Data driven modelling

Hakan Basarir, PhD

Introduction to Data-Driven Modeling in Mining Engineering

Content

Lecture #1: Introduction to Data-Driven Modeling in Geotechnical Engineering

Part 1:

- Introduction to Data-Driven Modeling
    - Fundamentals: Definition of data-driven modeling and its role in geotechnical engineering.
    - Differences from traditional empirical approaches in engineering geology and mining.
    - Applications & Relevance: Predicting rock properties, stability analysis, and tunnel support design.
    - Discussion on the challenges and benefits of using data-driven methods.
- Data Types & Sources in geotechnical engineering
    - Overview of data used in geotechnical contexts (e.g., geological surveys, borehole logs, MWD data).
- Data presented in used cases

Part 2:

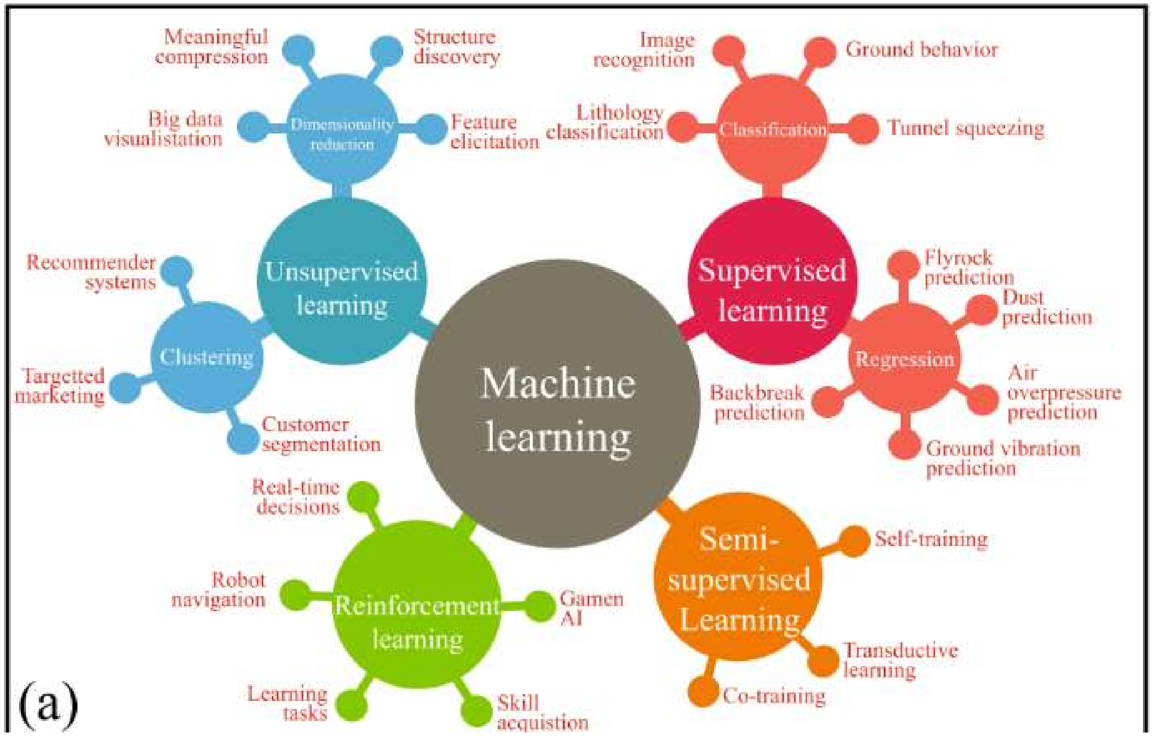
- Machine Learning Basics
    - Types of learning: Supervised, unsupervised, and reinforcement learning.
    - Focus on Supervised Learning: Why it is particularly suitable for geotechnical applications.
- Modeling Techniques
    - Regression Modeling: Linear regression, multiple regression, and their applications in predicting rock properties.
    - Classification Modeling: Decision trees, Random Forests, and applications in rock mass classification.
        - Brief overview of clustering techniques for pattern recognition.
- Performance Evaluation
    - Metrics for regression (RMSE, R^2) and classification models (accuracy, precision, recall).
    - Introduction to Explainable AI (XAI): Importance of interpretability in geotechnical projects.
    - Techniques like SHAP, LIME, and feature importance to enhance model interpretability.

