The Hunt to use Physics and Machine Learning to Predict Reservoir Properties

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Abstract
This presentation explores the use of Deep Neural Networks (DNN) to estimate reservoir properties using seismic data. Most geoscience projects do not have the large labelled datasets required to train DNNs. This presentation explores using both rock physics, and the statistics of the existing well control to generate a large number of pseudo wells and synthetics to train the neural network. The resulting DNN operator is then applied to the real seismic to predict some target elastic or rock property. This workflow has been successfully applied to a number of datasets from around the world including the Western Canadian Basin, the Gulf Coast and the North Sea.

Introduction
In 1998, the lead author, Jon Downton, was involved in a project with Lee Hunt where they used machine learning to predict the fluid content and thickness of the Halfway formation in Alberta. This lead to the drilling of three phenomenally thick, high porosity, wet reservoirs. The issue was that these high porosity wet sands had a low Vp/Vs ratio similar to that of gas sands and resulted in similar AVO responses. Since these high porosity wet sands were not represented in the well data that was used to train the neural network, the neural network was blind to this risk. Our takeaway from this experience was that we had to do more extensive rock physics and AVO modeling to understand the geologic variability of the play and whether it is possible to distinguish our objective in the presence of that variability. We developed a physics-based methodology to address these concerns and drilled some successful wells on another play. This resulted in the paper “Does the physics of an exploration play support AVO analysis in prospect evaluation?” (Li et al., 2000). This current paper is an extension of this work where we try to combine a physics-based workflow using machine learning.

In the subsequent twenty years since this work was done, machine learning has gone out of, and then back into, favour. One of the most popular current approaches is Deep Learning, which is used in hand writing recognition, image recognition and language translation. Deep Learning requires big data. Training datasets for image recognition usually consist of millions of images. In our geophysical projects we are lucky to have hundreds of wells that can be used for training. To overcome the issue of the lack of well data Downton and Hampson (2019) developed a hybrid theory-guided data science (TGDS) model (Karpatne et al., 2017) to augment the amount of data used to train the neural network. Rock physics theory is used to model the elastic parameter response due to changes in the rock and fluid properties of the local well control, and thus to generate a large number of pseudo wells. These pseudo wells are then used to model synthetic seismic gathers, which in turn are used to train a Deep Neural Network (DNN). The trained DNN is then applied to the real dataset. This paper shows the application of this workflow to an oil field in the North Sea. The reservoir interval is within the Palaeocene and in a remobilized injectite sand, which cross cuts a range of stratigraphy at very steep angles. These injectite sands, even though difficult to image, can add excellent pay zones with high porosity and permeability.

Method
The key idea is to augment the amount of training data by generating synthetic data based on the statistics from nearby wells and rock physics relationships. By using rock physics theory, a large number of pseudo wells can be generated, which span the range of expected geologic situations. Important wells from nearby fields, that do not necessarily tie the seismic under consideration, can be incorporated into the analysis. Additional wells could be incorporated into the analysis as drilled. The workflow consists of a number of key steps: seismic petrophysical analysis, establishing the statistics of the key parameters governing the model, generating elastic models based on the statistics and, finally, rock physics modelling (RPM). This produces a large number of pseudo wells. For each of these simulated wells we generate synthetic seismic
angle gathers. The collection of these gathers is called a “Synthetic Seismic Catalog” (Dvorkin et al., 2014). The synthetic seismic gathers are used to train the neural network. Lastly, the weights from the trained network are is applied to the actual seismic.

First, a petrophysical analysis is performed to calculate the input required for the RPM. In this case study, log measurements (gamma-ray, deep resistivity, density) were used to calculate the clay volume, total porosity, water saturation. These petrophysical logs will be used as input to the RPM.

Next, we determine and calibrate the rock physics model linking the elastic properties such as density, P- and S-wave velocities to the petrophysical properties. To model the unconsolidated and tight sands encountered in this area we use a RPM based on the Hashin-Shtrikman Hertz-Mindlin (HSHM) model (Dvorkin and Nur, 1996) that includes an extra parameter called the matrix stiffness index (Allo, 2019). In order to more accurately model the P-wave and S-wave velocities we model and invert for the matrix stiffness index as a function of depth. The workflow is quite general and can be adapted to use other rock physics models.

