A machine learning approach to quantitative interpretation

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Summary

Machine learning can play an important role in making subsurface quantitative interpretation workflows more efficient, consistent and potentially more accurate. Two workflows are shown in 1D and 3D applications. It is argued that the 1D cases are more about improving efficiency whilst the 3D cases have the potential to improve the accuracy. Examples are shown from conventional and unconventional basins. Beyond that it is demonstrated how one can combine deep learning and physics-based models to provide fast and accurate subsurface predictions.

Introduction

Machine learning can play an important role in making subsurface quantitative interpretation workflows more efficient and consistent which should ultimately lead to a more confident decision making process. There are two categories of machine learning workflows in subsurface quantitative interpretation and prediction:

1. Train in 1D and apply in 1D:
   a) Training step: a model is calibrated to a relatively small number of wells (logs, cores) in the relevant basin or sub-basin.
   b) Application step: the calibrated model is applied to all the other wells in the same region of interest.

This workflow is by and large about efficiency. For example, train a supervised model to predict, say, porosity, on 10 wells with manual interpretation, and apply to the other 90 wells.

2. Train in 1D and apply in 3D:
   a) Training step: a model is calibrated to the data (logs, cores) of all wells, or a representative subset of the wells, in and around the 3D volume.
   b) Application step: the calibrated model is applied in 3D to seismic attributes and seismic inversion results (e.g. elastic properties).

This workflow is mostly about improving accuracy and confidence. To date, upscaling the well-based models into 3D has been performed using Rock Physics, e.g. a Rock Physics Model (calibrated to well data) transforms elastic properties into rock properties such as porosity or pore pressure. Machine learning improves on this by incorporating more information than merely the elastic properties, such as: well coordinates (so that lateral trends are captured), depth below datum (to incorporate compaction trends), temperature information (e.g. from a basin model), etc.

However, it should be stressed that using machine learning to predict absolute quantities (e.g. porosity, pore pressure etc.) directly from seismic, a relative measure, is unphysical. Low frequencies must somehow be inserted, a process known as (model-based) seismic inversion. A facies-based seismic inversion (Zabihi Naeini and Exley, 2017) is optimal for this purpose, which means the outputs from this process are not only elastic properties but also a discrete facies distribution.

In this paper applications of the above two categories of machine learning workflows to some key quantitative interpretation workflows in both conventional and unconventional reservoirs will be discussed. In the conventional reservoirs case, a machine learning based petrophysical interpretation, workflow 1 mentioned above, will be discussed in which uncertainty in the prediction is captured using a Bagging approach. In the unconventional case, a machine learning approach based on workflow 2 above is shown for 3D sweet spot analysis by collectively predicting pore pressure, volume of Kerogen and geomechanical attributes. Both these examples are generally time consuming tasks if performed manually and hence it is demonstrated that machine learning can lead to both efficiency and accuracy. Beyond that it is demonstrated in workflow 2 how deep learning can be combined with physics-based models to provide fast and accurate subsurface predictions.

Automatic petrophysical interpretation with uncertainty estimate

Petrophysical interpretation of wells incorporates a holistic use of well data in which almost every aspect of the borehole/well data ought to be captured. The data should be processed consistently and rigorously across the study region. With this labour intensive task complete, the question then is how to use this knowledge most effectively. That has two aspects: 1) the regional knowledge is not effectively used for new wells unless done by an experienced interpreter and nonetheless it would still require manual interpretation, 2) when the experienced practitioners leave, the knowledge could be lost from the organisation. This is where the implementation of machine learning workflow 1 above could potentially address these challenges. Once an appropriate machine learning algorithm is trained then the applications to new wells can be extremely fast (i.e. in the order of seconds as opposed to a day or two for manual

10.1190/segam2019-3216138.1

interpretation). Also once the algorithm is trained then all the knowledge is effectively stored so the model can always be called on demand for a quick petrophysical interpretation. This is shown on some Central North Sea (CNS) wells. Interestingly, machine learning algorithms can be further improved by means of “transfer learning” if and when new data are available.

In this study 30 wells from CNS have been used for training. These CNS wells contain a comprehensive suite of petrophysical data which were derived through a rigorous, multi-phased regional analysis. Raw logs underwent detailed quality control (QC) and correction for borehole and environmental conditions and waveform sonic array data were QC’d in detail to ensure robust compressional and shear sonic logs were available for rock physics analysis. Full petrophysical interpretation was then performed, interval by interval and combining information from wireline and MWD, pressure data (MDT, RFT, Mudlogs etc.), core data (RCAL and SCAL), sedimentology, XRD and daily drilling reports. The final petrophysical interpretation database is internally consistent across a region covering some 37,000 km^2, and captures a wide variety of input data types over the full stratigraphic column from the Permian up to the Eocene.

