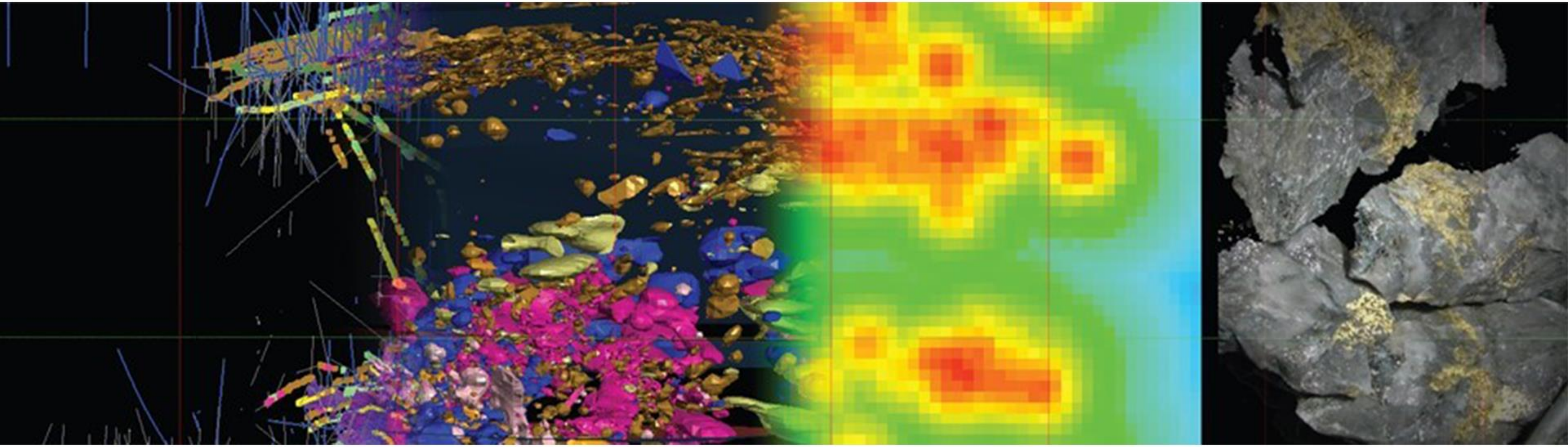
Applications of Machine Learning to Mineral Exploration



PROSPECTORS & DEVELOPERS ASSOCIATION OF CANADA

srk consulting

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SRK Consulting (Canada) Inc.

srk consulting

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Introduction

What is machine learning?

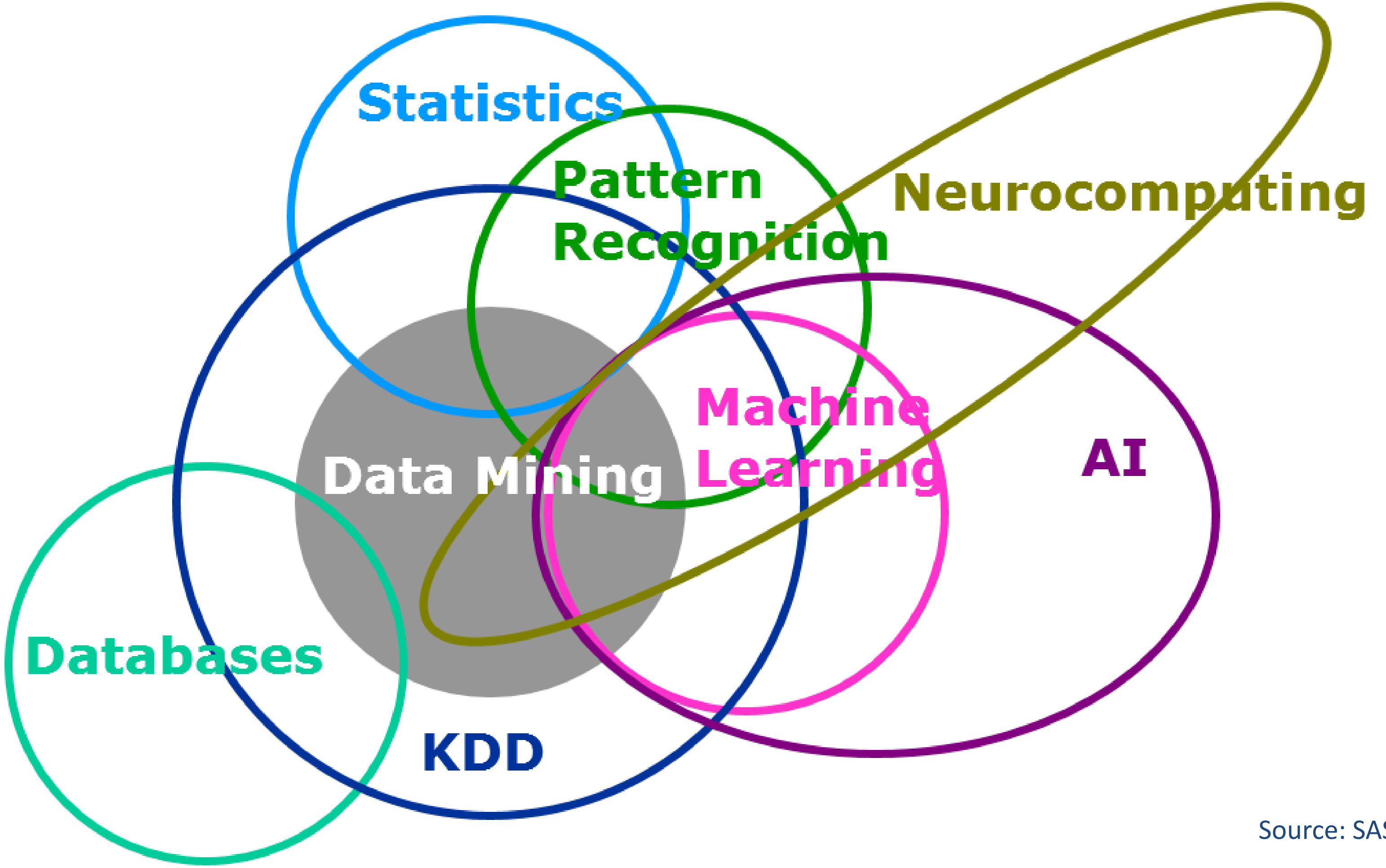
How is it applied?

Case studies and examples for prospectivity mapping, core logging, resource classification and magnetic survey enhancement

SRK Consulting

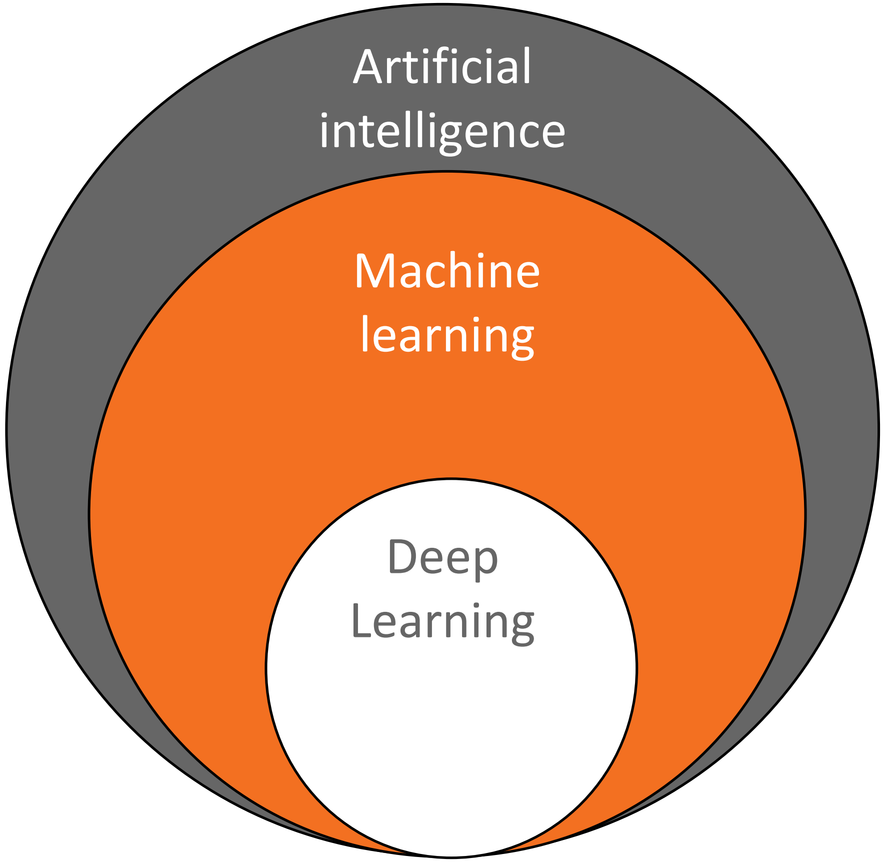
- Mining industry consultancy
- Established in 1974
- Globally employ over 1300 staff
- 43 Offices
- Services from exploration to mine closure
- Multi-National Staff
- Independent - 100% owned by employees

What is machine learning?



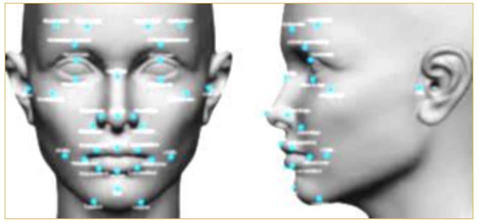
Source: SAS institute

What is machine learning?



- Advanced numerical method that allows data-driven **predictive modelling** by analysis of numerous variables **from example inputs**
- Term that originated in 1959 with IBM
- Field that grew up from artificial intelligence but is now distinct
- Started to flourish in the 1990s
- Deep learning took the lead in early 2010s

Examples of applications



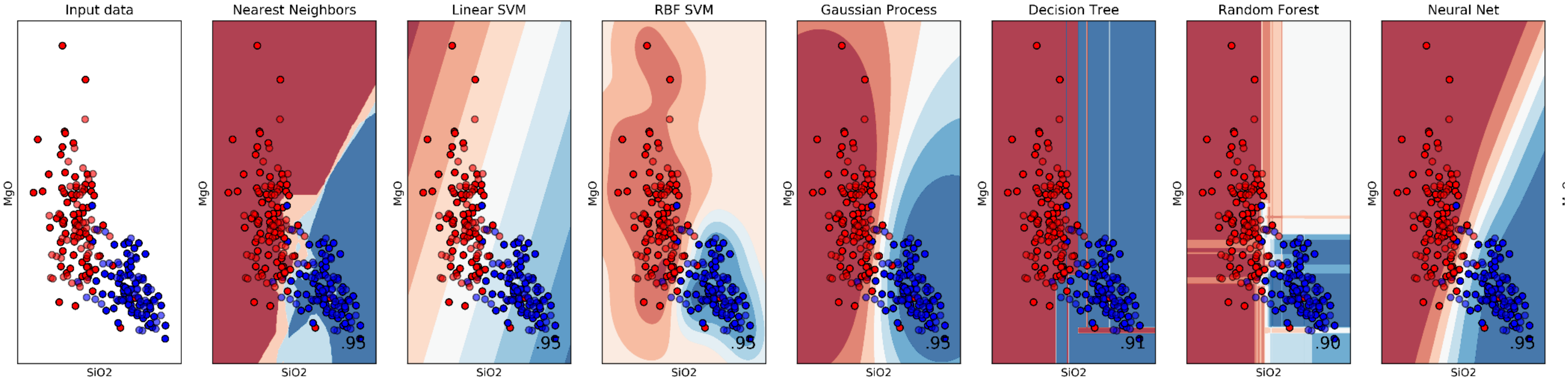
"In many applications, the performance of machine learning-based automatic detection and diagnosis systems has shown to be ***comparable to that of a well-trained and experienced radiologist****."*

Source: Wang & Summers in Medical Image Analysis (**2012**)

How does a computer learn?

Algorithms use training data to establish the relationship between variables.

$$Y = f(X_1, X_2, \ldots, X_n)$$

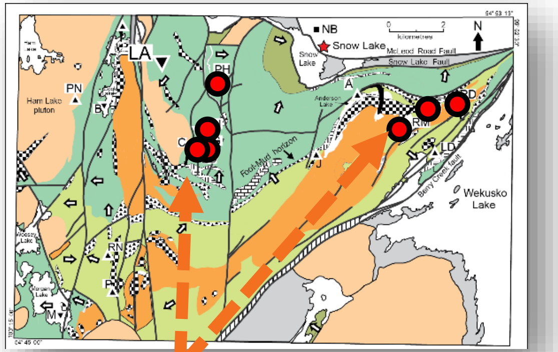


How does a computer learn?

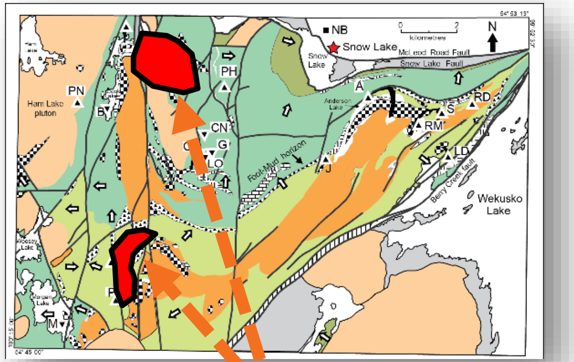
Training data → **Learning algorithm** → **Trained machine** → **Answer**

(data-driven)

Map: Galley et al., 2007



Known deposits



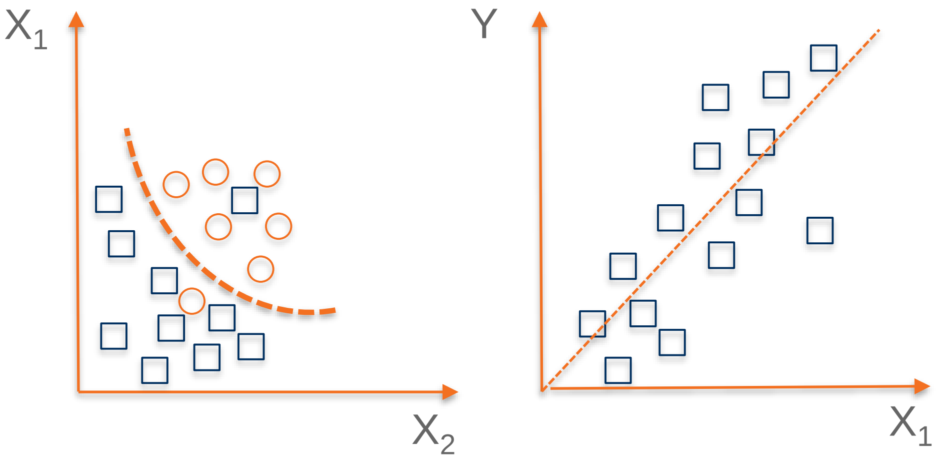
Query
(where are deposits in this camp?)

Generation of targets

Machine learning makes predictions without a direct human input (**but** requires upstream supervision).

