A speedy update on machine learning applied to bedrock mapping using geochemistry or geophysics: examples from the Pacific Rim (and nearby)

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INTRODUCTION

Artificial Intelligence (AI) has numerous and varied definitions, leading to confusion and disagreement about what it represents, and how it relates to mineral exploration. A general definition is most effective: AI is the artificial machine-based reproduction of tasks inspired by, or conventionally accomplished by humans (or other animals) using their natural intelligence. The form of AI applied to mineral exploration is called 'Domain Specific AI'; it is task-oriented and includes decades-old approaches to software automation and statistical modelling.

A core skill of experienced economic geologists is pattern recognition. This might include field-based work (e.g., recognising groupings of rock types, alteration minerals, or mineral textures related to mineralisation) or laboratory-based work (e.g., identifying groups of similar analyses from geochemical assays, or categorising spectral data from remote sensing devices). Machine learning (ML) is a subfield of AI that specialises in pattern recognition and is defined as any computer program that improves its performance at some task through experience or iteration. ML is well-studied and has routinely been applied towards mineral exploration over five decades. ML can automate parts of mineral exploration workflows, e.g., mapping or modelling geology, and can improve results by making them more objective, repeatable, or efficient.

This extended abstract briefly gives three examples of ML used to improve the interpretation of rock type in a mineral exploration or mining area, using geochemical or geophysical data.

CASE STUDY 1

In the first case study, remote sensing and geochemical data for a regional mineral exploration project in western Eritrea are used to produce separate maps of bedrock and of overlying transported material (Hood, 2018). These are then used for different exploration purposes: (i) to map drainage areas by regolith type, and identify areas prospective for placer Au, and (ii) to identify different felsic intrusive rocks in bedrock, under cover, by their geophysical signature (Figure 1). These identified rocks are then considered by site geologists and ranked by likely prospectivity, based on observations from outcrop and chip sample assays. Results provide a means to narrow the search space for upcoming exploration drilling, planned in early 2019.

CASE STUDY 2

The second case study uses whole rock geochemical data collected within the Minto Cu-Au mining area in northwest Canada to produce cross-sections of granitoid dykes and sills. This interpretation is possible despite overprinting ductile deformation and metasomatism which overprint primary mineral textures, obscuring diagnostic textures from logging geologists. The workflow combined unsupervised and supervised ML algorithms to discriminate the lithology of drill core samples (Hood et al., 2018). This workflow is given as a replacement for the manual task of visually assessing a lithological discrimination plot. Machine learning provides objectivity and reproducibility to a task that can be highly subjective because it is usually done by eye, and manual groupings relate to the user's individual experience.