Facilitated by deep learning, a bootstrap aggregating method, known as Bagging (Geron, 2017), which is a form of ensemble learning, was implemented for training. The implemented algorithm allows one to understand the uncertainty across different machine learning models to the same extent as if the data was given to different petrophysicist for interpretation in which each would come up with a different answer. Instead here deep neural networks play the role of an interpreter. The input logs were gamma ray, p-sonic velocity, resistivity, neutron, density, and depth logs. The algorithm was trained to predict volume of sand, shale, limestone and fluid saturation logs simultaneously. Estimating uncertainty is key, especially in cases where there are not enough data coverage for all lithologies and/or the lack of good quality data. The bagging approach proposed here provides a fast and also accurate enough solution for the first pass, enabling petrophysicists to validate the results using the completion plots and well reports. The result on one of the blind wells used for cross-validating the model is shown in Figure 1. The bagging approach first computes the petrophysical logs simultaneously along with the uncertainty estimate for each curve (Figure 1-top). Note, this process takes seconds as the application to new wells are fast once the algorithm is trained. The practitioner can then monitor the outcomes, cross check against completion logs (Figure 1-middle) and finalise the outputs accordingly (Figure 1-bottom). As can be observed the machine learning predictions demonstrate a good accuracy when compared with the full manual interpretation but in a fraction of time and with an uncertainty estimate.

3D sweet spot analysis

Predicting the facies distribution is of course critical for petrophysics (workflow 1 may be used) and reservoir modelling (a 3D facies image is a direct result of the facies-based seismic inversion). An accurate prediction of pressure and stress is critical to drill wells safely (e.g. avoiding breakout and drilling induced tensile fractures whilst drilling) and completing them (e.g. optimising hydro-fractures), and is also a key fluid-drive mechanism, and as such may correlate to production, especially in unconventional wells (Green et al., 2018). A pore pressure model may be calibrated as part of workflow 1 above, to propagate to all wells not used in the training (time saving over doing all wells manually, at ca. 2 days per well) and may then be used to predict pore pressure in 3D as part of workflow 2.

Especially in unconventional plays, wells are drilled at an unprecedented rate. Performing classical workflows for facies classification, petrophysics, pore pressure and geomechanics prediction on all these wells can be impractical (if not impossible) due to turnaround considerations. This, together with technical challenges in terms of complex stratigraphy, multiple play types, laterally variable rock properties and the complex interaction between pore pressure and geomechanics, calls for more consistent, sophisticated, and faster analytical tools. Hence a supervised deep neural network approach is introduced as an alternative tool for facies classification, petrophysical, pore pressure and geomechanics analysis enabling the use of all the previously collected and interpreted data to devise solutions which simultaneously integrate wide ranging well data.

The deep neural networks can work in a cascaded manner such that the outputs from one forms the inputs to the other. That means the outputs from a neural network trained to simultaneously predict multi-mineral volumes and porosity are fed to a subsequent neural network to predict pore pressure. Of course crossvalidation was performed to QC the outcomes at each step. At the final step, to extend the prediction to 3D, a neural network is designed in such a manner that certain properties, e.g. pore pressure, are derived from elastic logs solely (so that this neural net, once properly trained, can be used in workflow 2). The ensuing 3D earth model of facies, rock properties, pore pressure and stress state is derived with a faster turnaround time than standard workflows, and is also potentially superior in a way that it can incorporate other 3D quantities such as well coordinates, depth below datum, temperature, etc. Figure 2 shows a 3D view of potential sweet spots obtained using a conditional

10.1190/segam2019-3216138.1

combination of pore pressure, stress state and volume of Kerogen outputs from deep neural networks applied in 3D using the seismic inversion elastic attributes as an input. Interestingly this workflow can readily be extended to predict well productivity credibly prior to drilling wells leading to a robust validation of this innovative technology.

