



MINERAL RESOURCE ESTIMATION CONFERENCE 2023





Introducing Deep Learning & Interpreting the Patterns: A Mineral Deposit Perspective

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Machine Learning (ML):



Core Concept

Artificial Intelligence (AI)

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

Machine Learning (ML)

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

Algorithms

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

Algorithms

Neural Network (NN)



Artificial Intelligence (AI) in the Mining Sector

Automated Machinery



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

Predictive Maintenance



Predictive maintenance on machinery & equipment to minimise downtime

AI Geology Insights



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

ML Introduction

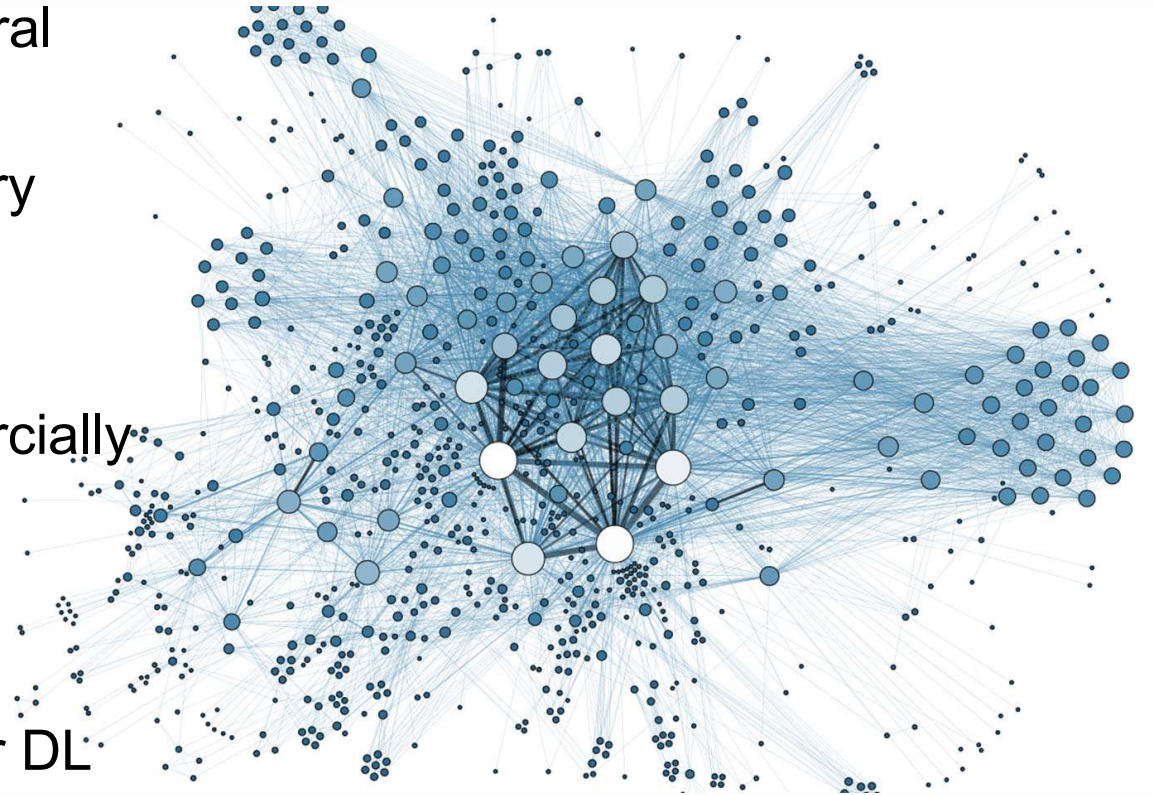
- ML algorithms learn from historical data; better forecast future patterns &/or trends
- ML is best suited to environment with lots of data and complex patterns
- ML is powerful tool revealing complex patterns in data easily missed by human eye and traditional statistics
- Learn to map between input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





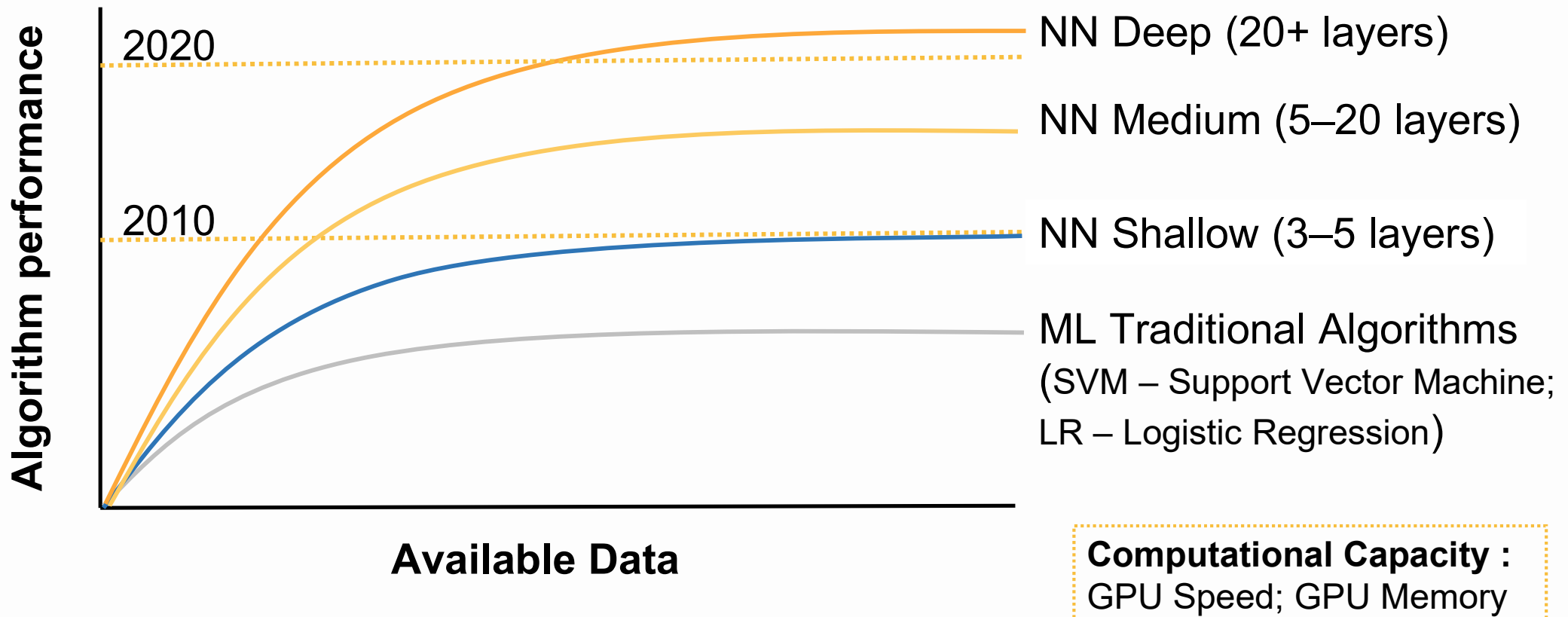
Deep Learning (DL) – Introduction

- Powerful ML algorithms; multiple neural network layers – artificial neurons
- Image recognition: eg 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



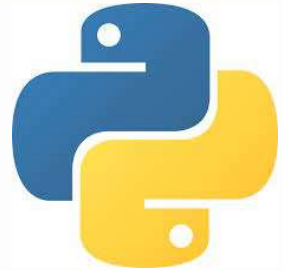


Data vs Performance

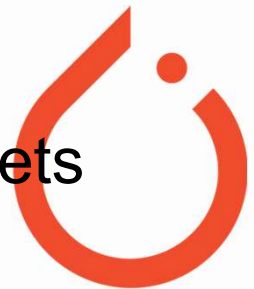




Why Python?



- ML & 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 – ML library (open-source); interfacing with neural nets
- CUDA – Library for interfacing with state-of-the-art GPUs



