Application of Deep Machine Learning for Direct Estimation of Hydrocarbon Pore Thickness

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Keywords

Deep Machine Learning, Probabilistic Neural Network, Deep Feed Forward Neural Network, Hydrocarbon Pore Thickness

Summary

Precise reserve estimation is the most crucial aspect of a field during exploration and development. The understanding of fluid content, extension of the reservoir, and net pay are key parameters in planning a field development. To achieve these objectives, the often used geophysical datasets acquired during various stages of the field are the well logs and 3D seismic data. Well logs have good vertical resolution but poor horizontal resolution whereas seismic data has a good horizontal resolution but poor vertical resolution. Wells and seismic are often integrated either using a physics based approach like inversion or data science approach like machine learning or a hybrid of the above two methods, inversion followed by linear regression.

Simultaneous inversion derives acoustic impedance, AI and shear impedance, SI or ratio of P-wave velocity and S-wave velocity, Vp/Vs of the subsurface layers. These elastic attributes can be further used to derive reservoir properties like water saturation, porosity, volume of clay using traditional multi linear regression (Russell et al., 1997) or Artificial Neural Networks, ANN (McCormack, 1991). The traditional workflow involves derivation of the reservoir properties first using linear regression or ANN and then estimation of hydrocarbon pore thickness using a cut off values on petro physical properties. Hydrocarbon pore thickness summed over the area of hydrocarbon pool gives *in situ* hydrocarbon pore volume which is a measure of reserve. We propose a method to directly train our dataset for hydrocarbon pore thickness using linear regression, neural network or deep neural network (Bengio, 2016, Tanya et al., 2018). Direct estimation workflow involves only one step of data training compared to the traditional method for hydrocarbon pore thickness estimation using three steps and, thus, is easy and less compute intensive. Here, we are comparing the results of the direct workflow with currently used workflow. The results from the direct estimation workflow are better correlated to the well control and are more spatial continuous. Operationally, the workflow is simpler and faster to implement.

Introduction

Multi Linear Regression (MLR) is a common method of predicting a reservoir properties using attributes of seismic data. MLR establishes a linear relationship between the property to be predicted and multiple attributes of seismic and derived data, e.g. impedances from post or pre-stack inversion.
In contrast, an ANN establishes a nonlinear relationship. Mathematically, an ANN roughly mimics the way the human brain is thought to work.

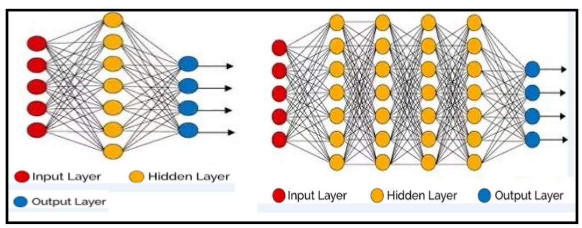

Figure 1: A Schematic diagram of Artificial Neural Network (left), Deep Neural Network (right).

The Neural network (Figure 1) is composed of an input layer, hidden layers and an output layer. Each layer is composed of several neurons, each of which is connected with the neurons of the previous and subsequent layers. Each neuron is a nonlinear function, thus given a network of sufficient depth and complexity an ANN can model any nonlinear function. ANNs are a form of supervised learning that is they use a portion of the labelled data to train the neural network. The learning algorithm then generalizes from the training data to unseen situations and the resulting model is statistical. Before these networks can be used to perform a predefined task, they must be "trained" with data and existing

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knowledge/inferences. Different principles can be used for training these networks giving rise to varieties of neural network algorithms like Probabilistic Neural Network(PNN), Radial Basis Function(RBF) neural network etc.

Deep Feed Forward Neural Network (DFNN) is another form of supervised learning based on the recent advance in deep learning (Lecun et al., 2015). The key difference between a basic neural network like PNN and deep learning algorithm, e.g. DFNN is that the number of hidden layers in deep learning are more, thus enabling these algorithms to model greater complexity. The weights are solved as large nonlinear inverse problem using iterative techniques. The important parameters are the number of hidden layers, number of nodes in each layer and number of iterations for solving the large nonlinear inverse problem.
In this case study, Multi Linear Regression, Probabilistic Neural Network and Deep Feed Forward Neural network methods are used for comparing the hydrocarbon pore thickness estimation from conventional and direct workflows.

