Deep Learning - A New Paradigm for Orebody Modelling

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ABSTRACT

A key input to any concept, study, plan or budget is the geological or resource model. Conventionally these models require a great deal of subjective manual interpretation and estimation using whichever method generates the least error. The end to end process, depending on the size of the model and the scale and complexity of the variables, can take several months which is a drain on company resources and provides no tactical benefit or agility.

Models should provide the best emulation of geological processes and physical observations, and irrespective of methodology should be dependable and defendable. If this can be achieved rapidly with a measure of uncertainty then the opportunities to streamline business processes, reduce costs and make faster smarter uncertainty-based decisions will be realised.

The rise of computer-based modelling served to move orebody interpretation away from 1D paper to a 2.5D digital form, and for many years this method excelled above all others but at its core, its accuracy has always been subject to the skills, efficiency and subjectivity of the operator. More recently semi-automatic methods such as simulation of categorical variables and implicit modelling have become increasingly popular, but these methods also have limitations such as processing time and scalability.

The derivation of a measure of uncertainty around an estimate or model requires the application of an appropriate simulation method, which in itself takes too long to form part of any tactical process and is more often than not isolated to long term strategic planning.

The many disruptive technologies introduced by Industry 4.0 bring with them some exciting opportunities to streamline business processes, reduce costs and make faster smarter uncertainty-based decisions. As miners look to maintain a competitive advantage, healthy margins and effectively navigate technical and operational challenges in an agile manner. In what can be a volatile industry, the need to embrace digital transformation is becoming ever more important.

This paper introduces a new neural net deep learning approach that can rapidly (in a matter of minutes or hours) generate classified/domained orebody models, including the estimation of multiple numeric variables and uncertainties, directly from spatially referenced pre-coded sample data. This is the future of orebody modelling.

A case study is presented that demonstrates the application of the new deep learning method to the Roy Hill Iron Ore deposit in Western Australia along with a brief comparative analysis against a conventional resource estimate generated using ordinary kriging.

INTRODUCTION

Since 2017 Maptek and Roy Hill have been working several collaborative co-investment projects designed to explore ways of improving Orebody Knowledge and leveraging multiple Industry 4.0 disruptive technologies, one of which was the application of Deep Learning in orebody modelling.

Generating conventional geological models and resource estimates (collectively referred to in this paper as orebody models) for small complex orebodies, or large orebodies with big data can consume a great deal of company time and resources. Typically, a model such as the Roy Hill orebody model can take 3-4 months to produce — even with the introduction of process automation via workflows and complex integrated programming (Batchelor, 2019).

This makes the inclusion of new data and new learnings a slow process with significant change management that is executed on 6 monthly rolling planning cycles. As such, conventional orebody models are not able to provide any real tactical value in the short and even short to medium term horizon.

Worst still, any mistakes or oversights that require immediate rectification generate a great deal of work and stress for those involved, resulting in either significant overrun on modelling timelines, or in some cases acceptance of the flaws in the model. Whilst every effort is made to prevent such occurrences, human manipulation of tens of thousands of samples, and modelling discrete areas in isolation for eventual fusion into a single model, lends itself to at least one mistake being made. We are only human after all.

The neural net deep learning approach introduced in this paper can rapidly (in a matter of minutes or hours) generate classified/domained orebody models, including the estimation of multiple numeric variables and uncertainties — directly from spatially referenced pre-coded sample data. This means, provided the input data is valid, the risk of human error is largely negated. Even if the input data does contain an error, the impact of re-running the entire process is negligible due to the time taken to rebuild a model using this approach.

The deep learning algorithm first generates a neural net (NN) from the pre-coded samples, then using the NN constrains the interpolation of numerical attributes. Building a block model is then simply a case of converting neurons to voxels and then aggregating voxels to generate the blocks we are familiar with.

By removing conventional manual processes such as string editing, wireframing, model stitching etc. the only real constraint is the time it takes to interpret and code assays or downhole readings. Extend the application of machine learning to the interpretation and domaining component and a pseudo real time automated orebody modelling method emerges.