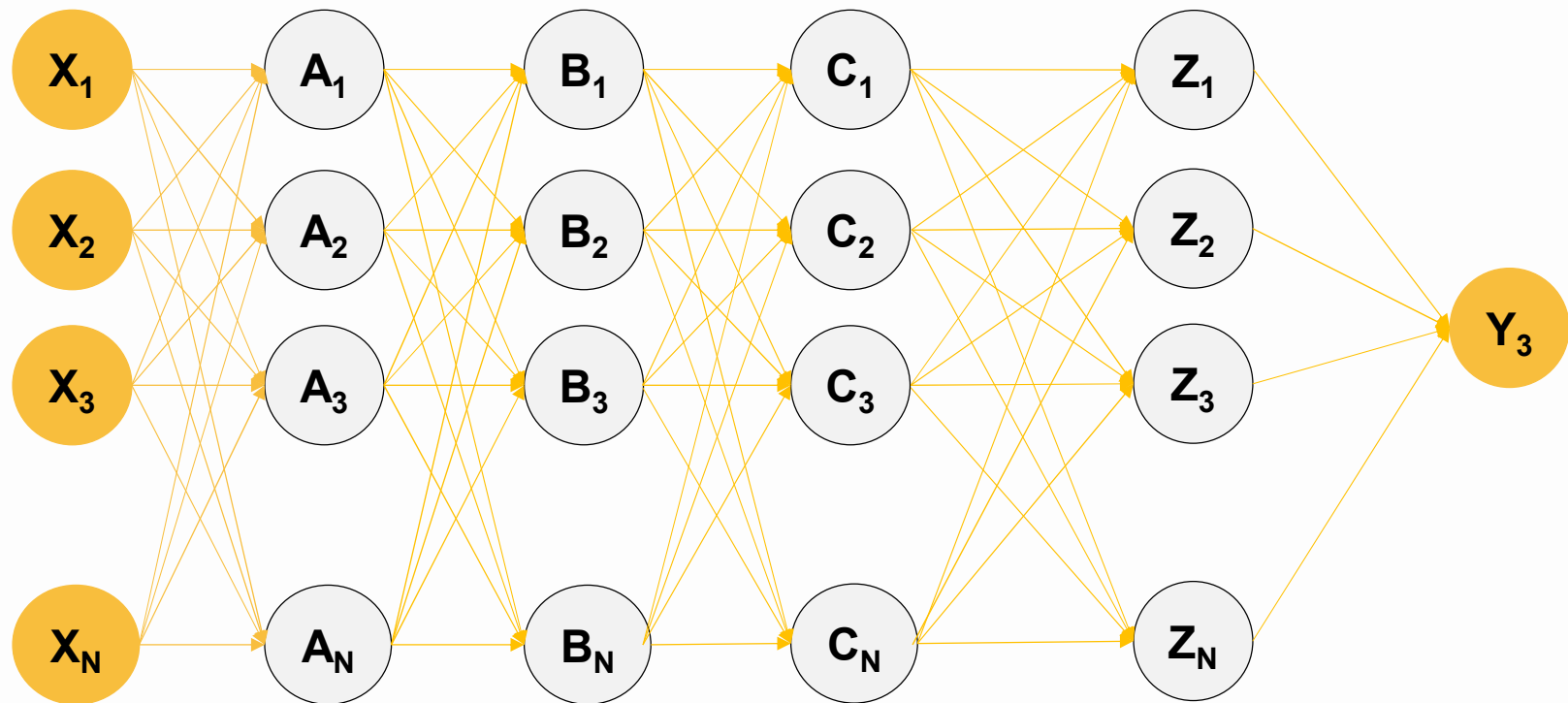


Neural Network

Input Layer

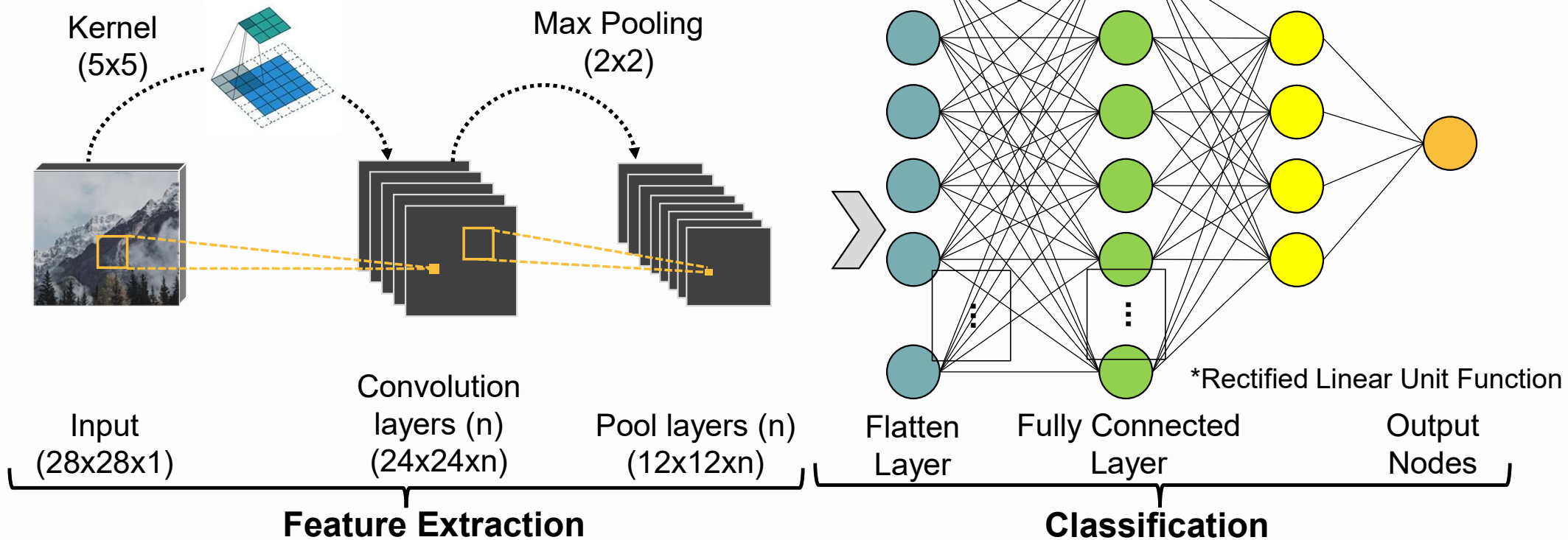
Intermediate (Hidden) Layers

Output Layer



Convolutional Neural Network (CNN)

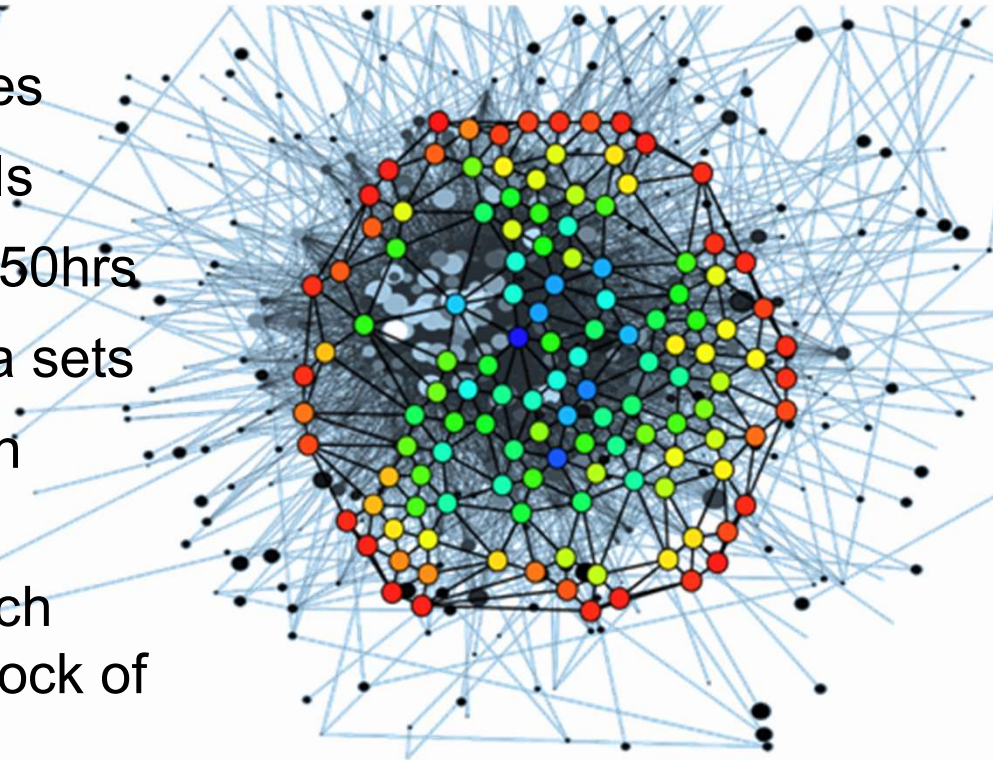
DL algorithm – successfully captures spatial dependencies in an image by applying relevant filters





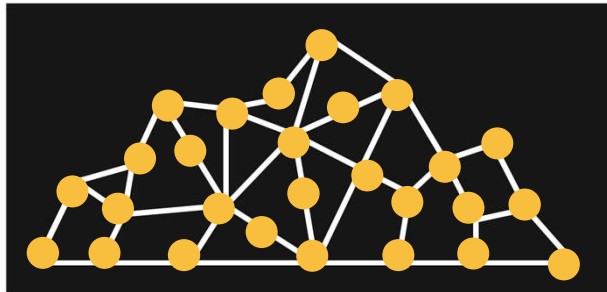
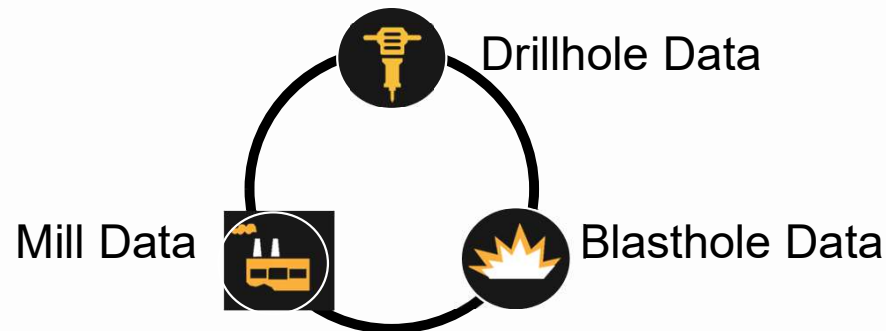
DL – Resource Modelling

- High density assay data; eg exploration drillholes, grade control holes & 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
- Statistic Inference – process used for each trained model to predict grade of each block of block model: ie ~2.5hrs, 10^6 blocks

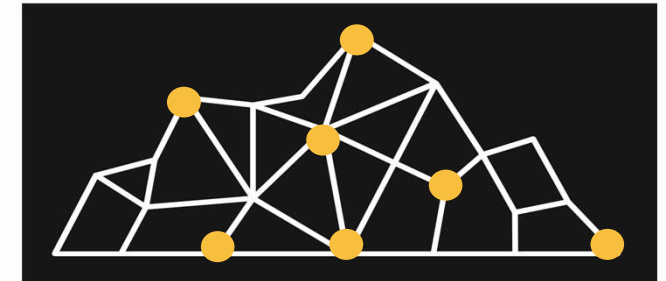
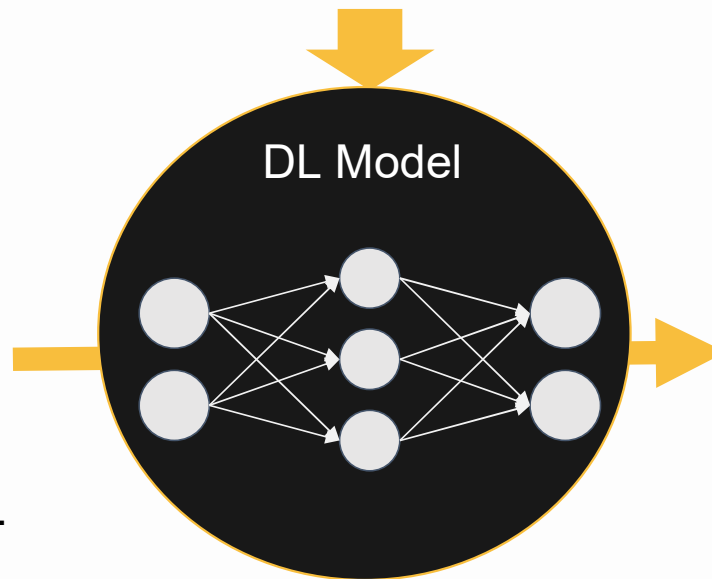




DL Answers Mineral Resource Questions?



