STRATUM: Corporate Case Study

Rock Strength Modelling with Stratum SATS

September, 2023

STRATUM AI

OPTIMIZING **ROCK STRENGTH** MODELLING

More accurate rock strength estimations allows for more stable blasting ore size, reduced blasting costs, improve slope stability in open pit mines, and reduced rockfall in UG mines.

STUDY CASE
GOLD DEPOSIT

MINE PROFILE
- *Gold epithermal deposit*
- *775k drillholes/grade control samples*
- *Open pit mine in high rainfall climate*

VALUE PREPOSITION

Create a more accurate rock strength (blasting sensitivity) model to ensure more stable blasting performance.

MAIN GOALS

- Reduce ore dilution and blasting cost by identifying easy-to-break material and reducing explosive usage when blasting this material.
- Reduce occurrence of oversized ore by identifying hard-to-break material and increasing explosive usage when blasting this material.

STUDY CASE
GOLD DEPOSIT

EVALUATION METRICS

TYPES OF ERRORS

1 Modelling Error
Drillholes → Blocks
Deviation from test drillhole assays

2 Mapping Error
Blocks → Blasting Sensitivity Index
Deviation from expected blasting sensitivity

Modelling Error metric	Description
ABD	**Average BSI Deviation** *Modelled vs measured-by-proxy BSI* *ARD = Abs(K(M(D)) – M(D))*

Mapping Error metric	Description
ABD	**Average BSI Deviation** Predicted BSI vs Measured BSI *ARD = Abs(M(D) – BSI)*
Rec Soft [BSI < 2.4]	**Recall of Blasting Sensitive Ore** *Percentage of ore measured as undersized (<2.4), predicted as undersized.*
Prc Soft [BSI < 2.4]	**Precision of Blasting Sensitive Ore** *Percentage of ore predicted as undersized (<2.4), measured as undersized.*
R^2	**Chi-square** *What is the goodness of fit between predicted and real BSI*

D = drillhole data
K = spatial estimation typically through kriging
M(D) = blasting sensitivity mapping

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BASELINE MODEL

The baseline estimate uses average logged rock quality index (RQD) as an estimate for blasting sensitivity.
0-2 = undersized drift-prone particle size post-blasting, 3 preferred particle size, 4-6 oversized particle size

Baseline (#1):
RQD as Proxy

X^{th} percentile strongest by RQD estimated as X^{th} percentile strongest by BSI
Ex: 90^{th} percentile strongest RQD estimated as 90^{th} strongest BSI

Baseline (#2):
RQD Linear Fit

Linear regression where BSI = A*RQD + b. A, b are computationally optimized via regression.

The RQD estimate used an average of a mechanically tested rock strength and logged fracture-based rock quality. For simplicity, it is collected referred to as RQD.

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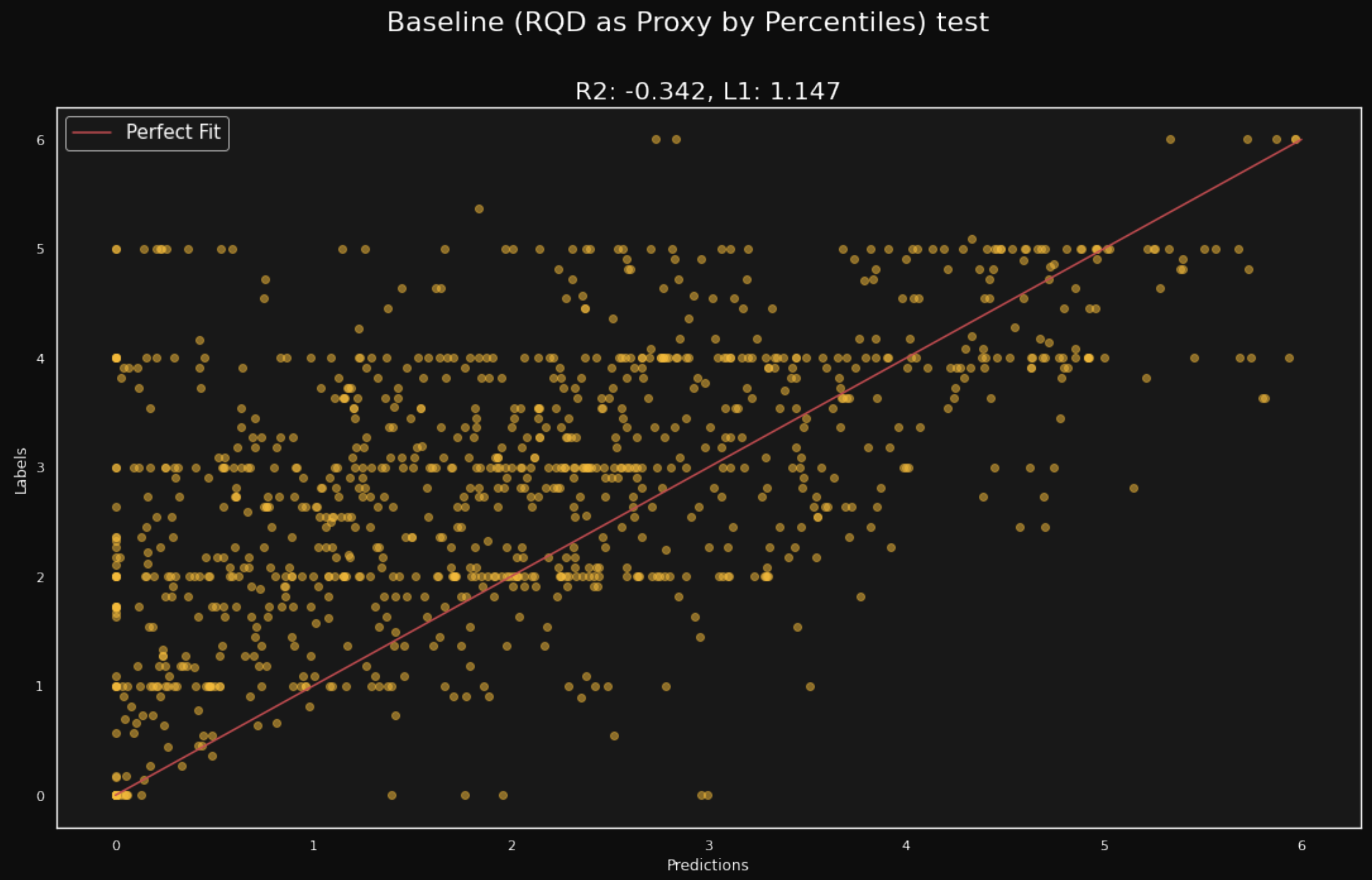
BASELINE (#1) MODEL ANALYSIS



Using a percentile-based mapping from RQD to BSI produces poor fit and high average deviation.

