Semi-Supervised Deep-Learning Applied To UK North Sea Well And Seismic Data

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DOI
10.3997/2214-4609.201803013

Publication date
2018

Document Version
Accepted author manuscript

Published in
1st EAGE/PESGB Workshop Machine Learning, 29-30 November, London, United Kingdom

Introduction

One innovative technology that is supporting the ‘digital transformation’ is the deep-neural-network (DNN; Hinton et al. 2006). The DNN can be distinguished from the more common neural networks by the larger number of hidden layers used to achieve sufficient pattern recognition ability. This multi-layer, pattern recognition, architecture is powerful and ideally suited to the data rich environment that exists at the heart of the oil and gas industry.

Elastic impedance analyses of both well and seismic data have long been used for determining lithological and pore fluid properties in subsurface data. Whilst well data has the benefit of directly measuring parameters such as *Vp*, *Vs* and *Rho* within the vicinity of the wellbore equivalent seismically derived parameters, away from the wellbore, are determined using amplitude-versus-offset (AVO) techniques. Pattern recognition of elastic impedances in both instances involves processing large volumes of data to classify each pattern specific to individual facies. Such classification problems are ideally suited to the application of a DNN.

In this study, we have applied a DNN, using semi-supervised learning (SSL) followed by the self-train process (Chapelle et al. 2006), to well and seismic data obtained from a UK North Sea oil discovery in order to automatically classify facies. This algorithm trains itself using well data, before applying itself to equivalent seismic data, allowing hydrocarbons to be volumetrically quantified across the discovery.

Method

Although there are several SSL methods, such as the generative model and graph-based model, we adapted the self-train method. The self-train method combines both labelled and unlabelled data during the training phase so that classified data, which has higher probabilities (larger than 98% in this study), becomes part of the training dataset in the next iteration. This approach is ideal when the availability of labelled data is limited by practical constraints. The SSL-based-DNN scheme we have implemented is summarised in Fig.1. The training dataset is subsequently cross-validated by confusion matrices.

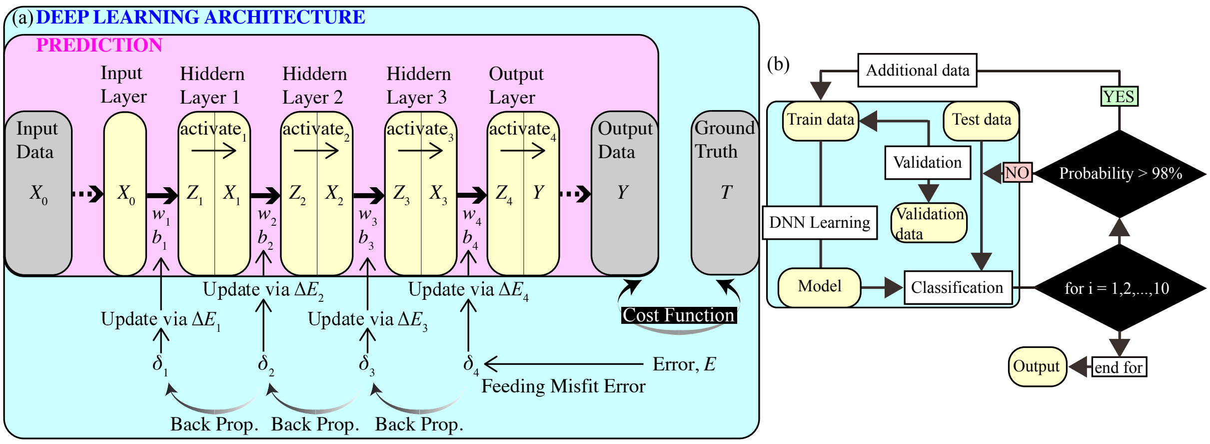

Figure 1 *The SSL-DNN architecture used in this study. (a) The details of DNN where X is the input data, Z is the output data from the previous layer, Y is the output, T is the actual label of Y, w is the weight, b is the bias, E(or* δ_4*) is the misfit between Y and T; and* ΔE *is the gradient of E. The activators in the hidden- and the output-layer are ReLU and softmax. The cost function is the cross entropy. The back propagation was carried out by stochastic gradient descent by choosing the mini-batch size and learning rate through an exhaustive-grid-search. (b) The processing flow of SSL where the cyan rectangle corresponds to the schematic in (a).*

