A 300% Increase in Petrophysical Productivity with Automatic Parametrization in DELFI

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Senior Petrophysicist - Digitalization

Agenda

- Automation in well log interpretation: immense challenge – high stake
- Methodology inspired by augmented learning
- Value and the way forward

Authors:

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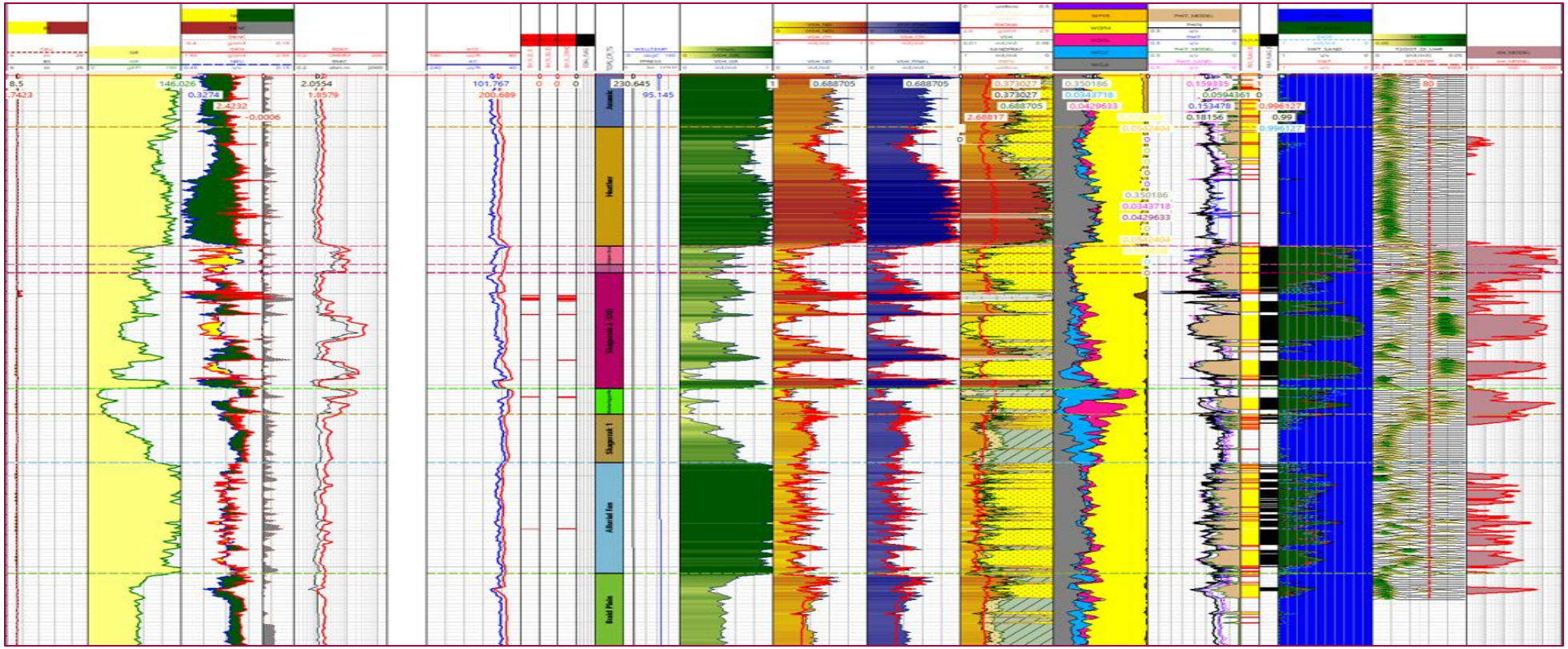
Automation in well log interpretation: immense challenge – high stake



Wellbore measurements:
- Density
- Resistivity
- Neutron Counts
- Other..

