Application of rock physics driven deep machine learning for hydrocarbon exploration

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Abstract
A robust and predictive subsurface model is a key requirement in several stages of exploration and development. Quite often, such a model is built through integration of wells and seismic data using a geological framework. Theory-based methods such as seismic inversion is the most commonly used tool to derive robust subsurface elastic properties models which are later transformed into reservoir properties such as porosity, volume of clay and water saturation using linear regression or nonlinear transforms like neural networks. In the early stage of exploration, where only few wells are drilled, very limited information is available for proper integration of wells and seismic data giving rise to higher uncertainty in the subsurface properties.

In recent times, advanced deep machine learning methods such as Convolutional Neural Network (CNN) is used extensively in various industries with a remarkable success. CNN requires a large amount of sample data for efficient training of the network which poses a serious challenge in exploration scenario. Rock physics guided machine learning can fill this gap of data limitation and can open the avenue of using deep machine learning algorithms in exploration fields. A rock physics model is established and validated on drilled well and later used to simulate various possible geological scenarios like variations in porosity, saturation, volume of clay and reservoir thickness. Each of these scenarios is treated as a new synthetic well and the incidence angle dependent reflectivity derived from the elastic property’s curves are convolved with real seismic wavelet to generate synthetic seismic dataset. Thus, hundreds of synthetic wells and corresponding seismic prestack gathers are now available as labelled data to train the CNN. In order to make the learning process of CNN more efficient and robust, a transfer learning step is used before its application to real seismic data.

Here we present a case study from Western Australia with limited well control. Acoustic impedance, porosity, volume of clay and water saturation models are generated using theory guided deep machine learning and interpreted along with seismic amplitudes, to reduce drilling risk and uncertainty.

Keywords: Hydrocarbon exploration, rock physics, deep machine learning, convolutional neural networks, reservoir properties

Introduction
In a typical exploration case, usually seismic data is used for structural interpretation and later seismic amplitude anomalies are interpretated to find and validate the prospects. A quick estimation of elastic and reservoir properties by integrating wells and seismic data is highly desirable, for reservoir delineation. However, lack of sufficient drilled wells always poses a serious challenge in estimating elastic and reservoir properties using theory based as well as machine learning methods. With the improvement in computational power in recent years, deep neural networks (Goodfellow et al., 2016) are used in the energy industry. But deep neural networks require a large amount of data for training, thereby limiting its usage. Downton et al. (2020) came up with a novel approach...
for data augmentation using a theory-based method. A rock physics model is used to simulate possible geological scenarios in the field. These hundreds of geological scenarios are then used in the deep neural network, a convolutional neural network in this case, to estimate multiple reservoir properties simultaneously.

**Geology of the area**

The study area of West Tryal Rocks gas field is located offshore at the Western margin of the Barrow Sub-basin, in the Carnarvon Basin of Western Australia. It was discovered by West Australia Petroleum Pty Ltd in 1973 (Meath et al., 1976). The productive structure at West Tryal Rocks lies at a depth of 3200 m with about 150 m of water column. It consists of an elongate north–trending uplifted block of Triassic and possibly Lower Jurassic reservoir rocks called the Mungaroo beds. The reservoir section dips to the north more sharply than does the sealing unconformity so that progressively younger pre-Cretaceous sediments sub-crop the unconformity in that direction. The shales of Middle to Late Jurassic age in the Barrow Sub-basin to the East are believed to be the primary source of hydrocarbons, although the overlying Muderong shale cannot be ruled out (Playford and Johnstone, 1959). The sands are generally medium to very coarse grained and possess good porosity and permeability.

There are 5 sand packs M, N, O, QR and T as observed in well WTR_4A shown in Figure 1. M sand is the major gas saturated pack and encountered in well WTR_4A and WTR_2. Full stack seismic data exhibits bright amplitudes over M, N, O sand packs as clearly seen in Figure 2. Prime objective of this work is to quickly derive reservoir properties using rock physics guided machine learning to understand if all favourable seismic amplitudes prospects correspond to clean reservoirs of good porosity and hydrocarbon saturation.

