American Mineralogist, Volume 109, pages 303–314, 2024

Apatite trace element composition as an indicator of ore deposit types: A machine learning approach

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Abstract

The diverse suite of trace elements incorporated into apatite in ore-forming systems has important applications in petrogenesis studies of mineral deposits. Trace element variations in apatite can be used to distinguish between fertile and barren environments, and thus have potential as mineral exploration tools. Such classification approaches commonly employ two-variable scatterplots of apatite trace element compositional data. While such diagrams offer accessible visualization of compositional trends, they often struggle to effectively distinguish ore deposit types because they do not employ all the high-dimensional (i.e., multi-element) information accessible from high-quality apatite trace element analysis. To address this issue, we use a supervised machine-learning-based approach (eXtreme Gradient Boosting, XGBoost) to correlate apatite compositions with ore deposit type, utilizing such high-dimensional information. We evaluated 8629 apatite trace element data from five ore deposit types (porphyry, skarn, orogenic Au, iron oxide copper gold, and iron oxide-apatite) along with unmineralized magmatic and metamorphic apatite to identify discriminating parameters for the individual deposit types, as well as for mineralized systems. According to feature selection, eight elements (Th, U, Sr, Eu, Dy, Y, Nd, and La) improve the model performance. We show that the XGBoost classifier efficiently and accurately classifies high-dimensional apatite trace element data according to the ore deposit type (overall accuracy: 94% and F1 score: 89%). Interpretation of the model using the SHAPley Additive exPlanations (SHAP) tool shows that Th, U, Eu, and Nd are the most indicative elements for classifying deposit types using apatite trace element chemistry. Our approach has broad implications for the better understanding of the sources, chemistry, and evolution of melts and hydrothermal fluids resulting in ore deposit formation.

Keywords: Machine learning, apatite, trace elements, ore deposit fertility, XGBoost, LA-ICP-MS