1. MODELLING ERROR

ABD	0.826

2. MAPPING ERROR

ABD	1.162
Rec Soft BSI < 2.4	85.4%
Prc Soft BSI < 2.4	52.7%
R^2	-0.317

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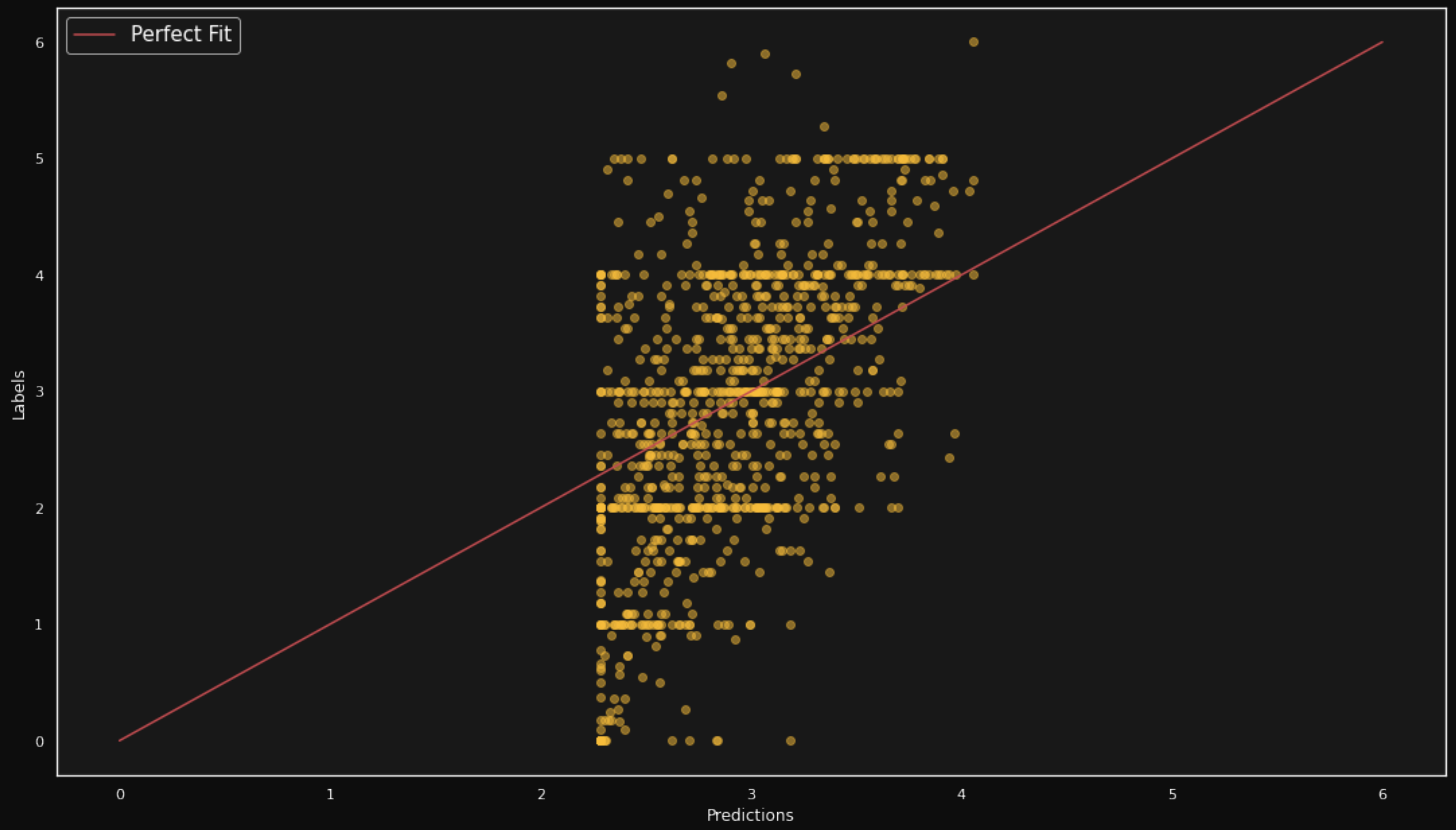
BASELINE (#2) MODEL ANALYSIS

Baseline (RQD Linear Fit) test



Using a linear regression mapping from RQD to BSI produces lower deviation, better fit however this comes at a price of model avoiding predicting on extremes (very weak/strong rock).