Learn from high density
multivariate geostatistical data...



...to model multivariate data in a
lower density environment



What Data Does DL Leverage?

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

Multi-Channel Data

Model can train directly on multivariate data sets
Learning which channels are relevant
Finding useful correlations

Multi-element assays

Other Structured Data

DL models can also input other structured data sets

Core logging; Core scanning,
Terraspec & XRD

Unstructured Data

Integrate expert insights & client requirements
Training & predicting process – hard & soft controls

Geology; Geometallurgy;
Economics



Jundee Gold Mine

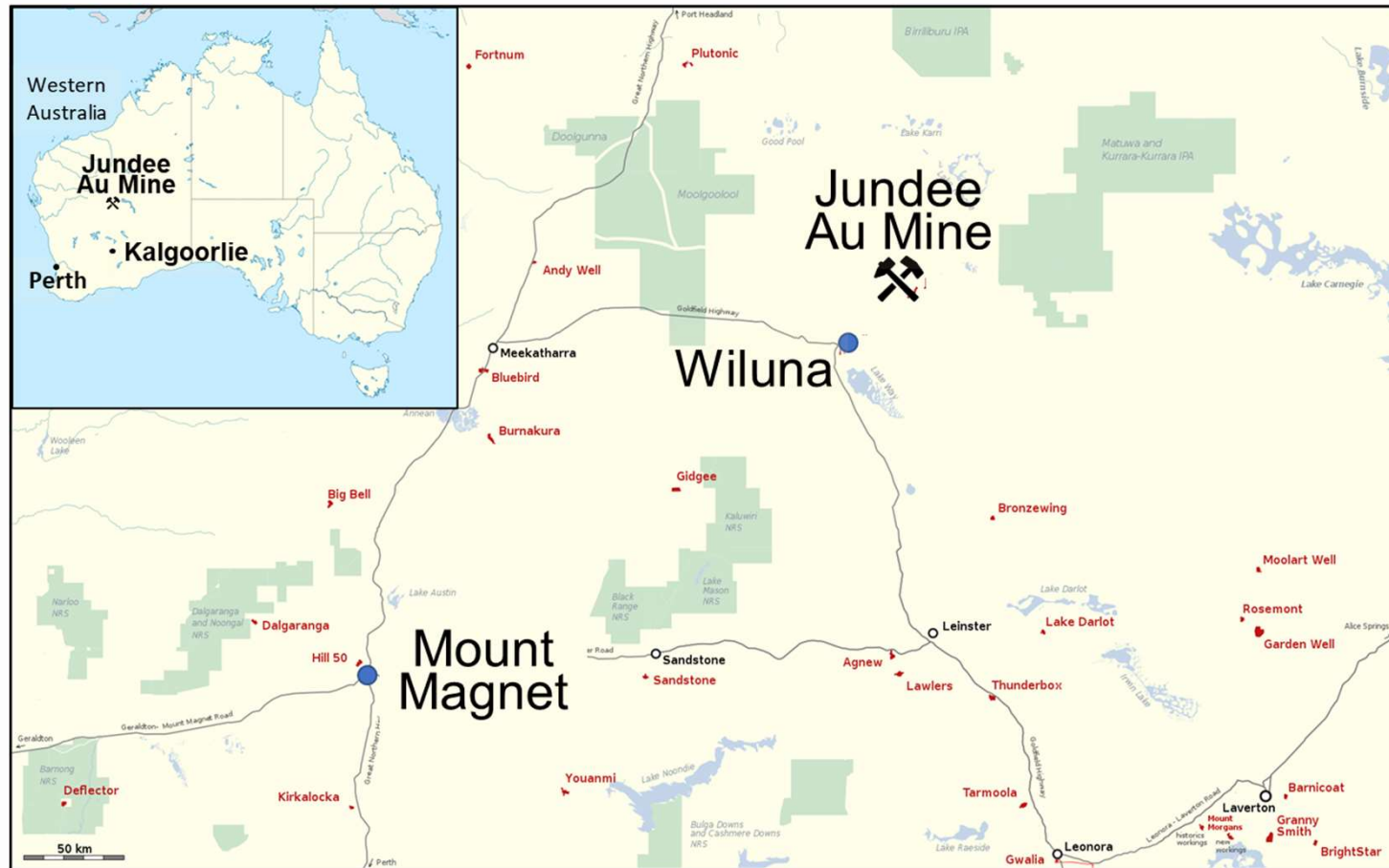


Jundee Gold Mine. Image supplied by Northern Star Resources Ltd.



Jundee – Location

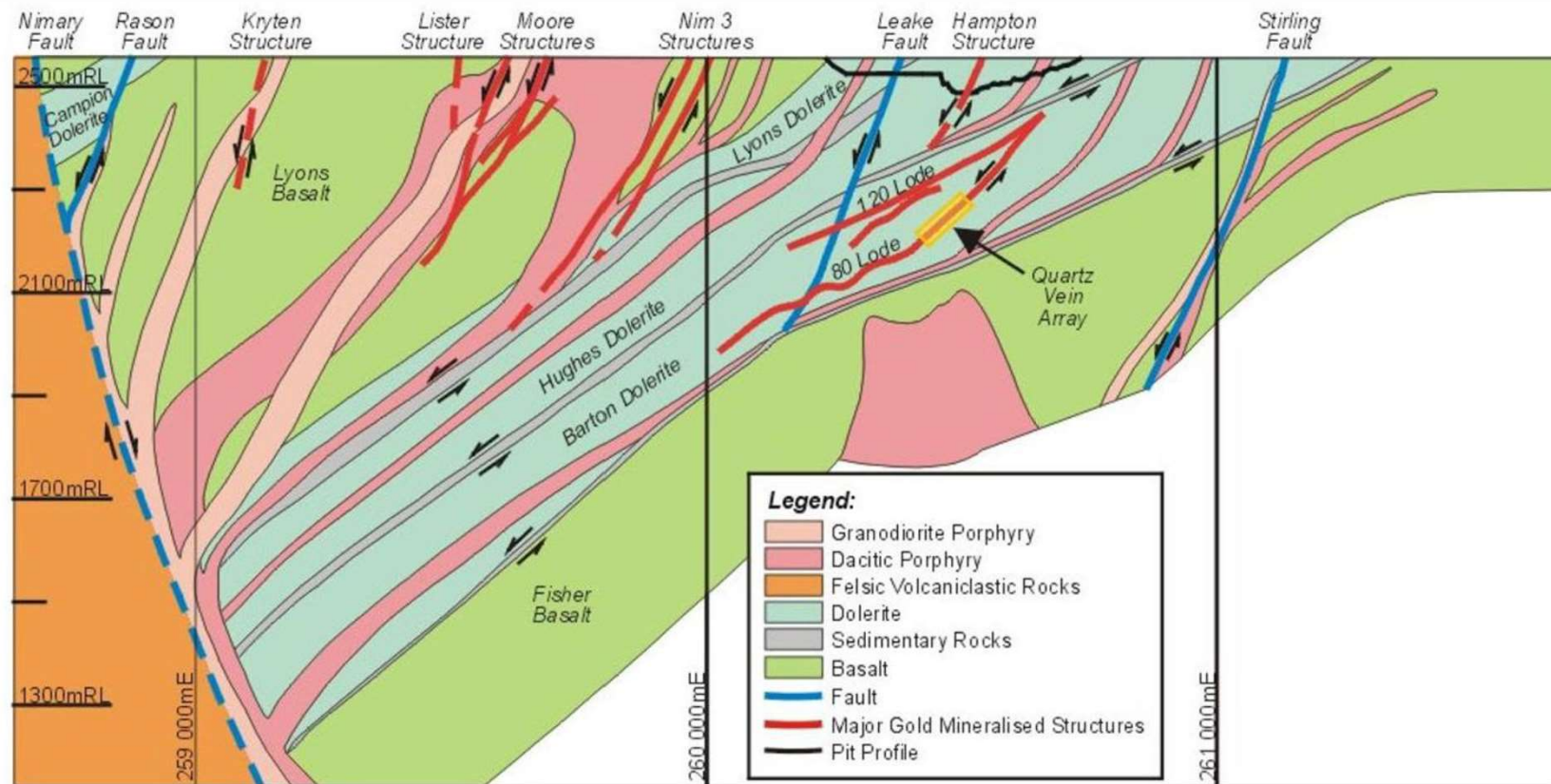
- Northern Goldfields, WA
45km NE Wiluna
- 520km N of Kalgoorlie
- 1995 OP production
- 1997 UG production
- 2014 Northern Star
acquired mine complex
- UG operation: active
- CIL include gravity circuit
- MRE ~5.4M oz Au





