collect. interpret. discover.

ML and AI across the Mining Value Chain

Innovation, Integration, and Predictive Analytics to Improve Rock Characterization and Optimize Decision-Making

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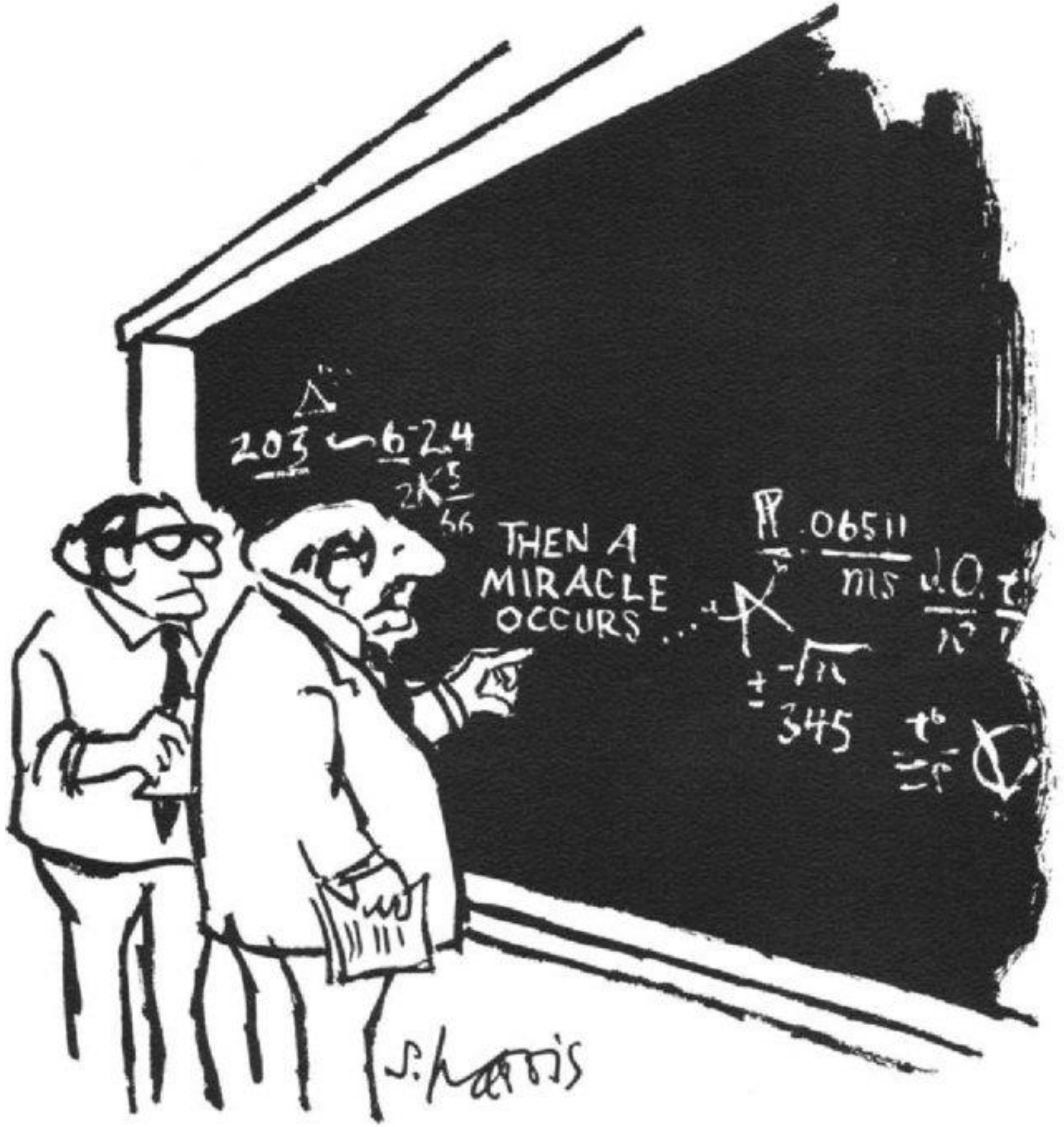
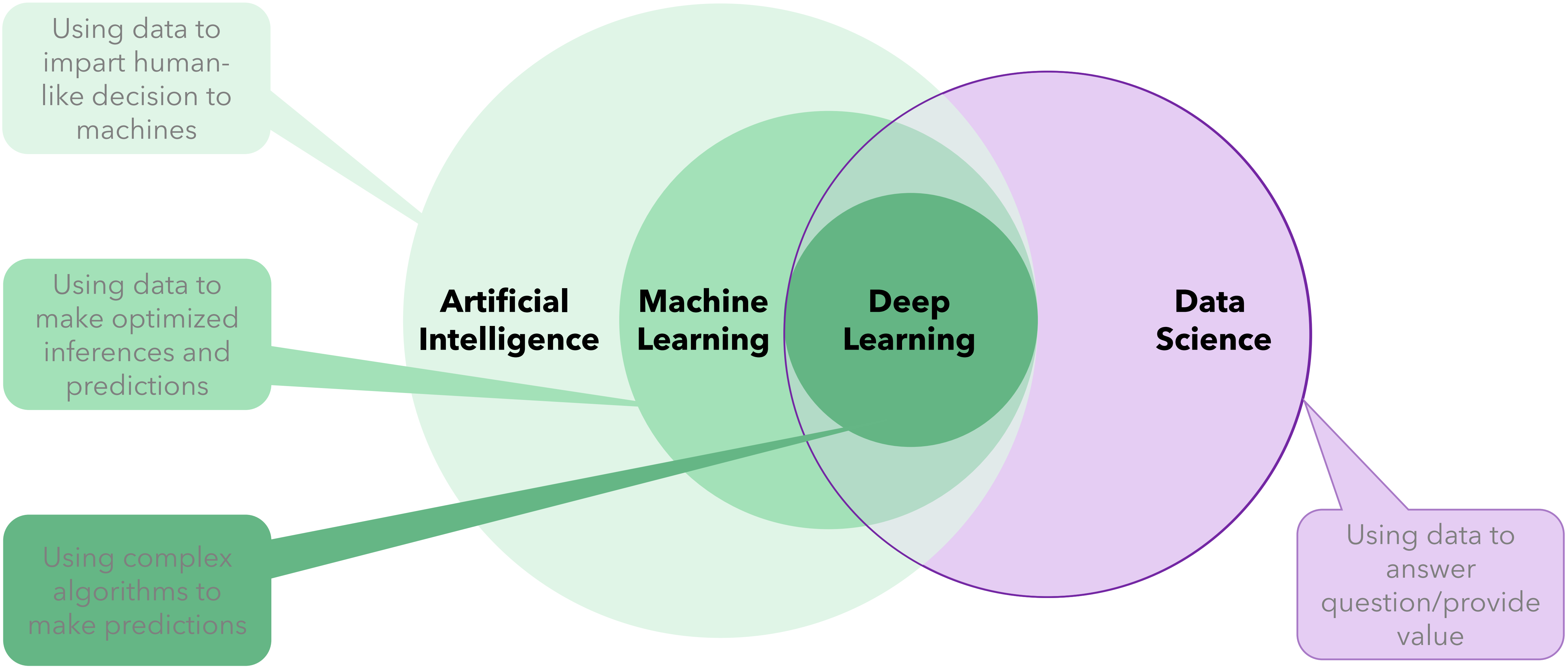
Outline