Petrophysics

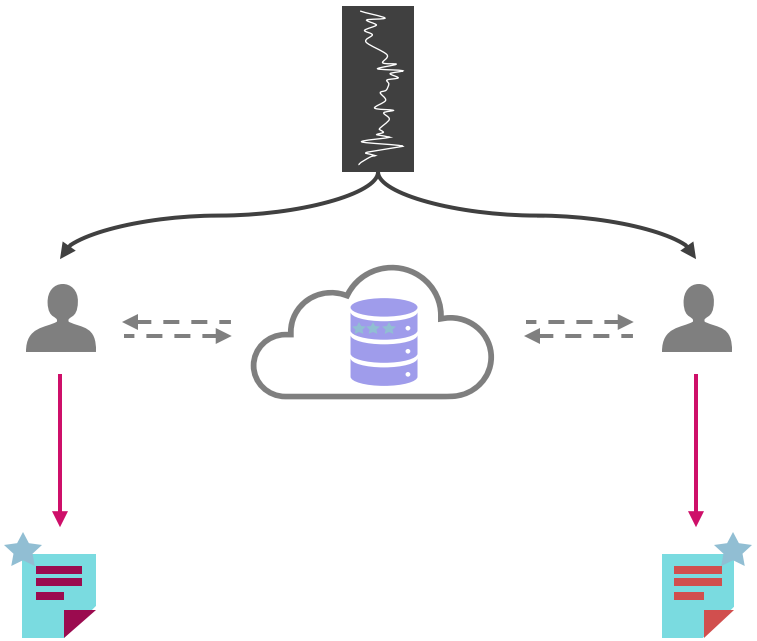
Geological zones + Parametrization

Formation properties:
- Pore Volume
- Oil & Water Saturation
- Permeability
- Other..

Automation in well log interpretation: immense challenge – high stake

Challenges with the traditional approach:

- Single well interpretation approach – **time consuming**
- Geological zones and parameters are stored in the individual projects and reports - **knowledge is trapped in silos**
- Manual integrating all available data is impossible
  - interpretation quality ↓
  - subjectivity in the results



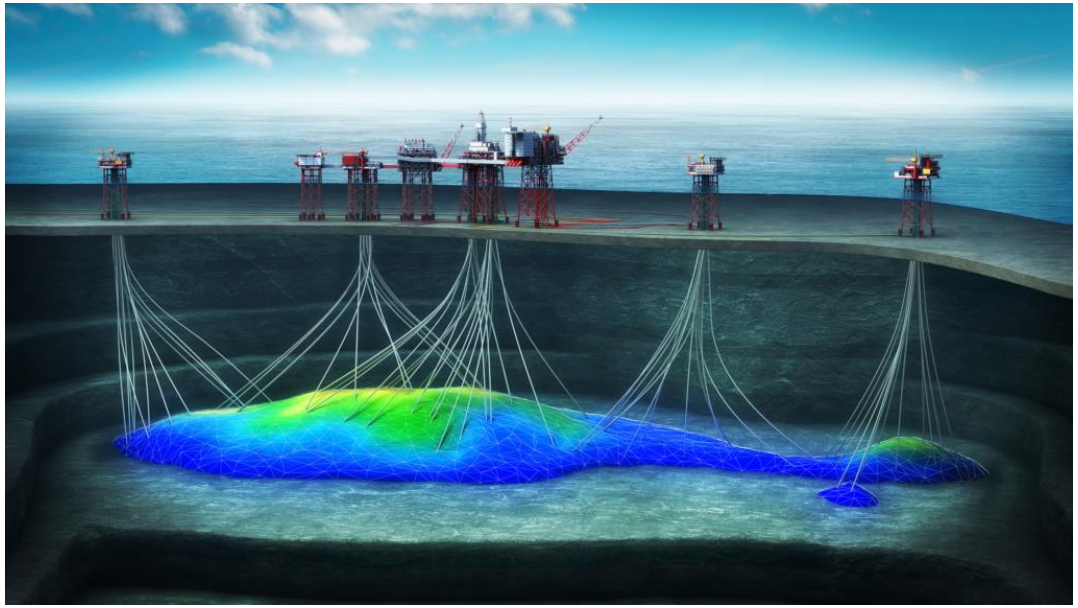
Goal:

