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Extended abstract

Implementation of seismic data quality characterisation using supervised deep learning

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Abstract. Success and failure in oil and gas exploration is heavily dependent upon the quantity and quality of the subsurface data used during the analysis. Traditionally, the quality of seismic data has been characterised through the domain expertise of geoscientists and through traditional analytical methods, such as frequency decomposition, autocorrelations and signal to noise ratios. Unfortunately, due to the non-linearity and spatial heterogeneity of the data, these analytical methods can be unreliable or difficult to interpret by geoscientists. Machine learning, in particular deep learning, has been shown to analyse subsurface data in a multitude of ways by integrating domain expertise with powerful non-linear mathematical analysis. Thus, it seems that deep learning could be a natural fit for evaluating seismic data quality. In this paper we outline the issues of what is considered good- and bad-quality seismic data and introduce the labelling scheme that was implemented for the supervised learning. Examples of the labelling are shown, as well as the challenges encountered during the extensive labelling process. Neural network architecture testing and validation of the architecture are shown. Finally, applications to three-dimensional datasets on the North West Shelf, how the results can be interpreted and potential further avenues of research are discussed.

Keywords: geoscience, machine learning, subsurface.

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Introduction

Seismic data have long been a staple for the exploration of hydrocarbons because they offer an image of the subsurface that can be correlated with well data to derive subsurface attributes and reservoir characterisation. Therefore, the quality of the seismic data has a direct effect on the understanding of the subsurface, and ultimately the justification for well planning. Because the seismic data play such a critical role in exploration, there has been significant research and progress into improving the seismic data quality by the industry since its inception. Research has been across all domains of seismic data, from improving acquisition equipment and design methodologies to introducing more mathematically rigorous algorithms for data processing and training of geophysicists. Concurrently, data quality assessment methods have continued to improve, with a strong focus on implementing data-driven and quantitative methods of analysis (Paternoster *et al.* 2009). These data quality assessment methods still require involvement and interpretation from skilled geoscientists, which offers opportunity for more efficient methods of analysis.

Better quality data demands more rigorous quality control

It is without question that seismic data quality has improved significantly and continues to improve year on year. The implementation of broadband acquisition and deghosting, pre-stack depth migration (PSDM) and full waveform inversion (FWI) are recent examples of technologies that have offered step change improvements in data quality. This has allowed explorers to analyse increasingly complex geological environments, new play types, such as subsalt and presalt, and use more accurate inversion methods. Consequently, the sensitivity of the analyses to the data quality has increased, with errors becoming more complex and subtle, such as identifying cycle skipping in FWI (Martinez-Sansigre and Ratcliffe 2014), wavelet verification of broadband data (Kleiss and Wall 2018) and understanding the effects of low-frequency content on reservoir characterisation (Tishchenko 2016). Furthermore, the data sizes have also increased with the new technologies, from two to three volumes in the past to over 30 volumes with a modern PSDM project. Thus, the industry's geoscientists face a challenging task to analyse greater amounts of data with more complex quality control (QC) methods.

Seismic data continue to be a highly complex and non-linear data type with many variables that affect final data quality. However, the geoscientist's interpretation will often be unable to correct for any data deficiency due to acquisition or processing and must simply identify areas where the data are unsuitable for various types of analysis. Deep learning offers an elegant approach whereby a geoscientist can provide seismic examples to train a neural network to identify deficiencies in new data. The natural output of a neural network is a probability cube that is quantifiable and easily interpreted to characterise the seismic dataset.

Deep learning for data quality classification on seismic data

Machine learning, specifically deep learning, has recently been a popular research topic in seismic data analysis (Qian *et al.* 2018), processing (Yu and Ma 2018) and inversion (Priezzhev *et al.* 2019). Success has been demonstrated in applying neural networks to verify the efficacy of pre-stack data processes (Bekara and Day 2019), but this has not been extended to the stack data domain where much interpretation is performed. The problem of extension to the stack domain is that many data artefacts or quality issues are not easily identified with traditional analytical processes or modelling that are frequently used as a labelling scheme for supervised deep learning (Zhao *et al.* 2019). We propose to use an interpretation-based labelling schema for multiple types of data artefacts on stack data, because human seismic interpreters can consistently identify these issues.

Data labelling approach and schema

Because a supervised learning approach was chosen for the deep learning network, an extensive data labelling schema was developed to ensure a consistent training and test dataset. Furthermore, it was decided to use a bounding box labelling approach because this could be used for classification and localisation network architectures. Semantic or instance segmentation was considered as a labelling schema, but the significant increase in complexity and time for labelling would prevent the labelling team from creating a sufficient number of labels for this project.