Simplified Geology

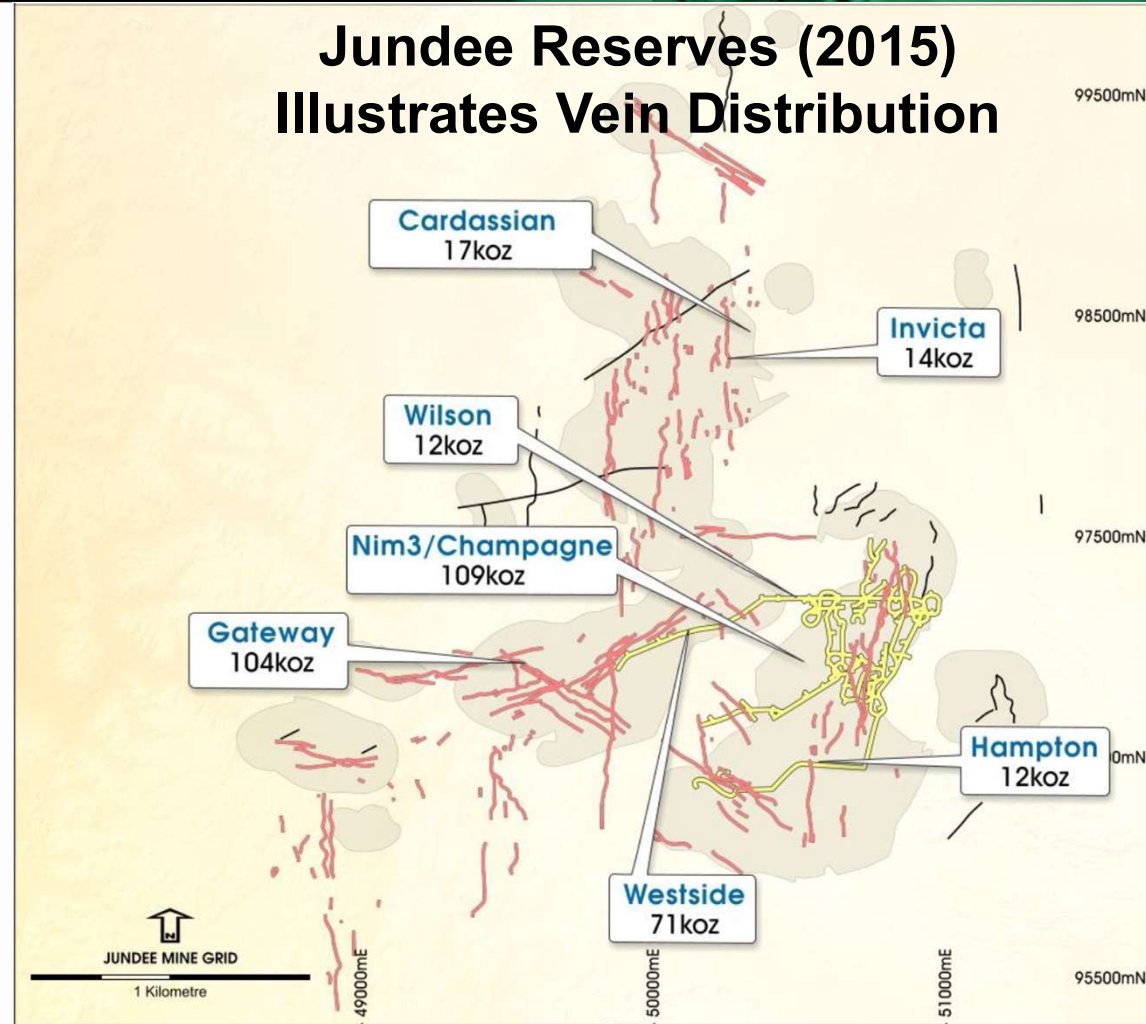
- Orogenic lode Au deposit
- Yandal greenstone
- Host rocks mafic units, intercalated with sediment; felsic volcanic
- Intruded by dacite & granodiorite porphyry
- Lamprophyres



Simplified interpreted geology section (Smit & le Roux, 2016)

Goal of 2022 ML/DL Pilot Study

- More accurately define orientation & location of narrow lode Au veins
 - 0.5 – 1m @ grades >10g/t Au
- Very tight spacing drilling
 - >500km UG & >1,200km surface drilling
- Kriging model – highly constrained domains: a challenge
- Accuracy of the model based on block level metrics: **Precision** & **Recall**

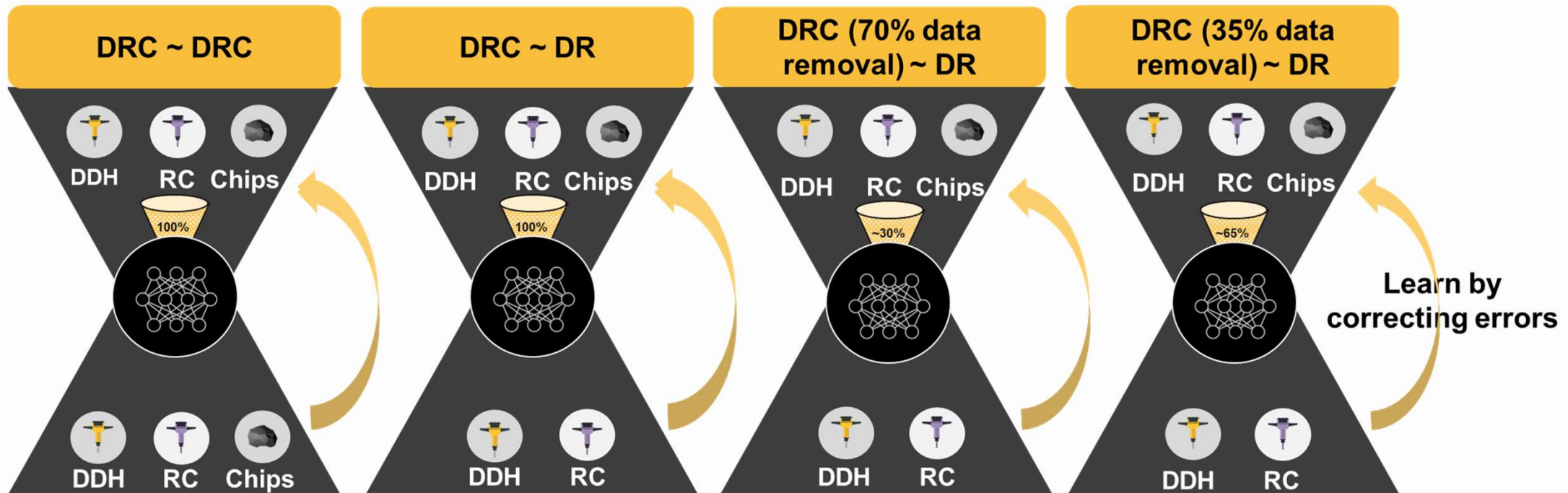




Results



Schematic Diagrams: Input ~ Output Models



D: diamond drillhole; R: RC drillhole; C: rock-chip samples; dr: % of data removal



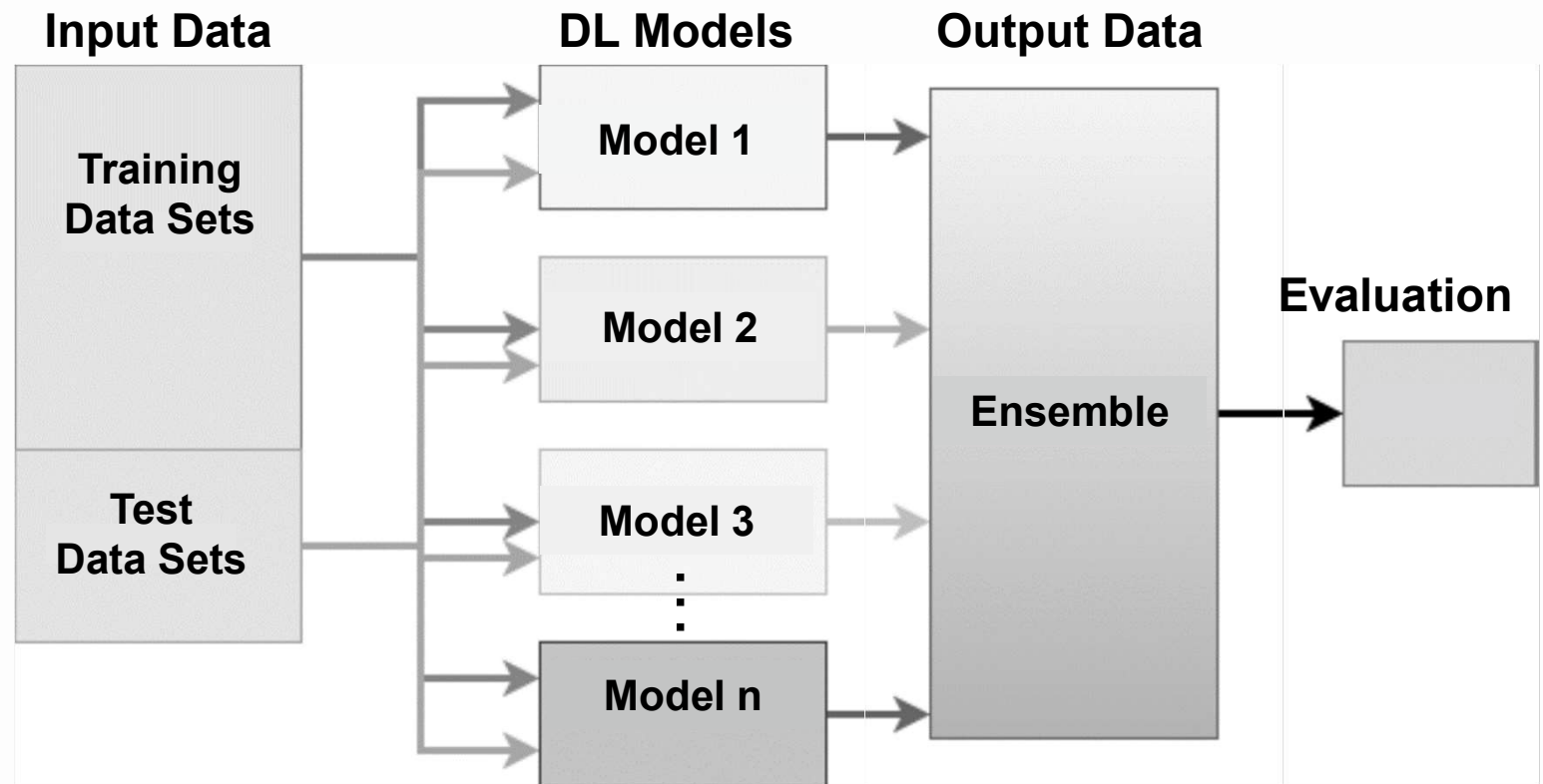
Results

- **Precision:** % blocks predict HG & reconcile HG rock-chip data: ie tracks frequency of false HG occurrences; that is when a HG block or vein predicted in the mine plan reconciles as waste (false +ve rate)
- **Recall:** % reconciled HG predicted as HG: ie tracks frequency veins that exist, but missed by the resource model (false -ve rate)
- Jundee – negative correlation between the two metrics
 - eg Optimise **Precision**, depress **Recall**
- Balance needed to optimising operations; eg reserve drilling, mine planning etc



