Novel Machine Learning Workflow for Rock Property Prediction in the Geologically Complex Pre-Salt Santos Basin, Brazil

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Summary

We carried out a unique workflow for rock property prediction based on supervised artificial neural networks to characterize carbonate reservoirs in the Santos Basin, Brazil. Seismic amplitude, horizon, and depth-based features were used and credibly related to conventional reservoir properties like porosity. We demonstrate the usage of modern data science and model architecture optimization techniques. As a result, we fine-tune the predictive models to reduce over-fitting and achieve better model generalization. We can provide confidence estimates for the rock property predictions. As a part of this study, we also conducted a controlled experiment to measure prediction accuracy's sensitivity to having 4, 8, and 13 wells in model training. The resulting workflow eliminates the subjective background model building and wavelet estimation processes. The machine learning methods produce high-resolution rock property volumes to facilitate a faster mapping of reservoir heterogeneity than traditional methods. In this structurally complex pre-salt carbonate play, all results generated using this state-of-the-art technology have excellent matches to blind well control.

Introduction

The heterogeneous lacustrine carbonate reservoirs of the Santos Basin pre-salt have limited modern day analogues. Seismic characterization approaches provide a critical step in describing the reservoir (e.g. porosity, facies), which ultimately impacting reservoir forecasting and reservoir management decisions. In this study, we primarily focused on obtaining acoustic impedance and porosity - though also show a potential application for permeability.

The area for this study was selected based on the high well density available and good quality OBN seismic products available.

In this study, we try to mitigate uncertainty associated with the following data science and domain-specific challenges.

Data Science Challenges

- Finding ideal MLP architecture:
  - Number of hidden layers,
  - Number of neurons in hidden layers,
  - Type of activation functions.
- Training data size vs. model's # of independent variables.
- Backpropagation hyperparameters:
  - Learning Rate / Learning Rate Scheduling,
  - Early Stopping,
  - Weight Regularization.

Domain-Specific Challenges

- Geoscience data environment and diversity
  - Each basin structure and lithology are different
  - Each seismic survey is different
- Seismic Data is band-limited
- Data is sparse (especially relevant to wireline logs)

The challenges mentioned eventually manifest themselves in final predictions as overfitting or underfitting and varying performance levels away from training wells. Figure 1 shows a simplified example of over/underfitting.

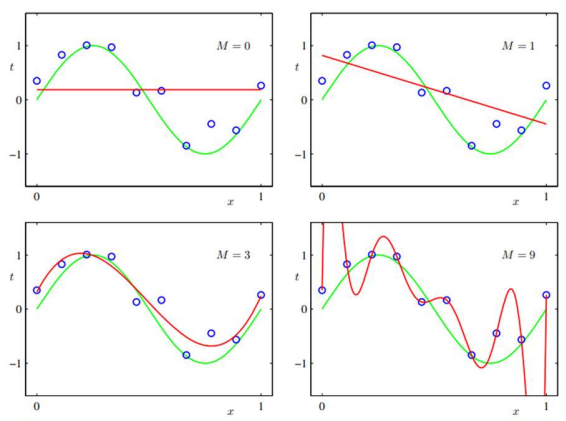


Figure 1: Manifestation of under/overfitting on simple and noisy sinusoidal data with polynomial basis functions. (Bishop, 2006)

To improve generalization performance and reduce overfitting or underfitting, we use modern tools such as Early Stopping, Hyperparameter Optimization, Ensemble Learning, Multi-Input-Multi-Output Training, and Weight Decay (Regularization). We use a more straightforward weight decay technique, the L2 norm of the weights as a penalty term, in the cost function, analogous to Ridge Regression (Hastie et al., 2009). We experimented with Dropout Regularization (Srivastava et al., 2014), which is a more non-linear way of applying weight decay to ANNs for regularization. It can also introduce sparsity to the solutions when used correctly with enough training data.

In this dataset, we apply all the above techniques to calculate the predictions efficiently and effectively. Taylor et al., 2020 show a slightly modified version of this work on a different

application of this method to aid drilling engineers with real-time calculations.