Introduction to Data-Driven Modeling in Mining Engineering

Objective: To understand the role of data-driven modeling in addressing complex geotechnical challenges.

Key Topics:
Fundamentals of data-driven modeling
Differences from traditional empirical methods
Applications in engineering geology and mining
Discussion on the challenges and benefits of using data-driven methods

Introduction to Data-Driven Modeling in Mining Engineering



Data-driven modeling is an approach that uses large volumes of data to build predictive models by identifying patterns, relationships, and trends directly from the data using statistical methods, machine learning, or artificial intelligence, instead of relying on predefined theoretical equations! (can also use theoretical equations to get the data.

This approach is particularly useful in fields where complex, non-linear relationships exist, allowing for more adaptive and accurate solutions compared to traditional, theory-based models.

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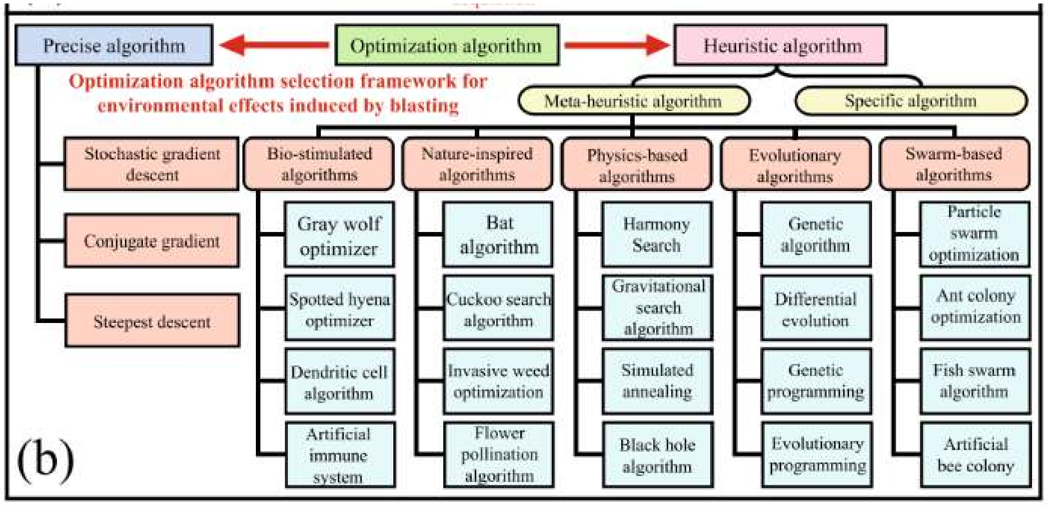
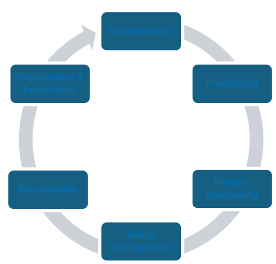


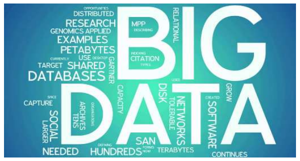
Fig. 9 The main classification of ML algorithms and the selection of OA algorithms. **a** Classification and application of ML algorithms; **b** The category of OA algorithms

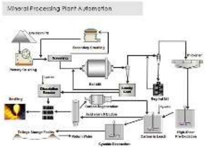
AI based optimization algorithms using machine learning models optimize operations to improve processes like scheduling, maintenance, and resource allocation.
As ML models adapt in real-time, reducing downtime, increasing efficiency, and cutting costs. By automating decision-making, they ensure operations are both efficient and responsive to changing conditions, enhancing productivity and safety.

