Predicting Unconventional Shale Reservoir Properties from Seismic and Well Data Using Convolutional Neural Networks

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Summary

Convolutional neural networks (CNNs) are used to simultaneously predict elastic and reservoir properties from seismic and well data for an unconventional shale reservoir. In this methodology the seismic-to-reservoir property relationships are learned from well log data and seismic angle gather data. To overcome the issue of limited training well data, synthetic data are utilized to train the CNN. The synthetic data are generated from the statistics of the original well data in the study area and a rock physics model (RPM) suitable for unconventional reservoirs. The RPM enables systematic changes of key reservoir properties, such as porosity, thickness, kerogen and clay volumes, to generate a well sampled training dataset that captures the geologic variability within the study area. The synthetic well logs and seismic data are then used to train the CNN. The resulting operators are applied to the real seismic data to make the reservoir predictions. These predictions can often be improved by incorporating the real data into the training by performing transfer learning. This allows the CNN to account for differences between the real and synthetic data thus improving the results. This is important in this Barnett dataset where the seismic-to-well tie is poor at the zone of interest. The main objectives of this study are CNN rock property estimates of effective porosity, quartz, kerogen, clay volumes and elastic mechanical properties. The CNN results better resolve the zone interest, show better lateral continuity and better match the well control, including two blind wells, than estimates based on a more traditional machine learning workflow using multilinear regression and hand selected attributes.

Introduction

The goal of this study is to accurately predict unconventional reservoir properties from seismic and well data using convolutional neural networks (CNNs). There is a great interest in the use of Deep Learning (Goodfellow et al.,2016) to automate complex workflows and reduce project times. Downton and Hampson (2021) show that CNNs can more efficiently predict reservoir properties as compared to traditional machine learning methods (Hampson et al., 2001) which use seismic attributes as input. However, there is often insufficient training data (i.e. well control) to properly train a CNN. Downton et al. (2020) overcome this issue using a hybrid theory-guided data science

(TGDS) model (Karpatne et al., 2017). A two-component model is built where the outputs of the theory-based component are used as inputs to the data science component. Rock physics theory is used to perturb the original well control to generate many synthetic wells spanning the range of the expected geology. Seismic theory is then used to model synthetic seismic gathers to create a Synthetic Seismic Catalogue that contains both the target logs and input features. The Synthetic Seismic Catalogue is used to train and validate the CNN. The trained CNN is then applied to the real dataset. Downton et al. (2020) demonstrate this workflow on a North Sea Oil field utilizing an unconsolidated (soft) sandstone rock physics model (RPM) (Dvorkin and Nur, 1996). This current work replaces the RPM with an inclusion model (Key and Xu, 2002) more suitable for unconventional reservoirs.

This work details the necessary modifications to perform this workflow on unconventional reservoirs demonstrating the methodology on a Barnett Shale dataset located in the Fort Worth Basin, Texas. Success requires identifying brittle, fracable, productive layers with high quartz content (Varga et al., 2012; Pendrel and Marini, 2014). Accurate determination of effective porosity requires reliable volumes of clay, quartz, kerogen, and other heavy minerals with results verified by core porosity. Identification of brittle productive layers also requires reliable elastic properties volumes. In our Barnett Shale dataset, seven wells are used to generate hundreds of synthetic wells and seismic data. The resulting synthetic data are used to train the CNN to estimate elastic and rock properties. First elastic properties such as density, P-wave and S-wave impedance are estimated. Incorporating the real data into the CNN training via transfer learning provides a mechanism to incorporate differences between the real and synthetic data significantly improving the elastic property results. The second CNN simultaneously estimates the effective porosity, quartz, kerogen and clay volumes. The CNN reservoir property estimates are higher frequency and match the blind well control better than multilinear regression (MLR) estimates based on seismic attributes.

Synthetic Catalog Generation

We generate a Synthetic Seismic Catalogue composed of a series of pseudo-wells and synthetic seismic gathers. The pseudo-wells are generated based on the statistics of wells in the study area and rock physics theory. The key steps in this workflow consists of:

1) A petrophysical analysis to generate the necessary petrophysical logs for input to the RPM.

