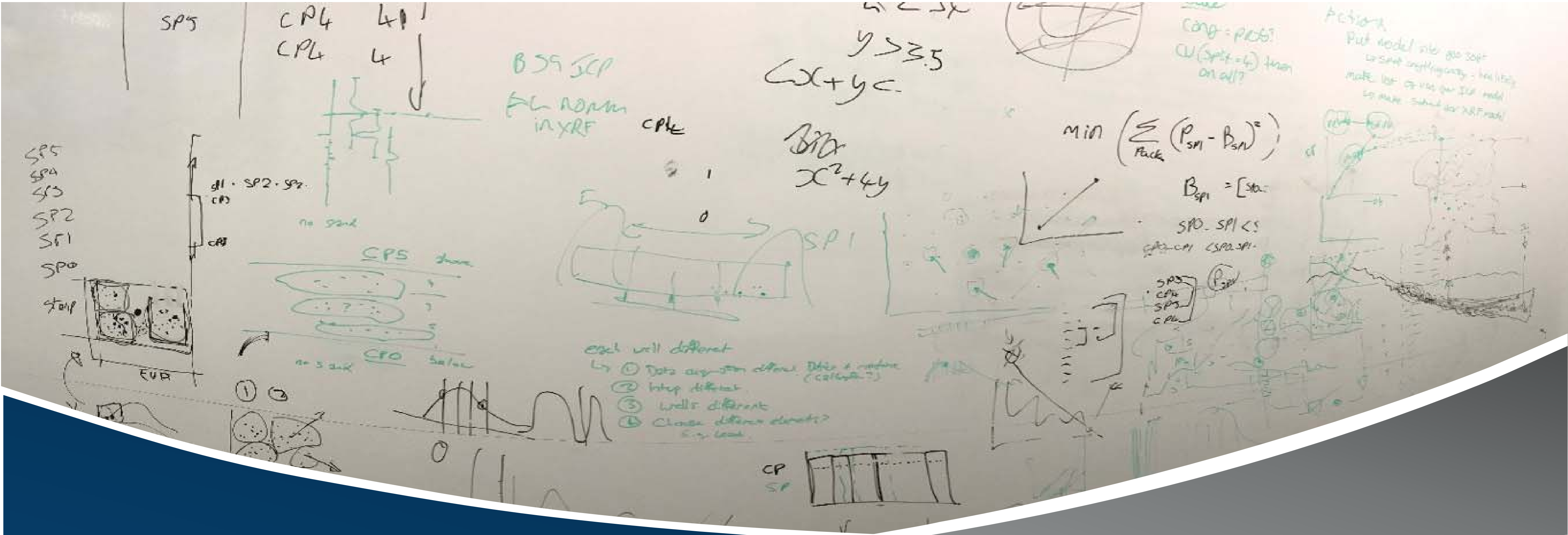

Supporting critical well delivery decisions by utilising Machine Learning (ML) to aid interpretation of wellsite XRF data

R Webber, B Fletcher*, **CNOOC International**

June 2023

* BP

cnooc

Forward Looking Statement

“This presentation includes "forward-looking statements" within the meaning of the United States Private Securities Litigation Reform Act of 1995, including statements regarding expected future events, business prospectus or financial results. The words "expect", "anticipate", "continue", "estimate", "objective", "ongoing", "may", "will", "project", "should", "believe", "plans", "intends" and similar expressions are intended to identify such forward-looking statements. These statements are based on assumptions and analyses made by CNOOC Limited and/or its subsidiaries (the “Company”) in light of its experience and its perception of historical trends, current conditions and expected future developments, as well as other factors the Company believes are appropriate under the circumstances. However, whether actual results and developments will meet the expectations and predictions of the Company depends on a number of risks and uncertainties which could cause the actual results, performance and financial condition to differ materially from the Company's expectations, including but not limited to those associated with fluctuations in crude oil and natural gas prices, the exploration or development activities, the capital expenditure requirements, the business strategy, whether the transactions entered into by the Company can complete on schedule pursuant to their terms and timetable or at all, the highly competitive nature of the oil and natural gas industries, the foreign operations, environmental liabilities and compliance requirements, and economic and political conditions in the People's Republic of China. For a description of these and other risks and uncertainties, please see the documents the Company files from time to time with the United States Securities and Exchange Commission, including the Annual Report on Form 20-F filed in April of the latest fiscal year.

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Agenda

01 Study Objective

02 Chemostrat Machine Learning (ML) project

03 What makes a successful ML project?

04 Q&A

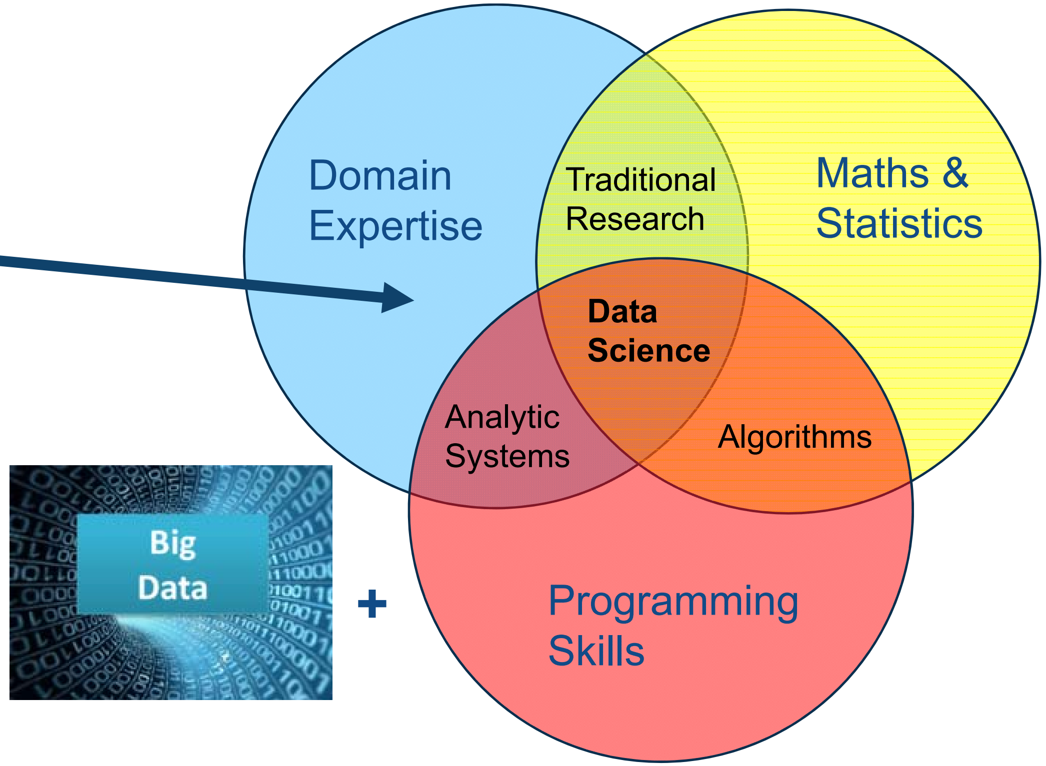
Overview:

This presentation is given from the perspective of a subsurface geoscience / engineering worker…

… with some domain expertise and statistical knowledge

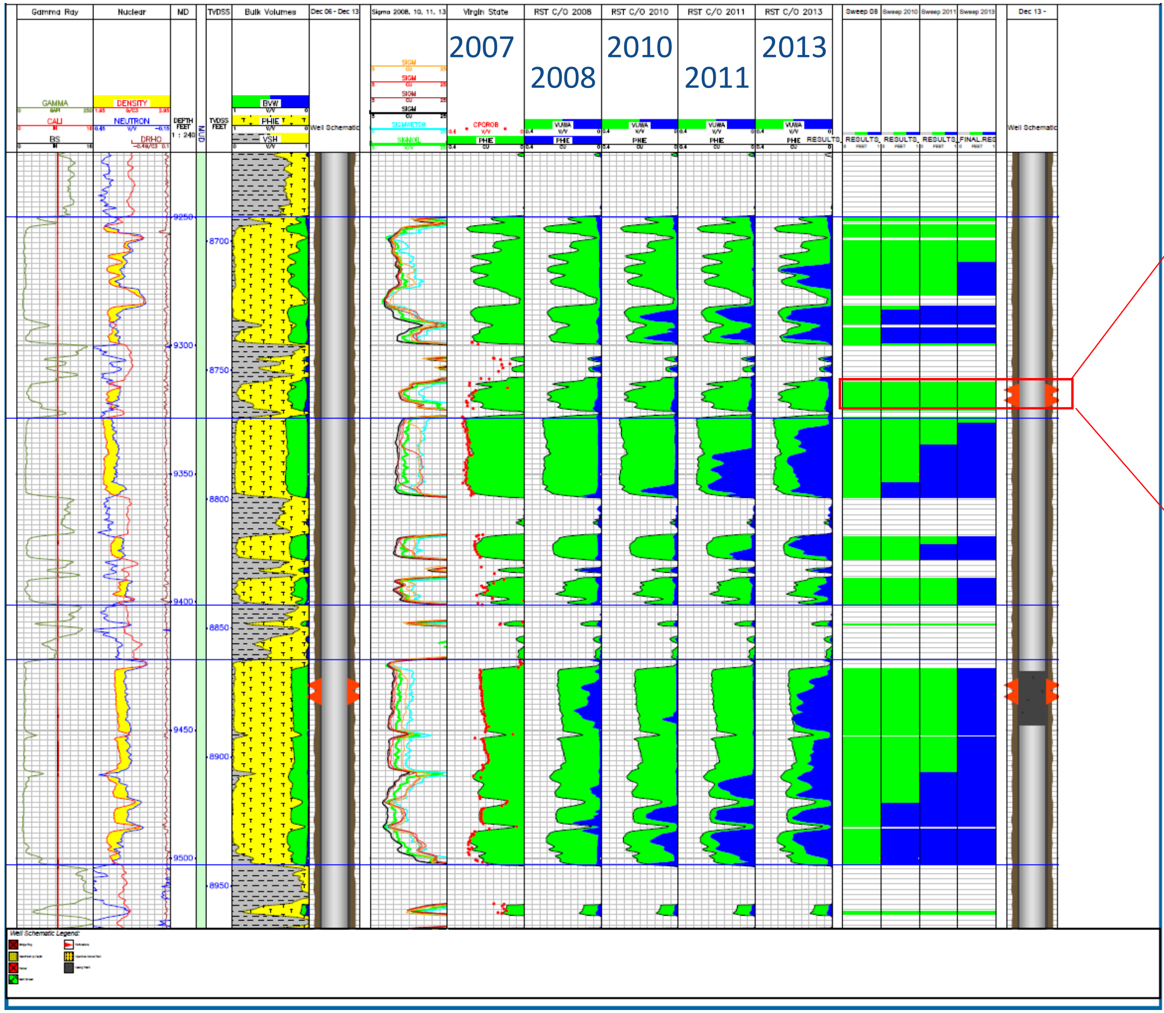
… with more limited practise in machine learning

