A growing Machine Learning approach to optimize use of prestack and poststack seismic data

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SUMMARY

Machine Learning and Neural Networks have been used in the oil and gas industry for several years. The main focus of these technologies has been to predict facies distribution from seismic data, or to cluster log data into electro-facies. Some tentative methods for expanding their applicability have been tested, but to date, these have failed to become part of the main interpretation workow stream. The question is how machine learning technology can be used to perform fault interpretation, AVO analysis and geobody detection more quickly and easily. We propose a new type of machine learning approach to accelerate daily interpretation tasks.

INTRODUCTION

Machine learning algorithms are now able to perform highly complex tasks, such as on-the-y speech translation, image detection, and combinations of the two. The underlying strength of machine learning is its ability to deal with massive amounts of noisy data (Seltzer et al., 2013) from various sources, and learn from it to then identify, transform and deliver understandable information to an end user. Seismic interpretation is certainly one of the most suitable domains for this approach, because it deals with exponential increases in data. The more data we acquire, the more we need to generate multiple attributes, leading to an expectation of highly accurate interpretations on the part of the geoscientist. However, having more data does not immediately translate to more information. Often, due to a lack of time or insufficient tools, interpreters cannot exploit all the data available on their company's hard drive. Recent evolution in machine learning have shown that it is possible to consider one network architecture for different tasks, as long as enough data is available to train the machine. Our aim is to propose a fast track machine learning method which will help interpreters in several aspects of their daily work. This machine learning algorithm will be applied to probabilistic fault detection, AVO analysis and geobody detection.

METHODOLOGY

Subsurface conditions are not predictable. They may be detected through seismic interpretation, which comprises advanced deduction based on the experience and expertise of the geoscientist, and available data, mainly seismic. It is therefore necessary to consider an uncertainty associated factor from the early seismic interpretation stages. One solution for quantifying uncertainty from seismic data is to take into account several inputs rather than a single one, to calculate probabilities during interpretation processes. However, the estimation of probabilities using a mathematical algorithm needs to be supported by a technology enabling on-the-y quality control, and interactive analysis of parametrization variations on the result of the machine learning process. In the context of unsupervised learning from seismic data for what can be related to anomaly or geologic feature detection (AVO, faults or geobodies), growing and topologically flexible networks can provide a generic learning model. This approach seems well adapted to our main three detection objectives (anomaly, structure and stratigraphy).
For such purpose, artificial neural network inspired from Growing Neural Gas (GNG) (Fritzke, 1995) provides a good solution for matching the data high dimensionality, when referring to data such as prestack, or for enabling the usage of several poststack seismic attributes. However, as any self-organizing network, growing networks are attracted by data density. As the objective is to overcome this issue to map anomalies, the algorithm needs to be adapted to focus as well on outliers (Hodge and Austin, 2004). To fit with this objective, the solution is to perform the neural network training stage based on the following steps:

1. Train the network on all points of the interval of interest,
2. Detect outliers from previous stage,
3. Train only on outliers,
4. Cluster the neurons on a network topology approach,(Figure 1),
5. Estimate probability of belonging to a particular cluster, for each point in the interval of interest.

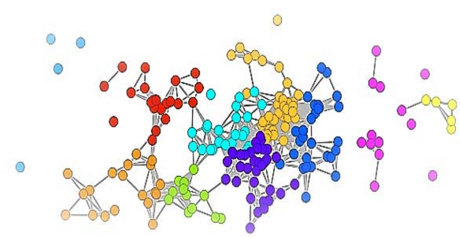

Figure 1: Projection of the 15-dimensional neural network onto 2 dimensions. For visualization purposes, each neuron is affected to a class, based on network topology.

The result of the learning process can therefore be interactively translated into classes and associated probabilities, to generate new displays and provide a better image for interpreters.

RESULTS

Since a Neural Network is well able to simultaneously interact with several attributes, this methodology provides a solution for detecting and identifying areas of interest and anomalies from seismic data. AVO analysis, structural interpretation and geobody detection are some interpretation processes where applying this technique provides great added value.

Acceleration of fault interpretation workflow

Fault interpretation is a tedious task, and all commercial technical solutions offer different methods to simplify not the interpretation itself, but the process. This interpretation stage requires time, and uses a variety of seismic attributes which contribute to an understanding of the structural framework, fault extension and connectivity. Each seismic attribute provides different information, most likely at different resolutions (semblance versus curvature). We know that each seismic attribute brings specic information, but we also know that the human capability to simultaneously synthetize all the seismic information in order to best interpret the structural pattern is limited. Machine learning is valuable in that it integrates the relatively high-dimensionality information in an understandable manner, and quantifies the probability of fault presence and connectivity.

Figure 2 and figure 3 show the result of structural attribute clustering using a growing network approach. The associated probabilities provide a way to quantify the fault position, considering as many attributes as needed. Semblance, Eigen-based coherence, dip, azimuth and curvatures, combined with some derivatives, are used as input data to train the neural network. As learning from a large pool of structural seismic attributes, parametrization of each attribute does not impact the result much . Default parameters can be used without having to perform specific ne-tuning for each attribute. The result is a true image of the structural framework in record time.

