STRATUM: Corporate Case Study

Recovery Mapping for Gold Ore with Stratum SATS

November, 2022

STRATUM AI

OPTIMIZING **RECOVERY** MODELLING

“With complex or marginal assets, optimizing recovery practices while increasing mill productivity directly affects the profitability of a mine over the course of its life”

RECOVERY PROJECT

DATA INSPECTION

Trans ore is visually confirmed to be a mix of transitionary material and mixed oxide-sulfide material. The former has high potential of being high recovery under specific conditions. Ability to sort oxide-sulfide and trans will be key in recovery estimation.

Visual inspection of mine refines hypothesis that there are large continuous regions of oxide ore located under sulfide area in some areas of the mine. Site geology team suggests historical subterrain rivers is the common cause.

Oxide-sulfide Trans ore

True Trans ore

It may be possible to sort oxide-sulfide material and real transitionary material using the Sb grade because Sb grade in verified transitionary material has a unique grade signature.

STUDY CASE
GOLD DEPOSIT

MINE PROFILE

- *Gold epithermal deposit*
- *775k drillholes/grade control samples*
- *Complex mixed-sulphidation deposits*

VALUE PREPOSITION

Create a more accurate recovery block model based on **10-element drillhole assays.**

MAIN GOALS

- Increase mill recovery by identifying low recovery blocks and then keeping them out of the mill.
- Increase mill-throughput by sorting uneconomic & economic trans ore and milling the latter.

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GOLD DEPOSIT

EVALUATION METRICS

TYPES OF ERRORS

1 Modelling Error
Drillholes → Blocks
Deviation from test drillhole assays

2 Mapping Error
Blocks → Recovery
Deviation from leach pulp sample test

ARD — **Average Recovery Deviation**
Modelling grade vs assayed grade recovery estimation

MRD — **Median Recovery Deviation**
Modelling grade vs assayed grade recovery estimation

ARD — **Average Recovery Deviation**
Recovery estimation vs real recovery

MRD — **Median Recovery Deviation**
Modelling grade vs assayed grade recovery estimation

R|PR [40%,80%] — **Real Recovery where Predicted Recovery**
Real recovery in samples predicted as 40-80% recovery (transitory region)

R^2 — **Chi-square**
What is the goodness of fit between predicted and real recovery

STUDY CASE
GOLD DEPOSIT

BASELINE MODEL EQUATIONS

These are the equations used to estimate recovery currently at the mine.

Output Standardized

If $S > 0.4 \mid Fe/S > 10$:	$Recovery = \min(0.92, (Au-0.156)/Au)$
If $S > 0.4$ & $3 < Fe/S > 10$:	$Recovery = \min(0.85, (Au-0.156)/Au)$
If $S > 0.4$ & $Fe/S < 3$:	$Recovery = 1 - \max(0.78*Au - 0.17*Fe/S, 0.157)/Au$

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GOLD DEPOSIT

BASELINE MODEL ANALYSIS

The regression fit (based on leach pulp test samples) shows room for improvement independent of modelling error.

1. MODELLING ERROR

ARD	0.282
MRD	0.202

2. MAPPING ERROR

ARD	0.144
MRD	0.102
R|PR [40%,80%]	50.3%
R^2	0.817

STUDY CASE
GOLD DEPOSIT

BASE LINE MODEL EVALUATION

Is **modelling** or **mapping** causing deviations between estimated and real recovery?

	Modelling Error	Mapping Error
ARD (average recovery deviation)	0.282 (66.2%)	**0.144 (33.8%)**
MRD (median recovery deviation)	0.202 (66.4%)	**0.102 (33.6%)**

- Recovery error is driven by both errors, **66% modelling** and **34% mapping error**.
- Modelling error is larger but is typically harder to reduce. It is likely especially large as recovery equations are getting trapped in impossible ratios as Au, Fe, S modelled independently.

STUDY CASE
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 recovery using **1,2, & 3 features.**