The interpretation team identified six classes of labels for data quality that could be identified on full stack data, and these are listed in Table 1. Both positive and negative categories for each label were performed because this provides the neural network with both upper and lower probability bounds to improve training accuracy. The bounding boxes were picked on two-dimensional (2D) seismic sections on three-dimensional (3D) seismic datasets from the North West Shelf of Australia and constrained to 128×128 samples or direct multiples of this (e.g. 256×256, 128×256 etc.). This labelling schema allowed for flexibility in implementation of common neural network architecture sizes without significant data labelling preparation efforts.

The schema was chosen because the attributes were all considered to be relatively easily recognisable on stack seismic data, not easily rectifiable by seismic interpreters and possibly having significant effects on the quality of the interpretation. The attributes can be categorised into three domains: migration issues, noise content and qualitative assessment. Examples labelled data for good and poor quality fault imaging are shown in Fig. 1. The initial goal of a minimum of 200 labels per labelling class was achieved over 23 offshore 3D seismic surveys across the North West Shelf of Australia, of which 70% of the labels were to be used as training and 30% for blind testing. The labelled data were further augmented with common techniques, such as axis flipping, stretching and rotating deformations, to increase the labelled data sizes and improve training accuracy.

Deep learning architecture and training

The design of the project is to use a deep learning convolutional classification network that converts an image of the seismic stack into a prediction confidence value (%) for each feature. The initial goal was to use a single network to predict all quality classes because this could provide the neural network the most information about the seismic data. This

Table 1. List of label classes and descriptions

Label attribute	Good-quality description	Poor-quality description
Migration swings	No cross-cutting 'swings' or 'smiles' observed	Migration artefact seen as a 'swing' or 'smile' that cross-cuts data and does not geologically conform
Fault image	Well-imaged fault plane with sharp reflectors and no obvious fault shadowing effect	Poor imaging along, around or beneath fault, such as fault shadows, lack of sharp or rounded truncations, misplaced fault planes
Multiples	No cross-cutting events associated with multiples observed	Cross-cutting, non-geologically conformable events that are clearly related to seabed or interbed multiples seen
Coherency	Clear, uniformly imaged reflectors with natural geological terminations; horizon propagation easily performed	Incoherent reflectors, non-geological jitter or random noise seen in data
Frequency	Reflectors have frequency content consistent with surrounding data and appropriate for mapping of geological events	Frequency of reflectors inconsistent with surrounding section, frequency spectra biased too low or high for effective interpretation
Balance	Sufficient balance top to bottom that geological features can be interpreted but lithological boundaries are still defined and differentiated	Gain control heavily applied with little differentiation in amplitudes from shallow to deep

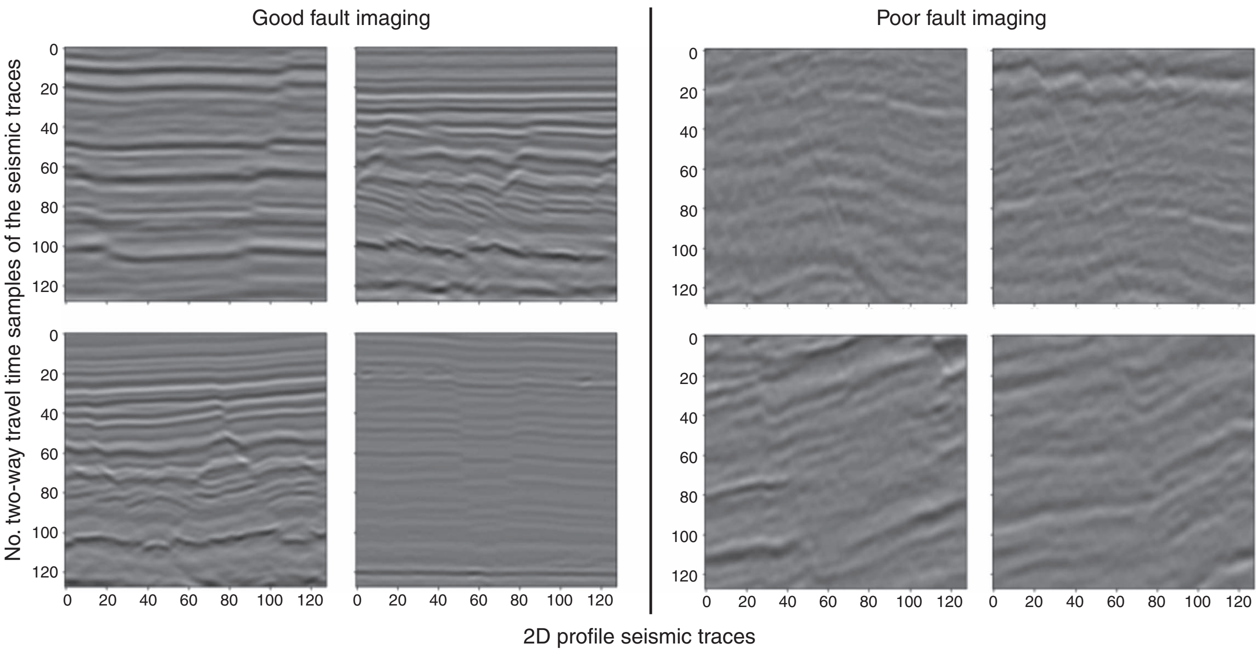

Fig. 1. Examples of labelled data used to train fault imaging network. See Table 1 for full descriptions of good and poor fault imaging.