Ensembling Models

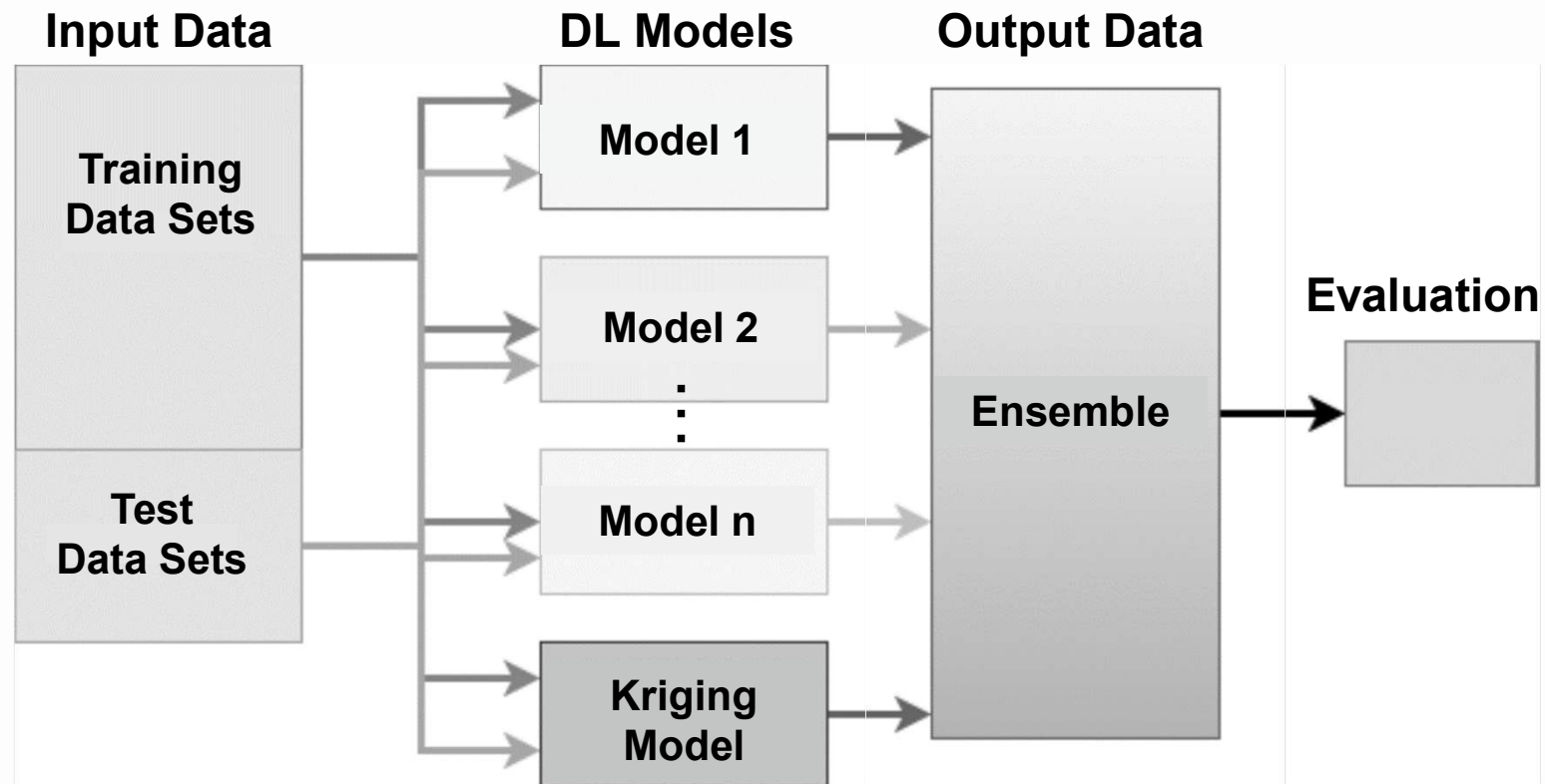
- Models created by different data sets
- Averaging out errors
- Models same or similar results – higher confidence of accuracy





Ensembling Hybrid Models

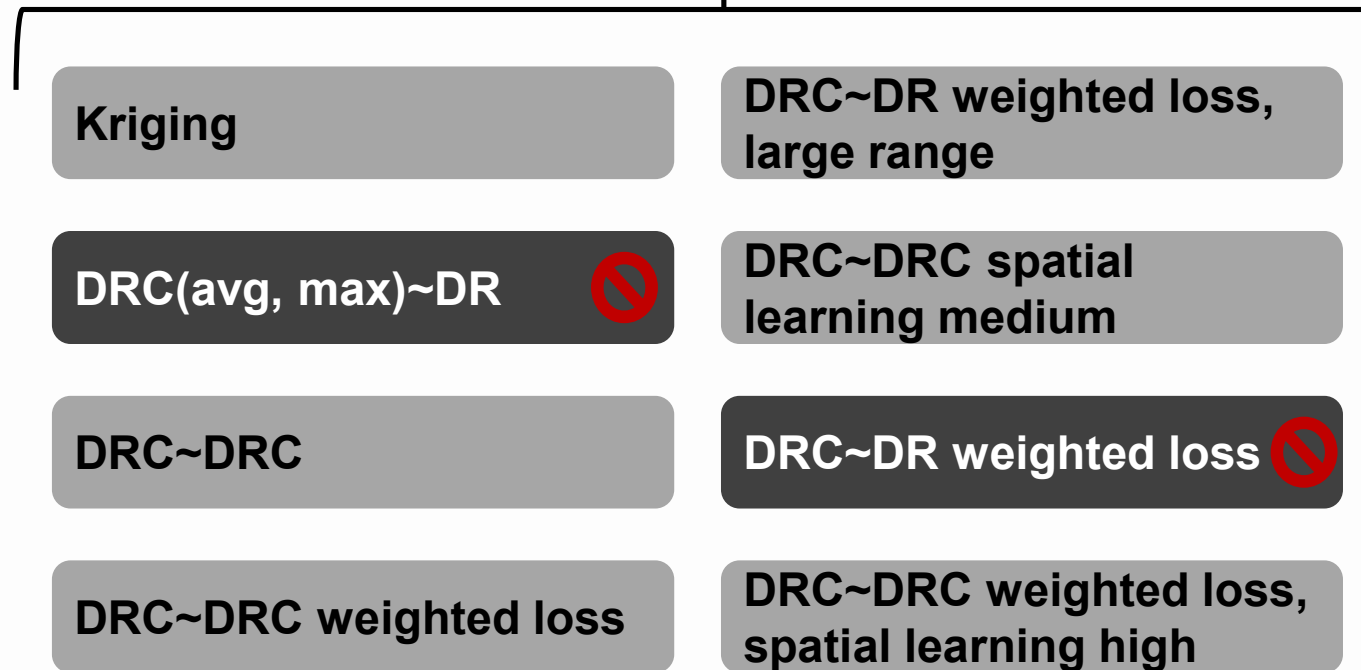
- Kriging model inc.
- More accurate
- Ensemble leverages
 - Human (kriging) & DL patterns
- Adjust weights of models to optimise
- DL or kriging – not a binary choice: a continuum



Best Precision Optimised Hybrid Ensemble

- Kriging (26.5%) to “hybrid” (34.9%)
 - ~32% rel. improvement
- Best block model
 - Combines advantages of DL + kriging
- Kriging – geological domains
- Higher confidence of HG blocks – add to mine plan

Top 8 Models

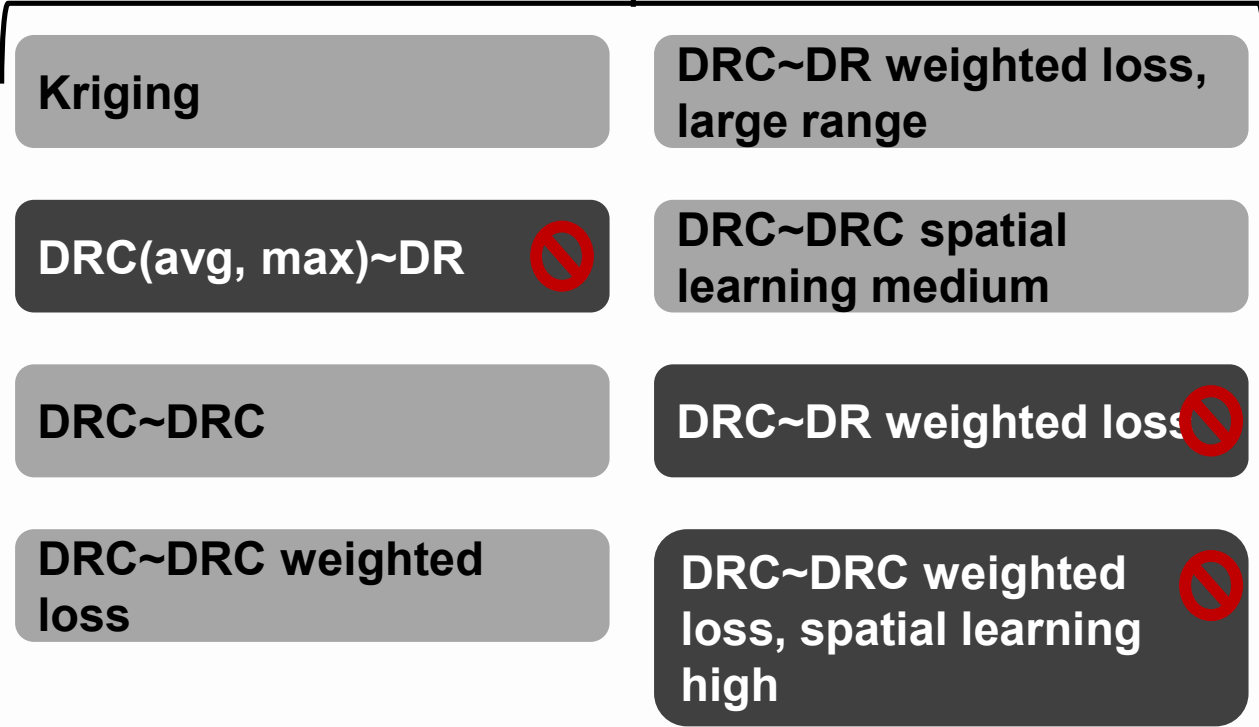




Best Recall Optimised Hybrid Ensemble

Top 10 Models

- Kriging (14.3%) to “hybrid” (26.2%)
 - ~83% relative improvement
- Ensembling include kriging
- Best block model: not dependent solely on DL patterns
- Kriging – geological domains
- Exploration guide to additional resource – targeted drilling