1. MODELLING ERROR

ABD	0.985

2. MAPPING ERROR

ABD	0.883
Rec Soft BSI < 2.4	41.3%
Prc Soft BSI < 2.4	68.2%
R^2	0.279

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GOLD DEPOSIT

LINEAR MODELS

- Linear models are a useful starting point for any mapping function.
- The primary advantage of linear models over models with hard boundaries is that they are well equipped to handle impossible element ratios that may arise from using modelled grade as input
- We identify **the best linear models** that predict rock strength using **1,2, 3, & 4 features.**

Best 1-Feature
Linear Model

RQD

Best 2-Features
Linear Model

RQD ALTR

Best 3-Features
Linear Model

RQD ALTR
LITH

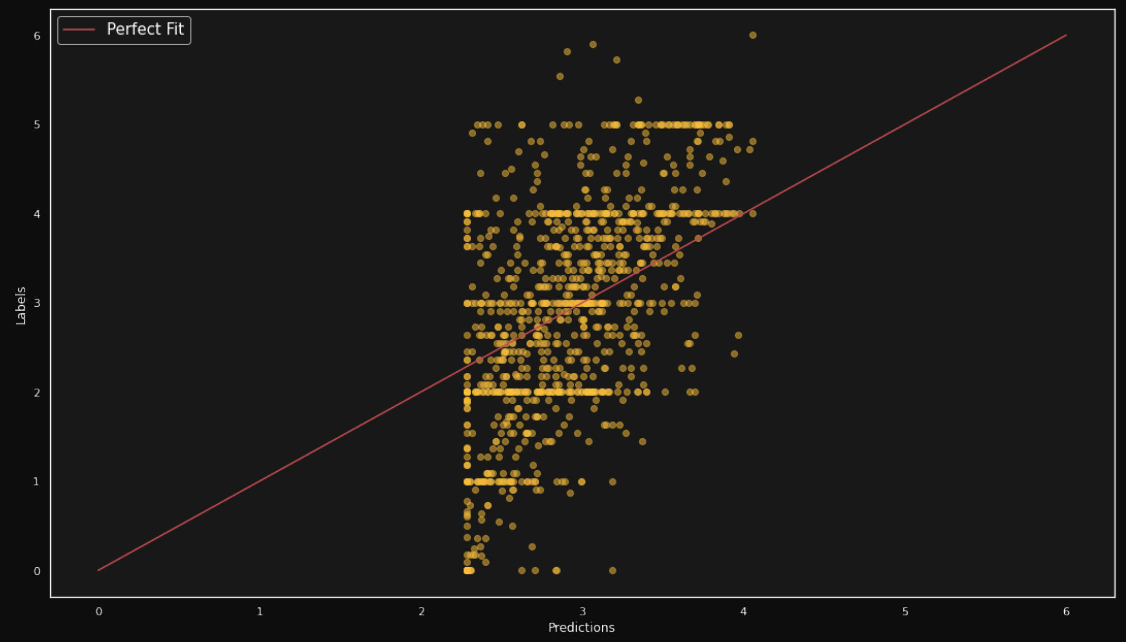
Best 4-Features
Linear Model

RQD ALTR
LITH OX

STUDY CASE
GOLD DEPOSIT

LINEAR MODELS

Baseline (RQD Linear Fit) test



1. MODELLING ERROR

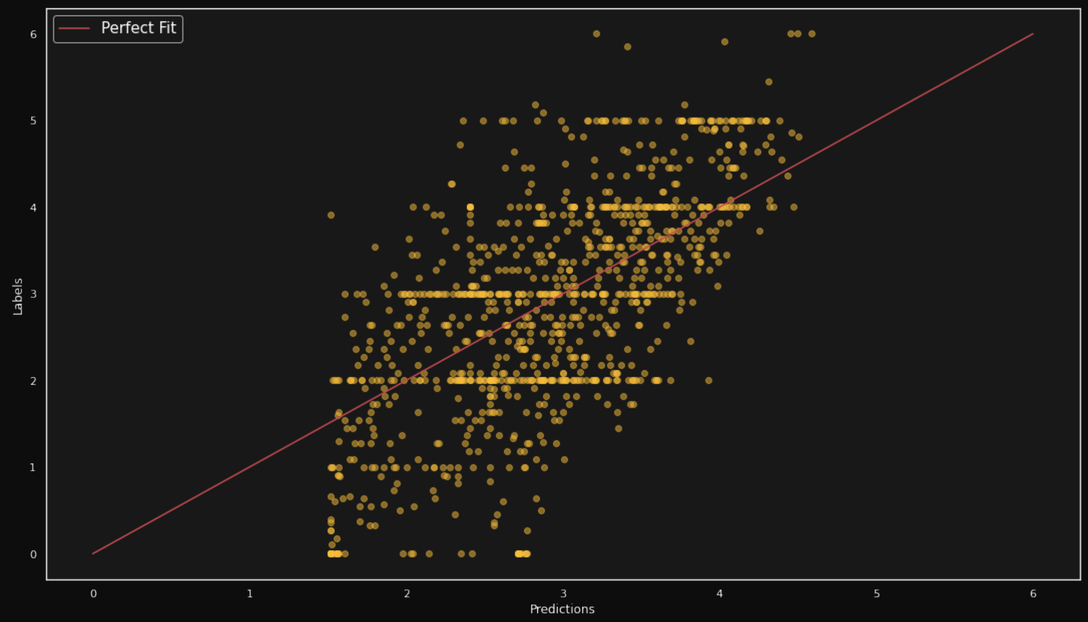