Case Study

Here, we investigated the problem of hydrocarbon pore thickness estimation using data from Amberjack Block 109 from the Gulf of Mexico in the Mississippi Canyon. The study area is 24 km^2 over the west flank of a faulted anticline. 3D prestack seismic data, five wells with full suite of logs and structural interpretation in the form of key horizons are available for this study. In this area, the Middle Pliocene reservoirs are trapped in 2 sequences, Upper Delta and Lower Delta with muds in between (Mayall et al., 1992). The upper delta is further divided into 4 reserves, Green progradational unit and upper Red transgressive unit (Latimer et al., 1996) as summarized in Figure 2.

The Green reservoir, our zone of interest for this study, is a sequence of clinoforms with continuous reservoirs. The overlapping sands have both structural and stratigraphic components, partially controlled by faults.

Here, a Simultaneous Inversion workflow (Hampson et al., 2005) is used to derive the acoustic impedance, shear impedance and Vp/Vs ratio volumes. These elastic property volumes along with the seismic amplitude volume are used to estimate reservoir properties, viz. water saturation, porosity and volume of clay.

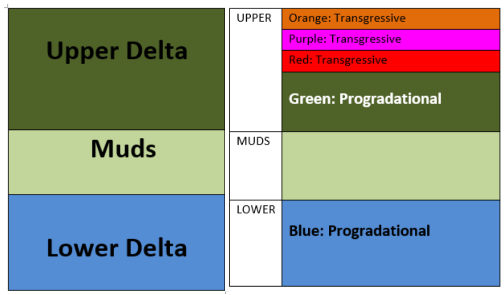

Figure 2: A schematic diagram of sequence stratigraphy

The supervised learning algorithms were trained at the well locations for each of these reservoir properties separately using three different methods, viz. Multi-linear regression, neural network and deep neural network. These reservoir properties are then used in the hydrocarbon pore thickness estimation using equation 1.

$$F_{HCP} = \sum_{i=1}^{i=m} h_{ni} \emptyset_i (1 - S_w) \dots\dots\dots\dots\dots (1)$$

Where, h_{ni} at each data point has value of 1 for pay and 0 for non-pay based on a cutoff of Vclay, and 'i' is the index of a sample. The above traditional workflow is described in Figure 3.

This paper compares two different workflows to estimate the hydrocarbon pore thickness. The first workflow as outlined in Figure 3 is based on Colwell and Kjosnes (2018). The Workflow uses machine learning to first estimate the water saturation, volume of clay and porosity and then uses these intermediate results to predict the hydrocarbon pore thickness. The fact this workflow involves three separate machine learning steps means it is quite time consuming. As an alternative, this paper suggests using machine learning to estimate the hydrocarbon pore thickness directly as described in Figure 4. In this direct workflow, a hydrocarbon pore thickness log is calculated for each well at each sample point using equation 1. The input attributes to the machine learning are the elastic properties from the inversion and the seismic amplitude volume.

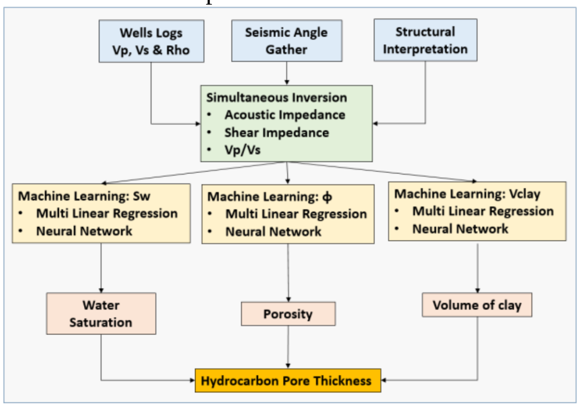

Figure 3: Workflow for hydrocarbon pore thickness estimation in a conventional way.

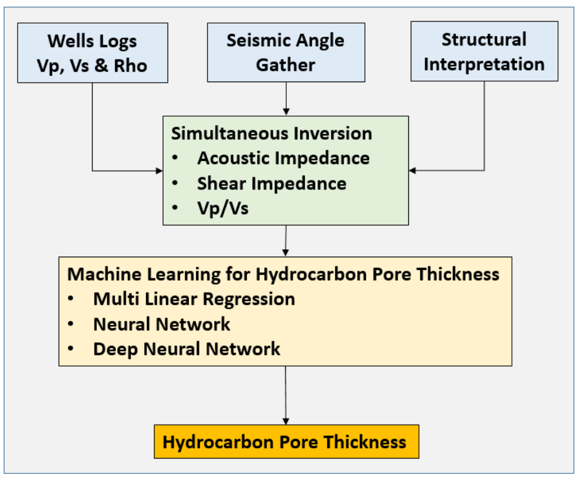

Figure 4: Workflow for direct hydrocarbon pore thickness estimation.