Method

We present a multidisciplinary approach that integrates modern data science techniques and geophysics. We use a class of feedforward artificial neural networks (ANN), more precisely termed a Multilayer Perceptron (MLP), as the base predictor in our workflow. MLPs are now widely used, but there has been much *hype* surrounding them. However, they are as simple as non-linear statistical models used for regression and classification problems (Hastie et al., 2009). Dramsch, 2020 is a good overview of ANNs in Geoscience.

We train many MLPs to form an ensemble predictor that generalizes well to learn mappings between well log data, seismic reflectivity data, and secondary seismic attributes. The latter are the inputs to the MLP, and wireline logs are the targets (outputs). We also utilize the 3D position of amplitudes and well logs by associating time or depth-related features (extracted from horizon interpretations) with the associated seismic inline and crossline positions.

We show an example of an MLP with a simplification of input features and targets in Figure 2. In the input layer, the circles are neurons that are a vector representation of data to be used in prediction, whereas in the output layer, the circles are neurons that are a vector representation of wireline logs (rock properties) we are predicting. The hidden layers encompass neurons that map the input variables to the output variables and need to be trained with available data to make accurate predictions that generalize to unseen data.

Hyperparameter Tuning using k-fold cross-validation and the grid search method provides us with optimal architecture and training parameters for seismic and rock properties of interest.

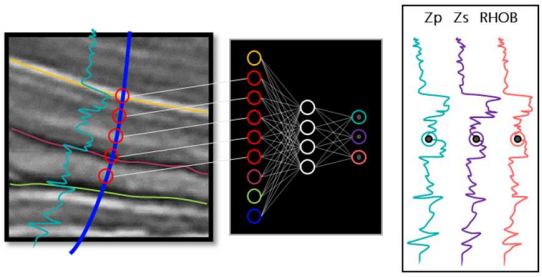


Figure 2: MLP with 1 input, 1 hidden, and 1 output layer

Bootstrapping provides us a way to reduce our exposure to being trapped at local minima. The method involves training multiple candidate MLPs using a random subset of the training data and also by resetting initial MLP weights at each run. Poorly converged models get discarded. There could be more physics constraints added to this step (i.e., compare forward-models with measured data, smoothness)

The *aggregation* step takes bootstrapped models and generates a final prediction and a standard deviation value for each sample. We call the standard deviation value the confidence indicator, and it represents the spread of the predictions of individual candidate MLPs. Averaging results are the preferred way to ensemble models compared to averaging model weights (Hastie et al., 2019).

Figure 3 shows our workflow of bootstrapped aggregation, which is also known as *bagging*. Each MLP in the figure gets trained on a subset of the training/validation data. When we are in the inference stage, we use trained models in new data points and generate target predictions with an ensemble.

To summarize, our workflow consists of these steps:

1. Prepare input and target data, then ingest
2. Scaling (normalization or z-score standardization)
3. Structural and waveform feature extraction
4. Hyperparameter tuning via parameter grid search and k-fold cross-validation.
5. Train optimal model N times with different subset of training data and initial weights (bootstrapping)
6. Analyze ensembles, discard weak performers
7. Bootstrapped Aggregation
8. Output final prediction and confidence interval
9. External blind well QCs
10. If results are satisfactory, repeat the above steps and include the external blind wells. If the initial model provided good results, omit step 4.

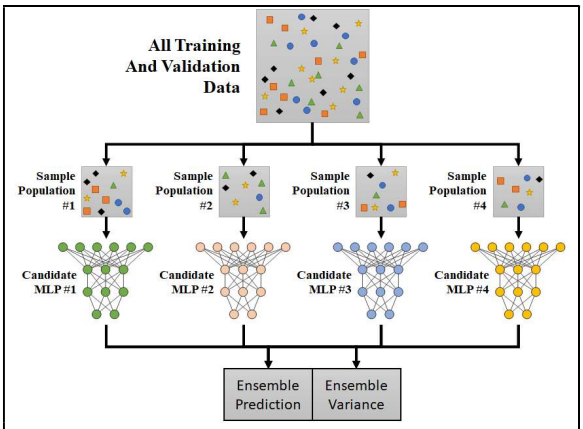


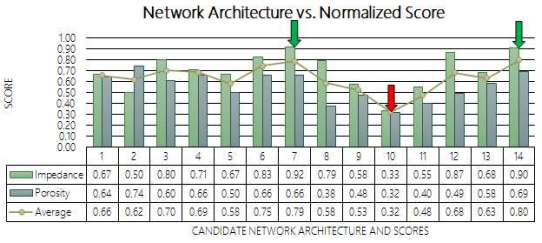
Figure 3: Workflow diagram for *bagging*-based ensemble learning.

