Stratigraphic sequence estimation from seismic traces using convolutional neural networks

Fantine Huot, Bruce Power and Joe Stefani

ABSTRACT

We train a 1D convolutional neural network to estimate stratigraphic sequences from seismic data, and evaluate which frequencies are required to obtain accurate estimates. While seismic volumes are typically unlabeled data, well logs allow us to label portions of seismic data with their corresponding geological stratigraphy. We boost the training set by generating additional synthetic well logs using Markov chain modeling. We demonstrate that the estimation accuracies increase with seismic frequency content, and while accuracies remain fairly low for frequencies under 50 Hz, we achieve accuracies over 80% when pushing towards higher frequencies.

INTRODUCTION

Well logs allow us to label portions of seismic data with the corresponding stratigraphy. Herein, we are provided with 60 well logs from the Wilcox formation in the Gulf of Mexico. We preprocess the data to derive the elastic moduli using rock physics diagnostics in order to generate corresponding seismic traces using convolutional modeling. We then generate additional synthetic wells with similar statistics by Markov chain modeling to boost the size of the data set. We then proceed to train a 1D convolutional neural network to estimate the stratigraphy directly from the seismic data and evaluate which frequencies are required to obtain accurate results.

DATA PROCESSING

Wilcox formation well logs

We were provided with the logs from 60 wells from the Wilcox formation in the Gulf of Mexico (Figure 1). The data are sampled every 15 cm along the borehole, and the region of interest spans about 500 m to 1,000 m for each well at a depth of about 8 km. The provided data values are depth, resistivity, P-wave velocity, S-wave velocity, gamma ray, neutron porosity and density (Figure 2a). The computed volume of shale (vshale) attribute is also provided.

Figure 1: Locations of some of the wells from which the logs were provided. (Image source: www.offshore-energy.biz) [**NR**]

Rock physics diagnostics

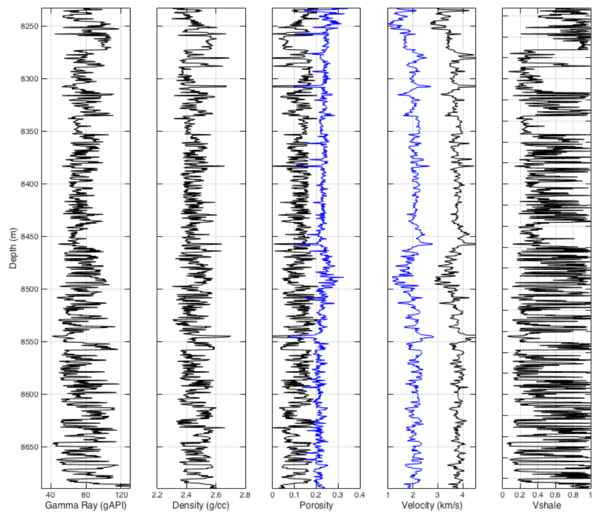
We use rock physics diagnostics to find a lithology model to match the log data and consolidate the elastic properties, as described by Mavko et al. (2009) (Figure 3). The modeled elastic properties are then compared to the log measurements (Fig 2b) and seem to match the data fairly well, allowing us to fill in any missing values and remove outliers.

Synthetic seismic generation using convolutional modeling

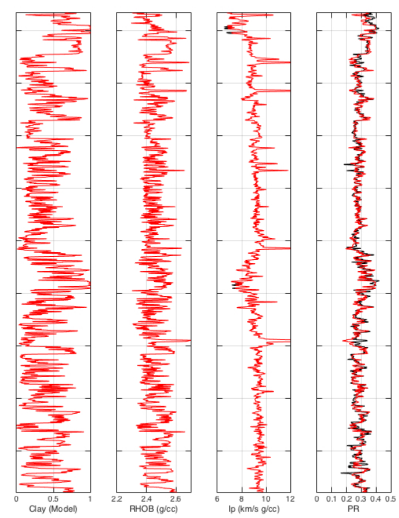
We then generate synthetic seismic traces from the well log data, using convolutional modeling to generate common-depth gathers (Figure 2c). The travel times, angles and offset are computed via ray-tracing, and the amplitudes at each interface are computed using the Zoeppritz equations. The final reflectivity series are then convolved with a Ricker wavelet at various frequencies ranging from 10 to 200 Hz. While the higher frequencies are not realistic, they are computed in order to evaluate which frequencies are required to obtain accurate estimates with the learning algorithm. We interpolate the seismic traces to match the sampling rate of the logs to have correspondence between the seismic data and the stratigraphy labels.

