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Can boosting boost minimal invasive exploration targeting?

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With an increasing demand for critical raw materials, good predictive models that allow minimal invasive exploration are of great importance. We evaluated different machine learning techniques with an emphasis on boosting algorithms and implemented them in a toolbox for ArcGIS. Performance was tested on real exploration datasets with respect to accuracy, performance, stability and robustness.
Boosting algorithms are ensemble of methods used in supervised learning for regression and classification. They combine weak classifiers (classifiers that perform slightly better than random guessing) to obtain robust classifiers [1]. Each time a weak learner is added, the learning set is reweighted to enhance misclassified points.
Our test area is the Iberian Pyrite Belt (IPB), one of the oldest mining districts in the world that hosts giant and supergiant massive sulphide deposits. The spatial density of ore deposits, the size and tonnage make the area quite unique [2] and due to the available data and number of known deposits well-suited for our purpose.
We combined different geophysical datasets as well as layers derived from geological maps like distance to faults or lithological units as predictors. Different algorithms were tested and compared to Adaboost [3] in several experiments (variation of the train/test ratio, using data augmentation).
We found performance results relatively similar for the machine-learning algorithms with boosting (especially BrownBoost) slightly outperforming logistic regression and SVM (Accuracy of 0.96 vs 0.89 and 0.93 respectively). Data augmentation led to improved results by around 5% in this setting. Variations in the split ratio lead, as expected, to a reduction in accuracy but we observe relative stability until a critical point (ca. 90 train deposits out of 350 total deposits) and then dropping rapidly from 26 deposits downward.
In comparison to other machine learning methods, adaboost is easy to use because of relatively short training and prediction times, higher resistance to overfitting and the user is required to tune only two parameters. Furthermore, it allows working with continuous datasets unlike widely used methods in prospectivity mapping, e.g. Weights of Evidence. In the preliminary results, the Adaboost algorithm shows high accuracy in real datasets, making it an excellent data-driven alternative for prospectivity mapping. The work was conducted as a co-operation between Esri Germany and Geological Survey of Finland (Mineral Prospectivity Modeller project).

1.Zhou Zhi-Hua (2012). Ensemble Methods: Foundations and Algorithms. Chapman and Hall/CRC. p. 23. ISBN 978-1439830031.
2.N. Adamides (2013), Rio Tinto (Iberian Pyrite Belt): a world-class mineral field reopens: Applied Earth Science, v. 122, no. 1, p. 2-15.
3.Y. Freund, R. Schapire (1995). A Decision-Theoretic Generalization of on-Line Learning and an Application to Boosting.