ABD	0.985

2. MAPPING ERROR

ABD	0.883	Rec	41.3%	Prec	68.2%	R^2	0.279

$$BSI = \lambda_1 RQD + \lambda_0$$

Best 2-Feature (RQD + ALTERATION) test



1. MODELLING ERROR

ABD	0.967

2. MAPPING ERROR

ABD	0.867	Prec	51.3%	Rec	67.8%	R^2	0.425

$$BSI = \lambda_1 RQD + \Sigma(\lambda_i * ALTERATION(i)) + \lambda_0$$

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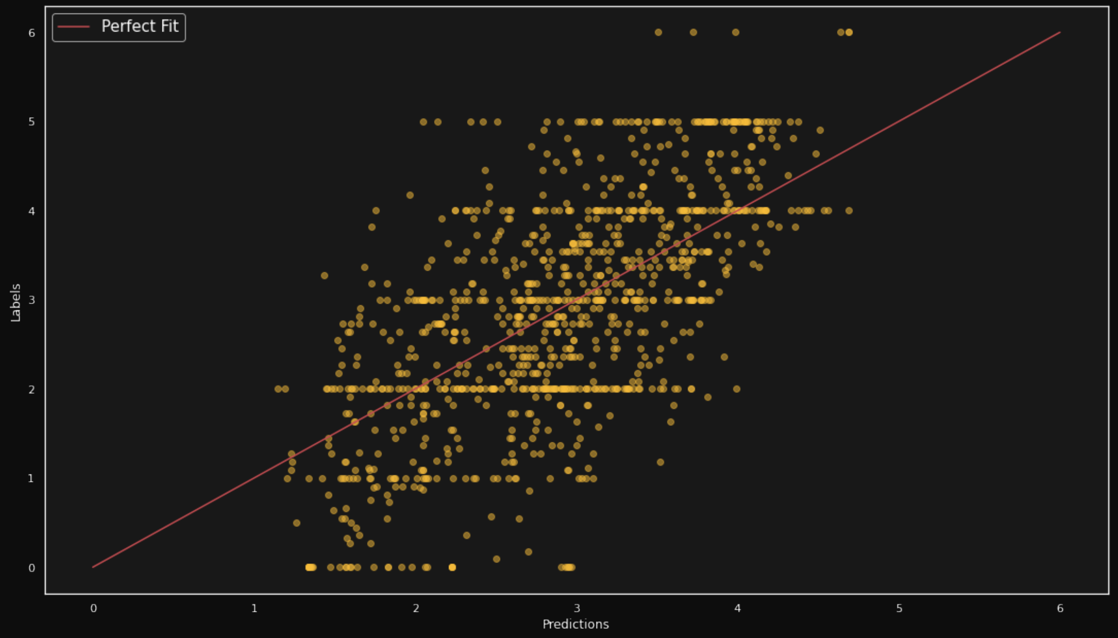
GOLD DEPOSIT

LINEAR MODELS

Best 3-Feature (RQD + ALTERATION + LITHO) test



1. MODELLING ERROR

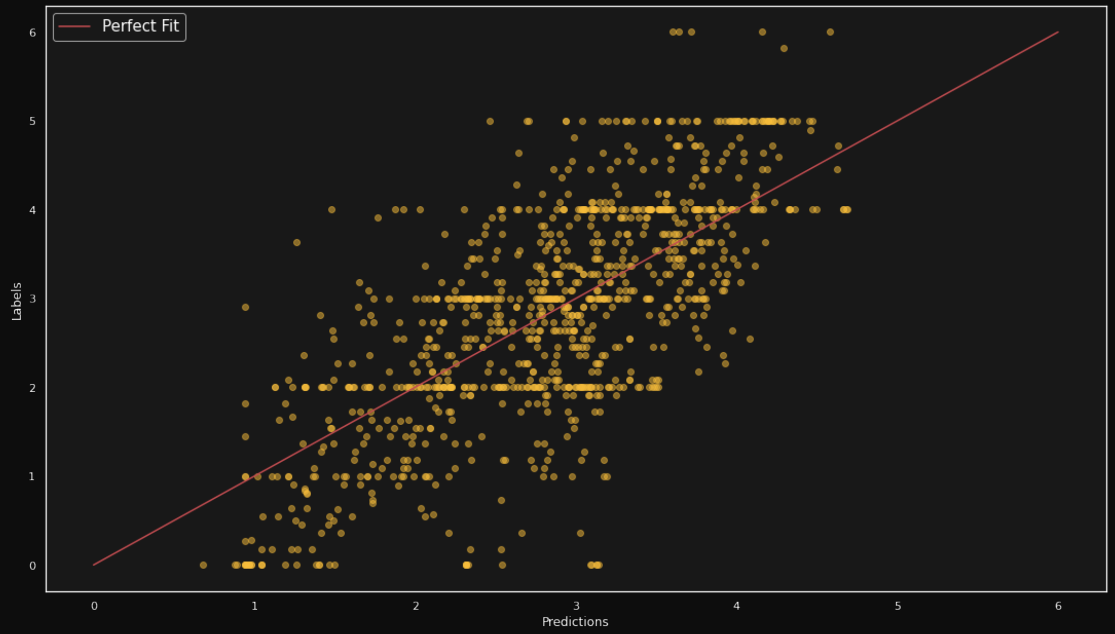
ABD	1.034

2. MAPPING ERROR

ABD	0.750	Rec	59.1%	Prec	69.7%	R^2	0.461

$$BSI = \lambda_1 RQD + \Sigma(\lambda_i * ALTERATION(i)) + \Sigma(\lambda_j * LITHO(j)) + \lambda_0$$

Best 4-Feature (RQD + ALTERATION + LITHO + OX) test



1. MODELLING ERROR

ABD	0.964

2. MAPPING ERROR

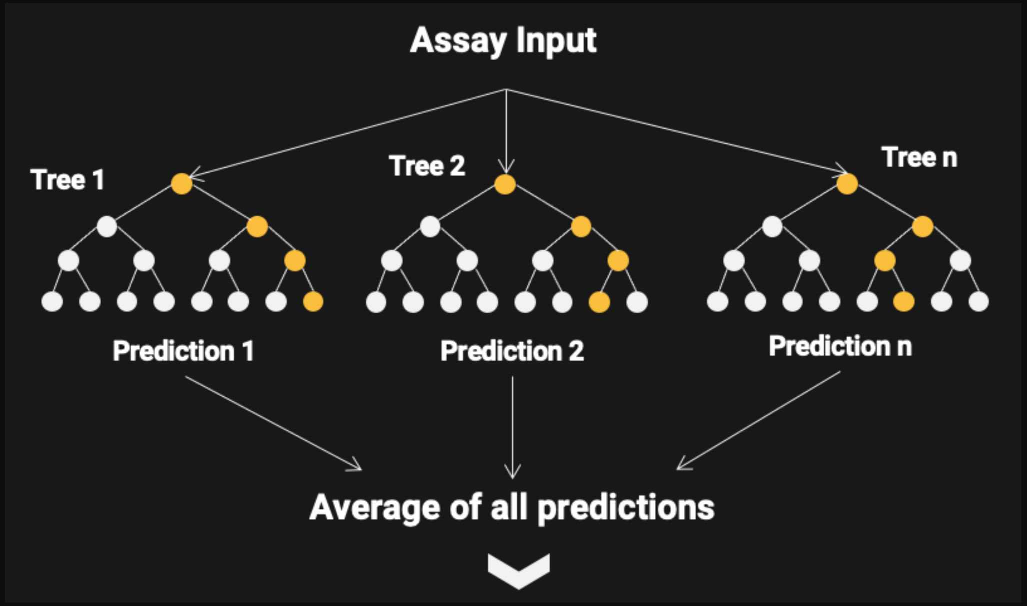
ABD	0.686	Prec	64.7%	Rec	77.0%	R^2	0.539