- Part 1: Demystify Machine Learning and AI
  - Case Study #1: Image analysis to predict the location and orientation of ore shoots
- Part 2: Data Integration Strategies
  - Case Study #2: Ore body knowledge to support mining decisions

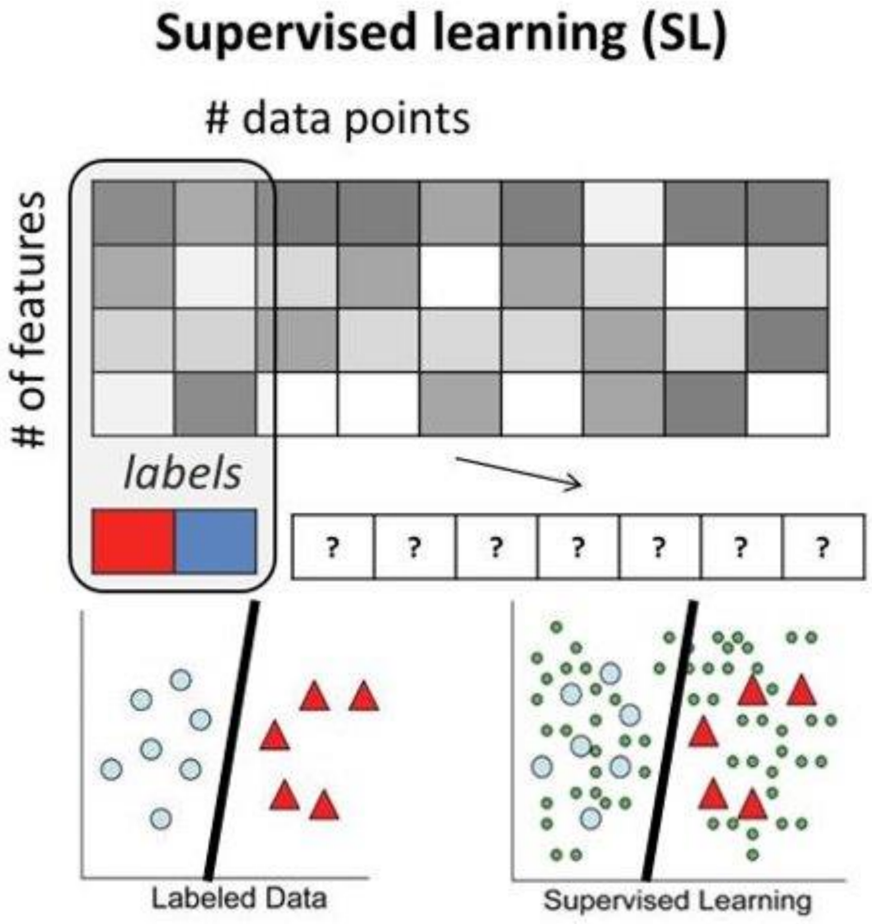


"I THINK YOU SHOULD BE MORE EXPLICIT HERE IN STEP TWO."

Some terminology…



Categories of Machine Learning



Use a discrimination function based on prior observations to apply labels for unknown data

Unsupervised Learning

Find groupings of data in high-dimensionality space, with limited preconceptions of how the data are arranged

Machine Vision to Predict Location and Orientation of Ore Shoots in 3D

LithoLens™ Overview

Image Analysis extracts numeric data from drillcore photography

- Proprietary machine vision technology used to automatically and consistently examine old core images to create fresh and accurate geological logs.

- This tool turns old core photos into intact, georeferenced core images and uses deep learning algorithms to enhance the images and extract valuable geological information.

	A	C	D	E	F	G	H	I	K
1	HOLEID	GEOLFR	GEOLTO	Geotec	Geotechl	GeotechRQI	FtDrilled_D	RQD_pct	Recovery_p
2	iCHU23-05	0	3	HQ	0.3	0	3	0	10
3	iCHU23-05	3	6	HQ	2	1	3	33.3333	66.6667
4	iCHU23-05	6	10	HQ	3	1.4	4	35	75
5	iCHU23-05	10	15	HQ	4.8	2.9	5	58	96
6	iCHU23-05	15	20	HQ	4.8	3.2	5	64	96
7	iCHU23-05	20	25	HQ	4.9	2.2	5	44	98
8	iCHU23-05	25	30	HQ	4.6	2.4	5	48	92
9	iCHU23-05	30	35	HQ	4.8	4.4	5	88	96
10	iCHU23-05	35	40	HQ	4.4	4	5	80	88
11	iCHU23-05	40	45	HQ	4.8	1.9	5	38	96
12	iCHU23-05	45	50	HQ	4.7	3.1	5	62	94
13	iCHU23-05	50	55	HQ	4.9	4	5	80	98
14	iCHU23-05	55	60	HQ	4.3	2.3	5	46	86
15	iCHU23-05	60	65	HQ	4.8	4.8	5	96	96
16	iCHU23-05	65	70	HQ	4.8	2	5	40	96
17	iCHU23-05	70	75	HQ	4.9	2.5	5	50	98
18	iCHU23-05	75	80	HQ	4.9	4.6	5	92	98
19	iCHU23-05	80	85	HQ	4.7	4.4	5	88	94
20	iCHU23-05	85	90	HQ	4.8	0	5	0	96
21	iCHU23-05	90	95	HQ	5	0	5	0	100
22	iCHU23-05	95	100	HQ	5	0	5	0	100
23	iCHU23-05	100	105	HQ	4.7	1.4	5	28	94
24	iCHU23-05	105	110	HQ	4.8	0	5	0	96
25	iCHU23-05	110	115	HQ	5	1.6	5	32	100

Machine Learning Opportunities

Case Study – Kootenay Silver

Step 1
Establish input features

- Identify available datasets
- Feature engineering: transformations and dimension reduction.

