Introduction

Quantitative predictions of subsurface properties from 3D seismic datasets are highly valuable at all stages of the E&P cycle and attaining them is the focus of significant effort and investment. Established methods combining inversion and rock physics studies have been developed and are well known (Avseth et al., 2010). Methods are applied appropriately depending on the precision and scale of the study required, data availability and the geophysical/geological constraints of the problem.

The expansion of data science and machine learning methods into the computational geosciences, and in particular the use of modern neural networks for modelling and prediction (Lecun and Bengio, 1995; Goodfellow et al., 2016), opens up new application possibilities within inversion workflows within the above mentioned workflows. In fact, there has been some efforts in the past, with limited success, to apply neural networks to the seismic inversion problem (Röth and Tarantola, 1994; Calderón-Macías et al., 2000; Hampson et al., 2001). However, outside of the domain of seismic inversion, these approaches are being widely used to study and solve inverse problems in general (Adler and Öktem, 2017).

In this study, a dataset from the Sleipner Vest area of the Norwegian North Sea has been used. The Sleipner Vest field was discovered in 1974 and is a producing gas and condensate reservoir in the middle Jurassic sandstones (Hugin, Sleipner Formations). This area was chosen for our study due to significant coverage of exploration wells with wireline log coverage in the region (Fig. 1, background), and availability of a public PSTM seismic dataset (Fig. 1, inset) containing 11 usable wells within the license area. We focus on using neural networks to directly predict both 3D elastic and reservoir properties from 3D seismic partial angle stack data, velocity and a combination of measured and modelled well logs at wells (such combination can vary depending on data availability). We predict seismic scale acoustic and elastic properties in order to demonstrate the degree to which these can be recovered from our training set with appropriate quality checks (QC) based on measured data at wells. Subsequently, upon gaining confidence in the QC based on measured data, a similar neural network architecture is trained to predict a 3D porosity volume using modelled porosity logs as in this case there were no measured porosity at wells within the 3D seismic volume. However, the modelled porosity logs are obtained via a regional study involving 230 wells and quality checked using core samples in 125 wells.

Figure 1 Study Area. (background map) The structural setting and distribution of 230 wells used for modelling at well scale are shown. The Sleipner Vest field lies west (white box). (inset map) Sleipner Vest field outline with the extents of the public 3D PSTM seismic survey shown in red. Of the 13 wells within the survey area, 11 were used in training models at seismic scale. (right) stratigraphic column in the basin.
Predictions of elastic and rock properties from seismic data for well 15/9-12. Predicted values (in red) have been extracted at the well bore location and are compared with the respective upscaled property curve from the well (shown as ‘target’ in blue). Properties shown are (a-b) Acoustic Impedance, (c-d) Density, (e-f) VP/VS (g-h) Porosity. Plots are grouped in pairs where the left hand-side track shows blind prediction and the right hand-side track shows the predicted mean and standard deviation of the spatial model ensemble used to make the final predictions.

**Method**

We apply a supervised learning approach to directly predict elastic and rock properties from a seismic dataset. The family of neural networks that we use are fully convolutional autoencoders (Long et al., 2015), with typically between 8 and 16 convolutional layers supported by a hyperparameter optimisation scheme. In this case the target properties are derived from well log data (wireline, core, CPI). Wells were first tied to the full stack dataset and target property logs were upscaled to seismic resolution. The input features selected for training and prediction are; seismic full and partial stacks (near, mid, far) and interval velocity obtained from depth imaging. At each of the 11 wells, small patches of seismic data were carved along the well path whilst fully accounting for deviation. This was used to create a compact training set across all the wells.

In order to arrive at a robust predictive model for each of our target properties; namely Acoustic Impedance (AI), VP/VS, density and porosity, each model was trained using a spatial k-fold cross-validation scheme. This type of cross-validation scheme allows us to explore a number of facets of the optimisation problem; for example we can identify outliers (either because of data quality issues or because a single well may inherently be different geologically or seismically) whilst also assessing how the model generalises to unseen data via blind metrics on all wells. Another advantage of such approach is that one can keep all the k trained models from the cross-validation experiment and use them as an ensemble when making the final prediction. In practice this leads to a more stable ensemble prediction (mean) with an accompanying variance measure which can be interpreted as model confidence.