S-Only
Linear Model

S

Best 1-Feature
Linear Model

S/Fe

Best 2-Features
Linear Model

S/Fe Au/As

Best 3-Features
Linear Model

S/Fe Au/As S/Ca

STUDY CASE
GOLD DEPOSIT

LINEAR MODELS

1. MODELLING ERROR

ARD	0.203	MRD	0.132

2. MAPPING ERROR

ARD	0.143	MRD	0.095

Recovery = -0.218*S + 0.0147*S² + 0.968

1. MODELLING ERROR

ARD	0.216	MRD	0.129

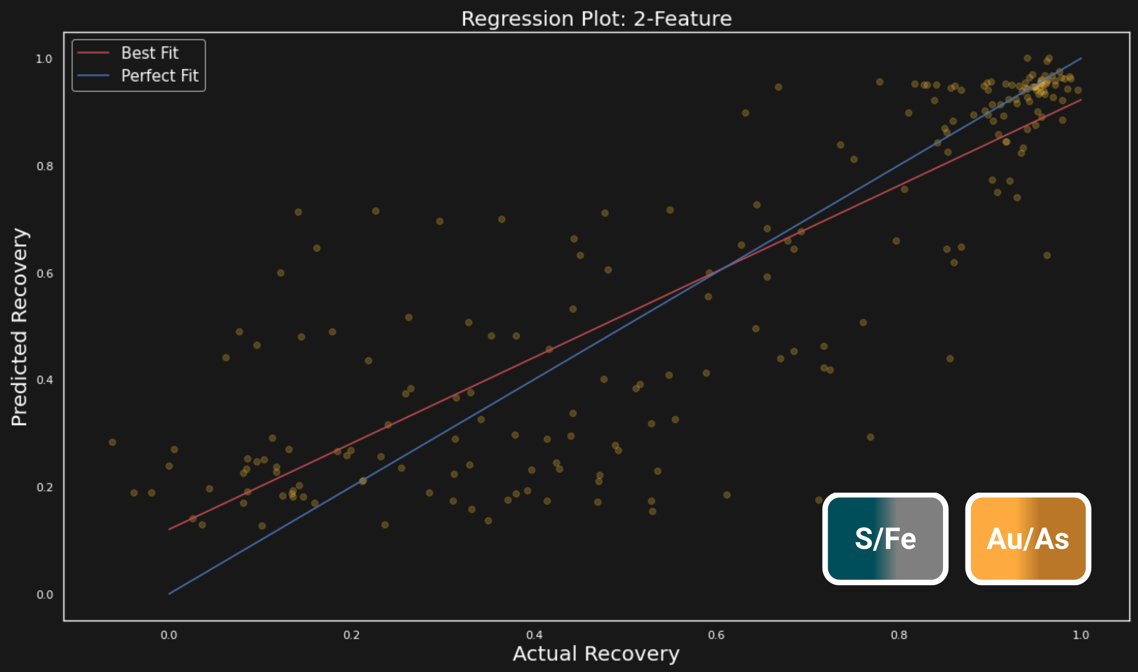
2. MAPPING ERROR

ARD	0.126	MRD	0.091

Recovery = -0.702*(S/Fe) + 0.962

STUDY CASE
GOLD DEPOSIT

LINEAR MODELS



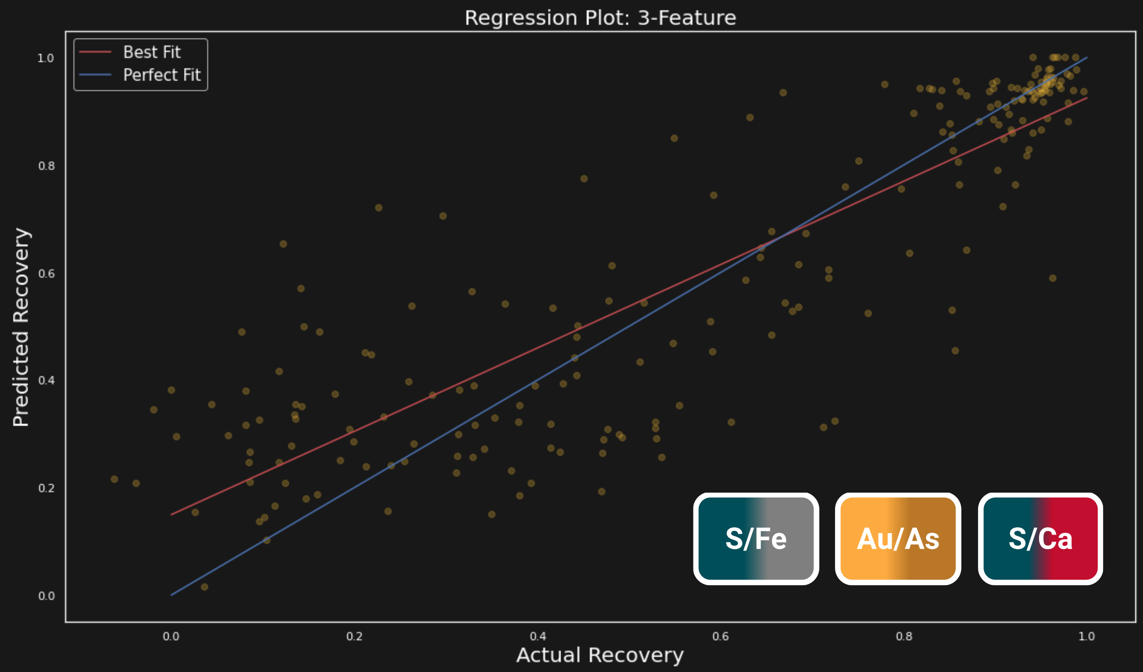
1. MODELLING ERROR

ARD	0.223	MRD	0.133

2. MAPPING ERROR

ARD	0.122	MRD	0.087

Recovery =-0.721*(S/Fe) + 5.25*(Au/As) + 0.946



1. MODELLING ERROR

ARD	0.264	MRD	0.209

2. MAPPING ERROR

ARD	0.114	MRD	0.070

