GC Two Data Reduction Schemes: A Shallow Oil Field Example*

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General Statement

Contemporary exploration and development efforts are often blessed and plagued by a multitude of seismic data used to facilitate prospect risk and drilling decisions. While a plethora of data can sometimes shed light on subtle and difficult issues associated with lithology or pore fluids, identifying which seismic attribute is best or second best can be time consuming and perhaps futile, depending on the number of wells to which the seismic attribute is trying to calibrate.

Geoscientists with "too much" data can either choose which data attributes are best, based on some tabulation or crossplot, or attempt to combine different data sets in a linear-based process such as cross-plotting. In both instances, while it is paramount to identify the best attribute, it can be exhausting to determine this objectively using conventional approaches and even more difficult to identify subsequent attributes that may offer a higher-order solution.

In this article, we review two progressive approaches to systematically reduce the amount of data (reduce data dimensions) while synthesizing a best attribute from an ensemble of seismic input attributes.

Neural Networks

Two learning networks commonly used for data dimensional reductions are unsupervised and supervised neural networks. Instead of choosing the best attribute, neural networks can combine or group multiple attributes into a meta-attribute, synthesizing the best answer for all the training constraints. While unsupervised neural networks have been proven effective processes in macro- and meso-scale depositional facies characterizations, published results from supervised neural networks have more often demonstrated effective reservoir-scale characterization studies by using neural network mapping rather than neural network classification methods. Supervised neural networks can also be performed in classification mode and this article compares the two classification network results over a shallow oil field.

Selecting the most effective neural network is a crucial to maximizing interpretation benefits, yielding an accurate representation of the subsurface that can efficiently support exploration and production efforts. To that end, a comparison of two neural networks, supervised (multilayer perceptron or MLP) and unsupervised (unsupervised vector quantizer or UVQ) in classification mode is performed using Oligocene Catahoula oil-bearing sands overlying a shallow salt structure along the Gulf Coast, where well control is abundant and is used to ground-truth the seismic classifications of shale, brine-sands and oil sand extent and thickness. (UVQ is very similar to Kohonen self-organizing maps. They both solve linear problems and classify attributes based on internal data structure. The difference between the two is that KSOM updates the winning neuron and its' nearest neighbors, while the UVQ just updates the winning neuron.)

Extraction of the seismic facies (classes) volume at various wells within the 3-D volume permits direct comparison of the two techniques with known geology, permitting an unbiased evaluation and demonstrating the advantages of supervised neural networks for the classification of pertinent geologies.

Area of Interest

This study examines relatively unconsolidated sands and shale overlying a shallow piercement salt dome along the upper Texas Gulf Coast. The Oligocene-age sands and shales lie within the Catahoula Formation, the up-dip fluvial equivalent of the Frio Formation. The depositional setting is a single to multi-story fluvial channel-fill, crevasse splay and flood plain deposit. Sand thickness ranges from 24 to 87 feet and is of high porosity (30 to 36 percent). Hydrocarbons are commonly found only in the upper sand package within this multi-story system. The drive mechanism is a moderate to strong bottom and edge water drive. When not brine-saturated, the Catahoula sands generally produce 20 to 22 API Gravity Oil with a GOR of 100 to 300 CF/BBL. To date the Catahoula has produced 9,035 MBO and 4.9 BCF from approximately 400 wells at a depth ranging from 2,100 to 2,300 feet. Production is predominantly oil, with gas production from a minor gas cap that commonly converts to oil as the gas is withdrawn, with most gas produced as evolved free gas during separation at the surface. Both neural networks attempt to classify the three predominant geologies or facies within the zone of interest; shale, brine or wet sands and oil sands, our three seismic facies. With a surfeit of well control and a small 3-D seismic survey, this field is well suited to examine neural network techniques.

Neural Network Comparisons

Figures 2a and 2b are Catahoula horizon slice outputs from the UVQ and MLP neural networks, respectively, reducing the 20 attribute inputs to one neural network attribute output synthesizing a more concise answer. Comparing Figures 2a and 2b, one immediately sees shortcomings with the UVQ slice (Figure 2a) – the oil sand reservoir extent is smaller on the up-dip portion of fault block A with UVQ than on the MLP slice in Figure 2b. With the UVQ result, the oil reservoir is also not recognized in fault blocks B, C and D. Fault block A has produced 1,425 MBO out of 33 wells; fault block B, 330 MBO out of 11 wells; fault block C, 299 MBO from 14 wells; and fault block D, 320 MBO from 11 wells. The MLP classification result presents a more accurate reservoir definition in these fault blocks.