The two results of the workflows are compared in Figures 5, 6 and 7 where different machine learning approaches are tried. Figure 5 shows a comparison of the hydrocarbon pore thickness estimate for Green reservoir over an interval of 50 ms using MLR. Figure 5a shows the result of using the MLR method to separately predict water saturation, porosity and volume of clay within Green reservoir and then estimate the hydrocarbon pore thickness for the Green reservoir using equation (1). The results using MLR method for direct hydrocarbon pore thickness estimation are shown in Figure 5b. The hydrocarbon pore thickness estimated using the direct workflow is more accurate around Well 3 and has better spatial continuity.

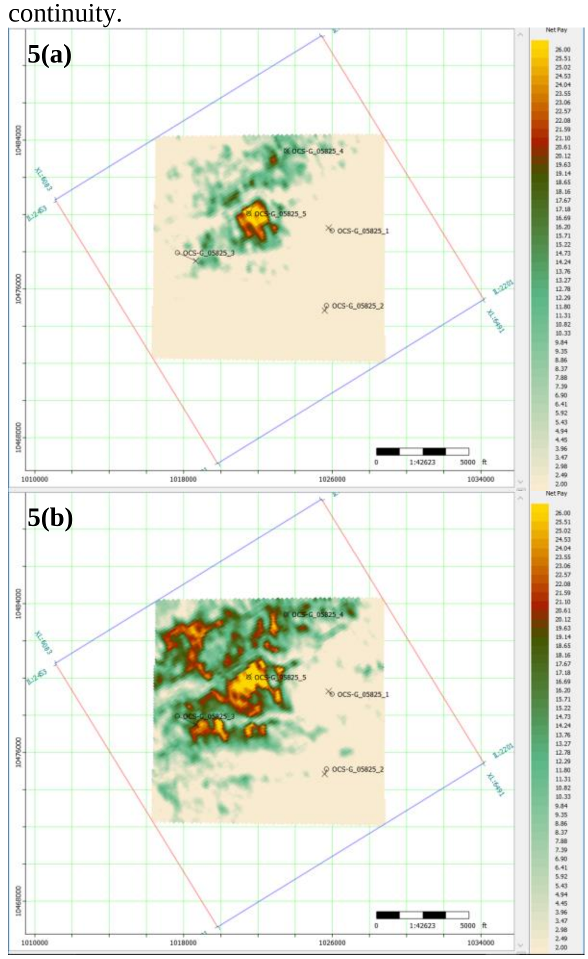

Figure 5(b): Hydrocarbon pore thickness estimation using multi linear regression from (a) conventional and (b) direct workflow.

Similar to the case of using MLR, we used a basic neural network viz., PNN, for i) predicting water saturation, porosity and volume of clay separately followed by hydrocarbon pore thickness estimation and ii) the new workflow for direct estimation for hydrocarbon pore thickness. Here, we used the best combination of attributes derived from inversion and seismic amplitude volume as input for PNN. Hydrocarbon pore thickness maps over an interval of 50ms for Green reservoir using PNN for both the workflows are shown in Figure 6.