Recovery =-0.706*(S/Fe) + 10.7*(Au/As) + 0.0103*(S/Ca) + 0.753

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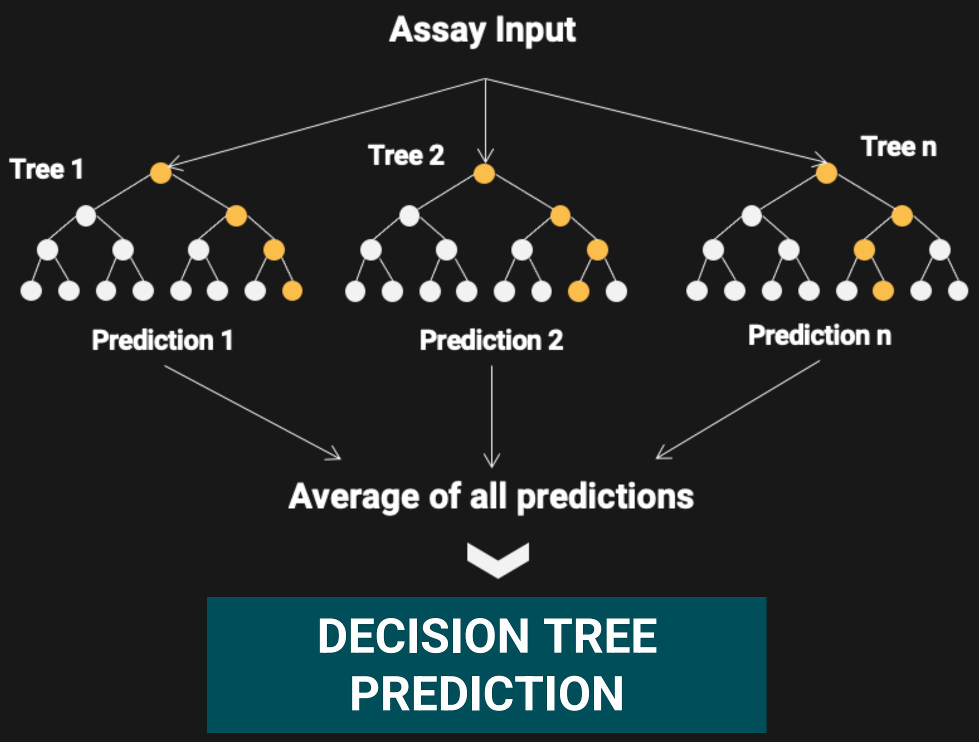
GOLD DEPOSIT

STRATUM
DECISION TREE MODEL

DECISION TREE ARCHITECTURE



- Stratum's Decision Tree Model is a proprietary resource modelling-specific adaption of a decision tree-based machine learning technique.
- Random Forest is based on the theory that the best estimate is an **average** estimate of **several simple** boundaries/equations.
- Ex: predict recovery based on S + Fe/S, S + As/Au, As/Au + S^2 and then average the answer.
- **Stratum adapts the standard Random Forest** technique by allowing two-way information exchange between modelling & mapping to reduce occurrence of impossible feature ratios (as verified by site team).