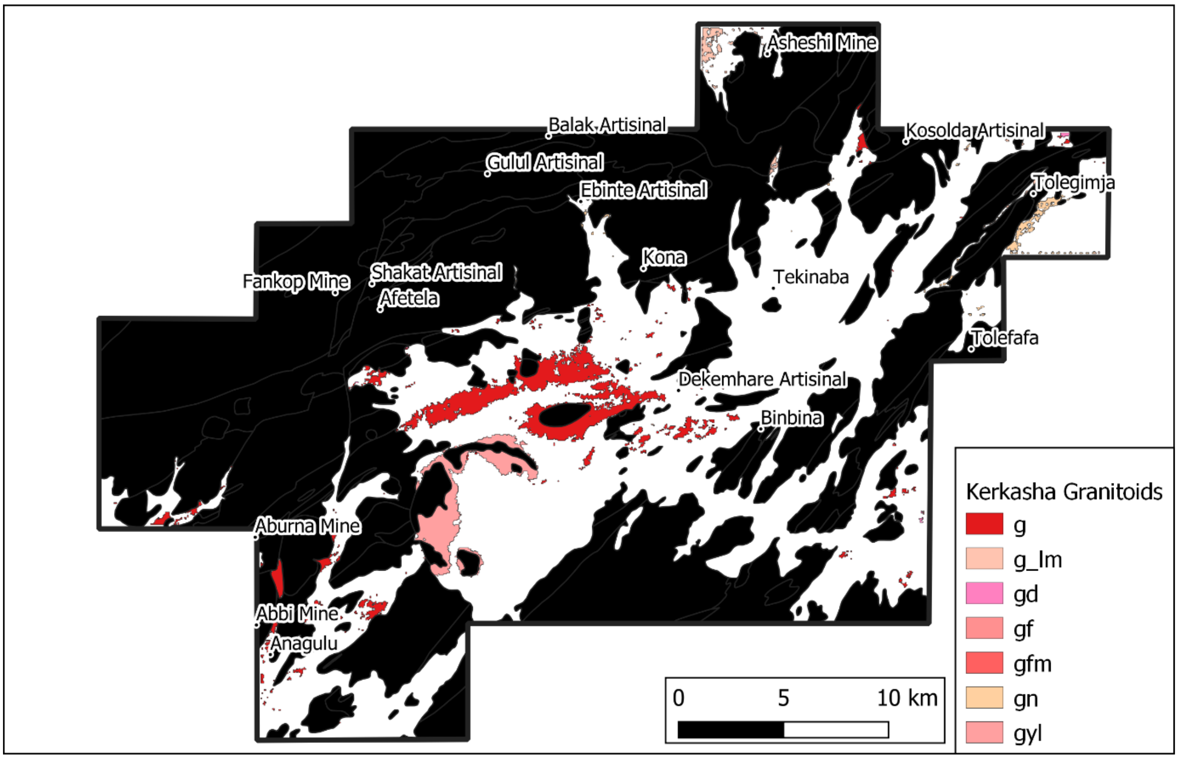

Figure 1. A one thousand square kilometre greenfields exploration area, where historic mapping identified large areas of transported cover which obscures bedrock. Using airborne magnetic surveying and pXRF soil geochemical data, different prospective felsic intrusions have been mapped under cover (hot colours), to assist RC drill targeting. Figure has historic map units coloured black, except for colluvium and alluvium, to highlight where ML mapping adds value.

In the workflow, data are first normalised and then clustered into natural groupings that represent protolith lithologies or rock-type subunits. These clusters then inform supervised classification to assign protolith equivalent labels to samples of altered rocks. The results allow reconstruction of protolith geometry. The revised geometry was used to rationalise how rock types have influenced partitioning of hydrothermal fluids and ductile deformation (Figure 2).

CASE STUDY 3

In the final case study, a statistically-robust approach (Ague and van Haren, 1996; Hood et al., In Review) is used to quantify and model metasomatism overprinting bedrock at the Waihi epithermal Au deposit in New Zealand (Barker et al., In Review). Whole-rock geochemical data from drill core were first processed using multivariate methods to transform them from compositional space (i.e., summing to a constant such as 100 weight percent) to Euclidean mathematical space (i.e., appropriate for statistical analyses). These transformed data were then used to construct synthetic data matrices, produced in a way to better represent the variable composition of protolith and metasomatised samples. Matrices are then used to compute mass balance estimates for geochemical elements using a Monte Carlo method (Figure 3A), an approach which facilitates calculation of confidence intervals about the averaged results. The element enrichment and depletion values were plotted in 3-D to investigate potential metasomatic trends (Figure 3B). Results indicate silicification of host rocks is achieved by the addition of SiO_2 (average addition = 50%), coincident with plagioclase destruction and loss of Na_2O and CaO (average depletions of 28% and 76%, respectively). Mapping normalised alteration using this method reveals spatial patterns that are not visible in the raw geochemical data, and helps the identification of the footprint of the hydrothermal alteration zone, assisting exploration efforts.