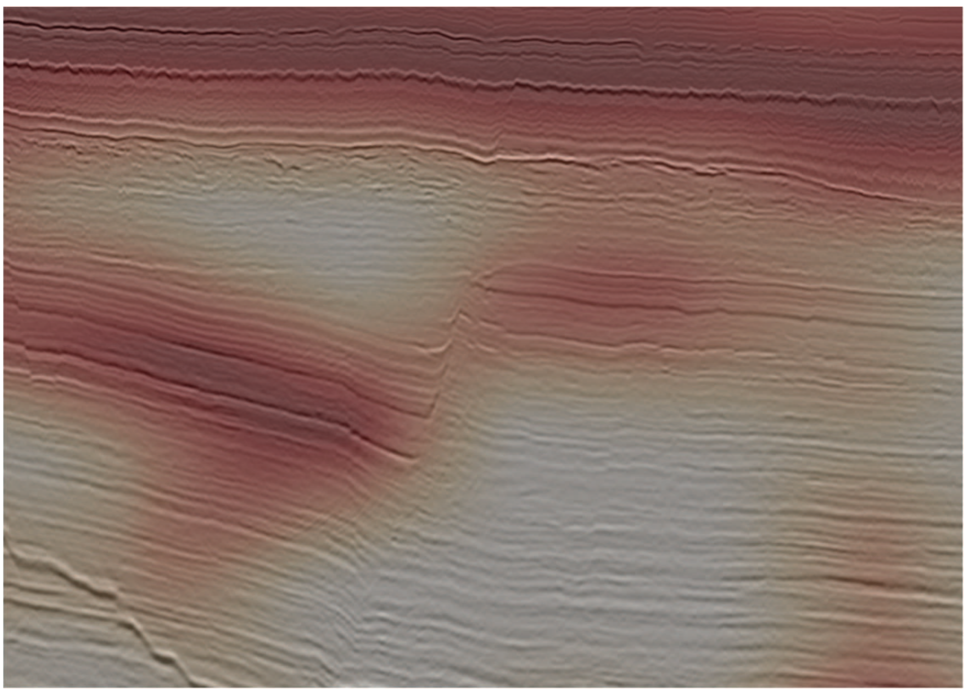

Fig. 2. Example of inference result of fault imaging network on a blind test dataset from the North West Shelf, Australia. The image shows the probability of good-quality fault imaging overlain on a full stack seismic section, where red indicates good data.

would require every label to be defined for every class, and finding sufficient labels proved to be extremely challenging. It was decided to label each of the six classes independently and then train six networks independently with the same architecture.

The convolutional neural network was implemented in Python (Python Software Foundation) using the Google Tensorflow framework (Google LLC). It comprised six convolution layers plus one fully connected layer at each end. Each convolutional layer is made of two convolution sublayers, two batch normalisation sublayers and one max pooling sublayer. The network starts with 16 channels, which is doubled at each layer while reducing size and height by 2 at each layer. This yields a network with approximately 5 million parameters.

The neural network architecture could sufficiently train all classes to a testing accuracy >97%, except for the multiples category, which only achieved 76.5% accuracy. Qualitative assessment of the results for the multiples and balance categories concluded that larger context than 128 × 128 windows would be necessary to improve results. This is supported by how geophysicists analyse data for these attributes, because the data are reviewed at larger scales for assessment.

Results and conclusion

All the inference results on a test dataset displayed geological conformance and identification of good data quality regions. The results overall favoured higher amplitude, shallow sections of seismic data, which may have been a bias presented in the labelled data. Qualitative assessment of the fault imaging, migration smiles and coherency inference results were the best performing and most accurately reflecting both good and poor data quality. Fig. 2 shows an example of the inference result of the fault imaging network overlain on a full stack dataset, where it accurately identifies fault shadowing. The seabed multiples network missed some obvious cases with strong multiple content, which justified a larger input window for context. The balance attribute network would need much larger images, ideally to have entire traces, to correctly characterise the data. A much larger labelled dataset across more surveys for training and testing would improve all the results, and likely have a more generalisable inference network. We plan to re-evaluate the labelling schema based on this work and create a larger labelled dataset to improve the inference results.

Conflicts of interest

The authors have no financial or personal relationships that would inappropriately influence their work here.

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