Ensembling / Compositing Models

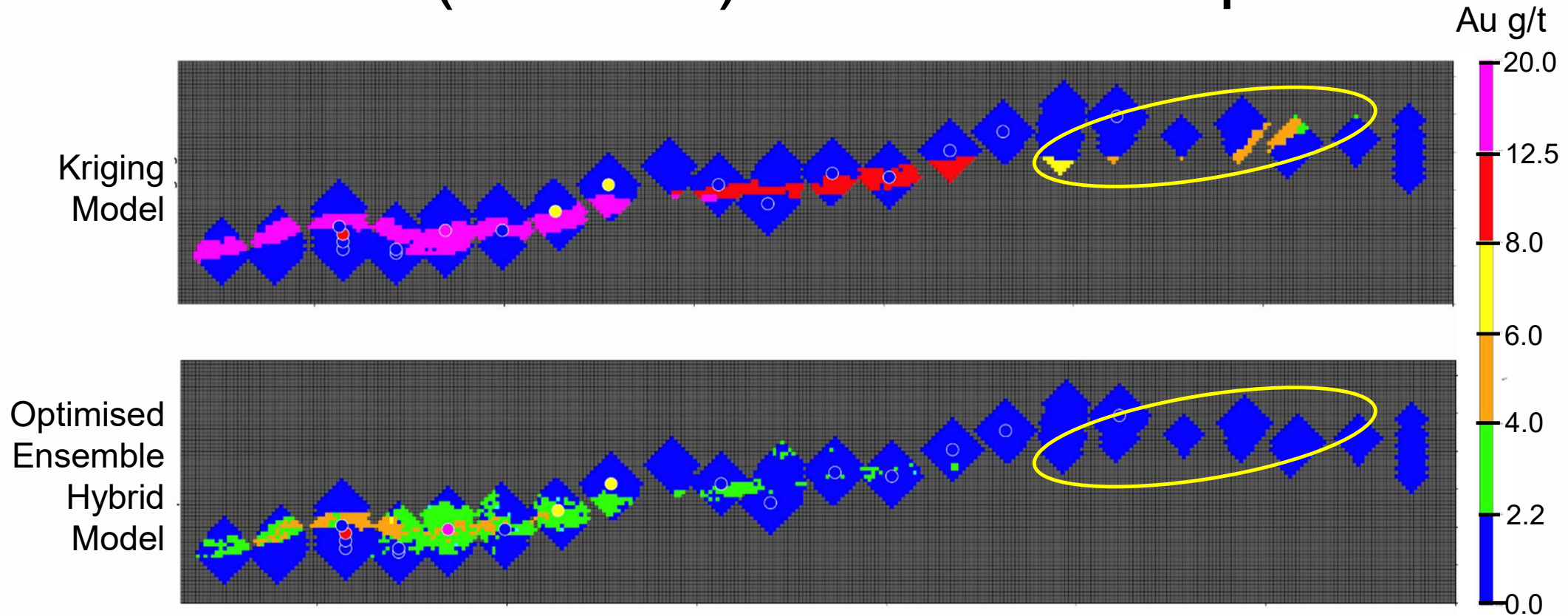
- Ensemble configurations
 - Maximises **Precision** (ie maximise HG prediction)
 - Maximise **Recall** (ie minimise missed mineralisation)

Model Name	Precision (%)	Recall (%)
Kriging	26.5	14.3
Ensemble Precision Optimised	34.9	14.5
Ensemble Recall Optimised	26.5	26.2

- Ensemble resource model – compositing all tested resource models
 - Remove models that do not improve the overall **Precision** or **Recall** models (Optimised **Precision** & **Recall**) from the ensembles

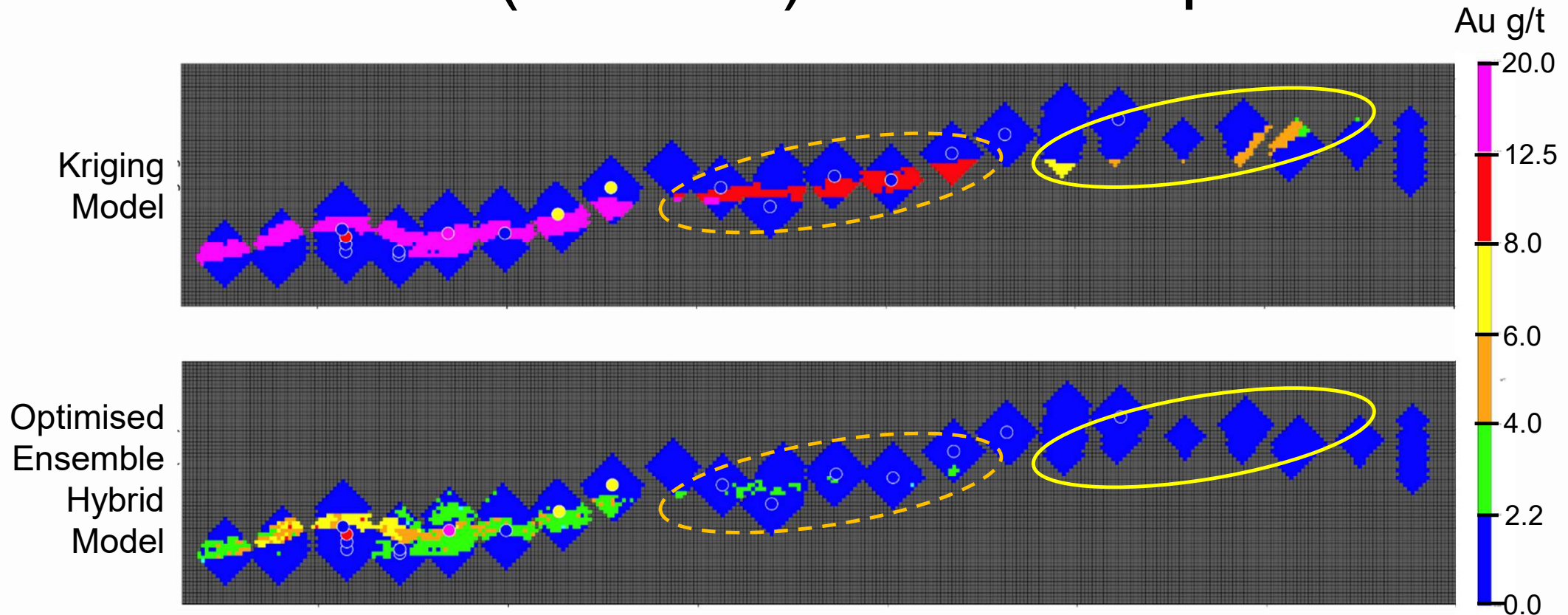


Model Plans (Z=2202) – Precision Optimised





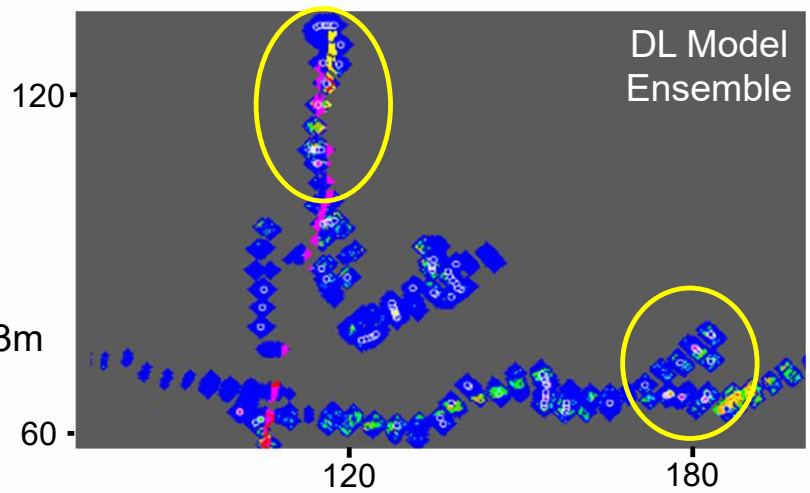
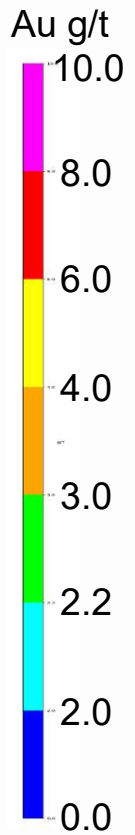
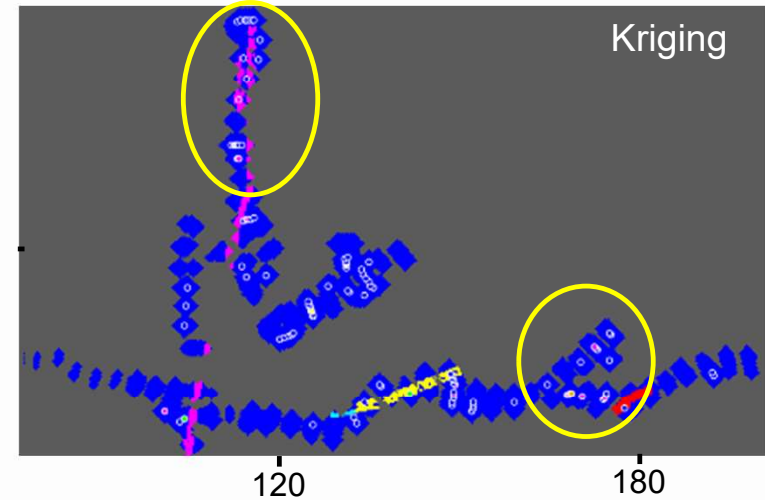
Model Plans (Z=2202) – Recall Optimised



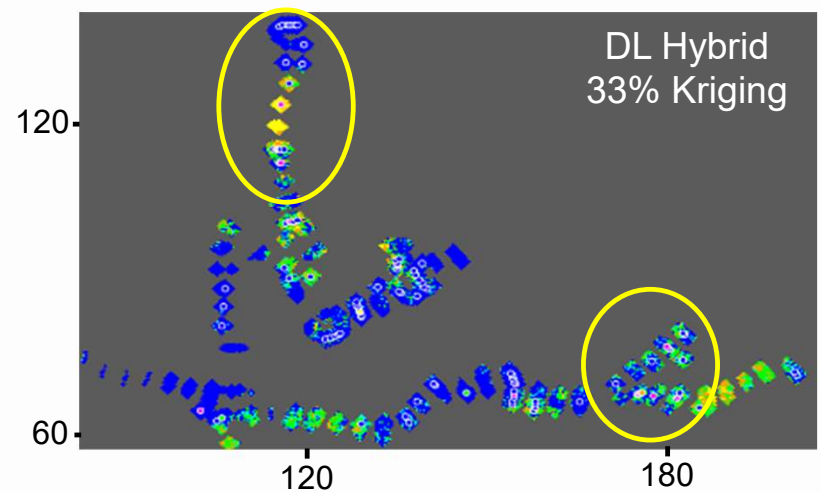
Model Plans (Z=1022)

