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Prospectivity of Western Australian iron ore from geophysical data using a reject option classifier

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ABSTRACT

There has recently been a rapid growth in the amount and quality of digital geological and geophysical data for the majority of the Australian continent. Coupled with an increase in computational power and the rising importance of computational methods, there are new possibilities for a large scale, low expenditure digital exploration of mineral deposits. Here we use a multivariate analysis of geophysical datasets to develop a methodology that utilises machine learning algorithms to build and train two-class classifiers for provincial-scale, greenfield mineral exploration. We use iron ore in Western Australia as a case study, and our selected classifier, a mixture of a Gaussian classifier with reject option, successfully identifies 88% of iron ore locations, and 92% of non-iron ore locations. Parameter optimisation allows the user to choose the suite of variables or parameters, such as classifier and degree of dimensionality reduction, that provide the best classification result. We use randomised hold-out to ensure the generalisation of our classifier, and test it against known ground-truth information to demonstrate its ability to detect iron ore and non-iron ore locations. Our classification strategy is based on the heterogeneous nature of the data, where a well-defined target "iron-ore" class is to be separated from a poorly defined non-target class. We apply a classifier with reject option to known data to create a discriminant function that best separates sampled data, while simultaneously "protecting" against new unseen data by "closing" the domain in feature space occupied by the target class. This shows a substantial 4% improvement in classification performance. Our predictive confidence maps successfully identify known areas of iron ore deposits through the Yilgarn Craton, an area that is not heavily sampled in training, as well as suggesting areas for further exploration throughout the Yilgarn Craton. These areas tend to be more concentrated in the north and west of the Yilgarn Craton, such as around the Twin Peaks mine (~27°S, 116°E) and a series of lineaments running east–west at ~25°S. Within the Pilbara Craton, potential areas for further expansion occur throughout the Marble Bar vicinity between the existing Spinifex Ridge and Abydos mines (21°S, 119–121°E), as well as small, isolated areas north of the Hamersley Group at ~21.5°S, ~118°E. We also test the usefulness of radiometric data for province-scale iron ore exploration, while our selected classifier makes no use of the radiometric data, we demonstrate that there is no performance penalty from including redundant data and features, suggesting that where possible all potentially pertinent data should be included within a data-driven analysis. This methodology lends itself to large scale, reconnaissance mineral explorations, and, through varying the datasets used and the commodity being targeted, predictive confidence maps for a wide range of minerals can be produced.

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1. Introduction

The viability of an ore deposit is governed not only by its geological features, but also by economic factors such as global demand and market value. Consequently, economic geology links together frontier geological science with an economic framework; what defines an economically viable ore deposit can alter over time as a consequence of changes in the cost of exploration, extraction and production as well as demand in the global market (Pohl, 2011). As ore deposits, which are both easy to find and extract, are being depleted, there is a rising cost associated with finding new ore deposits using existing exploration techniques. The increase in computational power and in the availability of high-resolution data allows for new methodologies to be developed for the purposes of data-driven mineral exploration, in an effort to reduce exploration costs in finding large ore bodies.

The challenge in developing effective targeting aids that generalise to new geographic locations is in developing methods and models that exploit available data without over-fitting, and lend themselves to continuous improvement as more/higher-quality data become

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available. Of particular importance is understanding the impact that factors such as data redundancy, correlation between datasets, sample-sizes and data-dimensionality have on the effectiveness of the models and outputs generated by their amalgamation. In this paper we have used a multivariate analysis of geophysical databases to develop a methodology that utilises machine learning algorithms (MLAs) to build and train a classifier to predict the presence and absence of iron ore deposits throughout Western Australia. Importantly, our classifier is designed to be applied over large areas of land (on the order of 1000 km), as such, while generalising well for the exploration of iron ore over multiple cratons and orogenies, it is not specifically adapted for local geology and regional–local scale exploration. As such, we utilise a training and evaluation methodology, which takes into account the various aforementioned factors and attempts to make use of available data in the most effective way.

As conceptual targeting of potential sites at a province/district to regional scale is one of the largest challenges facing geoscience (Hronsky and Groves, 2008) this methodology will assist with first order, large-scale exploration. Mineral exploration consists of a number of successive but interlinked stages, starting with planning and large-scale reconnaissance exploration, before moving towards smaller scale appraisals and explorative drilling, and then finally assessment drilling and mine development (Moon and Whateley, 2006; Pohl, 2011). Generally, as the stages progress the associated economic risk decreases, but the expenditure required increases (i.e. more money is spent on stages that have a higher confidence of success) (Moon and Whateley, 2006). The methodology outlined in this paper is designed to fit in the early reconnaissance stage of mineral exploration, assisting and facilitating in the identification of potential target locations for a commodity. The nature of this methodology fits well in the exploration method, as it has a low expenditure. However, unlike existing reconnaissance exploration, we believe that there is less associated risk with this methodology. While formal mineral exploration already consists of the analysis of geophysical data, our approach differs in that we minimise human bias and use computational methods that allow for the combination and analysis of large amounts of high-dimensional data to create a prospectivity map of a target commodity. We argue that studies in the past such as Groves et al. (2000) and Nykänen et al. (2008) in which targeting "layers" are independently combined together are suboptimal. They do not take into account that many geological/geophysical statistics are not independent, resulting in under-exploited data separability (Brown et al., 2000; Porwal et al., 2003; Singer and Kouda, 1999). In this paper a multivariate approach is taken where we explicitly attempt to deal with these issues, thus combining various data sources into a single model that involves feature extraction and classification to both cope with the dependence between variables, and make trade-offs between the number of dimensions, available data and classifier complexity.

