LSTM WITH FORGET GATES OPTIMIZED BY OPTUNA FOR LITHOFACIES PREDICTION

THIS IS A NON-PEER REVIEWED PREPRINT SUBMITTED TO EARTHARXIV

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March 14, 2022

ABSTRACT

One of major technical competitions in energy industry relates to how optimally deep-learning architectures we can design. Optimization of hyperparameters is treated as labor-intensive. However, it is important to tune the parameters especially when we deal with relatively small targets, yet high-impact consequences can be resulted. In this study, we adapt Optuna, the global optimizer, for tuning the hyperparameter of the deep-learning scheme of the extended long-short term memory with forget gates. We apply this framework for predicting lithological facies. Although the macro difference with and without Optuna is not significant in this study, our results indicate that Optuna could make large commercial impacts when targets are small yet difficult to be captured.

Keywords Deep learning · LSTM · Hyperparameter optimization · Optuna · Oil&Gas · lithofacies classification

1 Introduction

Machine-learning (ML) continues to be integrated into subsurface studies and is already situated at the heart of technological research in the upstream oil and gas industry. A variety of ML applications have been implemented to address a range of geological and geophysical problems in seismic inversion [e.g., 10, 11], seismic facies analysis [e.g., 9], seismic processing [e.g., 8], reservoir modeling [e.g., 3], and likewise using well logs for petrophysical and lithological analysis [e.g., 2, 6].

Seismic inversion has been used as one of the key tools in subsurface studies for exploration and reservoir characterization by E&P companies. Over time it is expected that ML workflows will initially supplement, before gradually replacing traditional seismic inversion using new automated processes. In the new era, as ML develops, the technical strength of companies will depend on how the architecture of machines is optimized in association with the input data quality, computational cost and the output accuracy. Additionally, the industry is also dealing with how best to utilize big data, such as data from thousands of wells in mature oil and gas basins. Well data is one of the drivers that potentially provides the industry with additional value (such as miss pay and probabilistic evaluation) to identify missed opportunities in exploration. Thus, we are interested in investigating differences and impacts of the global optimizer for tuning the hyperparameters of ML specifically for well-log application.

In this study, we examine the performance of Optuna [1], the latest global optimizer, by tuning hyperparameters of the extended LSTM (long-short term memory) with forget gates [7] using log data obtained from three wells, 21/6b-8, 21/6b-9, and 21/7b-4 (https://ndr.ogauthority.co.uk), in the UK Central North Sea. The target of the LSTM is to predict facies when a set of logs are given.

2 Method and Dataset

Facies prediction in well data analysis could be a depth- or time-series task, so we adapt the LSTM scheme which, in theory, captures the sequential relationship of data in depth or time. One can consider using a fully connected deep-neural network when adequate amount and quality of data is available. However, there are only three wells available in the area of our interest in the UKCS, thereby we decide to use LSTM to attempt to improve predictability. It has been pointed out by, for instance, Gers et al [7], that the LSTM tends to remember the data features which are close to a target sample (shallow in depth and early in time). Hence, with deep learning, we adapt an extended LSTM with forget gates so that longer duration of features (e.g., characteristics of different facies) can be kept. Figure 1 shows a schematic image how the extended LSTM with roget gates works.