LithoLens™ Features

Color extraction data: counts of color (n=25) pixels in the core image (in area %)

Geotechnical: number of fractures per interval and others

Textures (90 textural metrics): image textures

VeinNET: vein identification, vein frequency, and percentage of veining

Geochemical Features: processed geochemical results

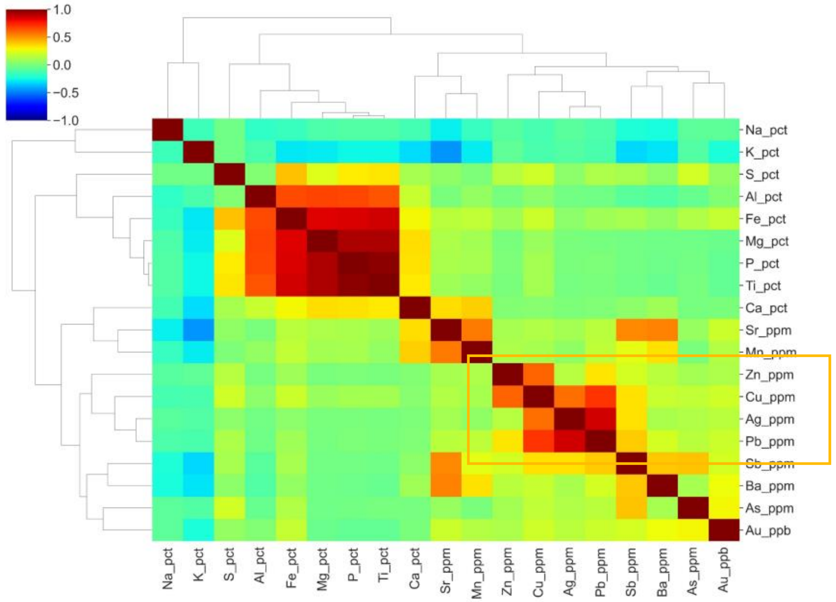
Many features, especially within the texture group, are correlated: dimension reduction techniques are used

CDH-20-110
Source: Kootenay Silver Investor Update (Jan 2024)

LithoLens™ - Machine Learning Opportunities

Step 2
Establish target variables

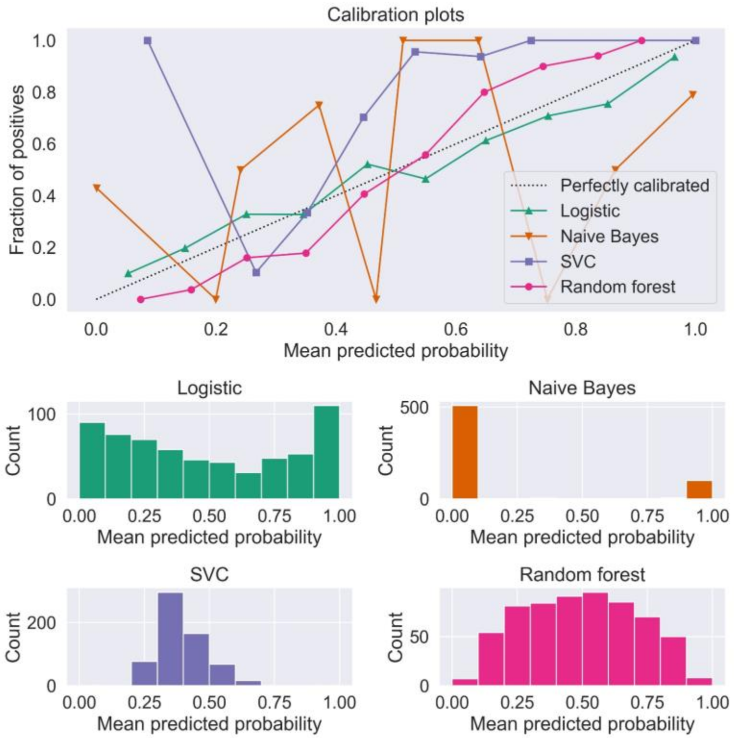
- **Locally defined** anomalous or cut-off grade
- **Project specific** mineralization factor
- Could be mineralization or other geologic feature – alteration, lithology, etc.

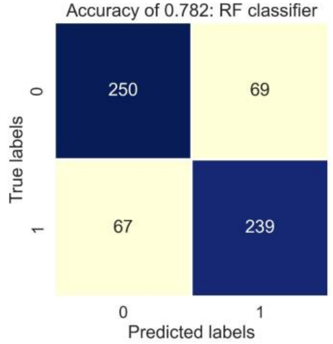


Example of correlated elements

Step 3
Supervised ML training & evaluation

- Multiple algorithms trained and evaluated using engineered inputs labelled with mineralization factor.