STUDY CASE
GOLD DEPOSIT

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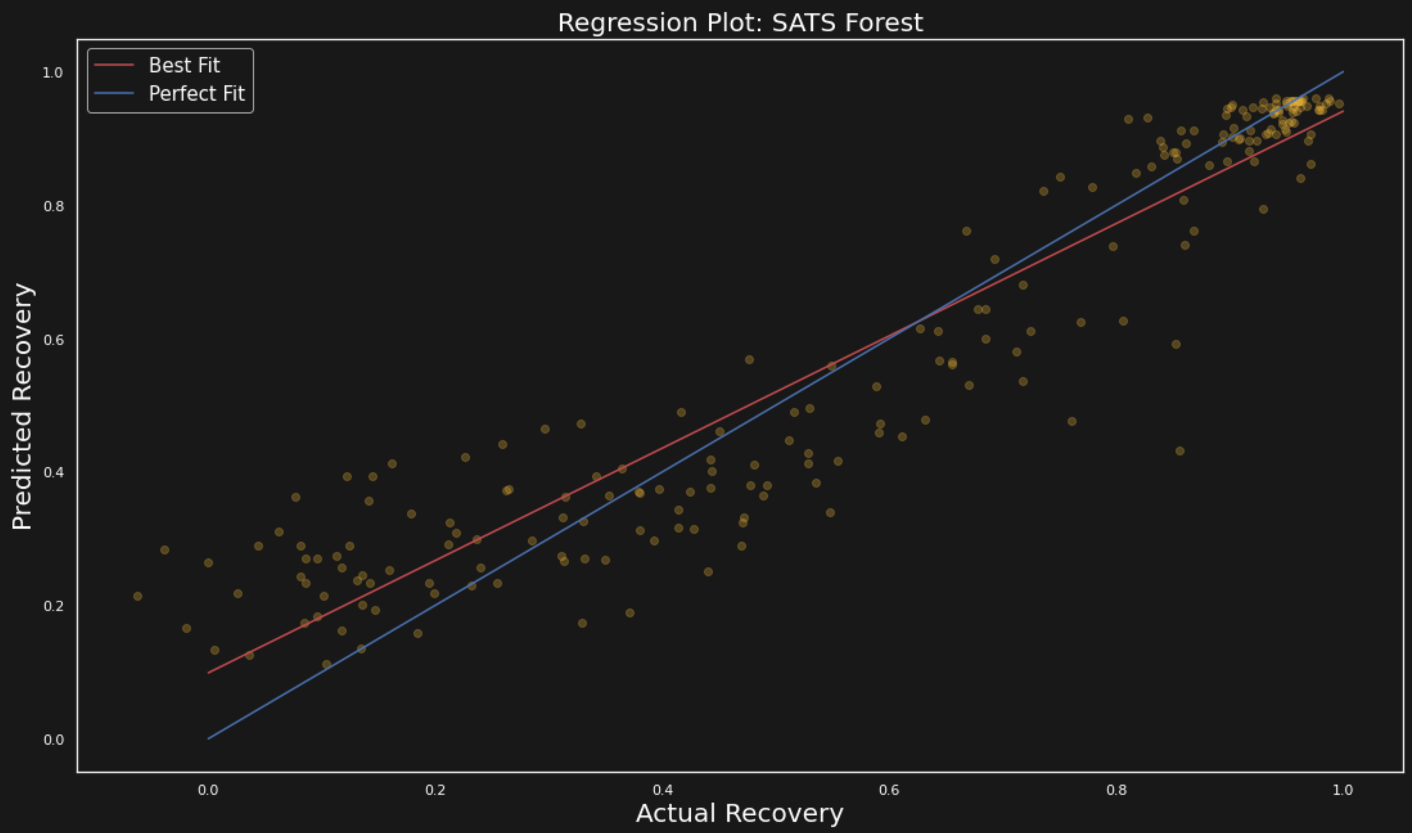
DECISION TREE MODEL



10% higher absolute recovery when mining areas predicted as having recovery [40%,80%].