Results and Discussion

Output classified facies can be visualised using elastic impedance cross-plots (Fig. 2a) after the application of the SSL-DNN to a single training well. The resulting decision boundaries are specific only to the immediate data provided rather than preconceived rock physics trends. To further validate the SSL-DNN concept we upscaled the classification model to equivalent seismic data (Fig. 2b) in order to compare the learning from the training well with two blind wells. Despite the uniqueness of the decision boundaries, obtained from the single well, the upscaled classified facies show an excellent match with the two blind wells. In order to use SSL more regionally, with different facies and depths of burial to consider, additional training wells would be required. Other SSL methods may also prove useful in this regard including the generative model or so-called active-learning approach to account for noise sensitivity, input data types and seismic inversion accuracy.

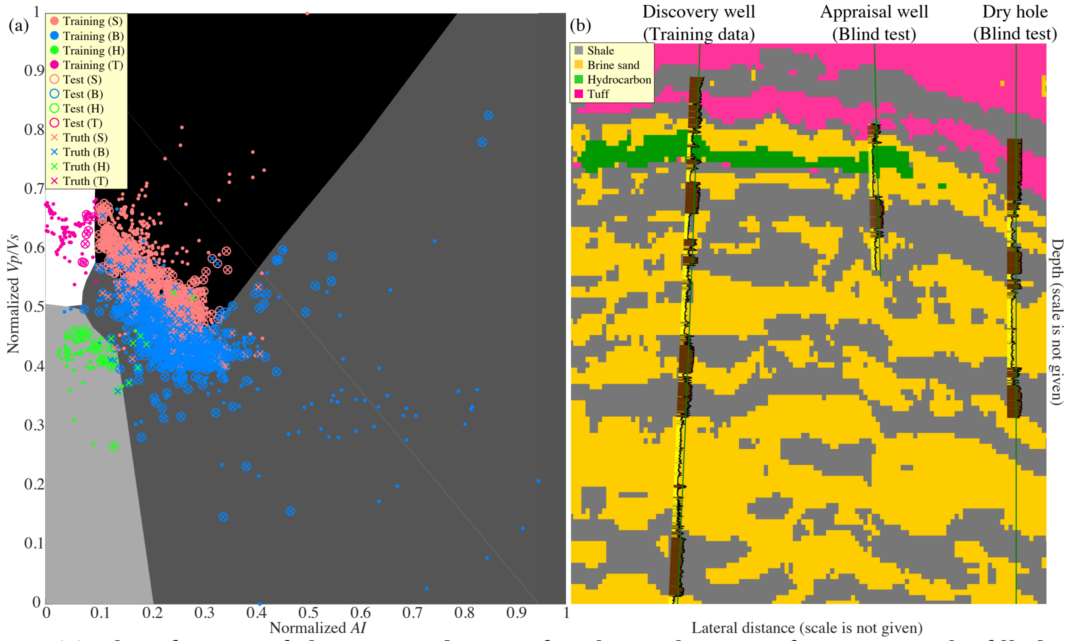

Figure 2 *(a) Classification of elastic impedances after the application of SSL-DNN. The filled circles are the training data, empty circles test data and the crosses are the ground truth for the test data. (b) Seismic upscaling using the model shown in (a). Four different colours correspond to the classified facies shown in the legend. The Vshale logs provide correlation with upscaled facies.*

Conclusions

We presented the application of semi-supervised deep-learning using the self-train method to classify elastic impedances from both well and seismic field data from the UK North Sea. The results indicate that the methods used have the potential to accurately determine facies and hydrocarbon distributions at a field scale. This technology could, given sufficient training data and further development, provide a paradigm shift in QI geoscience capability.

Acknowledgements

We would like to thank Ping Petroleum for permission to publish. We also thank CGG for supplying the seismic data used and Ikon Science for their rock physics work on the well data.

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