Why DD and optimisation in mining?

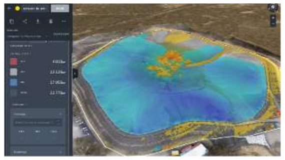


Why DD and optimisation in mining?





How to link ?



How to optimise ?

Example flow: A case study from blasting

Drilling = f(rock properties, drilling machine props)
Blasting = f(rock properties, blasting agent, blast design parameters, environmental factors)
Crushing = f(rock properties, blasting output, crusher variables, customer demand)

Example flow: A case study backfill

Mixture of water, cement, rock or tailing. Used to fill the void or produced stope.

O1: Strength: UCS
O2: Workability: Shear strength, Slump
O3: Cost!

Key design parameters:
Cement percentage (C):
Solid contents (SD):
Water content (W):

$$C = \frac{Mc}{(Mc + Mt)} * 100$$

$$SC = \frac{(Mt + Mc)}{(Mc + Mt + Mw)} * 100$$

$$W = \frac{Mw}{(Mc + Mt)} * 100$$

Example flow: A case study backfill

Generate model to be used as objective function/s

TABLE 8 Constructed multiple regression models for the prediction of UCS, yield stress, and cost.

Predictive model	Adjusted R^2
Cost = −15.74 + 2.33CD + 0.203SD	99.97
Yield stress = −9138.48–15.94CD + 124.17SD	86.81
UCS = EXP(0.185CD + 0.153SD + 0.00388T-6.7415)	79.91

Example flow: A case study backfill

We used multi-objective particle swarm optimization (MOPSO) algorithm in their work for finding solutions that were a mixture of designs of CPB meeting the considered objectives. It is not possible to find one optimal solution which can meet all objective functions, instead a set of optimal solutions, named Pareto, can be obtained.

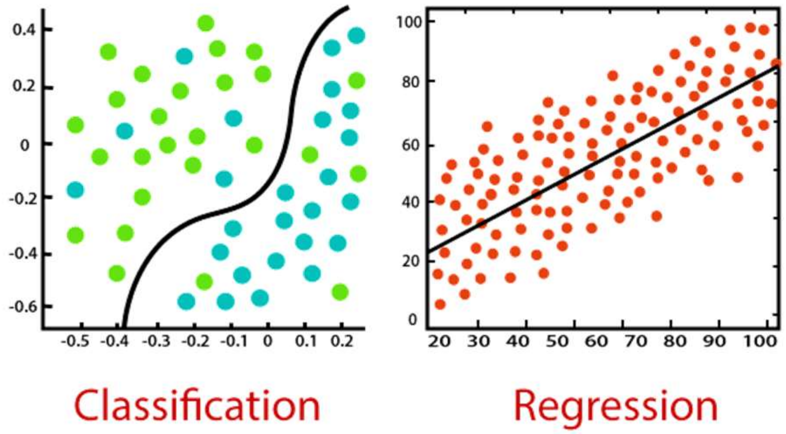
Batch No.	CD, %	SD, %	28 days UCS, kPa	Yield stress, Pa	Cement cost, AUD/m^3
C1_1	7.01	78.57	799.54	505.18	16.54
C1_2	6.70	78.91	796.16	552.68	15.89
C1_3	6.83	78.68	788.29	522.56	16.16
C1_4	6.53	78.99	780.64	565.18	15.51
C1_5	6.69	78.78	778.49	536.78	15.831
C1_6	6.81	78.62	777.83	514.97	16.10
C1_7	6.46	78.99	771.92	566.95	15.36
C1_8	6.71	78.64	765.55	519.64	15.86
C1_9	6.32	79.00	751.83	570.22	15.01

CPB should have UCS between 750 and 800kPa in 28days, yield stress should range from 500 to 800Pa, and maximum cement cost should be 17 AUD/m3.