1. MODELLING ERROR

ARD	0.164
MRD	0.117

2. MAPPING ERROR

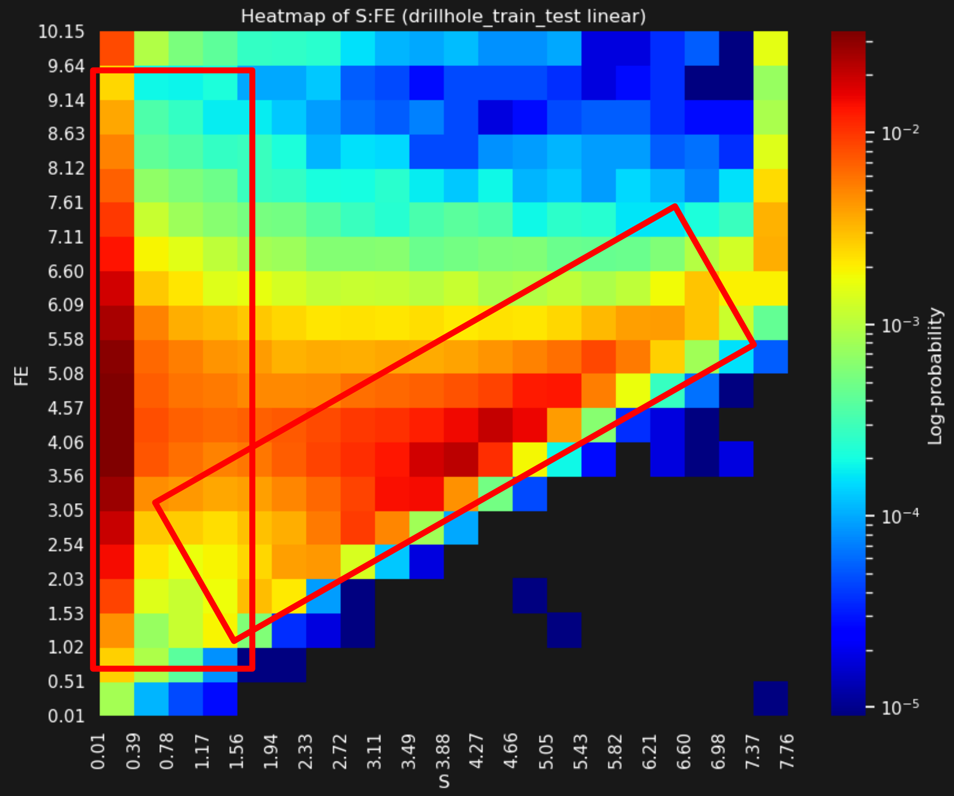
ARD	0.077
MRD	0.047
R|PR [40%,80%]	59.9%
R^2	0.946

Structure of Decision Trees — Varies but typically first boundary S/Fe, then one of (S^2, S/Au, Au/As, S/As). Decision trees vary significantly after first 2 decisions.

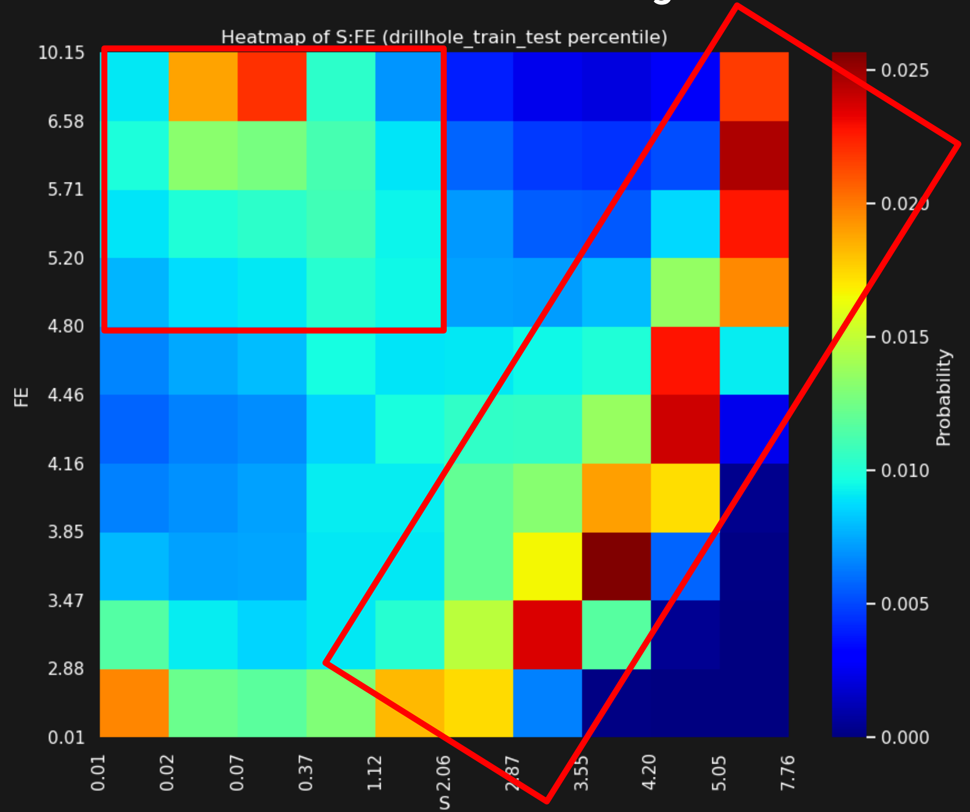
RECOVERY PROJECT
CORRELATION INSPECTION

NON-LINEAR CORRELATIONS IN TRANSITORY SULFUR REGION
SULFUR & IRON (FE)

