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Integrating Spatial Information and Geochemistry for Improved Lithological Classification of Drill Hole Samples

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ABSTRACT

At Sunrise Dam Gold Mine (Western Australia) geochemical data has been collected from drill hole samples in order to improve the quality and consistency of geological logging and rock classification. Traditional visual logging of the drill core has proved very difficult due to multiple phases of alteration and the similarity in appearance of many of the lithological units. Classification of lithological units from geochemical data can provide consistent results; however using geochemical data without reference to its spatial context can result in very noisy downhole plots (i.e. the presence of numerous small units). This paper introduces a method of integrating spatial information by first grouping the drill hole samples into spatially continuous domains then applying clustering to these spatial domains. The results of this new method are compared against traditional techniques in order to demonstrate the noise reduction that can be achieved.

INTRODUCTION

The traditional method of visual logging of drill holes by geologists can be problematic due to the subjectivity of the process. Routine collection of geochemical data and the application of automated clustering techniques has the potential to greatly assist geologists to generate more reliable geological logs. However, classification of geochemical samples without reference to their spatial context can result in very noisy classification when viewed as down-hole plots; i.e. there are numerous small geological units. These small units may be unnecessary because (1) they do not reflect actual geological boundaries but are due to natural compositional variance within one rock unit; (2) they represent very small rock units that are below the scale of interest; (3) they represent a mixed sample.

There are two approaches to this problem:

1. include spatial or geostatistical information in the classification, so that the classification considers samples which are closer (or connected) in space to be more similar (e.g. Fouedjio, 2016); or
2. segment the drill hole into relatively homogeneous 1D domains based on their composition and then cluster by domains rather than by individual samples.

The second approach will be addressed in this paper. This approach most closely imitates the method used by a geologist when manually logging a drill hole; i.e. the geologist will classify a continuous region between geological boundaries as a single unit (domain). Boundaries are defined here as locations where there is a change in composition that is larger than the local variation. We compare results from the domaining and clustering method with clustering without domaining and with an expert classification system.

SAMPLE DATA

Sunrise Dam Gold Mine (SDGM) lies within an Archaean greenstone belt in Western Australia, Figure 1. The rocks which host the Vogue deposit at SDGM consist largely of volcanic rocks (ultramafic, mafic, andesitic, dacitic) and minor felsic intrusive dykes. The rocks have undergone metamorphism and several phases of hydrothermal alteration, some of which are associated with gold mineralization (Blenkinsop et al., 2007; Baker et al., 2010; Hill et al., 2013; Hill et al, 2014). Rock types can be difficult to distinguish visually and this has resulted in inconsistent and unreliable geological logging of lithological units. Geochemical data has been collected in order to improve the quality and consistency of rock classification. As part of a collaborative project funded by AngloGold Ashanti three drill holes were sampled and studied in detail and are the subject of this experiment.

Figure 1: Sunrise Dam Gold Mine, Western Australia.

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METHODS

Clustering by Expert Analysis

Initially, the data was classified using expert analysis, Figure 2. Variables were chosen based on the assumption that Al, Ti and Cr are immobile during alteration. Ratios are used to overcome dilution and dilation effects. The two ratios used are Al/Ti_n = Al_2O_3%/TiO_2%/22 (i.e. mantle normalized) and Cr/TiO_2 = Cr ppm/TiO_2%.