2) Selection and calibration of the RPM. In this study, an effective medium theory following Keys and Xu, 2000 is used to model this unconventional shale reservoir. To accurately estimate the measured logs, the RPM is calibrated by performing an inversion for the aspect ratio.
3) Establishing the statistics of the well log data for use in the simulations. In practice the well logs are typically non-stationary requiring that each well is broken up into a series of lithofacies layers, for which the statistical parameters are determined.
4) Generating a series of pseudo-wells by simulating petrophysical logs based on the statics determined in step 3. To ensure that the pseudo-wells sample the range of possible geologic scenarios, the thickness, porosity, clay and kerogen volumes of the reservoir layers were perturbed resulting in 189 pseudo wells. Lastly, the calibrated RPM from step 2 was used to generate the elastic properties from these petrophysical logs.
5) Synthetic angle gathers are then generated for each pseudo-well using a convolutional model in which the P-wave reflection coefficients calculated using the Zoeppritz (1919) equations are convolved with a wavelet extracted from the real seismic data.

Finally, the CNN is trained and validated using the pseudo-wells and synthetic seismic gathers. More details for each of these steps can be found in Downton et al. (2020).

Convolutional Neural Network

The CNN architecture is based on those used to perform image classification (LeCun et al., 1998). The input data are 20 by 20 pixel images generated by running a 20 point sliding time window over an angle gather consisting of 20 angles (Figure 1). In this case study, two convolutional layers are used, each followed by a maximum pooling layer. Each convolutional layer consists of 64 kernels of size 3x3, followed by a rectified linear unit (ReLU) activation function. The output of the second maximum pooling layer is flattened and input into a fully connected network with one hidden layer with 60 nodes. Dropout is used to help regularize the problem. The CNN can be used either for classification or regression. In this work elastic and rock properties are estimated, so linear activation functions are used in the output layer. Multiple outputs are supported to improve the operational efficiency. In this study, the CNN was first run with three outputs to estimate density, P-wave and S-wave impedance as a quality control on the process and to provide the mechanical properties required to estimate a brittleness volume. Then four rock properties were estimated including effective porosity, quartz, kerogen, and clay volumes. Note the size of the input image, the size of the convolutional filter, the number of convolutional layers, the number of nodes of the fully connected hidden layer, dropout threshold, and number of epochs are all hyperparameters that can be adjusted. The second network used for rock property estimation has 72,493 trainable parameters though this varies depending on the choice of hyperparameters.

The CNN is trained on the synthetic data. There are about 14,000 images to train and validate the CNN. The CNN operator is then applied to the real seismic data. The real seismic angle gathers are processed in a manner suitable for seismic inversion and scaled comparable to the synthetic data using an algorithm similar as performed for seismic inversion.

