

Artificial Intelligence Applied to Mineral Exploration Targeting

Inteligência Artificial Aplicada a Vetorização de Depósitos Minerais

Elias Martins Guerra Prado Centro de Geociências Aplicadas – CGA Serviço Geológico do Brasil - SGB









Introduction



CURRENT CHALLENGES OF MINERAL EXPLORATION



High Global Demand



Reduction of Reserves



Restricted Labor Market



Preservation of Natural Resources







CURRENT CHALLENGES OF MINERAL EXPLORATION



Restricted L Market

vation of **Jacural Resources**









Introduction



CURRENT CHALLENGES OF MINERAL EXPLORATION



High Global Demand



Restricted Labor Market





Reduction of Reserves



Preservation of Natural Resources







INDUSTRY 4.0

4th Industrial Revolution

2000s

1780s

1870s

1970s













Steam Engine

Electricity

Electronics



Automation of process



Real-time monitoring



Decision-making based on big data











AI/Machine Learning

Systems and simulations capable of providing decisive geological information for exploration and mining



Robotics/Drones

Autonomous robots to perform repetitive and strenuous tasks. Loaders, excavators, drills, etc...



IoT/Sensors

Sensors that collect and transmit data during the extraction and processing of the ore



Virtual Reality

Simulations and training. Control, maintenance and inspection of equipment



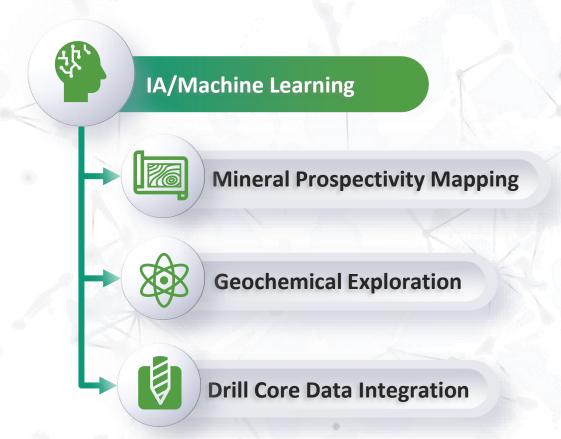


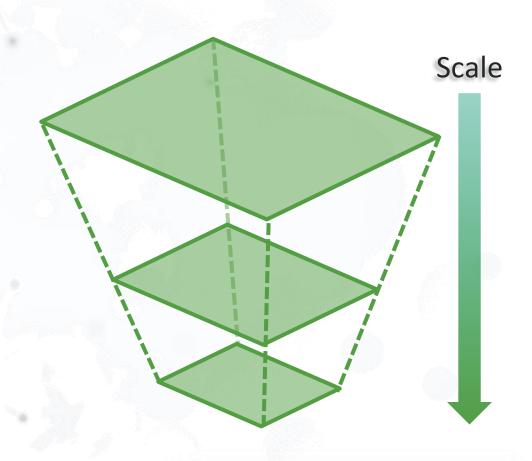


MINING 4.0



MINERAL EXPLORATION TARGETTING

















Mineral Prospectivity Mapping

Integrate aerogeophysical, geological, and geochemical data to generate prospectivity maps, assisting in target selection at the province/district scale.

Publications over the last years show that **ML models** produces **better** results **than traditional methods** as WofE. **XGBoost**, **SVM**, and **Random Forests** are among the best performing algorithms.