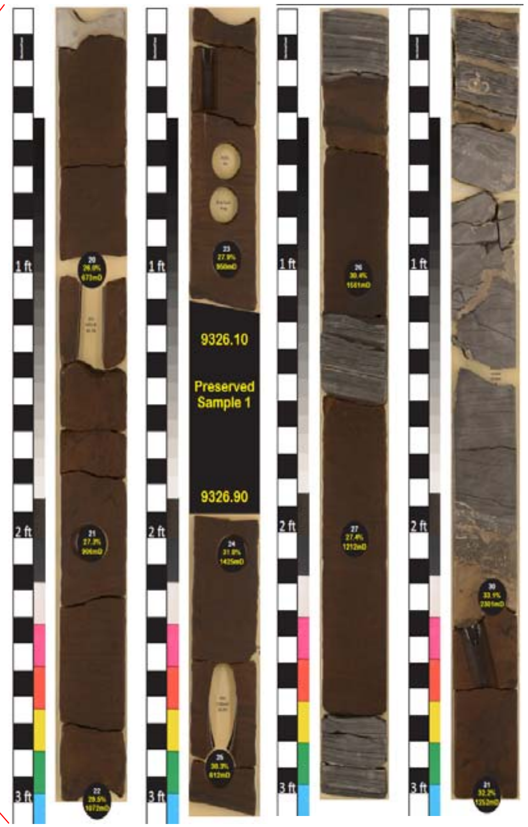
… hoping to develop some ideas for success in this area



Edited from Image by NIST big data workgroup
https://commons.wikimedia.org/wiki/File:Data_science.png

Field development challenge - locating the remaining oil

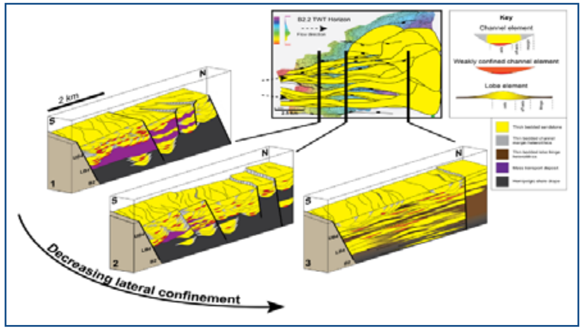




Water sweep is variable in different zones. Optimising future production relies on identifying specific zones with remaining oil potential, and then understanding the distribution of these zones.

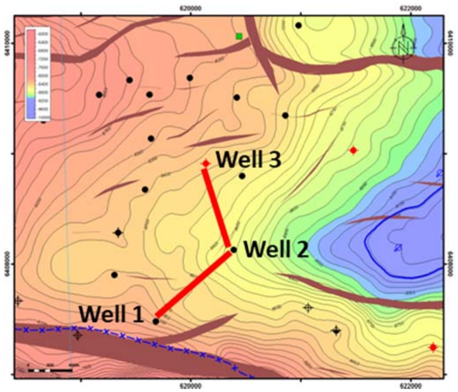
Submarine turbidite geological correlation challenge

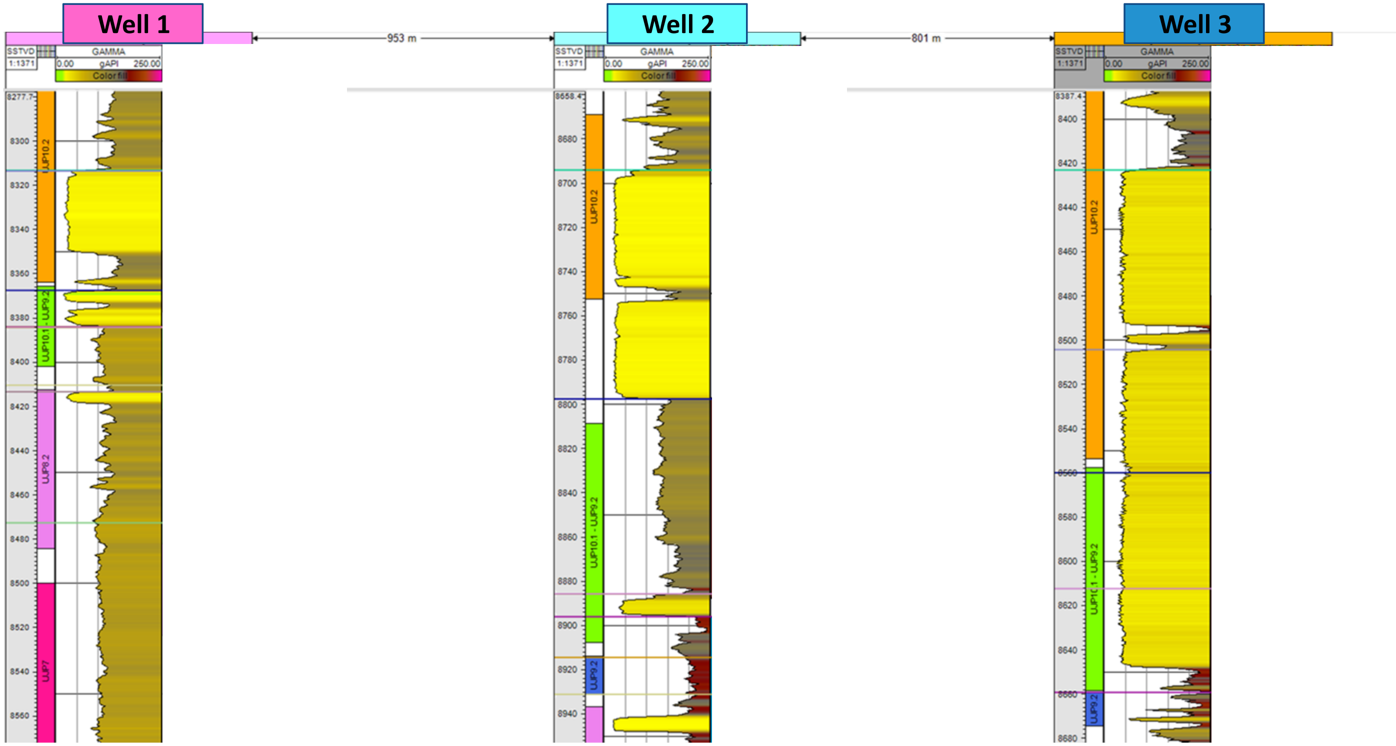
Upper Jurassic Deep
Marine Turbidite system



Depositional model:

- Channel architecture
- Erosion and Mass Transport Debrites (MTD)
- Not layer cake

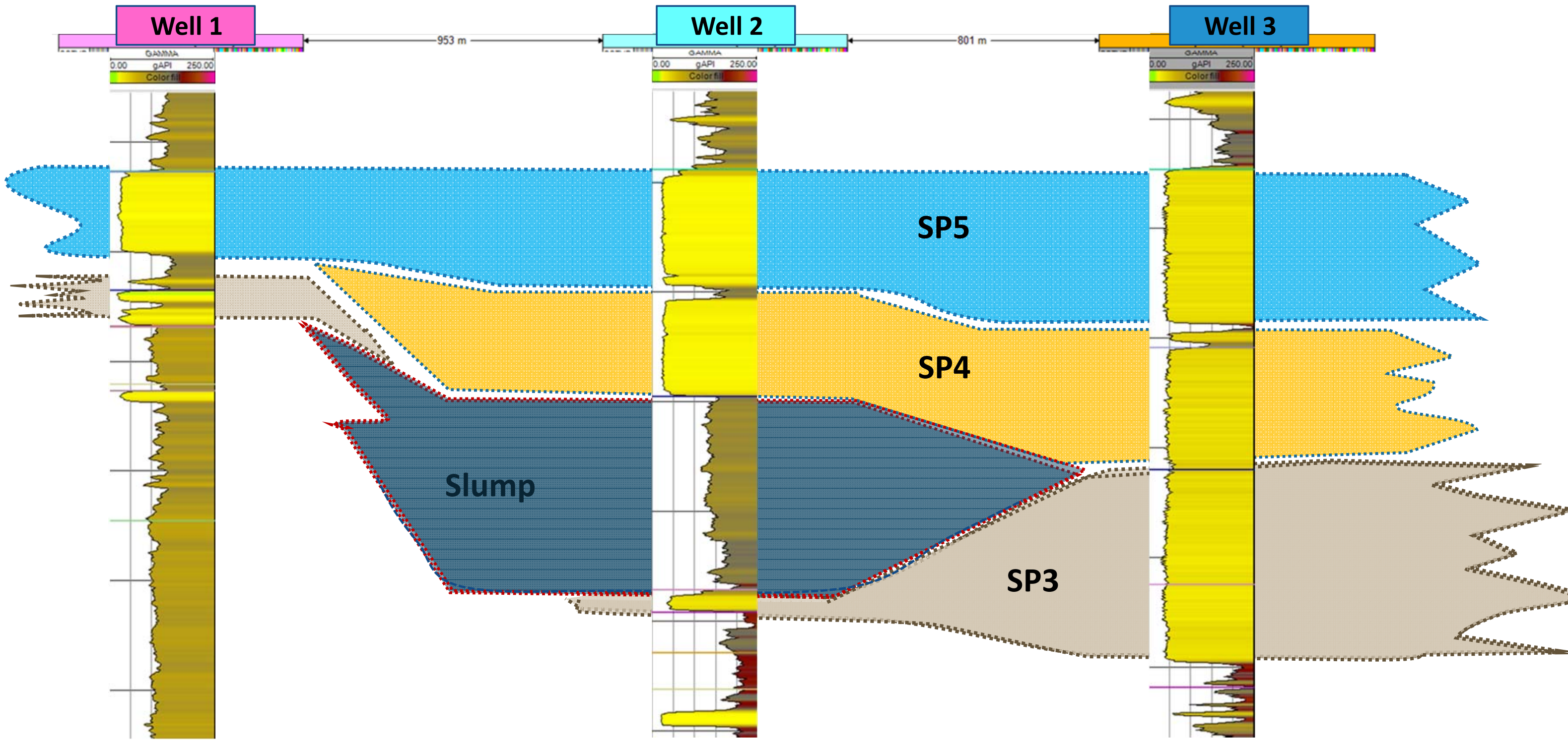


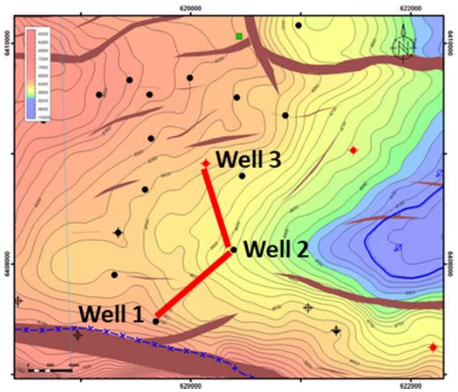


It is very difficult to accurately identify sandstone zones using log data.

