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Mineral Prospectivity Mapping on Point Data using Graph Deep Learning Regression: Case Study of Copper Occurrence in Northern Ireland

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Over the past decade, machine learning (ML) has become an increasingly important tool within geoscience that can support conventional mineral exploration approaches. Here, we present a simple approach for graph deep learning-based mineral prospectivity mapping (MPM) that uses geochemical data collected during standard exploration practices, requires minimum preprocessing, and generates better results than the conventional method. Critically, we structured data into a graphical format and defined the problem as a regression problem instead of a commonly used binary classification problem. We used two deep graph learning techniques: graph isomorphic network (GIN) and graph convolutional network (GCN). Both GIN and GCN performance were benchmarked against results obtained using a random forest (RF) approach, a widely used machine learning algorithm for MPM. Our new method requires two types of point-format information: exploration data and mineral occurrences. As a case study, we consider prospectivity mapping for copper mineralization using stream sediment geochemistry point data from Northern Ireland. Both GIN and GCN graph deep learning approaches perform better than the RF benchmark method, with GIN giving the best performance (R2 = 97.9%), GCN being intermediate (R2 = 89.6%), and RF showing the relatively poorest performance (R2 = 61.7%). Compared to RMSE values for the benchmark method (RF), GIN reduces prediction error by 77%, and GCN reduces this error by 45%. Alongside a significant improvement in identifying known deposits, we also show that GIN can ‘virtually’ identify new prospective regions in the study area by comparing two sets of mineral occurrence data collected during different periods of time, which may be subsequently confirmed via on-site investigation. Given the minimal amount of conventional data and preprocessing required, these graph deep learning algorithms show notable potential to replace conventional techniques (e.g., RF) and can be easily adopted to a broad range of exploration scenarios.