$$BSI = \lambda_1 RQD + \lambda_2 OX + \Sigma(\lambda_i * ALTERATION(i)) + \Sigma(\lambda_j * LITHO(j)) + \lambda_0$$

STUDY CASE
GOLD DEPOSIT

STRATUM DECISION TREE MODEL

DECISION TREE ARCHITECTURE



DECISION TREE PREDICTION

- Stratum's Decision Tree Model is a proprietary resource modelling-specific adaption of a decision tree-based machine learning technique.
- Random Model is based on the theory that the best estimate is an **average** estimate of **several simple** boundaries/equations.
- Ex: predict recovery based on ALT, LITH, RQD, Ca then average the answer.
- **Stratum adapts the standard Random Model** technique by allowing two-way information exchange between modelling & mapping to reduce occurrence of impossible feature ratios (as verified by site team).

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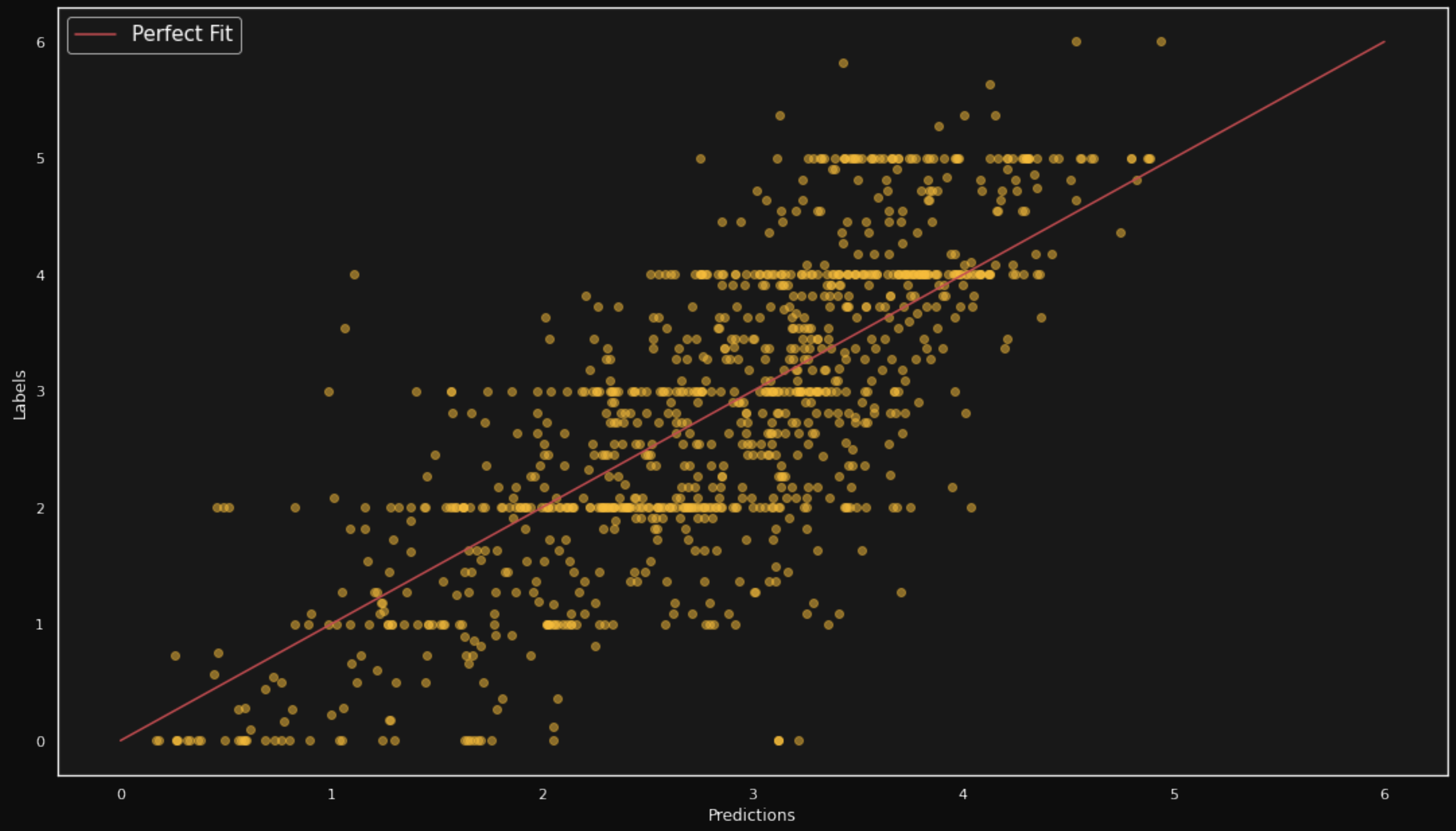
STRATUM
DECISION TREE MODEL

SATS Forest test



Random model outperforms traditional methods in both modelling and mapping error by leveraging geological patterns both from logging and geochemistry.