Important aspects:

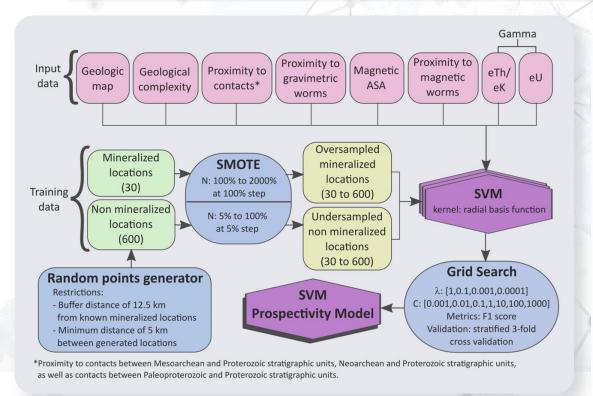
- Feature engineering has a big impact on results
- Data balancing techniques should be used to increase the number of labeled samples
- **Explainable AI** algorithms can identify important relationships between the dataset and the mineralized zones





Mineral Prospectivity Mapping

MODELING OF CU-AU PROSPECTIVITY IN THE CARAJÁS MINERAL PROVINCE (BRAZIL) THROUGH MACHINE LEARNING: DEALING WITH IMBALANCED TRAINING DATA



Ore Geology Reviews 124 (2020) 103611

Contents lists available at ScienceDirect

Ore Geology Reviews

ELSEVIER

journal homepage: www.elsevier.com/locate/oregeorev



Modeling of Cu-Au prospectivity in the Carajás mineral province (Brazil) through machine learning: Dealing with imbalanced training data



Elias Martins Guerra Prado^{a,b}, Carlos Roberto de Souza Filho^b, Emmanuel John M. Carranza^c, João Gabriel Motta^b

- ^a CPRM Geological Survey of Brazil, Brasília, Distrito Federal, Brazil
- b Institute of Geosciences, State University of Campinas (UNICAMP), Campinas, São Paulo, Brazil
- c University of KwaZulu-Natal, Westville Campus, Durban, South Africa

ARTICLE INFO

Keywords:

Mineral prospectivity mapping Carajás mineral province Imbalanced training data

Synthetic minority over-sampling technique

ABSTRAC

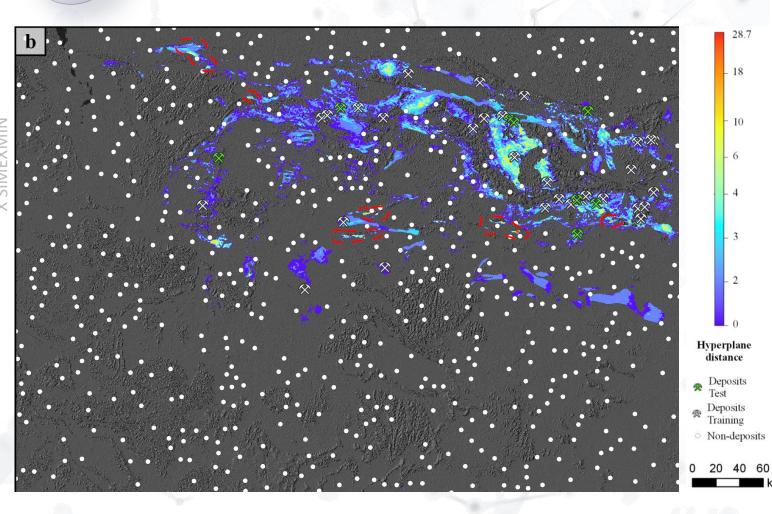
Machine learning (ML) is becoming an appealing tool in various fields of Earth Sciences, especially in mineral prospectivity mapping (MPM) to support mineral exploration. ML algorithms are designed to assume a relatively balanced amount of training data for the estimation of the decision boundaries between the classes of interest (i.e., in MPM: mineralized- and non-mineralized locations). However, in MPM the numbers of mineralized non-mineralized locations are naturally imbalanced, as the number of known mineral deposit occurrences (as a

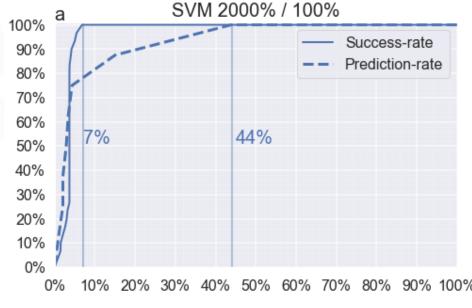
proxy of mineralized or pocitive class) are naturally much smaller than the number of non-min