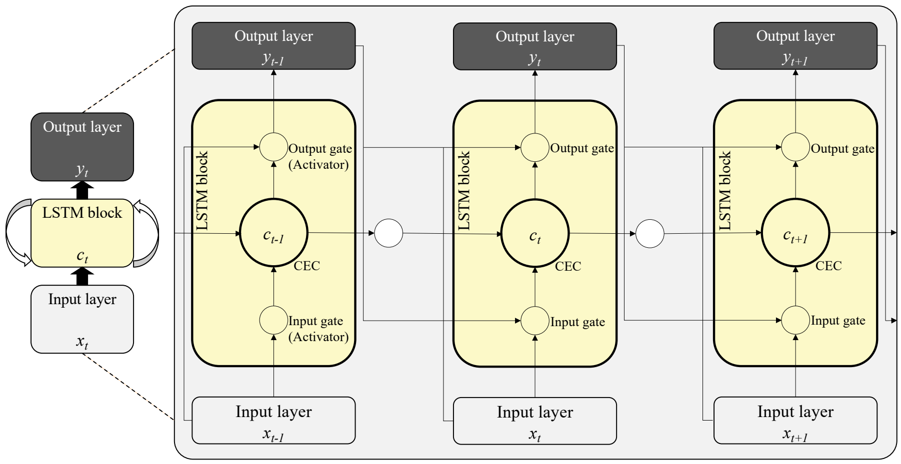

Figure 1: Schematic image of the extended LSTM with forget gates introduced by Gers et al [7]. The standard LSTM, which is shown on the most left-hand side, is extended by adding forget gates to tune the weight of learning in the middle of processing. CEC stands for constant error carousel whose function is to keep error of learning.

Following Bergstra and Bengio [4], who reported that the learning and dropout rates were sensitive to the total performance of ML, we optimize a learning rate (from 0.1 to 0.0001), a dropout rate (from 0.0 to 1.0) and an optimizer of stochastic gradient descent (RMSprop or Adam) among dozens of hyperparameters. Afterward, we use Optuna which is similar to HyperOpt [5] with some differences in optimization approach. While both are global optimizers based on sequential model-based, such that tree-structured Parzen estimator is adapted to calculate probability model, Optuna has a function called pruning which terminates the training evaluation process at any time when training performance is deemed inadequate and below a certain metric. The differences between a usual fully-evaluation process and Optuna's process, which improves the learning process of Optuna, are shown in Figure 2 schematically. In this schematic example, the number of epochs is set to be three hypothetically for the sake of clarifying the pruning process (Table 1.).

In this study, we train and validate the model for predicting facies using data from two out of the three wells, chosen from an area of interest in the UKCS. The third well is chosen as a blind test to evaluate the model and predict the facies by comparing with the actual results. Gamma ray, resistivity, density and sonic logs are the well data used for training and predicting lithological facies as shown in Figure 3. The entire workflow of our training and prediction steps are shown in Figure 4

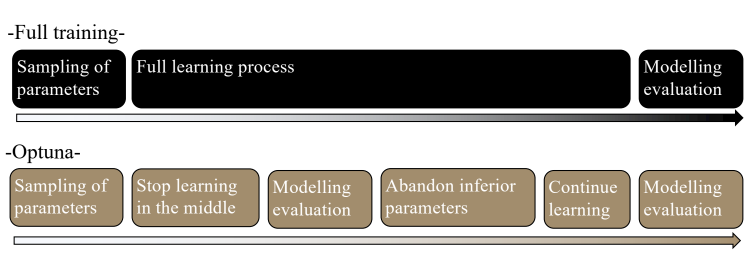

Figure 2: Different evaluation process of hyperparameters between full training and Optuna.

Loss	Epoch #1	Epoch #2	Epoch #3
Trial #1	100	80	60
Trial #2	120	100	90
Trial #3	110	75	65
Median	110	80	65
Trial #4	95	90	Pruned

Table 1: Explanation of Optuna's pruning. The median values of loss are calculated using three trial scores per epoch. The 3rd epoch of the 4th trial is pruned since its loss for the 2nd epoch is higher than the median obtained so far.

