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EXPLORATION MANAGER’S CONFERENCE 2023

INTRODUCING DEEP LEARNING & INTERPRETING THE PATTERNS:

AN OREBODY KNOWLEDGE PERSPECTIVE

David First (Chief Geologist) &
Daniel Mogilny (Co-Founder), Stratum AI

MACHINE LEARNING (ML)

CORE CONCEPTS

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ARTIFICIAL INTELLIGENCE (AI)

Computer systems that perform tasks and make decisions that mimic and possibly exceed human intelligence

MACHINE LEARNING (ML)

Branch of AI that focuses on creating models that learn automatically from data and experiences to make decisions without being explicitly programmed

- **SUPPORT VECTOR MACHINE**
- **LOGISTIC REGRESSION**

DEEP LEARNING (DL)

Powerful type of ML model that learns complex patterns from large amounts of data, mimicking neural networks found in the human brain

- **NEURAL NETWORK (NN)**

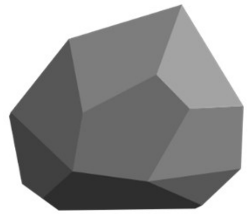
AI IN THE MINING SECTOR

AUTOMATED MACHINERY

Automation and optimisation of mining machinery such as haul trucks and drills

PREDICTIVE MAINTENANCE

Predictive maintenance on machinery and equipment to minimise downtime



AI GEOLOGY INSIGHTS

AI driven exploration, resource modelling, and improvement of mill processes

MACHINE LEARNING ML
INTRODUCTION

- ML algorithms learn from **historical data**; better forecast future patterns &/or trends
- ML is best suited to environment with lots of data and **complex patterns**
- ML is powerful tool revealing complex patterns in data easily missed by human eye and traditional statistics
- Learn to map between input and output data
- Complete seemingly **“unprogrammable” tasks**
- e.g. machine translation (i.e. translate text; voice and speech recognition)

DEEP LEARNING (DL)
INTRODUCTION

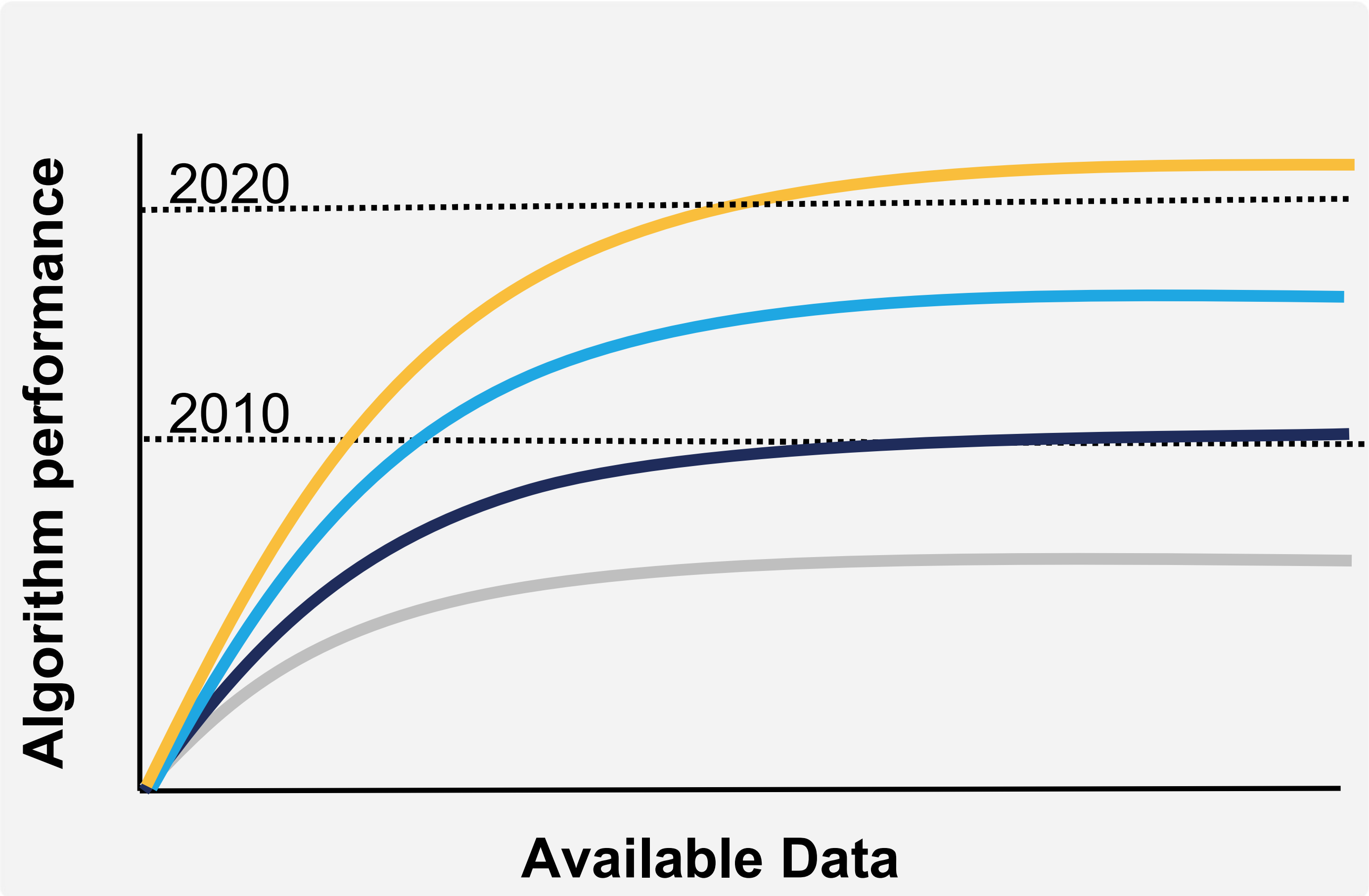
- Powerful ML algorithms; multiple neural network layers – **artificial neurons**
- Image recognition; e.g. medical imagery
- Large volumes of data plus very high **performance GPUs**
- Powerful GPUs only became commercially available at scale since ~2016
- Orebody or deposit requires:

>75,000 data points (assays); DL

25 – 75,000 data points; kriging or DL

<25,000 data points kriging

DATA VS PERFORMANCE



NN **DEEP** (20+ LAYERS)

NN MEDIUM (5–20 LAYERS)

NN SHALLOW (3–5 LAYERS)

ML TRADITIONAL ALGORITHMS
(SVM – SUPPORT VECTOR MACHINE; LR – LOGISTIC REGRESSION)

Computational Capacity:
GPU Speed; GPU Memory

WHY PYTHON?

- ML and data science – language of choice
- Python is NOT special
  - Best viewed as a simple tool to interface with neural nets, data
- Most ML algorithms written in Python
  - No need to recreate ‘wheel’
  - Easier for onboarding new software engineers to ML companies
  - Simplicity – allows engineers to focus on logic rather than software development
- PyTorch (dev. Linux and Meta AI); ML library (open-source)
  - interfacing with neural nets
- TensorFlow; dev. Google and Google Brain)
- CUDA – Library for interfacing with state-of-the-art GPUs

ALGORITHMS & OVERFITTING

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WHAT ARE ML ALGORITHMS?

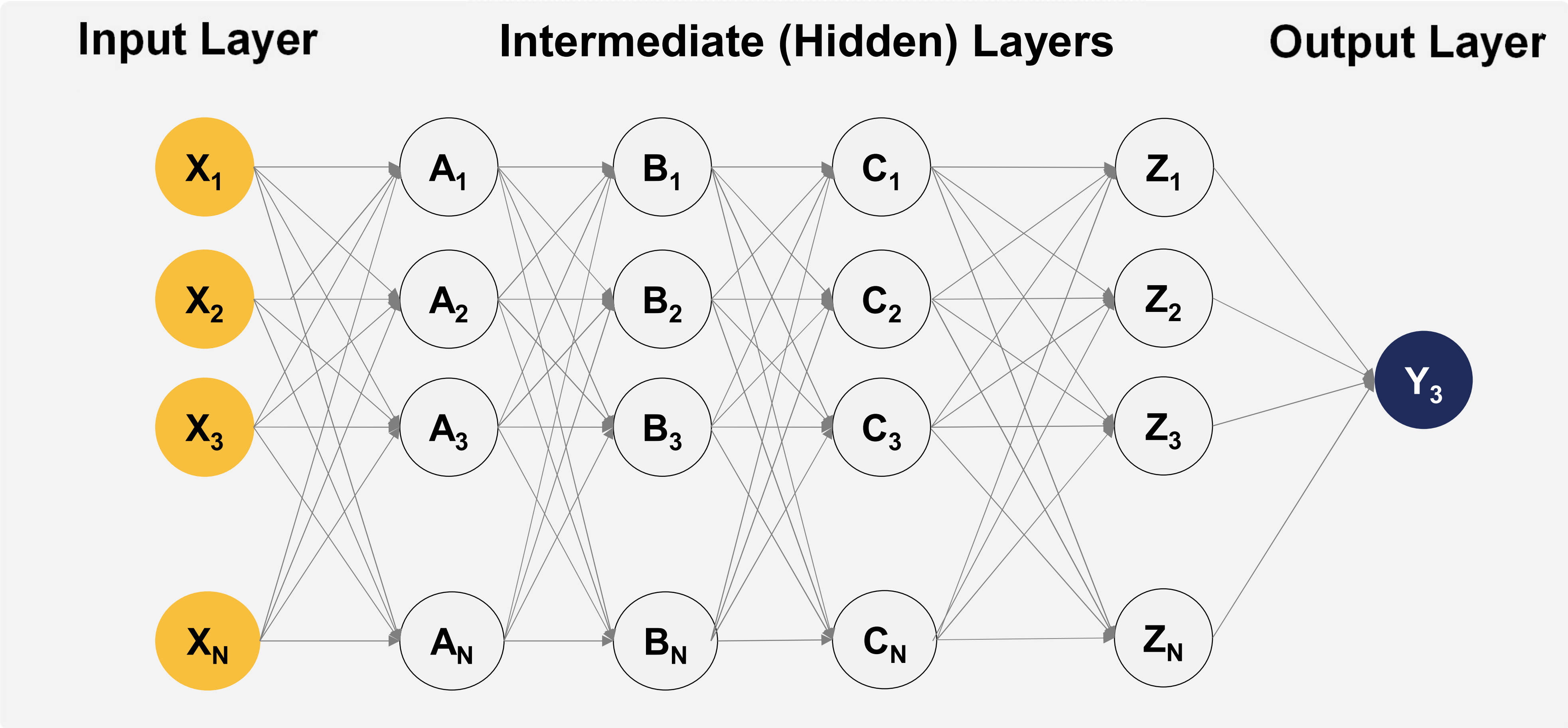
- Mathematical model mapping methods used to learn or uncover underlying patterns embedded in the data
- Group of computational algorithms that perform pattern recognition, classification and prediction on data by learning from existing data (training set)

WHAT IS OVERFITTING?