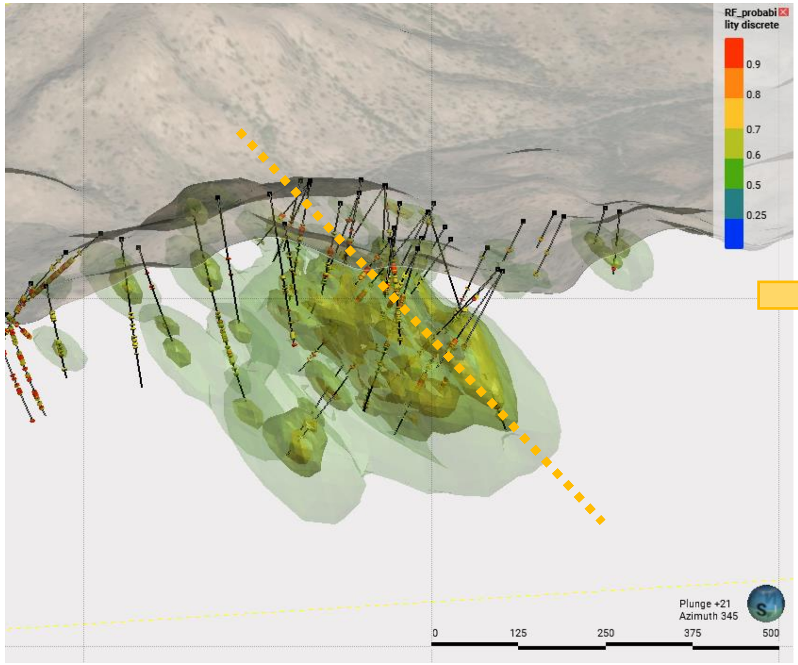


Project specific algorithms are chosen based on the shape of the calibration curve and the precision and recall scores

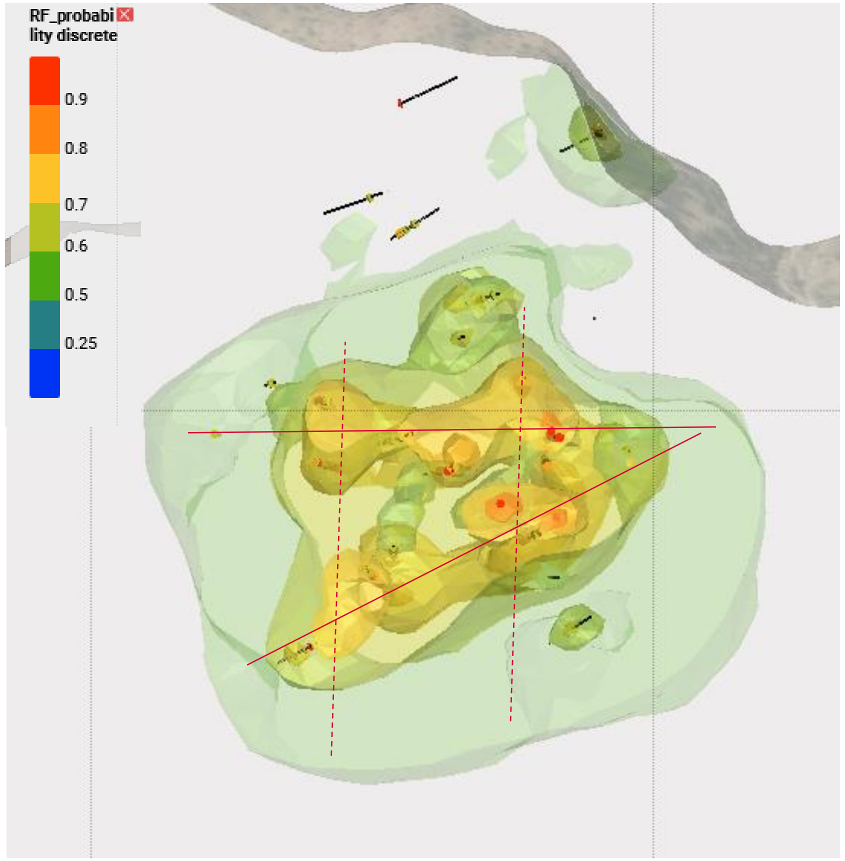
LithoLens™ - Machine Learning Opportunities

Step 4
Interpretation and 3D Modeling

- Integrate with geological conditions and exploration expertise
- Define areas with higher probability of mineralization or other target variables



3D view of ore zone



Long section through ore zone

- Identify prospective horizons, structures, ore shoots, etc.
  - Infill and expansion drill hole targets
- Understand the geologic and structural context to expand project scale understanding
  - Apply lessons learned to regional targeting