For this example, the unsupervised UVQ method has incorrectly estimated the occurrence of known hydrocarbons. This is based upon the more than 60 wells in these fault blocks as shown in the Figure 1 encompassing fault blocks A-D. In light of this, the question one should ponder is what might an unsupervised network miss where well control is not as abundant? Comparatively, the supervised MLP has reduced and refined the input attributes to a much more concise and effective interpretation of oil-sands, wet-sands and shales based on well control. In conjunction with the horizon extractions, to further assess the quality of both neural networks, we have sampled the UVQ and or MLP inversion volumes at well locations and present them in geologic cross-sections hung on the specific reservoir of interest – to compare the “soft data” (seismic) with the “hard data” from the well logs.

Figures 3a and 3b show two north-south cross sections over the northeastern portion of the field datumed on the top of the upper Catahoula reservoir. The upper Catahoula is shaded in red with the lower Catahoula shaded in green, and the vertical axis is in feet above or below the datum. The traverse of this cross-section is posted on Figure 1. Figure 3a shows the color-filled UVQ seismic facies in track 2 with green denoting oil-sand facies, blue for the brine-sand facies and tan for shale. Similarly, Figure 3b presents the MLP classification results in track 2. Cross sections in this figure show the target oil facies class not lying substantially above or below the Catahoula reservoir and that the vertical extent of the reservoir is roughly equivalent to the predicted seismic class.

Cross sections in Figure 3a and 3b compliment the horizon-slices in Figures 2a-b. The four southern-most wells on the right side of the cross section produce from the Catahoula sands, as denoted by the oil symbols. The UVQ cross-section shows thin and limited oil-sand facies (green) for wells G and H, but misclassifies wells E and F in the productive fault block B. Well A located down structure and demonstrably wet reveals a false oil sand prediction for this interval. Clearly the UVQ methodology does not predict the oil sands adequately. Where the upper Catahoula interval produces oil, the MLP result in Figure 3b better matches the production intervals and oil occurrences of the Catahoula. Wells in this figure not used for MLP training (blind wells) are shaded light purple at the base of the appropriate MLP cross-sections, for example, wells E and F. In section 3b wells E, F, G and H are correctly predicted to be productive in the Catahoula with no false positives. In the overlying sand, well G has a false negative, as the Figures well is productive in this sand, and in well H the deeper sand below the Catahoula has a false negative – although the actual production is in a sand stringer above this localized sand. Results from the MLP, while better than the UVQ, still do not capture all oil-bearing sands since the learning is never perfect, however, the learning or training interval appears to be sufficient for the Catahoula.

Conclusions

As shown in this abbreviated article, supervised neural network MLP can classify multiple attributes just as unsupervised neural networks do. For both techniques, 20 different seismic attributes are reduced to one attribute – a seismic facies classification volume. This Tertiary sand example has several salient points that may help in choosing what type of neural network might be best for a given exploration or development need while reducing data dimensions.

1) UVQ determines areas within the 3-D that have similar seismic attributes in a multi-attribute, multi-dimensional sense that may or may not relate to reservoir properties, while MLP and other supervised methodologies relate a multi-attribute, multi-dimensional response directly to reservoir properties and or geologic setting.

2) The unsupervised UVQ neural network in this example while reducing dimensions did not predict the known reservoir facies as accurately as the supervised MLP neural network did, and the UVQ had more pronounced false positives. While false positives do happen, the relative oil-

sand probability volume from the MLP computation (not shown) helps discount false positives with the MLP application. In this example for reservoir delineation, the MLP is the better choice for dimension reduction.

3) Well control is important for training, evaluating and trusting neural networks. While the MLP process utilized well data to develop a learning set, the UVQ process requires well data to attempt to explain the classification. One can incorporate the wells in the process before (supervised) or after (unsupervised) but they are required for interpretation. In this example, using the MLP method with well control reduces the seismic data dimensionality in a manner that better relates the seismic back to the well log described reservoir or geologic setting.