Stratigraphy labeling

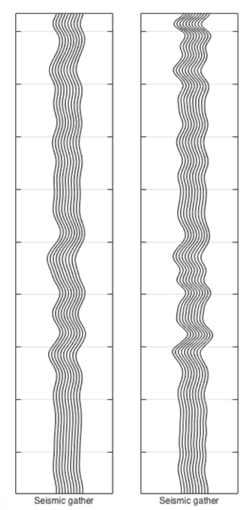
The difference between well log resolution (0.3 m) and seismic resolution (about 200 m) makes it difficult to label the seismic data using the vshale log values, for averaging them over large windows would not be very informative. Therefore, we label the data by chunks, and divide them into five categories:



(a)



(b)



(c)

Figure 2: (a) Provided well log data for one of the wells. From left to right: Gamma ray, density, bulk porosity (black) and neutron porosity (blue), P-wave velocity (black) and S-wave velocity (blue), computed vshale. (b) Rock physics diagnostics. From left to right: selected clay content lithology model, measured bulk density (black) vs modeled bulk density (red), P-wave impedance directly computed from the input data (black) vs modeled P-wave impedance (red), Poisson's ratio directly computed from the input data (black) vs modeled Poisson's ratio (red). The selected lithology model fits the log data fairly well and is the one we adopted for consolidating the elastic properties before proceeding to convolutional modeling. (c) Examples of corresponding seismic common-depth gathers obtained by convolutional modeling with a Ricker wavelet at 40 and 60 Hz for different offsets. [**CR**]

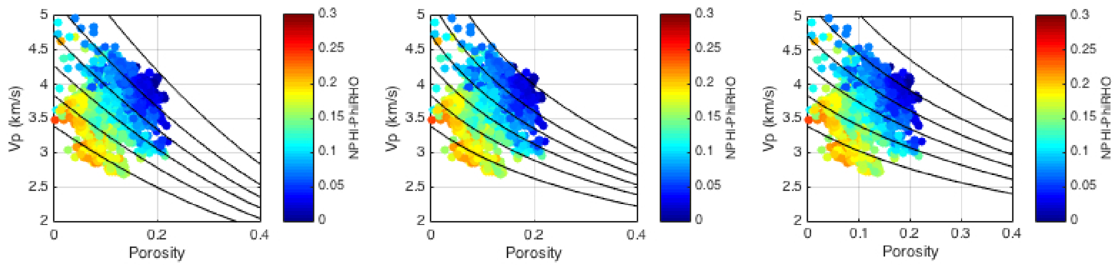


Figure 3: P-wave velocity plotted versus porosity, color-coded by lithology. The color scale corresponds to the difference between neutron porosity and bulk porosity, which is an indicator for clay content. The overlaying curves correspond to different lithology models (from left to right: Raymer, soft sand, constant cement). From these plots, the most appropriate model appears to be the one in the center, as the lithology curves match the data best. [**CR**]

1. Blocky stratigraphy mostly shale
2. Fine stratigraphy mostly shale
3. Blocky alternations
4. Fine stratigraphy mostly sand
5. Coarse stratigraphy mostly sand

SYNTHETIC WELL LOG GENERATION USING MULTI-SCALE MARKOV CHAIN MODELING

The loss of resolution when transitioning to seismic data makes our training set too small to obtain good performance with a neural network, so we boost the data set by generating additional well logs using Markov chain modeling.

The distribution of vshale is fairly bimodal (Figure 4), so we model the vshale values using two states, 0 and 1, with a cut-off value at 0.4. By reducing the number of possible states we increase the value of the statistics to populate the transition probabilities in the Markov chain.

Figure 5 presents results obtained with different lengths of Markov chains. The Markov chain using only one previous state generates logs that are too laminated to be realistic, but longer chains and increased stationary probabilities yield realistic vshale alternations. A separate Markov chain is constructed for each of the 5 types of stratigraphy. A macro-level Markov chain then determines the alternations between these different types.

We populate the synthetic logs with elastic properties picked out of the total distribution of elastic properties in the field data for low and high vshale (Figure 6).