- Automation in well interpretation
  - Breaking down the silos
  - Learning from experts
- Reduce ↓ the interpretation time by **more than 70%**
- Increase consistency ↑
- USING MORE DATA

Valhall and Hod Field – Big Data Problem

FIELD OVERVIEW

- Field on the Norwegian Continental Shelf
- Discovered in 1974
- Big dataset with >400 wells and multiple vintages
- ~400 wells interpretation (3 days/well = approx. 3-4 years)
- Lateral variation of properties throughout the field



New interpretation for the geo model:

- Include over- and underburden in interpretation
- Apply new method including uncertainties
- Re-interpret 100+ wells

If we have data, let's look at data.

If all we have are opinions, let's go with mine.

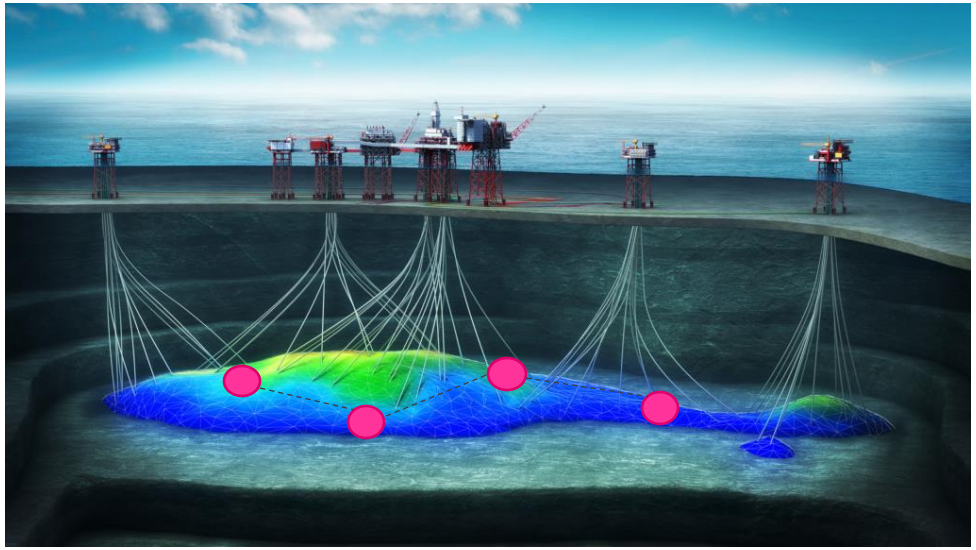
- Jim Barksdale

Methodology inspired by augmented learning and virtual reality

Inspired by the contemporary meaning of **augmented learning** in the context of education, virtual, and augmented reality

Concept - providing information at the right time and right place and with context

The goal: field-wide representation of historical interpretations in the cloud augmented with the context