Batch No.	CD, %	SD, %	28 days UCS, kPa	Yield stress, Pa	Cement cost, AUD/m^3
C2_1	7.43	78.03	754.44	431.48	17.42
C2_2	7.48	78.25	788.11	459.02	17.58
C2_3	7.66	77.92	774.61	414.51	17.94
C2_4	7.34	78.21	763.66	456.17	17.25
C2_5	7.43	78.03	754.93	432.07	17.42
C2_6	7.73	77.87	778.15	406.88	18.08
C2_7	7.84	77.90	798.60	409.84	18.35

the production engineer was looking for the same UCS (750–800kPa) in 14 day shorter period than the first case and acceptable yield stress ranging from 400 to 500Pa.

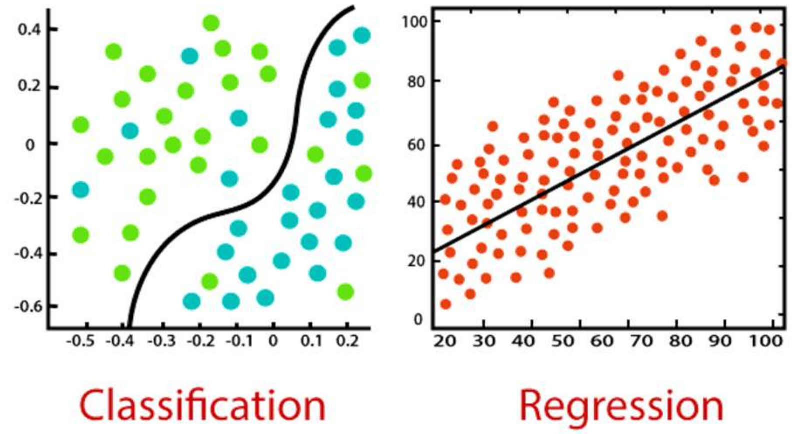
Introduction to Data-Driven Modeling Techniques and methods



Classification involves the quantization of a set of input vectors into a predefined set of classes. Regression can be defined as a classification with a potentially vast number of classes, even theoretically infinite (Friedland 2024). The learning algorithm in this type of machine learning is trained on labeled data. The data is termed "labeled" because it comprises pairs—one part being the input, represented as a vector, and the other part being the desired output, which serves as a supervisory signal.

Examples are logistic regression, decision trees, SVM, KNN, RF.

Introduction to Data-Driven Modeling Techniques and methods



Regression modeling is a machine learning technique used to predict a continuous numeric outcome based on input variables. The model learns the relationship between these variables from historical data to make accurate predictions on new data. Popular regression algorithms include linear regression, polynomial regression, and neural networks, RF, SVM.

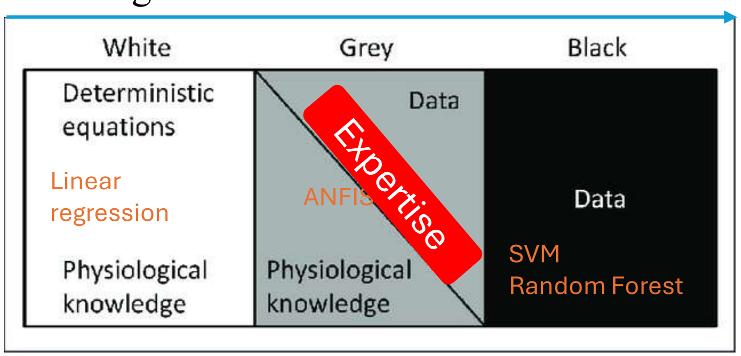
Introduction to Data-Driven Modeling Techniques and methods

Machine learning technique comprises models with varying structures, categorized as white-box, black-box and grey-box models.

Which box ?

