Applications of Graph Machine Learning for Geophysics Interpretation

Tasman Gillfeather-Clark*, Tom Horrocks*, Daniel Wedge*, Eun-Jung Holden*
*Centre for Exploration Targeting, School of Earth Sciences, The University of Western Australia, 35 Stirling Hwy, WA, 6009, Australia

Centre for EXPLORATION TARGETING

Introduction

- Interpretation in the context of geophysics involves extracting meaning from geophysical signals to support or challenge a geological model (Jacoby and Smilde, 2009; Wellmann and Caumon, 2018; Pérez-Díaz, Alcalde and Bond, 2020).
- These interpretations can be done across many datasets combining difference sources of data to minimise model uncertainty. The quality of the resulting interpretation is closely linked to the interpreter's skill.
- However, interpreter skill is difficult to objectively assess and is a primary source of uncertainty in geological modelling (Polson and Curtis, 2010).
- Defining and understanding interpretational error and uncertainty, and distinguishing it from data error and uncertainty, is critical for effective geological modelling (Bond et al., 2007; Bond, 2015; Pérez-Díaz, Alcalde and Bond, 2020).
- Machine learning has seen widespread adoption to this end and to support and interrogate more complicated interpretation (Poulton, 2002). In my work I look at the interpretational task of depth to basement mapping, using two classifiers for first break classification in seismic data and boundary detection in 3D airborne electromagnetic inversion data. Below I propose a method to answer the question below.

In the same way that an interpreter would combine their interpretations of different datasets, how do we combine unique classifier predictions derived from different datasets to solve a common task?

Seismic Data
1D Convolutional Neural Network

- A key task in basement detection in seismic refraction data is first break picking.
- To frame this as a supervised learning task we generated a set of features (X) and labels (Y) values to train our classifier:
  - X – Our seismic trace data and wavelet transforms
  - Y – Interpreted first break as provided with the dataset, then converted to a series of zeros before the first break and ones after the first break.
- We tested a range of architectural variants and found a Convolutional Neural Network to be the best performing (Gillfeather-Clark et al., 2021).

AEM Data
Relational Graph Neural Network

- Conductive horizons within the AEM data were interpreted to delineate between the cover and the resistive basement. If an interpreter were uncertain about their seismic interpretation they would turn to the AEM data.
- Graph Neural Networks are a recent advancement that uses explicitly defined relationships between data points to improve predictive performance.
- We can build a graph between the seismic data and nearby AEM stations to classify where the AEM thinks the basement surface would be for a given seismic station.
- These labels generated by the GNN from the AEM data can be used to support classification of the seismic data.