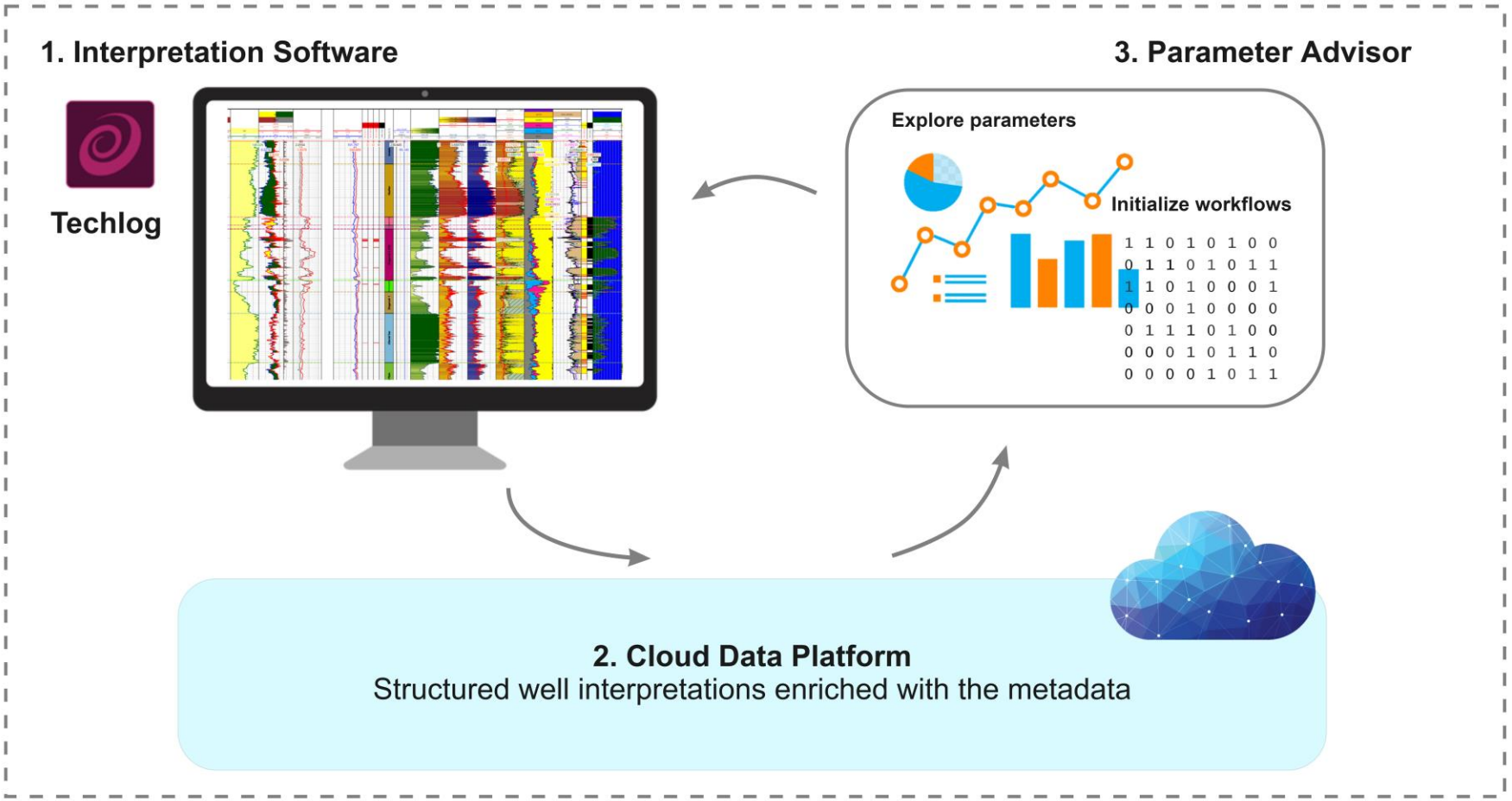


Learn from experts who previously uploaded their knowledge to the cloud

Cloud technologies and high-performance systems – data storage, visual interfaces, knowledge engineering