Submarine turbidite geological correlation challenge

Correlation #1

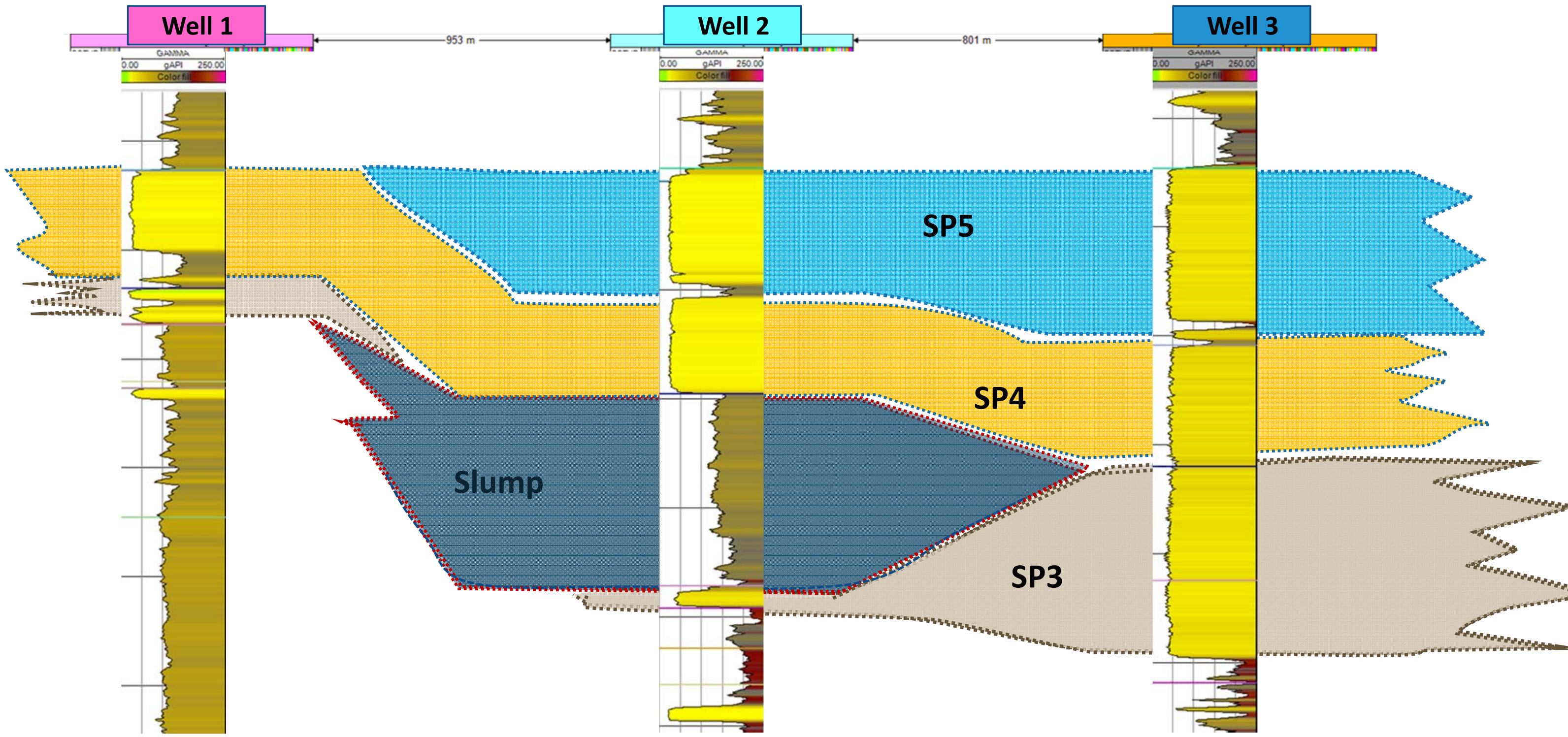


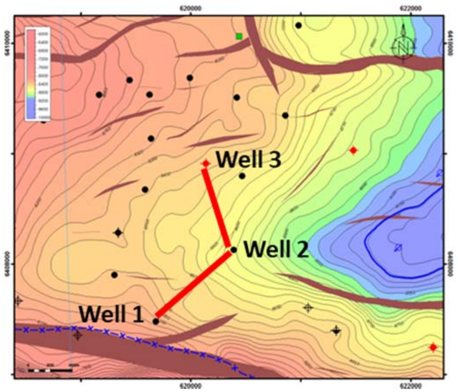


It is very difficult to accurately identify sandstone zones using log data.

Submarine turbidite geological correlation challenge

Correlation #2

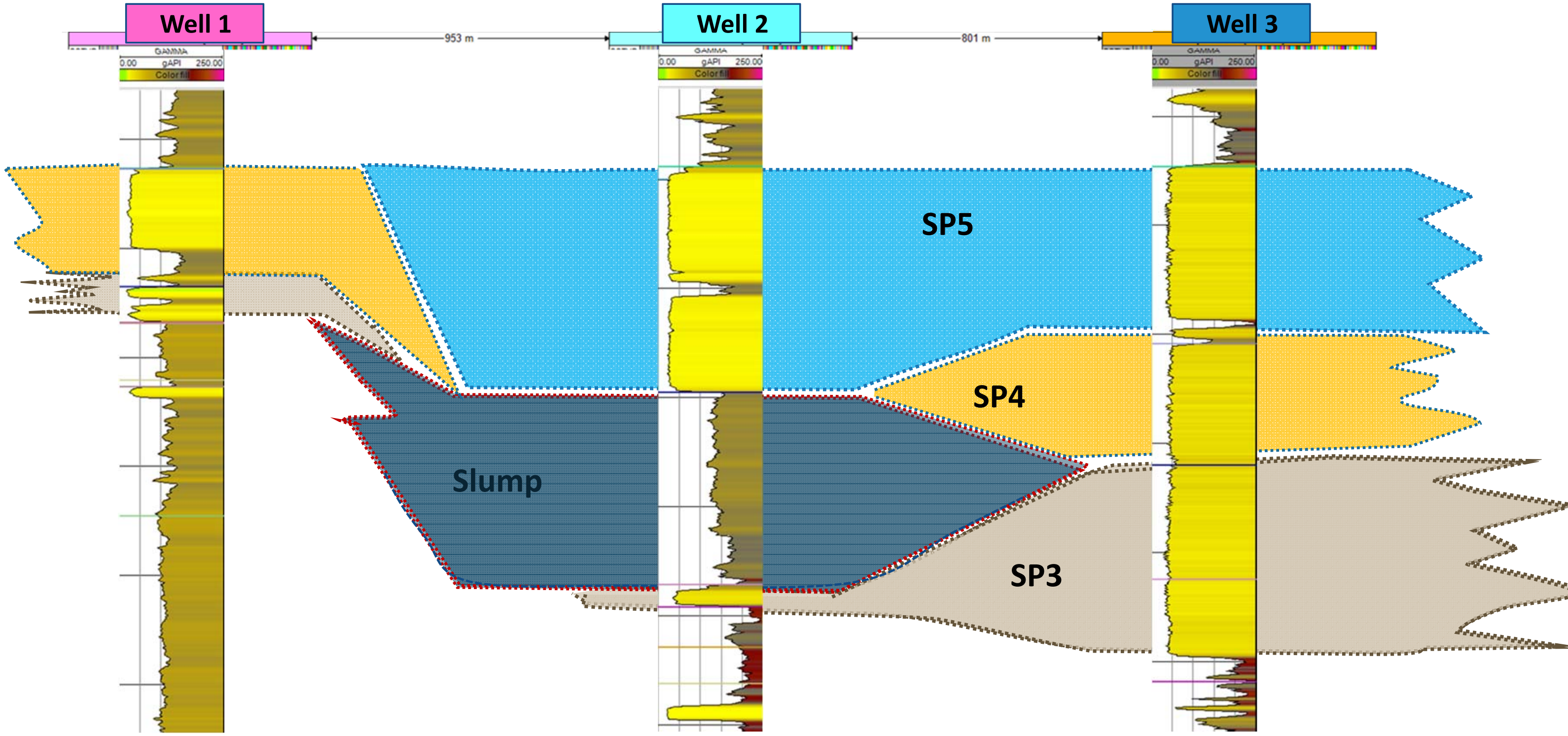


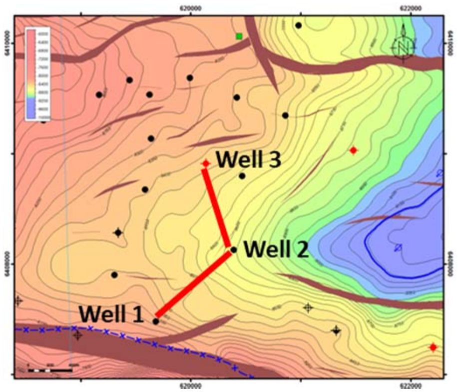


It is very difficult to accurately identify sandstone zones using log data.