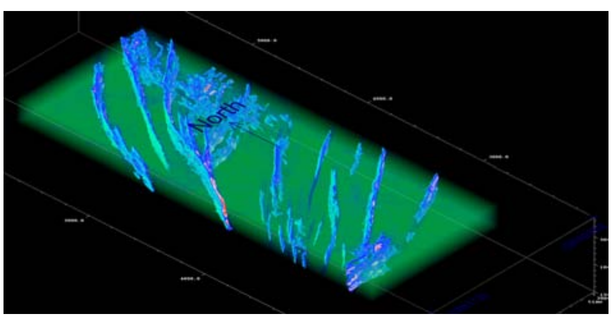

Figure 2: Opacity rendering on the result of neural network result clustering. Fault planes are clearly visible on the most likely class prediction volume. Probabilities will add more detail.

It is easy to see the improvement in identifying faults versus discontinuities related to noise.

Automated AVO analysis investigation

Neural networks are by definition data type-agnostic and therefore can be applied to prestack data. The objective is to identify and classify the different types of AVO/AVA responses. With this method, the geoscientist, analyzing the intrinsic characteristics of a potential reservoir, receives a probabilistic estimation of the similarity between the AVO/AVA seismic response and the theoretical response, and eventually the identification of potential anomalies related to processing. Figure 4 illustrates an example of 2 seismic facies neuron sets showing different AVA signatures. While seismic facies 2 may correspond to an AVA Class 1 type (Rutherford and Williams, 1989), facies 9 displays a signature that could possibly be associated with the presence of multiples.

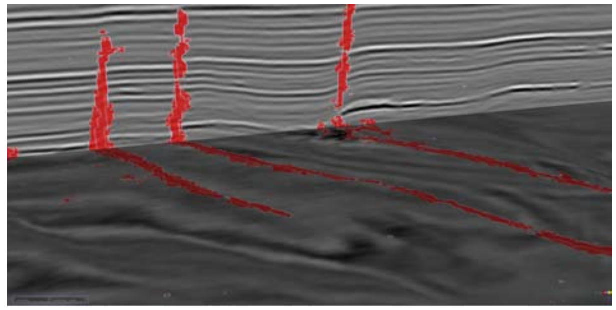

Figure 3: Red zones show a very high fault probability. The thickness of the fault zone provides an envelope for the fault position.

The different neuron classes obtained using this technique are compared to synthetic AVA models generated at wells. The comparison helps to identify expected anomalies versus non-expected behavior. The trained neurons are then used to estimate probabilities that each point in the seismic will be attached to a specific neuron family. The probability estimation allows the creation of a most probable seismic facies volume, which is directly readable in terms of AVA effects (Figure 5 and Figure 6). This method provides additional information, empowering interpreters to assess the 3D distribution of potential seismic anomalies at an early stage.

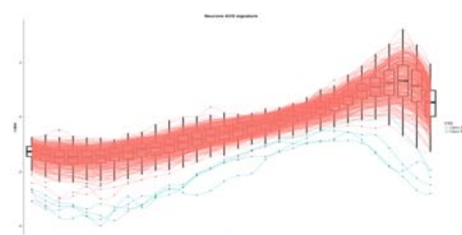

Figure 4: Neuron amplitude responses with angles show that class 2 (red) and 9 (blue) have different AVA responses. Class 2 (red) exhibits an AVA Class 1-like reservoir top signature (inverse polarity). However, both classes show some amplitude decrease in the ultra-far angles, possibly due to frequency variations with angle.

The different neuron families obtained with this technique, can easily be compared to synthetic AVA models generated from wells. The comparison brings a way to identify expected anomalies, versus non expected ones (Figure 7).

Delivering a probabilistic geobody detection

One of the main contributions of this technique is associating a set of probabilities to each data point. These values characterize the likelihood of each data point belonging to a given class.

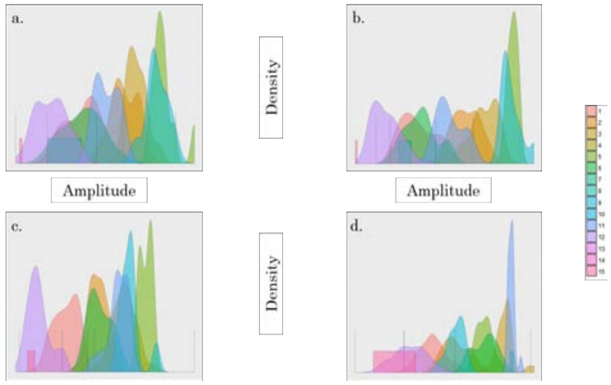

Figure 5: Distribution of a) near b) mid c) far d) ultra-far amplitudes for all classes over all the neural network neurons. Distribution varies depending on class.