![Figure 1: Recorded and petrophysical logs in WTR_4A. Panels from left to right represent calliper, gamma ray, resistivity, volume of shale, porosity, water saturation, acoustic impedance, density, ratio of acoustic and shear velocities (V_P/V_S), respectively. The extreme right panel shows the well tops corresponding to M, N, O, QR and T sands from top to bottom.](image)

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Figure 2: Segment of an arbitrary line seismic section passing through two wells (WTR_2 and WTR_4). Overlaid on the section are the sand markers of interest as well as the gamma-ray curves filtered to seismic bandwidth. The arbitrary line trajectory within the survey is shown in the inset on the top right.

**Rock physics guided synthetic data generation for deep machine learning**

Here, we have used well WTR_4A as input for training the CNN and kept the well WTR_2 for blind well validation. An unconsolidated sandstone model (Dvorkin and Nur, 1996) that is further extended by Allo (2019) to include stiffer sandstones through the matrix stiffness index (MSI) is established using well WTR_4A (Saputra et al., 2022). Well curves per layer statistics, vertical variability and rock physics model are used together to generate possible geological scenarios for porosity, water saturation, volume of clay and sand thickness. This generates hundreds of synthetics wells with the corresponding elastic responses. A real seismic wavelet is used to generate synthetic AVO signatures using Zoeppritz equation (Zoeppritz, 1919) for each synthetic well. This generates many synthetic wells and synthetic seismic data, as shown in Figure 3, allowing us to use deep neural network for training and validation purposes.
Figure 3: Synthetic seismic gather showing multiple scenarios within zone of interest. Only a few cases out of hundreds of generated scenarios are shown here.

Convolutional neural network (CNN)

A CNN is used to simultaneously estimate acoustic impedance and reservoir properties. CNN is generally used in image classification (LeCun et al., 1998) in various industries and requires a large amount of labeled data for training. Theory guided data augmentation fulfills the basic requirement of a large dataset, thereby allowing CNN to be used in subsurface property prediction in this case. CNN is composed of 2 steps, convolution, and pooling, as shown in the schematic diagram in Figure 4.

The input for the CNN is 30x80 image size where 30 is the number of angle traces present in the seismic prestack gather and 80 is the size of the rolling time window. As we have a large number of synthetic wells for training, we have a choice to use a large number of hidden layers in deep neural network. We have selected 250 hidden layers in this study. 100 epochs are tested with 30% data used for validation. A 3x3 filter size is used with 2 convolutional layers. The output of the second maximum pooling layer is flattened and used as an input into a fully connected network. The CNN is first trained and validated using synthetic wells and synthetic seismic data. Once the CNN is trained with the synthetic data, seismic and model scalars are estimated using the real-world seismic wavelet. These scalars are used again at the synthetic well, thereby improving the match between well and CNN predicted properties.

So far, synthetic data has been used for training and validation purposes in CNN, whereas we would like to incorporate real seismic data as well within the training. Hence a step of transfer learning is used in the process. After training the CNN on the synthetic data, the convolutional layers are frozen, then a subset of the real well
and real seismic data are used to update the weights of the fully connected part of the network, as shown in Figure 5.

Figure 4: Schematic diagram of convolutional neural network.

Figure 5: Schematic diagram for Transfer Learning. The red blocks indicate that the weights prior to fully connected layers are now fixed.
Transfer learning helps in incorporating real data and thereby improving the match between predicted and well properties, as shown in Figure 6.

Figure 6 shows the input and predicted properties in well WTR_4A indicating the robustness of training and prediction. Also, very reasonable match observed on blind well WTR_2 as shown in Figure 7 (b), (c) and (d) displaying CNN predicted volume of clay, porosity and water saturation passing through training as well as blind well WTR_4A and WTR_2 respectively.