2. Background geology

Though iron ore is one of the most economically important natural commodities, there is still some uncertainty about its genesis. This is due, in part, to an absence of modern analogues with respect to both the process of formation (Bekker et al., 2010) and also the scale at which the deposits form (Morris, 1985). Additionally, ambiguities about Archean and Proterozoic geology, climatic conditions and seawater chemistry (e.g. Canfield, 2005; Lyons et al., 2009; Planavsky et al., 2011) have also caused numerous mechanisms and ideas being proposed over time for the source and transport paths of iron, the timing of deposition of iron formations and the subsequent enrichment of iron formation to iron ore. For instance, while it is generally accepted that all major iron ore deposits occurred in an oceanic setting, the source of the iron within the oceans was thought to originate from continental erosion until, an alternative hydrothermal source was proposed (Isley, 1995).

Banded iron formations (BIF) are defined after James and Trendall (1982) as a rock with thin laminations of chert alternating with iron minerals, and can be broadly classified into two categories based on their depositional environment, Algoma-type and Superior-type (Gross, 1980). Algoma-type deposits are found through Archean and Proterozoic formations, and are associated with volcanic centres and exhalative submarine processes, and typically contain some greywacke or volcanic units (Gross, 1980). They are typically found within Archean greenstone belts (Bekker et al., 2010; Goodwin, 1973; Isley and Abbott, 1999) and are usually smaller, both in terms of tonnage of ore (largest deposits around 10^7 Mt) and in spatial extent than Superior-type deposits. Comparably, Superior-type deposits are more common in Proterozoic aged formations and are associated with a near-shore continental-shelf depositional setting, usually found with carbonates, quartzite, black shales, and small amounts of volcanogenic rocks (Gross, 1980). The Superior-type tend to be larger, up to 10^{14} Mt, and also occupy a larger spatial extent (Bekker et al., 2010; Huston and Logan, 2004; Isley, 1995). Both types of iron formation are associated with oxide, silicate and carbonate facies (Gross, 1980; James, 1954), while Algoma-types may be associated with polymetallic sulphide facies if they occurred in close proximity to a volcanic centre.

2.1. Geological setting

Australia is host to both Algoma- and Superior-type deposits, though it is predominantly known for its massive Superior-type deposits occurring throughout the Hamersley Basin in the Pilbara Craton (Fig. 1). The Pilbara Craton consists of a Paleo-Neoarchean core overlain with a strong angular unconformity by Neoarchean–Paleoproterozoic volcano-sedimentary sequences (Blake and Barley, 1992; van Kranendonk et al., 2002). The core consists of a granite–greenstone terrane that outcrops towards the north, collectively called the North Pilbara terrain (Fig. 2). The North Pilbara terrain has been subdivided into three distinct granite–greenstone terranes, the East Pilbara granite–greenstone terrane (3.72–2.85 Ga), the West Pilbara granite–greenstone terrane (3.27–2.92 Ga) and the Kurunna terrane (3.3–3.2 Ga) towards the southeast of the craton, and two intracratonic sedimentary basins, the Mallina Basin (3.01–2.94 Ga) and the Mosquito Creek basin (~3.3–2.9 Ga) (van Kranendonk et al., 2002). Smaller Algoma-type deposits occur in the Eastern Pilbara granite–greenstone terrane amongst the Gorge Creek Group and Cleaverville Formation (Huston and Logan, 2004). The volcano-sedimentary sequences, collectively referred to as the Hamersley province, overlay the southern part of the craton and are of principal interest to this study as they contain some of the largest and richest iron ore deposits in the world. The stratigraphy of the Hamersley province is divided into five key groups. The lower three, the Fortescue Group (2770–2630 Ma), the iron rich Hamersley Group (2630–2470 Ma) and the Turee Creek Group (2470–ca.2350 Ma) all conformably overlay one another and comprise the Mt. Bruce Supergroup (Taylor et al., 2001). The upper two groups, the Lower and Upper Wyloo Groups (2209–2150 Ma and 2000–1800 Ma respectively), are separated from the Mt. Bruce Supergroup by a first order regional unconformity (Taylor et al., 2001). The Fortescue Group is characterised by mafic–clastic sedimentation, while the lower and middle units of the Hamersley Group are indicative of a deep-water environment consisting of volcanoclastic sedimentary and some carbonate sedimentary units and the Turee Creek Group consists of coarser, clastic sedimentary rocks overlaying iron formation, suggesting a transition from a deep to shallow sea environment (Blake and Barley, 1992; Simonson et al., 1993). Iron ore is found extensively throughout the Hamersley Group. Deformation is more pronounced in the south of the Hamersley province where the younger units outcrop, with the older basal units in the north of the province only being gently folded (Taylor et al., 2001).

The Yilgarn Craton is a large, Archean aged section of crust within Western Australia, to the south of the Pilbara Craton. Similar to the Pilbara Craton, it is comprised predominantly of Mesoarchean low-grade metamorphosed granite–greenstone belts, though it also contains

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