Seismic Prediction

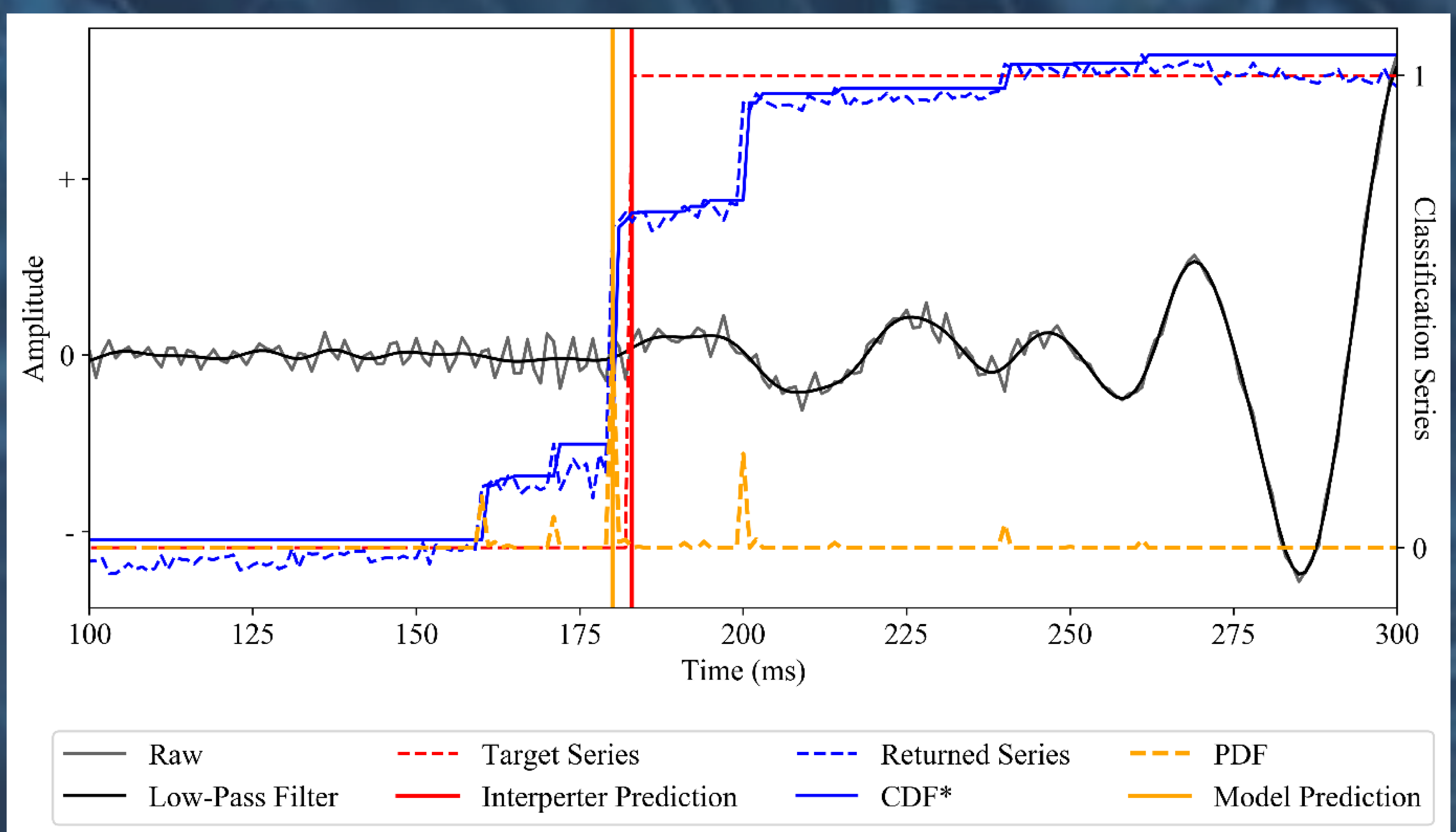

Figure 1: Different stages of processing applied to the returned prediction.