Some types of machine learning algorithms

Supervised Learning

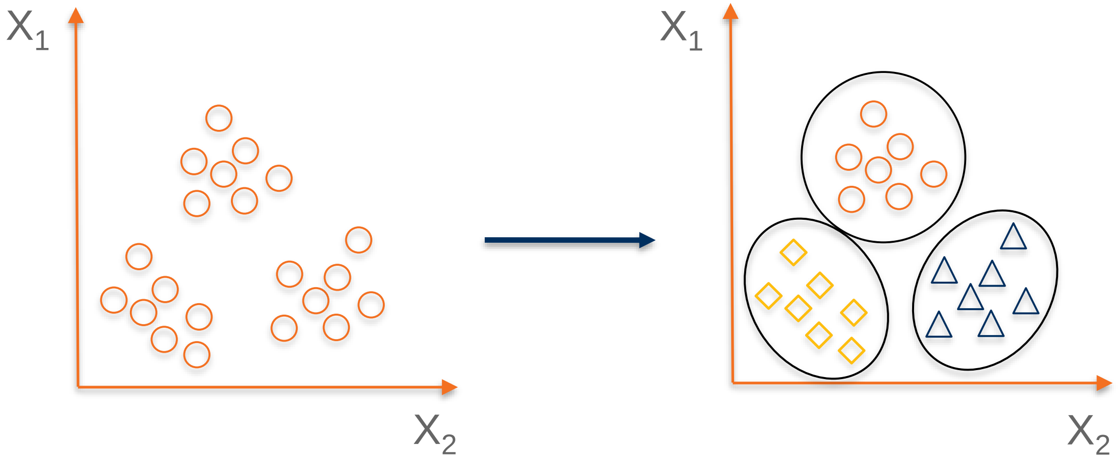


Classification

Regression

Uses known (labelled) data for training to make **predictions**

Unsupervised Learning

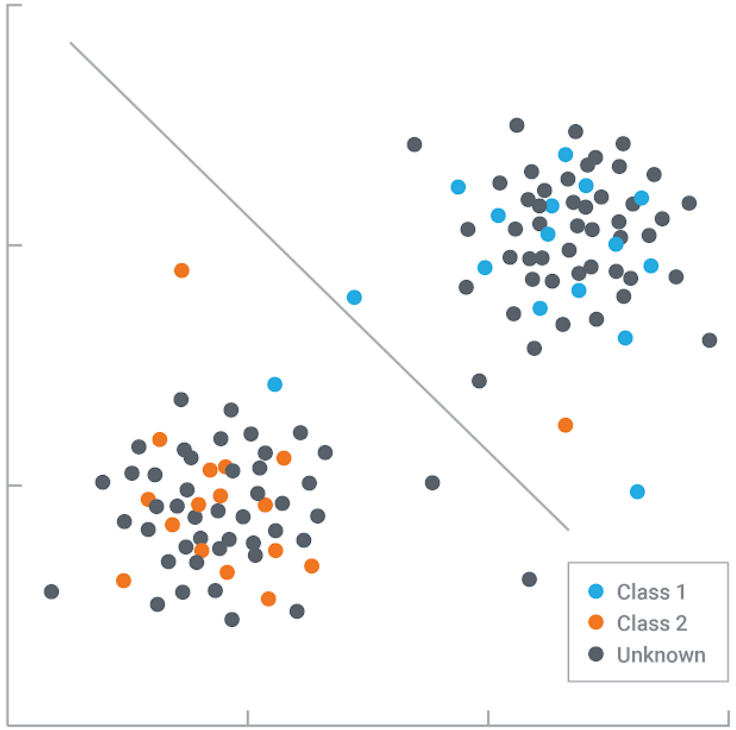


Clustering

Identifies natural patterns in the data

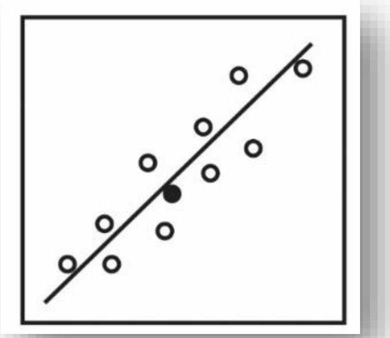
From learning to predicting

- The main goal of training an algorithm is to make predictions.
- The machine has learned a function *y=f'(X)* from existing data. It will apply this function to new data to predict *y* from *X*.
- The function learned by the machine is *f'*, an approximation of the exact function *f*. It is not perfect, but hopefully it is good enough for the application.

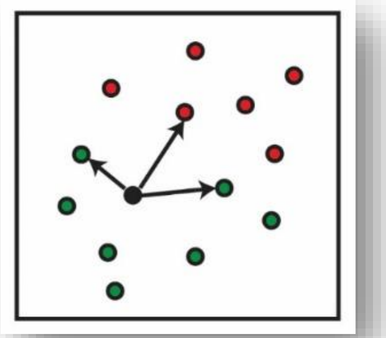


Source: chatbotsmagazine.com

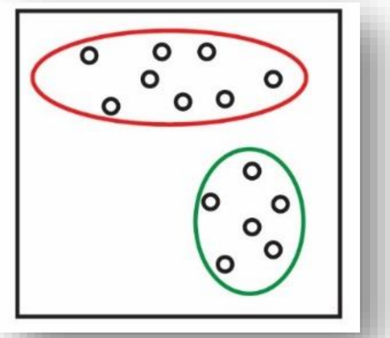
Machine learning algorithms



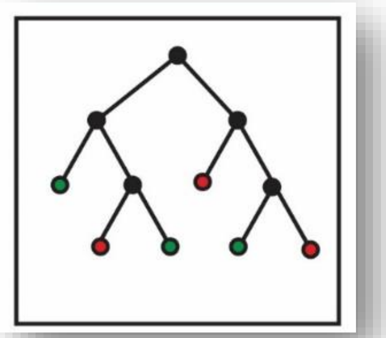
Regression



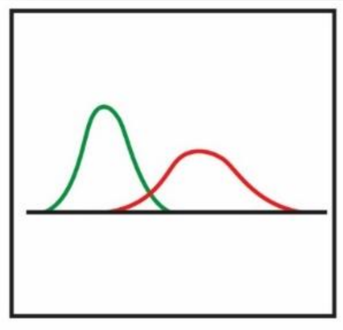
Instance based



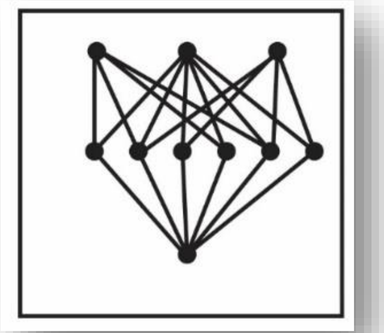
Clustering



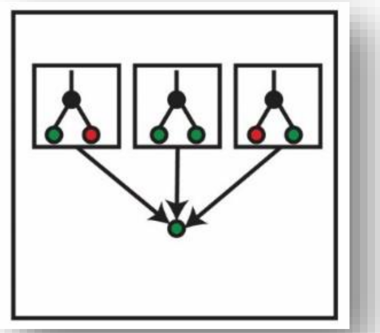
Decision tree



Bayesian probability



Neural networks and deep learning

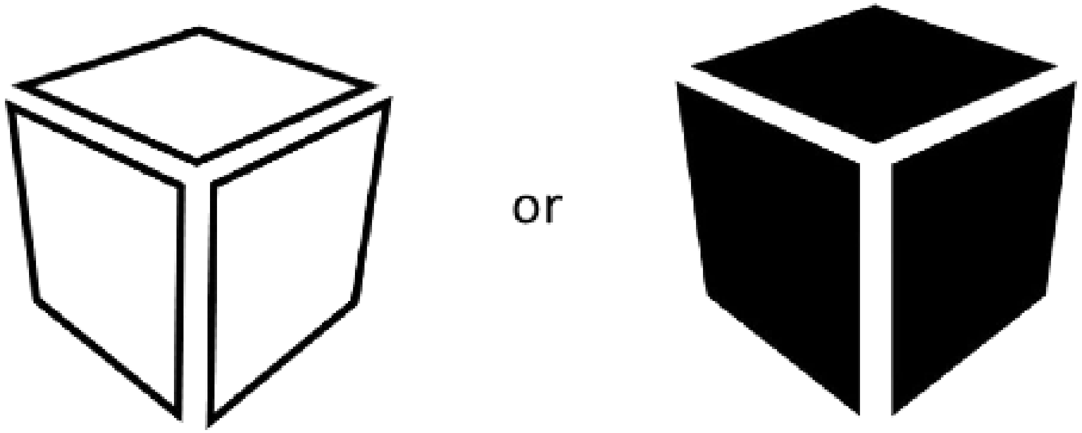


Ensemble methods

Understanding the machine

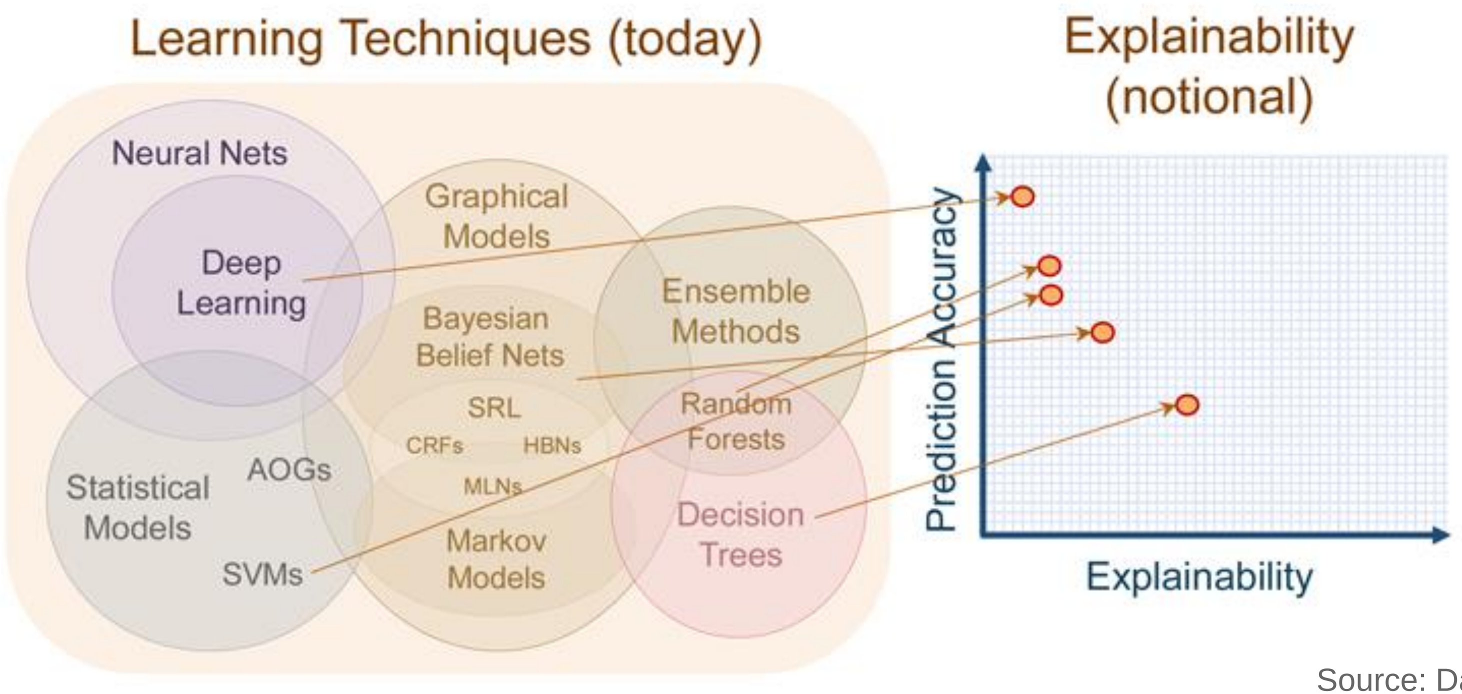
A machine learning algorithm takes input data and predicts output data.

The underlying function can be simple to understand, or beyond human comprehension.

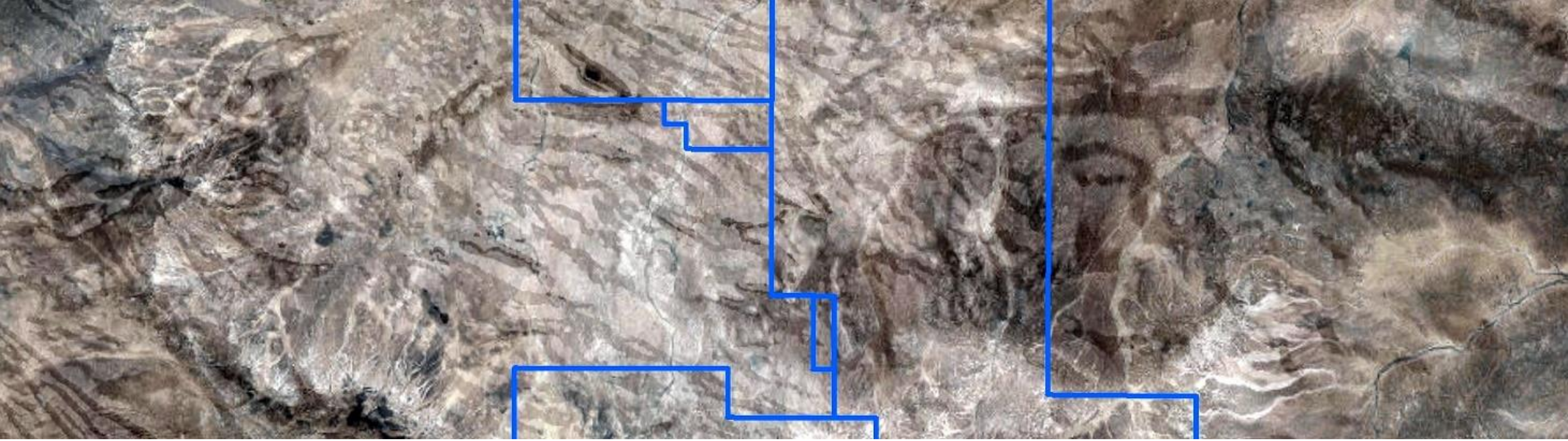


Understanding the machine

- An entire spectrum of explainability
- The more complex the model, the better the prediction, and the lower the explainability



Source: Darpa



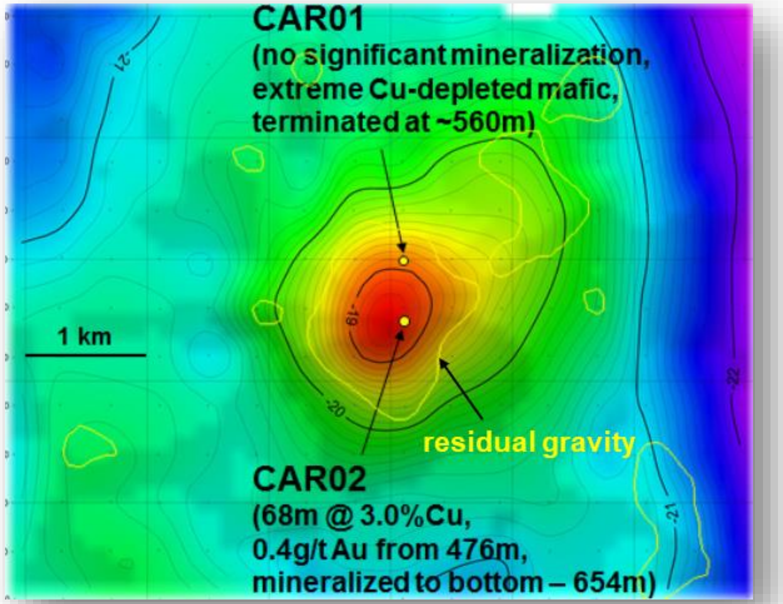
2D Prospectivity Mapping: Mt Woods Inlier, South Australia