Further, these reservoir models are analysed by generating slices for M sand capturing samples from M sand horizon to 30ms below for seismic (RMS amplitude), volume of clay (arithmetic mean), porosity(maximum), and water saturation (arithmetic mean), as shown in Figure 8.
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Figure 7: Equivalent segments of arbitrary line sections passing through two wells (WTR_2 [blind] and WTR_4) and extracted from (a) input seismic data, (b) CNN predicted volume of clay, (c) CNN predicted porosity, and (d) CNN predicted water saturation volumes. Overlaid on the section are the sand markers of interest as well as the gamma-ray curves filtered to the seismic bandwidth.
Figure 8: Horizon slices generated for M sand distribution in a 30 ms interval below the M sand marker for analysing the reservoir model predictions. The RMS seismic amplitude is shown in (a), the CNN predicted volume of clay is shown in (b), the maximum value of porosity is shown in (c), and the arithmetic mean value for the water saturation is shown in (d).

Figure 8(a) shows the RMS amplitude map over the M sand sequence and shows two distinctive high amplitude areas as shown by upper and lower polygons. Presence of hydrocarbon corroborating with high amplitude in lower polygon as observed in both the wells WTR_4A and WTR_2 provides a boost to look for more favourable high amplitude prospects and most likely in upper polygon. In lower polygon, CNN derived reservoir properties low volume of clay, high porosity, and low water saturation in figure 8(b), (c) and (d) provides good correlation with high amplitude and results are in line with validation well WTR_2.
Our observation in upper polygon shows that CNN derived properties do not indicate same favourable good reservoir as shown in lower polygon. In the absence of any drilled information in upper polygon high amplitude prospects, CNN derived properties such as porosity, volume of clay and water saturation provide additional insight into play/prospect analysis and informed decision making.

Conclusions

It is observed that rock physics guided machine learning solves two purposes simultaneously. Rock physics helps to simulate geological possible scenarios of reservoir which is very helpful in scarcity of wells. Once we have large number of simulated scenarios in the form of synthetic labelled data, a deep neural network can be used for training and validation purpose thereby allowing us to train for complex nonlinear relationships. Convolutional neural network, a sophisticated neural network for image classification, enables us to estimate various subsurface properties simultaneously, thereby providing additional dimension of data analysis for prospect identification and ranking in exploration type of scenarios.

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Jyoti is working as Geoscience Advisor at GeoSoftware, Perth, Australia. She received her M. Tech degree in Applied Geophysics from Kurukshetra University, Haryana, India, in 2013 and joined CGG. Jyoti has more than 9 years of experience in seismic reservoir characterization specifically in seismic AVO and inversion technology. Jyoti has multiple years of coaching, mentoring, and supporting E and P companies for reservoir geophysics, trainings and project support consultancy in India and far east region. Her interest lies in integration of multidisciplinary datasets using advanced geostatistical inversion technology and machine learning. She is an active member of SEG, USA and AEGC, Australia.

Hemant Kumar Dixit has more than twenty plus years of experience working as a geophysicist emphasizing on seismic interpretation and seismic inversion technology. His core expertise lies in integration of seismic petrophysics and rock physics, together with the successful application of inversion technology for reservoir evaluation and assessment. He has applied many new and exciting technologies to a great range of basins in India, Europe, and the Far East.

Hemant has multiple years of experience in teaching reservoir geophysics, project consultancy, tailored made training programs and technical lectures to national and international conferences. Prior to working with GeoSoftware as a business manager (India, Sri Lanka, and Bangladesh), Hemant had responsibilities of geophysical advisor in reservoir services CGG in Mumbai, with Schlumberger in London and Reliance Industries Limited (India) also in Mumbai in a wide range of geophysical roles. He served as a member of the technical committee of SPG, India, editorial team member of GEOHORIZONS magazine published by SPG, India and served as freelance technical reviewer in SEG for The Leading Edge and Interpretation publications. He is member of SPG, India and lifetime member of AEG (Association of Exploration Geophysicist, India).