Submarine turbidite geological correlation challenge

Correlation #3



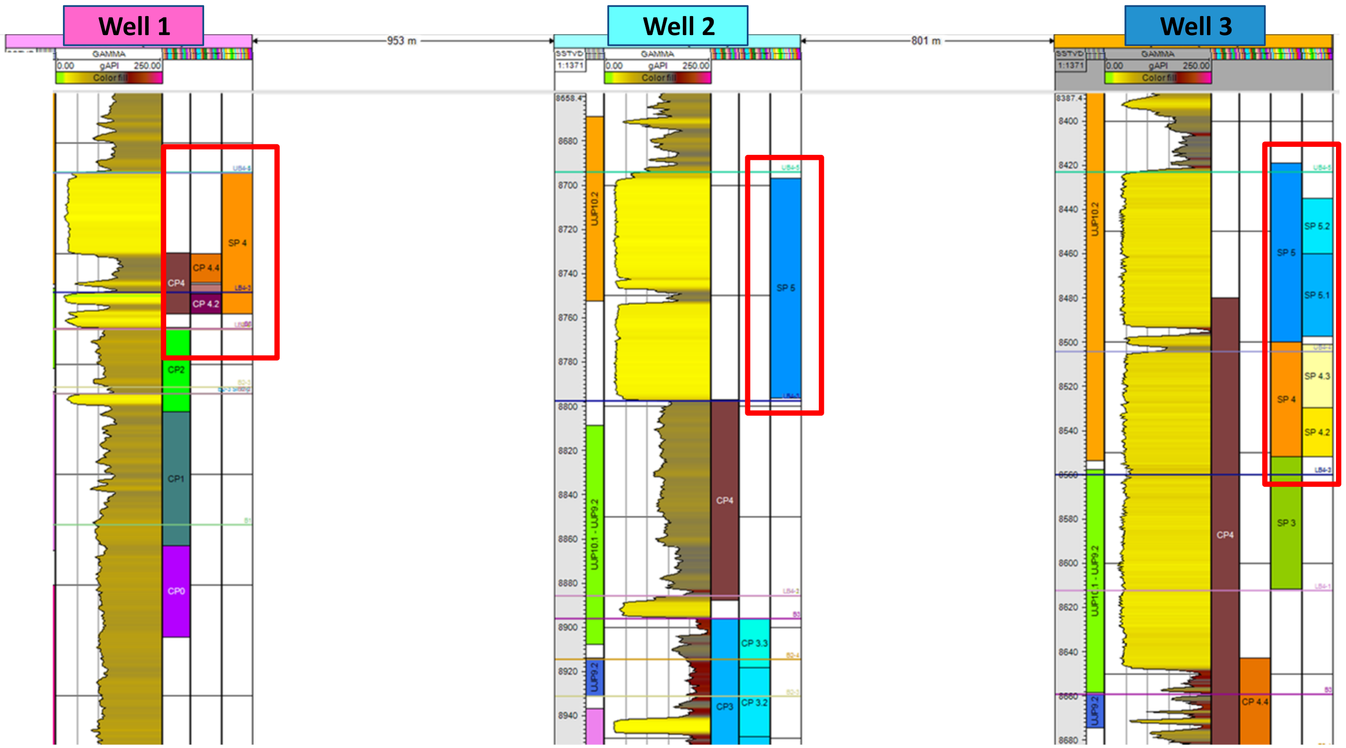


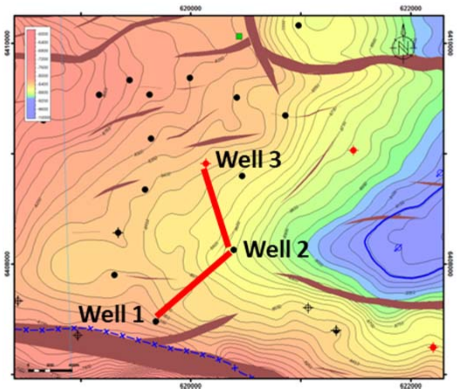
It is very difficult to accurately identify sandstone zones using log data.

Submarine turbidite geological correlation challenge

Chemostratigraphy is a technique that characterises rock successions using inorganic geochemical data.

Unique clay packages and sand packages can be identified to inform correlation work



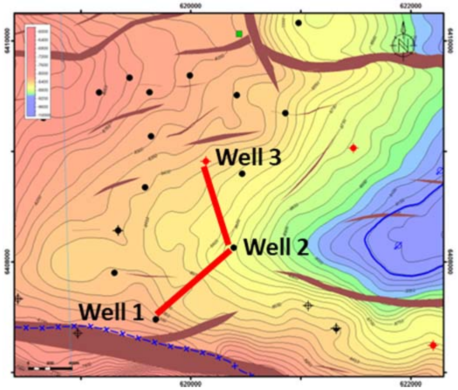


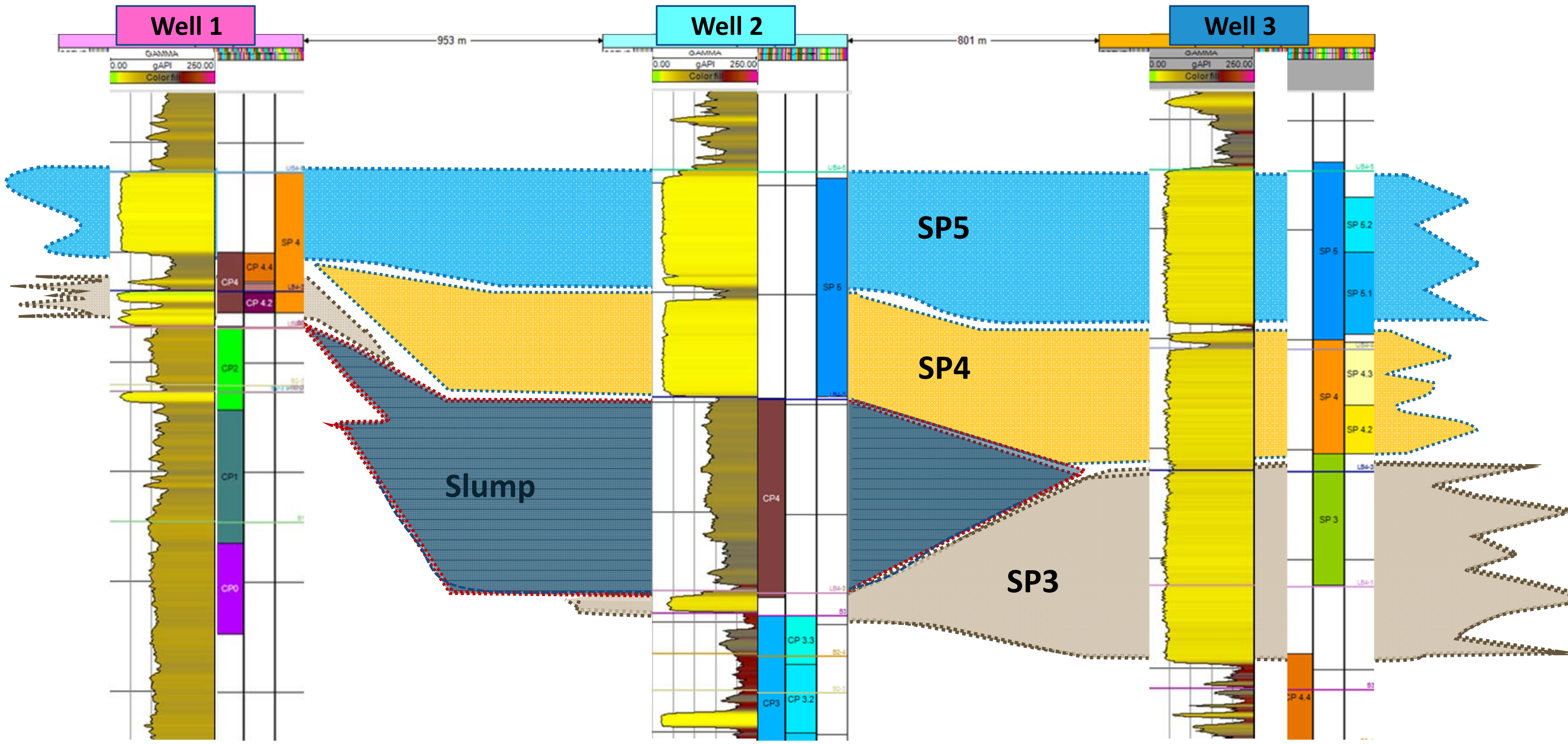
Chemostratigraphy provides critical information to support correlation work.