Results easy to understand

modeling is a machine lear

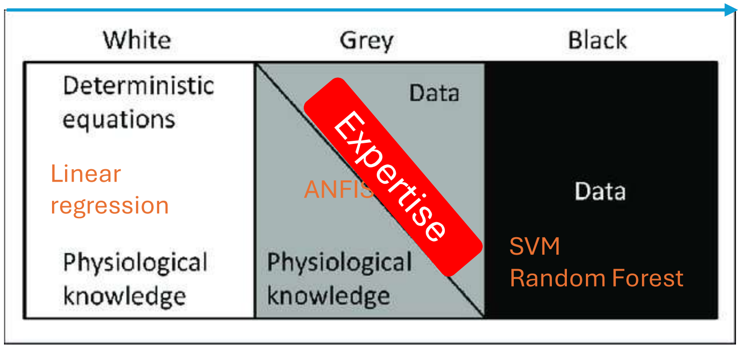


Models hard to explain from a mathematical point of view (but often "better")

Introduction to Data-Driven Modeling Techniques and methods

All require judgement by experts

Results easy to understand



Models hard to explain from a mathematical point of view (but often “better”)

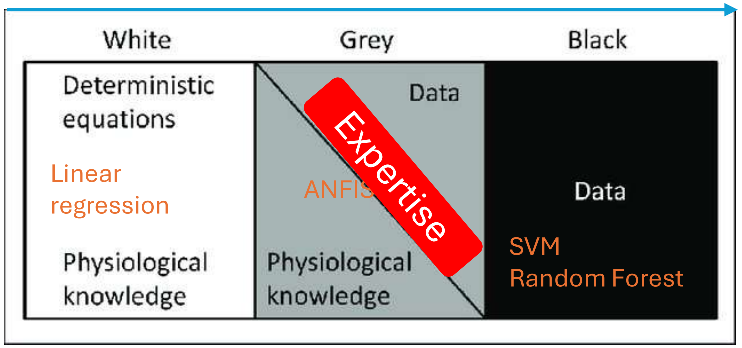
White-box models pertain to transparent machine learning processes that generate accountable predictions. These models emphasize processes, enabling users to interpret the models and determine the relative importance of the corresponding predictor variables. The transparency allows users to identify potential errors when the model coefficients contradict established physics-based knowledge (Fung et al. 2021). Examples of white-box models include linear regression and decision trees algorithms.

Pak L. Fung, Martha A. Zaidan, Hilkka Timonen, Jarkko V. Niemi, Anu Kousa, Joel Kuula, Krista Luoma, Sasu Tarkoma, Tuukka Petäjä, Markku Kulmala, Tareq Hussein, 2021. Evaluation of white-box versus black-box machine learning models in estimating ambient black carbon concentration, Journal of Aerosol Science, Volume 152.

Introduction to Data-Driven Modeling
Techniques and methods

All require judgement by experts

Results easy to understand



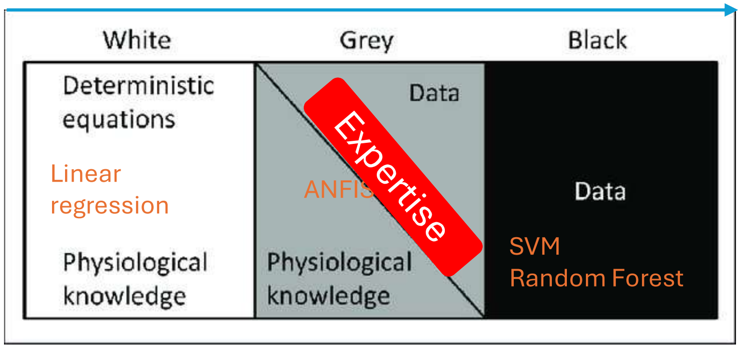
Models hard to explain from a mathematical point of view (but often "better")

Black-box models are statistical or machine learning models where the parameters lack physical meaning. These models are often appealing due to their flexibility and ease of construction. They utilize operational data to train their internal parameters, but as the name implies, black-box models typically act as observers since their estimated parameters may have minimal relevance to the actual physical process (Katipamula and Brambley 2005). Black-box models are exemplified by artificial neural networks and XGBOOST algorithm.