Digital Environment for Automatic Parametrization

DELFI Environment



Key words and filters to find the right parameters

Manual Key Words

- Lithology and Fluid Type
- Conveyance Type: WL – LWD

Uncertainties

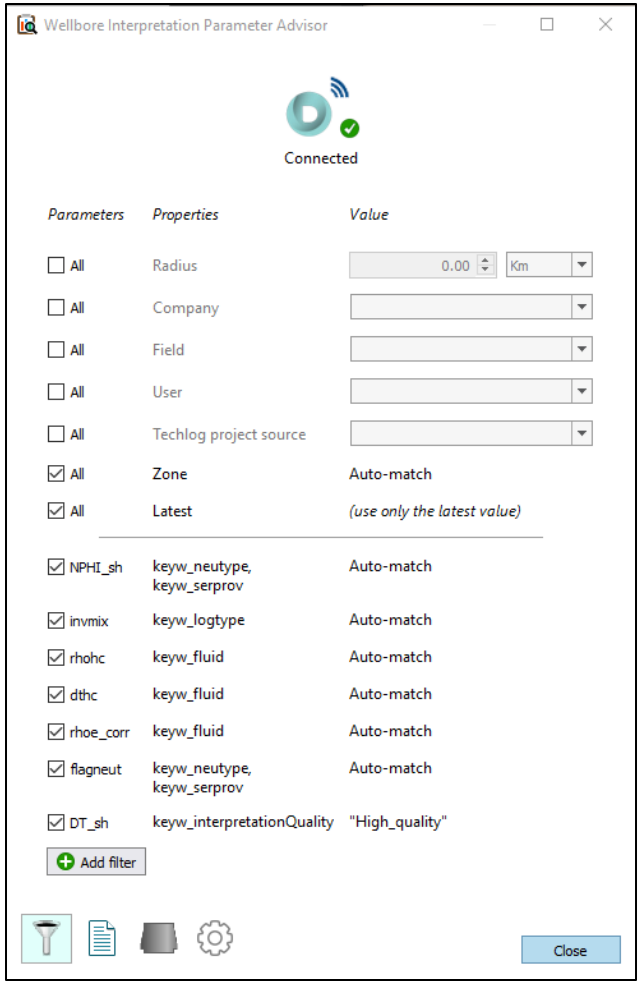
- Formation Water Resistivity
- HC density
- M, N

Automatic Key Words

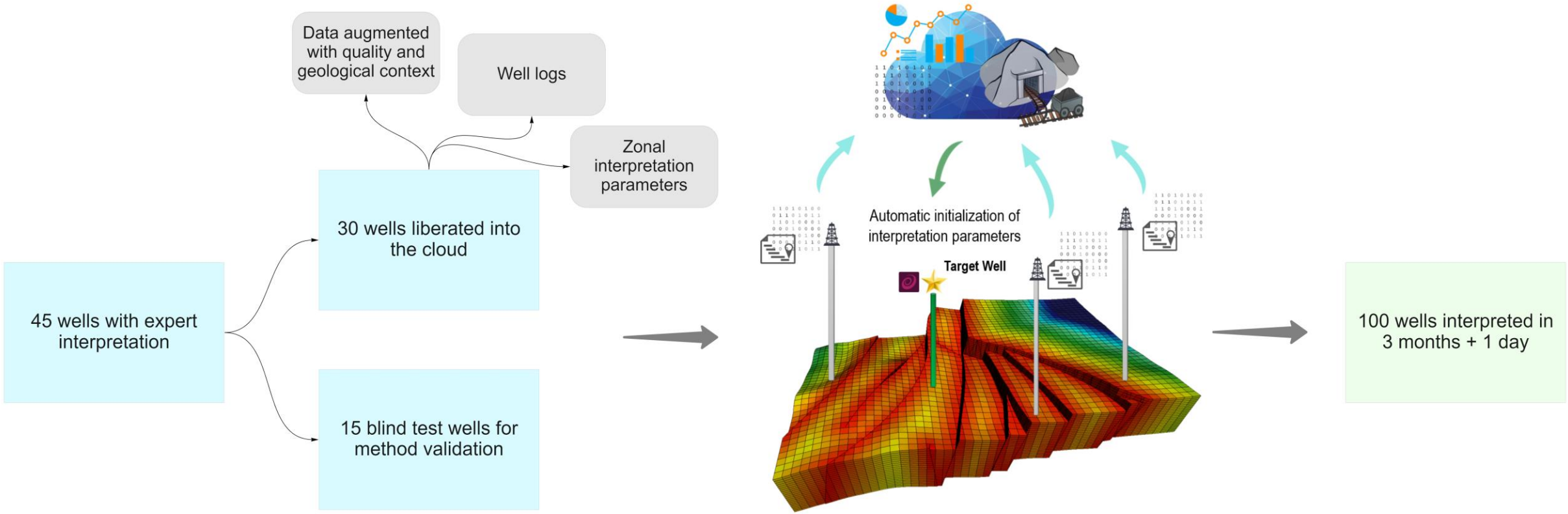
- Well Vintage
- X, Y, Z location of the zone