1. MODELLING ERROR

ABD	0.628

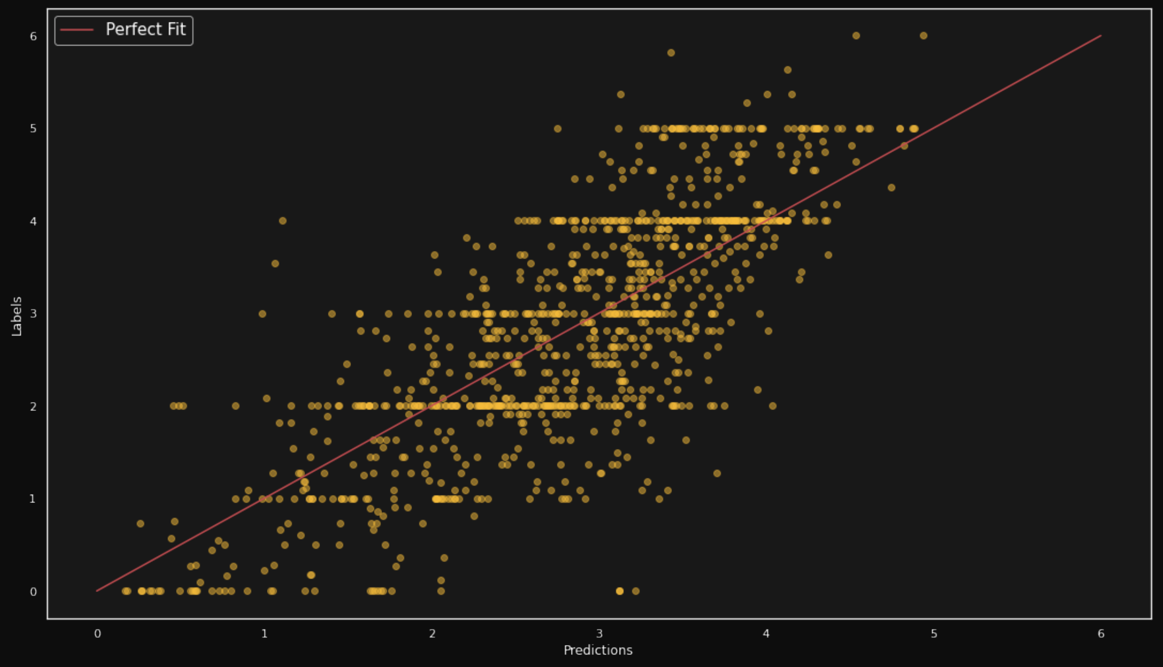
2. MAPPING ERROR

ABD	0.529
Rec Soft BSI < 2.4	68.0%
Prc Soft BSI < 2.4	78.1%
R^2	0.629

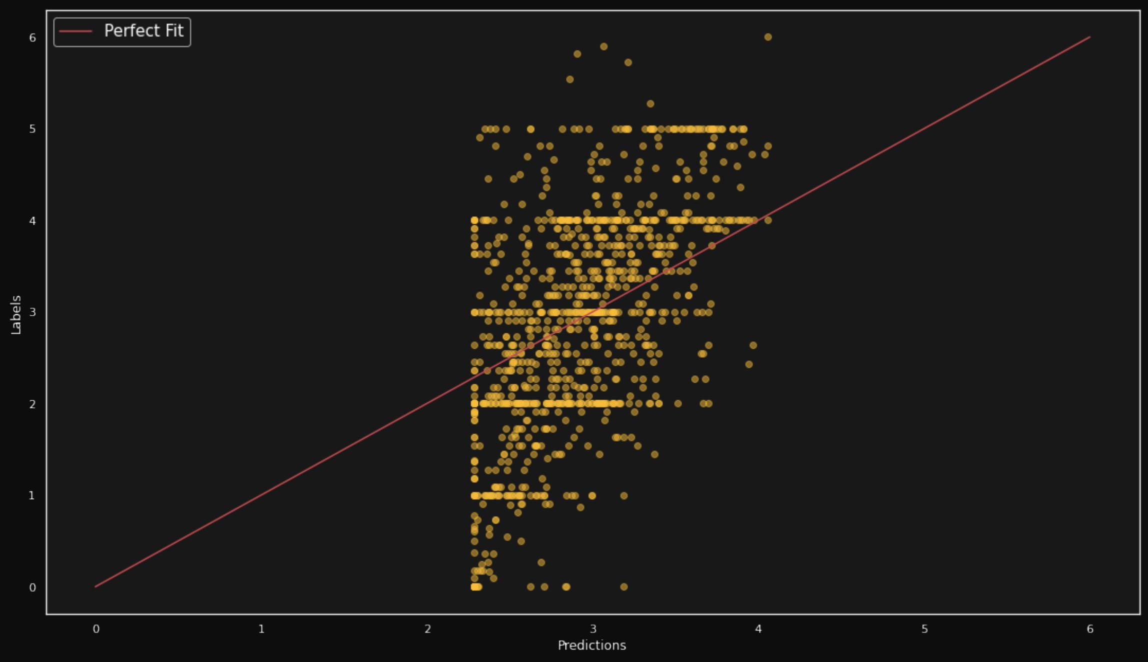
STUDY CASE
GOLD DEPOSIT

COMPARISON

Stratum SATS Model



Baseline #2 (RQD)