Dataset and Results

In this study, we are using a seismic survey that was acquired using ocean-bottom-nodes (OBN). The data has been signal processed and imaged using state-of-the-art

methods such as Time-Lag Full Waveform Inversion (TL-FWI), Interbed Multiple Attenuation (IMA), and Least-Squares Reverse Time Migration (LS-RTM). These methods address common imaging challenges observed in pre-salt Brazil fields:

- Velocity model building in stratified salt
- Removing interbed multiples
- Compensating uneven illumination.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Impedance	0.67	0.50	0.80	0.71	0.67	0.83	0.92	0.79	0.58	0.33	0.55	0.87	0.68	0.90
Porosity	0.64	0.74	0.60	0.66	0.50	0.66	0.66	0.38	0.48	0.32	0.40	0.49	0.58	0.69
Average	0.66	0.62	0.70	0.69	0.58	0.75	0.79	0.58	0.53	0.32	0.48	0.68	0.63	0.80

Figure 4: Normalized model performance based on various metrics per MLP architecture.

Only a post-stack (full stack) dataset and an interval velocity volume were available during this study. The total area of the subset seismic dataset was 111 km^2. Figure 5 shows an inline and a crossline extracted from the survey and four of the training wells. We anticipate further improvements may be possible using angle stacks as additional inputs.

We start with the extraction of seismic and interval velocity traces at training well locations. We use a time-windowing approach to inform the MLPs of vertical context and the waveform characteristics. Then we extract horizon-based time/depth thickness features to be used as an additional input feature.

The field poses a dual-porosity challenge. In practice risk of miscalculating effective porosity is mitigated using pre-stack / angle-stack AVO information. However, in this study, no angle stacks were available. We chose to train a multi-output MLP that trains a larger model to predict two properties: Acoustic Impedance (Zp) and Effective Porosity (PHIE). Since we are working with a full stack seismic dataset instead of a near-stack, we believe there are various factors for helping the machine learning approach to extract information to shed light on the dual-porosity challenge. The inclusion of depth and thickness information to guide predictions being one of them. The full stack will also include stacked AVO effects, even if they are subtle. Given enough training data, the algorithms have the potential to find correlations.

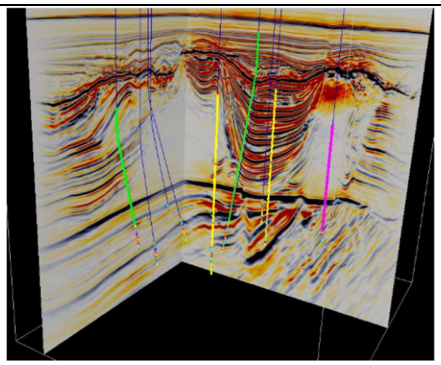


Figure 5: Inline and Crossline display of pre-salt play (PSDM dataset). The First 4 wellbores and markers are also displayed.

After selecting targets and features, we experimented with various Hilbert Transform based seismic attributes and have not found any strong correlation with the properties we are predicting.

Figure 4 shows a normalized multi-metric score for different network architectures we evaluated. We analyzed metrics such as values out of range per property, the ensemble's variance, number of free parameters in MLP, and MSE of prediction error in training wells because we only used four wells to train the models in the first set. Green arrows show two equally performing models, and we chose #7.

We then bootstrap the data and train the MLPs. As a result, we generated 20 candidate MLPs. Figure 6 shows each candidate network result at a random seismic location. The top figure shows all 20 MLPs. After removing non-convergent and low-performance MLPs, we end up with an ensemble of 14 MLPs. The bottom figure shows the identical spatial location after removing candidate networks based on stability metrics mentioned in the previous paragraphs.

In the second set, we add four more wells to our training data and re-train the same architectures from scratch. Then we choose a new ensemble and QC the results. As part of the blind well validation, Figure 7 shows the mean acoustic impedance and effective porosity from the ensemble of MLPs, comparing results with 4-well and 8-well training at 5 blind wells.