Submarine turbidite geological correlation challenge

Correlation #1

Not supported by Chemostratigraphy



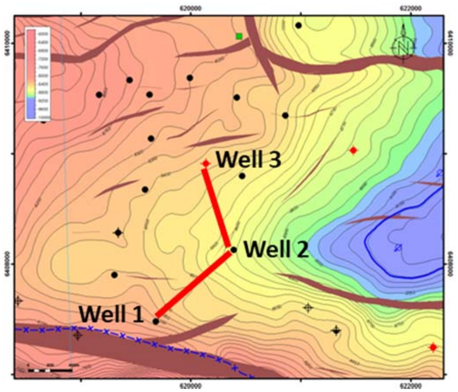


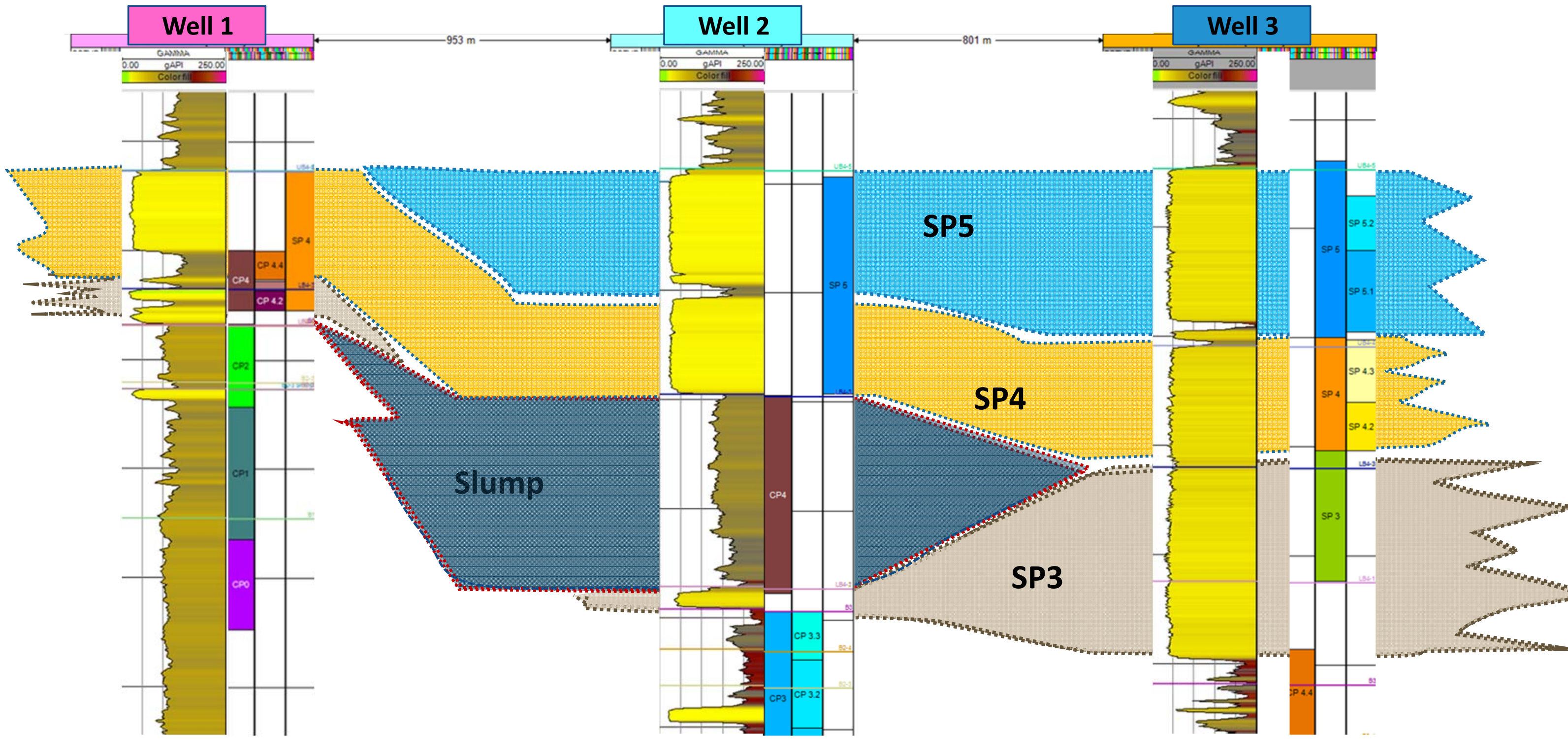
Chemostratigraphy provides critical information to support correlation work.

Submarine turbidite geological correlation challenge

Correlation #2

Not supported by Chemostratigraphy



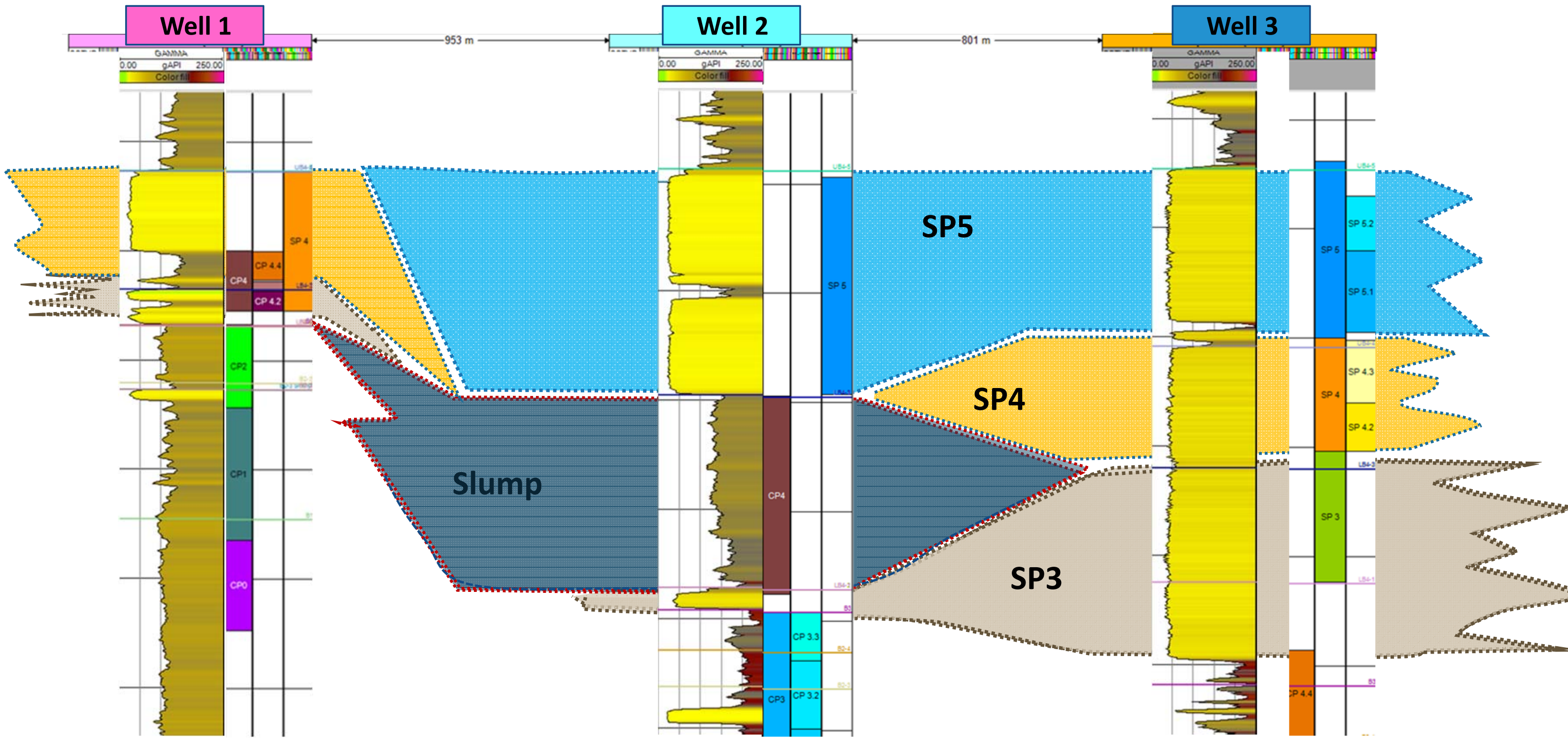


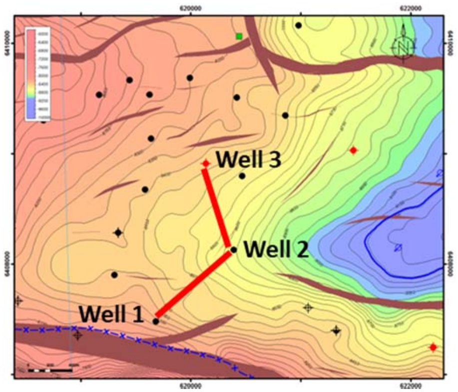
Chemostratigraphy provides critical information to support correlation work.

Submarine turbidite geological correlation challenge

Correlation #3

Supported by Chemostratigraphy



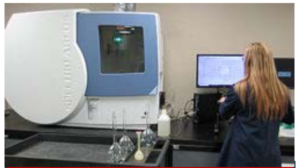


Chemostratigraphy provides critical information to support correlation work.

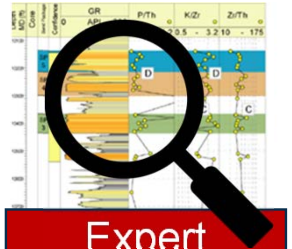
Historical Chemostrat Interpretation method

Helicopter

Courier



Lab analysis



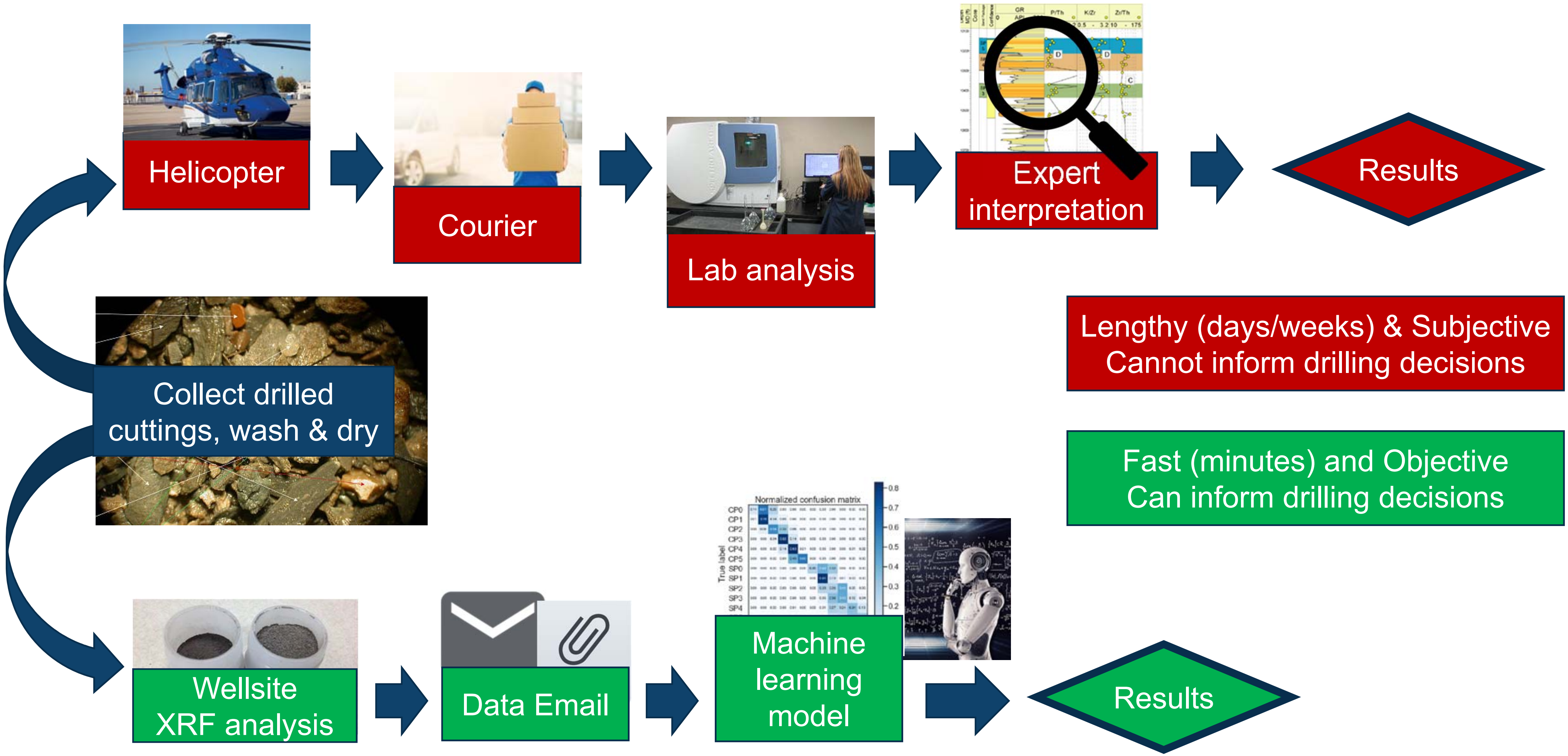
Expert interpretation

Results

Collect drilled cuttings, wash & dry

Lengthy (days/weeks) & Subjective
Cannot inform drilling decisions

Chemostrat Machine Learning Objective



Manual interpretation versus machine learning workflow.