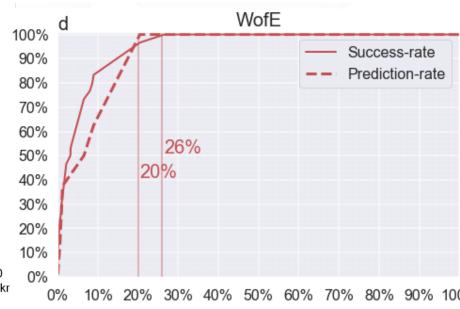




Mineral Prospectivity Mapping







18

distance

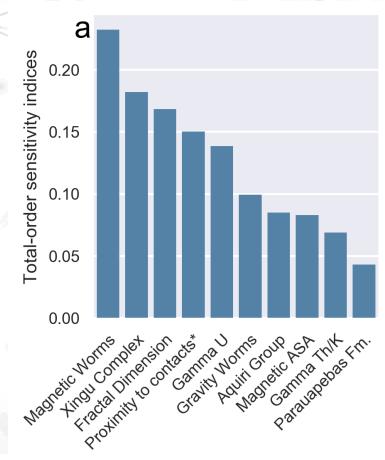
Deposits

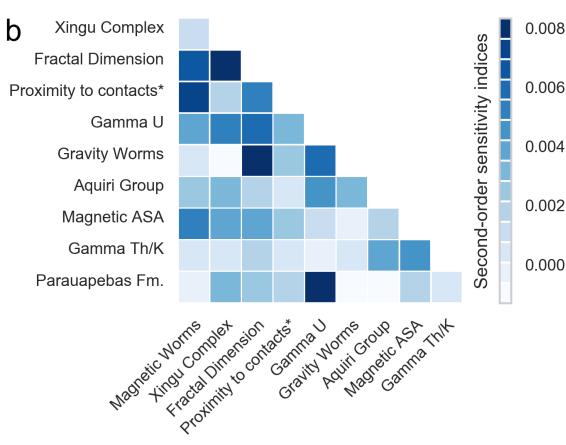
Training





Mineral Prospectivity Mapping









Geochemical Exploration

Use of geochemical data for vectoring towards the mineralization

ML models have shown great potential for the processing and classifying geochemical datasets

Important aspects:

- Dataset organization and pre-processing is usually time consuming
- Specific normalization techniques need to be applied (BoxCox, CLR)







SIMEXMIN

Al Applications to Mineral Exploration Targeting





Geochemical Exploration

EXAMPLES:

Metallogenic fertility classification of arc magmas (Nathwani et al., 2022)

Prediction of rock **precursors** for **mass balance** calculation (Trépanier et al., 2016)

Prediction of unknown elemental concentrations (Zhang et al., 2022)

Mineralium Deposita (2022) 57:1143-1166 https://doi.org/10.1007/s00126-021-01086-9

REGULAR ARTICLE



Machine learning for geochemical exploration: classifying metallogenic fertility in arc magmas and insights into porphyry copper deposit formation

Chetan L. Nathwani^{1,2} · Jamie J. Wilkinson^{1,2} · George Fry³ · Robin N. Armstrong¹ · Daniel J. Smith⁴ · Christian Ihlenfeld³

Computers & Geosciences 89 (2016) 32-43



Contents lists available at ScienceDirect

Computers & Geosciences



journal homepage: www.elsevier.com/locate/cageo

Research paper

Precursors predicted by artificial neural networks for mass balance calculations: Quantifying hydrothermal alteration in volcanic rocks



Sylvain Trépanier ^{a,b}, Lucie Mathieu ^a, Réal Daigneault ^{c,*}, Stéphane Faure ^a