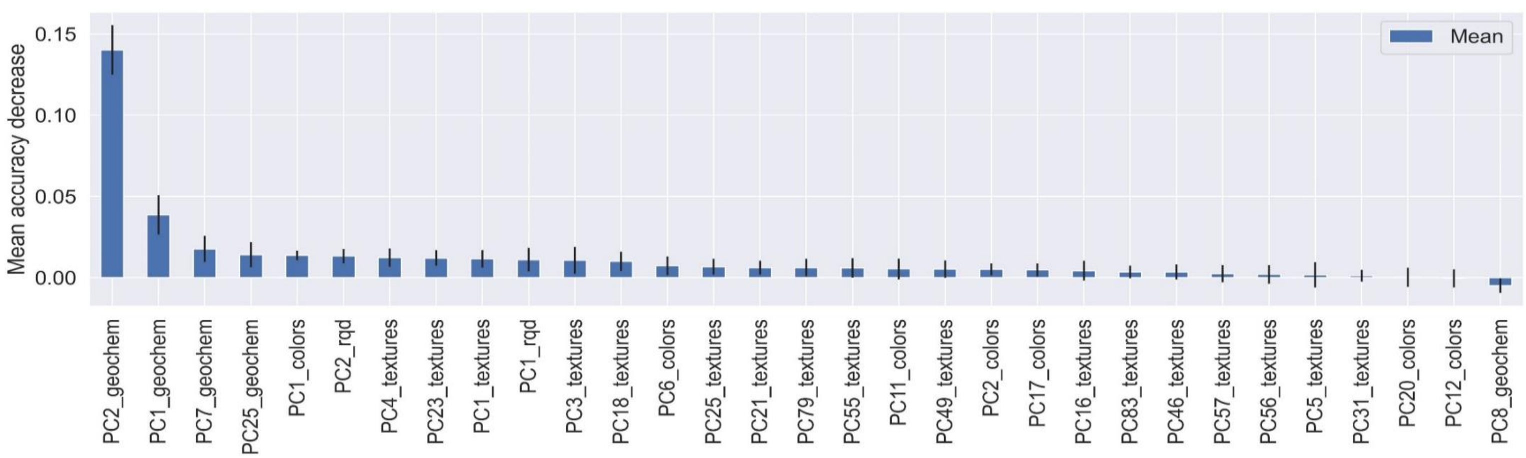
LithoLens™ - Machine Learning Opportunities

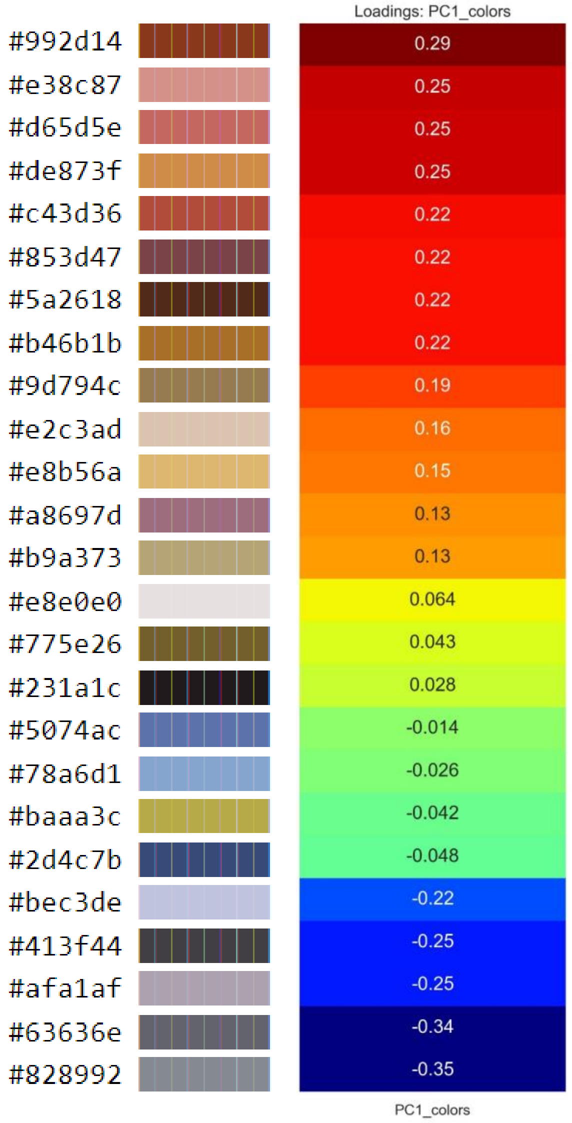
What other information comes out of the predictions?