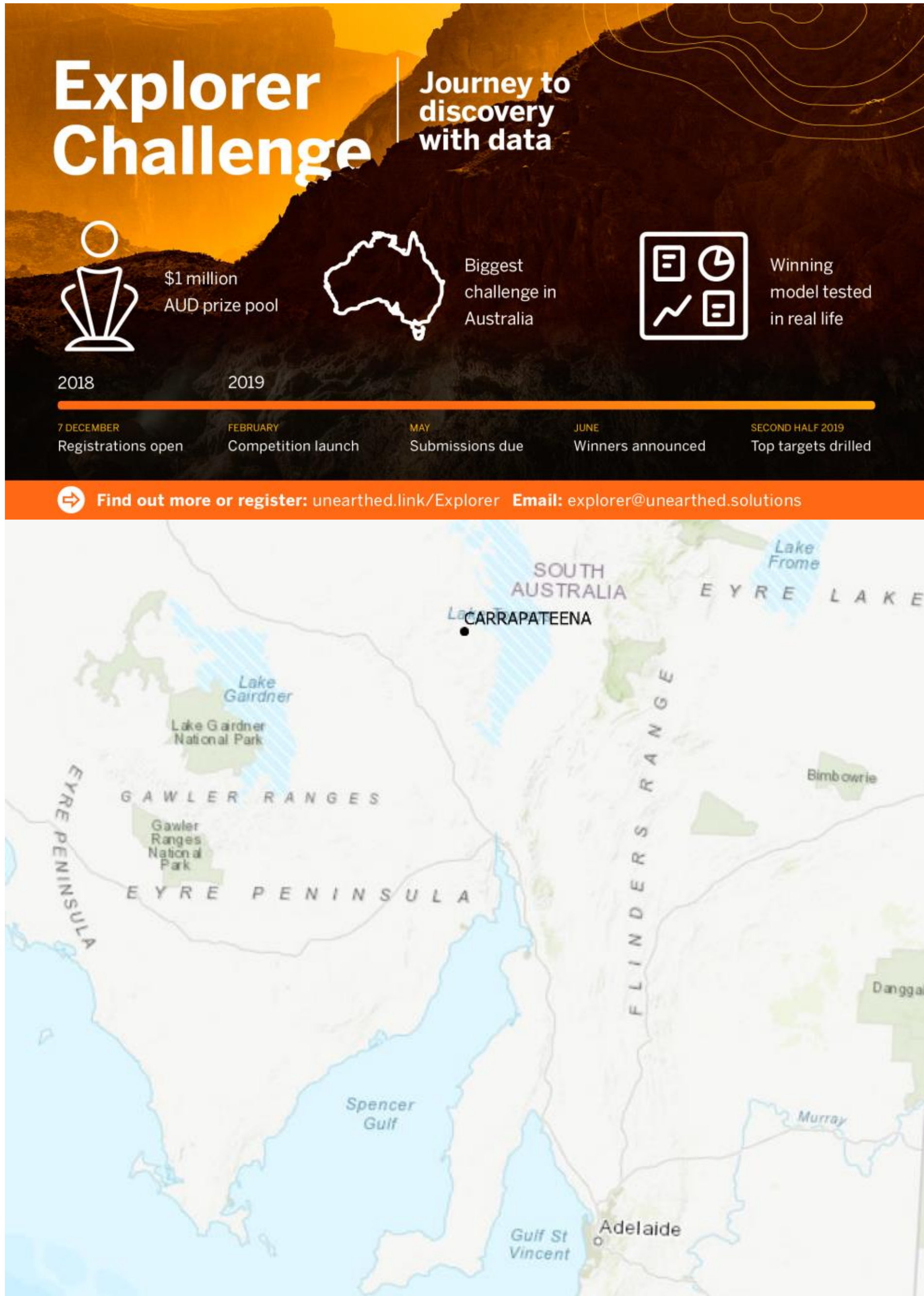
Where Machine Learning, Data-Driven and Expert-Driven targeting conspire:

A Case Study of ‘Modern Minerals Exploration’ from the ’Explorer Challenge’ – Mt Woods Inlier, South Australia

The explorer challenge

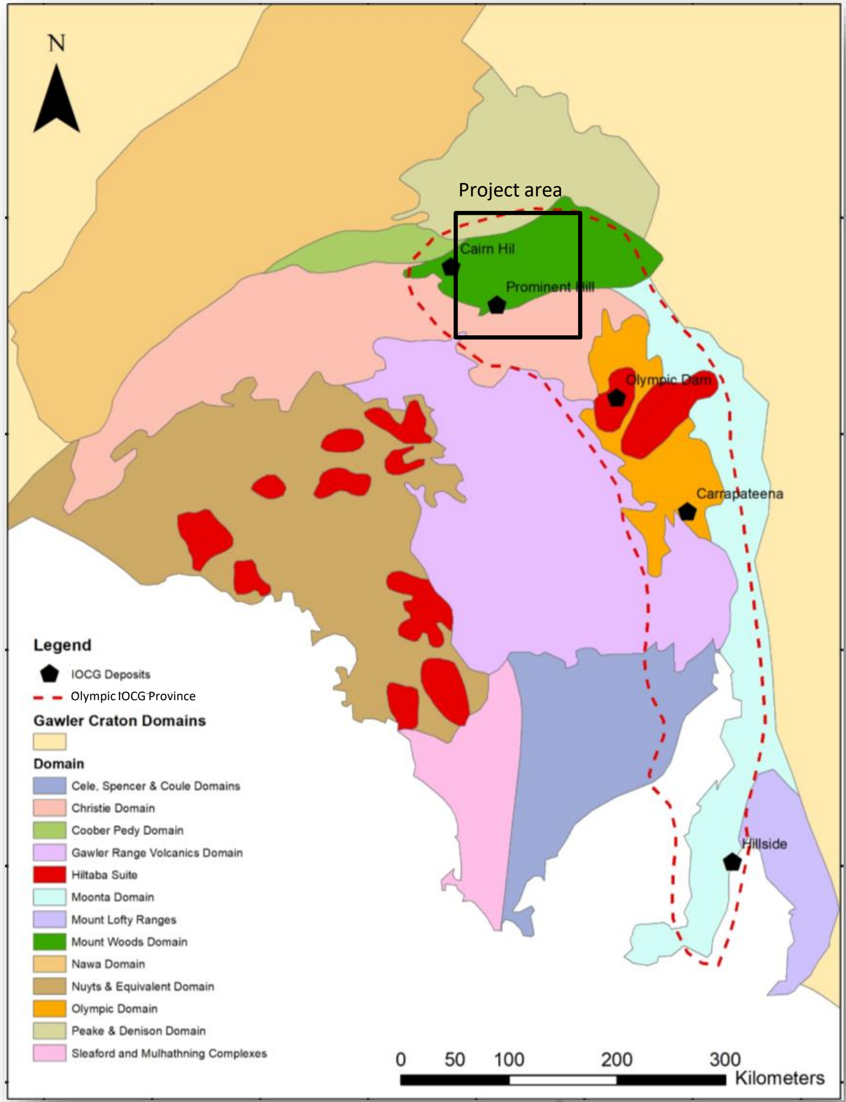
- In an effort to accelerate a new discovery, OZ Minerals opened up several TB of private data for the ‘Explorer Challenge’ competition
- IOCG discoveries in the Gawler Craton to date have largely been made targeting discrete magnetic and/or gravity anomalies
  - ‘bump hunt’



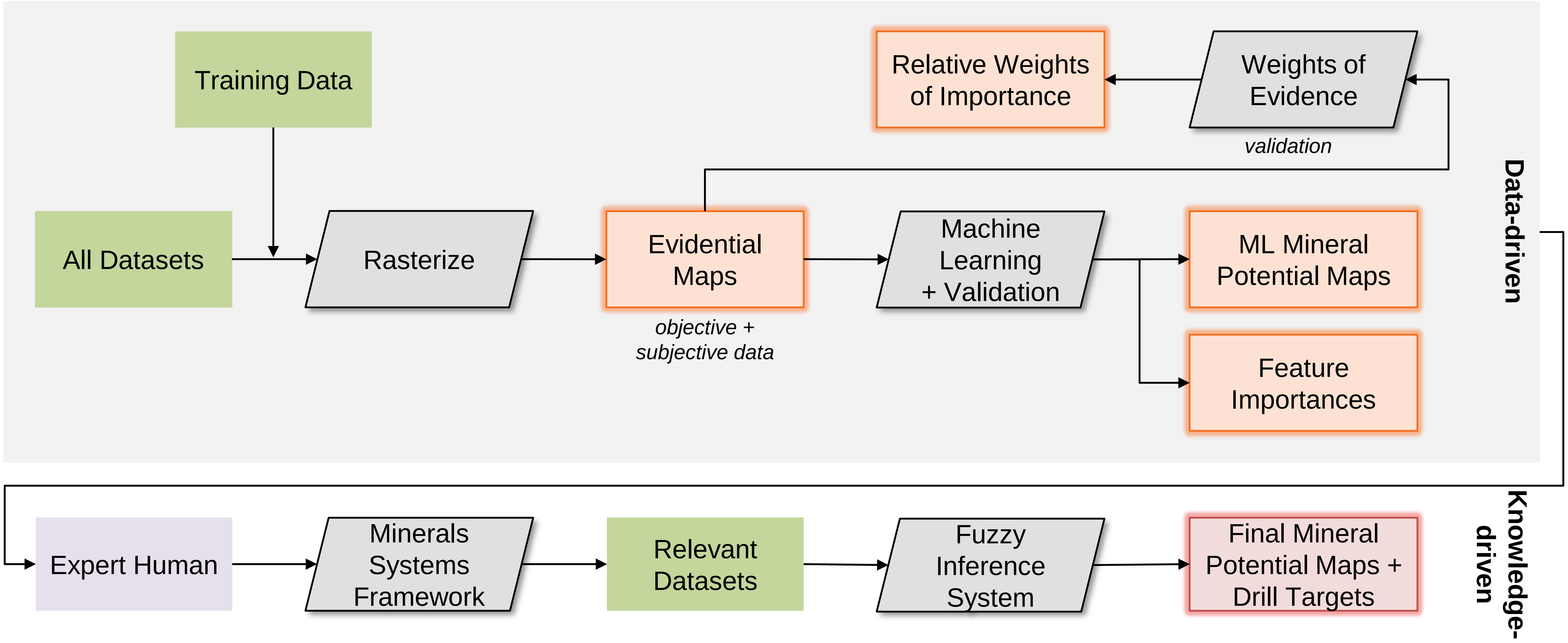


Mount Woods inlier

- Lies within the northern Gawler Craton
- Prominent Hill deposit lies on the southern margin of the MWI
  - ➢the only major IOCG deposit in the MWI
- Unconformably overlain by up to 400m of Palaeozoic to Mesozoic sediments
  - – obscures much of the basement rock
  - ➢presents a challenge to exploration

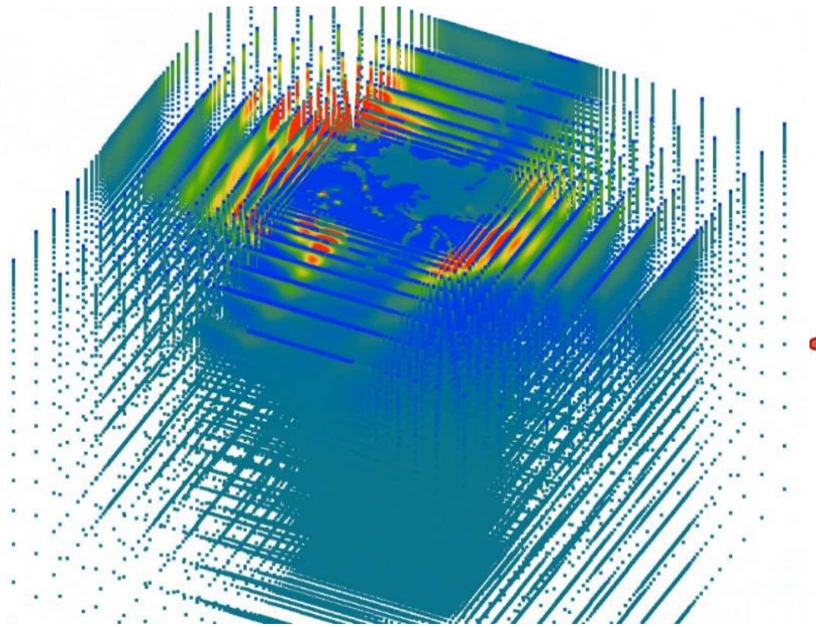


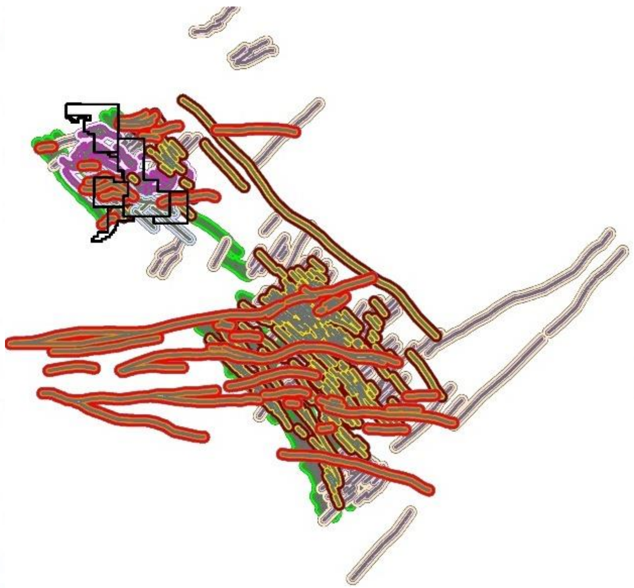
Integrated targeting workflow
Scalable from continental to mine scale

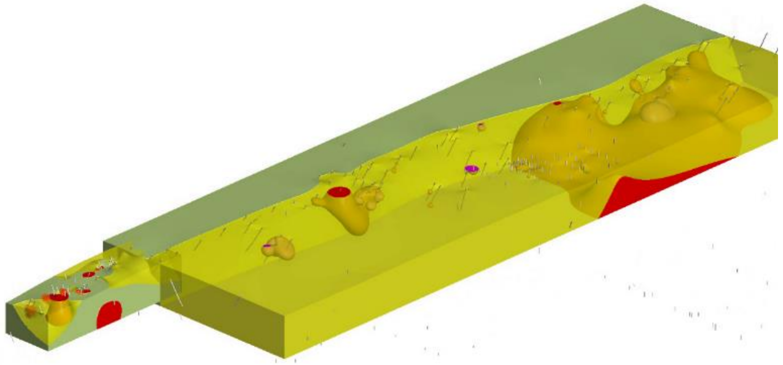


Data collection, integration, interpretation

- >50 evidential maps were created – using:
  - datasets provided for the competition
  - public datasets available (e.g. SARIG)
  - re-interpretation of regional structure







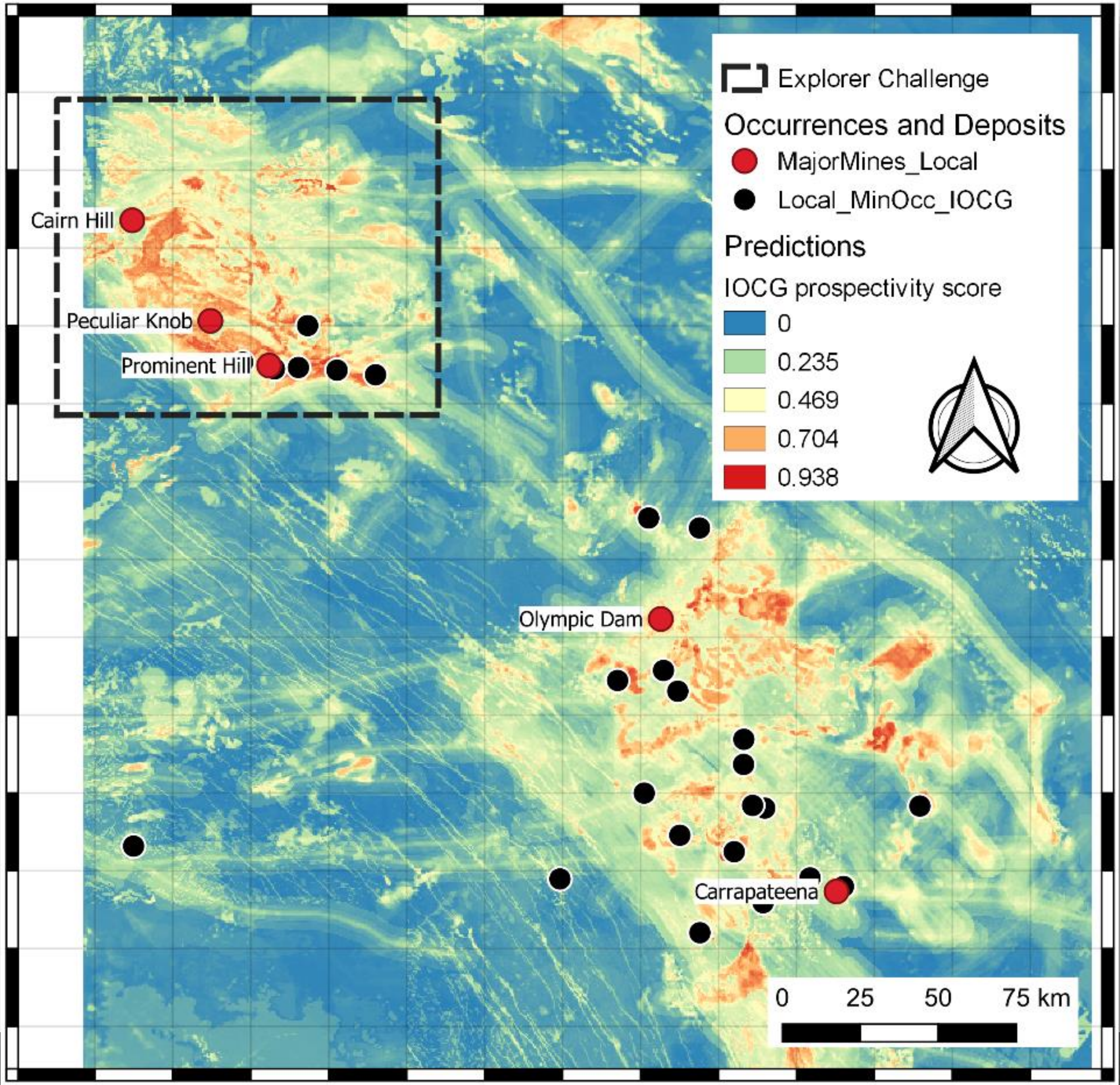
Data-driven prospectivity mapping

A pre-tuned balanced random forest algorithm was trained for each deposit type with 9 existing occurrences or more (IOCG deposits, deposits related to regionally metamorphosed rocks, porphyry deposits, and deposits related to surficial processes and unconformities).