(& UNDERFITTING)

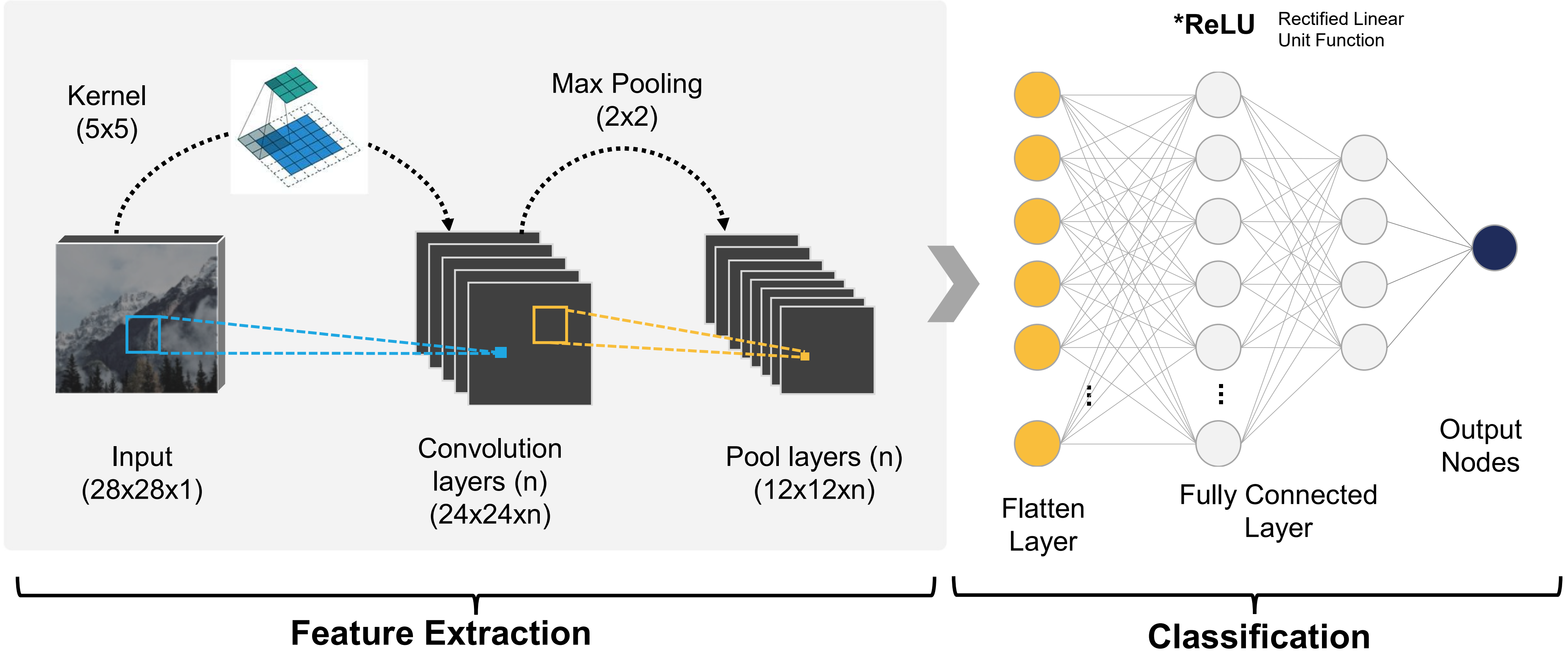
- Model cannot generalise and fits too closely to the training dataset instead.
  - Due to unrepresentative or insufficient data samples not reflecting all possible input data values.
- Underfitting – cannot capture the underlying pattern in the data; i.e. only performs well on training data, but performs poorly on testing data

NEURAL NETWORK



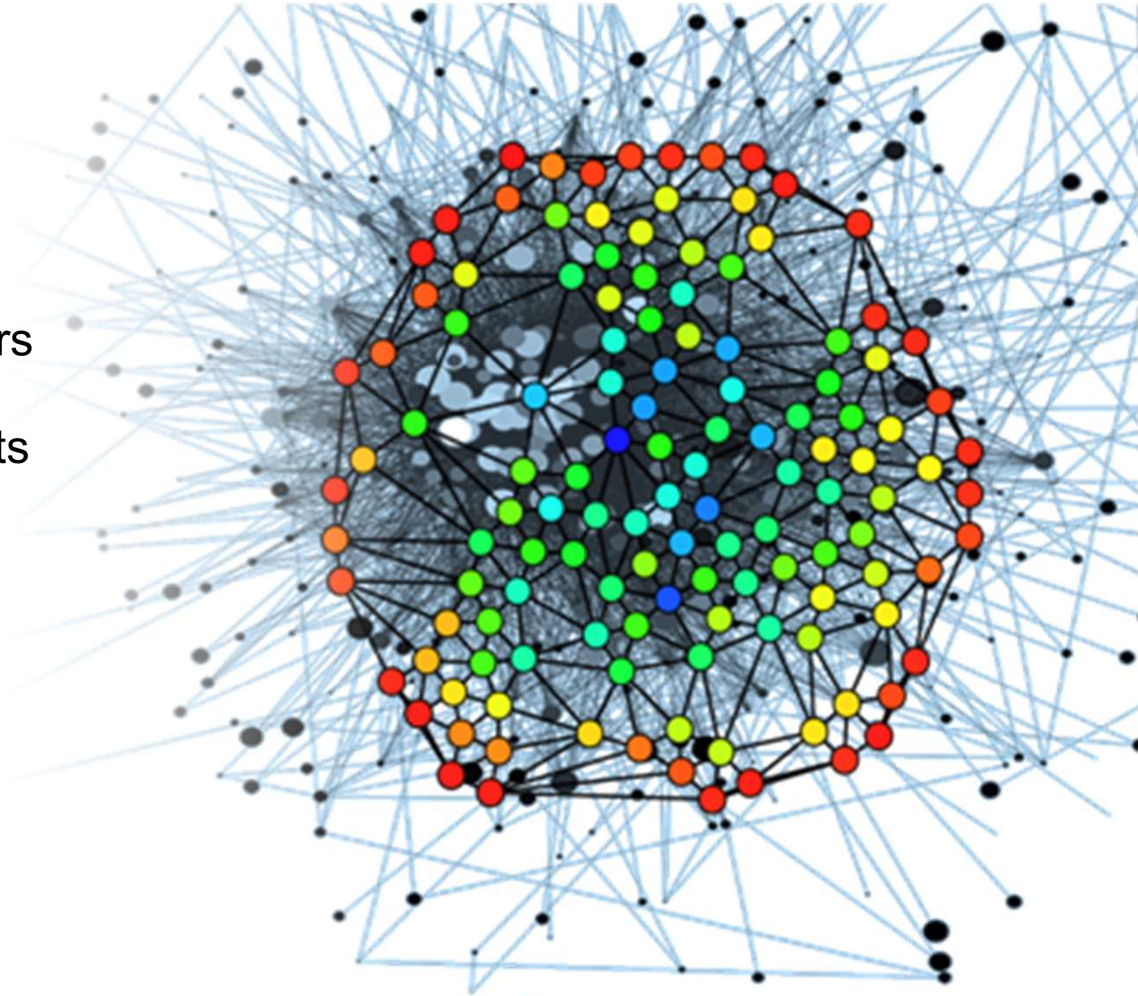
CONVOLUTIONAL NEURAL NETWORK

DL algorithm – successfully captures spatial dependencies in an image by applying relevant filters



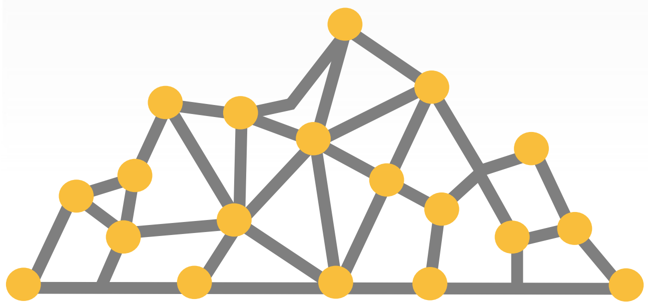
DL – RESOURCE MODELLING

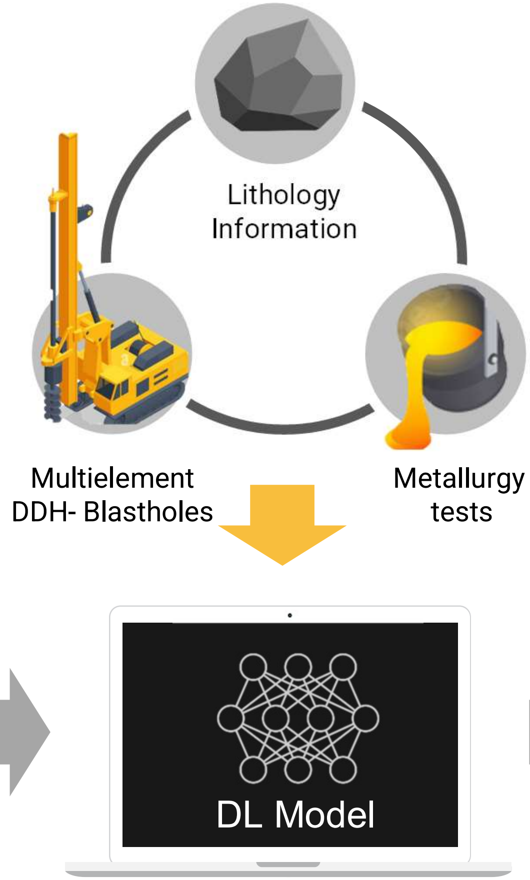
- High density assay data; e.g. exploration drillholes, grade control holes and blastholes
- Identify best model; train 30 – 150 models
- Trained using 2x A6000 GPUs for 90 – 150hrs
- 100 – 150 iterations (epochs); entire data sets
- Data pre-processing; 96 vCPU cores with 128GB RAM
- Statistical Inference – process used for each trained model to predict grade of each block of block model; e.g. ~2.5hrs, 10^6 blocks



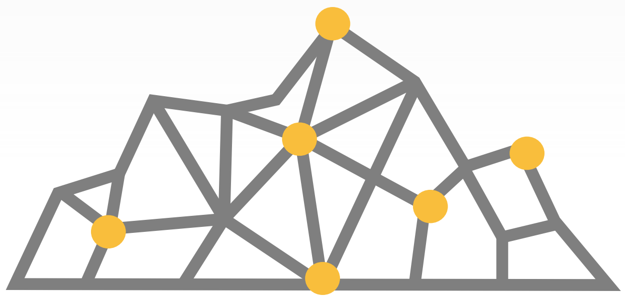
DL ANSWERS MINERAL RESOURCE QUESTIONS?