Having established the RPM, we next need to characterize the statistics of the available log data in order to generate realistic synthetic data. The statistics of the key parameters governing the RPM is established using the following procedure:

a) break the logs into “lithofacies intervals” that share common statistics i.e means and trends;

b) calculate the mean trend and covariance matrix of each of these lithofacies;

c) determine the vertical variogram that best fits the clay volume data variogram in order to model the vertical continuity of the data.

![Figure 1](image1.png)

**Figure 1** Elastic property logs (Vp, Vp/Vs, Density), petrophysical property logs (Porosity, Water Saturation, Clay Volume) used for automated lithofacies classification, lithology log and lithofacies log. All logs are color-coded by lithofacies.

The lithofacies classification is performed automatically as a two-step process. In the first step binary decisions (shale or sand, wet or hydrocarbon (HC), porous or tight) are performed to split the well into a series of lithologic categories. In the second stage, the thin lithology layers are reassigned the adjacent lithology that is statistically closer in terms of mean or Mahalonobis distance. Using this process, we obtain...
lithofacies that constitute rock units with common statistics and a thickness comparable to the seismic resolution, as illustrated in Figure 1. Figure 1 shows one of the four wells analysed in this study after going through this analysis. The colors represent the lithofacies. For each lithofacies we calculate a depth dependent linear trend and covariance matrix.

**Figure 2** Well curve simulations performed for P-wave velocity (upper), S-wave velocity (middle) and Density (lower)

Having determined the statistics it is then possible to generate many pseudo wells. For each well and each lithofacies the rock properties are simulated based on the above statistics. In addition, key reservoir properties such as the thickness and saturation can be varied in a stepwise fashion. This ensures that there are training examples for a variety of different reservoir thicknesses and fluids. After establishing the rock properties for each pseudo well, the RPM is used to calculate the elastic properties.

Figure 2 shows the resulting P-wave velocity, S-wave velocity and density for a number of pseudo wells in which the reservoir thicknesses and saturation are being varied. Figure 3 shows a number of representative synthetic gathers generated from these simulated pseudo wells.
Results
Lastly, the pseudo wells and synthetic data are used to train the DNN. The well curves (e.g. P-wave impedance, porosity, saturation) serve as the target while the synthetic data serve as the input data to the DNN. The pseudo wells are broken up into training and validation datasets. The DNN is trained on the training subset. It is important to highlight that the actual 3D seismic data and the original wells are blind to the DNN training process.

The estimated non-linear operator is time shift invariant, i.e. the synthetic gathers do not need to be aligned in time with seismic and no time-to-depth correlation on the pseudo curves is needed. To apply the DNN operator to the real data, the real data needs to be scaled since it differs in amplitude from the synthetic data. This is the same problem that must be dealt with by prestack elastic inversion so we use the same method to scale the seismic data. The non-linear operator derived using the synthetic data is then applied to the seismic angle gathers. Different operators are needed for each target variable. In this case we created operators for Density, P-wave and S-wave Impedance, Porosity and Saturation.

Figure 4 shows a comparison between P-impedance predictions obtained from pre-stack inversion and from the DNN approach. The input to both analyses are five angle stacks and a low-frequency P-wave impedance background model. The predictions of the DNN tie the well control better than that of the deterministic inversion and seem to have better lateral continuity. Note that the DNN prediction separates the producing wells D and A from the wet well B.
One of the advantages of the methodology is that any reservoir property (i.e. elastic property calculated from the rock physics model or input parameters to the rock physics model) can be estimated. For instance, we show porosity predictions obtained from the DNN approach in Figure 5. Note that this type of properties are not easily and routinely included in the forward model for seismic-based inversions. The present technique could thus prove useful in estimating reservoir properties without relying solely on a rock physics transform linking inverted elastic attributes and rock properties.

Conclusions

In this study, we demonstrated how rock physics and AVO modelling can be combined with deep neural networks in order to predict reservoir properties from seismic. The advantage of using rock physics modelling in this machine learning workflow is twofold. First, along with a detailed statistical analysis of the available log data, it allows us to generate many realistic seismic synthetic gathers. Second, it provides a way to model scenarios that may not be encountered at the well location.

This method involves log data conditioning, statistical analysis and rock physics model construction and calibration. These steps are crucial so as not to introduce systematic bias in the synthetic training dataset. The incorporation of the synthetic data allows for the construction of more accurate and deeper neural networks. Elastic attributes and rock properties can then be estimated with enhanced resolution, as shown on the North Sea case study.
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References