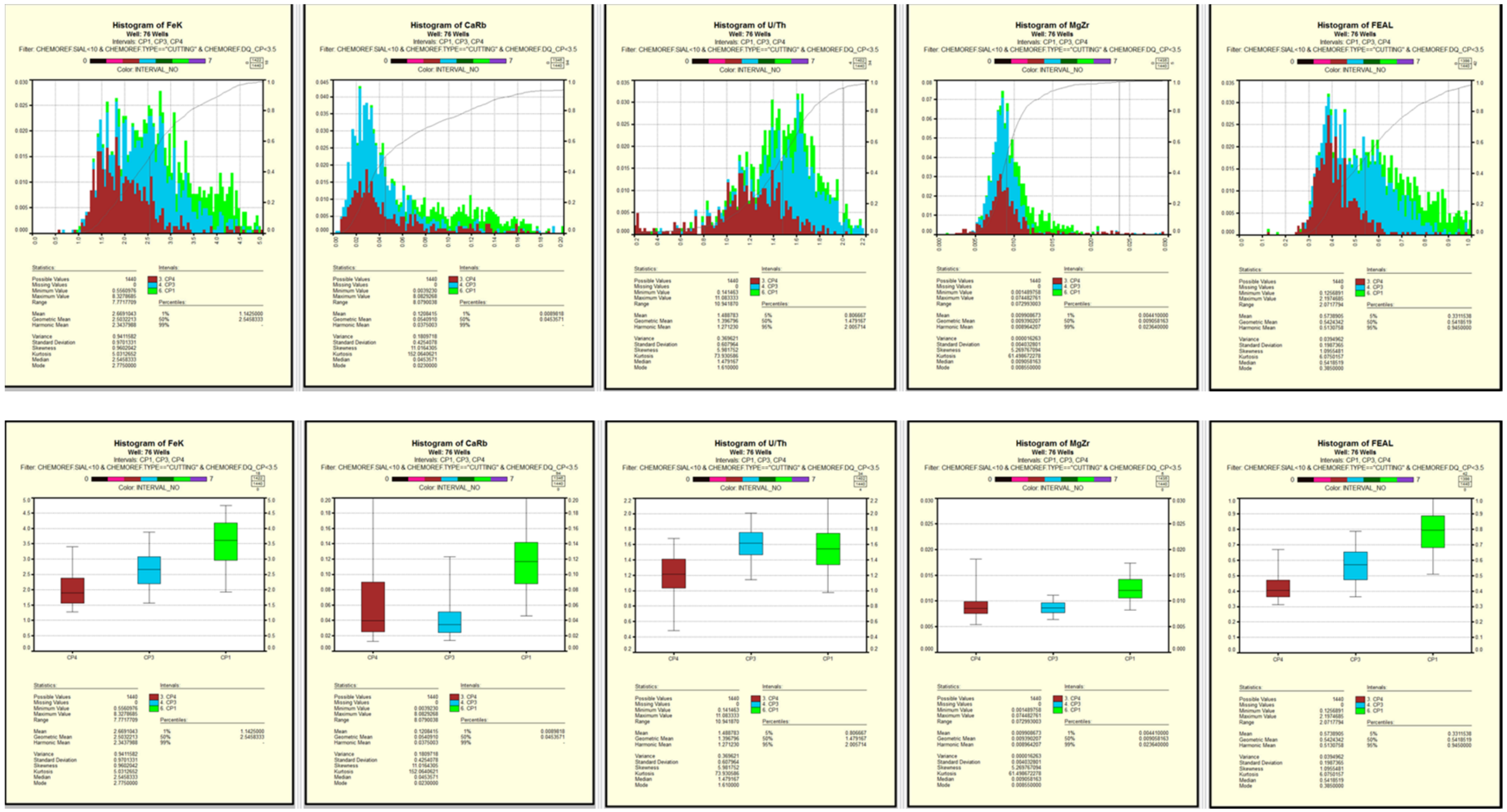
The Chemostrat Project - feasibility

Before starting it is recommended to analyse the dataset to establish if any trends are apparent that can support a machine learning approach… Is there a concept to support the predictive capability of the dataset?

Frequency histograms and box plots that show the various elemental ratios (Fe/K, Ca/RB, U/Th, Mg/Zr, Fe/Al) filtered by Clay Package.

This analysis demonstrates variation in the range of elemental abundance for each clay packages.

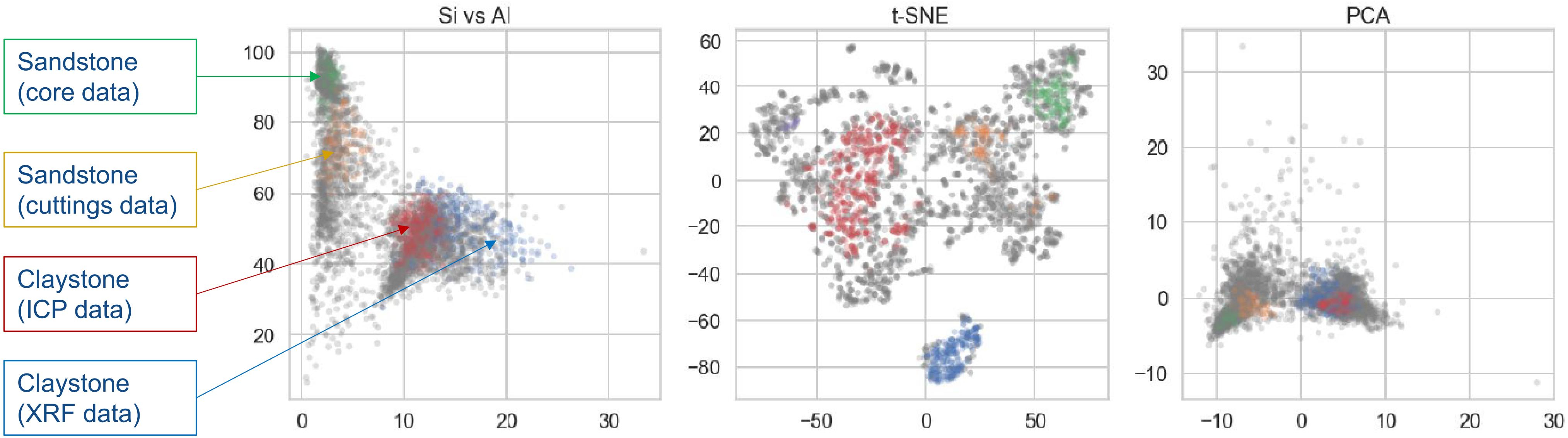
There is enough overlap in each of these ranges to preclude use of simple cut-offs to discriminate clay packages, but clearly enough difference (not total overlap) to suggest machine learning might work.



Key:
- Clay Package 4
- Clay Package 3
- Clay Package 1

The Chemostrat Project – data challenges

Some obvious data challenges were uncovered by initial clustering of the data. Clustering revealed differences in the datasets that was related to the type of data, rather than the underlying geology.



Clusters in three plots (from left to right): raw Si against Al abundances; after processing by t-SNE ; after two component PCA analysis.
The colours show four clusters which are described in the table right.

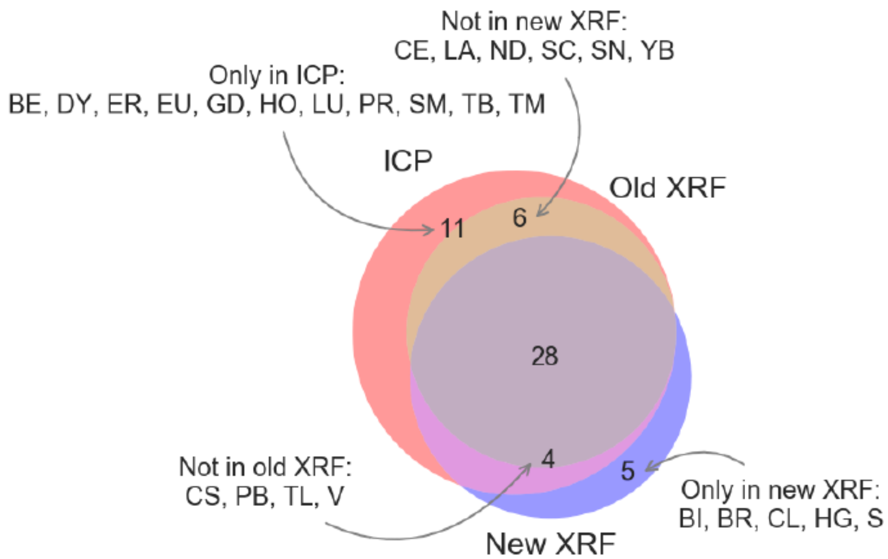
Colour	Rock type	Data type
Green	Sand	Core
Orange	Sand	Cuttings
Red	Clay	ICP
Blue	Clay	XRF

Cuttings and core datasets appear quite different. Cuttings data are of lower quality, but the data is more readily available and the only data type available offshore.