Vein Complex

- Kriging model predicts N/S central vein
- DL ensemble model predicts the eastern E/W vein
- Hybrid ensemble misses no mineralisation



0.3m x 0.3m x 0.3m
blocks

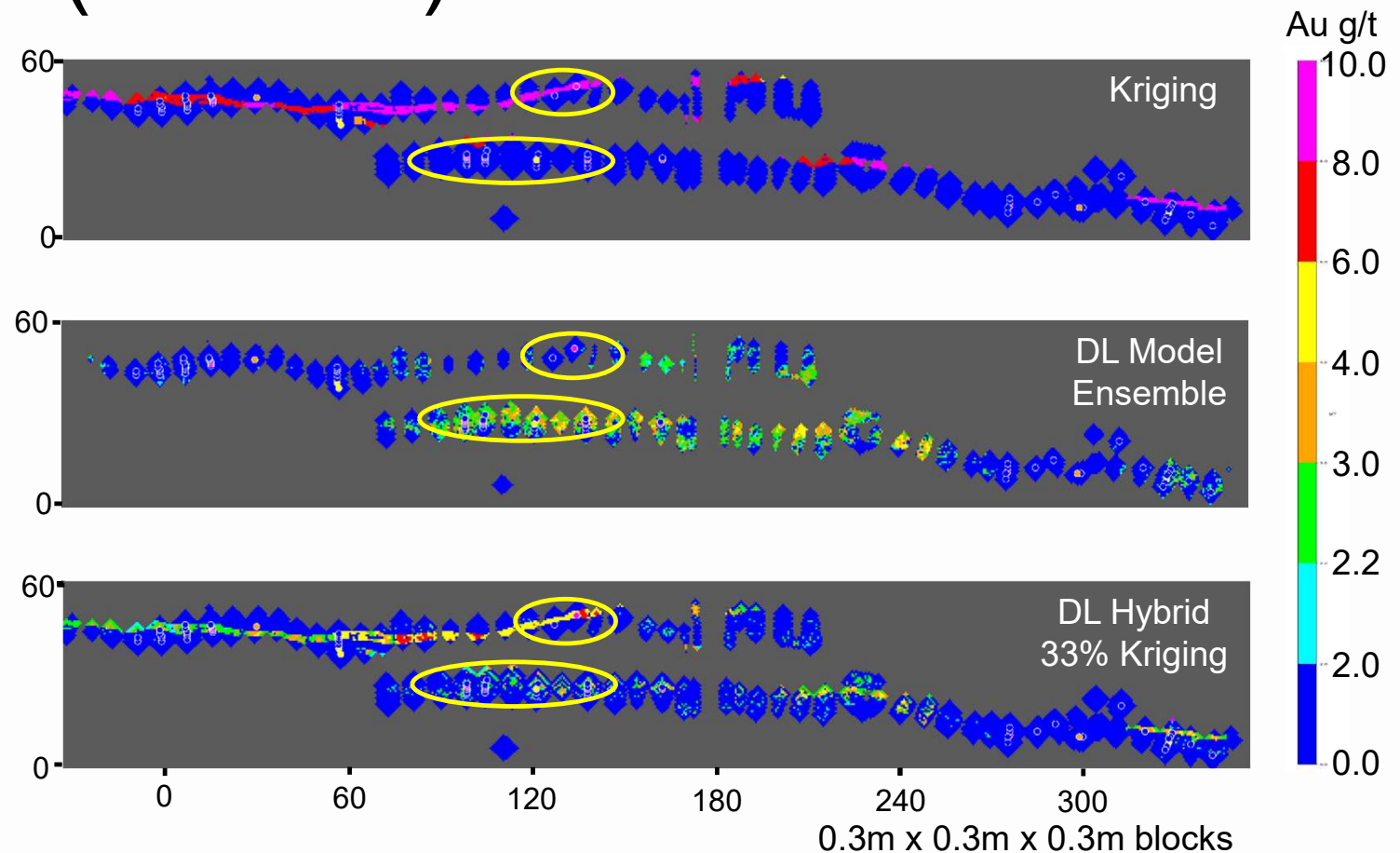




Model Plans (Z=2015)

Two Ore Veins:

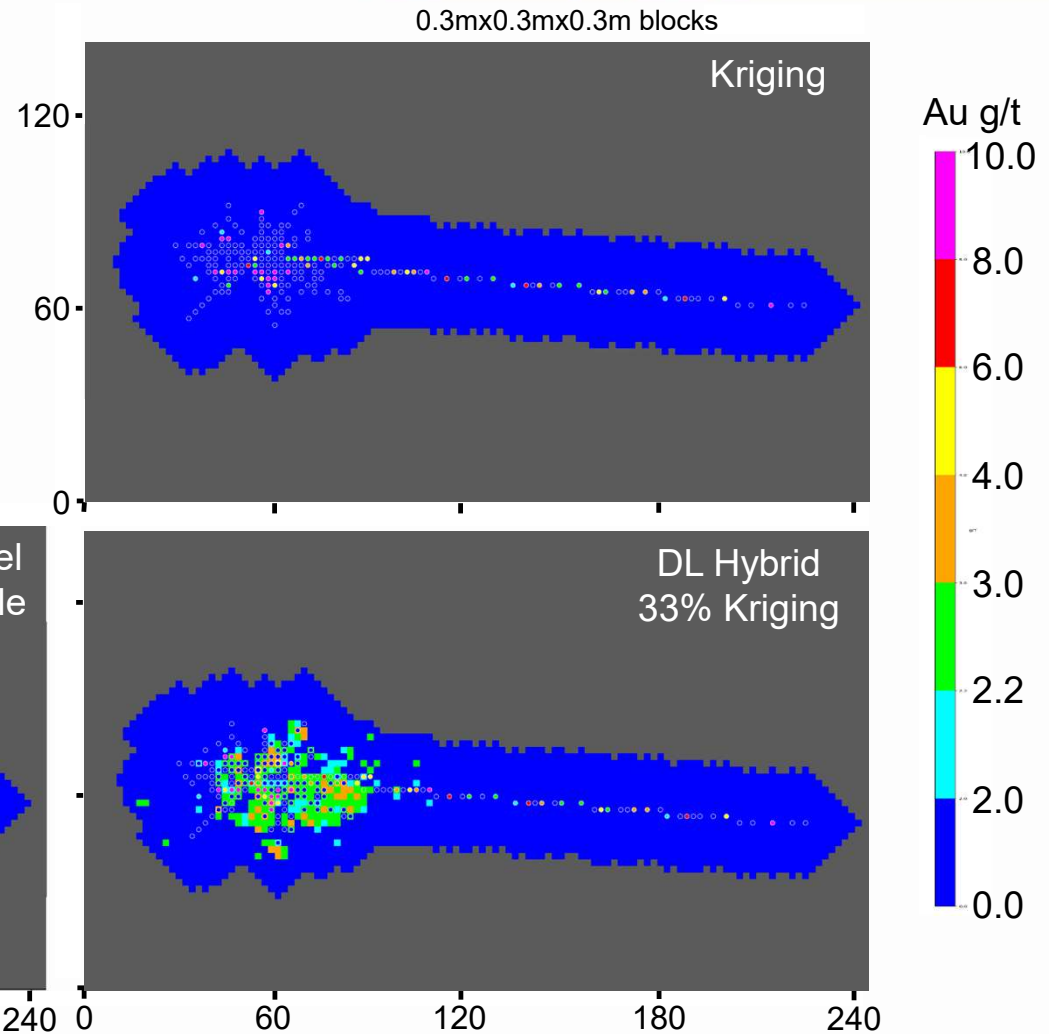
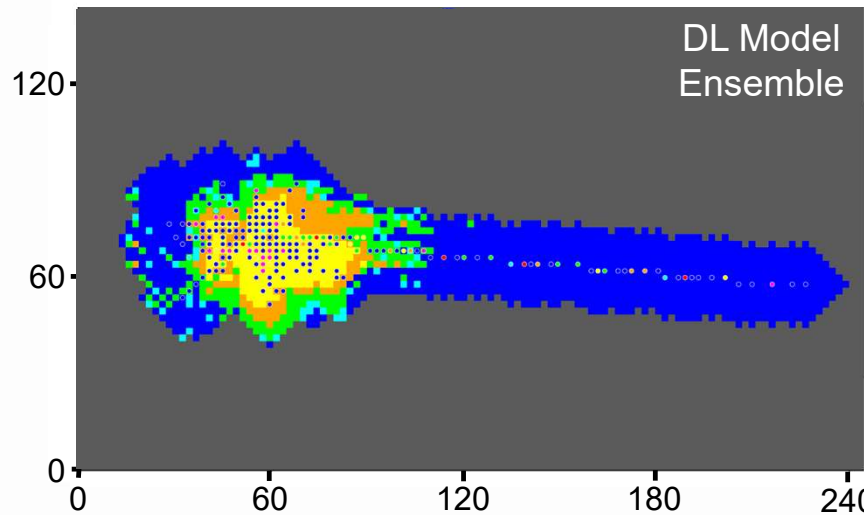
- Kriging model predicts upper vein
- DL ensemble model predicts the lower vein
- Hybrid ensemble misses no mineralisation



Model Plans (Z=3015)

Vertical Ore Shoot & Vein

- Kriging model misses mineralisation
- DL ensemble model predicts high grade, but poorly constrained
- Hybrid ensemble constrains high grade