Logic:

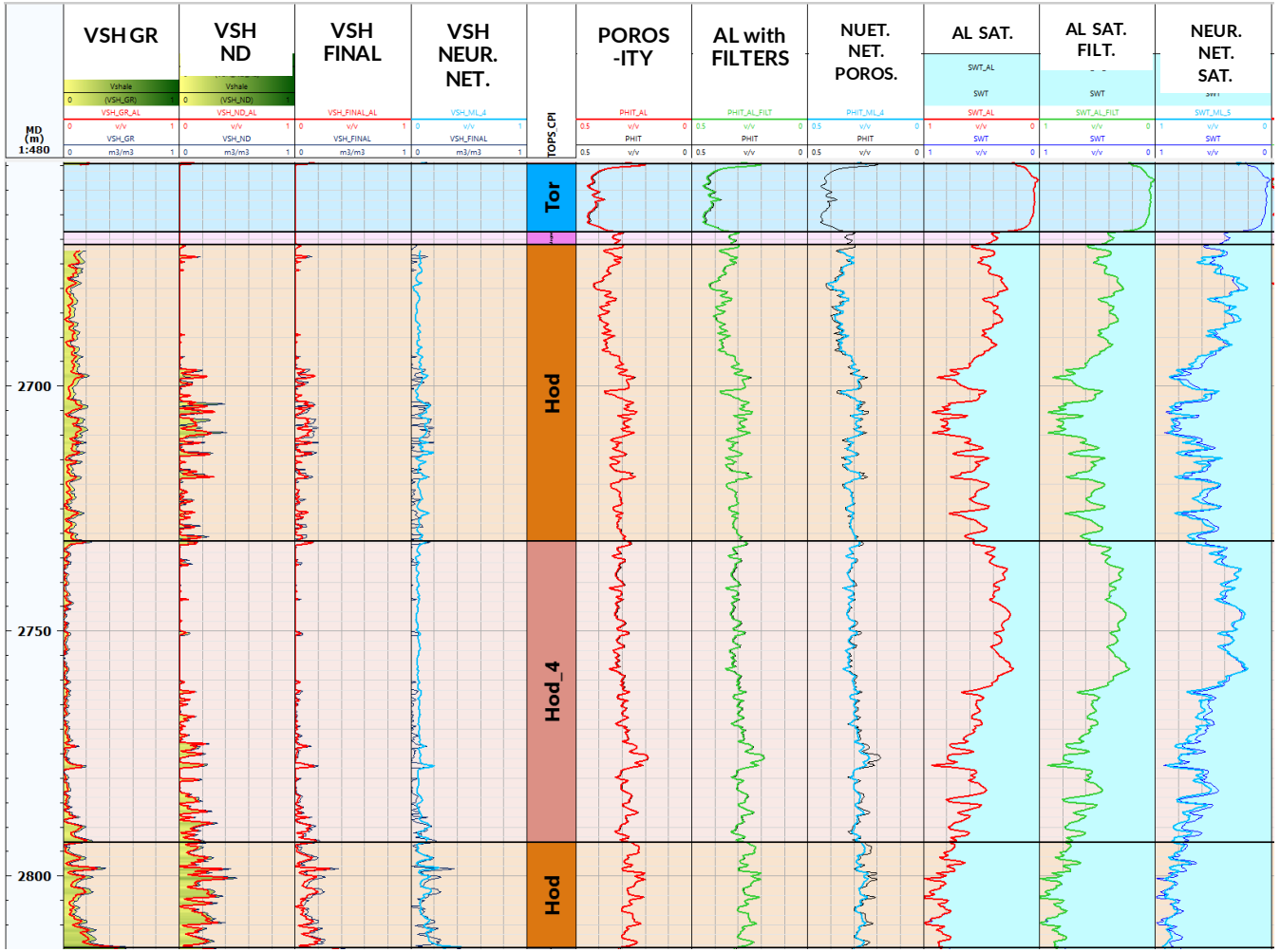
1. Search the parameter database in the cloud
2. Filter the parameters with the same geo and data acquisition context using key words
   - Invasion mix – conveyance type
   - HC density – fluid type
3. Average and weight the parameter with the distance to the target zone
4. Automatic parametrization