Journal Pre-proof

- Advanced Geochemical Exploration Knowledge Using Machine Learning: Prediction of
- 2 Unknown Elemental Concentrations and Operational Prioritization of Re-analysis
- 3 Campaigns
- Steven E. Zhang^{a,b}, Julie E. Bourdeau^{a,b}, Glen T. Nwaila^b, Yousef Ghorbani^c





Drill Core Data Integration

Integration of **dense** drill core **datasets** to extract information about the distribution of the mineralized zones

ML models can identify complex patterns which classical methods are not able to identify in such dense datasets

Important aspects:

- Deep Neural Networks usually perform better
- Core scanning system enables the fast acquisition of training datasets
- Models can be used by autonomous systems to assist in ore sorting or contaminant detection

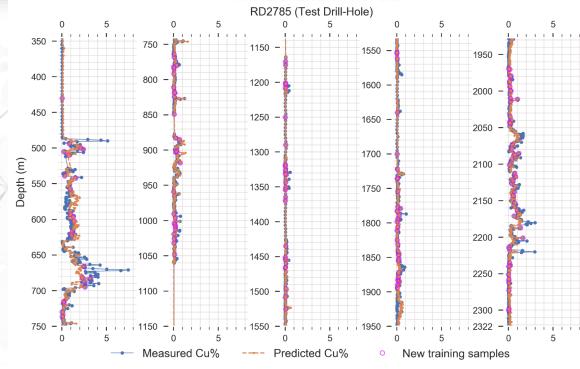


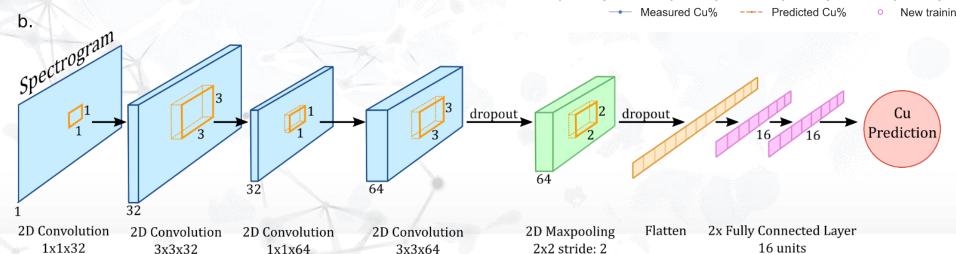
RMSE 0.39 % Cu



EXAMPLES:

Prediction of **Cu grade** by means of **hyperspectral** data (Prado et al., 2022)



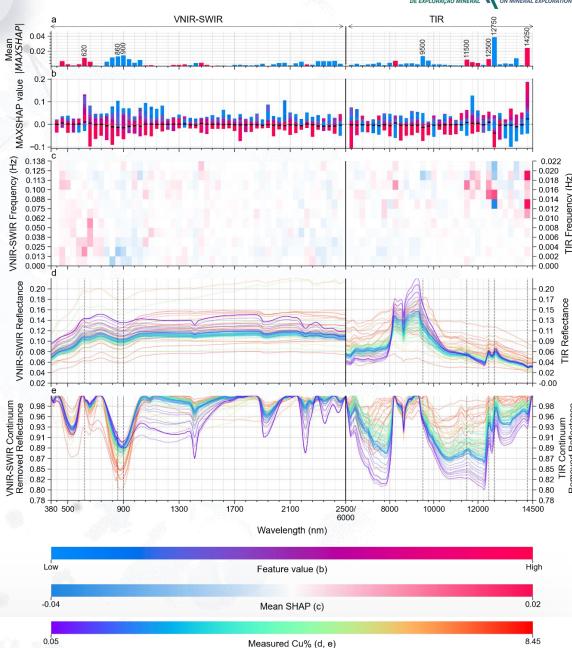






EXAMPLES:

Prediction of **Cu grade** by means of **hyperspectral** data (Prado et al., 2022)







Drill Core Data Integration

EXAMPLES:

Prediction of **mineralization** by means of **geochemical** and **petrophysical** data (da Silva et al., 2022)

Balancing
Sample Classes

Results & Validation

Sampling

Petrophysics

Geochemistry

Petrography

Petrography

Tree #1 Tree #2 ... Tree -#1000

Results & Validation

Interpretation

Journal of South American Earth Sciences 116 (2022) 1038

Contents lists available at ScienceDirect

EI SEVIED

Journal of South American Earth Sciences

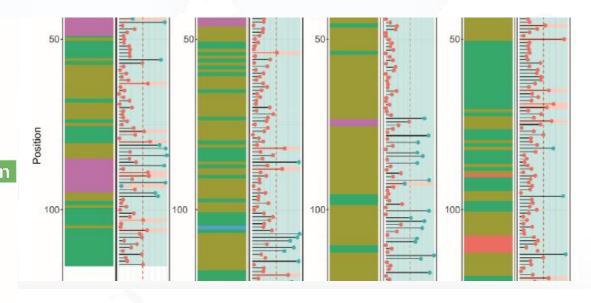
journal homepage: www.elsevier.com/locate/jsames



Check for updates

Predicting mineralization and targeting exploration criteria based on machine-learning in the Serra de Jacobina quartz-pebble-metaconglomerate Au-(U) deposits, São Francisco Craton, Brazil

Guilherme Ferreira da Silva ^{a, b, *}, Adalene Moreira Silva ^a, Catarina Labouré Bemfica Toledo ^a, Farid Chemale Junior ^c, Evandro Luiz Klein ^{b, d}



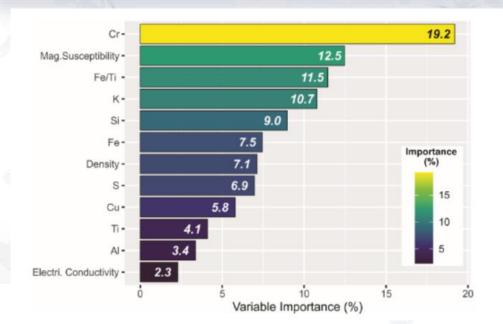




Drill Core Data Integration

EXAMPLES:

Prediction of **mineralization** by means of **geochemical** and **petrophysical** data (da Silva et al., 2022)





Contents lists available at ScienceDirect

FISEVIER

Journal of South American Earth Sciences

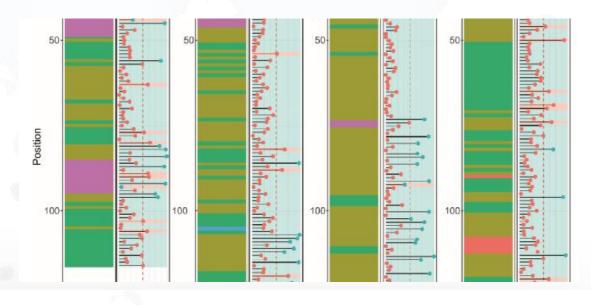
journal homepage: www.elsevier.com/locate/jsames



Check for updates

Predicting mineralization and targeting exploration criteria based on machine-learning in the Serra de Jacobina quartz-pebble-metaconglomerate Au-(U) deposits, São Francisco Craton, Brazil

Guilherme Ferreira da Silva ^{a,b,*}, Adalene Moreira Silva ^a, Catarina Labouré Bemfica Toledo ^a, Farid Chemale Junior ^c, Evandro Luiz Klein ^{b,d}



Concluding Remarks



- AI and ML are becoming indispensable tools in mineral exploration
- ML models can be used to extract valuable information from datasets at different scales
 - The next step is developing generalized workflows that integrate all stages of mineral exploration and User Interfaces (UI) that allow the use of these methods by non-specialists

Techniques that can be used to integrate Industry 4.0 technologies with the mineral industry contribute to the solid and sustainable development of mineral exploration







Obrigado!

#SIMEXMIN2022