FaciesNet: Machine Learning Applications for Facies Classification in Well Logs

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Abstract

Determining facies or rock types provides fundamental geologic information for hydrocarbon exploration and production. Previous studies in the past decade have adopted machine learning models to classify facies from well logs without considering stacking patterns of facies, which causes inaccurate predictions. We propose a novel machine learning architecture that captures geologic information, facies stacking patterns, and geologic correlations, *FaciesNet*. Our proposed model incorporates decoding and encoding deep convolutional neural networks with bidirectional recurrent neural networks to predict geologically meaningful facies from well log data. We conduct the experiments on real exploration data from different hydrocarbon fields and show that *FaciesNet* outperforms previous study approaches. *FaciesNet* can predict realistic sequences of facies and differentiate between reservoir and non-reservoir facies, while previous study approaches cannot.

1 Introduction

Facies or rock type classification based on physical property measurements (well logs) is essential subsurface information for hydrocarbon exploration and production. Physical property measurements, such as gamma ray, density, and resistivity, are extensive and available in all exploration wells. However, the ground truth of facies can only be determined from limited borehole rock samples (cores), which are limited due to their high cost of acquisition.

Conventionally, physics-based mathematical relations between physical properties and facies need to be determined for a specific area or a rock interval, which is subjective and time consuming. To resolve this issue, several studies have incorporated cost-effective data-driven machine learning algorithms using well logs alone to classify facies by solving multiclass classification problems (Bhatt and Helle., 2002; Qi and Carr, 2006; Basu et al., 2012; Allen and Pranter, 2016; Lolon et al., 2016; Sidahmed et al 2017; Bhattacharya and Mishra, 2018). Physical properties from well logs are used as

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independent features, while interpreted facies from cores are used as ground truth labels. Classifying facies based solely on features from well logs is challenging due to their differences in resolutions as well as overlapping feature values for different facies. Although previous study approaches are robust and able to predict facies at a degree of accuracy, the geologic information and facies sequences are missing, which causes the models to predict unrealistic sequences of facies. Moreover, these models cannot differentiate similar rock types that play different roles in exploration and production, such as clean sandstone (reservoir) and dirty sandstone (non-reservoir). The previous approach models tend to predict the most abundant facies in the dataset, which is often clean sandstone.

We recognize that facies in neighboring layers are correlated and stacking patterns of facies are significant for geological interpretation. A sequence-based machine learning model is, therefore, more appropriate than the traditional multiclass classification approach used in the previous studies. It naturally detects the sequence by learning from the previous facies before making a prediction. Since the sequence-based models are highly dependent on the quality of data, using direct well log values are not the best predictive features because of (1) different resolutions among different geophysical measurements in well logs and (2) the continuous transitions between two facies, which might lead to misclassification. To avoid these issues, we convert geophysical log values through depth to spectrograms using short-time Fourier transform (STFT) before feeding the spectrograms into a model since they provide more information than raw well logs as the spectrogram values change over depths (Figure 1). The texture-like spectrogram contains distinctive patterns that capture different characteristics of facies as well as the transition between two facies, which becomes discrete.

In this study, we develop a facies classification model using bi-directional recurrent neural networks (BRNNs) that incorporate sequences of facies into the prediction. This facies classification model classifies five facies deposited in deep-water depositional system using commonly available well logs from real exploration wells. In addition to BRNNs, we experiment with another architecture by adding decoding and encoding layers of deep convolutional neural networks (DCNNs) to extract latent information before feeding it into BRNNs layers. We also compare the results from our sequenced-based models with previous study approaches, such as Naive Bayes, decision tree, and random forest. The combination DCNNs and RNNs model can differentiate between five different facies, while the most accurate model from the previous study approaches, Naïve Bayes, only predicts three out of five facies. This is significant because Naïve Bayes is unable to differentiate reservoir and non-reservoir facies.