- Feature Importance information can highlight relationships in the data
- LithoLens™ features are built on visual information so can help find proxies for mineralization that can be seen by a geologist

In this case, red colors are shown to be more predictive of Ag than orange, suggesting a relationship between specific FeOx and mineralization

Feature Importance

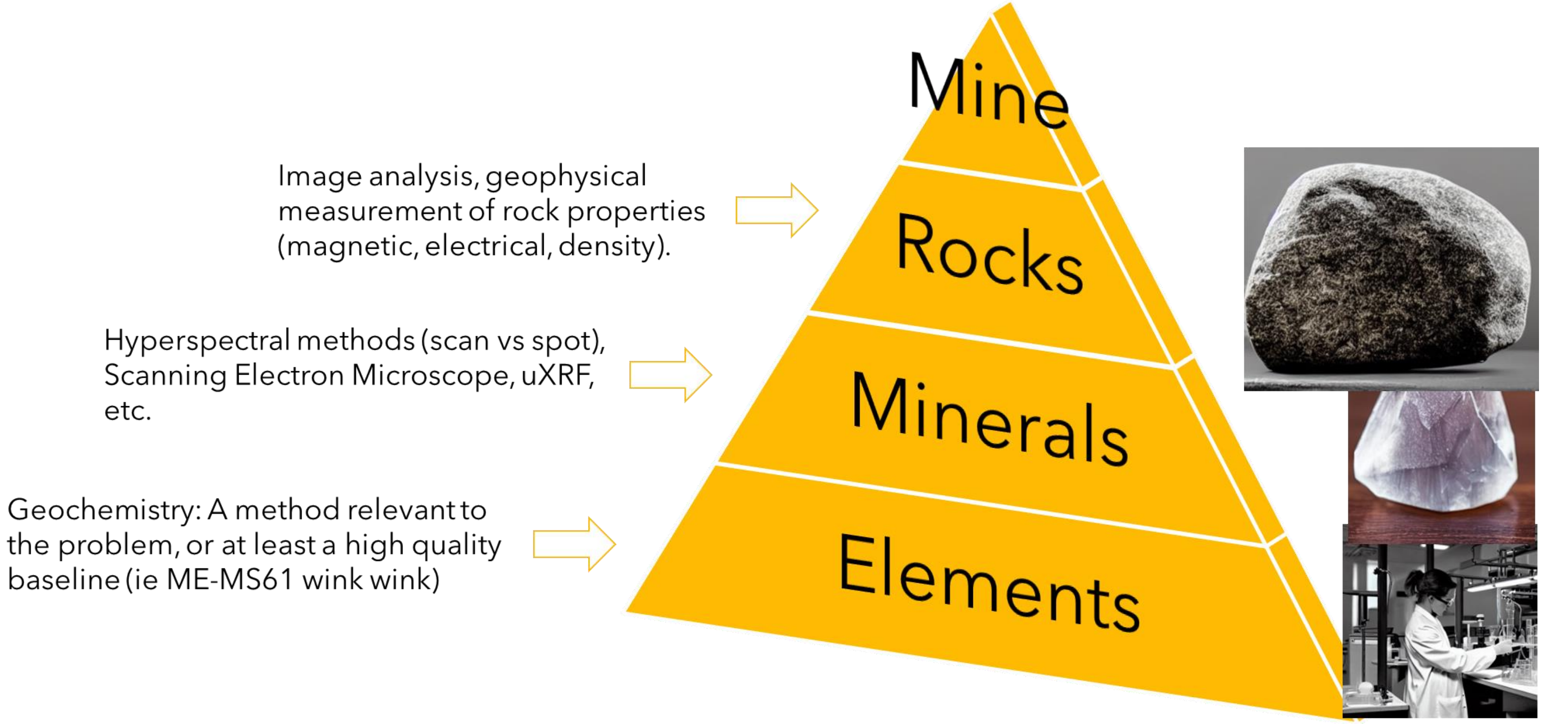




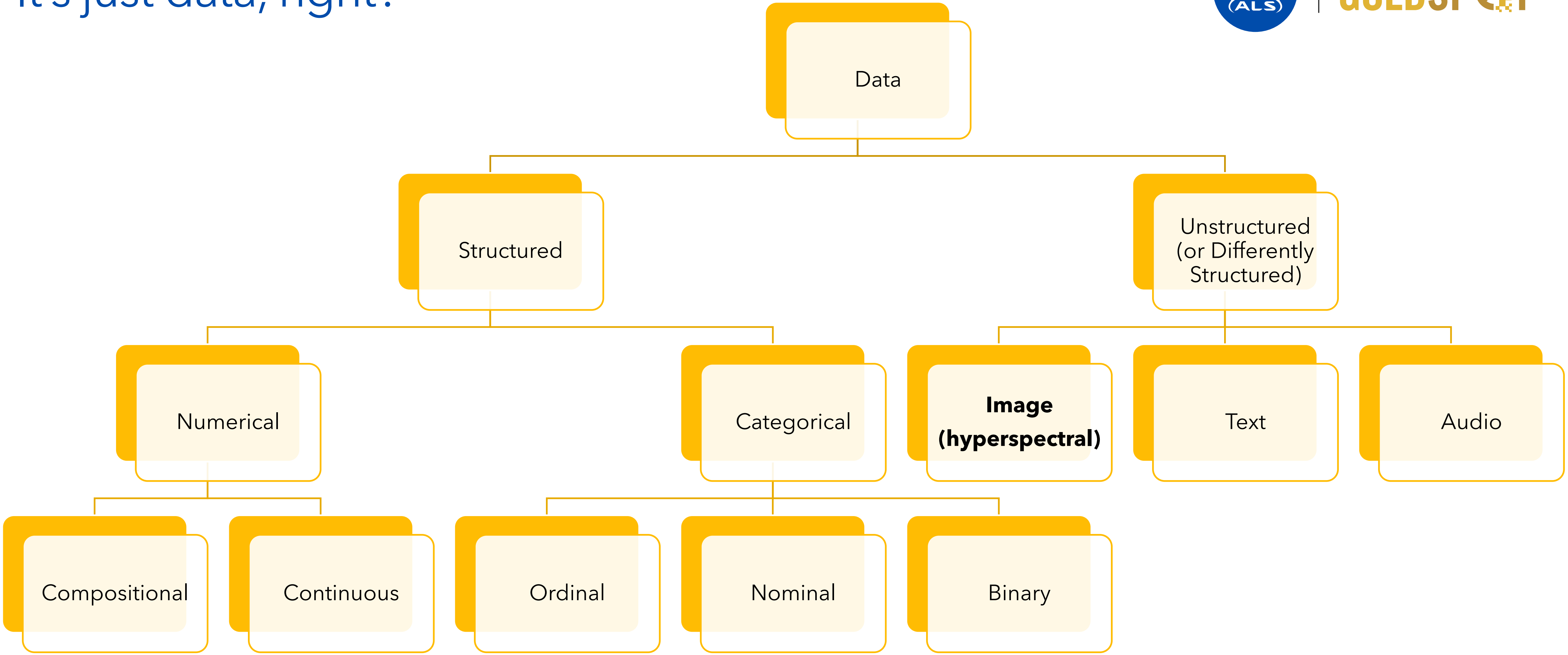
Data Integration Strategies

Introduction

- More value to be found by combining spectroscopy methods with other, complementary data types.
- As an example, shortwave infrared contains valuable information about presence/absence of SWIR-active minerals, and some indications of mineral chemistry.
  – By itself this is useful vectoring information in a magmatic-hydrothermal scenario (porphyry copper, epithermal gold, etc.).
  – Combining this information with compositional and/or textural information creates a much more holistic representation of the rock and more can be done, particularly in the machine learning space.



It's just data, right?



Pixel abundances

Wavelength Positions

Alteration intensity

Mineral Match

Ore vs Waste

Data Integration Strategies

- **Best to think about this before capturing data at all.**
  - What do I want to accomplish with this dataset?
  - What is the minimum spatial resolution needed to accomplish this?
  - How can I spatially relate my distinct data families, like spectroscopy, geochemistry, image features?
    - What types of data am I dealing with and how do they fit together?
  - ***Do a small but rigorous test (pilot study), and establish the pipeline.***

- **Point data**: ideally merge with other point data types. If this isn't possible and you must merge with data of a distinct spatial resolution (IE 2 m assays), keep in mind through all the subsequent process that the composition represents 2 m and the SWIR variables represent something like 1 cm2. In other words, watch out for spectral "nugget effects".
  - *Trott, M., et al. (2022). "Random forest rock type classification with integration of geochemical and photographic data." Applied Computing and Geosciences* ***15***.

- **Interval (ie Scanned) data**: composite scanned data into the assay interval:
  - Pixel abundances can be summed and renormalized to 100% over the interval
  - In the case of wavelength geometric features, calculate an average and variance or standard deviation over the interval.
    - *Trott, M., et al. (2023). "Alteration assemblage characterization using machine learning applied to high resolution drill-core images, hyperspectral data, and geochemistry." Geochemistry: Exploration, Environment, Analysis: geochem2023-2032.*

“The Curse of Dimensionality” aka The Cost of Integration

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z
A	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
B	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
C	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
D	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
E	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
F	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
G	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
H	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
I	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
J	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
K	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
L	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
M	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
N	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
O	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
P	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Q	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
R	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
T	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
U	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
V	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
W	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
X	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Y	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Z	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

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