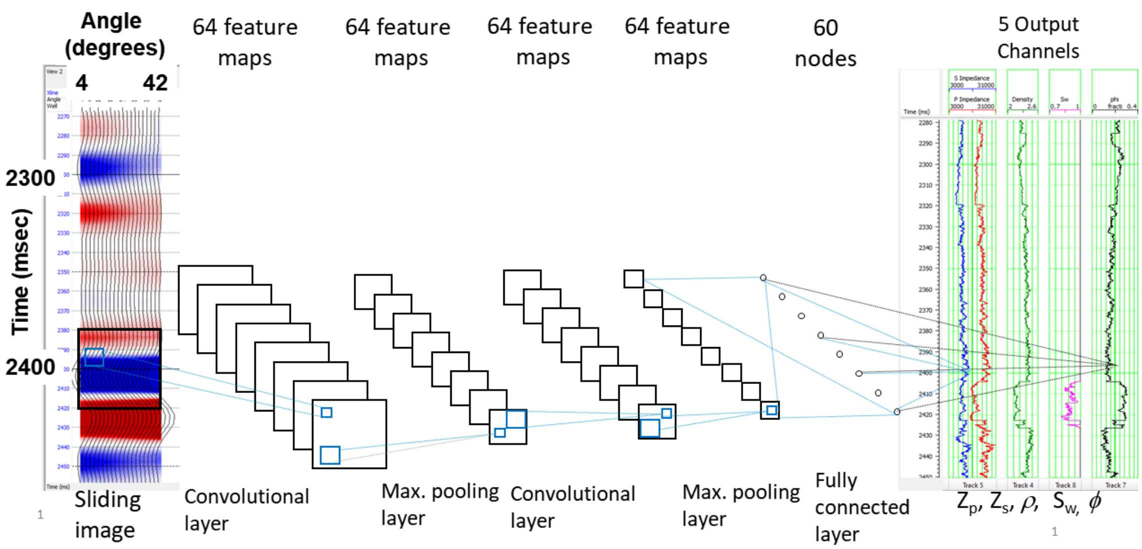

Figure 1. The input data to the convolutional neural network are 20x20 images constructed from CDP angle gathers. The CNN architecture in this study consists of 2 convolutional layers followed by max. pooling layers each with 64 features maps. The output of the 2nd convolutional layer is flattened, fed into a fully connected layer with dropout. The CNN estimates multiple output target logs.

Up until this point, the real data was not included in the CNN training. Ideally, we would like to include the real data to allow for theoretical differences between the synthetic and real data. The real data is incorporated into the CNN by performing transfer learning. After training the CNN on the synthetic data, the convolutional layers are frozen, then a subset of the real well and seismic data are used to update the weights of the fully connected part of the network. This fine-tuning of the fully connected weights improves the match to the well control. Figure 2b shows the CNN P-wave impedance estimate after transfer learning. The transfer learning allows the network to account for differences between the synthetic and real data. Consequently, the CNN transfer learning result matches the well control better than the deterministic inversion result (Figure 2a) which is based purely on a theoretical model. The CNN P-wave impedance estimate (Figure 2b) better resolves the thin high impedance unit near the top horizon and better matches the well control than the deterministic inversion.

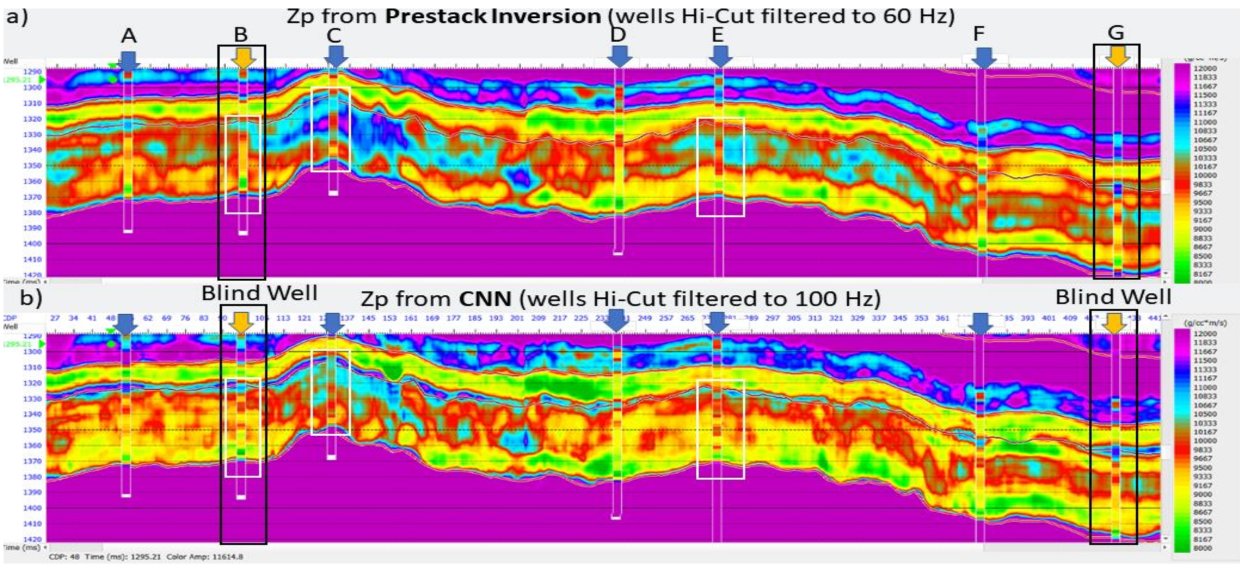

Figure 2. The CNN transfer learning estimate of Acoustic impedance b) is higher frequency and matches the well control better than the estimate due to deterministic inversion a) as highlighted by the white boxes. The CNN correctly predicts the low impedance unit at 1320 ms for well C while the deterministic inversion incorrectly predicts a high impedance as highlighted by the white box.