Clustering Using Spatial Domains

The sequence of steps for automated classification are as follows:

1. *Create spatial domains for each variable*: multiscale spatial domains were created using the wavelet tessellation technique, Figures 3a, 3b (Hill et al., 2015). A suitable scale/filtering of domains was selected which was a good match for the domains in the geologist's logs.
2. *Integrate multivariate spatial domains*: boundaries for each variable, at the selected scale, are combined to create one set of domains for each drill hole, Figure 3c (Le Vaillant et al., in review).
3. *Calculate Divergence Matrix*: Kullback-Liebler divergence (KLD, Kullback and Liebler, 1951) is used to compare the probability density distribution of data in each multivariate domain:

   $$KLD = D_{KL}(P||Q) + D_{KL}(Q||P)$$
   $$D_{KL}(P||Q) = \sum_i P(i) \log \frac{P(i)}{Q(i)}.$$

   A divergence matrix is generated for comparing domains, Figure 3d. This is an nD x nD matrix, where nD is the total number of domains.
4. *Calculate Similarity Matrix*: the KLD matrix is converted to a similarity matrix using a heat function (Figure 3e):

   $$e^{(-KLD^2/2\delta^2)}$$

   This transforms the range of values from 0 to ∞ in the divergence matrix to 0 to 1 in the similarity matrix, and reverses the order; i.e. identical domains have divergence of 0 but a similarity of 1.
5. *Spectral Clustering*: The similarity matrix is used to apply the spectral clustering technique to the spatial domains (Ng et al., 2001). Spectral clustering has been applied to the spatial domains as it is capable of dealing with data presented in the form of a similarity matrix rather than conventional vector data. Vector data requires a fixed length input but a similarity matrix is more flexible and can be generated from spatial domains with any number of data points.
6. *Label clusters*: clusters are labelled with appropriate rock type names.

RESULTS AND CONCLUSIONS

The results are compared with (1) spectral clustering without spatial information, (2) the original geologist's log and (3) the expert classification system, Figure 4. This figure demonstrates the ability of the spatial domaining to remove noisy features, which makes the geology simpler to interpret. For example, the presence of thin layers of mixed basalt-komatiite at 245–270 m in the second drill hole are now clear, whereas in the other methods they are obscured. The degree to which noisy features are removed depends on the scale selected by the user from the tessellation in step 1.

In this report spatial domaining and classification of domains has been applied in order to provide:

1. A rock type classification that is more reliable and consistent than visual geological logging because it is based on geochemical data on element ratios that are robust during alteration
2. A rock type classification that is less noisy than that which can be produced from clustering the data in feature space (either by expert or by automated clustering), i.e. without spatial information.

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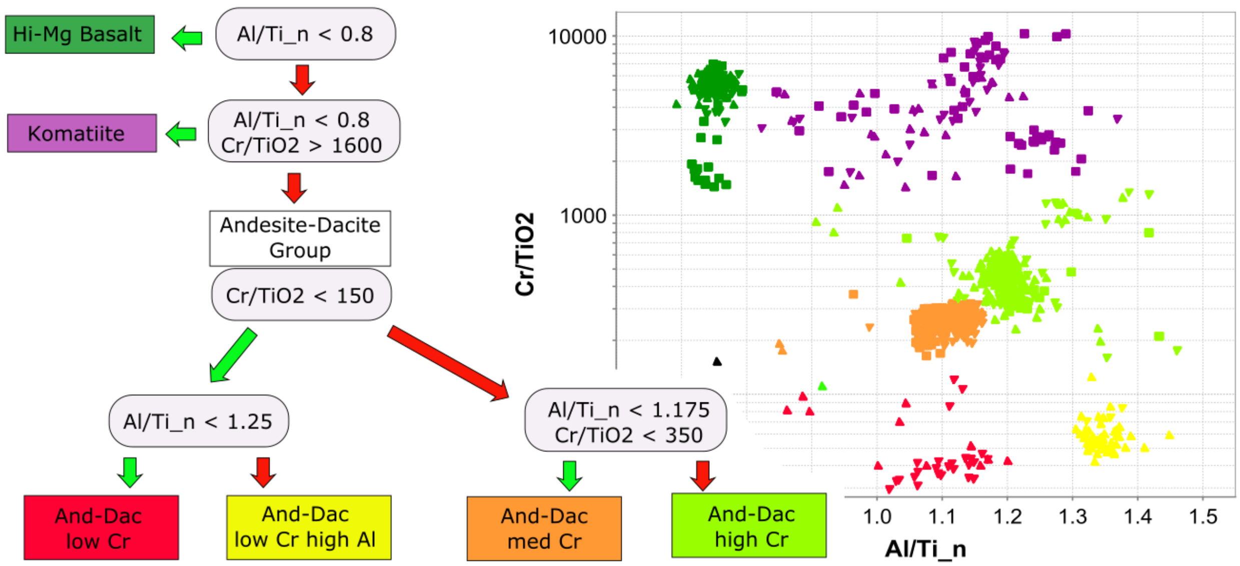