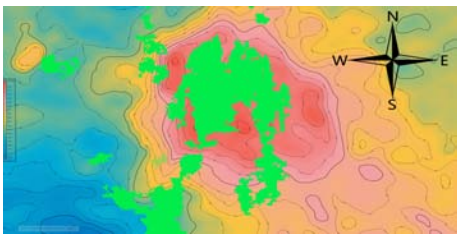

Figure 6: Green area shows where the Neural Network responses are similar to an AVO class 1 response reservoir top. The anomaly is displayed on top of the time migrated structure.

Obviously, if we define fewer classes, more data points will be part of the same cluster. We admit that in general, the size of each geobody is a function of the number of classes. When increasing the number of classes, more detail will be extracted, isolated and mapped as specific features.

From the probabilities associated with each class, we can expand the workflow beyond classification and enable structural geobody creation scenarios. From an initial set of structure related seismic attributes, the application of this technique allows the detection of fault geobodies, by specifying a cut-off on fault class probability value (Figure 8). Reducing the number of classes would potentially increase fault connectivity, while the opposite would generate more discontinuous fault bodies. Because of the 3D character of this approach, interactively evaluating the impact of parametrization on the result is of great added value in any seismic scale reservoir characterization and modeling worflow.

CONCLUSION

O & G operators are continuously improving the geoscientists working environment (including interpretation software and access to more data). The expectation is for the geoscientist

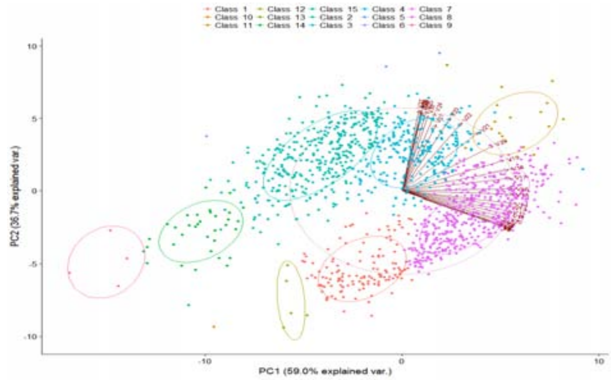

Figure 7: AVA neurons projected in principal component space show a very good cluster separation. The clustering enables us to isolate anomalies.

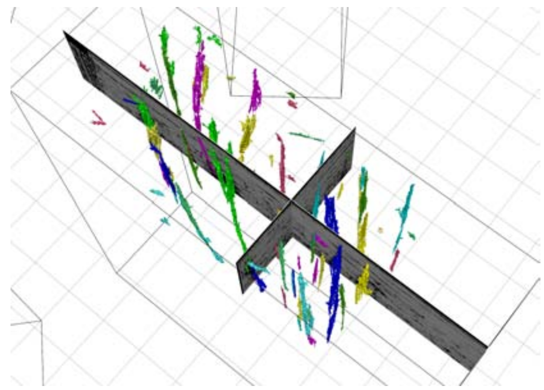

Figure 8: Result of probabilistic fault body detection, based on a Neural Network.

to provide pertinent and accurate interpretations of prospects and reservoirs. If we only consider traditional interpretation workows based on legacy techniques, then extracting consistent, quantified and precise information from available data will remain a challenge. The new generation of machine learning techniques brings new insight into G& G data analysis. Fit-to-purpose use of these techniques will facilitate interpretation in any type of geological setting. In the case of structural interpretation, we observe that the growing network approach accelerates the 3D consistent interpretation of faults, while adding information about probability, to be used for modeling structural framework uncertainty. For AVO/AVA analysis, we propose its application to perform AVO related anomaly detection, with the objective of mapping potential hydrocarbons.

ACKNOWLEDGEMENT

We would like to thank Paradigm for authorizing us to publish this abstract. Data courtesy of Ministry of Economic Development Unpublished Petroleum Report, New-Zealand.

EDITED REFERENCES

Note: This reference list is a copyedited version of the reference list submitted by the author. Reference lists for the 2017 SEG Technical Program Expanded Abstracts have been copyedited so that references provided with the online metadata for each paper will achieve a high degree of linking to cited sources that appear on the Web.

REFERENCES

Fritzke, B., 1995, A growing neural gas network learns topologies: NIPS'94 Proceedings of the 7th International Conference on Neural Information Processing Systems, MIT Press625–632.

Hodge, V., and J. Austin, 2004, A survey of outlier detection methodologies: Artificial Intelligence Review, **22**, 85–126, http://doi.org/10.1023/B:AIRE.0000045502.10941.a9.

Rutherford, S. R., and R. H. Williams, 1989, Amplitude versus-offset variations in gas sands: Geophysics, **54**, 680–688, http://doi.org/10.1190/1.1442696.

Seltzer, M. L., D. Yu, and Y. Wang, 2013, An investigation of deep neural networks for noise robust speech recognition: 2013 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), IEEE, 7398–7402, http://doi.org/10.1109/ICASSP.2013.6639100.