Finally, neural networks are very good tools that assist in interpretation. Choosing the best neural network for the task at hand may not be straightforward and should involve thorough evaluations to understand the strengths and weakness of each leaning network. For depositional studies with complexity and sparse well control, the options are limited. Where well control is available, use it and determine not only what each supervised and unsupervised neural network delineates, but also what they do not. What you do not know is usually what gets you. Or, as Mark Twain said, “It’s not what you don’t know that kills you, it’s what you know for sure that ain’t true.”

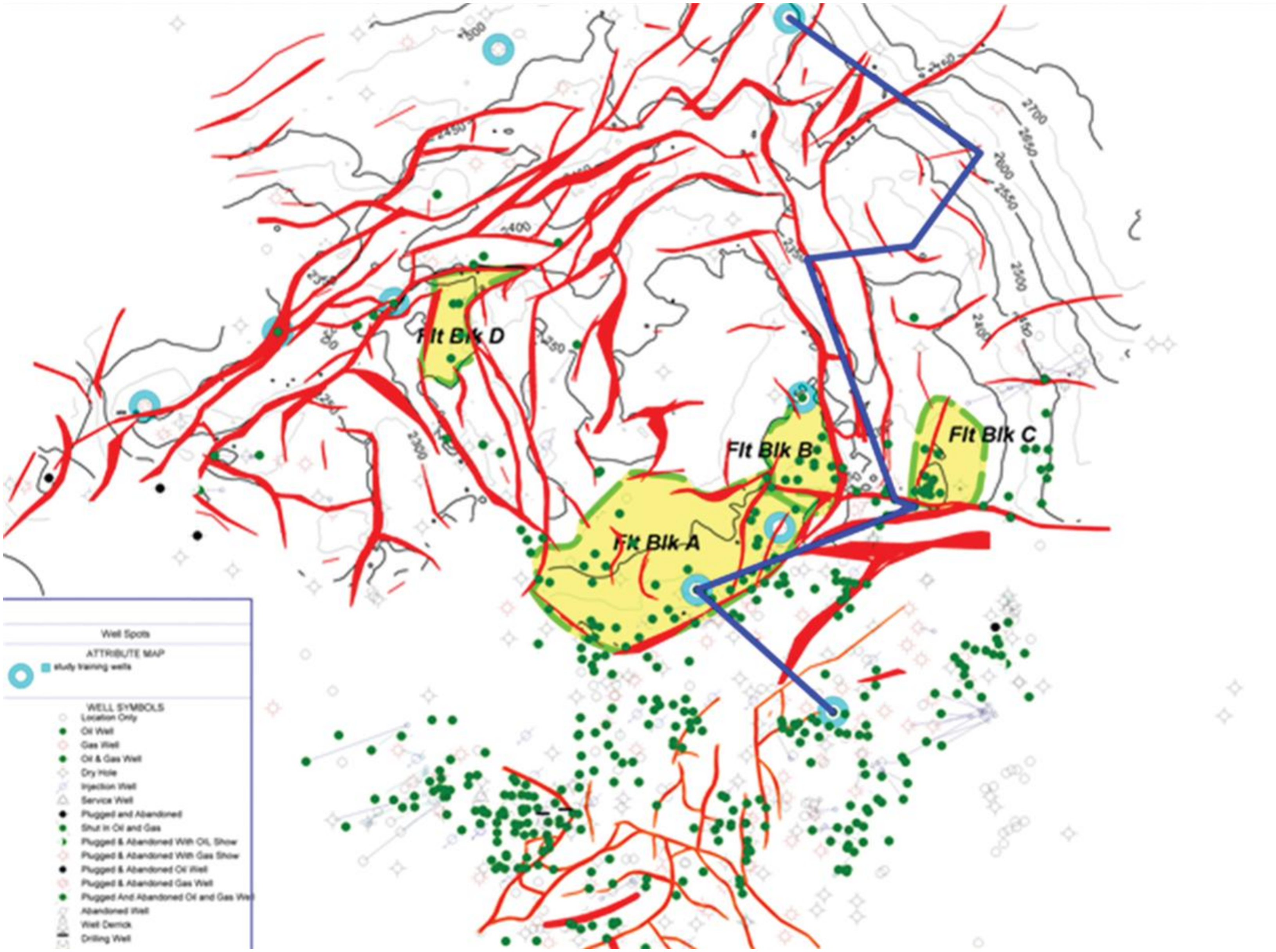
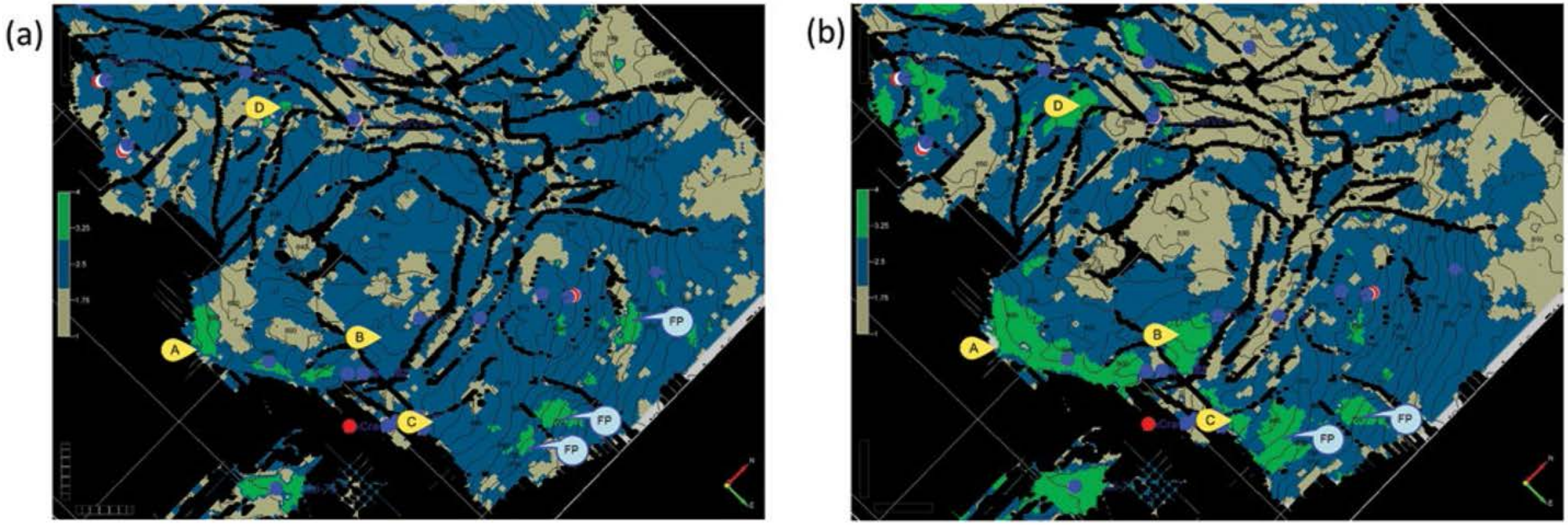
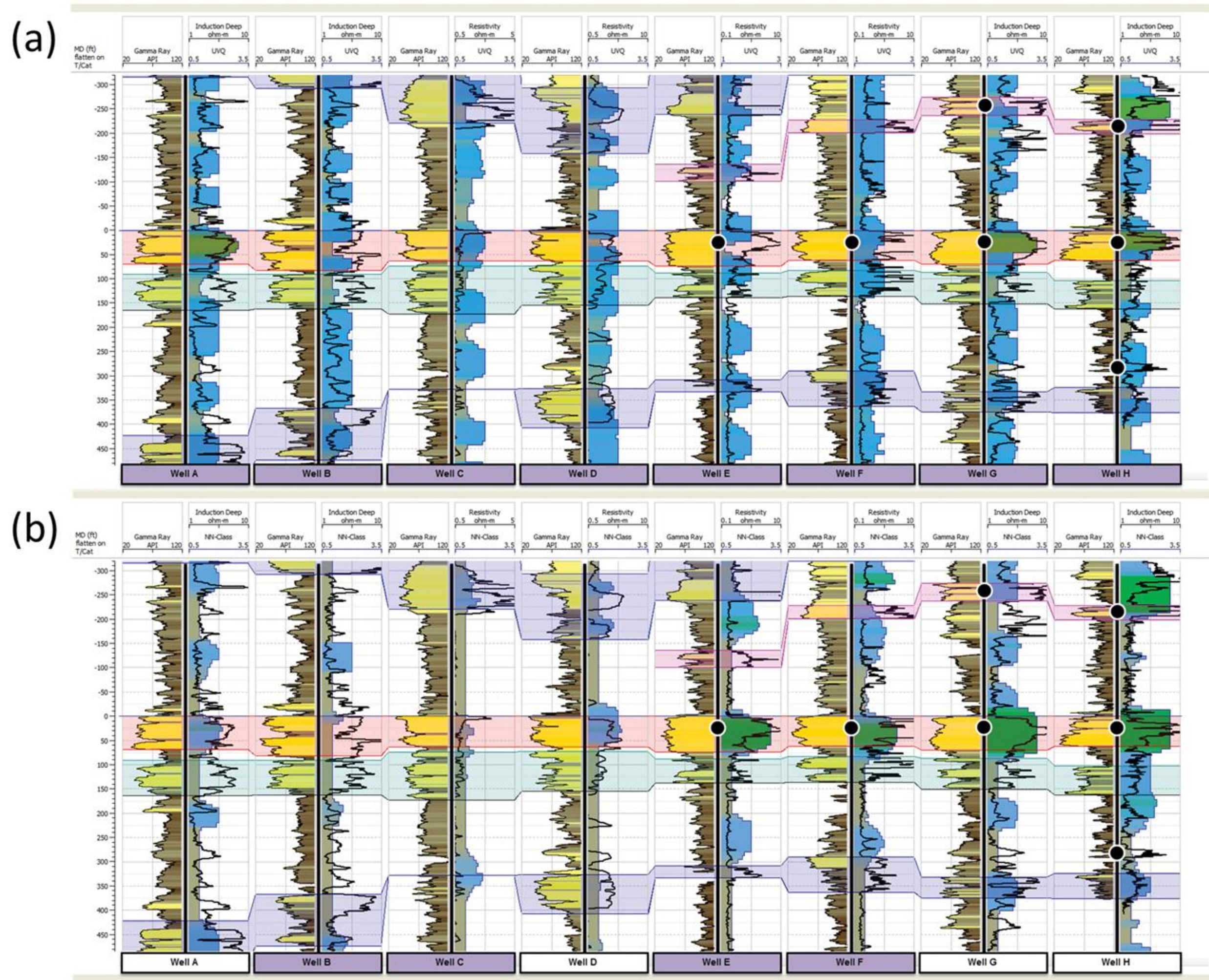