Figure 2: Manual classification of lithological units using normalize Al/Ti and Cr/TiO2. Green arrows = True, red arrows = False.

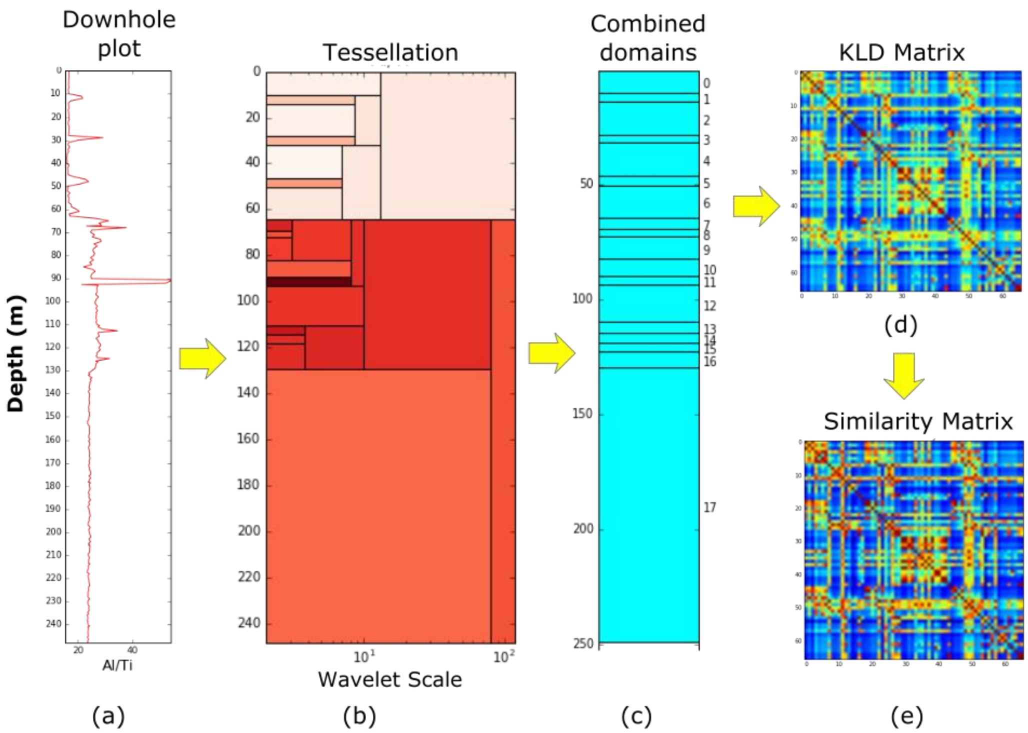

Figure 3: a) Downhole plot of Al/Ti for one drill hole. b) Wavelet tessellation of log (Al/Ti). Each rectangle in the tessellation represents the depth and scale of one domain, the colour is given by the mean value of samples in that domain. Tessellation has been filtered to remove weak features. c) Combined domain boundaries for two variables (Al/Ti and Cr/Ti) at a selected scale. d) Divergence matrix for all domains (red = low divergence). e) Similarity matrix for all domains (red = high similarity).