LEARN FROM **HIGH DENSITY** MULTIVARIATE GEOSTATISTICAL DATA...





...TO MODEL MULTIVARIATE DATA IN A **LOWER DENSITY** ENVIRONMENT



WHAT DATA DOES DL LEVERAGE?

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Models uses DL technology to learn complex geological patterns
Allows models to predict with higher accuracy grade of any given point

MULTI-CHANNEL DATA	OTHER STRUCTURED DATA	UNSTRUCTURED DATA
Model can train directly on multivariate data sets Learning which channels are relevant Finding useful correlations	DL models can also input other structured data sets	Integrate expert insights and client requirements Training and predicting process – hard and soft controls
MULTI-ELEMENT ASSAYS	**CORE LOGGING; CORE SCANNING, TERRASPEC & XRD**	**GEOLOGY; GEOMETALLURGY; ECONOMICS**

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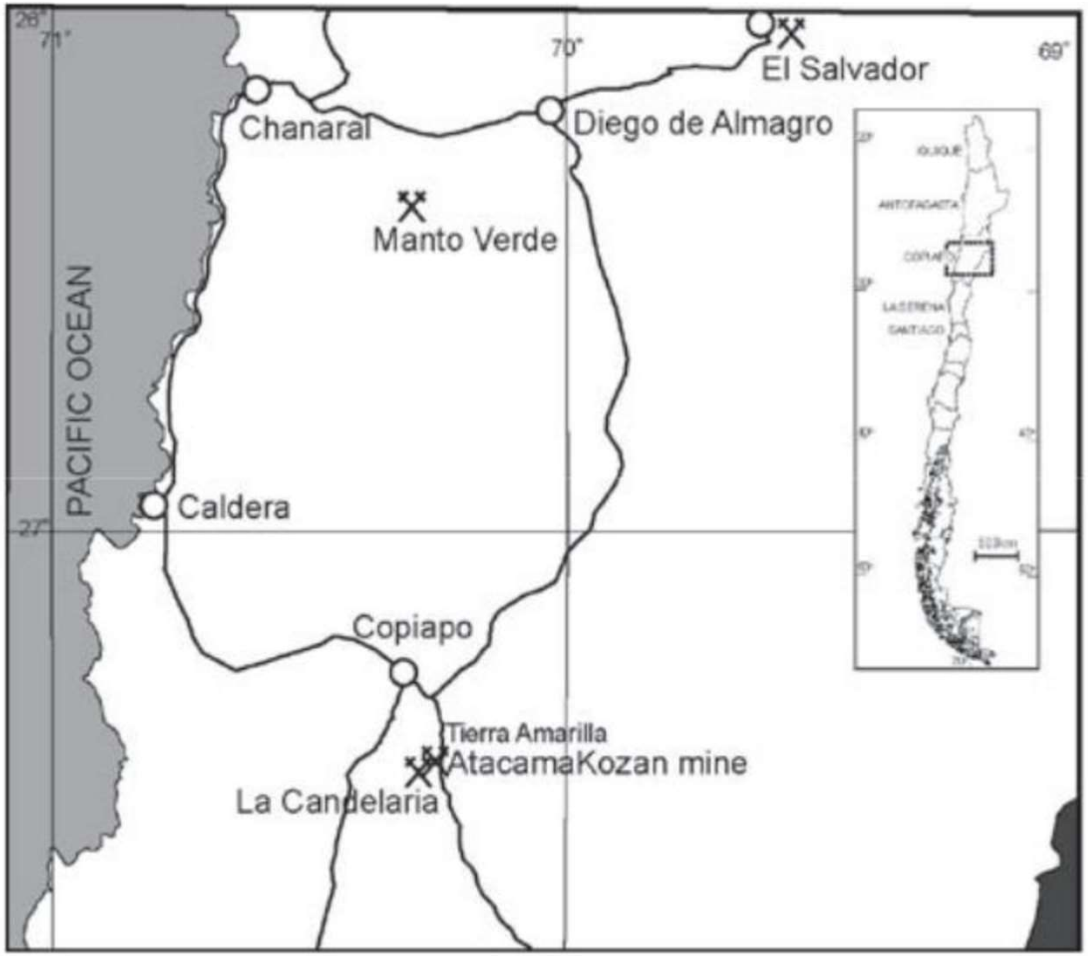
ML/DL PILOT STUDY IOCG

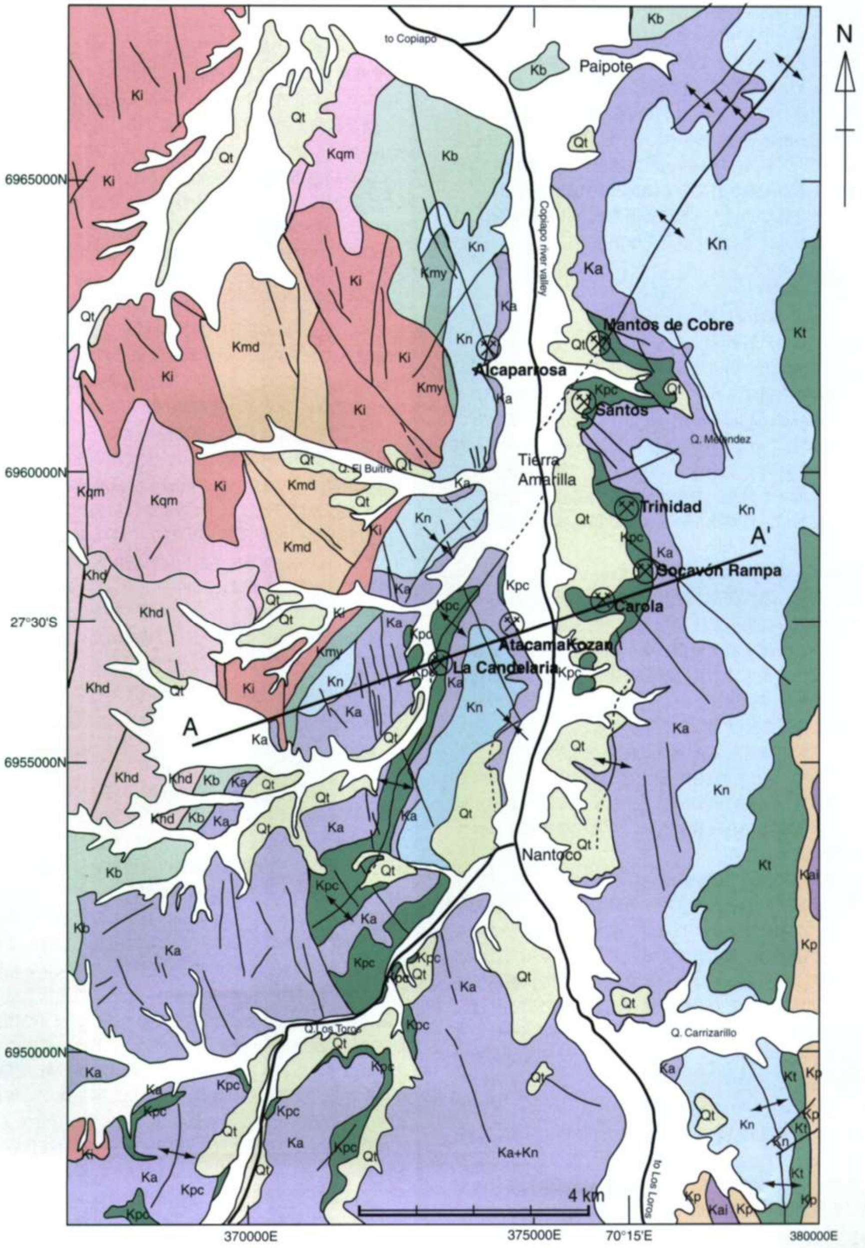
MANTO CU-AU MINE

REGION III, CHILE

MANTO – TYPE IOCG MINE
CANDELARIA DISTRICT

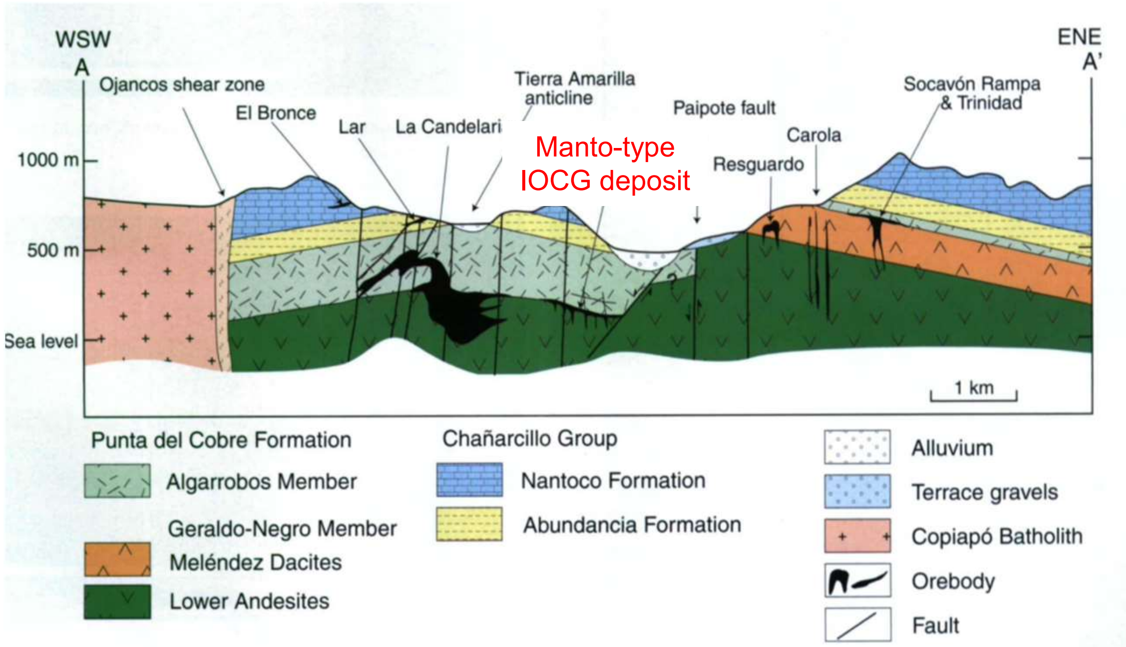
- Region III, northern Chile
- 16 km SSE of Copiapo
- Near **Atacama Fault Zone**
- Central Andean Coastal Cordillera and Chilean Iron Belt.
- Elevation ~500m
- Underground mine
- Ore body approx. **400m** below surface
- Primary ore crushers underground
- Conveyor (~3.5km) transport ore to surface