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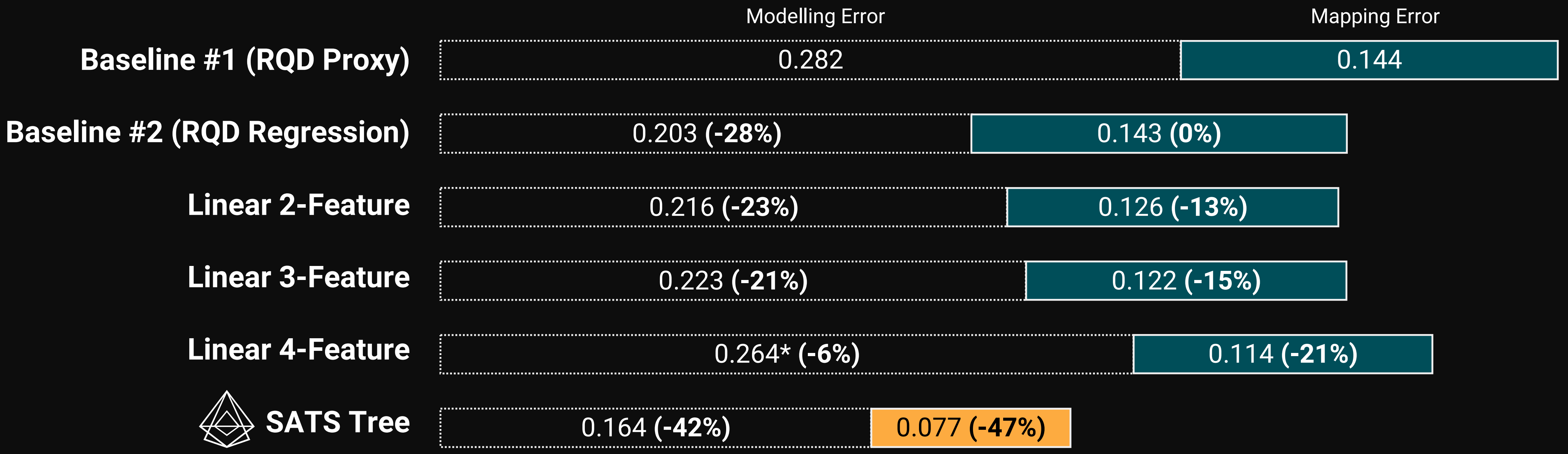
MODELS RESULTS

ARD Average Recovery Deviation by Model

*SATS Decision Tree has a **47% mapping error reduction over baseline**.*



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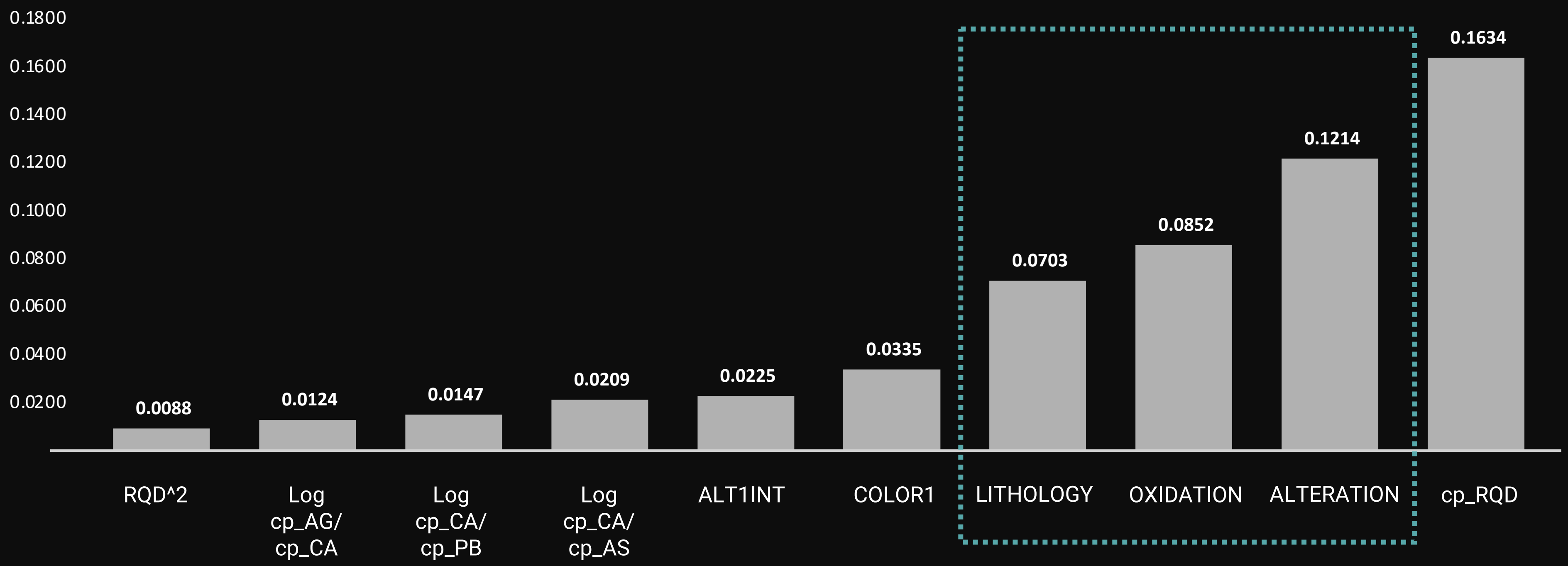
TOP 10 FEATURES

Feature Importance Analysis for Predicting Rock Strength



Notes : (1) cp = Composite

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RESULTS OVERVIEW

40% **LESS MAPPING ERROR**
by leveraging structural, multi-element patterns in blasting sensitivity index mapping.

38% **HIGHER RECALL OF SOFT ORE**
78% of over-blasted material predicted as over-blasted prior to blasting compared to 40% with only RQD.

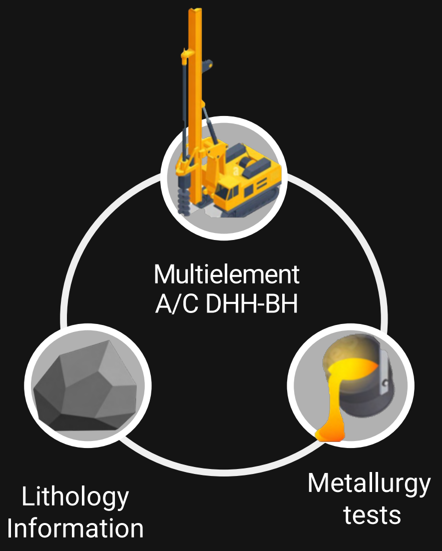
35% **LESS MODELLING ERROR**
due to reduced reliance on any one grade, ratio, or boundary as well ability to leverage higher density metal assays from RC drillholes.