The Chemostrat Project – data challenges

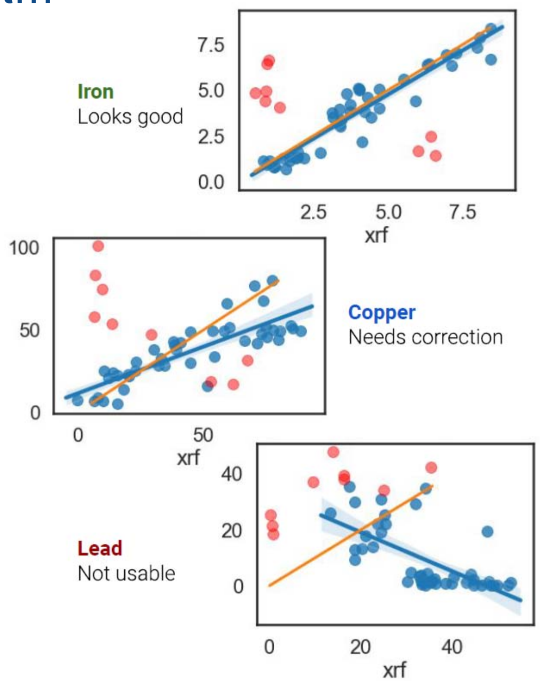
The vast majority of the Chemostrat dataset was acquired using ICP (Inductively Coupled Plasma).
The project objective required making zonal predictions using XRF (X-Ray Fluorescence).
We didn't anticipate the difference in the data sets or how much this would be an issue…

Issue (i) - ICP and XRF measure different elements…

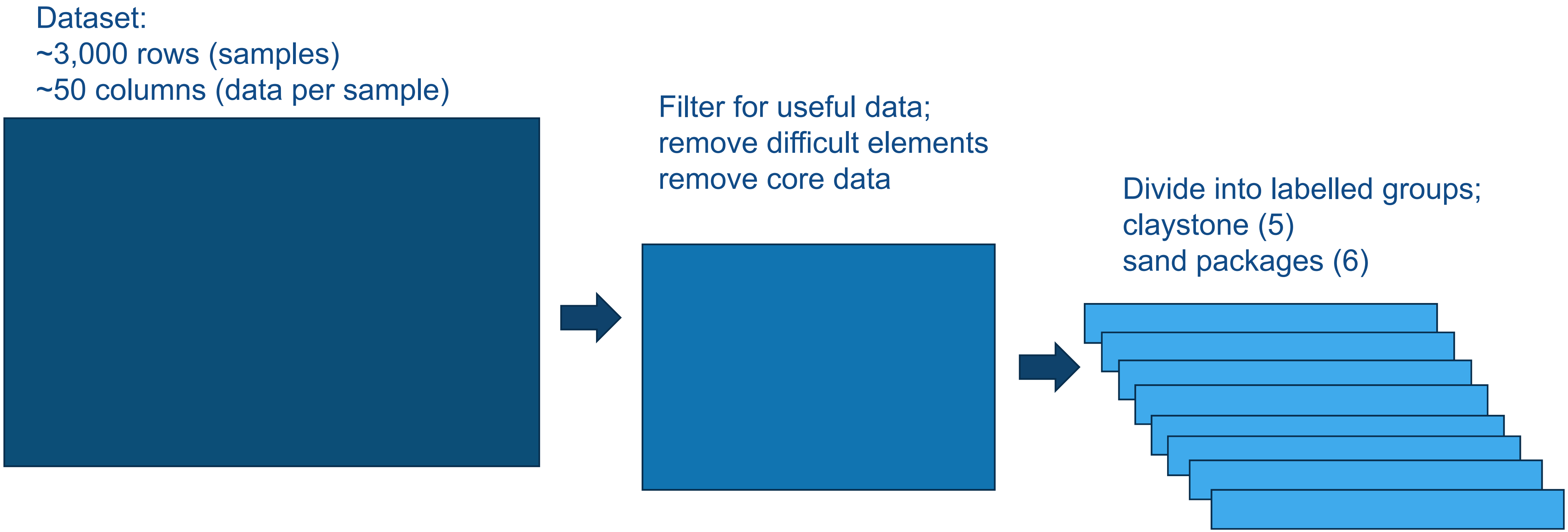


Issue (ii) - ICP and XRF measurement of the same element is different…

Plots of XRF against ICP for 3 elements (Fe, Cu, Pb).
Best fit line should follow ideal line.
Thin sands excluded.
Elements fit into three categories:
Iron looks good;
Can use in ML
Copper, looks okay;
Correct the data. Use in ML
Lead looks bad;
Cannot use in ML



The Chemostrat Project – data challenges

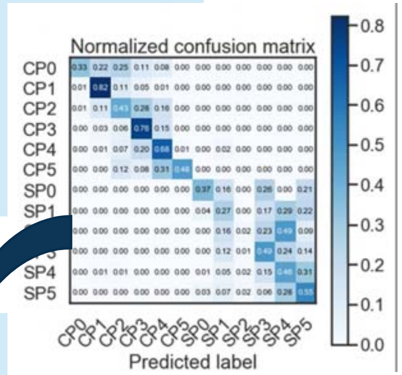


The dataset becomes small quite quickly.
ML needs > 50 data points for each label. Some sandstone packages had fewer than this.

Subsurface datasets are not as large as you may expect, for ML purposes

The machine learning results

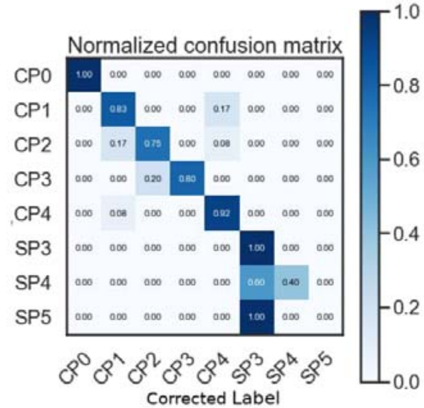
We successfully created a model to predict clay and sand packages from ICP data.
This validated the historical interpretation – I.e. it was repeatable, and provided a quantitative confidence score.
Clay packages show reasonable discrimination
Sand shows less discrimination



59%
Overall Accuracy

47%
Balanced Accuracy

We successfully created a model to train on ICP data with only elements with good similarity in both ICP & XRF, including correcting XRF to make it more like ICP



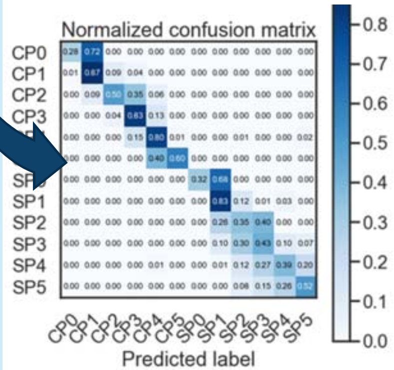
58%
Overall Accuracy

43%
Balanced Accuracy

Post processing applied to output probabilities from XRF and ICP models :