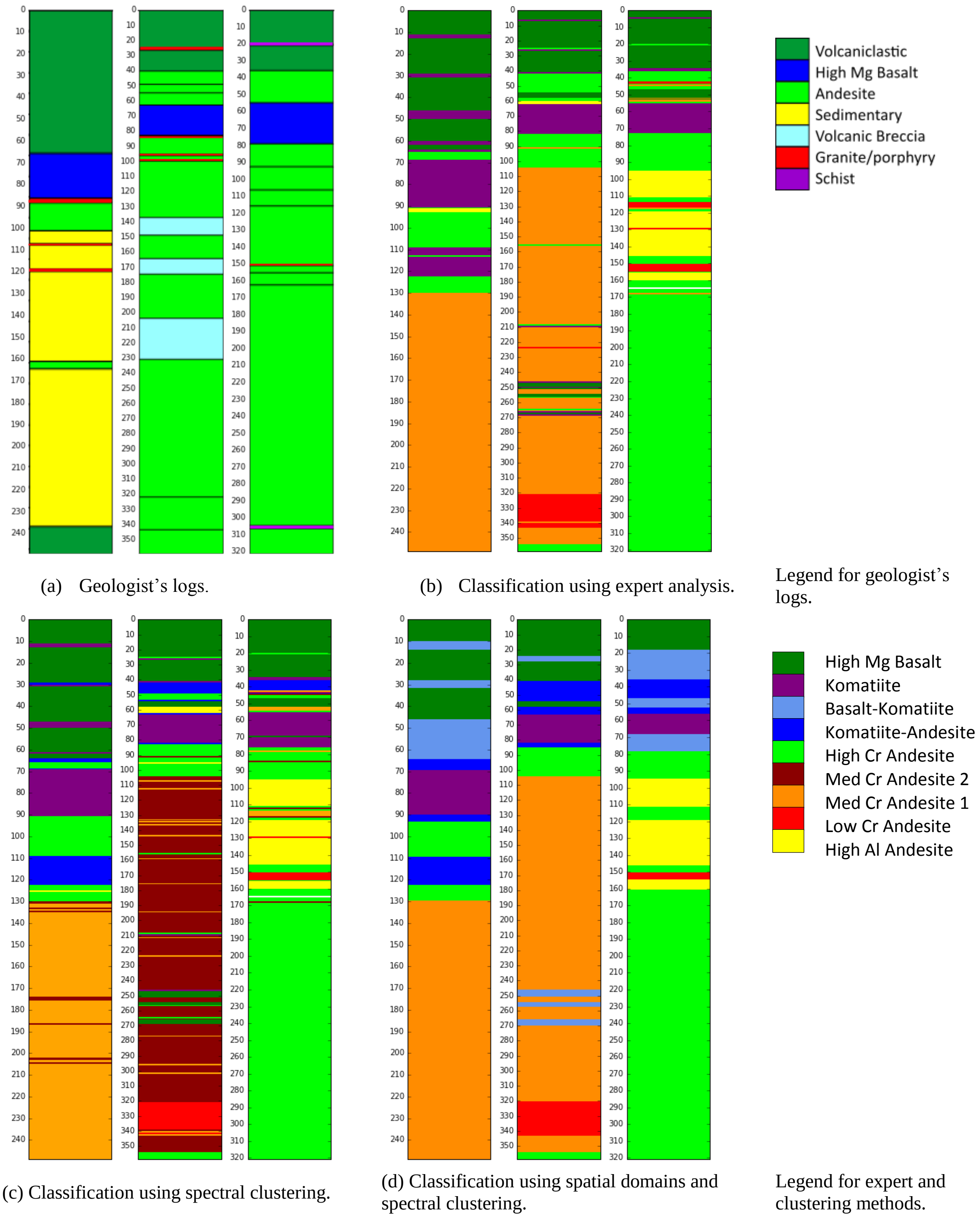

Figure 4: Comparison between geologist's logs from three drill holes (a) and three geochemical rock type classification techniques (b–d) for the holes.