CURRENT REALITY - DOMAIN GENERATION

A model should portray the best understanding of geological processes and observations, however, a volumetric interpretation of geological observations is only as good as the knowledge, experience, biases and patience of the geoscientist building the model. In reality, several possible interpretations could be generated by multiple geologists, and as such geological uncertainty is just as important as grade uncertainty. This geological uncertainty often gets overlooked primarily because unlike grade uncertainty, there is no easy way of capturing or communicating it.

In the 1990s the transition from analogue 2D hand drafted orebody modelling methods to digital 2.5D computer software methods was revolutionary to the art of orebody modelling. Today, the complex orebody, big data paradigm makes even this revolutionary methodology slow and cumbersome. By way of an example the Roy Hill deposit currently consists of >1,000,000m metres of reverse circulation drill hole data (so far) from ~50,000 drill holes, and a full re-model and re-estimation would take several months. Even modelling isolated areas and then stitching those areas back into a parent model and re-estimating can take over 3 months to complete. Because of this, models are generated no more frequently than every 6 months, which limits Roy Hill's ability to test geological hypotheses, or quickly embed new learnings globally and develop new models in the tactical horizon.

For some time, rapid techniques such as explicit and implicit modelling have offered faster, less cumbersome alternatives to conventional digital methods. These techniques suffer however from efficiency and scalability issues when applied to large complex orebodies or big data problems.

Using deep learning to predict categorical variables such as geological domains is a highly efficient process, requiring little in the way of input parameters, and can generate a result that includes a measure of prediction uncertainty. The uncertainty can then be used to make informed decisions from the exploration and project evaluation stages, through to planning and operational execution. Uncertainty can also be used to better quantify confidence when assessing resources and reserves stated compliant to the JORC code reducing the subjectivity around the process.

In his paper "*Science and Statistics*", published in the mid-1970s, George Box noted that "all models are wrong, but some are useful". This quote has become somewhat of a mantra to orebody modellers and could possibly be rewritten as "all models are wrong and through trial and error some will eventually prove useful some of the time and with some modification". The reality is that without the ability to reliably and efficiently capture localised model uncertainty, the only way to test a model's efficacy is to try and fail — which can be an extremely costly learning curve in a production environment.

Therefore, if using deep learning technology orebody models can be generated and regenerated rapidly with a measure of localised uncertainty, then perhaps the following or something like it will become the new mantra "all models are wrong, uncertainty makes them useful".

CURRENT REALITY - GRADE ESTIMATION

After data validation, interpretation, wireframing and volumetric modelling, the next step involves the interpolation or estimation of numeric values, such as grades and tonnes into blocks or cells. Estimation algorithms have been commonly deployed across industry in many software platforms.

Commonly used estimation techniques include inverse distance, kriging (multiple variants) and simulation (also with a variety of options). These have all been developed and redeveloped over time, chasing the goal of reduced estimation error, increased efficiency (speed) and in the case of simulation, a measure of uncertainty. Block dimensions are determined as a function of drill hole spacing and sample size, with a view to minimise estimation error while achieving a desired geological boundary accuracy.

Configuring estimation parameters for most commonly used techniques can be a cumbersome and time-consuming process. At Roy Hill a total of 84 variables are estimated across 14 geological domains using a combination of ordinary kriging and inverse distance weighting. To make the estimation preparation process more efficient and less prone to human error (e.g. data entry errors), a great deal of scripting has been employed. In total over 200,000 estimation parameter values are defined and need to be updated for every biannual estimation routine.

With respect to modelling uncertainty, conditional simulation (one of the most commonly adopted techniques) can be used to generate multiple realisations that can be post-processed to ascertain the uncertainty of a value at any given point in space. These methods are time, CPU, RAM and drive space intensive, so are typically used for due diligence assessments, or on reduced datasets, and are not as a rule incorporated into routine estimation cycles.

Some other simulation methods such as multi-Gaussian kriging can be used to determine uncertainty as an output of the estimation routine, but lack the multiple realisations and therefore detail provided by conditional simulation. (Ortiz, 2004).

Ultimately, all estimation and simulation routines require significant time and effort with regards to configuration, execution and analysis. They also depend on many human based decisions that invariably come with intangible biases that manifest in the overall estimate uncertainty and cannot be distinguished from data driven uncertainty. Then there is a dependency on spatial variance models, such as variograms and an assumption that the same model is globally representative, which is a long bow to draw in broad or complex orebodies.

In terms of efficiency and efficacy, conventional routines have many limitations.