- Balanced Random Forest algorithm generates both prospectivity maps and features importance values.
- Uses training occurrences to estimate the relationship between the data and mineralisation
- Reveals unbiased data-driven controls and trends in the data
  - unconstrained from 'accepted wisdom'

Data-driven prospectivity mapping

- Performed at cratonic scale
  - ➢very efficiently starts highlighting areas of high interest vs. low interest
- Areas of high interest can be honed in on with more detailed assessment
  - ➢via the Expert Knowledge-driven stage



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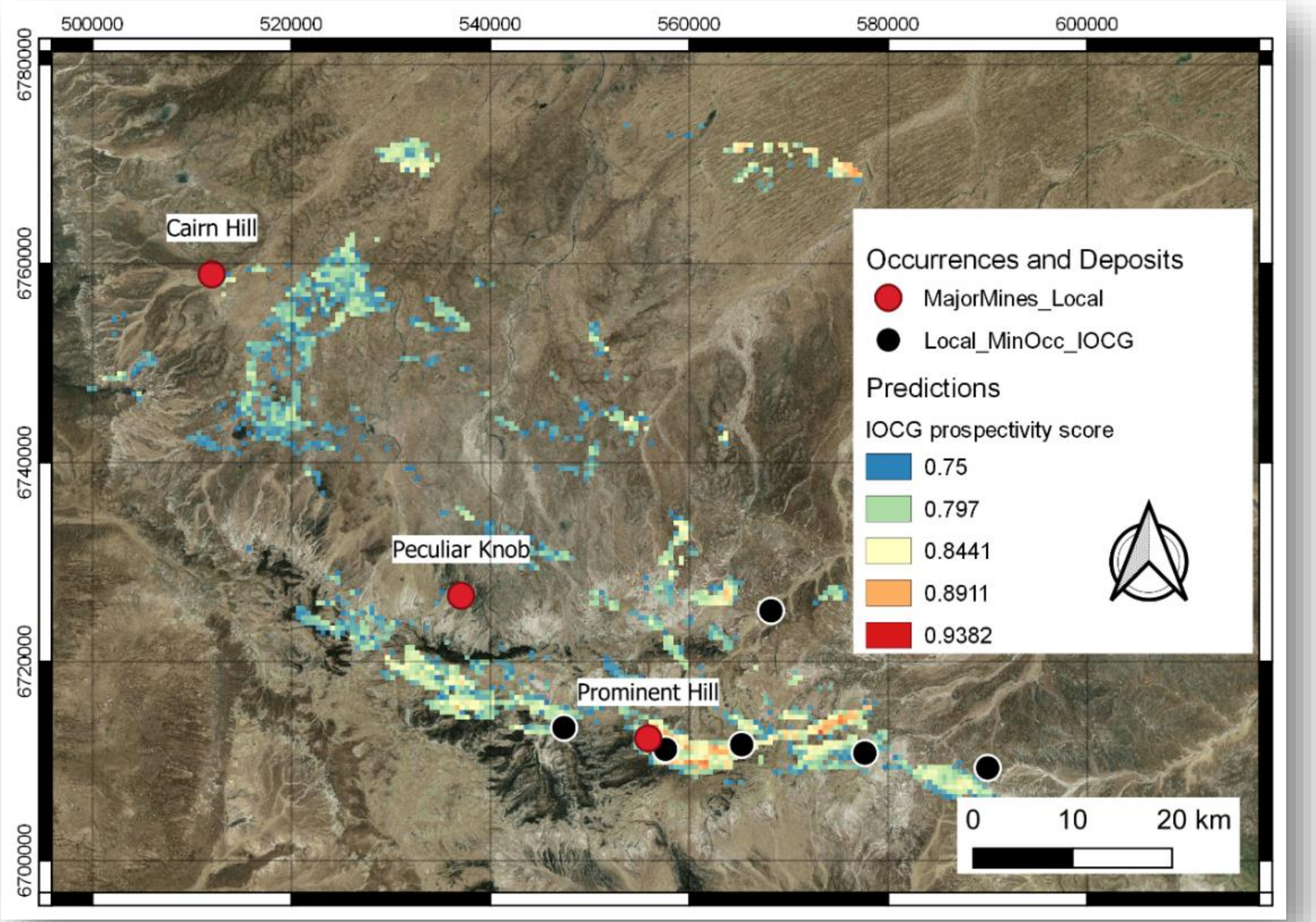
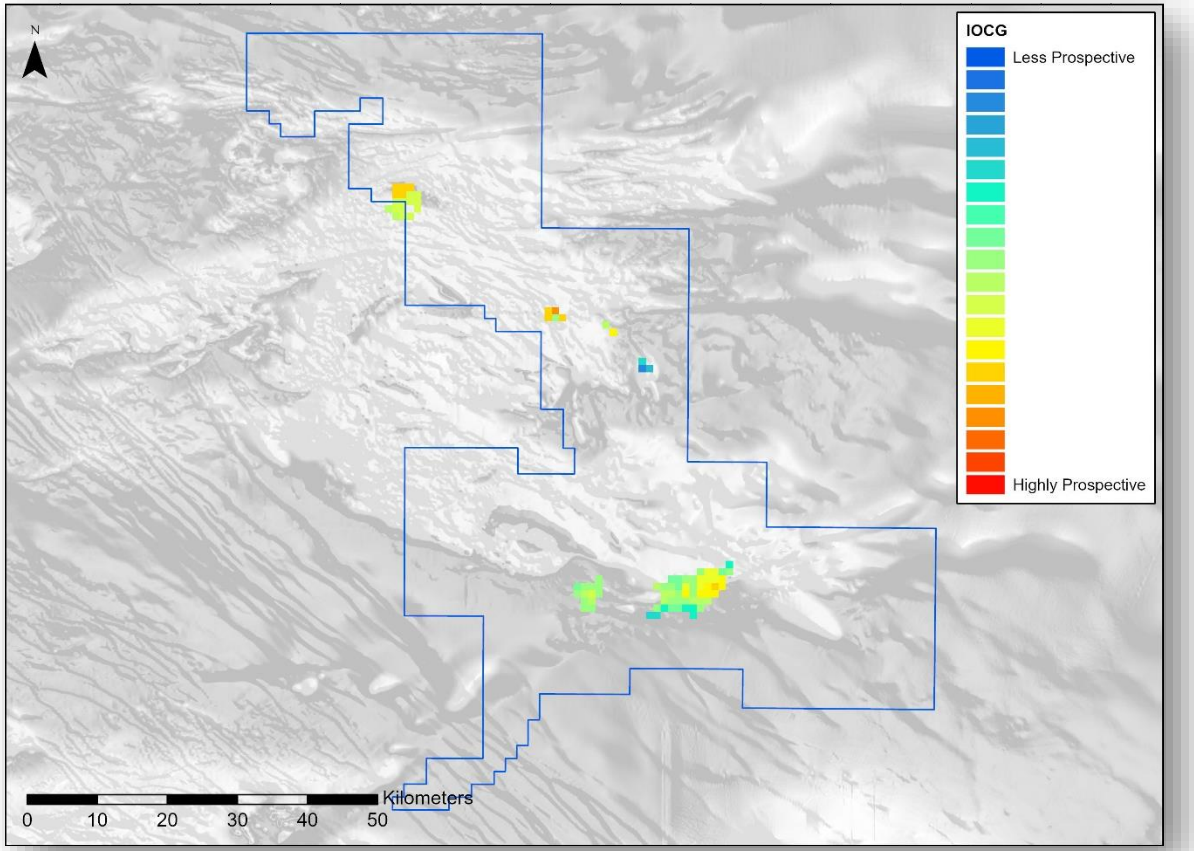
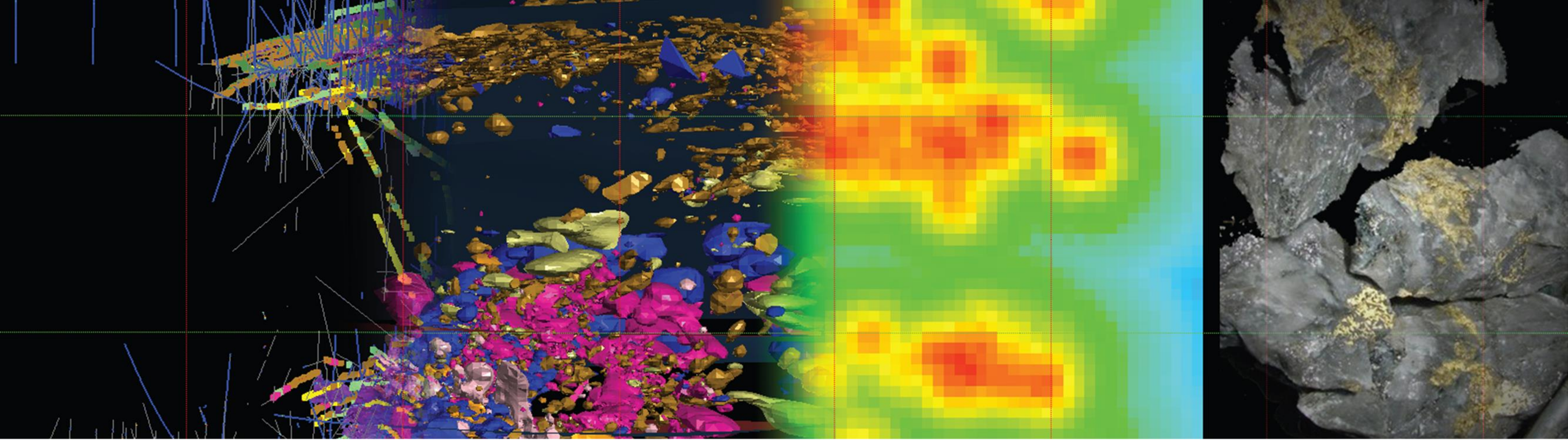


Expert-driven targeting

- Final target maps generated using fuzzy overlay methods in ArcGIS
  - performed at smaller scale
  - not reliant on pre-existing mineral occurrences
  - narrows down search area to those that meet the deemed important criteria

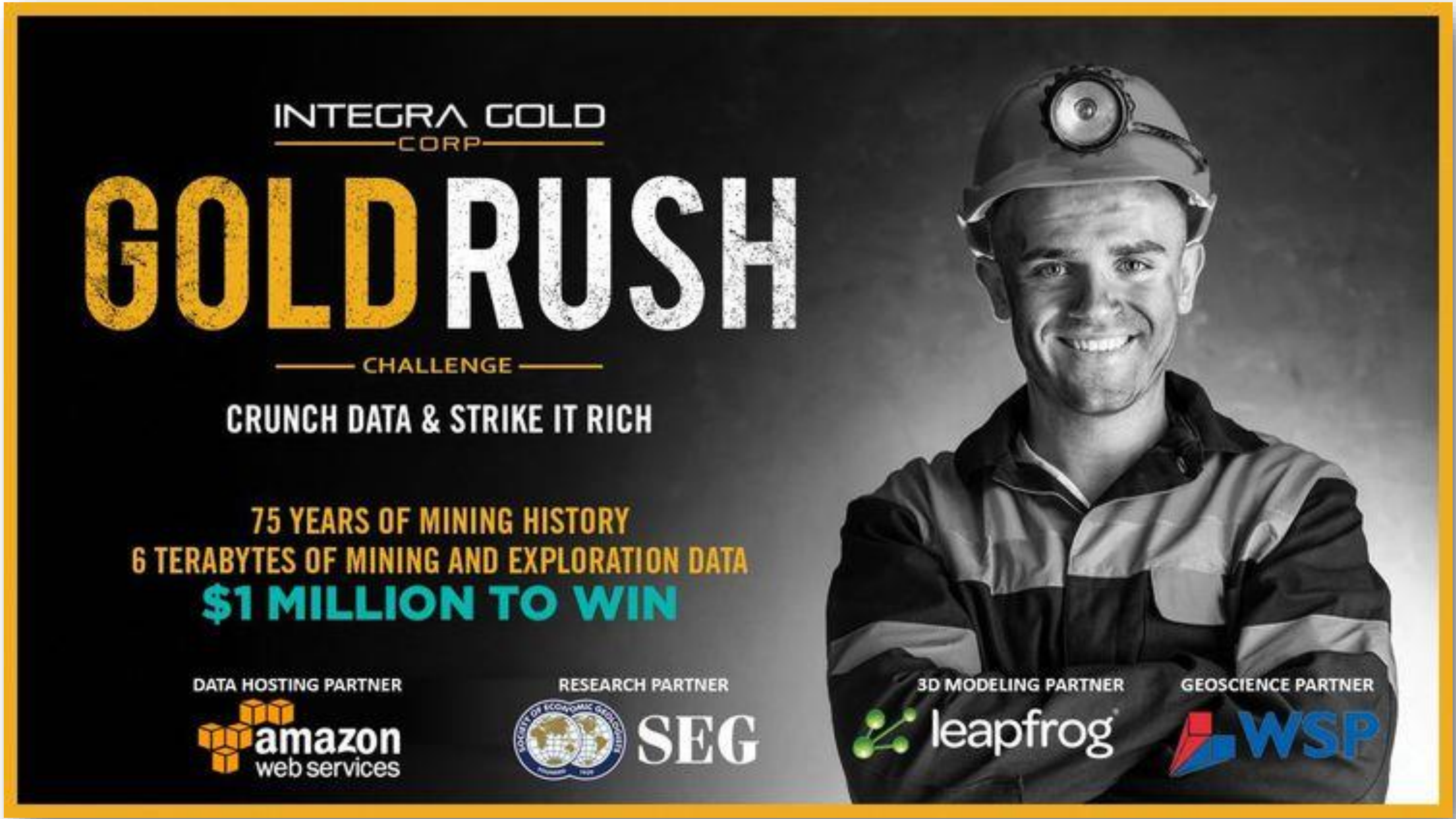
- **independently run for each commodity group targeted**