Introduction to Data-Driven Modeling Techniques and methods

All require judgement by experts

Results easy to understand



Models hard to explain from a mathematical point of view (but often "better")

Grey-box models are analytical models that are somewhat based on principles, with parameters that can still be linked to the physical response of the process. Compared to white-box models, they are faster to compute and easier to calibrate and construct. Compared to black-box models, they are more robust and suitable for parameter estimation. However, creating grey-box models requires expert knowledge and extensive measured data to train their parameters. Additionally, they may be less accurate than both black-box and white-box models (Katipamula and Brambley 2005). Grey-box models can be represented by adaptive neuro-fuzzy inference system (ANFIS) and random forest algorithms.

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Introduction to Data-Driven Modeling in Geotechnical Engineering

Definition: To understand the role of data-driven modeling in addressing complex geotechnical challenges.

Data-driven modeling refers to the process of using data analytics and machine learning techniques to derive insights and predictions from large datasets. Unlike traditional models that rely on theoretical assumptions, data-driven models learn patterns directly from the data.

Pros and Cons of ML vs conventional methods i.e. FEM

FEM

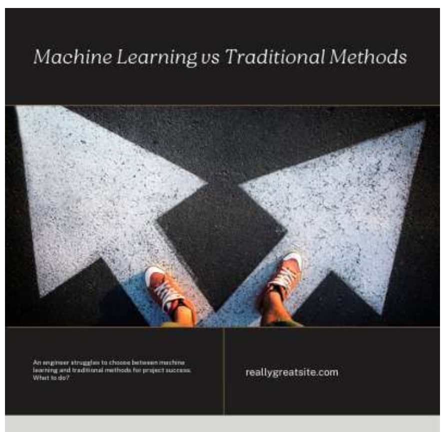
Cons!

- Material properties:
  CHILI vs DIANE?

- Boundary conditions:
  - Realistic enough ?

- Mesh dependency:
  - Good enough quality ?

- Governing equations:
  - Governing equations based on theoretical assumptions. Are they align well with the actual behaviour?



ML

- Cons!
  - Data Dependence: Do you have good enough data?

- Black Box Nature:
  - Can you see inside?

- Static Training:
  - Will the conditions be the same always?

Pros and Cons of ML vs FEM

FEM
Pros!

- Foundation in Physical Laws: FEM is grounded in well-understood physical principles, like equilibrium and conservation laws, giving engineers confidence that the model aligns with established mechanics.

- Interpretability: FEM solutions can be interpreted in terms of stress, strain, and deformation distributions, which engineers can analyze and validate against expectations.

ML
Pros!

- Adaptability: Unlike FEM, ML can adapt to non-linear, high-dimensional, and complex patterns that may be difficult to model explicitly, making it potentially more versatile in cases where empirical data is more relevant than theoretical assumptions.

- Reduced Assumptions about Materials: ML models do not require explicit material models; they learn patterns from data, potentially capturing nuanced behaviors and spatial variability that FEM cannot handle without extensive calibration.

Which one ML or FEM

Both FEM and ML have their own sets of assumptions and limitations. However, it is essential to acknowledge that FEM's reliability is not inherent; it is based on the validity of its assumptions, which can be as prone to errors as the data-dependency of ML. In fields where data is abundant, or where traditional assumptions about material behavior are not valid/well known, ML can be a powerful alternative or complement to FEM.

By recognizing the strengths and limitations of both methods, we can make better-informed decisions about which approach (or combination of approaches) to use for a given problem.