SIMPLIFIED GEOLOGY

- Manto-type IOCG deposit
- Near Atacama Fault Zone within the Central Andean Coastal Cordillera and the Chilean Iron Belt
- Lower Cretaceous Formation; andesitic lava, lapilli tuff, tuff, shale and sandstone. Overlain by limestone interbedded with shale, sandstone and tuff



GOALS OF 2022 ML

DL PILOT STUDY

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De-risk existing model for long-term adoption by demonstrating increased modelling accuracy

Positive effect on mine planning, ore control, total reserve estimation &/or resource definition drilling

More accurately define orientation and location of manto type mineralisation than kriging

Demonstrate enhanced ability of the model to **target mineralisation**

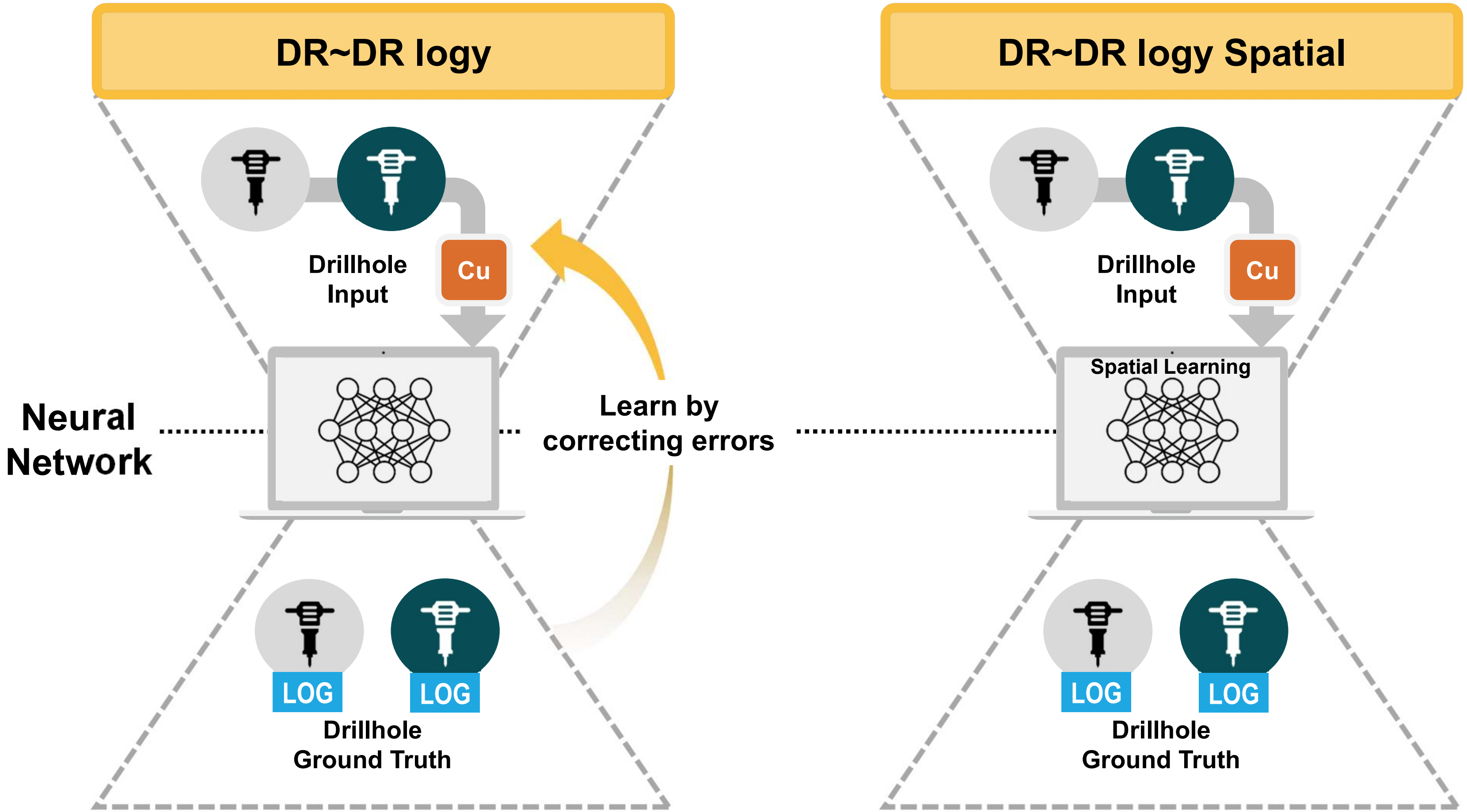
Better than current drilling practices

Kriging model challenged by highly constrained domains due to grade boundaries

Accuracy of the model based on block level metrics: **Precision and Recall**

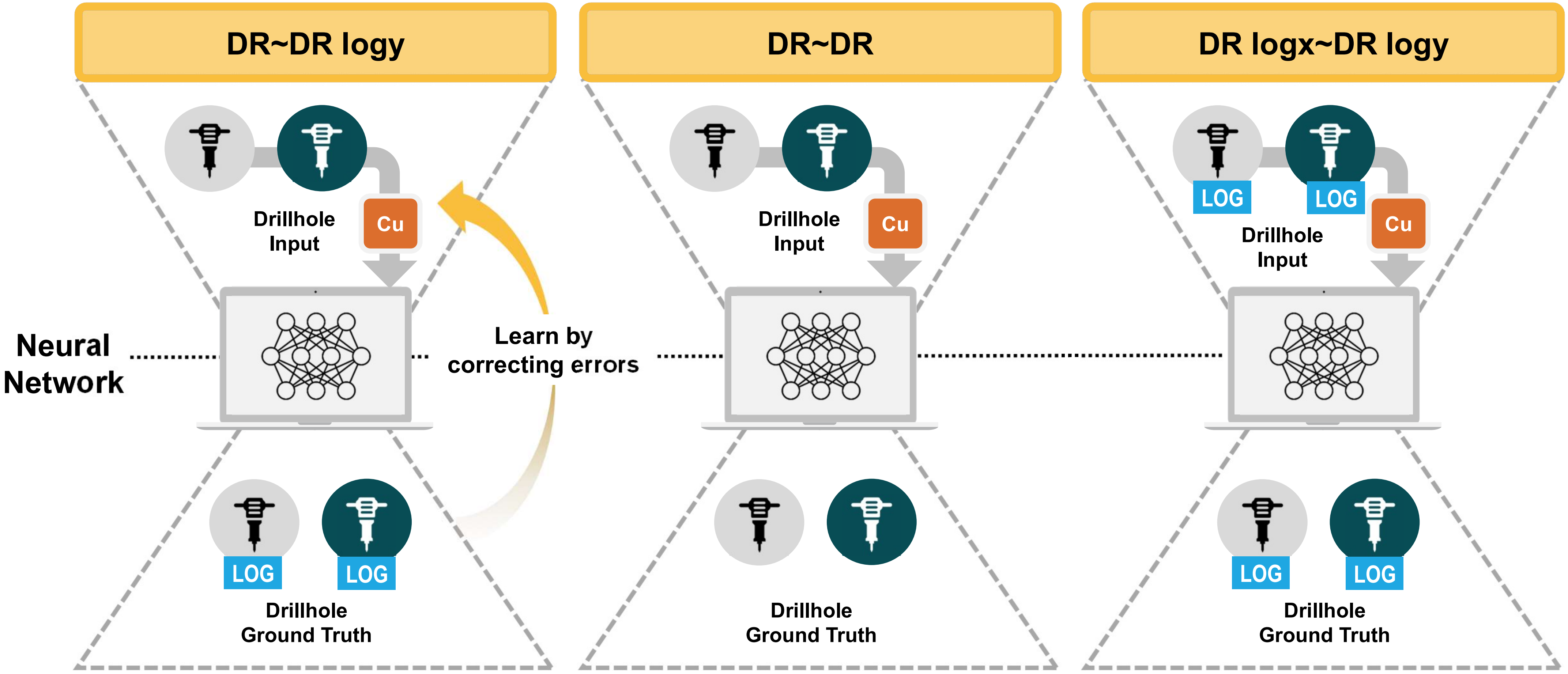
RESULTS

SPATIAL LEARNING



D – diamond drillhole; R – RC drillhole; logy – log y domain; Spatial – special sampling method in training

ALTERNATIVE DOMAIN MODELS



D – diamond drillhole; R – RC drillhole; logx – log x domain; logy – log y domain

SUPPLEMENTARY CHANNELS

ZERO-FILLED CHANNEL (ZFC):

- Unassayed core usually is designated 0% copper
- Significant room for error in visual interpretation, particularly in the ~0.1 - 0.2% Cu range if logged as barren
- Unassayed core could be weakly mineralisation
- Reduce source of error, ZFC channels indicates to the model whether a grade estimate is assayed (0) or visually barren and assumed to be 0% Cu (1)

SIMPLIFIED ROCK TYPE (ROCK):

- Use the ASSAY-cod column, convert and add as direct input to the model
- Assist with auto-domaining
  - Manto (1) set to 0
  - Breccia (2) set to 1
  - Manto + Breccia (3) set to 0.5

RESULTS

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PRECISION

% blocks predict HG and reconcile HG rock-chip data; i.e. tracks frequency of false HG occurrences; that is when a HG ore block predicted in the mine plan reconciles as waste (false positive rate)