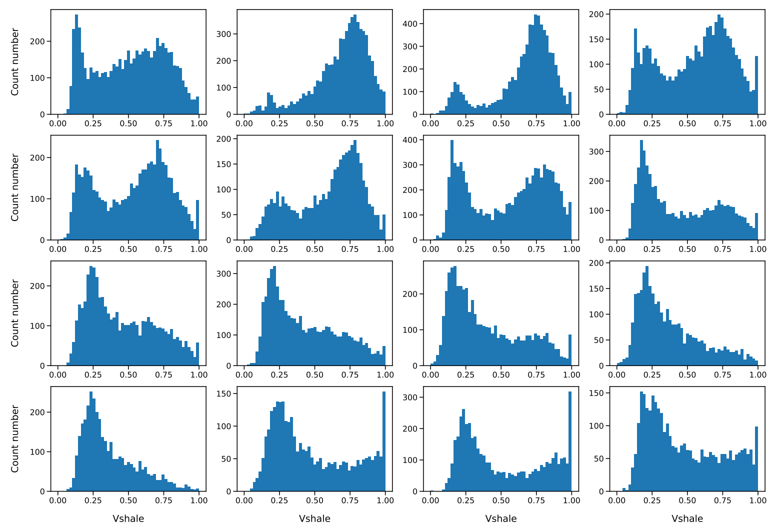


Figure 4: Distribution of the volume of shale over 16 different wells. As its distribution is fairly bimodal, we decided to use two states to model the volume of shale in the Markov chain. From the distribution, we set the cut-off value between the two states at 0.4. [**CR**]

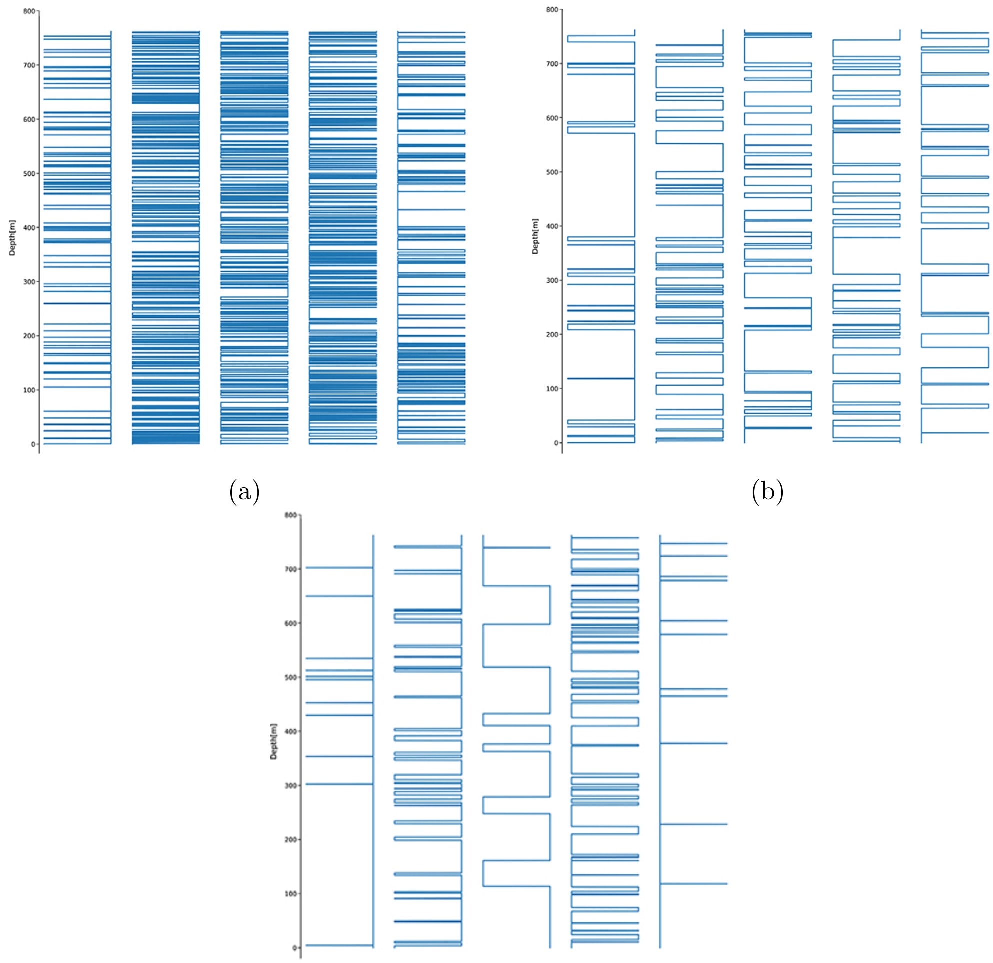
Data volume

After data processing and synthetic data generation, the data set results in 180,000 samples of field well log data and 500,000 samples of synthetic well log data. It is then normalized, and split into a training and a test set in a 80:20 ratio.