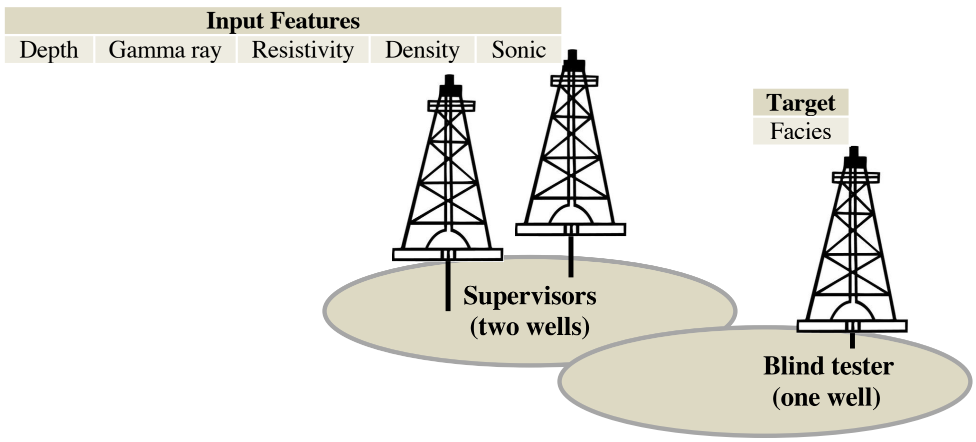

Figure 3: Input features from two wells included depth, gamma ray, resistivity, density, and sonic logs. For the target well, facies are predicted using the extended LSTM with forget gates.

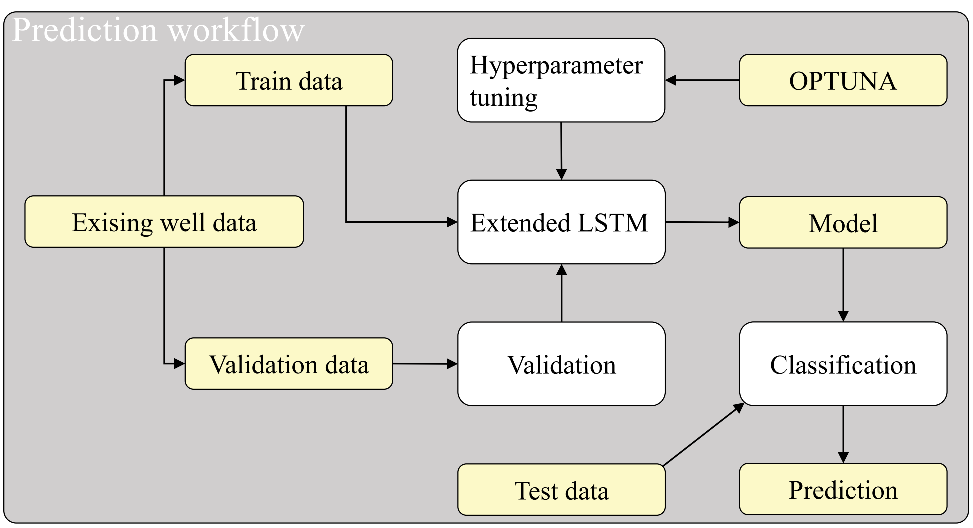

Figure 4: The workflow how prediction results to be gained by tuning hyperparameters of the extended LSTM with forget gates in this study.

3 Results and Discussion

We let Optuna try to optimize the hyperparameters 300 times although this number is completely arbitrary. However, unlike other global optimizers, the perception of the trial number does not necessarily correlate with the actual computational cost because of the Optuna's pruning feature. In Figure 3, the learning curves of 300 trials by Optuna are displayed. In this process, the loss is categorical cross entropy based on the metric of its accuracy. From Figure 5a, it can be noted that the later the trials are examined, the better the obtained learning curves are. As per drop and learning rate, Figure 5b optically provides where Optuna search the best combination of them by also exploring some parameters which are far from the cluster whose error tends to be low.

The final facies are predicted using the best combination of hyperparameters achieved automatically by Optuna. Figure 6 shows the result of facies prediction for the third well after training the machine using the five raw logs, each normalized between zero and one, from the other two wells. In the figure, the facies of the ground truth are compared with the prediction of a deep-learning without Optuna (where we use defaults parameters available in the deep-learning wrapper), and the prediction with Optuna.

The overall effects of using Optuna might be perceived as being small (Figure 6). In fact, the macro F1 score, the indicator of prediction accuracy, for Optuna is 86%, which is only 2% higher than the approach to the facies prediction without Optuna. However, the major and crucial differences could be found looking at the category of the oil-bearing sand, which is ultimately we are interested in, and actually is a small proportion of well data. We achieve 87% precision for predicting of the oil-bearing sand when Optuna is adapted otherwise it is zero. With only a manual approach to fine tuning the hyperparameters it would be take a huge number of runs and man power to achieve this optimized result with no guarantee the manual approach would even reveal this missed pay.