Figure 1. A well spot map of study area with all wells posted, illustrating the amount of hard data available, and the four fault blocks of discussion outlined and labeled in light green. Wells used for MLP (multilayer perceptron) training are annotated with light blue disks, and the cross-sections in [Figure 3a-b](#) are indicated by the blue traverse.



Figures 2a-b. Figure 2a (left) is the Catahoula reservoir horizon slice using the UVQ with three seismic facies. Green colors are predicted oil sands, blue colors are brine sands, and tan are shales. These classes are labeled through correlation to various wells, horizon structure and interpretive common sense (oil is trapped up-dip on the structure). Formation tops at well bores are shown by blue and red circles, labels A-D point to key fault blocks with major production, and “FPs” indicate false-positives. The oil extent is under-predicted at the crest of the structure and there are a number of false positives on the northeastern flank of the dome. Figure 2b (right) is an identical extraction from the MLP classification with three seismic facies - oil sand, brine sand and shale with the same color code as Figure 2a. These classes were trained by the MLP directly through a supervised learning process. The MLP oil reservoir representation at the top of the structure agrees much better with the number of producing wells (not posted). There are also false positives with the MLP, but they are reduced in size and can potentially be identified with the relative probability volume. Furthermore, other fault blocks with smaller oil reservoirs are visible on the MLP that are not with the UVQ in Figure 2a.



Figures 3a-b. North-south cross sections of select wells on northeast flank of dome, flattened on the top of the Catahoula are presented. Upper Catahoula sand is shaded in red. For each well, the gamma ray log is posted in the first track with deep resistivity log posted in the second track (black curve). Cleaner sands are colored yellow while shalier intervals are in browns and tans for the gamma ray. Producing symbols (indicating the production or occurrence of oil) are posted between the two tracks, and blind wells (wells not used for MLP training) are shaded light purple at the bottom of the cross sections. In Figure 3a, the UVQ seismic facies classification (variable color) is posted in track 2, with green indicating oil sand facies, blue indicating wet sand facies and shale or mudstone facies in tan. For Figure 3b, the seismic facies classifications posted in track 2 are for the MLP with the same color-coding. By sampling the seismic data at these wells and posting them with observed wireline logs, one can see that the MLP cross-section better agrees with the known data than the UVQ results do.