1D CONVOLUTIONAL NEURAL NETWORK

We train a 1D convolutional neural network over this data set. We define a sliding detection window of 200 samples along the seismic traces. The neural network has the following architecture:

- 10×1 convolution layer with rectified linear unit (ReLu) activation function
- Max pooling 2×1
- 5×1 convolution layer with ReLu activation function



(a) (b) (c)

Figure 5: Vshale alternation for 5 different types of stratigraphy using Markov chain modeling. (a) A Markov chain using only one previous state generates logs that are too laminated to be realistic. (b) This Markov chain uses the 3 previous samples plus the average over the 10 previous ones, and 20 previous ones. It results in more realistic alternations. (c) Results from the same Markov chain as used for (b) but with increased the probabilities for all the stationary modes. It yields different profiles for the 5 types of stratigraphy, and is the one we used in this study. [**CR**]

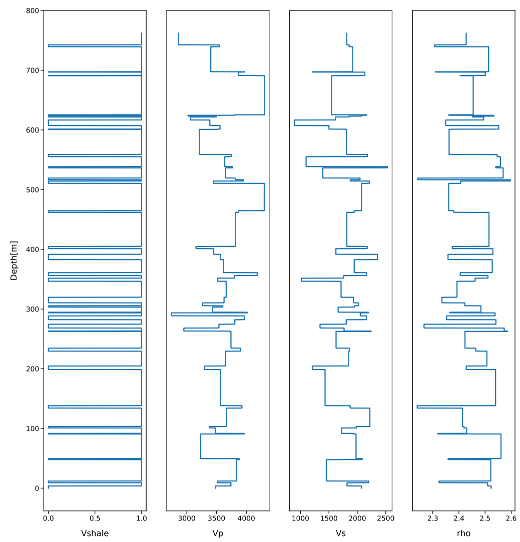


Figure 6: Elastic properties for a synthetic well of stratigraphic type 2. We populate the synthetic logs with elastic properties picked out of the total distribution of elastic properties in the field data for low and high vshale. [**CR**]

- Max pooling 2×1
- Fully connected layer with ReLu activation function
- Dropout with a probability of 0.75
- Fully connected output layer

A description of the different components of the convolutional network is provided in Huot (2018).

On seismic traces with frequencies under 50 Hz, this convolutional neural network obtains fairly poor accuracies, limited between 35 and 50% (but still superior to random guessing, which would be 20%, given that we have 5 labeled stratigraphy types) (Figure 7). Its accuracy increases with increasing frequencies. If we artificially push to high frequency, we see that this network can actually achieve accuracies above 80% if the frequency content is high enough.

DISCUSSION AND CONCLUSIONS

While the trained convolutional neural network did not achieve good performance on low frequency seismic traces, the suggests that the methodology might have some potential for seismic data with higher frequency content. In order to achieve better accuracy on low frequency seismic data, we would need to incorporate additional data, such as transitioning to 3D volumes to obtain depositional context.

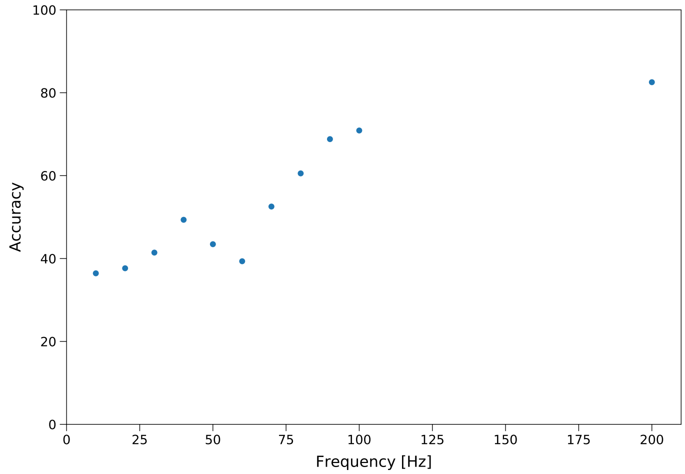


Figure 7: On seismic traces with frequencies under 50 Hz, this convolutional neural network obtains fairly poor accuracies, limited between 35 and 50% (but still superior to random guessing, which would be 20%, given that we have 5 labeled stratigraphy types). If we artificially push to unrealistically high frequency, we see that this network can achieve accuracies above 80%. [**CR**]

ACKNOWLEDGEMENTS

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