2 Data and feature extraction

Data Our dataset comprises predictive features from well logs and rock type identifications from cores. The well logs and cores data are from four exploration wells in the area with sediments deposited in deep-marine systems. The dataset from the four wells represents approximately 1200 ft of rocks. We use six common geophysical measurements from well logs with the resolution of 0.25 ft as independent features, including gamma ray (GR), shale volume fraction (VSH), density (DEN), compressional sonic travel time (DTC), shear sonic travel time (DTS), and neutron porosity (NEU). The ground truth facies are interpreted from cores by a geologist, including five different types of facies: (1) cemented sandstone, (2) heterolithics, (3) mudstone, (4) clean sandstone, and (5) dirty sandstone. The physical property measurements from six well logs are continuous through depth, while there are missing sections of cores since they were unrecoverable during the acquisition. Therefore, there are 1-2 m sections of missing labels in the dataset.

Feature extraction We convert each 10 ft section of the six geophysical properties from well logs to log-spectrograms using STFT with 5 ft of overlap in order to cover as many facies sequences as possible. Since there are intervals of missing cores, any 10 feet intervals with missing ground truth facies are discarded in the training and test sets. The dimensions of each log-spectrogram of each 10 ft section are 40×1024, where 40 is the number of labels corresponding to the resolution of well log data, and 1024 is the number of frequencies.

3 Proposed network architecture

We evaluate two architectures that include sequence-based machine learning models, which are BRNNs and a combination of DCNNs and BRNNs. BRNNs provide forward and backward directions

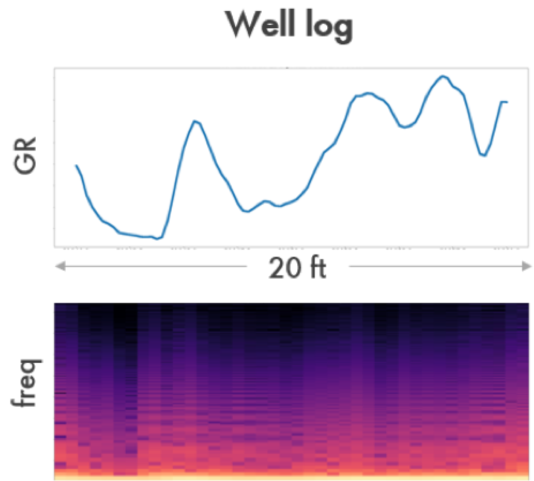

Figure 1: Spectrogram of 20ft interval of gamma ray (GR) log

that separate recurrent nets, both of which are connected to the same output layer, and incorporate the sequence information hidden in well log data. Our models are trained on three wells (136 samples) and validated their performances on an excluded well (34 samples).

3.1 Bidirectional networks

In order to capture stacking patterns of facies, we use BRNNs with gated recurrent units (GRUs). GRUs have been shown to exhibit better performance than long short-term memory (LSTM) in a smaller dataset that has less than 10k samples (Chung et al 2014). BRNNs split neurons of a regular recurrent neural network into two directions, and they consider the sequences and stacking patterns of the facies in both decreasing and increasing depth direction. This sequence-based machine learning model mimics petrophysicists' approach to develop a physics-based model from well log data. Since BRNNs cannot take multiple features at a time, we decide to use a log-spectrogram of gamma ray (GR) as a feature input because GR is the most distinctive feature to differentiate facies and has been used in conventional approaches by petrophysicists.

3.2 Convolutional and bidirectional networks

Facies can be best predicted by using a suite of well logs since different facies can have the same value in a single log. For example, sandstone and carbonate cemented sandstone can be distinguished from a density log because of their differences in density, but they have similar GR values. In order to incorporate multiple spectrogram images as input features, we add decoder and encoder DCNN layers prior to BRNNs layers (Figure 2). DCNNs are exceptionally good at capturing high level features in spatial domains and have demonstrated unparalleled success in computer vision related tasks. The encoder and decoder layers can extract latent feature maps from log-spectrogram images. The outputs from DCNNs layers are reshaped and fed into the BRNNs layers, and the last layer uses softmax as an activation unit to output the most likely facies at each depth. We investigate multiple numbers of encoding and decoding layers, filter sizes, and numbers of BRNNs layers.