MACHINE LEARNING APPROACHES

Deep learning (also known as deep structured learning or hierarchical learning) is a branch of machine learning methods based on artificial neural networks (ANN or NN). Learning can be supervised, semi-supervised or unsupervised.

Although the term ‘Deep Learning’ was introduced in the mid-1980s some of the earliest examples of Deep Learning algorithms can be traced back to the 1960s, and the impacts of deep learning in an industrial context were first felt the early 2000s. Around 2012, the Deep Learning Revolution began and today it is hard to imagine a world without it as it plays a vital role in a myriad of large global industries including medicine, pharmaceuticals, engineering, security and more recently mining.

Machine Learning in its various forms has been applied previously in resource estimation with varying levels of success. The most practical, commercially available simple NN algorithms are the Radial Basis Function (RBF) methods and while these methods can provide reasonable results from a small number of user-specified parameters, the results tend to reflect the ‘radial’ nature of the algorithm rather than the true underlying geological trends. Furthermore, RBF routines are very slow to apply to large datasets and are therefore limited in their application in much the same way as simulation techniques.

Over the years, Neural Network algorithms have promised to solve many generalised problems, without notable success. However, the digital transformation brought about by the Deep Learning Revolution, Industry 4.0 and the resurgence of Artificial Intelligence (AI) has shown that NNs can deliver impressive results across a wide range of fields including machine vision, speech recognition and natural language understanding and translation. Most of this technology is not new, but the scale at which it is applied has increased exponentially and NNs have been shown to improve significantly with scale.

The size of a NN is a function of the number of hidden layers (H) and number of “neurons” (N) in each layer. The term neuron comes from the original biological inspiration for the networks but can be thought of as a weighted-sum of the neurons in the previous layer, shown as a dot below.

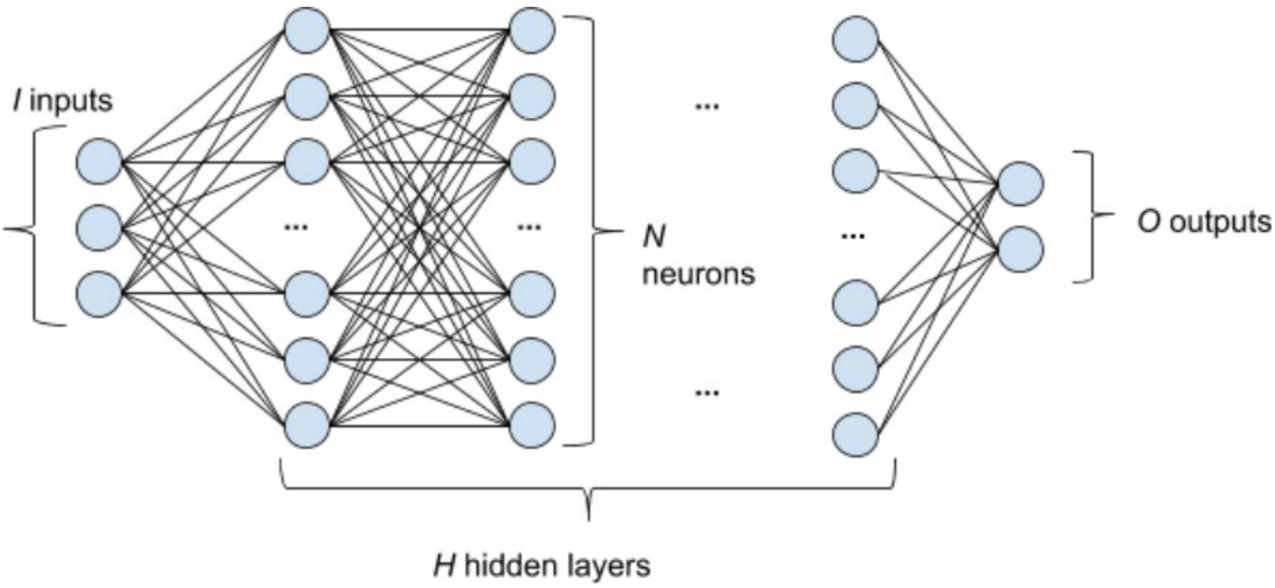

FIG 1 – Schematic architecture of a NN model.