AEM Prediction

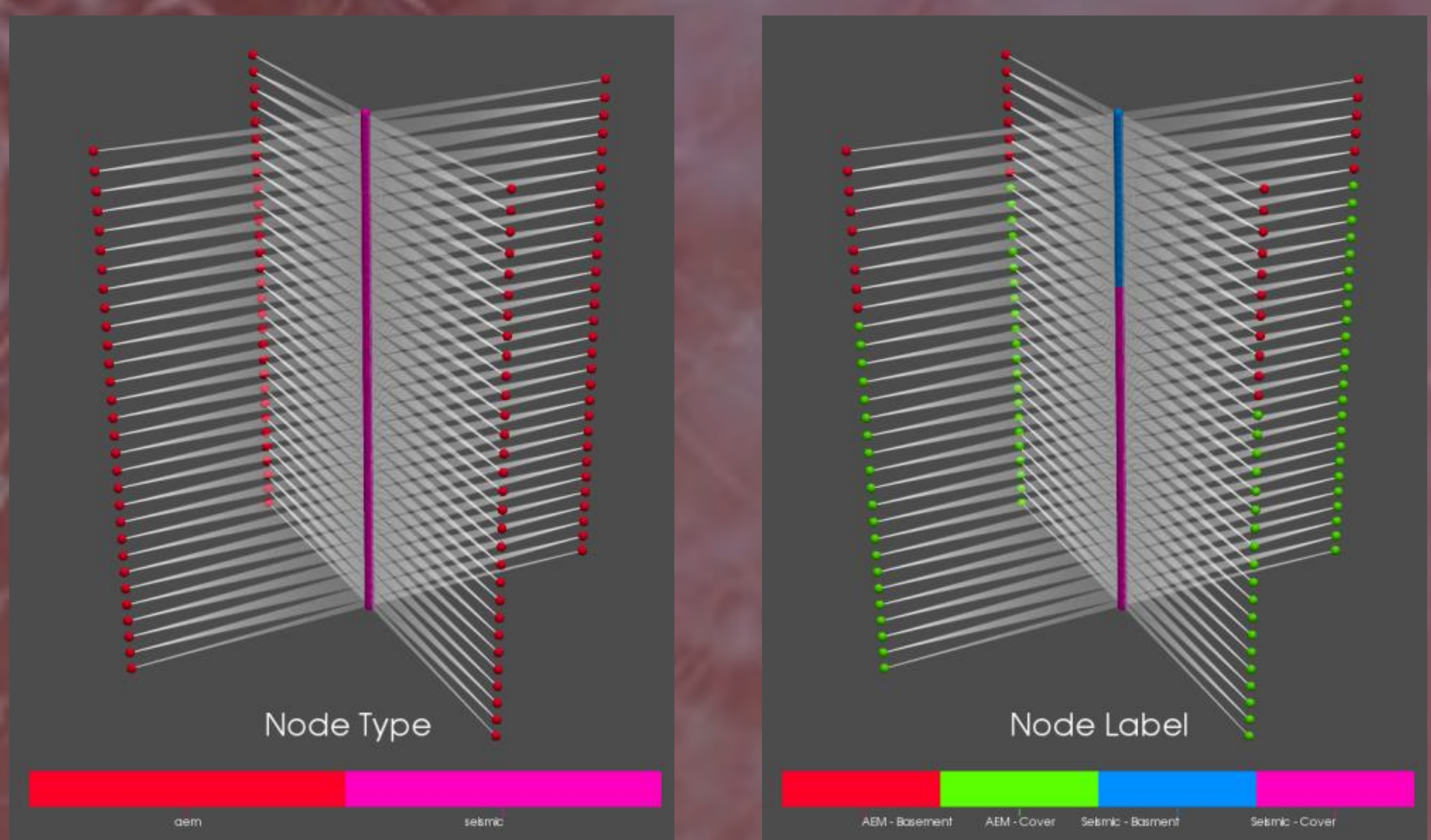

Figure 2: Visualisation of an example seismic station and the labels interpolated by a semi-supervised graph classification, from neighbouring AEM inversion stations.

CNN Time Series Classifier

Classifies time series data, which can be used to give indications of basement depth.

GNN Node Classifier

Interpolates interpretations made on AEM data over co-located seismic data.

Summary – Combining Classifiers

Benefits

- Individually characterise feature noise and label noise in each dataset:
  - We can identify where interpretations conflict between datasets
  - We can also indicate why, by evaluating which classifier was more correct!
- Better interrogation of individual datasets
  - We can identify where interpretation inconsistences are within a given dataset
- Data agnostic and minimise processing artifacts
  - Once an appropriate graph construction method is established any 3D data and its interpretations can be integrated to compare and characterise the data
  - Avoids the need to grid and interpolate data particularly for 3D datasets

Challenges

- Graph construction methods would need to account for different features, or some more regular spatial approach which is meaningful for the interpretation task.
- Graph Machine Learning is an emerging field, research on predictions where nodes have different feature spaces is limited.

Further Applications

- This method could be implemented to use AEM label prediction during training of the time series classifier in order to improve training and prediction performance on other unseen seismic data.

References

Bond, C.E. et al. (2007) 'What do you think this is? "Conceptual uncertainty" in geoscience interpretation', GSA today, 17(11), p. 4.

Bond, C.E. (2015) 'Uncertainty in structural interpretation: Lessons to be learnt', Journal of Structural Geology, 74, pp. 185–200.

Gillfeather-Clark, T. et al. (2021) 'A comparative study of neural network methods for first break detection using seismic refraction data over a detrital iron ore deposit', Ore Geology Reviews, 137, p. 104201. doi:https://doi.org/10.1016/j.oregeorev.2021.104201.

Jacoby, W. and Smilde, P.L. (2009) Gravity interpretation: fundamentals and application of gravity inversion and geological interpretation. Springer Science & Business Media.

Menke, W. (2012) Geophysical data analysis: discrete inverse theory: MATLAB edition. Academic press.

Pérez-Díaz, L., Alcalde, J. and Bond, C.E. (2020) 'Introduction: Handling uncertainty in the geosciences: identification, mitigation and communication', Solid Earth, 11(3), pp. 889–897.

Poulton, M.M. (2002) 'Neural networks as an intelligence amplification tool: A review of applications', Geophysics, 67(3).

Wellmann, F. and Caumon, G. (2018) 'Chapter One - 3-D Structural geological models: Concepts, methods, and uncertainties', in Schmelzbach, C. (ed.). Elsevier (Advances in Geophysics), pp. 1–121. doi:10.1016/bs.agph.2018.09.001.

Acknowledgements

This work was supported by both an Research Training Pathways Scholarship and Rio Tinto Iron Ore Scholarship

THE UNIVERSITY OF WESTERN AUSTRALIA

www.cet.edu.au

Curtin University