RECALL

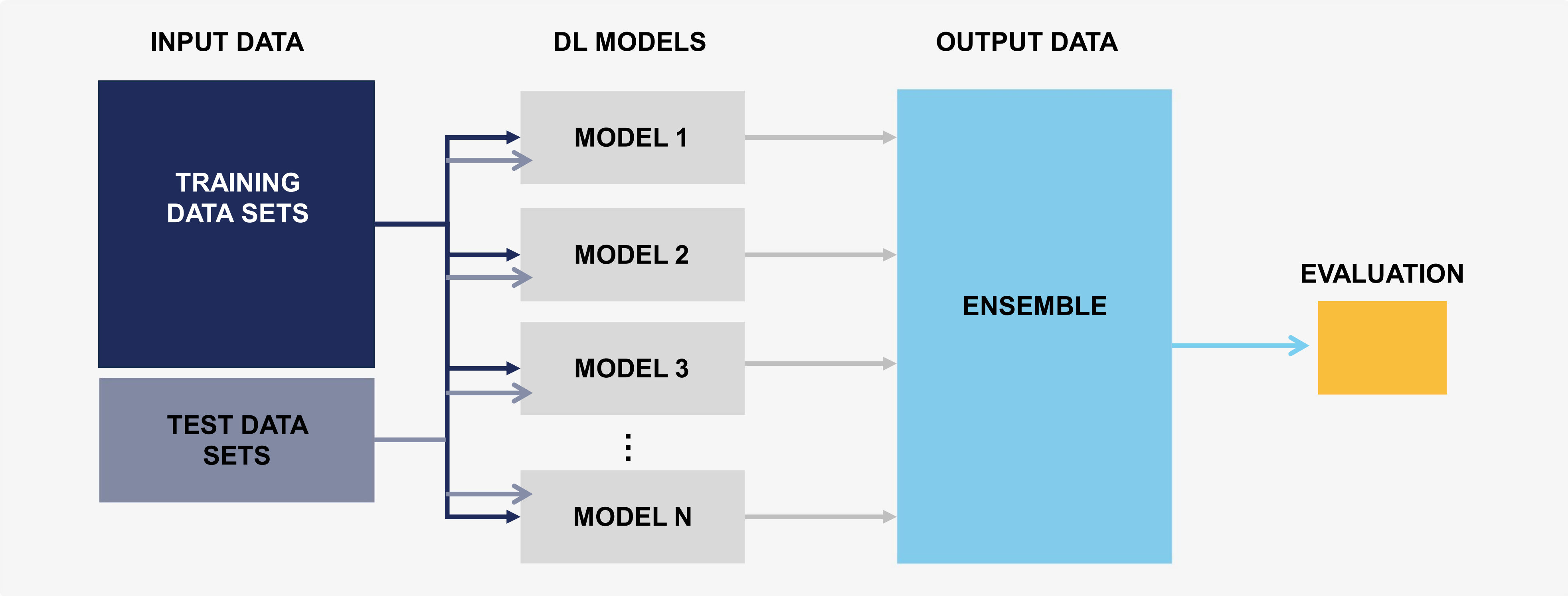
% reconciled HG predicted as HG; i.e. tracks frequency ore blocks that exist, but missed by the resource model (false negative rate)

Negative correlation between the two metrics; e.g. **Optimise Precision, depress Recall**

Balance needed to optimising operations; e.g. reserve drilling, mine planning etc

ENSEMBLING MODELS

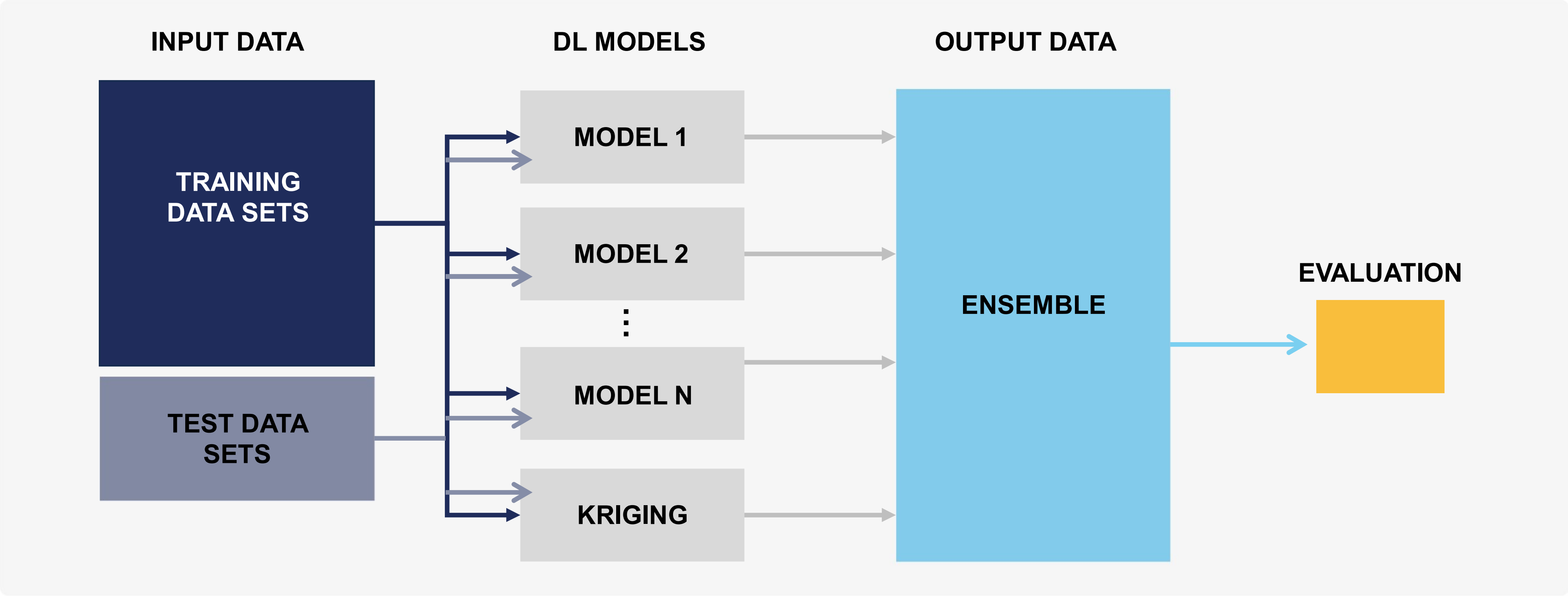
- Models created by different data sets
- Averaging out errors
- Models same or similar results –higher confidence of accuracy



ENSEMBLING HYBRID MODELS

- Kriging model included
- More accurate

- Ensemble leverages; human (kriging) and DL patterns
- Adjust weights of models to optimise
- AI or kriging – not a binary choice; a continuum



MODELS IN ENSEMBLE
NETWORK

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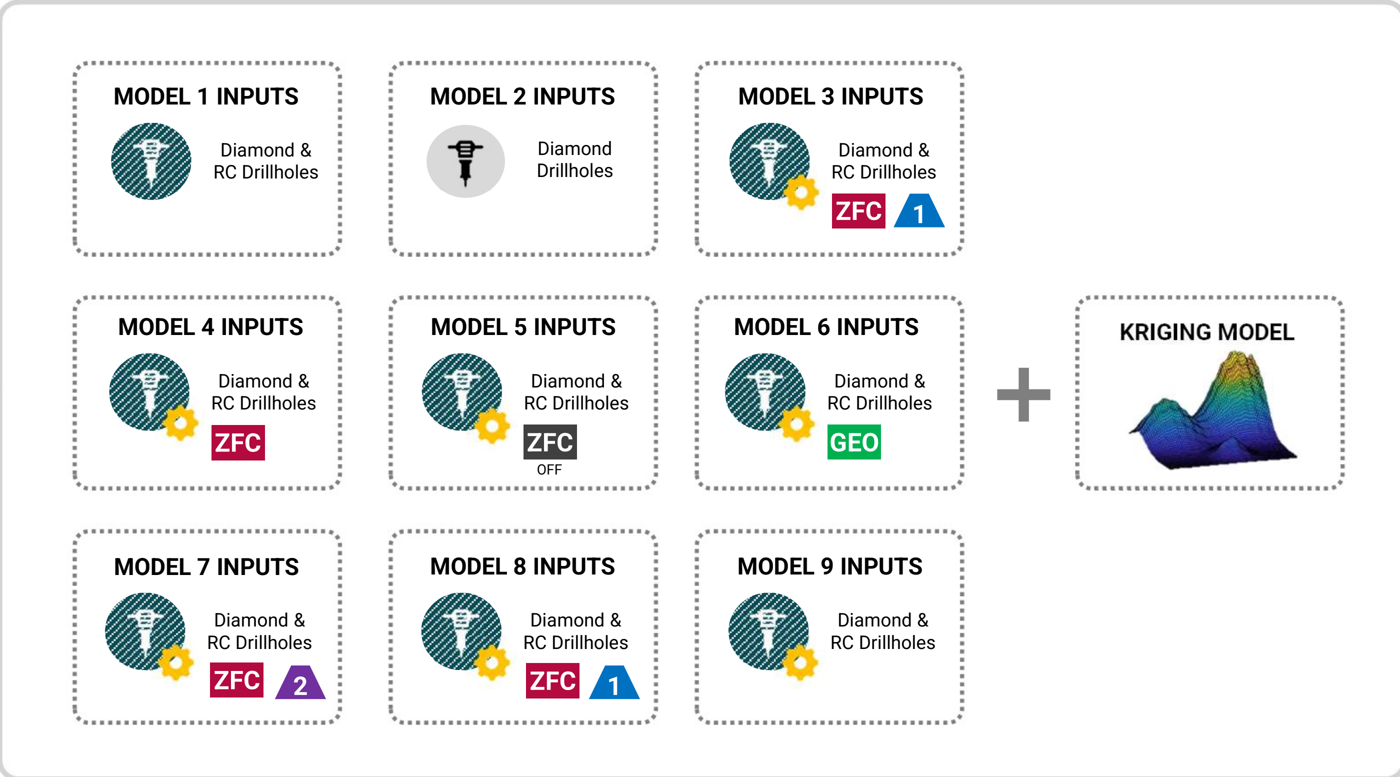
Top 9 Models + Kriging

Diverse set of 9 AI (ML/DL) models plus Kriging model



Legend:

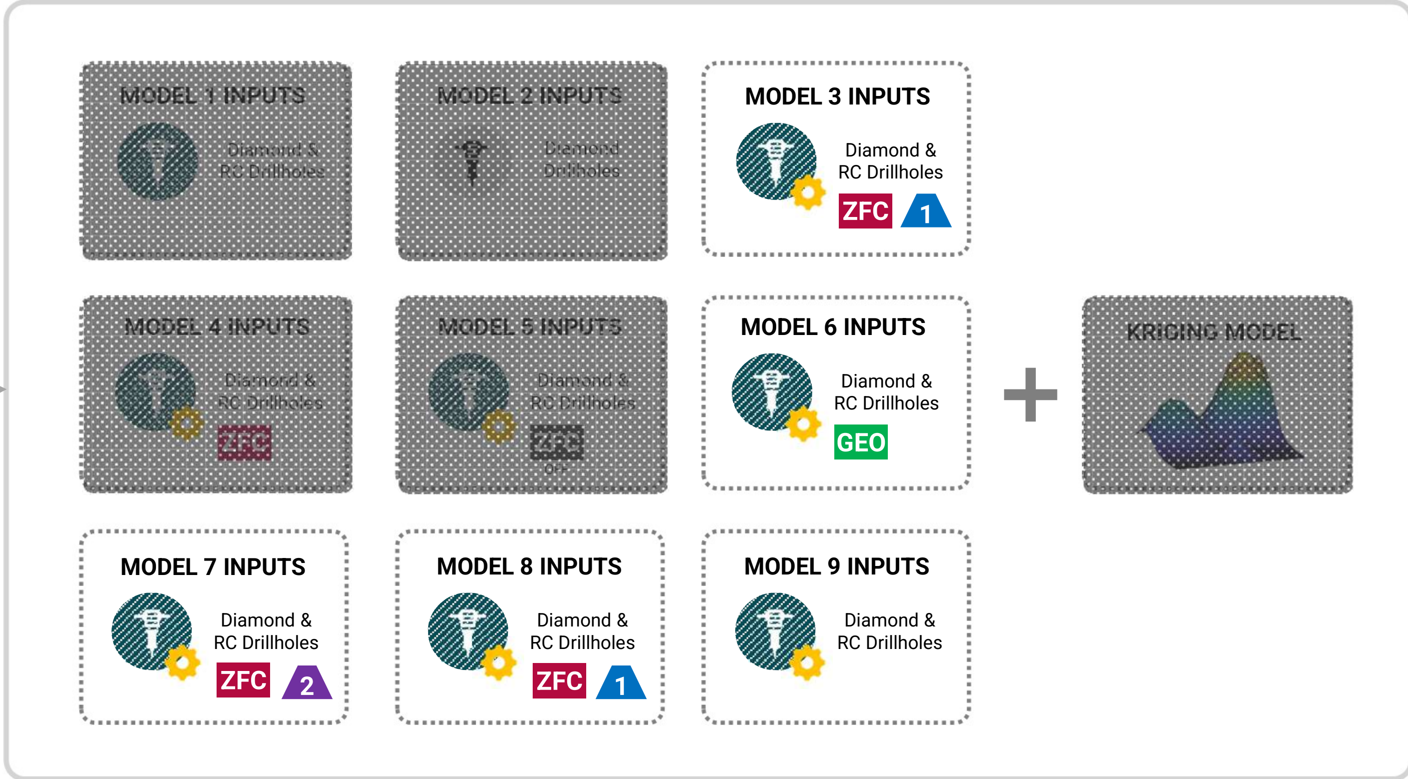
- special sampling method in training
- Additional inputs channel (ZFC or GEO= Geological info)
- Composite methods (1or 2)

MODELS IN ENSEMBLE
AI ONLY

Ensembling Method: **Averaging**

Top 9 Models + Kriging

Diverse set of 9 AI (ML/DL) models plus Kriging model



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MODELS IN ENSEMBLE
AI + KRIGING

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Ensembling Method: **Averaging**

Top 9 Models + Kriging

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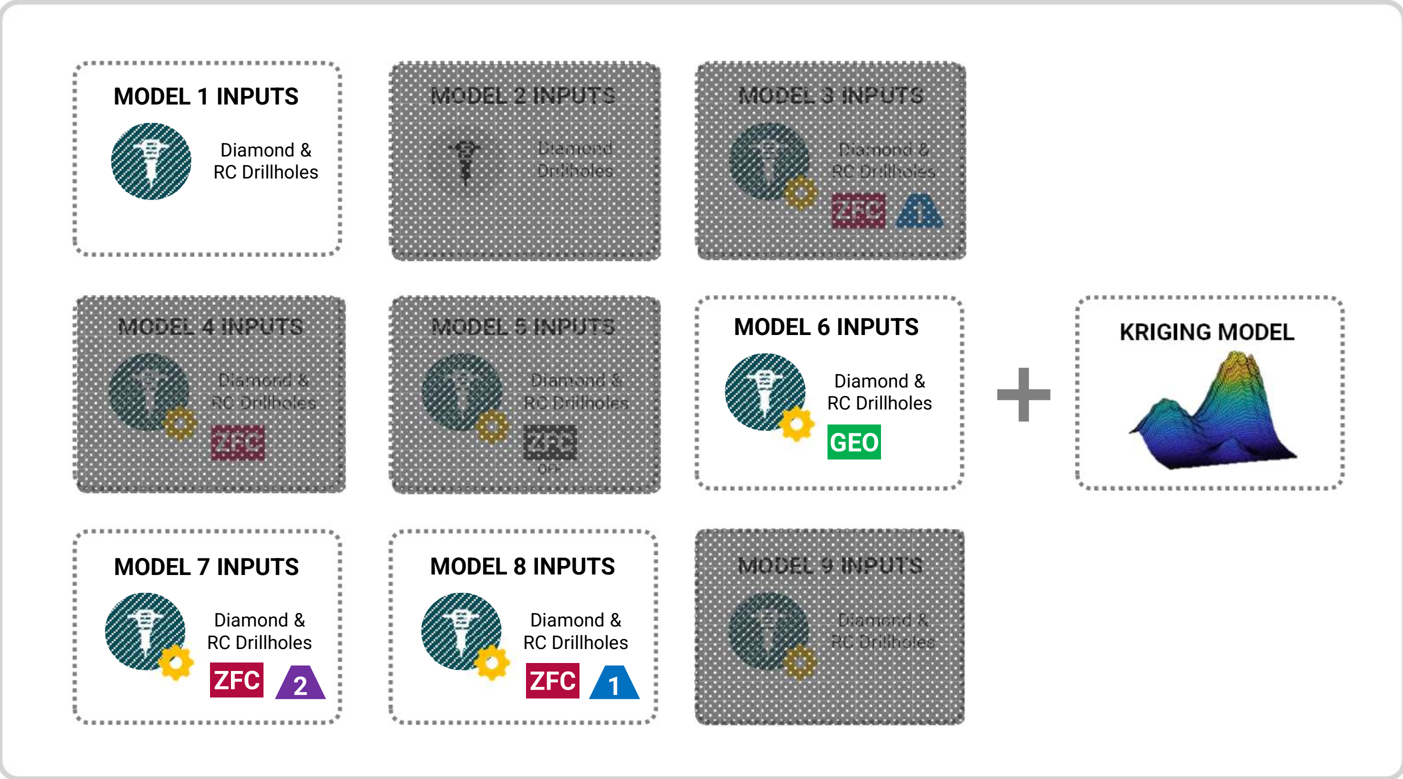

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ENSEMBLING MODELS
RECONCILIATION DDH

- **Ensemble models over kriging:**
  - Reduced rates of false positive (i.e. maximise HG prediction)
  - Reduced rates of missed mineralisation
- **Ensemble model that includes kriging has greatest improvement**
  - Best for guidance and mid-term mine planning
  - Result of incorporating less drilled zone into the model

MODEL NAME	FALSE POSITIVE (%) (>0.5% Cu)	MISSED (%) (>0.5% Cu)
KRIGING	67.2	82.7
ENSEMBLE AI MODEL ONLY	65.9	81.1
ENSEMBLE AI MODEL + KRIGING	64.4	75.8

ENSEMBLING MODELS

RECONCILIATION RESULTS – HIGHER THRESHOLD

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- **Ensemble models over kriging (DDH):**
  - Reduced rates of false positive (i.e. maximise HG prediction)
- Best for **de-risking** major developments

- Ensemble – AI + Kriging achieves the best performance at higher sensitivity
- When the model predicts HG, it has a significantly **higher chance of being HG,** than kriging's estimate while missing equal mineralisation as kriging

MODEL NAME	FALSE POSITIVE (%) (>0.6% Cu)	MISSED (%) (>0.6% Cu)
KRIGING	67.2	82.7
ENSEMBLE AI MODEL ONLY	64.4	82.6
ENSEMBLE AI MODEL + KRIGING	61.8	82.7

ENSEMBLING MODELS

RECONCILIATION RESULTS – LOWER THRESHOLD

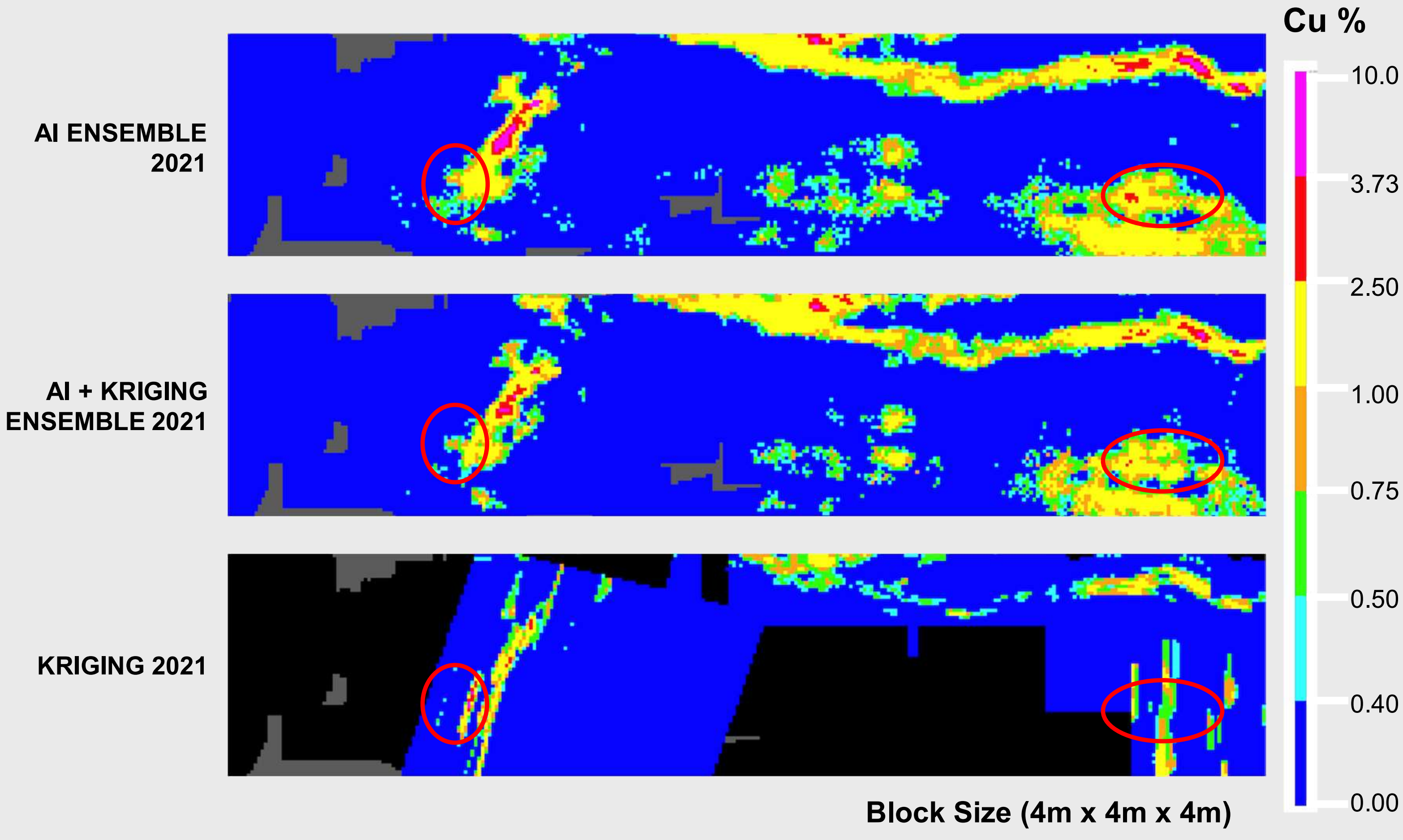
- **Ensemble models over kriging (DDH):**
  - Reduced rates of missed HG mineralisation
- Best for guided **drilling** to increase resource
- Ensemble – AI + Kriging achieves the best performance at finding missed mineralisation
- It finds significantly **more reconciled mineralisation** than kriging while having the same false positive rate