3D Prospectivity Mapping: Sigma-Lamaque property, Quebec

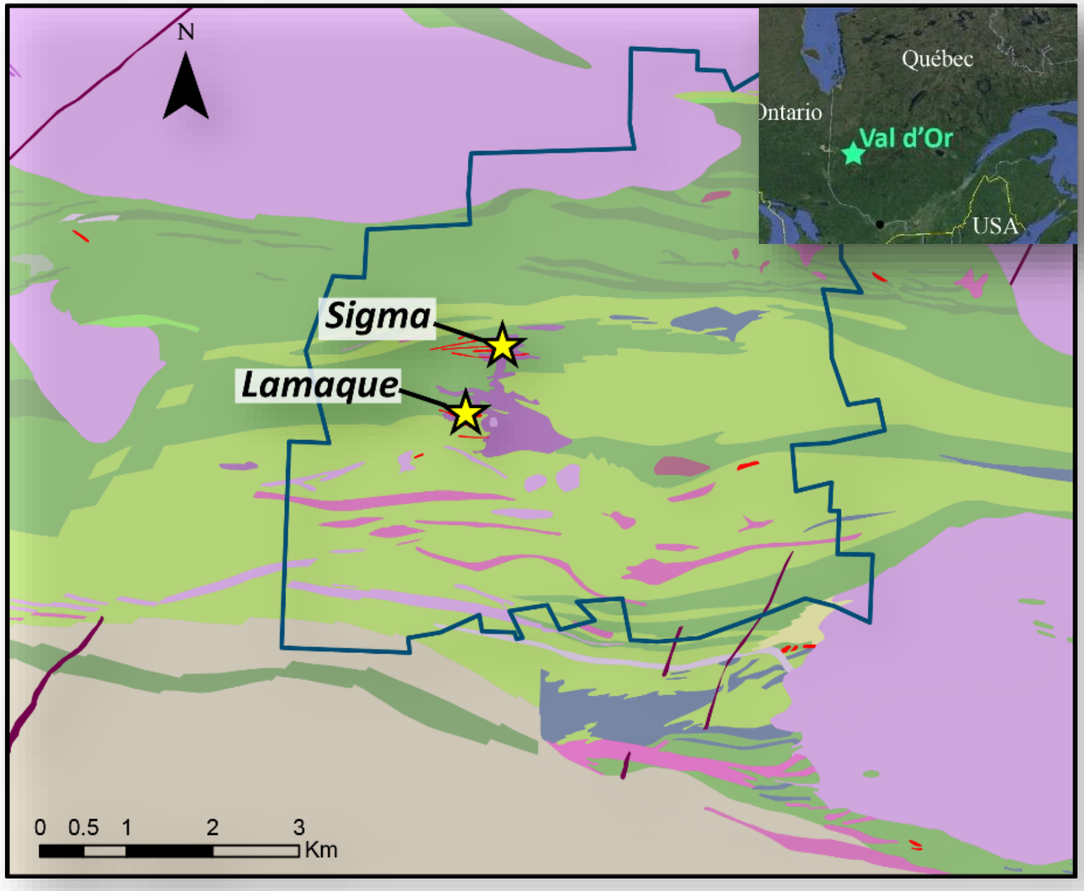
Data Miners team


INTEGRA GOLD
CORP
GOLD RUSH
CHALLENGE
CRUNCH DATA & STRIKE IT RICH
75 YEARS OF MINING HISTORY
6 TERABYTES OF MINING AND EXPLORATION DATA
$1 MILLION TO WIN
DATA HOSTING PARTNER
amazon web services
RESEARCH PARTNER
SEG
3D MODELING PARTNER
leapfrog
GEOSCIENCE PARTNER
WSP

The Sigma-Lamaque camp

Geology:

- Val d’Or Formation
- Shear zone hosted gold mineralization
- Host rocks are a series of competent intrusive units



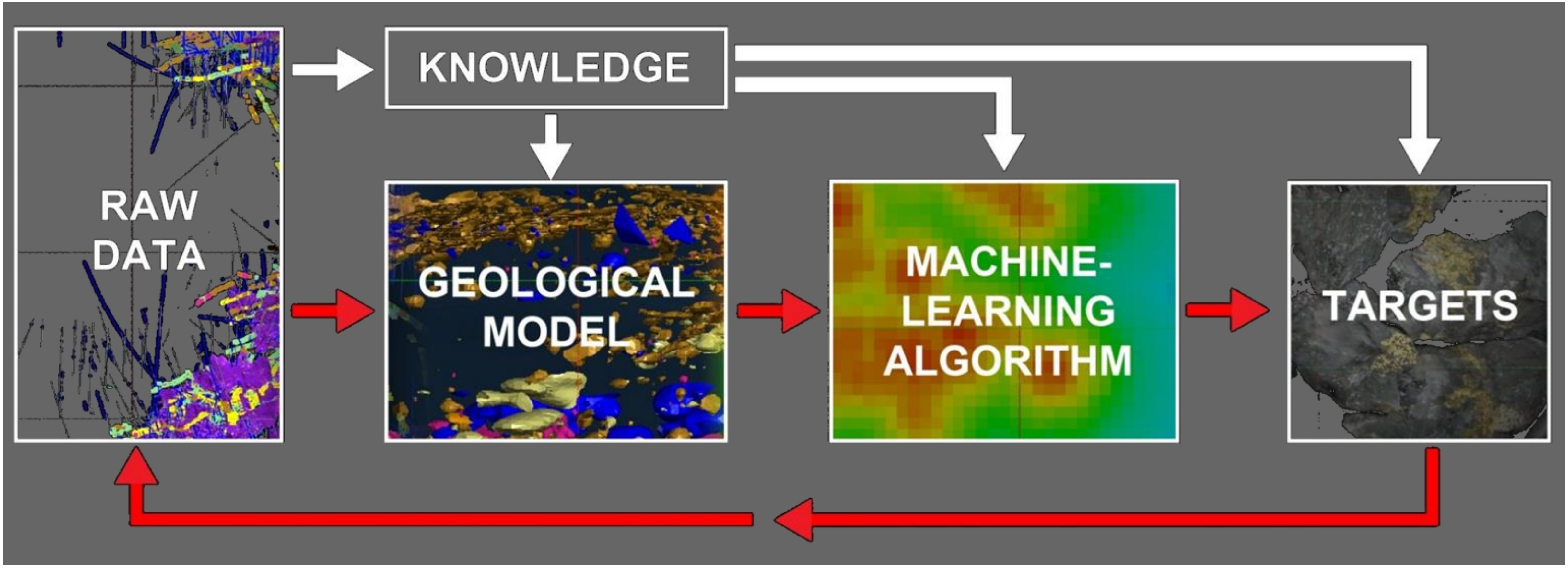
Implications for exploration

Translating metalogenic processes in geological evidences and in targeting proxies.

Need to deal with:

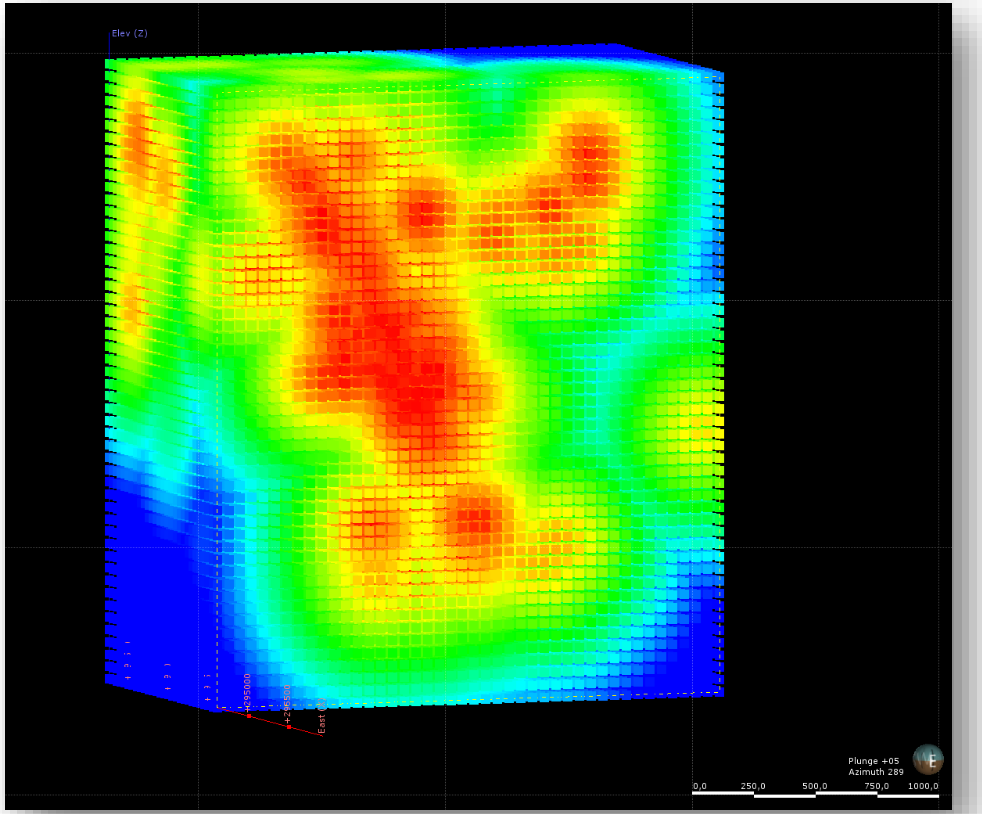
- Multitude of information sources (geology, geophysics, geochemistry, etc.)
- Huge amounts of data
- Multitude of exploration vectors
- Local specificities (not necessarily identified)

Targeting machine learning workflow



Evidential maps

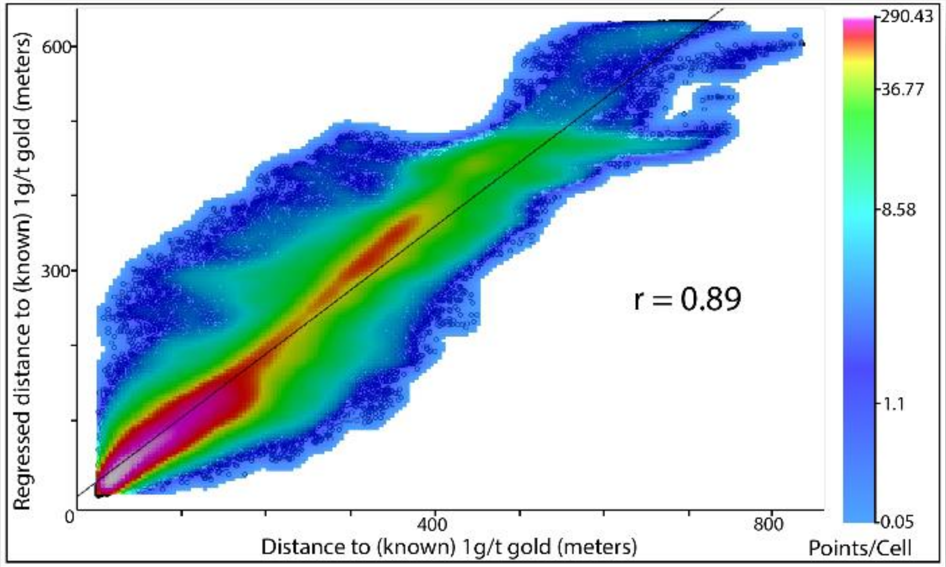
19 interpolants generated from the modelled geological features in a 25- x 25- x 25-metre grid of points.

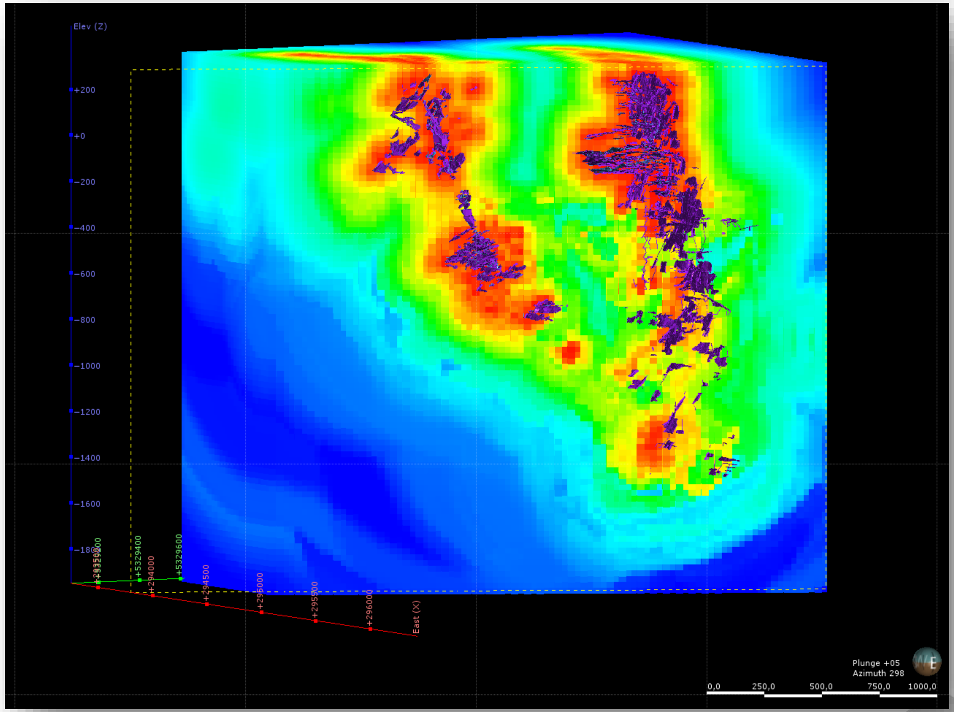


Distance from granodiorite in a 3D grid

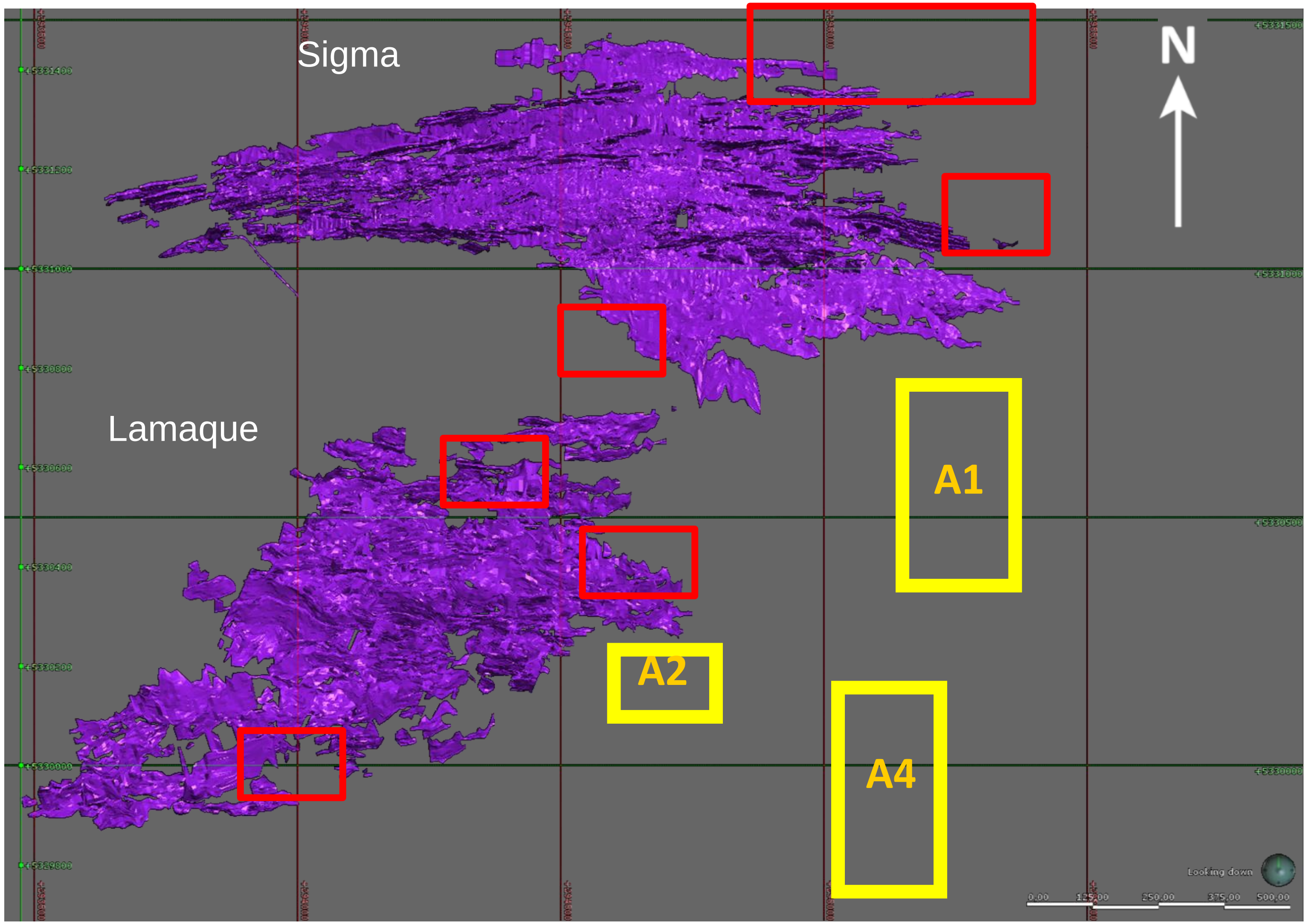
Training and prediction

- Variables to be predicted:
  1. Distance to (previously mined) stopes = distance to “Possible Economic Mineralization” (PEM)
  2. Distance to (known) 1g/t gold = distance to “Possible Mineralization” (PM)
- Regression algorithm on:
  1. Training set
  2. Testing set for QA/QC
  3. Fitting set





