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Use of theory-guided neural networks to perform seismic inversion

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Summary

Deep neural networks (DNNs) are one of the key technologies that have led to the proliferation of machine learning applications in everyday life. In the computing science literature the successful application of DNNs rely on big data. DNNs are data driven and require many examples of the likely situations that might be encountered. This is problematic in the geosciences since there is often only limited labeled data. This presentation explores the use of theory-guided data science (TGDS) solutions to overcome this issue. In particular two methods are explored. The first example uses theory to guide the design of the neural network to estimate P-wave impedance. The second example uses a hybrid theory data science model to predict P-wave and S-wave impedance along with rock properties. In both cases the TGDS estimates are compared to traditional theory-based inversion methods and compare favorably.

Methods

Historically, geophysicists employ theory-based methods such as seismic inversion, AVO and rock physics to describe the reservoir. These theory-based methods have low data requirements. For example, the convolutional model relating the P-wave impedance reflectivity to the zero-offset seismic response is a one-to-one transform.

Theory-guided data science (TGDS) methods combine data science approaches such as DNNs with theory-based methods to reduce the data requirements. Karpatne et al. (2017) summarize a number of different TGDS methodologies that have been applied across the physical sciences. These include: theory-guided learning, theory-guided design, theory-guided refinement, hybrid-models theory and data science, and augmenting theory-based models using data. This paper explores the use of theory-guided design and hybrid models of theory and data science.

In theory-guided design the physics is used to help design the neural network architecture. Zero-offset P-wave impedance inversion is based on two simple models; the zero-offset P-wave reflectivity calculation followed by the convolutional model (Lindseth, 1979). These two operations can be simulated using a convolutional neural network (CNN). The inversion is complicated by the fact that the low frequencies in the seismic data are typically missing. This is usually addressed by supplying a low frequency P-wave impedance model to the inversion. Thus in the TGDS approach we input both seismic attributes and a low frequency model. Figure 1 shows a comparison of the TGDS P-wave impedance estimate with that of a post-stack inversion performed using commercial software. The two results are practically equivalent with the major differences only occurring below the base of the well control.

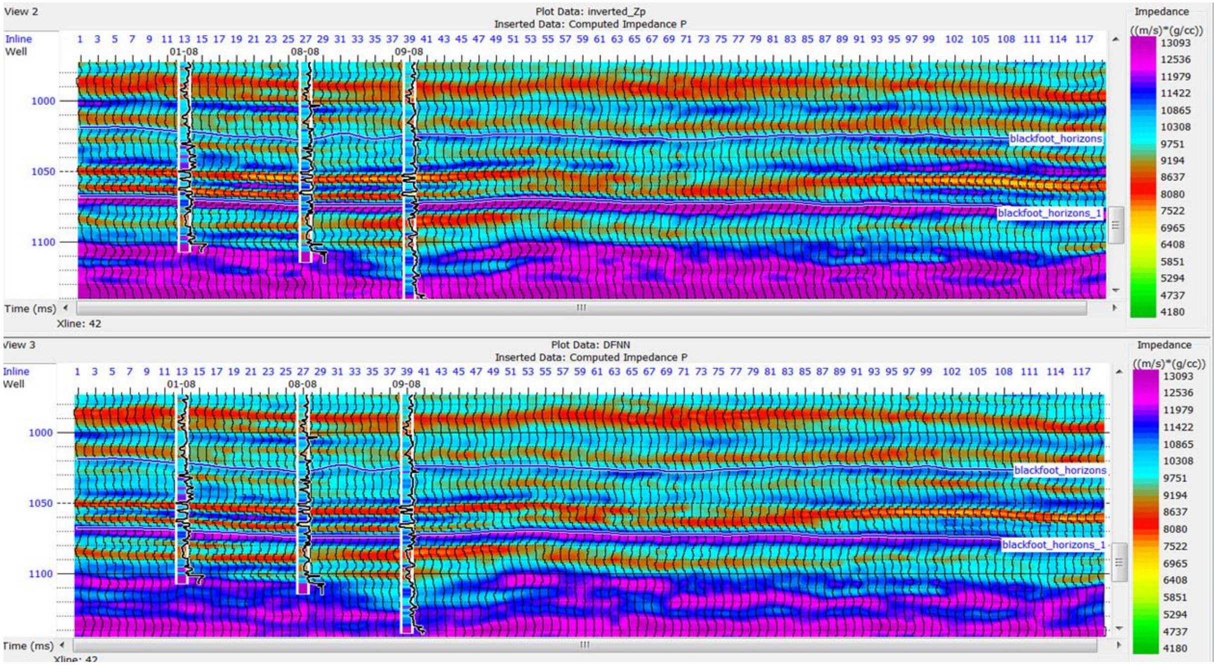

Figure 1: comparison between conventional post-stack P-wave impedance inversion (top) and DFNN (bottom). The P-wave logs are super-imposed at the well control.

In the second example a hybrid model that incorporates both theory and data science is used to predict both P-wave and S-wave impedances. Rock physics relationships based on the original well control are used to simulate a larger number of well logs and synthetics to create a large idealized set of training data. This synthetic data is then used to train a DNN to predict some target log. The target can be any of the generated well curves, including elastic parameters such as the density, P-wave and S-wave impedance. Alternatively, rock properties such as porosity, shale volume, saturation and lithology may be estimated.

This synthetic data workflow was tested on a Gulf Coast data set. The seismic data was preconditioned in a manner suitable for simultaneous inversion. The wells were tied to the seismic data and wavelets were extracted. We then used rock physics relationships based on the original well control to simulate a large, idealized set of well logs and synthetics (Dvorkin et al., 2014). Next, the synthetic seismic gathers were used to train the neural network. DNN operators were designed for each of the above targets and then applied to the seismic data. Figure 2 shows the density predicted by the DNN operator compared to the density predicted from deterministic simultaneous inversion (Hampson et al., 2005). The density from the DNN is higher frequency and matches the well control better than the deterministic inversion. The power of the technique is that rock and fluid properties can also be predicted. In this case the fluid saturation and lithology were also predicted.

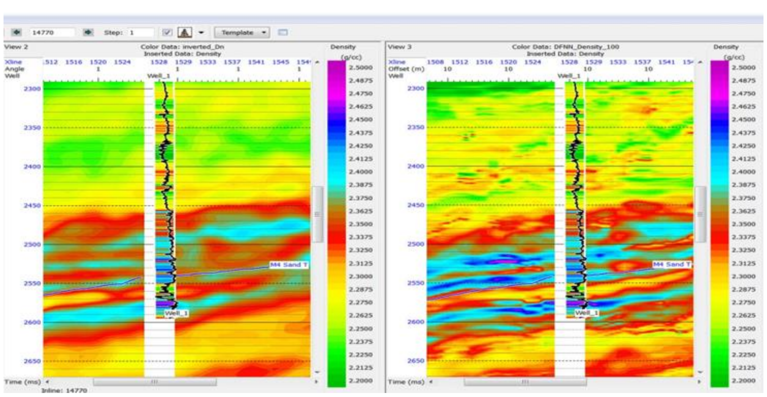

Figure 2: Comparison of density estimated by simultaneous inversion (left) and the DNN (right). Note the DNN ties the inserted well better.

Conclusions

In both the examples shown the TGDS approaches achieve results comparable to traditional theory-based inversion methods. The inclusion of the theory reduces the amount of data needed to train the neural network making the problem feasible to solve using data science methodologies. The theory-guided data science framework is more flexible than either the theory-based or data science methods alone. For example, in the second example it is relatively easy to output reservoir properties rather than elastic properties which are of greater interest to geologist and engineers.

References

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