Results

The main goal of this study is estimating elastic and rock properties that highlight better reservoir conditions in the Barnett Shale. To this end, the first CNN estimated the elastic properties in the target reservoir for an estimated brittleness volume and the second CNN simultaneously estimated the effective porosity, quartz, kerogen and clay volumes. To provide an objective comparison we also estimated these properties using multilinear regression (MLR) using seismic attributes as input following Hampson et al. (2001). Both the CNN and MLR were trained and validated on the synthetic data. Two wells were reserved as blind wells. Figure 3 compares the kerogen volume estimated using MLR and the CNN. The CNN result better resolves the zone of interest, matches the well control more closely and displays better lateral continuity. To honor the fact the CNN shows significantly more frequency content the wells displayed with the CNN are hi-cut filtered to 100 Hz while the MLR results are hi-cut filtered to 60 Hz.

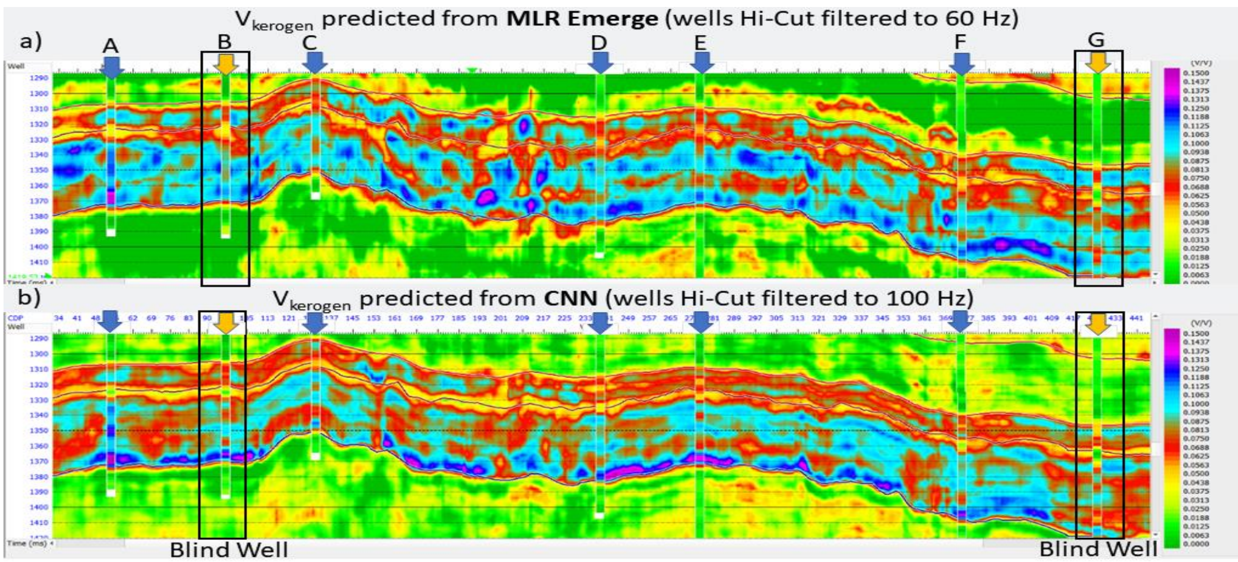

Figure 3. The kerogen volume b) estimated from the CNN is higher frequency and ties the well control better than that a) estimated using multilinear regression.

Conclusions

On this Barnett Shale dataset, we demonstrated how CNNs can be used to predict reservoir properties appropriate for unconventional reservoir characterization including effective porosity, quartz, kerogen, and clay volumes. The CNN estimates better resolve the reservoir and match the blind well control better than the MLR estimates. Key to performing this work is generating a well sampled synthetic training dataset, in this case using the Keys and Xu RPM. The modeling is similar to what an interpreter might perform to understand the seismic response of different reservoir conditions. Incorporating the real data into the training via transfer learning significantly improves the results and provides a means to incorporate differences between the real and synthetic data and is a key to improving the P-wave impedance estimate. The fact that the CNN can simultaneously predict multiple reservoir properties lead to significant efficiencies.

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