Predicting reliability of AVA effects using neural networks
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Summary
The assessment of AVA effects related to hydrocarbon presence is critical to help evaluating the comparative risk between prospects for ranking purposes. The expected AVA effect and its conformity to structure will increase the confidence in the presence of gas. However, the tasks associated to volumetric AVA characterization can be tedious, and some automation could provide relevant help. The use of unsupervised classification techniques on prestack data, combined with synthetic AVA responses generated through fluid substitution and wedge modeling scenarios provide a new method for AVA effect assessment and characterization.

Introduction
The detailed analysis of prestack data has proven to be a reliable way to increase drilling rate success. Simulating the AVA behavior, to match with the real seismic data, starts with a rock physics and fluid substitution sensitivity analysis, paired eventually with effect due to thickness variation (wedge modeling), both aiming at understanding the interaction between lithology, fluid and bed thickness settings.

In a seismic-driven reservoir characterization workflow, the interpreter must first be sure that the gathers have been correctly flattened to avoid any biased interpretation. Subsequently AVA analysis is performed using post-stack attributes, such as normal incident and gradient through cross-plot and correlation with well information, before eventually detecting geobodies to move to a quantitative aspect of the workflow. This typical flow is somehow using a limited amount of available data. Therefore if the geoscientist can manage to investigate and generate results from his analysis, he will mainly have to focus on what is predominantly visible in the data as the use of the full collection of gathers, although it brings a lot of information, is still a time consuming process.

We propose to use a Self-Growing Neural Network method (Hami-Eddine et al. 2012) to investigate synthetic seismic responses from fluid substitution and wedge modeling, and reconcile them with seismic data. The objective is to isolate zones in the seismic data where estimated probabilities are associated with true hydrocarbon indicators related to fluid effects versus dry hole indicators. In this paper, we will consider only AVA behavior to participate to the process, not considering a tuning effect responsible for the amplitudes we are observing in the dataset we have used to apply for the method.

Method
Self-Growing Neural Network (SGNN) is an unsupervised incremental machine learning algorithm, also referenced in literature as Growing Neural Gas (Fritzke 1995). This technique builds a topology referential defined dynamically by projecting the data space onto a map with a smaller dimension that keeps neighborhood relationships. This projection respects two criteria: i) Two neighborhood elements in data space must be neighbors in the topology space, ii) Regions with a dense level of information of data space must be assigned to several neurons. It will tend to create families of neurons based on their data similarity.

The SGNN we use for the application to prestack data adds to that process a systematic outlier detection process to characterize anomalies in the data space, which may correspond to hydrocarbon effects and/or tuning effects.

The SGNN neuron families are then propagated onto seismic by using a Bayes approach (Hami-Eddine et al. 2015).

Example
The Taranaki petroleum sedimentary basin is located along the west coast of New Zealand’s North Island. The Cretaceous and Tertiary sedimentation occurred in response to the break-up of the paleo-Pacific Gondwana margin. The basin is separated into two tectonic areas, the Western Stable Platform and the Eastern Mobile Belt. Currently the main oil and gas fields in production of the Taranaki Basin are located onshore. The area of interest is an offshore
Exploration area covered by a 3D survey where a set of 3D PSTM seismic and prestack data are available. Three offshore vertical exploration wells, drilled along the western edge of the Taranaki graben are available. Two are located within the 3D seismic survey. For the purpose of demonstrating the method, we have selected a single well approach, drilled on the top of a bright seismic anomaly, but which failed to encounter the expected fluid, based on a classical investigation.

The well data shows that the sandy Miocene turbidites have lower acoustic impedance than the encasing formations and should potentially behave like class II, class III or class IV AVA anomalies. The upper part of the Mangaa formation shows clear and bright amplitude that can be characterized as anomaly, compared to what is observed in the lower the lithology as defined from well data. First, the upper part has identified separated individual sandy unit which strongly contrast with interbedded marly-claystone units. The lower part shows a more complex configuration with stacked sandy units interbedded by shale. Second, there is an important change in the impedance of the sand with depth, the upper part showing a higher impedance contrast with the encasing formation.

As Well 1 has intersected a wet reservoir, despite the visible seismic amplitude anomalies; we want to apply this method to confirm AVA validity, before any new prospect (drilling) could be developed in the same reservoir. Fluid substitution was performed on Well 1 data to generate a synthetic gas response. The example demonstrated in this paper, considers a simple Gassman fluid substitution to replace fluid content. As we have a relatively low number of wells, with logs in the area of interest, fluid substitution was performed on Well 1, which intersected wet sands. The substitution to gas is showing a class 3 effect, according to Rutherford classification (Rutherford and Williams 1989). This type of synthetic gather will be used to train our unsupervised neural network. The application of the neural network to the seismic data will help to qualify zones most likely to correlate with hypothesis done in the fluid substitution process.

The training of the neural network is performed on synthetic AVA signatures. The neuron shapes can therefore be displayed as simple amplitude versus angle curves. We observe that we are able to gather neurons based on expected versus non expected type of AVA effect. The figure 2 illustrates the example of seismic facies 4 showing a typical class II signature. This is the expected AVA effect for a gas response based on the fluid substitution performed on well 1 for deeper targets.

The different synthetic responses, generated on Well 1 using different fluid substitution (Gassmann’s equation) scenarios, are used to feed the SGNN algorithm. They are representing the hard data to constrain the learning stage and train the neurons.

The trained neurons are then used to estimate probabilities for each point in the seismic to relate to a specific neuron family. The probability estimation leads to the creation of a most probable seismic facies volume, which is directly correlated to AVA effects and can be correlated with post-stack attributes, for interpretation purposes.

The conformity of the seismic facies to the neuron AVA response, shown in Figure 2, is quantified by the probability values. Figure 4, is showing the probability distribution of gas like anomaly on top of structure. Red zones highlight corresponds to probabilities higher than 70%.

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Figure 3: Most likely gas sand distribution corresponds to orange color is displayed on top of structural interpretation, top of the formation of interest. Brown shows probable wet sands, and green shale. Well is confirmed to intersect wet sands.

Figure 4: Probability map of class II effect. Conformity to structure will have to be addressed to evaluate the final rating of the prospect.

Conclusions

This classification technique applied on synthetic gathers generated using a fluid substitution approach associated with a Self-Growing Neural Network method (SGNN), demonstrates clearly its advantages in an expanded interpretation workflow and/or a reservoir evaluation and ranking process. This approach needs to be associated to a classical seismic-driven reservoir characterization workflow, which derives post-stack seismic attributes to quantify the evaluated information. The classification process is providing clusters which can directly be correlated to expected AVA effects versus not expected AVA effects.

However, we certainly need to consider pairing a fluid substitution approach with understanding the impact of bed thickness variations (tuning effect/wedge modeling) to fully reconcile the different possible scenarios, to generate the synthetic gathers with the real seismic information.

In our example, sand bodies are well detailed and the comparison of seismic facies lateral extension with neuron shape is giving critical information to the nature of the setting which created the AVA response. The algorithm discriminates AVA responses without requiring an explicit relationship between amplitude and offset. This discrimination should be an added value to any AVA study. As the result is a seismic facies cube, it enables easy extraction of the different geobodies and contributes to understand, within the reservoir model, the facies distribution (correlated with the seismic data), before propagating reservoir properties.

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