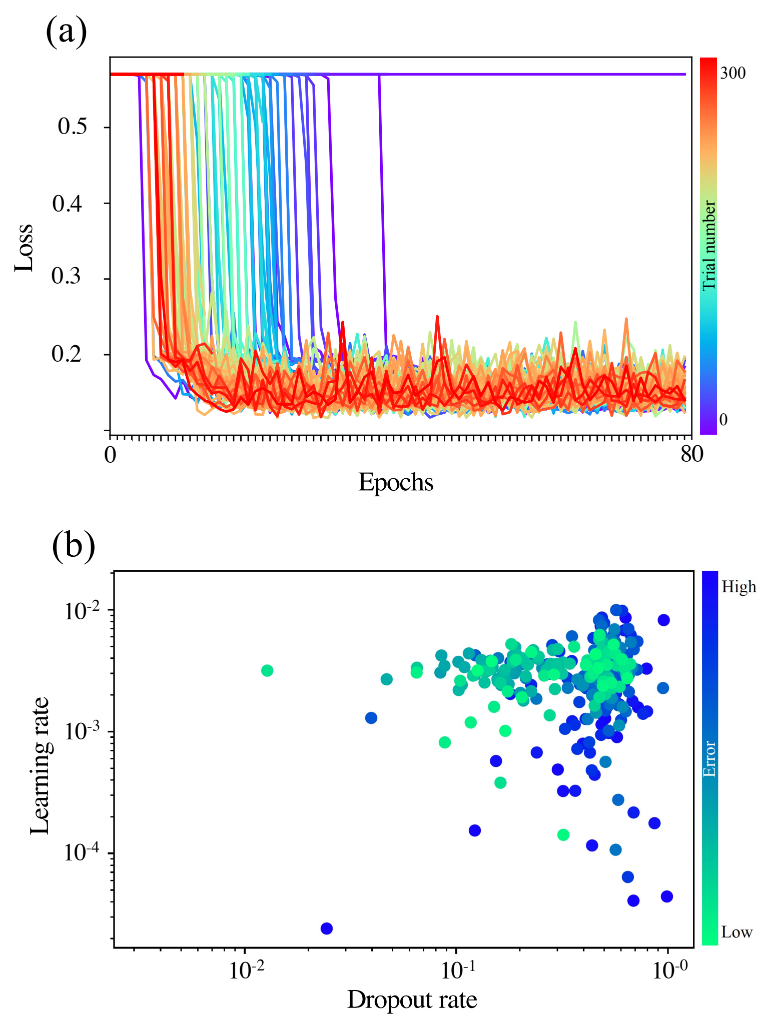

Figure 5: (a): Learning curves for 300 trials for facies prediction using Optuna. Not all 300 trials are displayed completely due to pruning function by Optuna; (b); A distribution of error values associated with a combination between drop and learning rate by using Optuna.