Target Definition & Validation

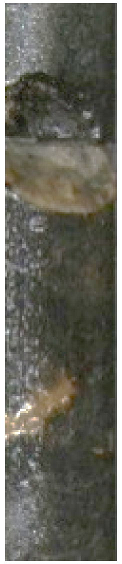


Training an Algorithm for Recognizing Lithologies Based on Core Photos and Generating Pseudo-Logs

Geolearn Solutions

$$Rock\ Name \approx f\Big($$  $$\Big)$$

Borehole data integration

$Rock\ Name \approx f($  $)$

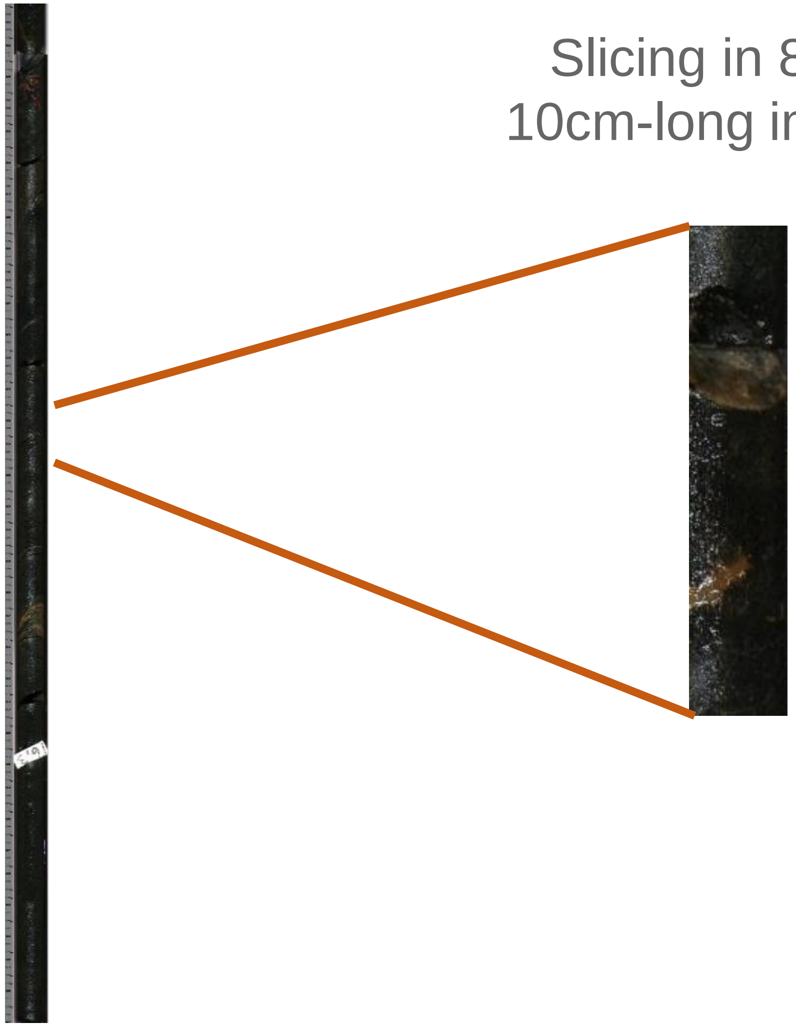
$RQD \approx f($  $)$

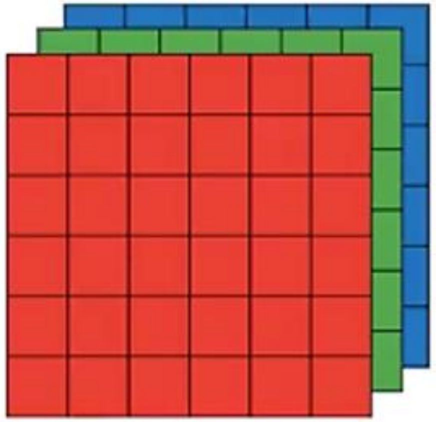
$Vein\ Density \approx f($  $)$

Extracting data from images

Slicing in 8723 10cm-long images

Extract RGB values for each pixel

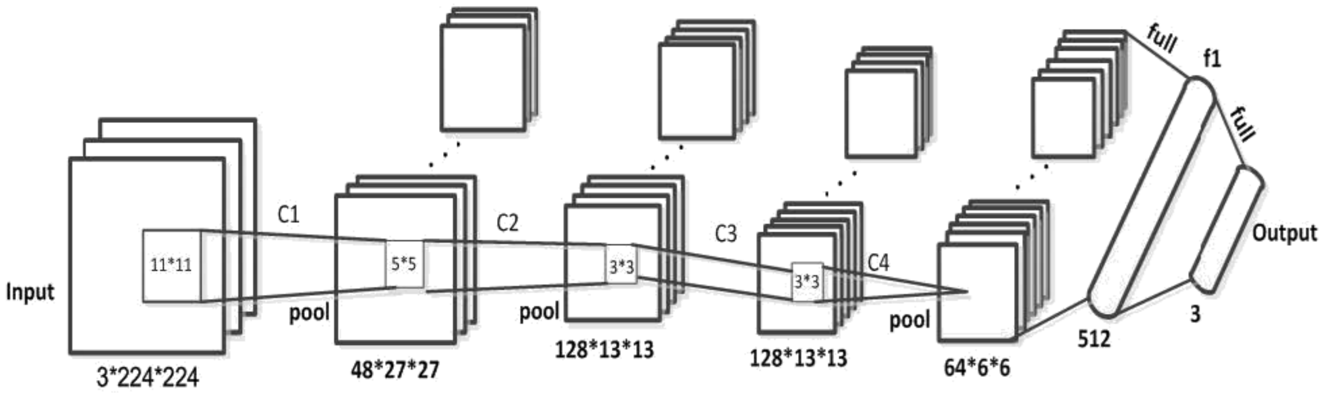




Training a Convolutional Neural Network

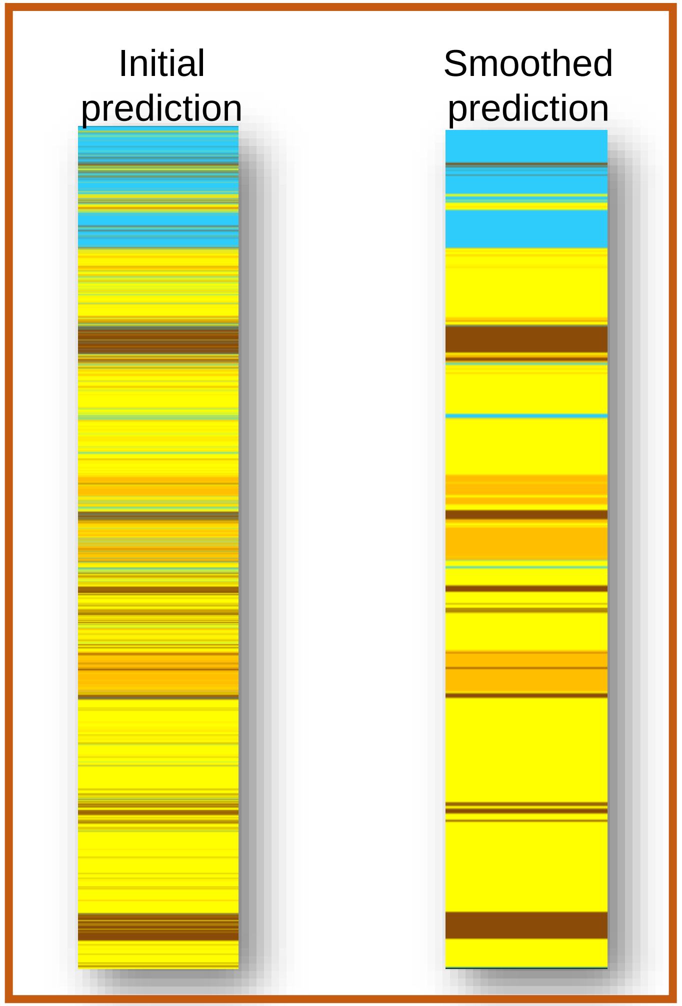
Convolutional Neural Networks (CNNs) use “raw” images as input. Textures and forms are extracted by convolutional layers.

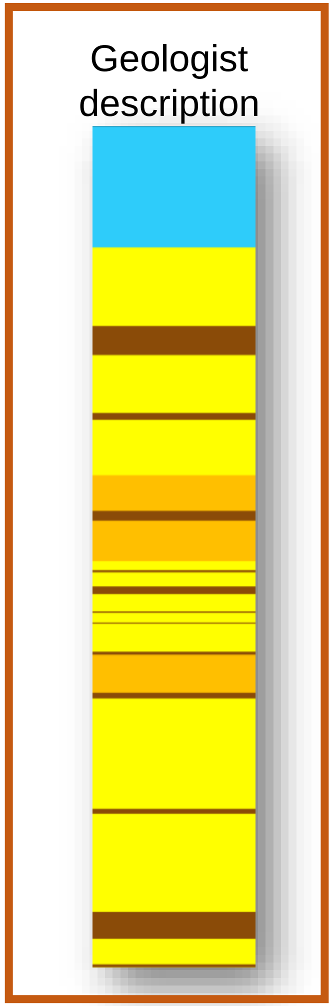
A CNN is used as a model. It is trained on half of the borehole images associated with their attributed rock unit (diorite, QFP, rhyolite and gabbro).



Cheng and Guo, 2017

Predicting lithology on test core images

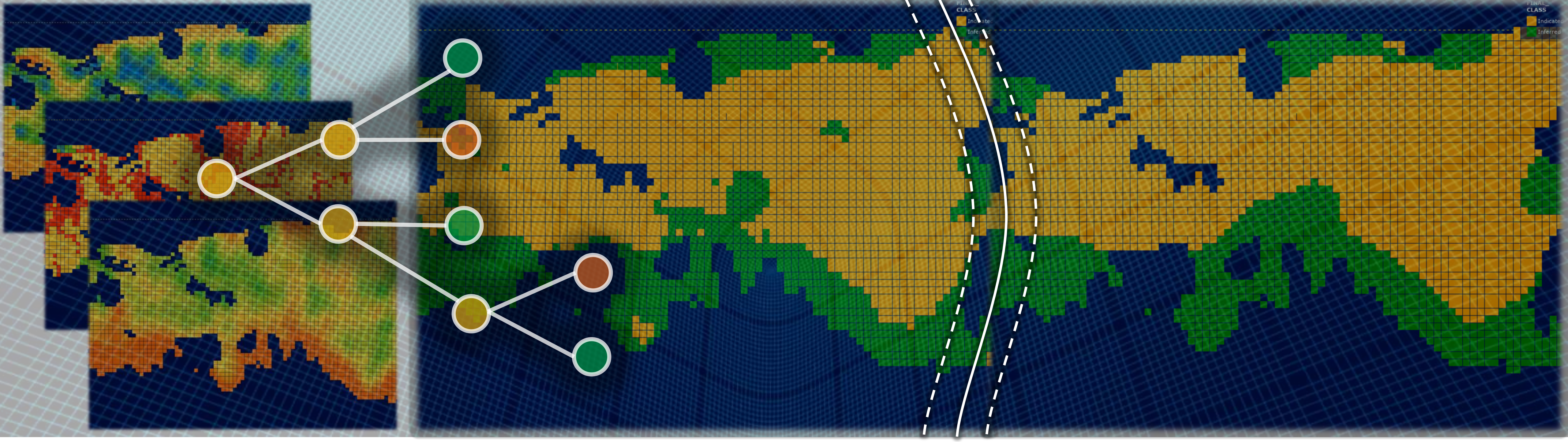




- 90% accuracy relative to geologist description
- Less than 10 minutes to build the log

lithology
diorite
QFP
rhyolite
gabbro

Why do we need smoothing?

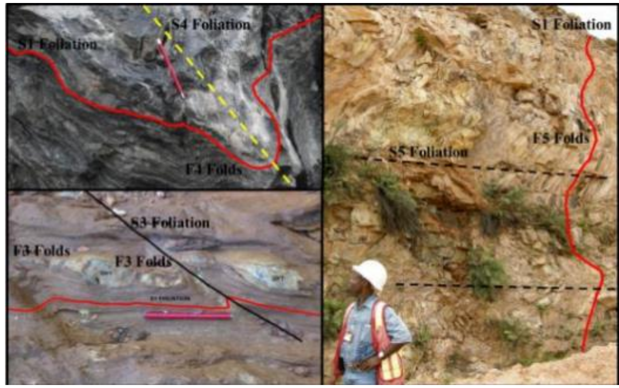


ML Applied in Mineral Resource Classification

Ilkay Cevik, Julian Ortiz Cabrera, SRK Consulting

Mineral resource classification

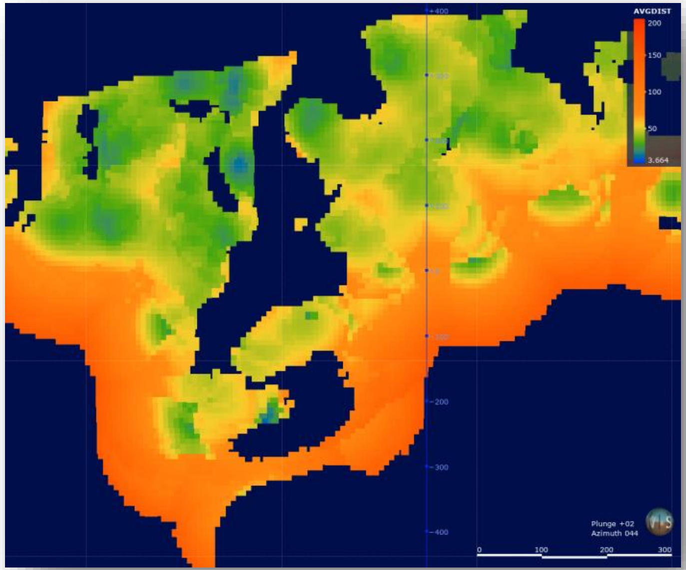
- Considers both qualitative and quantitative factors:
  - Data quality and integrity
  - Geologic confidence in mineralization continuity
  - **Confidence in the estimated grades and tonnage conversion**
  - Potential for eventual economic extraction



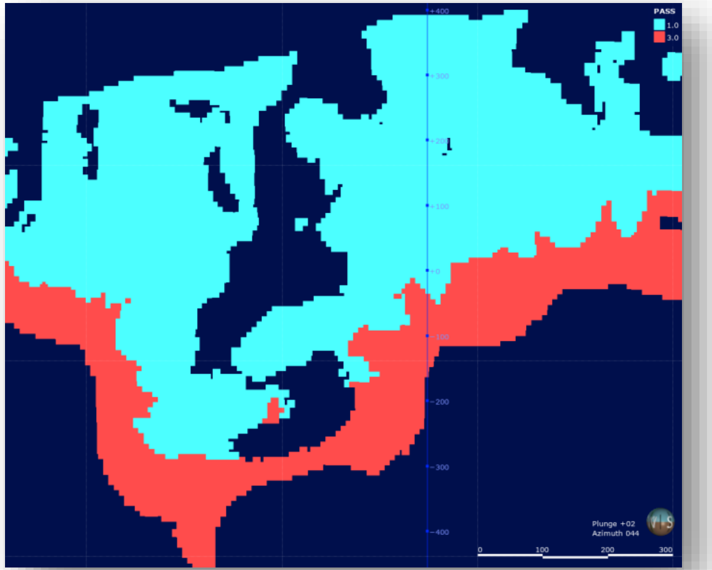
- Quantitative factors:
  - Geometric measures such as drill hole spacing or data density
  - Block model related parameters, such as estimation pass, number of data used, etc.