4 Experiments and results

Evaluation We evaluate the performance of models by comparing accuracy, balanced accuracy, precision, recall, and f1 score. Since our dataset is imbalanced, the accuracy and balanced accuracy might not reflect the true accuracy of the experimented models. Therefore, we integrated precision, recall, and f1 score of each individual class to describe classification performance.

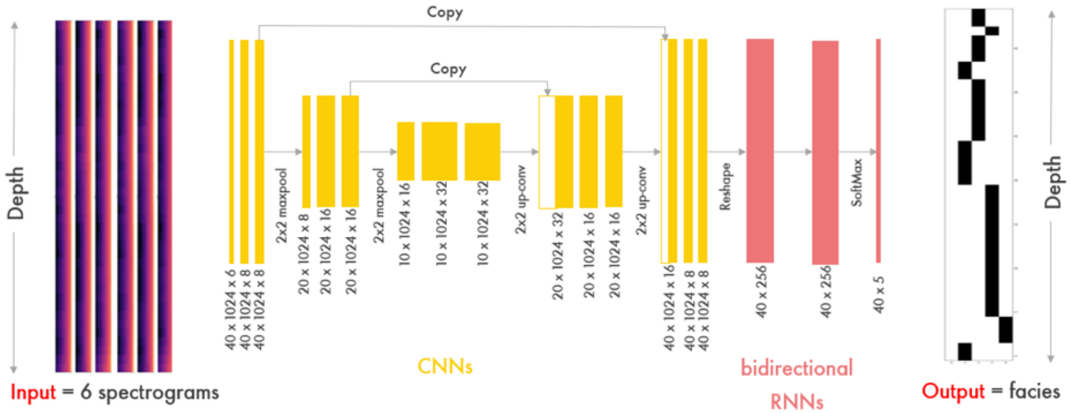

Figure 2: *FaciesNet* architecture

4.1 Facies classification with bidirectional networks

We test different numbers of BRNN layers and hidden states that best classify facies based on log-spectrograms of the GR. Our experiment includes training our dataset on models with 1, 2, and 3 layers of BRNNs with 16, 32, 64, and 128 hidden states of GRUs. We find that the highest test accuracy BRNN architecture of 64.11% is 3 layers of BRNN with 128 hidden states for each layer (Table 1).

4.2 Facies classification with convolutional and bidirectional networks

We experiment with different numbers of decoding and encoding DCNN layers, BRNN layers, and BRNN hidden states with both categorical cross entropy and dice loss functions. The architecture that has the highest accuracy and balanced accuracy on our test set consists of five layers of encoding and decoding DCNNs followed by 2 layers of BRNNs with 128 hidden states using dice loss function, called *FaciesNet* (Table 1). The accuracy of *FaciesNet* is 74.85%, and the balanced accuracy is 40.01%. Both accuracy and balanced accuracy of *FaciesNet* are higher than the BRNNs model.

4.3 Facies classification using traditional approach

In addition to sequence-based models, we also train our data on previous study approaches by using raw well log values as independent features and predicting facies at each individual depth without considering the facies sequence. We select 10 common machine learning models used in facies classification problems, including K-nearest neighbors, linear support vector machine, radial basis function support vector machine, decision tree, random forest, 1 hidden layer neural network, AdaBoost, Naïve Bayes, and quadratic classifier analysis. Using exactly the same training and test dataset as sequence-based models, the best 3 models based on their accuracies and balanced accuracies are Naïve Bayes, decision tree, and random forest (Table 1).

5 Discussion

Comparison between *FaciesNet* and bidirectional networks *FaciesNet* has a higher accuracy and balanced accuracy than the BRNN model (Table 1). *FaciesNet* incorporates six log-spectrograms of well logs as different layers of inputs providing more physical property information to differentiate different facies, while the BRNN model has limited access to the data since it can only take an image as an input. The lower accuracy and balanced accuracy of the BRNN model are expected since multiple facies shared similar values of gamma ray.