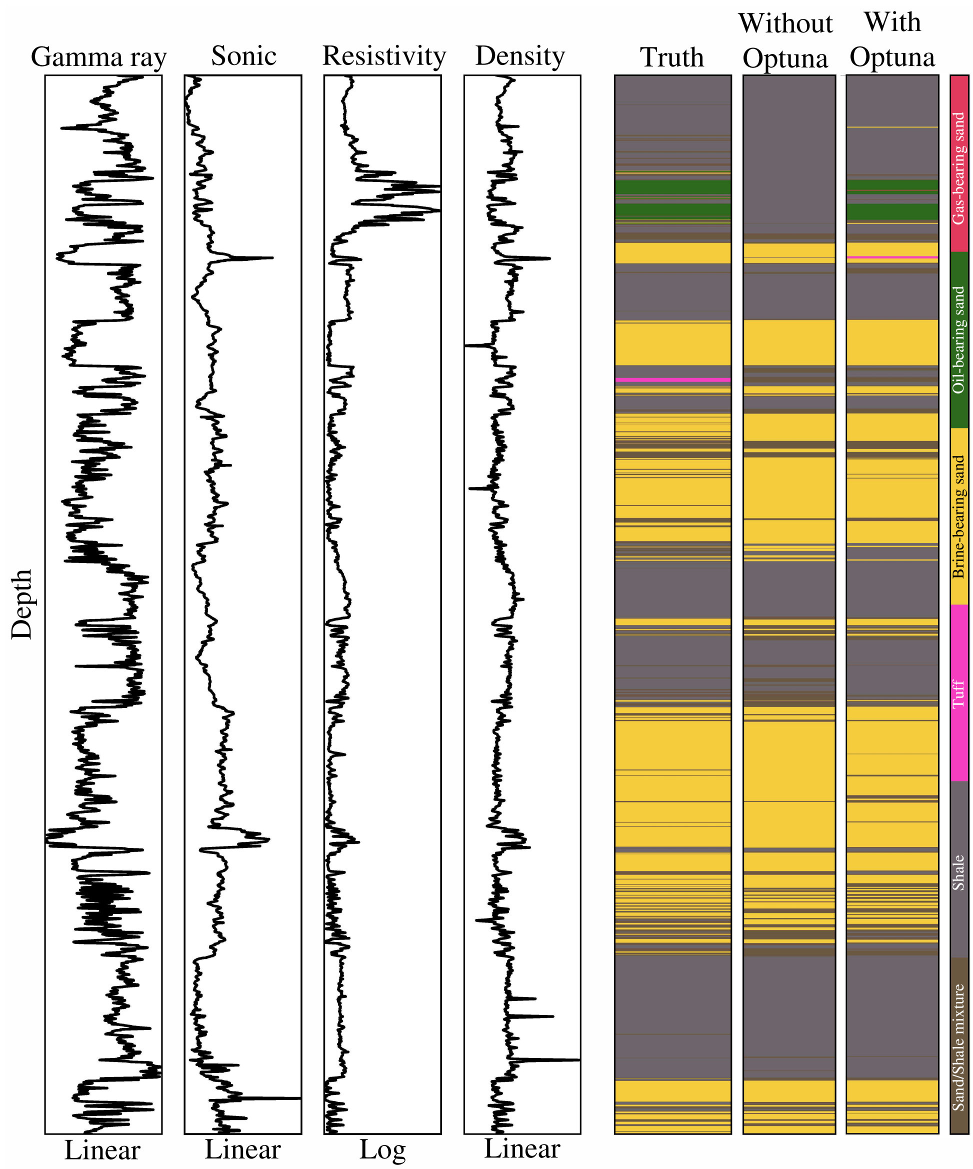

Figure 6: Prediction results with and without Optuna when five features (logs) are used. The ground truth is also shown as a reference. Each of five colors indicates different type of facies (sand-shale mixture, shale, tuff, brine-sand, oil-bearing sand, and gas-bearing sand).

In a mature basin like the UKCS where over 7800 wells have been drilled over decades of exploration and development, looking for missed opportunities is highly interesting for the most E&P companies operating in this region. Well data analysis in bulk to find even small hydrocarbon pay zones can have a very high impact at the play level. Even uneconomic pay can provide extremely important information about the hydrocarbon system, concerning for example the migration path of hydrocarbons in the region. This could potentially lead to large hydrocarbon finds nearby. ML application in analyzing such big data is a remarkable and efficient technique for identifying missed opportunities in exploration. However, it is of significant importance that ML is capable of recognizing the missed pays accurately. This is achievable by improving the global optimizer to fine tune the hyperparameters and efficiently.

4 Conclusions

This paper demonstrated how the latest global optimizer could be used for tuning hyperparameters of deep-learning architecture, using five features (log data) to predict lithological facies when five features were given. The data used in the study was chosen from actual discovery wells in the UKCS. The results obtained using Optuna appeared to be small in macro scale but very important in recognition of hydrocarbon pays which is the ultimate aim in oil and gas exploration. The technique is beneficial in finding missed opportunities across mature basins containing numerous wells, such as the UKCS.

Acknowledgments

In this study we use Keras and TensorFlow for deep-learning applications. The optimizer of Optuna is invented by Preferred Networks.

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