**Introducing deep learning and interpreting the patterns; a mineral deposit perspective**

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# ABSTRACT

Machine learning is creating value in all facets of the mining industry, from exploration to production. The authors provide an accessible, high-level introduction to AI, machine learning, and deep learning; widely recognized as one of the most powerful forms of machine learning. They will introduce deep learning tools like convolution neural networks, how they are already applied, and the economic considerations necessary for determining when deep learning may be the right solution to de-risking complex block modelling problems.

The authors present the results from the mineral resource modelling of an orogenic gold deposit, and demonstrate how statistically significant non-linear correlated elements are used as direct inputs to the resource model to assist the target element’s grade prediction for every block, by comparing deep learning with classical geostatistical techniques such as kriging. This demonstrates that 1) existing techniques for finding correlations between assayed elements do not reflect the complex geology of the asset 2) non-linear correlations that are difficult to model as simple mathematical functions are representative of geological patterns in a deposit, and 3) non-linear correlated assayed data fed as inputs increase the performance of the resource model as reconciled through blind tests. It will be further demonstrated that deep learning provides an enhanced de-risking tool for the modelling of geometallurgical parameters during the generation of more accurate block models.

To conclude, the authors hypothesize that the patterns represented by the deep learning block models may be revealing the results of overprinting geological processes that generated mineral deposits. For example, the primary hydrothermal processes that deposited metals created depositional patterns that become particularly complex as a result of being overprinted, in part or in whole, by secondary physicochemical processes. This may explain why non-linear geochemical correlative relationships have the capacity to generate more accurate block models of mineral deposits.