Comparison between *FaciesNet* and previous study approaches Although previous studies' approaches using multiclass classification models have higher accuracy and balanced accuracy, they

Table 1: Network accuracy and balanced accuracy

Model	Accuracy	Balanced accuracy
Naive Bayes	83.45%	56.97%
Decision Tree	83.69%	51.55%
Random Forest	84.88%	51.21%
BRNNs	64.11%	24.43%
FaciesNet	74.85%	40.01%

Table 2: Comparison of precision, recall, f1 score of *FaciesNet* and Naive Bayes models

FaciesNet	Precision	Recall	F1 score
Cemented sandstone	0.8125	0.2718	0.4063
Heterolithic	0.1895	0.2000	0.1956
Mudstone	0.6209	0.5125	0.5621
Sandstone	0.8485	0.9133	0.8797
Dirty sandstone	0.1320	0.1029	0.1157
Naive Bayes	Precision	Recall	F1 score
Cemented sandstone	0.8913	0.8542	0.8723
Heterolithic	0	0	0
Mudstone	0.5745	1	0.7298
Sandstone	0.9315	0.9401	0.9358
Dirty sandstone	0	0	0

are unable to predict heterolithic and dirty sandstone facies in the test set(Table 2). Being able to differentiate between heterolithic and mudstone as well as clean sandstone and dirty sandstone is significant in reservoir modeling for hydrocarbon exploration and production purposes. Moreover, *FaciesNet* predicts realistic sequences of facies compared to the previous study models that predict mostly two abundant classes, which are clean sandstone and mudstone (Figure 3). This result suggests that *FaciesNet* can train data from different exploration fields, unlike previous studies' approaches.

6 Conclusion

As a result of rigorous experiments, we propose a novel approach: *FaciesNet* integrating encoding and decoding DCNNs with a sequence-based machine learning model for facies classification for the first time. *FaciesNet* provides a mechanism for incorporating incrementally discovered patterns by extending prior knowledge from log-spectrogram of well logs to discriminate among different facies. Although our propose model has lower accuracy and balanced accuracy than the previous studies' approaches, *FaciesNet* can differentiate between reservoir and non-reservoir facies, which are clean sandstone and dirty sandstone as well as mudstone and heterolithics. Moreover, it gives meaningful geologic predictions and does not suffer when using heterogeneous and imbalanced data. In the future, we aim to develop a more accurate version of *FaciesNet* by adding more detailed and higher resolution geophysical data, such as borehole images.

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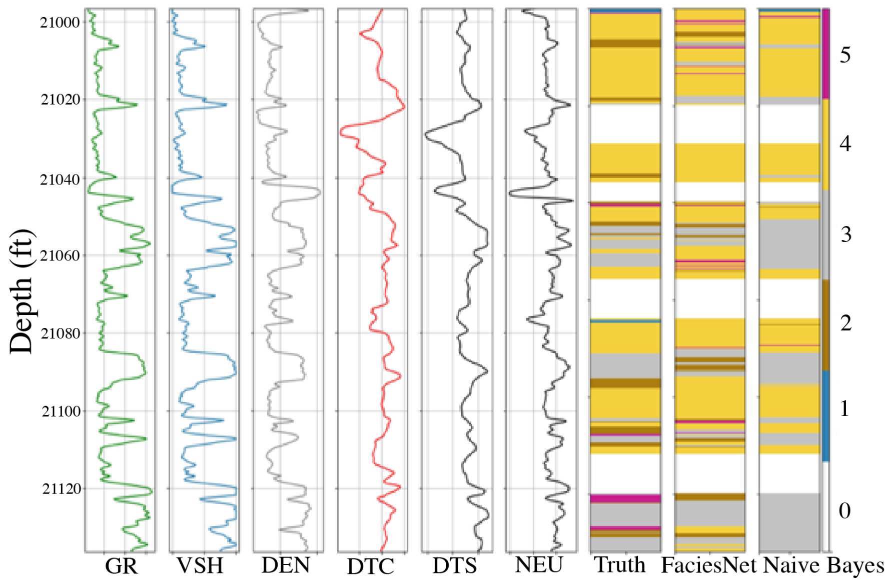

Figure 3: Well logs, ground truth, prediction from *FaciesNet*, and prediction of Naive Bayes of the test well. 0 is missing data; 1 is cemented sandstone; 2 is heterolithics; 3 is mudstone; 4 is clean sandstone; 5 is dirty sandstone

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