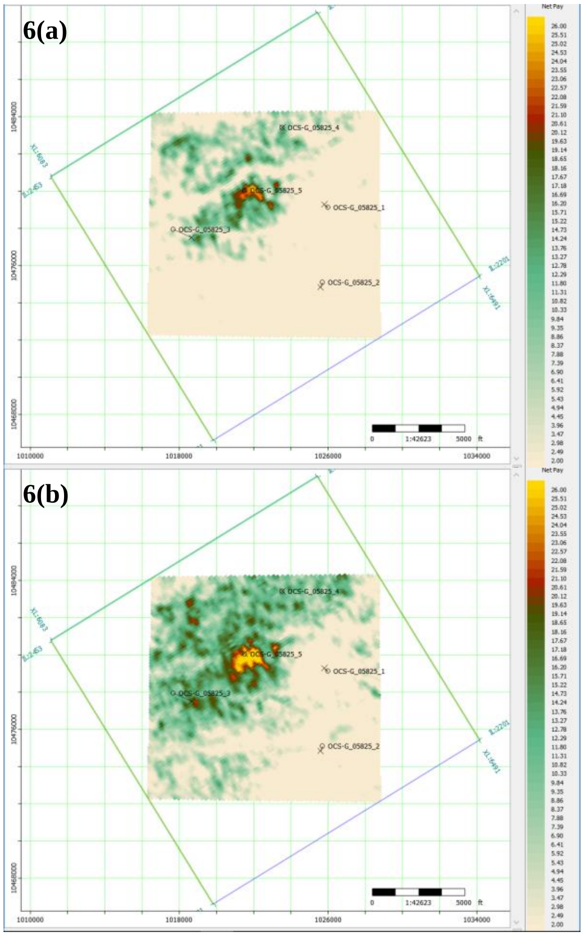

Figure 6: Hydrocarbon pore thickness estimation using PNN from a) conventional and b) direct workflow.

Finally, we used the deep neural network algorithm, DFNN, similar to previous two cases, MLR and PNN, for i) predicting water saturation, porosity and volume of clay separately followed by hydrocarbon pore thickness estimation and ii) directly for hydrocarbon pore thickness estimation using the direct workflow. Hydrocarbon pore thickness over an interval of 50ms for Green reservoir using DFNN from both workflows are shown in Figure 7.

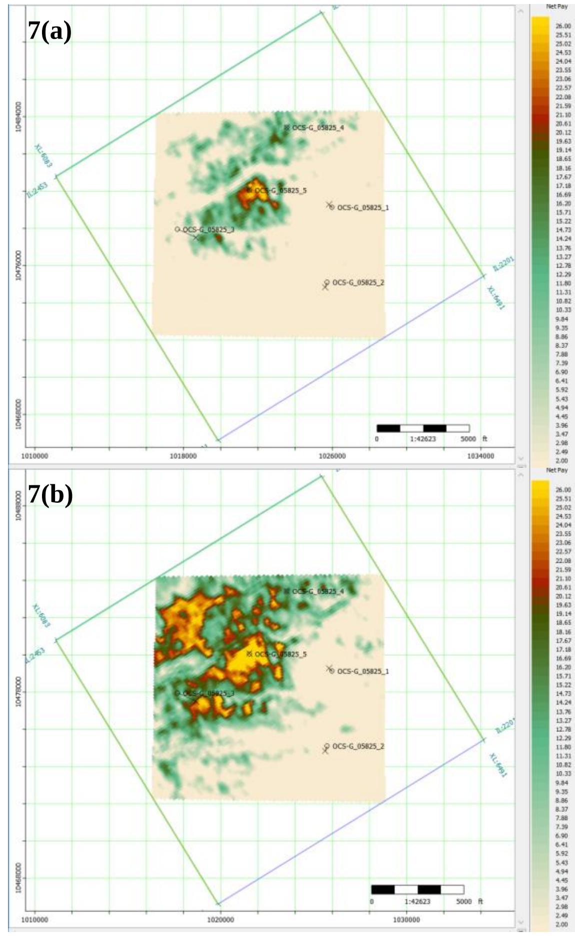

Figure 7: Hydrocarbon pore thickness estimation using DFNN from (a) conventional workflow and (b) direct workflow.

It is observed that the hydrocarbon pore thickness estimation using DFNN with the direct workflow is better compared to conventional workflow, in terms of better correlation at the well locations and better spatial continuity.

Comparing all the results together, it is inferred that for both the conventional and the direct workflows, deep learning methods provide better results compared to basic neutral network and MLR in terms of better correlation at the well locations and spatial continuity. Furthermore, the direct estimation using any of the methods is simpler and easier compared to using conventional workflow involving separate estimation of porosity, water saturation and volume of clay.

Conclusion

It is observed that hydrocarbon pore thickness estimation from direct workflow is better compared to the conventional workflow, irrespective of using Multi linear regression, PNN and DFNN, in terms of better training and better spatial continuity. The proposed workflow is less time consuming as we are training our data only at one stage, directly for hydrocarbon pore thickness estimation, compared to the conventional workflow, where we are training our data for each reservoir property separately and then using an appropriate cutoff to estimate hydrocarbon pore thickness. In summary, direct estimation of hydrocarbon pore thickness using deep machine learning is the best method to meet the objective.

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Acknowledgements

The author is thankful to Dr. Ranjit Shaw, Hemant Kumar Dixit, Santan Kumar and Jimmy Ting, CGG for their valuable guidance and continuous support during the work.