Inferred? Indicated? Measured?

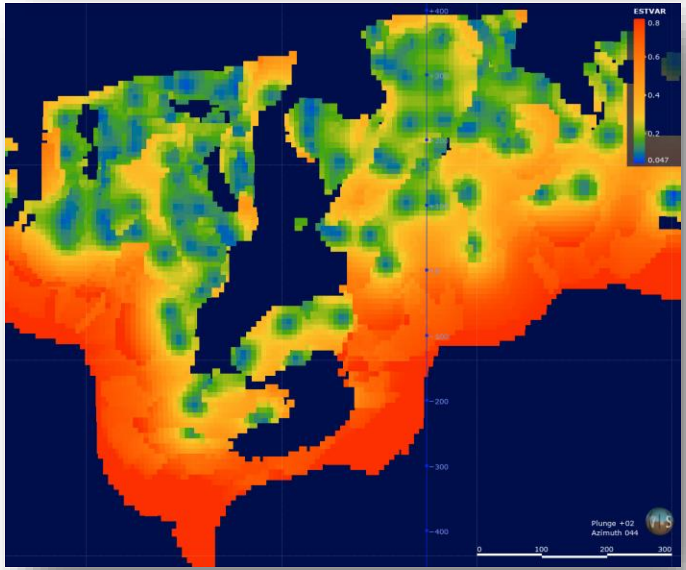
Avg. Dist



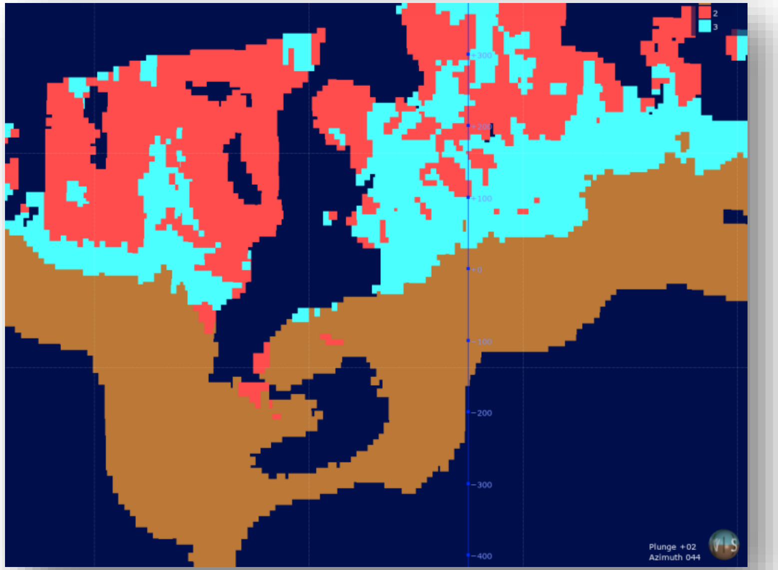
Kriging Pass



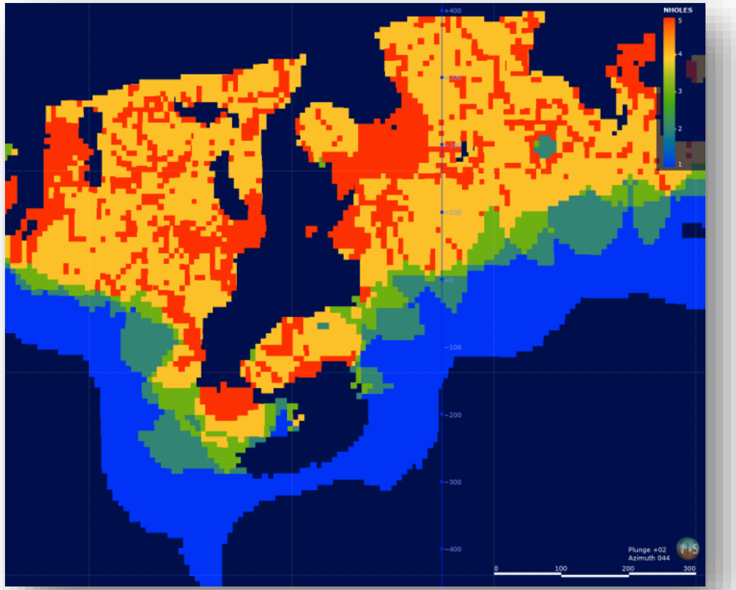
Est. Var.

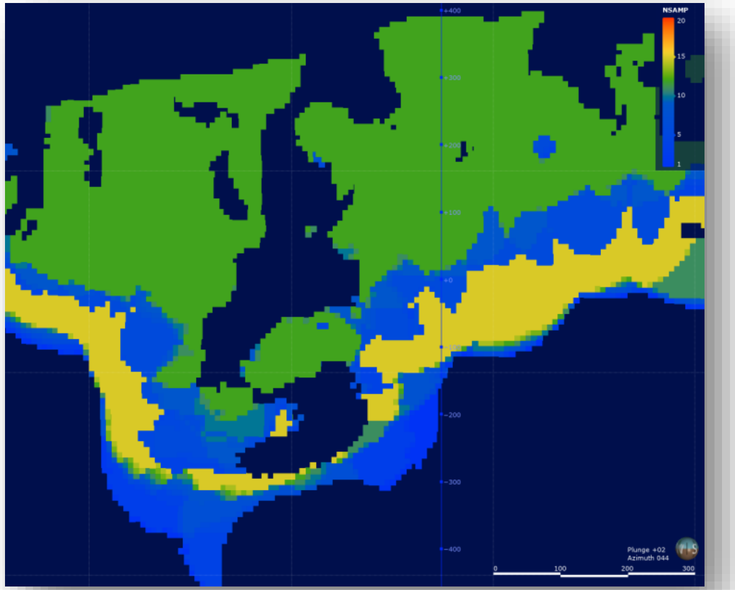


Geometric Class



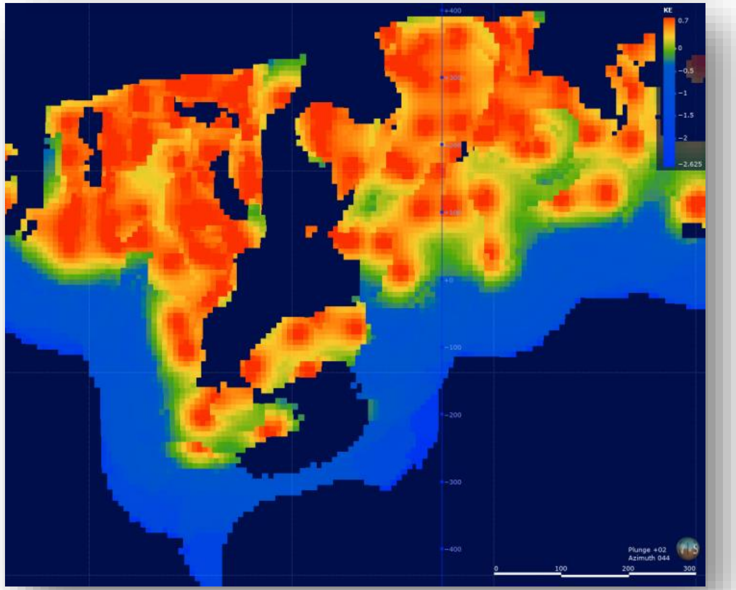
N. Holes



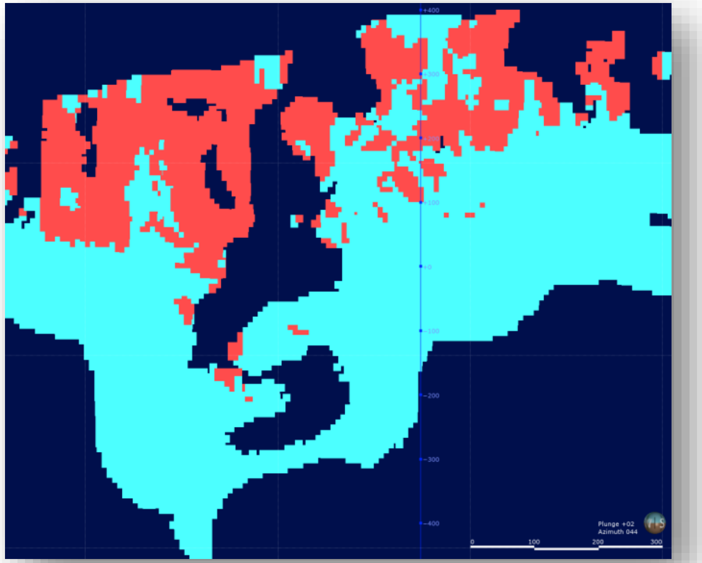


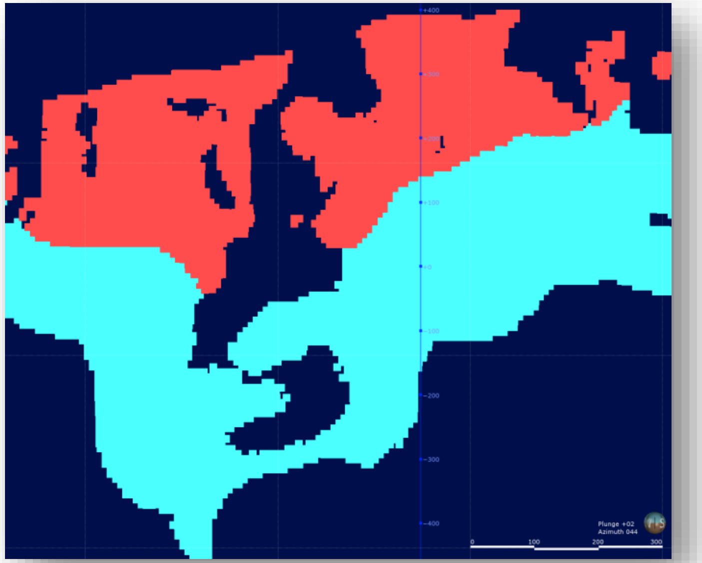
N. Samples

Kriging Efficiency



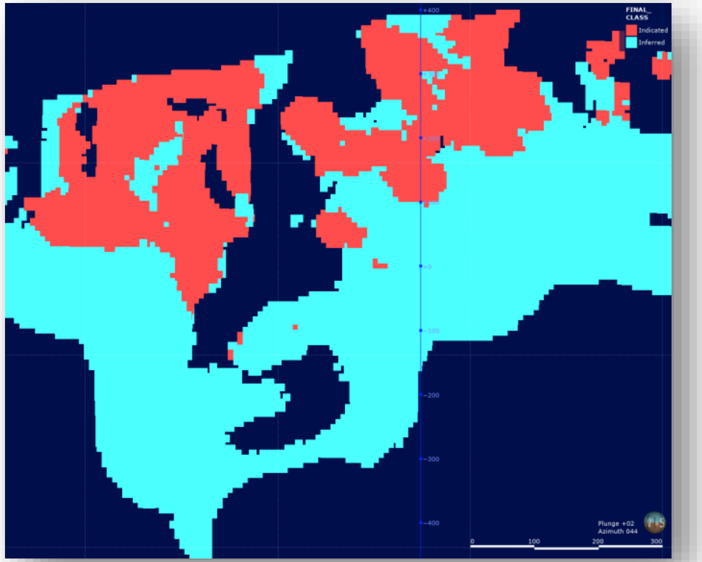
Initial Class (CP)

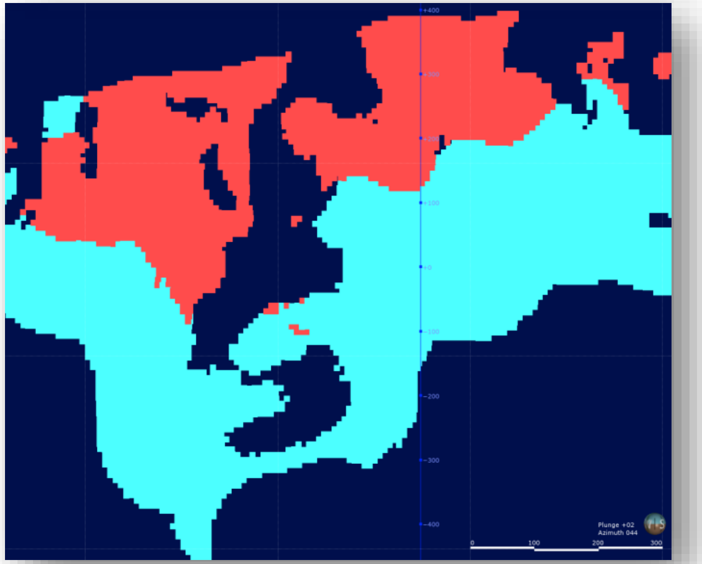




Smoothed Class (CP)

Initial Class (ML)