MODEL NAME	FALSE POSITIVE (%) (>0.4% Cu)	MISSED (%) (>0.4% Cu)
KRIGING	67.2	82.7
ENSEMBLE AI MODEL ONLY	67.4	79.5
ENSEMBLE AI MODEL + KRIGING	67.2	71.4

CROSS SECTION
VIEW EAST = 374043

AI and AI + Kriging Ensemble models identifies mineralisation extension of known manto structures

Missed by kriging and confirmed by recent drilling



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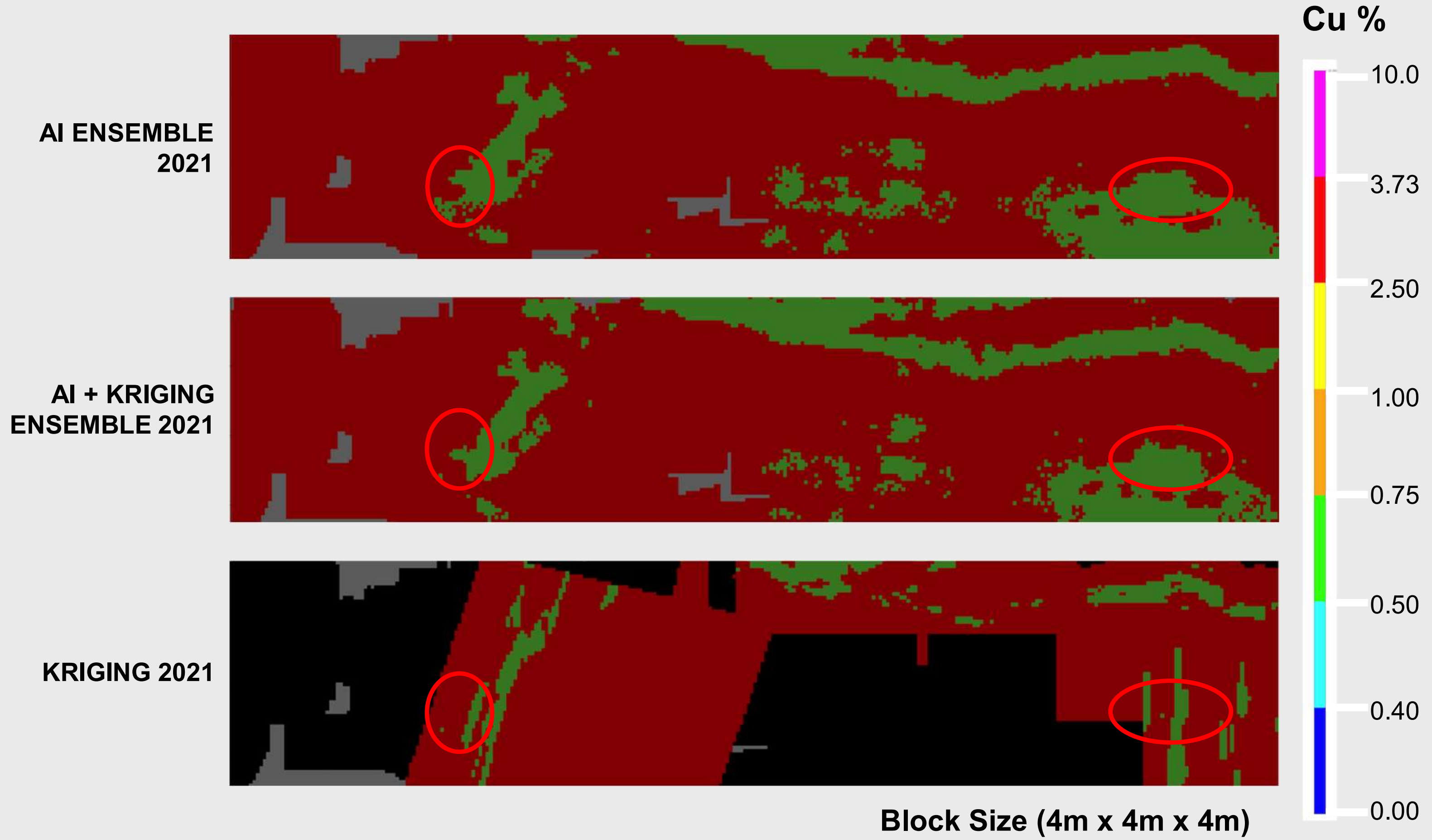
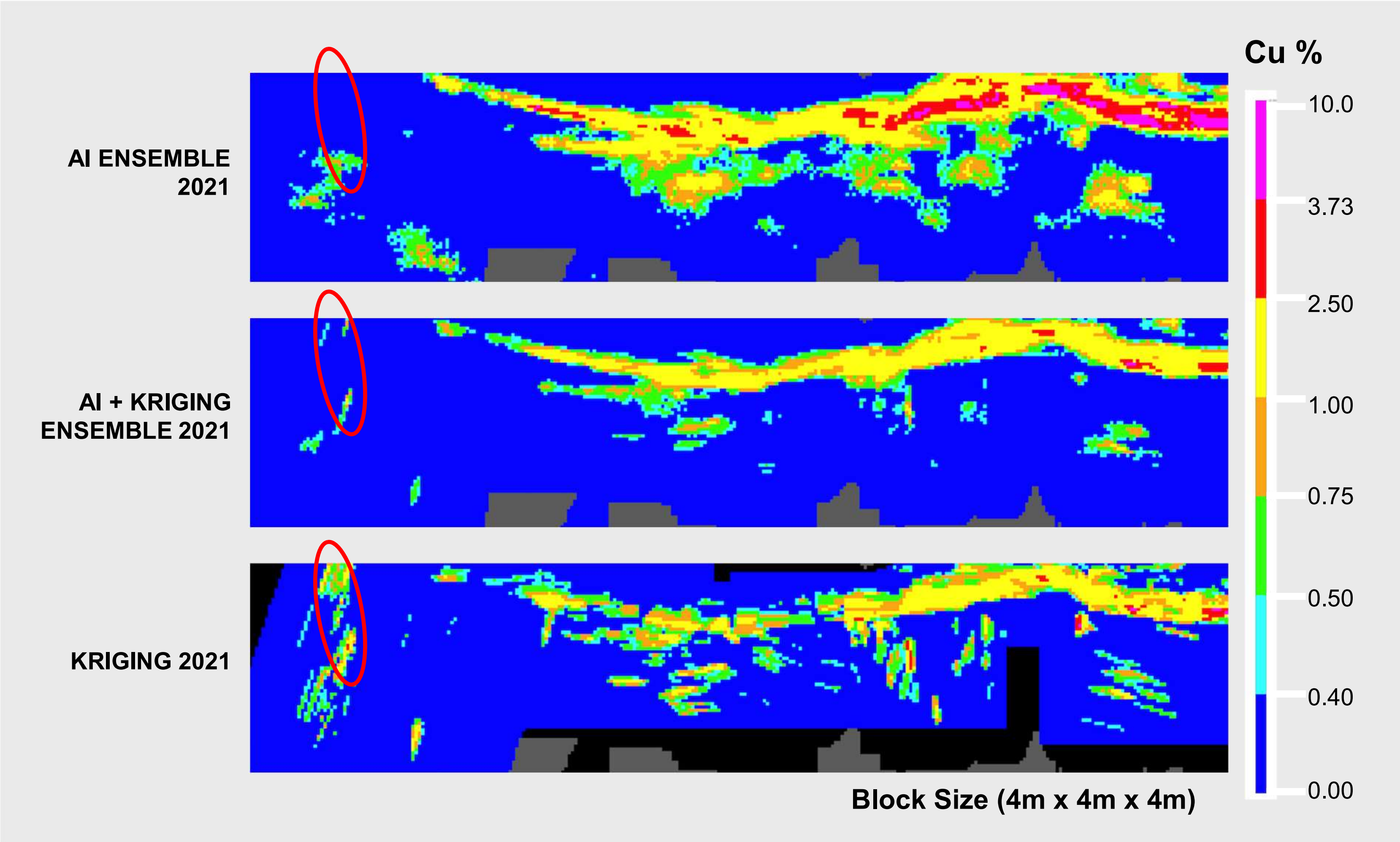


Ore	Waste

Cut-off grade 0.50% Cu

CROSS SECTION
VIEW EAST = 374379

The north zone is underpredicted by AI while Kriging correctly detects a portion of the mineralisation (geologist created domains)