The input size (I) and output size (O) are generally fixed by the application — in this case, the input size will be 3 — the X,Y,Z location of the point of interest, and the output size will depend on what is being queried — such as a series of grade values being estimated or the domain code being predicted.

Since each neuron in each layer is connected to each neuron in the previous layer and, if the number of neurons remains constant for each layer, the total number of weights in the model will be approximately N2 H. The size of the model when saved, and the total time it takes to compute a prediction are both approximately proportional to the number of weights in the model.

Some studies have used Neural Networks to model deposits. In 2010, Dutta et al used a Neural Net with H=1 hidden layer and N=12 neurons to model a gold deposit. More recently in 2017, Nezamolhosseini, Mojtahedzadeh and Gholamnejad, used H=3 hidden layers with N=20 neurons to model an iron ore reserve.

The recent phenomenal improvements to machine learning hardware and software now allow the creation of much larger models. Large increases in model size means any previous assumptions about the applicability of NNs to geosciences must be re-evaluated in light of these improvements.

BUILDING NN MODELS

A NN model is created directly from example data via a process known as training. A table of samples that matches inputs (X,Y,Z) to desired outputs (grade values and/or domain codes) is prepared and sent to the training algorithm — these data are usually taken from a composite drilling database.

There are a number of parameters which can be adjusted when building the NN, such as number of layers and number of neurons as well as more technical parameters such as the type of non-linearity, connection topology, batch sizes and learning rates. For a given site, tuning these parameters may lead to small improvements in the results, however the results presented here are generated from the same set of parameters. This is highly desirable as it allows a user with no knowledge of the underlying algorithm to use NNs to generate fast and accurate estimates.

CASE HISTORY

Roy Hill is the only independent iron ore operation with significant Western Australian ownership and has its Perth based integrated corporate headquarters and Remote Operations Centre (ROC) located at the Perth International Airport.

The Roy Hill iron ore deposit is located in the Chichester Range on the northern side of the Fortescue River valley, in the Pilbara region of North Western Australia. The mining area is located approximately 1300 km north of Perth and 100 km north of the regional centre, Newman. The export facility at Port Hedland is located 342 km by rail from the mine.

The organisation consists of approximately 2,400 full time staff running a conventional open pit, bulk mining operation from multiple production benches, feeding a 55Mtpa wet processing plant and railing to Port Hedland via a 344 km single line, heavy haul railway. Shipping is via a purpose built, dedicated two berth iron ore port facility.

The mineralisation at Roy Hill is hosted in the lower Nammuldi Member of the Marra Mamba Iron Formation (Figure 2) and consists of approximately 2Bt of >= 50% Fe iron ore resources with an average Fe content of 56.4%.