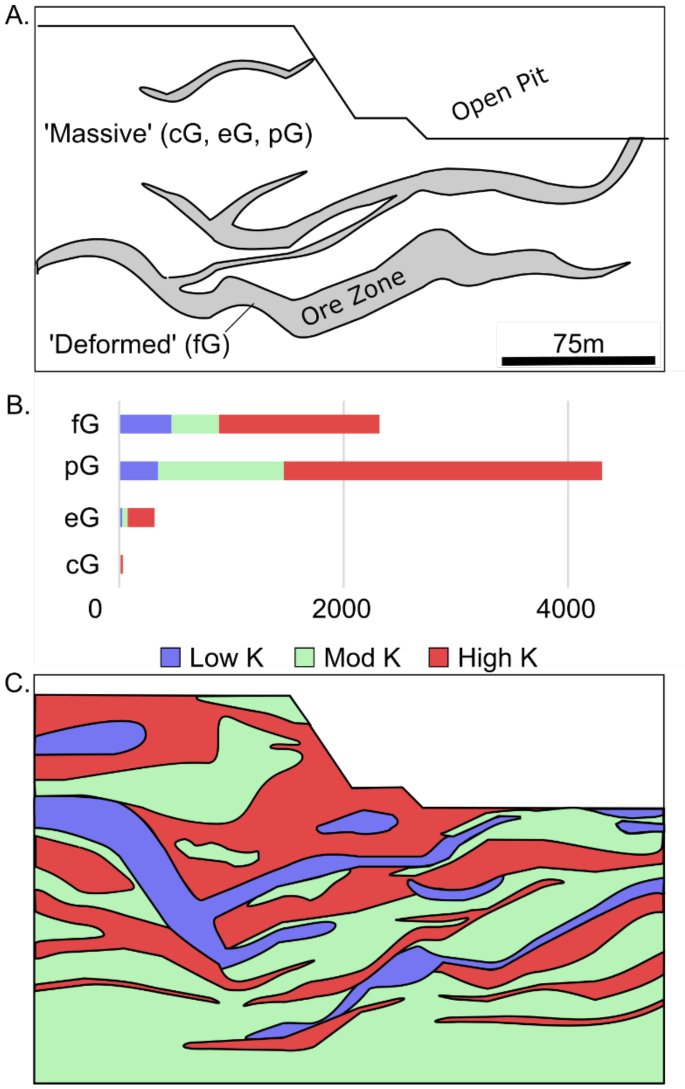

Figure 2. Cross section from Minto Cu-Au-Ag deposit with bedrock interpretation using ML and immobile element data. A. Original logging uses three textural codes to separate massive granodiorite units, and one generic code for deformed rock (Minto deposit ore zone). B. A combination of unsupervised clustering and supervised classification recast samples into three geochemically distinct groups, using immobile element geochemistry. These zones correspond to low, moderate, and high-K protolith rocks (K-feldspar megacrystic granodiorite). C. Plotting relogged samples on the cross-section from A produces an interpretation of Minto pluton geometry as dikes and sills.

CONCLUSIONS

There is practical value to merging ML with domain expertise in the exploration environment. Examples given in this abstract include interpreting lithological distribution in an area and calculating metasomatic domains. These interpretations are typical tasks when exploring for a deposit or trying to interpret one. Beneficially these tasks can be automated using ML, making their production more objective, repeatable, and efficient.

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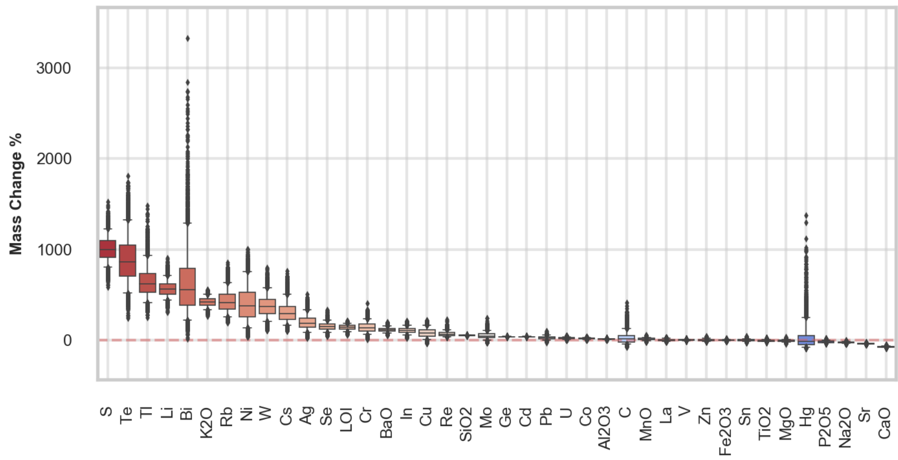

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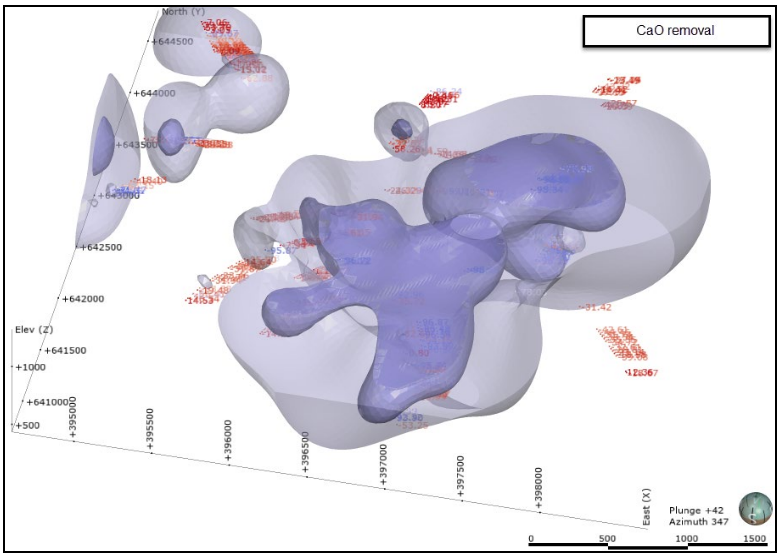

B.

Figure 3. Mass change estimates from ML. A: ranked box and whisker plots show the range of element change within the Waihi mining area. B: 3D zonation of CaO removal (dark blue, 50% shell,light blue, 25% shell) related to plagioclase destruction.

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