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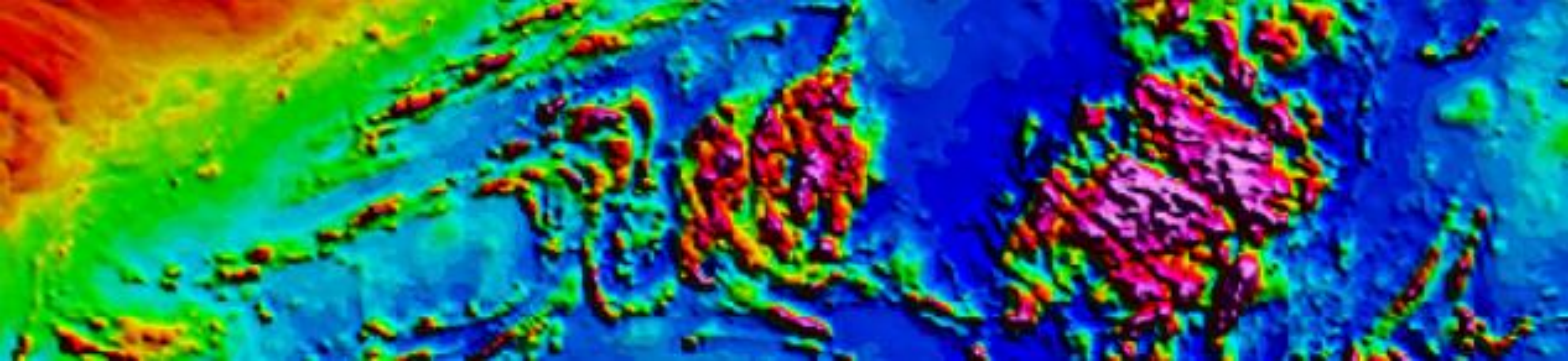
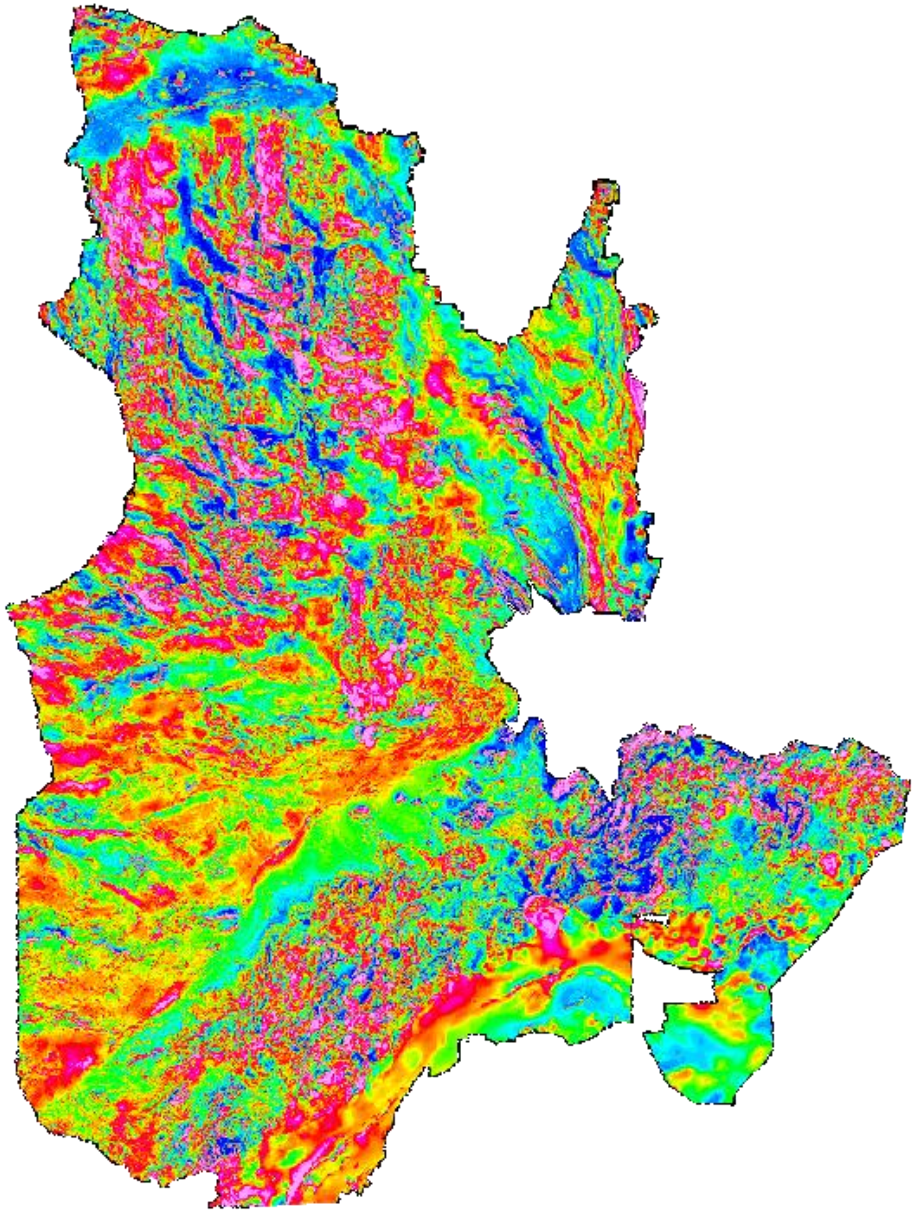
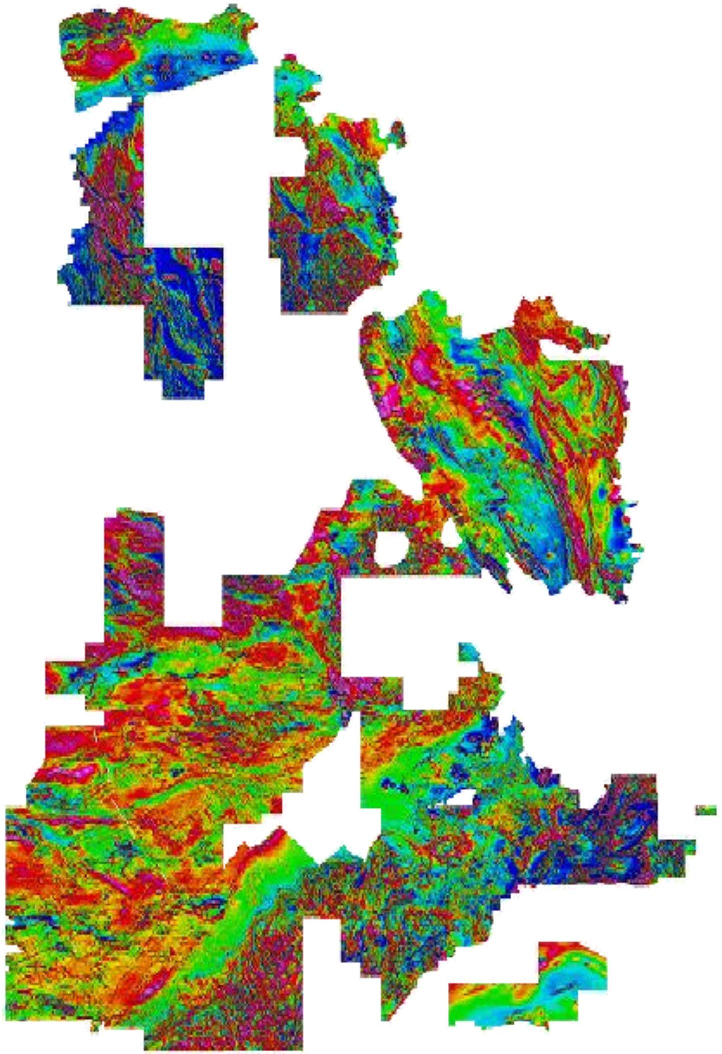
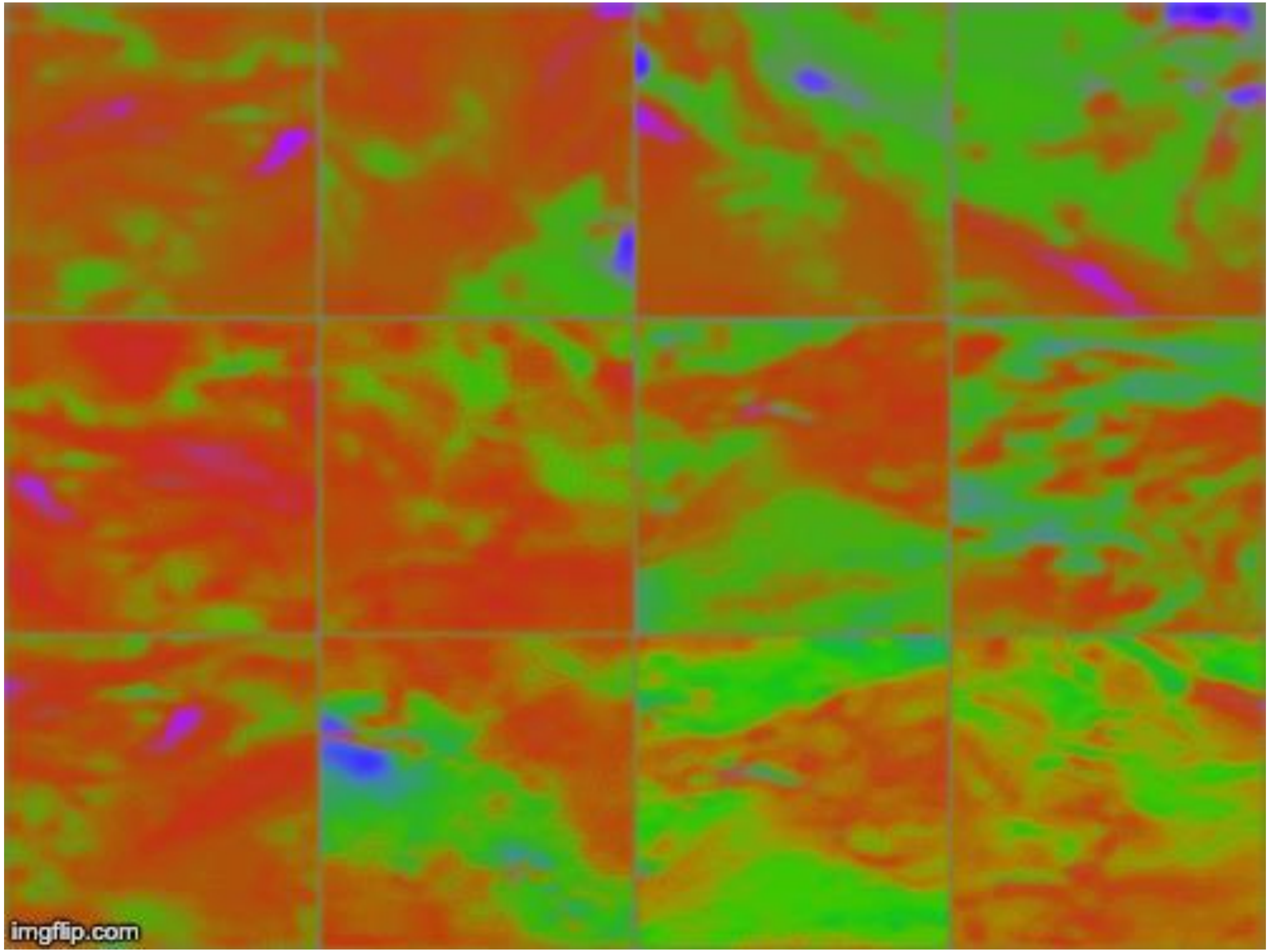


ML Applied to Geophysical Data Interpretation

Geolearn Solutions



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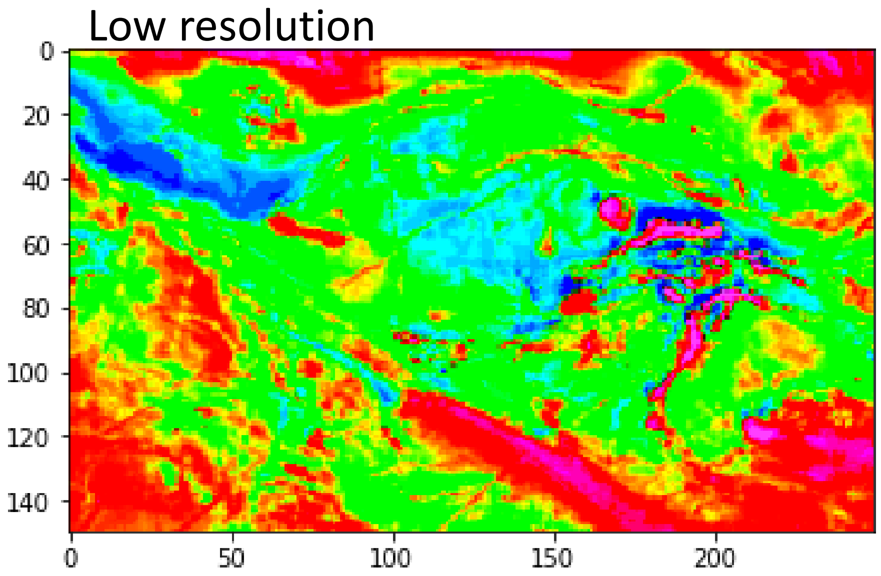

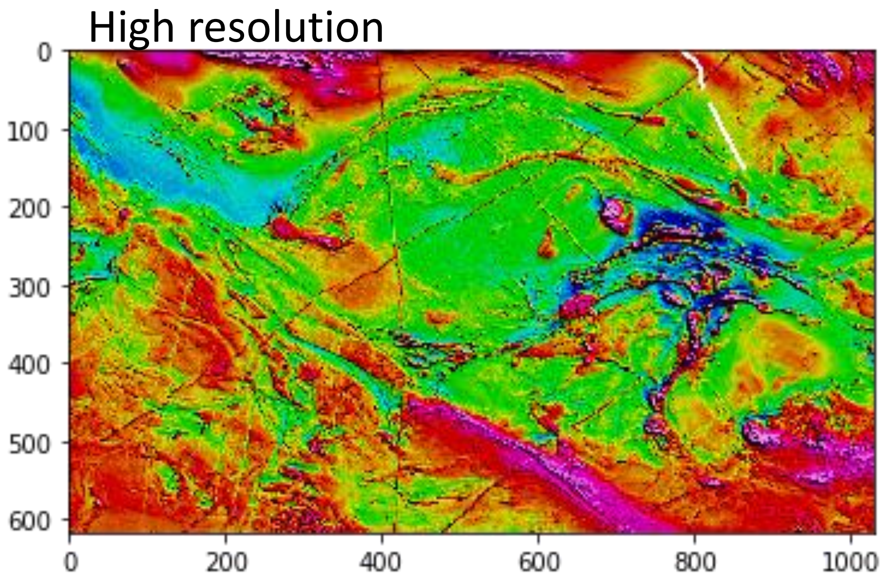

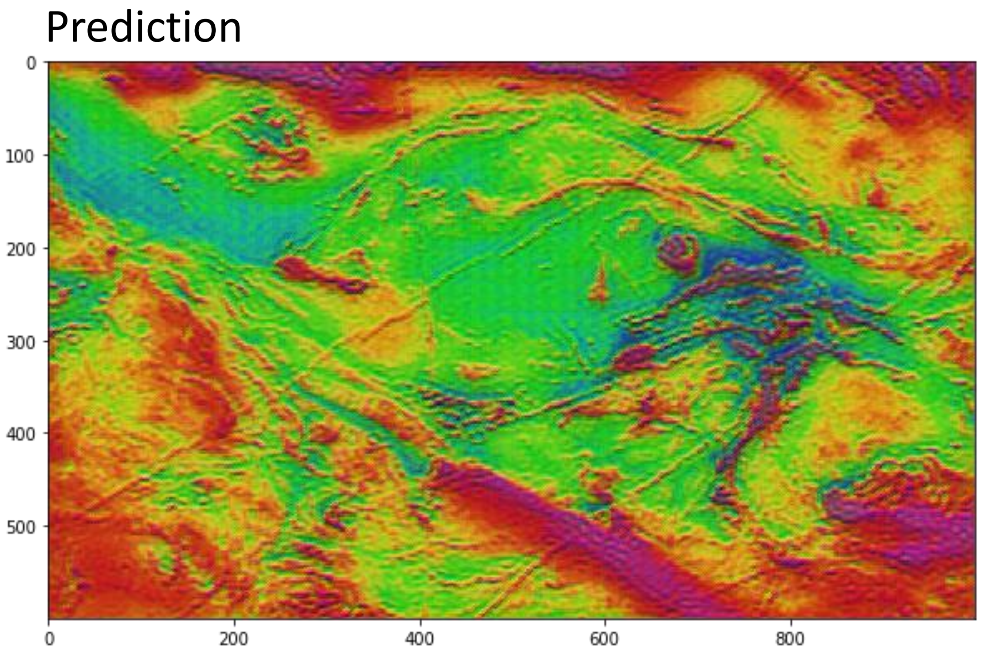

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Conclusions

Machine learning is a new tool in the mineral exploration industry. It will thrive at helping solve numerous problems, but building a successful application can be challenging.

Machine learning will thrive when used to:

- Accomplish menial tasks;
- Help with the interpretation of highly complex data;
- Make decision rapidly.

Conclusions

Machine learning is not the solution to all problems, and it must be integrated within existing practices, not replace them: machine learning is an innovation, not a revolution.

QUESTIONS?

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