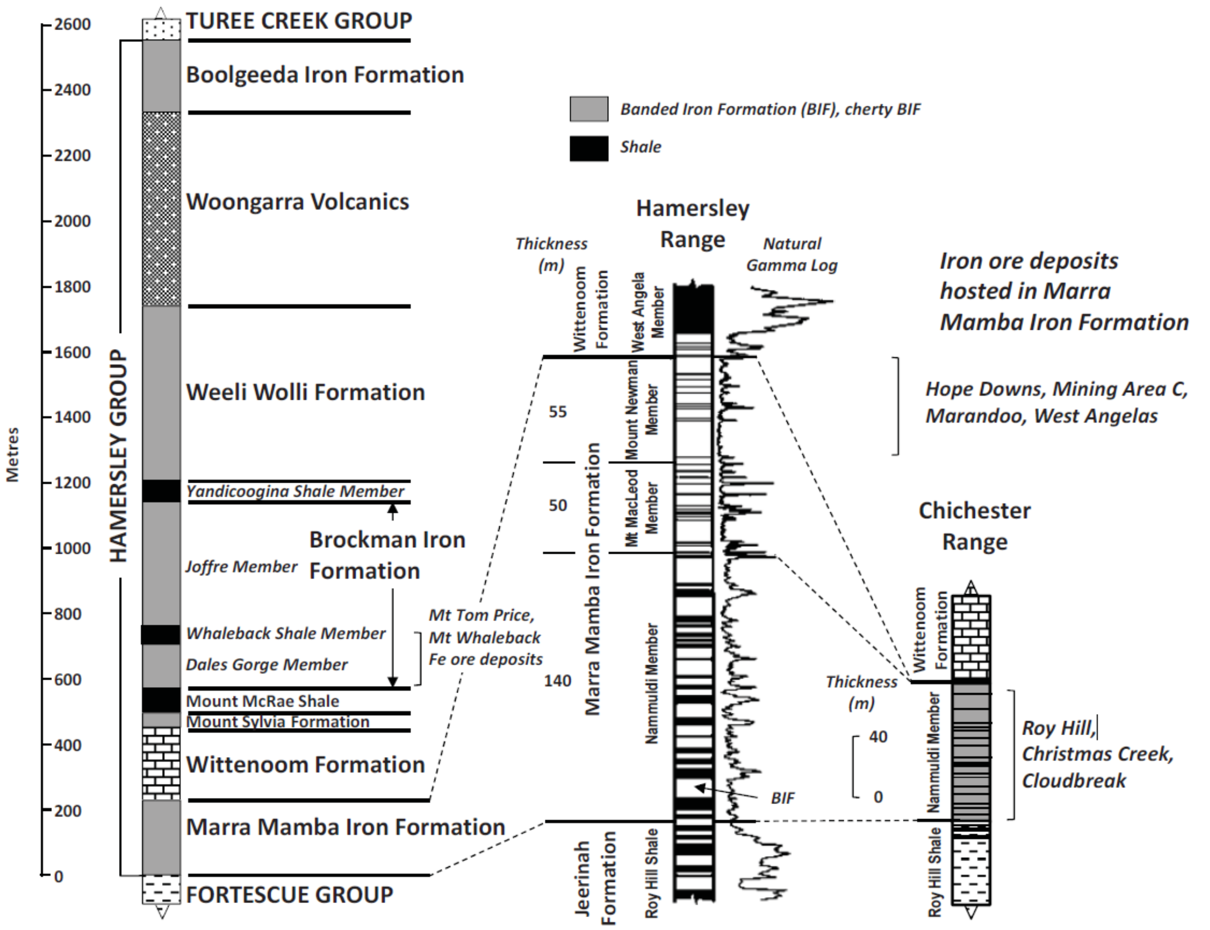

FIG 2 – Stratigraphic location of the Roy Hill iron ore deposit.

An Opportunity for Disruptive Experimentation

Orebody knowledge is a key component of the Roy Hill Smart Mine program, which aims to create tomorrow's mine today, and in 2017 Maptek and Roy Hill formed a collaborative co-investment project to explore ways of improving orebody knowledge by leveraging multiple Industry 4.0 disruptive technologies, one of which was Deep Learning.

'Smart' at Roy Hill is more than technology alone, it is leveraging technology as a disruptor and enabler in ways that free us from routine and mechanistic processes, allowing more time for critical and creative thinking, analysis and reasoning. Combining this with behavioural science and social skills such as influencing, coaching and empathy creates an opportunity and vision to shape the workplace for the better.

Vulcan software has been used for modelling the Roy Hill orebody for over ten years. In the past 6-7 years Roy Hill has put a great deal of effort into automating their processes via systems integration and programming in order to rapidly manipulate datasets and replace repetitive mechanistic tasks.

Two key activities that have been extremely difficult to streamline are the generation of geological interpretation and volumetric modelling and subsequent grade estimation. Roy Hill generates anything between 70,000 to 100,000 new RC samples every six months, which require interpretation and modelling by a small team of 3 geologists in a 4-month window. The process of generating new geological models can be resource intensive, leaving little time to stop, think, develop and consider insights.

As such, it is not surprising that Roy Hill chose geological modelling and estimation as a critical focal point for the application of AI. Some work had been completed previously by Roy Hill using Naïve Bayesian inference for the prediction of geological domains. Although this was a small step, it was a step in the right direction as it demonstrated how powerful probabilistic modelling and machine learning techniques could be.

The main outcome for the Deep Learning project was, in as few steps as possible, to build geological models and perform estimations directly and rapidly from sample data that had undergone minimal pre-processing. Furthermore, it was a requirement that the resultant output was comparable to many well accepted conventional methods and with a level of uncertainty.