Linear Scaling



Percentile Scaling



STUDY CASE
GOLD DEPOSIT

MODELS RESULTS

ARD Average Recovery Deviation by Model

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

	Modelling Error	Mapping Error
Baseline	0.282	**0.144**
Linear S-Only	0.203 (-28%)	**0.143 (0%)**
Linear 1-Feature	0.216 (-23%)	**0.126 (-13%)**
Linear 2-Feature	0.223 (-21%)	**0.122 (-15%)**
Linear 3-Feature	0.264* (-6%)	**0.114 (-21%)**
SATS Tree	0.164 (-42%)	**0.077 (-47%)**

STUDY CASE
GOLD DEPOSIT

MODELS RESULTS

MRD Median Recovery Deviation by Model

*SATS Decision Tree has a **54% mapping error reduction over baseline**.*

	Modelling Error	Mapping Error
Baseline	0.202	**0.102**
Linear S-Only	0.132 (-35%)	**0.095 (-7%)**
Linear 1-Feature	0.129 (-36%)	**0.091 (-11%)**
Linear 2-Feature	0.133 (-34%)	**0.087 (-15%)**
Linear 3-Feature	0.209* (+4%)	**0.070 (-31%)**
SATS Tree	0.117 (-42%)	**0.047(-54%)**

STUDY CASE
GOLD DEPOSIT

RESULTS OVERVIEW

47% **LESS MAPPING ERROR**
by leveraging multi-element patterns in recovery mapping.

10% **HIGHER ABSOLUTE RECOVERY**
at mill when mining areas predicted from assay to be 40-80% recovery. The average recovery increased from 50% to 60% in transition region.

42% **LESS MODELLING ERROR**
due to reduced reliance on any one grade, ratio, or boundary.

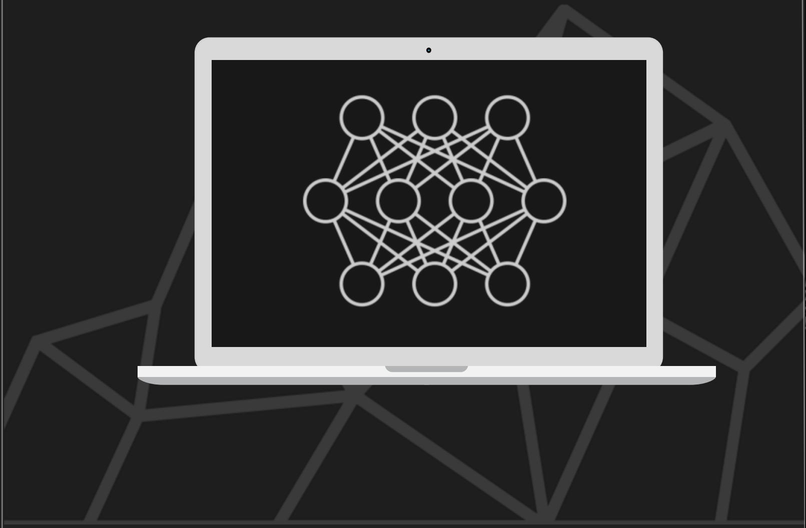
71% **LESS BLOCKS**
where recovery difference between modelled/assayed grade exceeds 40%.

STRATUM MODELS
HOW IT WORKS

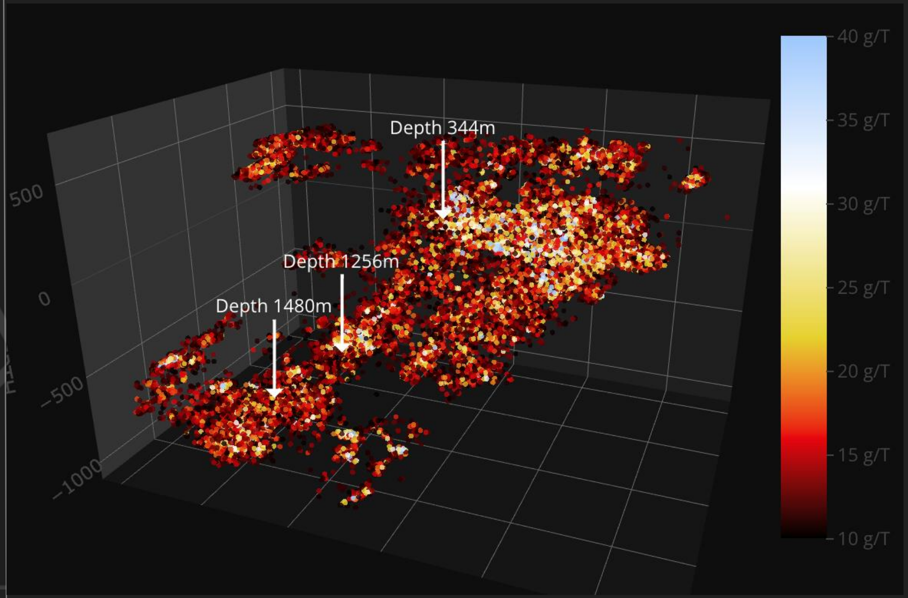
We produce a continuously updating **resource model (AI Model)** that tells companies the **location** of minerals in the ground for cost-efficient extraction

