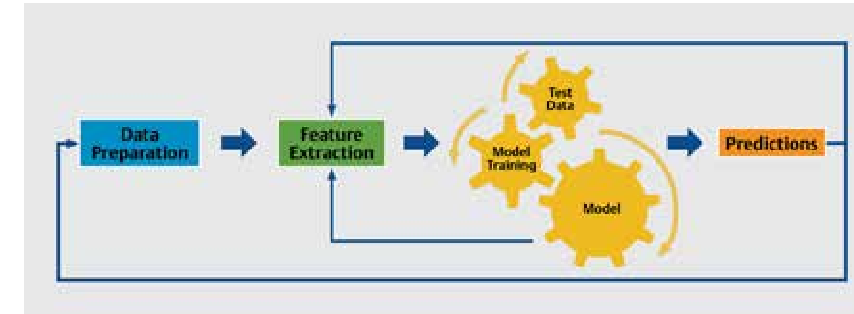


*Figure 3: The core steps of machine learning algorithms*

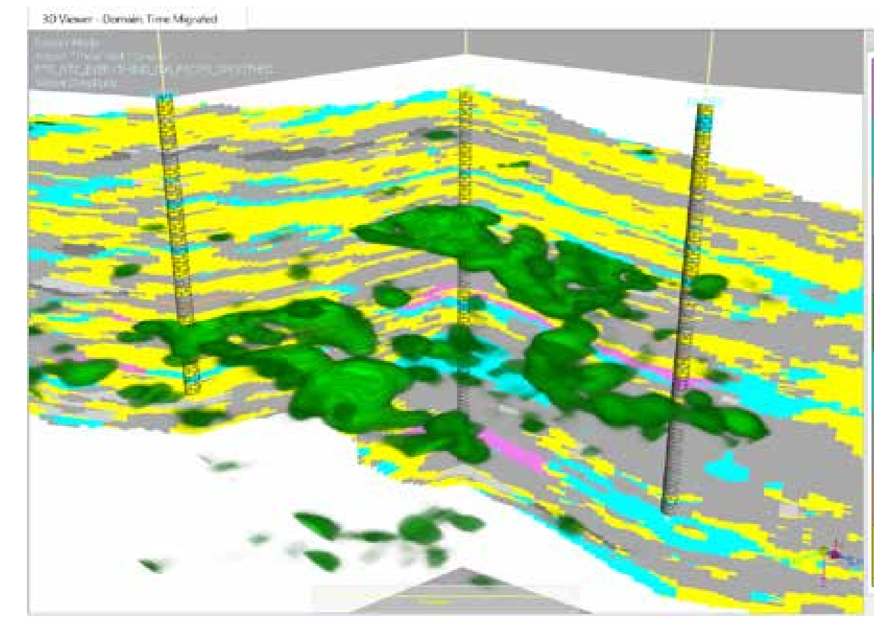

*Figure 4: 3D semi-opaque voxel cloud view of the oil-filled packstone probability cloud*