EDITORIAL

Machine Learning-Based Mapping for Mineral Exploration

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Abstract

We briefly review the state-of-the-art machine learning (ML) algorithms for mineral exploration, which mainly include random forest (RF), convolutional neural network (CNN), and graph convolutional network (GCN). In recent years, RF, a representative shallow machine learning algorithm, and CNN, a representative deep learning approach, have been proved to be powerful tools for ML-based mapping for mineral exploration. In the future, GCN deserves more attention for ML-based mapping for mineral exploration because of its ability to capture the spatial anisotropy of mineralization and its applicability within irregular study areas. Finally, we summarize the original contributions of the six papers comprising this special issue.

Keywords Mineral exploration · Machine learning · Random forest · Convolutional neural network · Graph convolutional network

Over the past 40 years and more, various methods have been successfully employed in GIS-based mapping for mineral exploration (Bonham-Carter 1994; Porwal and Carranza 2015; Carranza 2008; Zuo 2020). In more recent years, machine learning (ML) algorithms have been increasingly applied in computer-based mapping for mineral exploration. Among these ML algorithms, random forest (RF) and convolutional neural network (CNN) are two of the most frequently used methods. RF is an ensemble ML algorithm that aggregates several weak tree classifiers in order to create a single strong classifier (Breiman 2001). It does not require input data conforming to any parameterized distribution or any preprocessing to account for different data types. On the one hand, RF continues to receive much attention in ML-based mapping for mineral exploration because of its strong ability to capture the complex and nonlinear spatial associations between locations of discovered mineral deposits and evidential

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geological features in order to predict locations where undiscovered mineral deposits likely exist (Rodriguez-Galiano et al. 2014; Carranza and Laborte 2015a, b, 2016). The RF model typically yields high accuracy and generalization performance because its "random" aspect enables it to resist over-fitting, and its "forest" aspect of aggregated decision trees increases its accuracy. On the other hand, CNN is a classical deep learning algorithm that incorporates information about the invariance of two-dimensional shapes using schemes of local area connection, weight sharing, and downsampling (LeCun et al. 1998). CNN takes fixed-size images (pixel-patches) as inputs, accounts for the connectivity of neighboring pixels, and extracts rich spatial information within a local region by applying convolutional layers and pooling layers. By considering the spatial structure and interrelationships of neighboring prediction units, CNN can effectively capture the spatial coupling relationship between locations of discovered mineral deposits and evidential geological features (Zhang et al. 2021; Li et al. 2021a, b, 2022).

In contrast to RF and CNN, the graph convolutional network (GCN) is an emerging network architecture that it is drawing substantial interest, particularly in fields in which the effective handling of graph-structured data is required to model relationships between samples (or vertexes) (Kipf and Welling 2017). The GCN aggregates neighbor information and updates vertex information across network layers based on graph structure. In the field of computer-based mapping for mineral exploration, the flexibility of the graph structure enables a full accounting of the spatial anisotropy of mineralization. In addition, the GCN feeds all data and a graph containing connectivity information into the network; this allows for the modeling of middle- and long-range spatial relationships between samples (i.e., locations of discovered mineral deposits and evidential geological features) (Zuo and Xu 2023). Therefore, GCN warrants more attention in future computer-based mapping for mineral exploration because it can capture the spatial anisotropy of mineralization and it can be applied within irregularly shaped (in contrast to typically rectangular) study areas (Zuo and Xu 2023; Xu et al. 2023; Xu and Zuo 2023; Zuo et al. 2023).

This special issue was developed from a session on "Machine learning-based mineral prospectivity mapping (MPM)" chaired by Prof. Renguang Zuo and Prof. Emmanuel John M. Carranza at the 21st Annual Conference of the International Association for Mathematical Geosciences, held in Nancy, France, from August 29 to September 3, 2022. This special issue documents case studies and current research demonstrating the progress of ML-based mapping in mineral exploration. A total of 15 manuscripts were received, among which six manuscripts were accepted and included in this special issue. Two manuscripts are still under review and will be published in a regular issue if accepted, and the remaining seven manuscripts were rejected.

This first paper by Mao et al. (2023) presents an interpretable nonlinear Bayesian decomposition modeling approach for MPM. To attain both nonlinear modeling ability and interpretability, the Bayesian decomposition modeling adopted a divide-and-conquer strategy to decompose the model into parts with respect to individual predictor variables. The individual predictor variables were transformed through nonlinear mapping functions and then linearly integrated to generate an interpretative mineral prospectivity model.

In the second paper, Parsa et al. (2022) use a dataset of orogenic gold mineralization in the Sturgeon Lake transect of Ontario, Canada, and carry out two experiments to answer two questions pertaining to MPM: (1) whether using additional geologically significant labeled samples can further improve the generalizability of MPM models, and (2) whether simply using binary variables, instead of multiclass and continuous variables, can mitigate the severity of poor generalization in MPM. Their results provide insights into factors controlling the generalization of prospectivity models.

The third paper by Chen and Xiao (2023) applies a projection pursuit random forest (PPRF) to model prospectivity for porphyry Cu-Mo deposits in the Eastern Tianshan orogenic belt, northwestern China. Their results indicate that the PPRF method not only outperforms the ordinary RF method in terms of the overall MPM accuracy, but also exhibits lower sensitivity to unbalanced data. Therefore, the PPRF method represents a data-driven alternative for MPM.

In the fourth paper, Zhang et al. (2023) provide a novel class-balanced focal loss function to address the issue of data imbalance in MPM. This loss function incorporates both a class-balanced loss function and a focal loss function. The former addresses the information imbalance within the feature space, while the latter focuses on dealing with class imbalance. In addition, the authors introduce Bayesian hyperparameter optimization as an effective approach to automatically tune the intricate hyperparameters of deep learning models for MPM.

The fifth paper by Chen and Lu (2023) presents a comparative study of anomaly detector, semi-supervised classifier, and supervised classifier based on the K-nearest neighbor (KNN) algorithm for detecting mineralization-related geochemical anomalies. This comparative study suggests that supervised and semi-supervised classification models are more adept at identifying mineralization-related anomalies in the presence of discovered mineral deposits, as compared with anomaly detection models.

In the sixth paper, Wang et al. (2022) propose a novel framework for geological mapping based on geochemical survey data. This framework uses a direct sampling multiple-point statistics technique to produce spatially continuous and adequate samples by reconstructing geochemical values at unsampled locations based on sparse geochemical survey data. It applies the CNN to automatically learn the lithological features and further conduct classifications based on multilevel convolutional operations that consider the spatial information within neighboring samples.

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