How about combining ML and FEM

Working flow

STEP	1	2	3	4	5
OBJECTIVE	Identification of GBT and failure mechanisms	Set up of geotechnical model	Estimate of basic support needs based on classification systems	Analytical study of ground behavior and stability og bedded rock	Numerical analysis of ground behavior, support performance and design optimization
INPUT	Rock mass structure, joint spacing, tunnel span, rock competence, joint conditions, in-situ rock stress	-Rock mechanical parameters of rock, joints and rock mass -In-situ stresses -Ground deformation	Geological mapping and inspection of the rock mass at the face	-Geometrical parameters of the bedding and tunnel -Rock strength and deformability properties -Bolt design, loading, and in-situ stresses	-Tunnel geometry -Geotechnical model -Deformation monitoring -Tunnel support based on output from steps 3 and 4
METHOD	-Classification of GBT proposed in Terron-Almenara et al. (2023) -Layered Ground Behavior Chart (LGBC) in Section 4.3	Rock testing, investigation holes, measurement of in-situ stresses, mapping, monitoring of deformations	Classification systems: -RMR -NPRA -Q-system	Limit equilibrium solutions based on the Voussoir analogue: -Lang and Bischof (1982) -Diederichs and Kaiser (1999) -Abousleiman et al. (2021)	-UDEC analyses -Model calibration -Evaluation of ground response in terms of displacements and stresses -Assessment of support loading and design optimization
OUTPUT	-Potential failure mechanisms in the rock mass -Associated load conditions (approximate distribution and size)	Detailed geotechnical model considering the in-situ ground conditions	An empirical-based estimation of the rock mass quality and basic needs of tunnel support	Design optimization based on tunnel stability and support peformance in bedded rock	-Optimized tunnel support design -Potential reduction of rock support consumption

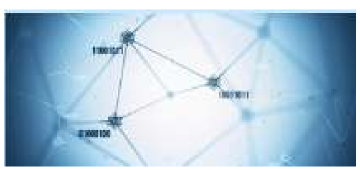
?

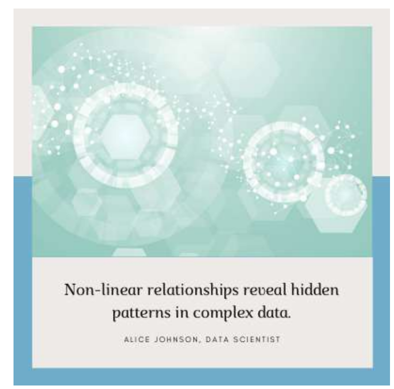
Fig. 12 Analysis methodology for the hybrid design of rock support in models A2 and B2 in layered rock, based on Terron-Almenara et al. (2023). Description of the analysis steps is numbered and presented below in the text

- Terron-Almenara, Jorge; Holter, Karl Gunnar; Høien, Are Håvard. (2023) A Hybrid Methodology of Rock Support Design for Poor Ground Conditions in Hard Rock Tunnelling. *Rock Mechanics and Rock Engineering*
- *Basarir, H., Development of a classification system …. Model the machine efiled … get more data … produce comprehensive ML model covering mroe variables*

How Data-Driven Models Uncover Hidden Patterns

- **Pattern Recognition**: Machine learning techniques (like neural networks and decision trees) can detect intricate patterns by analyzing large volumes of data.
- **Non-linear Relationships**: Unlike traditional models, data-driven approaches can capture non-linear relationships between variables (e.g., rock strength vs. depth, moisture content, or stress conditions).
- **Multivariate Analysis**: By simultaneously considering multiple input variables, these models can uncover interactions that might be missed by simpler empirical methods.





ML in mining engineering

Machine learning is a powerful tool in geosciences because it excels at handling complex, variable, and uncertain data—typical characteristics of geological systems.

Unlike traditional models that rely on fixed equations and assumptions, ML can identify patterns, relationships, and insights directly from large, diverse datasets. This flexibility enables geoscientists to make more accurate predictions, optimize resource exploration, and improve decision-making under uncertainty.

ML can adapt to new information, continuously improving its predictions as more data becomes available, making it especially valuable in dynamic environments like subsurface exploration.

ML in mining engineering

Some well known examples are

Rock property assessment

Stability analysis

Seismic data analysis

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What else..