The project presented both technical and philosophical challenges. The team was presented with a paradigm shift around what modelling is, why we do it a certain way, and what's really important to customers in terms of output and end use. Then considering these questions we asked ourselves how it could or should be done differently so as to ensure Roy Hill was well positioned for the future.

A key element in the innovation journey was recognising and managing our inherent biases and dependencies on mental models and allowing ourselves to be more data driven. This is easier said than done, given we as technical professionals develop mental models over the course of many years, and anything that challenges our 'instincts' is naturally met with distrust and disdain.

Deep Learning for Grade Estimation

For the proof-of-concept a small area of well-defined drilling (25mE x 25mN) was selected in the Delta region in the North East of the 23kmE x 23kmN deposit. Data for the area consisted of pre-domained 2m RC Fe sample assays.

The process was executed by invoking a Python executable in the Vulcan T shell interface using a command line consisting of the following parameters:

1. the name of the ascii file containing the sample data (.csv file)
2. a top and bottom wireframe (.00t files) used to constrain the model build e.g. a footwall and topographic surfaces
3. a block definition file (.bdf file) containing the model schema and variables requiring estimation
4. the required output model name (.bmf file).

All data was then encrypted, compressed and subsequently uploaded to an Amazon Web Service (AWS) where automated assignment of estimation parameter settings, geological modelling, grade interpolation and uncertainty analysis was performed.

Upon completion of the Deep Learning process the Vulcan block model was created, encrypted, compressed and downloaded to the origin Windows project directory for analysis. The end to end process going from sample to model was completed in less than an hour, something that would take months using a manual method.

Examples of the resultant domain generation and grade estimation can be seen in the following figures:

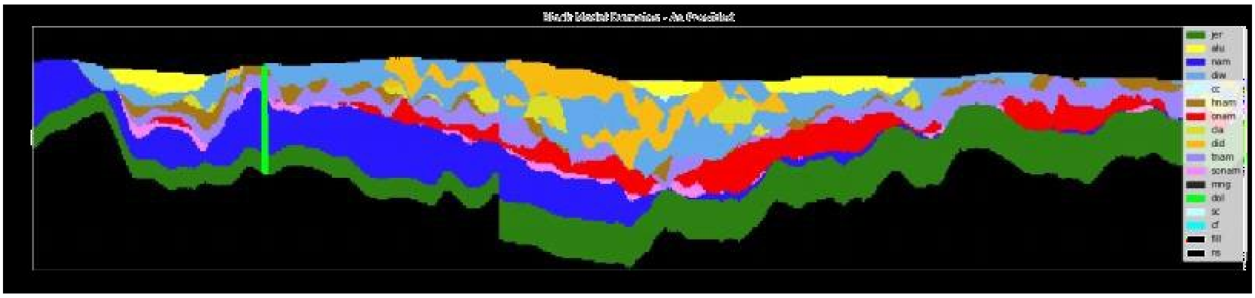

FIG 3 – Cross section through the Roy Hill iron ore deposit generated using conventional wireframing.

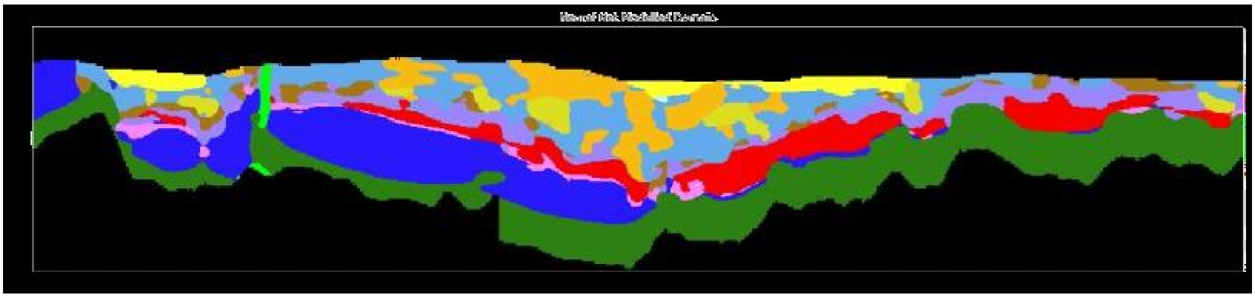

FIG 4 – Cross section through the Roy Hill iron ore deposit generated using Deep Learning.