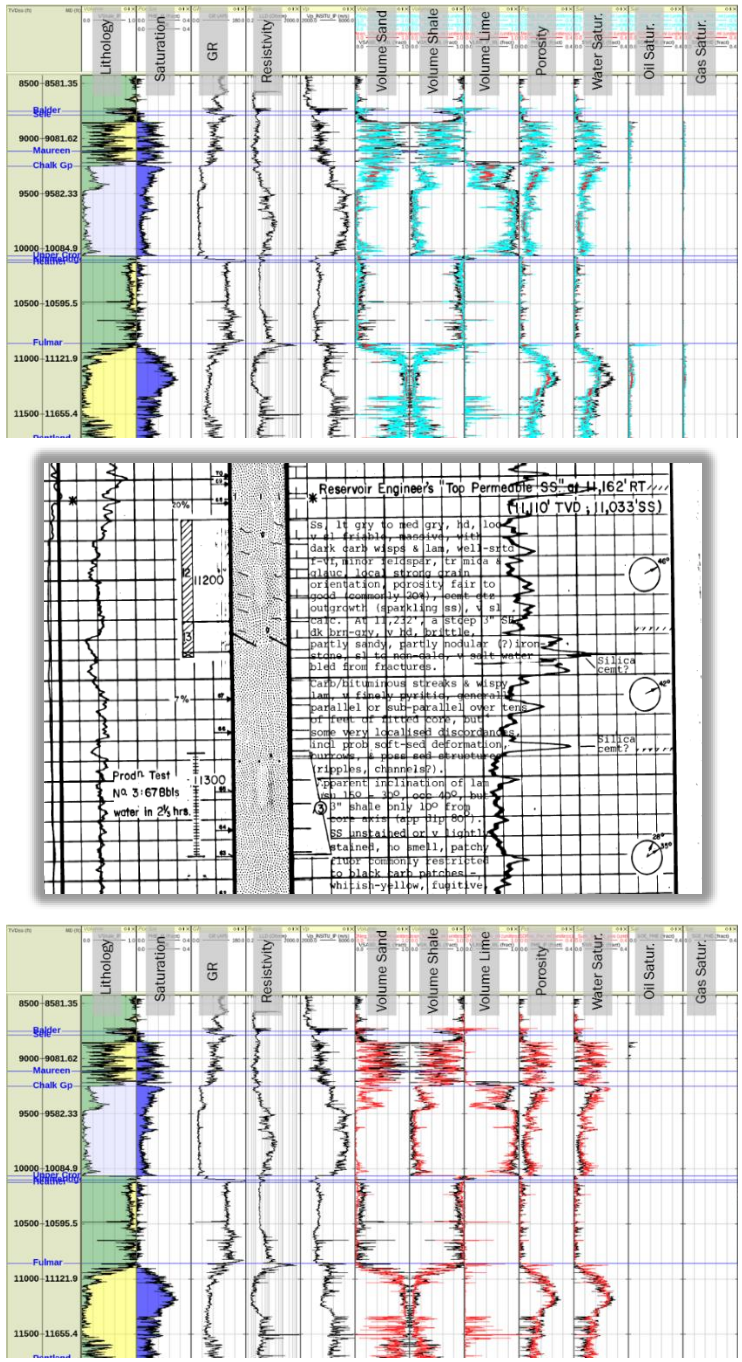

Figure 1 Top: well log panel summarising the result of petrophysical interpretation done manually (black) and automatically by means of bagging various neural network models (blue curves show the uncertainty around the mean in red). Middle: cross check with the completion log whether sands are brine bearing at ~ 11300 ft depth. Bottom: final outputs in red versus manual interpretation in black.

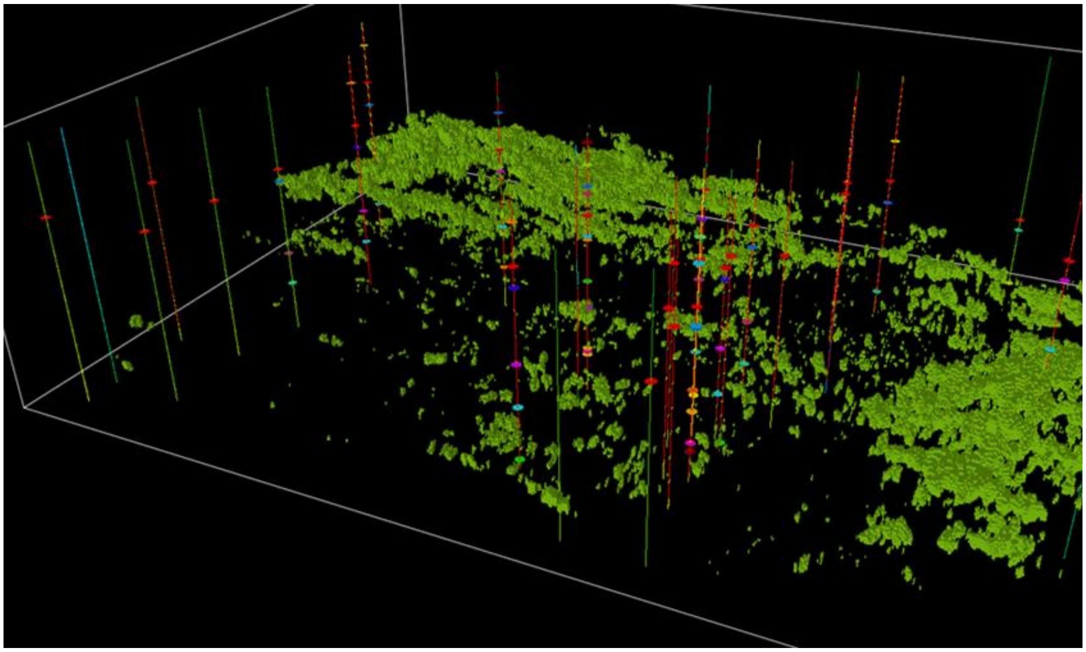

Figure 2: 3D geobody based on conditional cut-offs of pore pressure, stress state and volume of Kerogen predicted in 3D using a deep neural network.

Conclusions

Two machine learning approaches are proposed to make some key quantitative interpretation workflows faster and potentially more accurate. Examples in both conventional and unconventional reservoirs are demonstrated and furthermore a Bagging approach is introduced to capture the uncertainty. It is also shown that deep neural networks in combination with physics based models can provide fast and accurate subsurface predictions. In this case a chain of deep neural network performed various predictions based on well logs in which the last chain was trained using only elastic well logs. That facilitates the application to 3D using the elastic properties obtained from seismic inversion.

10.1190/segam2019-3216138.1

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