1 **Input mine data to neural network**

2 **AI learns geological patterns from historical data**

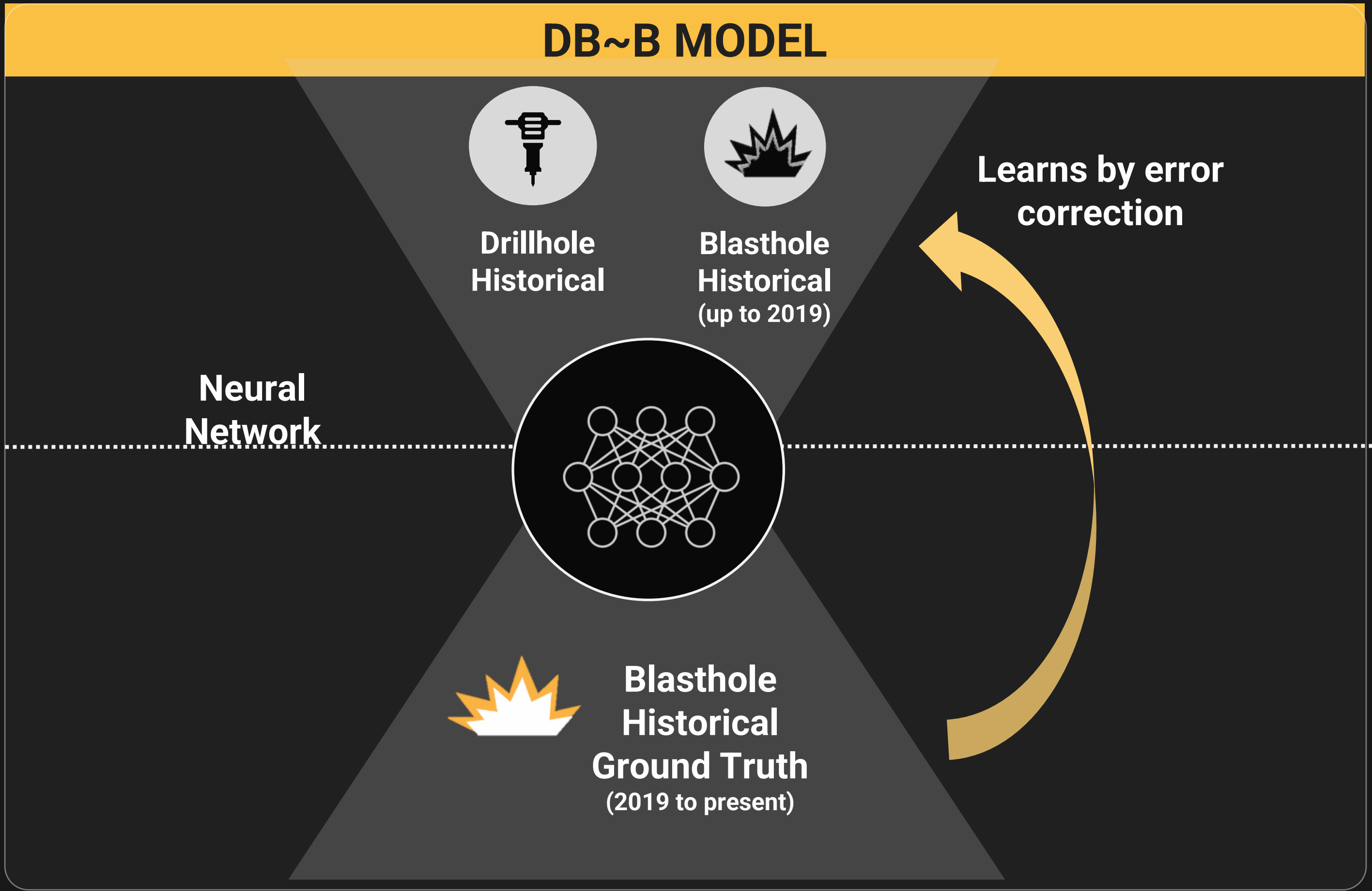


3 **Output 3D model of precise ore locations for clients**

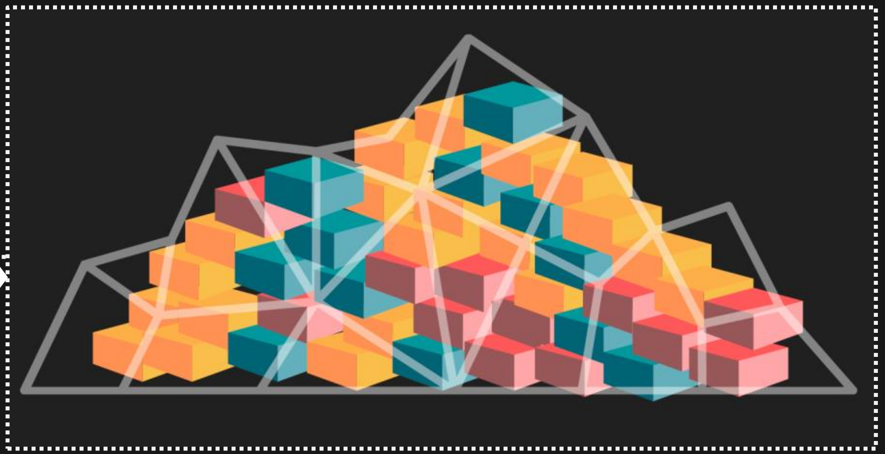


STRATUM MODELS
HOW IT WORKS

BASELINE AI MODEL EXAMPLE



Prediction: Block Model



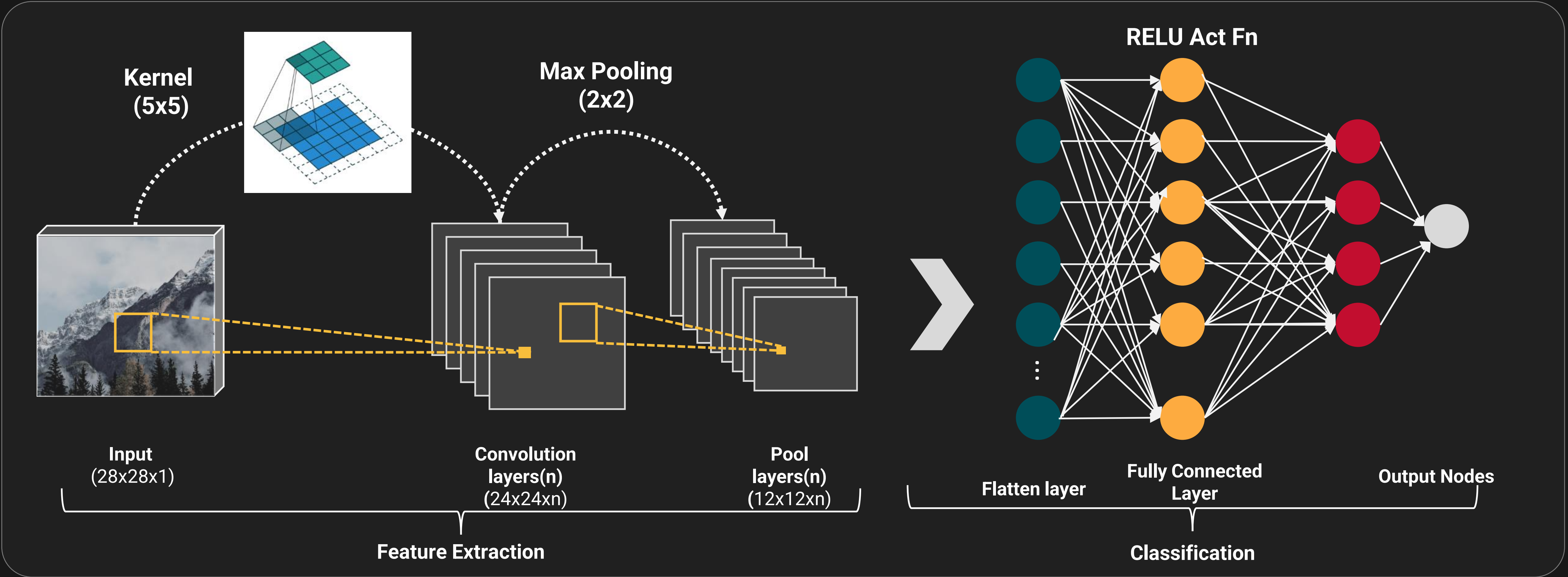
The model uses **Deep Learning** to learn geological patterns that cause grade variation and generates a block model for any element in the deposit.

STRATUM MODELS

HOW IT WORKS

CONVOLUTIONAL NEURAL NETWORK

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



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LOW RISK – HIGH YIELD – AI DRIVEN