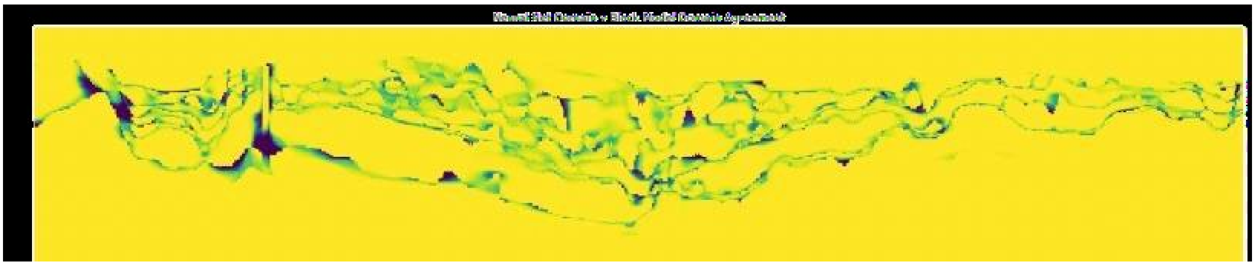

FIG 5 – Cross section through the Roy Hill iron ore deposit generated using deep learning showing prediction uncertainty.

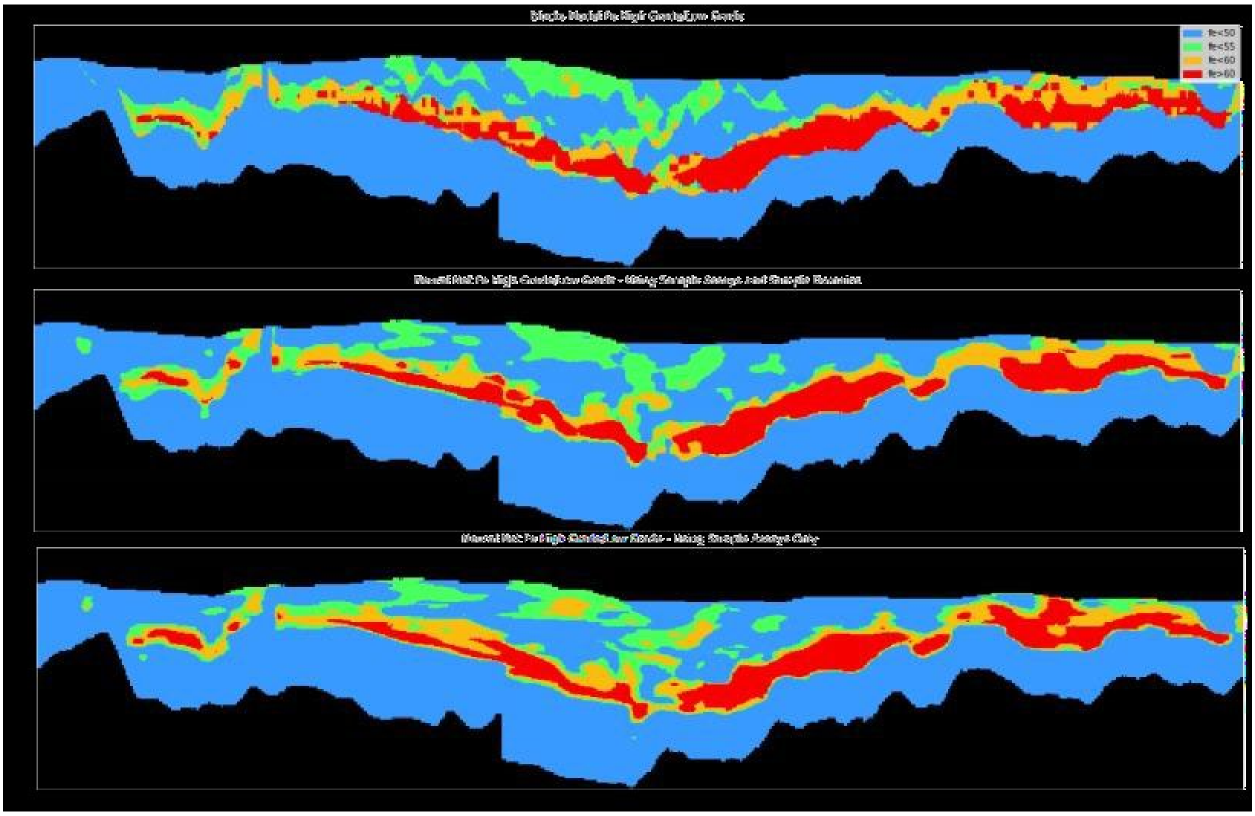

FIG 6 – Sections through the same locations as in Figures 3-5, showing from top to bottom: iron ore grades estimated using ordinary kriging in the wireframe generated model; iron ore grades estimated using deep learning and domained sample data; iron ore grades estimated using deep learning and undomained sample data.

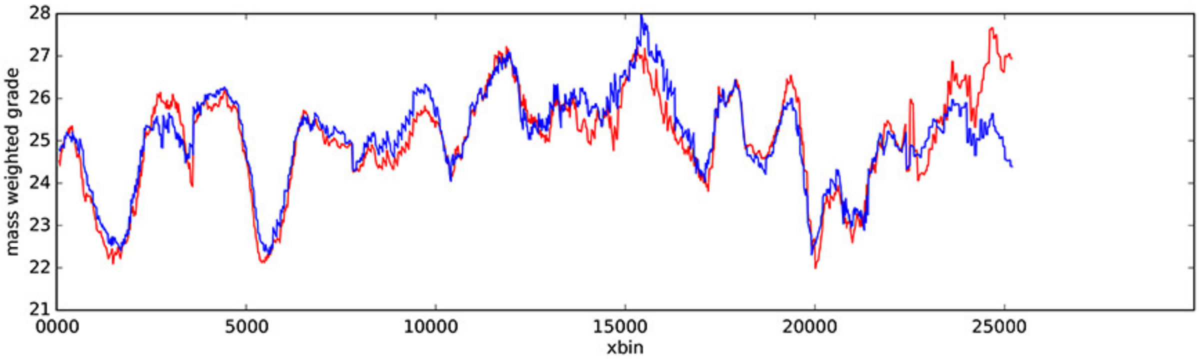

FIG 7 – East-West sectional validation plot of cumulative Fe grades along a 25km section line showing the ordinary kriged Fe estimates in red and deep learning Fe estimates in blue.

Initial results from the Deep Learning method are highly comparable to a kriged estimate — a very positive outcome. At a statistical level the data compares well, and at a geological level Deep Learning comes very close to mimicking a manual orebody model — with some opportunity for improvement around stratification.

Initial results from the Deep Learning MVP were very encouraging, however, change is never a smooth or simple process and a key next step in gaining wider industry acceptance will be the demonstrated application of Deep Learning to multiple orebody styles, work that is already underway and also generating very encouraging results.

CONCLUSIONS

After more than two years of research and development a Deep Learning MVP solution has been successfully applied to the modelling of the Roy Hill iron ore deposit, as well as being used to evaluate several other deposits and deposit types.