**Results**

Assessment of predictions at well locations show high degrees of correlation between predicted and target measured quantities (Fig. 2). We make two assessments; firstly the blind prediction made at each well (using a single model from the ensemble that was not trained on that well) is compared to the target, this tells us both about how well represented this well is within our training set distribution and also the
Figure 3 (a-c) Crossplots showing predictive performance at well 15/9-12 for AI, Density and VP/VS ratio respectively. Perfect predictions would align across the 1:1 trend line. AI and density predictions are plotted against measured (upscaled) wireline logs, whilst VP/VS predictions are against VP/VS data where VS is itself modelled via a regional study. To reassure the quality of the modelled VS log, (d) shows the performance of Vs modelling on regional blind wells.

ability of a model trained on the remainder of the wells to generalise to this unseen example. Secondly, we assess the performance of the model ensemble against the target curve where we expect to see a high degree of correlation in the mean prediction and a low standard deviation across the ensemble. The ensemble standard deviation itself is an indicator of model confidence. Figure 2 shows these assessments at well 15/9-12 where predictions of acoustic and elastic properties achieve explained variance scores of $>0.82$ and $>0.90$ for blind and ensemble accordingly. Predicted porosity also shows high explained variance $>0.77$ tracking the overall trend, and capturing blocky sands and channels appropriately.

Seismic scale models are trained on composite logs that themselves are or contain predictions made from other wireline log data. In the case of AI and density there is significant measured data coverage with a small percentage (less than 5%) of infill predictions only. In the case of VP/VS, VS is entirely predicted and for porosity the majority is modelled (away from intervals with CPI porosity). In Fig. 3 (a-b) shows that we maintain a high level of correlation between predicted AI and density versus measured (upscaled) log curves. Figure 3 (c) shows VP/VS predictions versus target data (which as mentioned are based on modelled VS). Fig. 3 (d) shows the regression performance of the DTS prediction model trained on the original 230 wells, giving us increased confidence in the VP/VS predictions. The fact that we can produce accurate predictions of elastic properties at seismic scale for the wells within our training set, via similar models and methodology gives us some additional support for our porosity predictions.

Predictions were made in 3D over the entire seismic survey extent. Figure 4 shows crossline sections intersecting well 15/9-12. Overall, results are well conditioned spatially which is encouraging given that each trace is treated independently with no explicit spatial regularisation applied. In the Jurassic (Fig. 3 below BCU horizon), despite dropping seismic frequency content, we see the Viking Gp and Vestland Gp reflected in line with the respective log response and extending laterally along the horizon. This is particularly prominent in the AI section. Shallower intervals are also well represented with transitions conforming to the apparent sequence boundaries within the seismic. Of particular note are the consistent responses to the non uniform channel and sand injectite features within the Frigg Fm (directly above the top Heimdal horizon). We note that the strongest response we see here are in the VP/VS and porosity predictions and we would expect this to be complemented by similar responses in the AI prediction, which highlights the potential for further tuning of our model for that interval.

Conclusions

We have presented an approach to predict elastic and rock properties from partial angle-stack seismic data using a supervised deep learning method. Based on well-log data at well locations we train a deep convolutional neural network to predict AI, VP/VS, density and porosity. Hyperparameter tuning of the model architecture combined with spatial cross-validation allows us to find an optimal set of model parameters as well as to construct an ensemble of predictive models that allows one to analyse the variance.
of the predictions. The proposed approach was applied to the Sleipner Vest study area on the Norwegian Continental Shelf. Our results show that deep convolutional neural networks can predict properties at Basin-scale from seismic angle-stacks and an interval velocity model directly, showing good agreement with measured data on a blind well QC. After training at wells, the obtained ensemble model can be applied to the entire seismic dataset. Good lateral continuity within key geological formations can be observed and individual features such as injectites are mapped and well-captured in our predicted property volumes. The property inversion approach presented, allows fast inversion for key reservoir rock properties that enables one to perform quantitative interpretation of seismic data for hydrocarbon exploration settings in a much faster time frame.

References