- SP4 above SP2
- SP3 in CP4
- No sand below CP0

Creates more meaningful geological output, helpful in sands

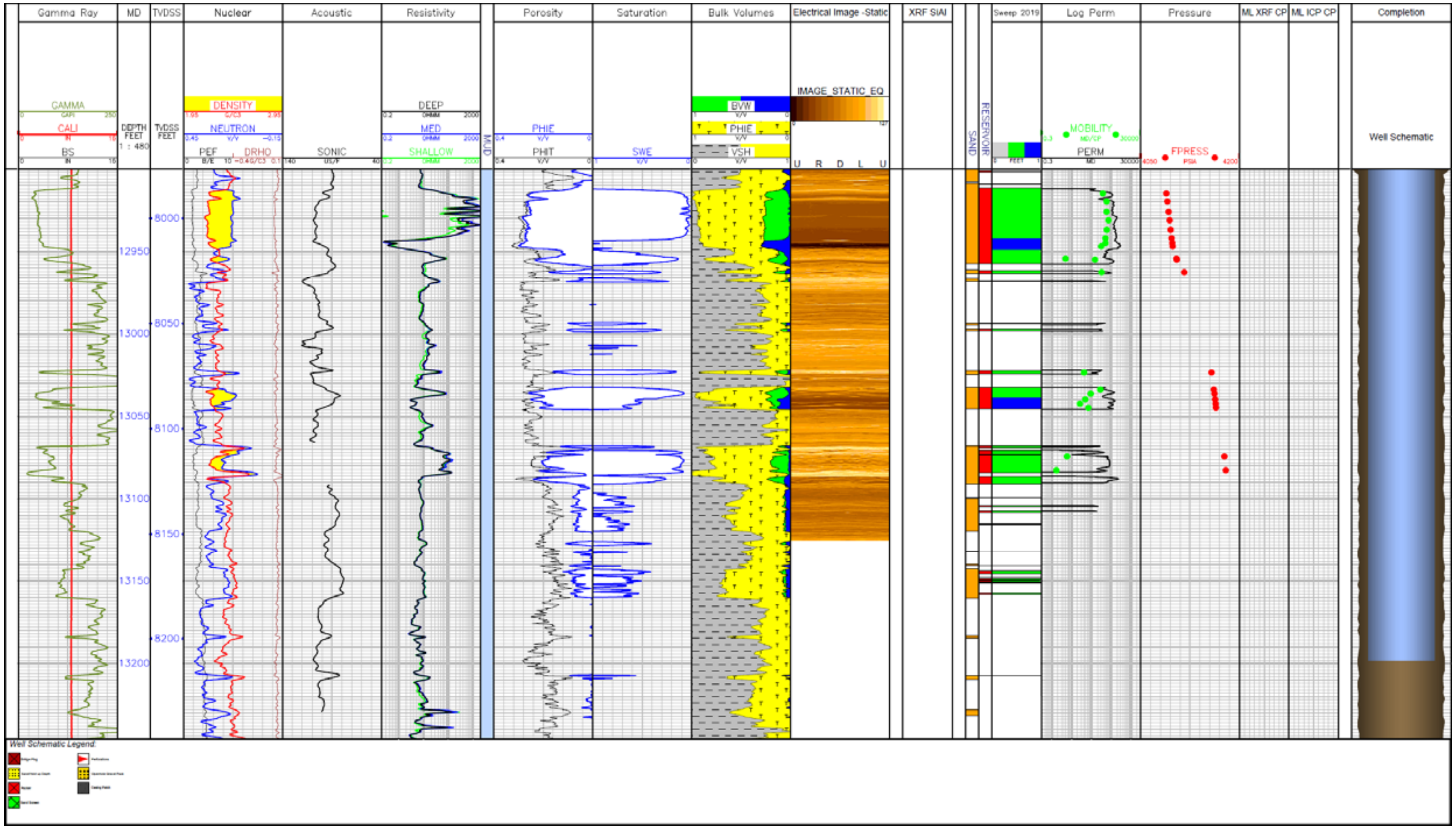


67%
Overall Accuracy

56%
Balanced Accuracy

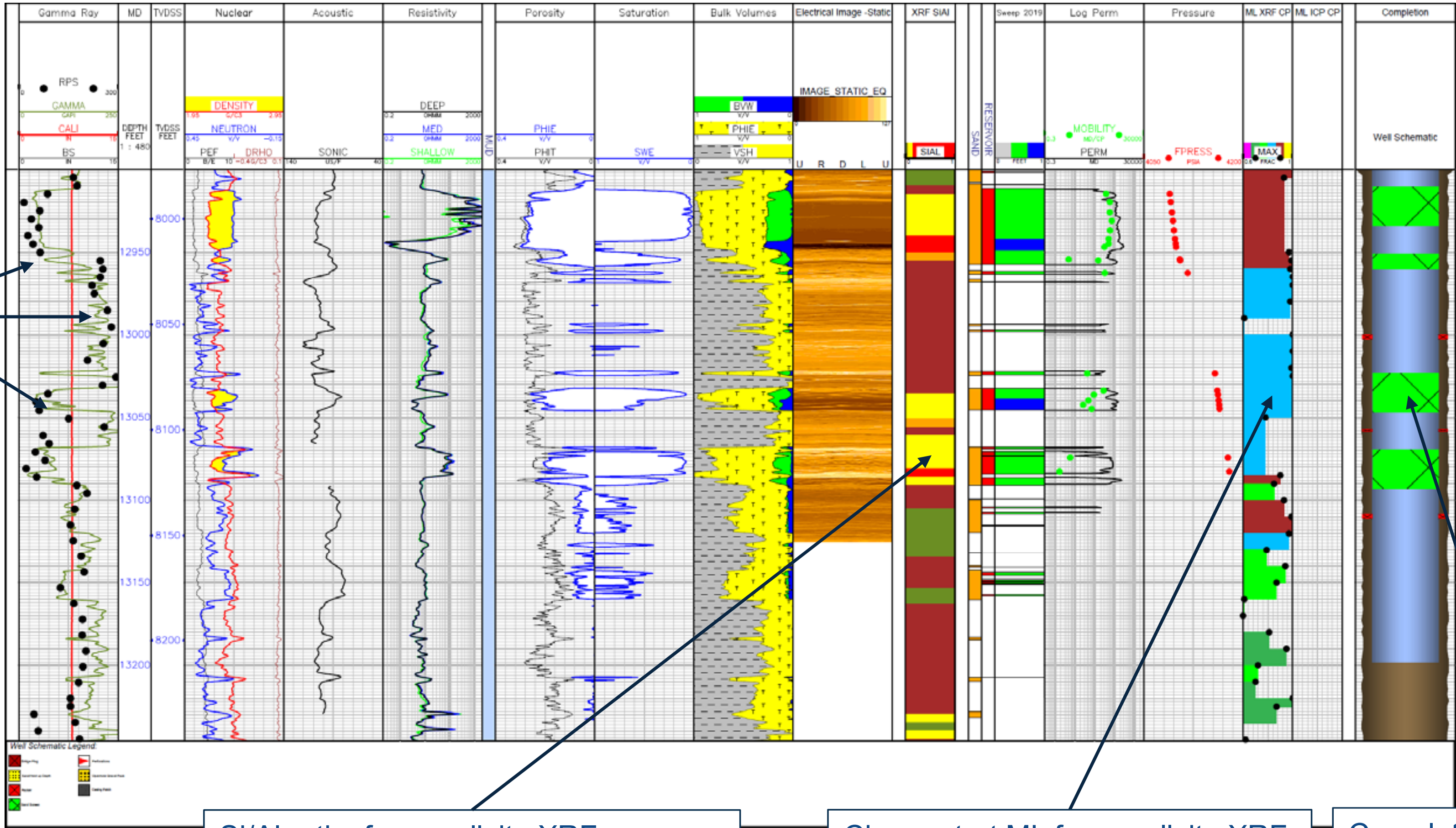
The XRF Chemostrat model was deployed with wellsite XRF for several wells in the Buzzard infill drilling campaign, to support completion decisions. This expanded the XRF dataset.

An example well where Chemostrat ML applied



The additional information from Chemostrat ML…

Synthetic GR from well site XRF analysis of cuttings



Sand screen

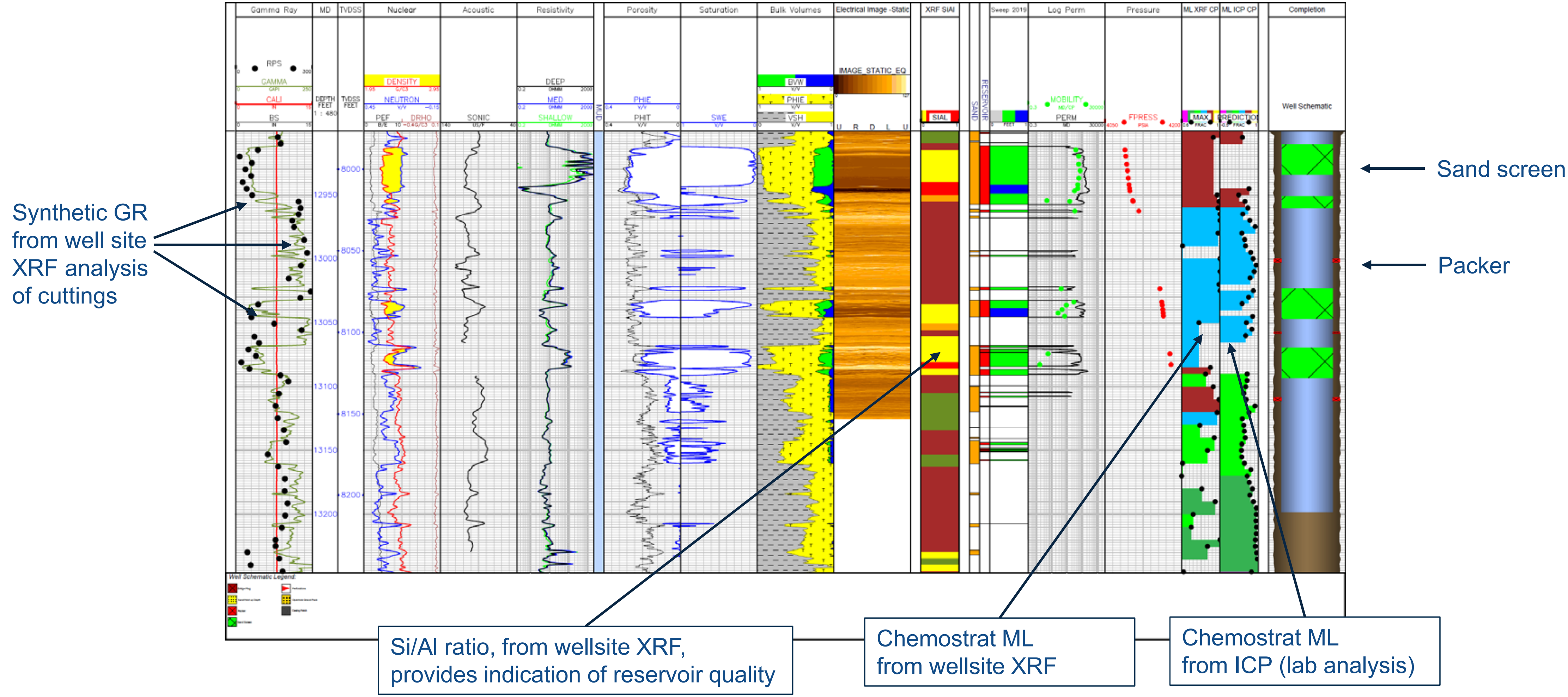
Packer

Si/Al ratio, from wellsite XRF, provides indication of reservoir quality

Chemostrat ML from wellsite XRF clay package prediction supports correlation

Completion choices made with confidence

The additional information from Chemostrat ML…



The continued Chemostrat ML journey…

Feasibility Study

Onsite project ~3 week project (Inc. data science training)

New data

Project update ~3 week project

Successful application throughout Buzzard infill, extended infill & BP2 drilling campaigns

New data

Phase 1 complete. Extension Project approved (Sep 22)

Internal study

Outsourced study

Outsourced study

Outsourced study

Study objectives:

(i) Feasibility

(ii) Reproduce labels. Validation of 20 years of manual interpretation
(iii) Early operational deployment

(iii) Retrain model on expanded dataset. Operational improvement

(iv) Improve dataset, fill gaps / issues, improve labels (interpretation)

Out of scope:
Defining new interpretation framework / sand package / clay package framework

In Scope:
Evaluate new interpretation framework

2019 | 2020 | 2021 | 2022 | 2023

Some thoughts on the attributes of a successful ML project

- ❑ **Value –**
  - Confidence in getting a return in the effort / investment, learnings or expected improvements in understanding the question
- ❑ **Feasibility**
  - A strong concept for predictive capability. Physical relationships.
  - Something that already works. E.g. automation of a manual system.
  - Something that you can see in a simple plot, but maybe with some overlap.
- ❑ **A simple and highly specific objective. An actual ML question…**
  - Is this A or B (or C…)? *Classification (discreet classes)*
  - Is this weird? *Anomaly detection*
  - How much – or – how many? *Regression (continuous values)*
  - How is this organised? *Clustering, dimensionality reduction*
- ❑ **A sound basis for expecting an improvement with ML**
  - Improved speed of interpretation? Efficiency
  - Include more data than an expert interpretation can handle?
  - Remove subjectivity? Quantify uncertainty?
- ❑ **Confidence that the dataset supports a ML approach,**
  - Is it big enough, is it of sufficient quality?
- ❑ **A good combination of Expertise in ML & Subject Knowledge**
- ❑ **A clear view to how the project will be sustained, given success**

- ✓ *Is there value?*
- ✓ *Is it feasible?*
- ✓ *Is it specific?*
- ✓ *Does it sound too good to be true?*
- ✓ *Will ML be better than the current approach?*
- ✓ *Is the dataset good enough?*
- ✓ *Do you have the expertise?*
- ✓ *How sustainable is it?*

Conclusions

- Machine Learning has been successfully applied to solve a subsurface challenge.
- Some benefits include:
  - Increased speed of interpretation
  - Increased quality of interpretation
  - Removal of subjectivity
  - Quantification of uncertainty
  - Deeper understanding of the dataset, and potential issues with it
  - Deeper understanding of the subsurface challenge
- The likelihood of delivering a successful machine learning / data science project can be enhanced by following some of the ideas developed here.

Thanks

The authors with to thank the Buzzard Co-Venture partnership for permission to publish this presentation…

Harbour Energy

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THANK YOU