The next steps for Roy Hill consist of working with Maptek to further enhance the method's ability to generate stratigraphic layering, as well as identifying where the method can be used immediately to greatest effect.

Despite the Mining Viable Product (MVP) still having some limitations, immediate value can be gained through the application of this method in the following areas:

- validation and augmentation of routine orebody modelling processes
- rapid evaluation of other resources and projects
- short-term geological modelling and grade control
- Measure Whilst Drill (MWD) derived blast parameter estimation
- determination of geological risks associated with drill spacing and configuration, and
- improved estimation of non-additive (e.g. geometallurgical) variables.

Collaboration with Roy Hill on this project has seen all participants gain a greater appreciation for each other's creativity and ability to let go of firmly held beliefs. It required a great deal of agility and an ability to pivot as the project evolved, and a constant need to look at the bigger picture instead of focusing on single processes or systems.

Expansion of the application of Deep Learning to a much broader spectrum of geological styles is currently in progress, and Maptek is working to make a commercial build of the Deep Learning solution available to the wider mining community by the end of 2019.

Ultimately these technologies have the potential to change the *what, how and why* of mining in quite profound ways. A key reason for Roy Hill entering into shared IP arrangements with its vendors is to ensure projects such as this get benefit from wider technical community feedback, and it is hoped commercialisation will spark much debate and new thinking.

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