Figure 8 shows the mean +/- 1 standard deviation result at three fully blind wells after the 13-well training. 92% of logged PHIE is within +/- 1s.d., and 64% for acoustic impedance. Well A's proximity to a training well resulted in a narrow range in the MLP ensemble

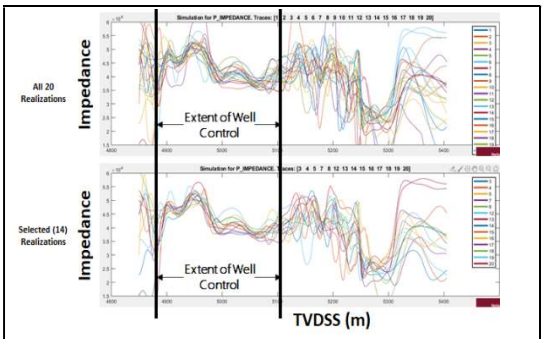


Figure 6: Candidate MLP predictions away from training wells.

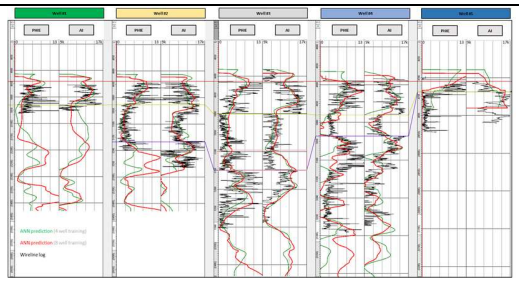


Figure 8: Mean PHIE and AI ANN results using 4-wells (green) and 8-wells (red) in training plotted at 5-wells fully blind at this stage of the project. Wireline data is shown in black. The correlation panel is flattened at the top reservoir. The degraded performance in deeper intervals at Well #3 and Well #4 can be understood in part due to igneous lithologies not present in initial training wells and a deterioration in seismic data quality in these intervals.

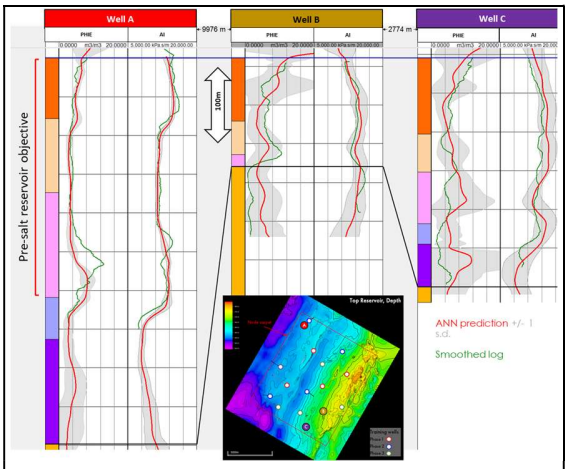


Figure 7: Mean (red) and +/- 1 standard deviation (shaded gray) PHIE and AI results at three wells fully blind to the ANN, with smoothed log shown in green. 92% of blind well PHIE sits within +/- 1 standard deviation of the ANN, with interval average porosity within 3 p.u. at all reservoir levels. 64% of blind well AI sits within +/- 1 standard deviation of the ANN. Notice well A is situated very close to a training well, contributing to overconfidence in the prediction of individual ANN ensemble members and explaining the small variance

Conclusions

Using a mixture of adequately tuned machine learning-driven prediction to earth models represents a significant improvement compared to using MLPs without considering model complexity and the data environment.

We demonstrated that we could generate acceptable results with only 4 wells for a pre-salt and structurally complex carbonate reservoir. However, doubling the training data to 8 wells provides a notable improvement as expected. The inclusion of 5 additional wells still improved the results. However, not as significant a step as going from 4 to 8 wells in training.

The prediction of reservoir properties (such as porosity) via an ensembled ANN approach are in good agreement with blind well data. The standard deviation products provide access to property uncertainty estimates which are not typically produced during conventional post-stack inversion.

Acknowledgments

We want to thank Petrobras and GALP for permission to show these results. We also want to thank Quantico Energy Solutions for making the technology available and permitting us to present this work. We thank Gareth Taylor for his review of the article and his constructive comments and suggestions.