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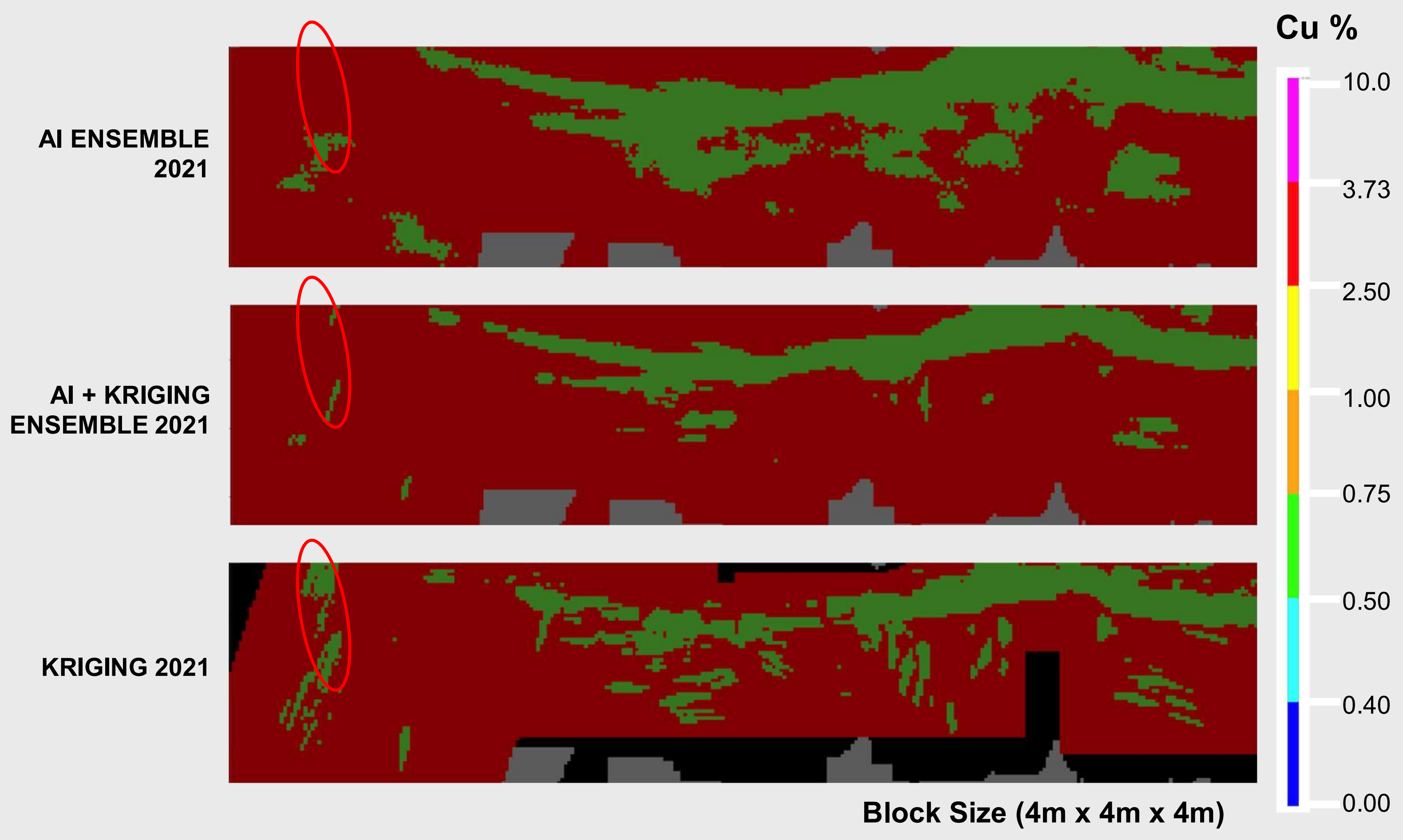


Ore	Waste

Cut-off grade 0.50% Cu

DISCUSSION

DISCUSSION

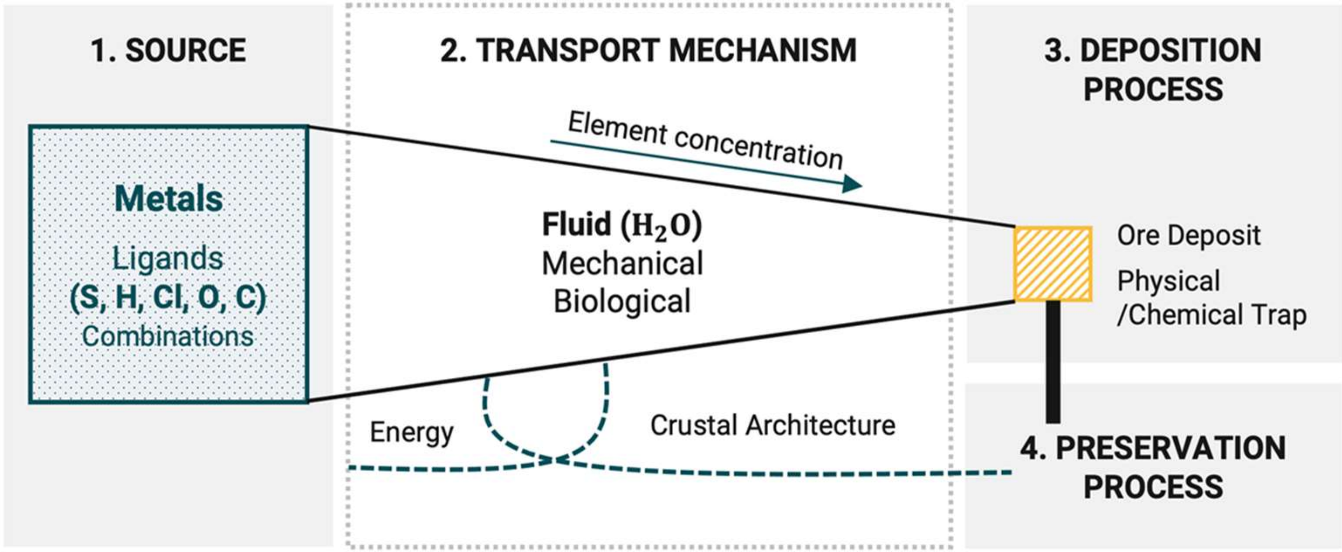
DL Patterns

- Not abstract, random or synthetic
- Not geostatistical interpolation
- DL patterns reveal overprinting geological processes
- Insight into mineral deposit genesis - OBK

MINERAL DEPOSIT GENESIS

Geological Processes – Metal Distribution

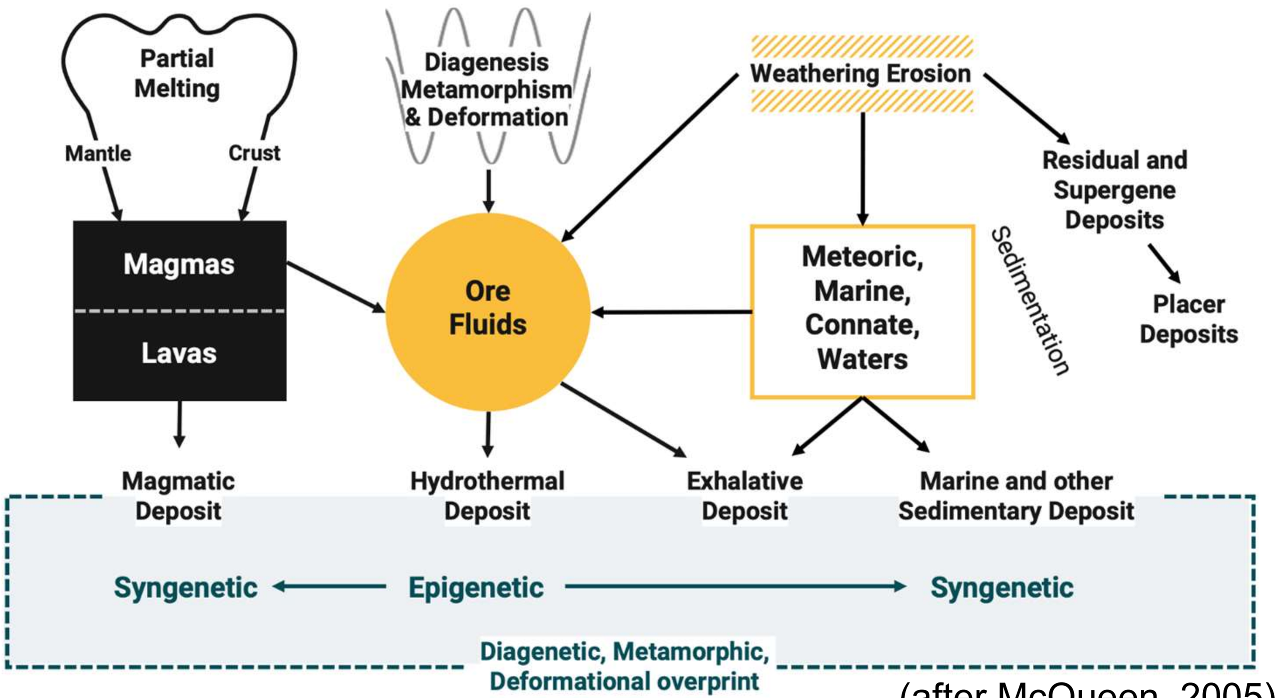
1. Source of ore metals and ligands
2. Transportation mechanisms
3. Depositional processes
   - physical / chemical traps
4. Preservation processes



(after McQueen, 2005)

ORE DEPOSIT GENESIS

- Overprinting / secondary geological processes
- Enrich &/or deplete ore deposits
- DL patterns (ore grades) geological processes



(after McQueen, 2005)

CONCLUSIONS

CONCLUSIONS

CNNs learn from historical production data

- Does not rely on pre-existing kriging domains

Ensembling (composite) **best models** – enhanced results

Ensembling with kriging – better than DL or kriging alone

DL patterns **more accurate** – if lots of historical data to learn from

- Ore categorisation, geometallurgical and geotechnical models

DL patterns due to primary and secondary geological processes

DL patterns may provide **useful insight into deposit gene**sis

DL resource modelling will improve as GPUs become more powerful

WRAP UP & CONTACTS

First, D.M., Sucholutsky, I., Mogilny D. & Yusufali F., 2023. Introducing deep learning and interpreting the patterns – a mineral deposit perspective; in Proceeding Mineral Resource Estimation Conference 2023, Publication Series No 2/2023 pp 2-14, (The Australasian Institute of Mining & Metallurgy)

www.stratum.ai

STRATUM AI

DAVID FIRST PRESENTING
Chief Geologist
david@stratum.ai

DANIEL MOGILNY ATTENDING
Co-founder
daniel@stratum.ai

ILIA SUCHOLUTSKY
VP Research Geologist
ilia@stratum.ai

FARZI YUSUFALI
Co-founder
farzi@stratum.ai

amira

STRATUM AI