ML in mining engineering

Where data come from ?

Data Source	Data Collected	Applications	Data Type	Challenges/Advantages
Borehole and Core Sample Data	Rock/soil samples, core logs, geotechnical properties (e.g., UCS, RQD)	Stratigraphy, rock quality, rock mass classification (e.g., RMR, Q-system)	Qualitative & Quantitative	Limited spatial coverage, high variability, data gaps
Measurement While Drilling (MWD)	Drilling parameters: penetration rate, torque, rotation speed, bit pressure	Estimating rock strength, lithology changes, drilling optimization	Continuous & Quantitative	Continuous data, better subsurface understanding
Geophysical Surveys	Seismic waves, GPR, resistivity, magnetic data	Mapping subsurface structures, fault detection, groundwater exploration	Quantitative & Spatial	Expert interpretation needed, affected by subsurface noise
In-Situ Testing and Monitoring	SPT, CPT, pressuremeter tests, inclinometers, piezometers, strain gauges	Assessing soil strength, groundwater levels, slope stability monitoring	Quantitative & Time-Series	Site-specific data, reflects actual conditions
Laboratory Testing	Soil/rock properties: density, permeability, shear strength, compressibility	Foundation design, slope stability, geotechnical property analysis	Quantitative	Sample disturbance, may not fully capture in-situ conditions
Remote Sensing & Satellite Data	Satellite imagery, LiDAR scans, aerial photos	Monitoring surface deformation, landslide detection, subsidence analysis	Quantitative & Spatial	Large-scale monitoring, remote site accessibility
Historical & Archival Data	Historical records, site investigation reports, case studies	Risk assessment, geotechnical model refinement, predictive accuracy	Qualitative & Historical	Data quality varies, may not align with current methods
Real-Time Monitoring Systems	Sensor readings: deformation, pore pressure, strain	Early warning systems, real-time stability monitoring, construction safety	Continuous & Time-Series	Proactive risk management, real-time decision-making

ML in mining engineering

Machine learning has become increasingly valuable in mining engineering due to its ability to optimize complex processes, reduce operational costs, and enhance safety.

Mining operations involve handling large volumes of data from various sources, such as drilling, blasting, and equipment sensors.

ML can efficiently analyze this data to identify patterns, optimize resource extraction, predict equipment failures, and improve decision-making.

Unlike traditional methods, ML models can continuously adapt to new information, allowing for real-time adjustments in dynamic mining environments. This leads to better resource management, reduced downtime, and increased productivity..

ML in mining engineering

Some examples are

- Ore grade estimation
- Drilling and blasting optimization
- Rock property assessment
- Predictive maintenance of mining equipment
- Autonomous vehicles and robotics
- Mineral processing and recovery optimization

Some examples !

Round table

Please prepare and upload a single page document summarizing,

What is your (thesis) topic

Can you define the problem?
What are the variables?
What will be the objective/s?

Do they need to be optimized.

What are input parameters for your problem,

Lecture next: Advanced Modeling Techniques and Model Selection

Lecture #1

- How to Select the Appropriate Modeling Technique
  - Case studies demonstrating model selection: Regression vs. classification.
  - Discussion: The flexibility of modeling approaches—how it varies from project to project and person to person.
  - Examples of model selection based on my research publications.
- Introduction to Hybrid Modeling
  - Gray Box Modeling: Combining physical models with data-driven approaches.
    - Fuzzy Inference Systems (FIS): Applications in geotechnical parameter estimation.
    - Adaptive Neuro-Fuzzy Inference Systems (ANFIS): Using ANFIS for complex geotechnical predictions with examples from your publications.

Lecture next: Advanced Modeling Techniques and Model Selection

Lecture #2

- Examples of Black Box Modeling Techniques
  - Random Forests (RF): Applications in classification and regression tasks in geotechnical projects.
  - Gaussian Process Regression (GPR): Understanding its use for uncertainty quantification.
  - ……
  - ……
- Optimisation examples using PSO