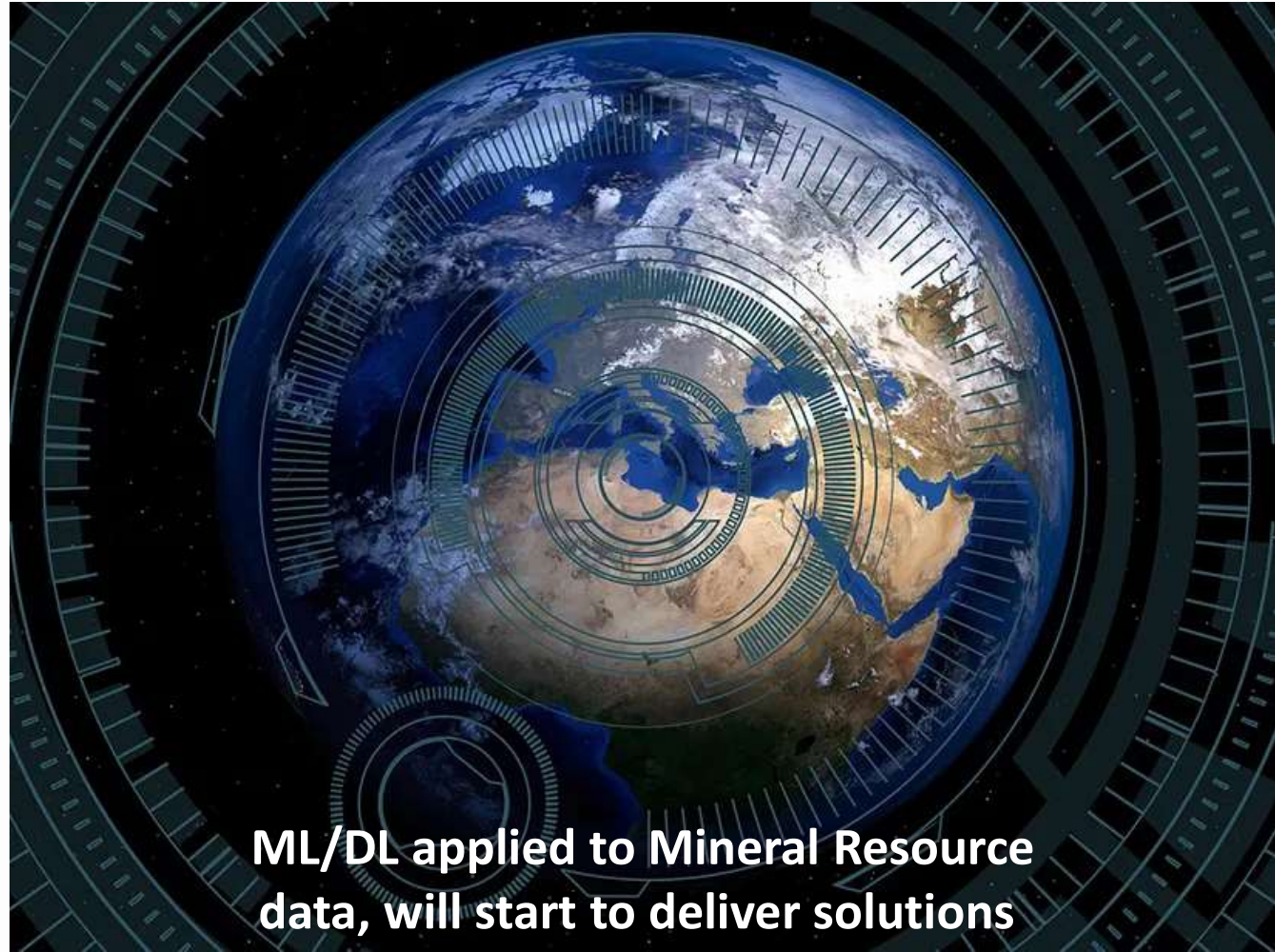
Discussion



Discussion

DL Patterns

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



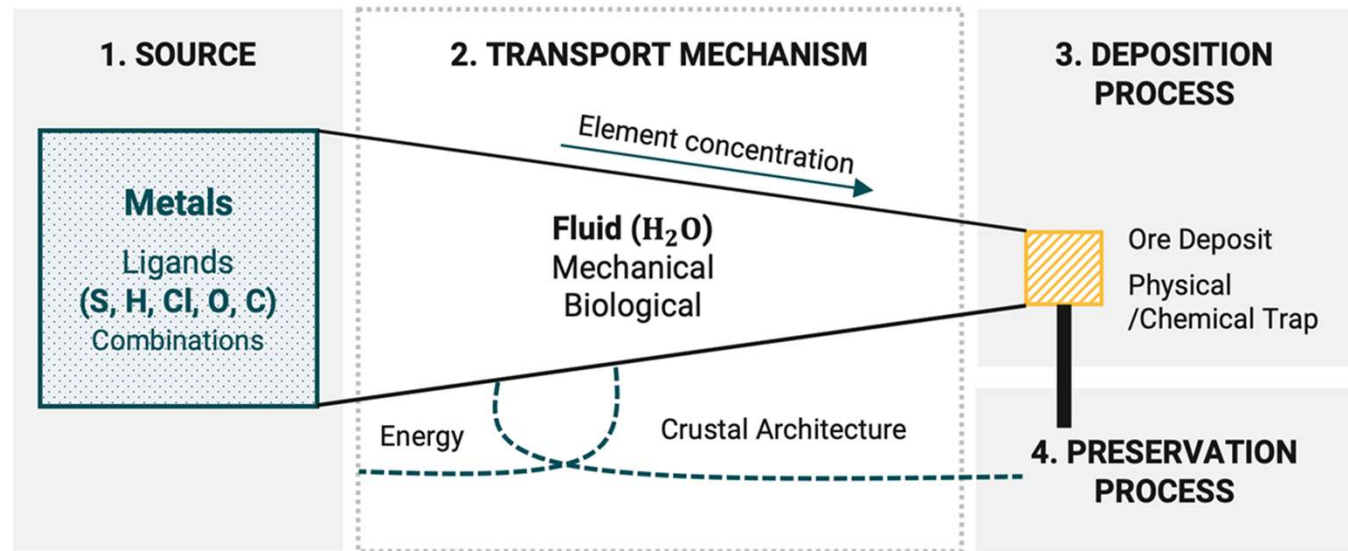
ML/DL applied to Mineral Resource data, will start to deliver solutions



Mineral Deposit Genesis

Geological Processes – Metal Distribution

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

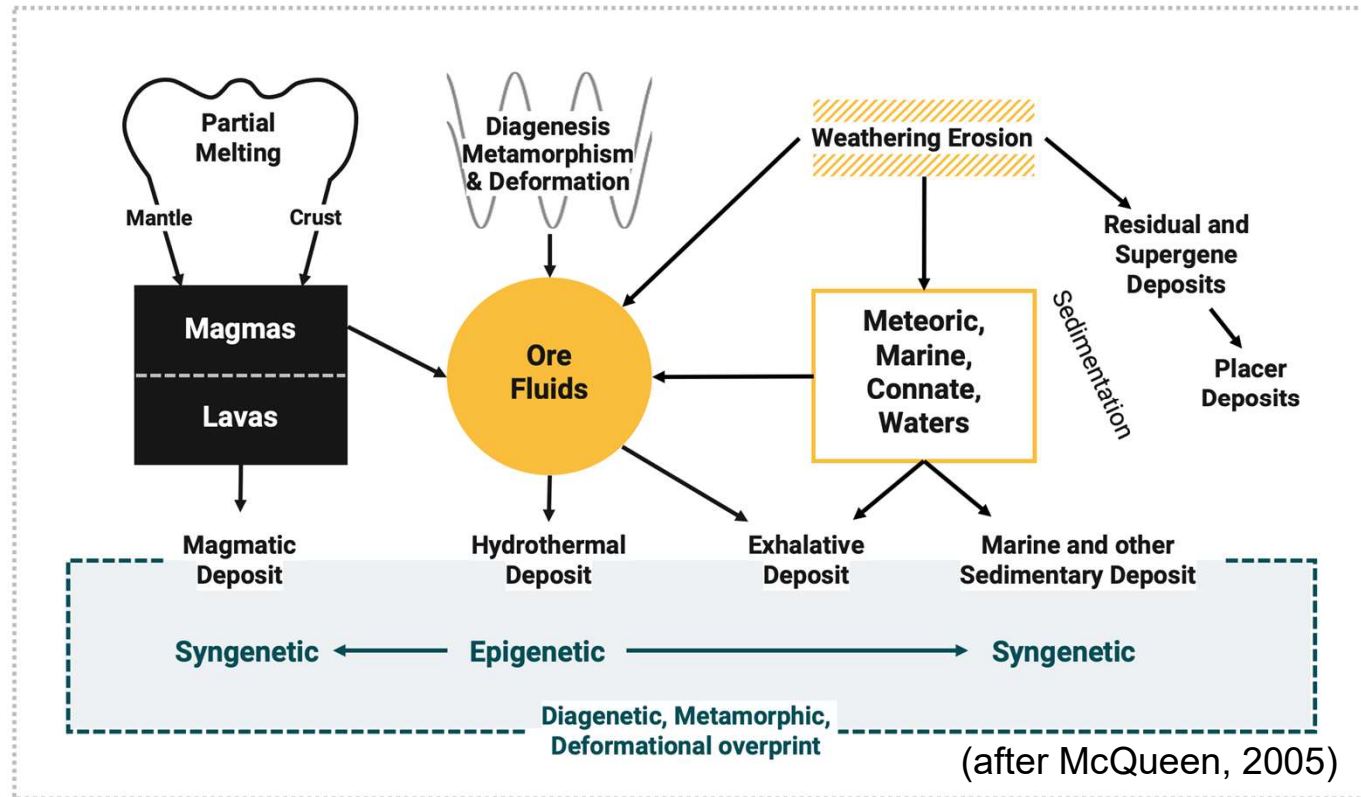


(after McQueen, 2005)



Ore Deposit Genesis

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





Conclusions



Conclusion

- 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 & geotechnical models
- DL patterns due to primary & secondary geological processes
- DL patterns may provide useful insight into deposit genesis
- DL resource modelling will get better as GPUs get more powerful



Acknowledgements

Northern Star Resources Ltd for permission to access the Jundee database & the interactive contributions by their employees; Heath Anderson, Leon Griesel, Patrick Moore & others, with respect to formulating the baseline & providing constructive feedback on the generated block models.



Wrap Up & Contacts

Mineral Resource Estimation Conference – on-line paper

- David First (Chief Geologist) david@stratum.ai (presenting)
- Ilia Sucholutsky (VP Research) ilia@stratum.ai
- Daniel Mogilny (Co-Founder) daniel@stratum.ai (attending)
- Farzi Yusufali (Co-Founder) farzi@stratum.ai



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