LESS DEPENDENCE ON DIAMOND DRILLING
Ability to model blasting sensitivity from logging, assay data from RC chips rather than exclusively diamond drillholes (RQD, RS) allows for more of resource within measured/indicated confidence.

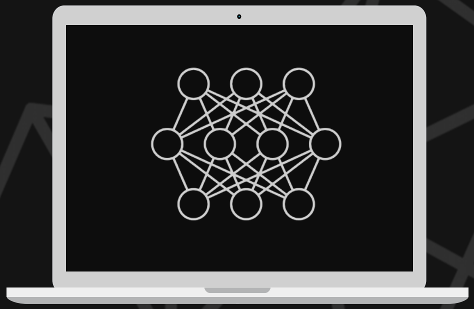
STRATUM MODELS
HOW IT WORKS

We produce a continuously updating **resource model (AI Model)** that tells companies the **location** of minerals in the ground for cost-efficient extraction

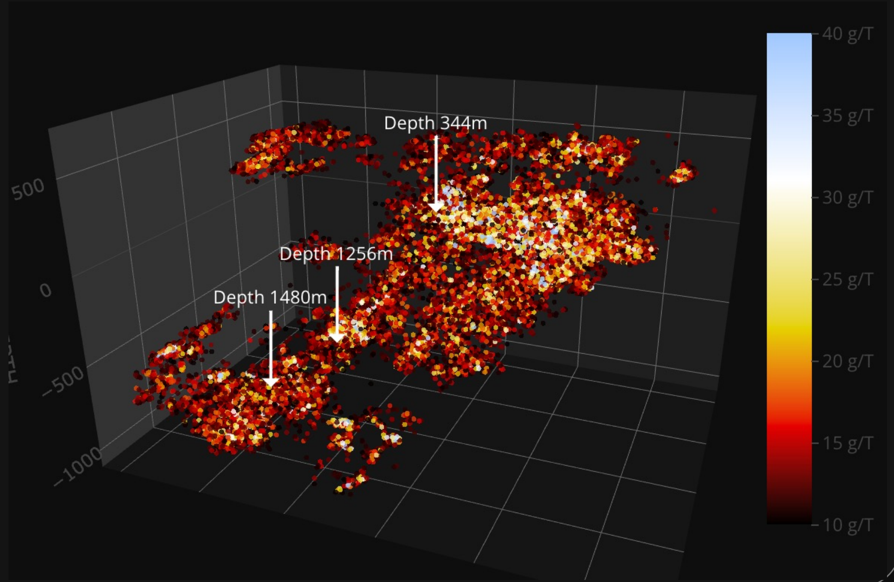
1 Input existing mine data to neural network



2 AI learns geological patterns from historical data

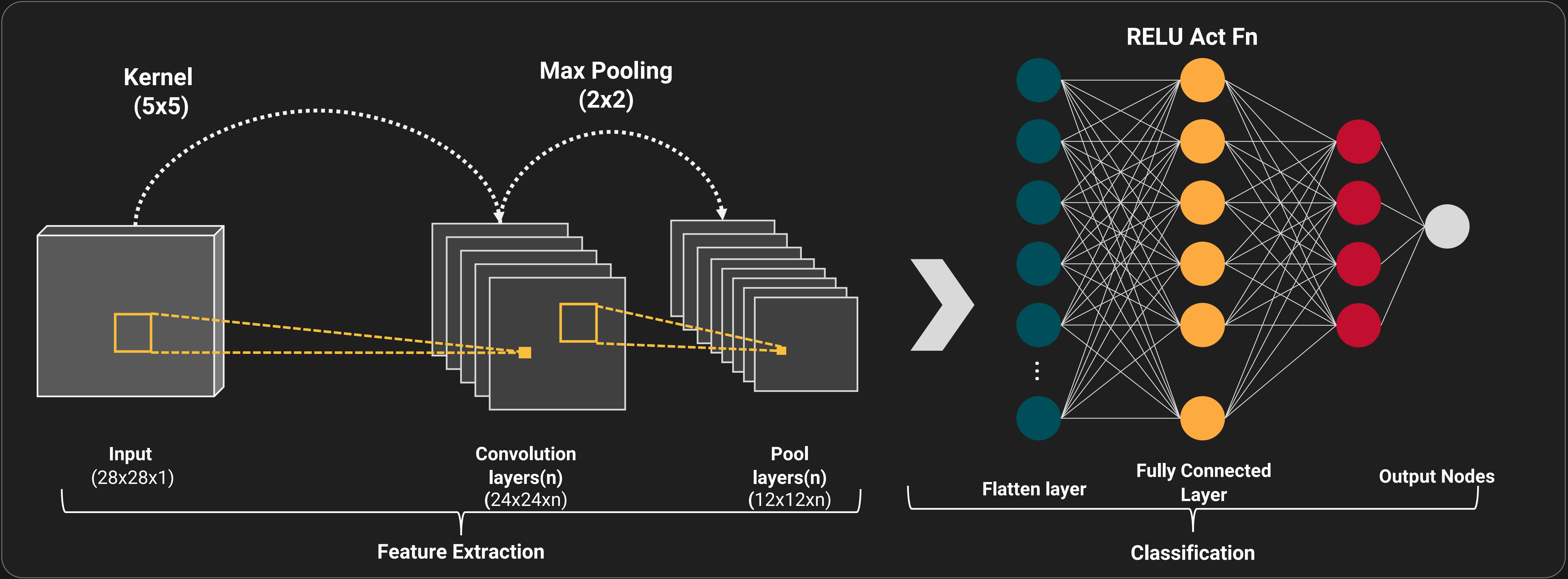


3 Output 3D map of precise ore locations for clients



STRATUM MODELS
HOW IT WORKS

CONVOLUTIONAL NEURAL NETWORK
Successfully capture the spatial dependencies in an image through the application of relevant filters



STRATUM

LOW RISK – HIGH YIELD – AI DRIVEN