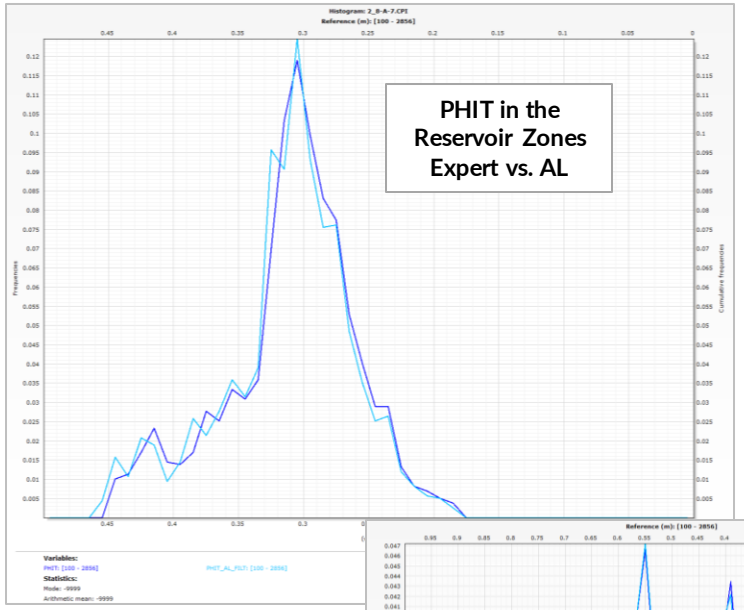
Automatic Parametrization in DELFI - Methodology



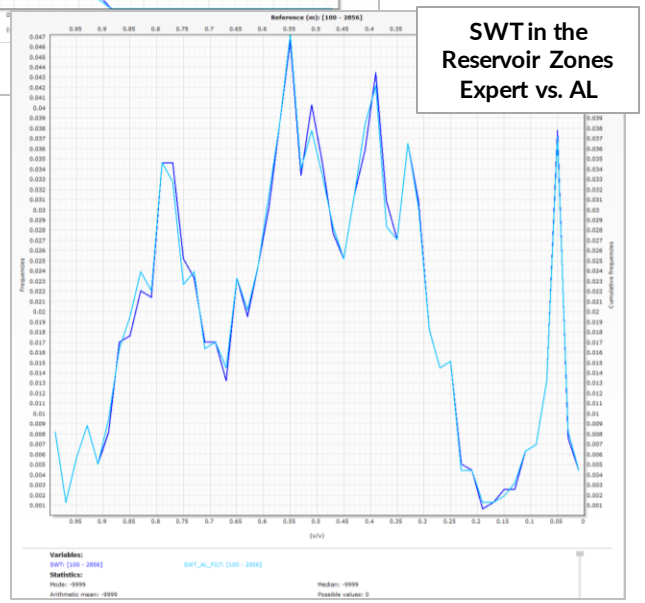
Results



RED – Augmented Learning
BLUE – Machine Learning
Black – Expert Interpretation



PHIT in the Reservoir Zones Expert vs. AL



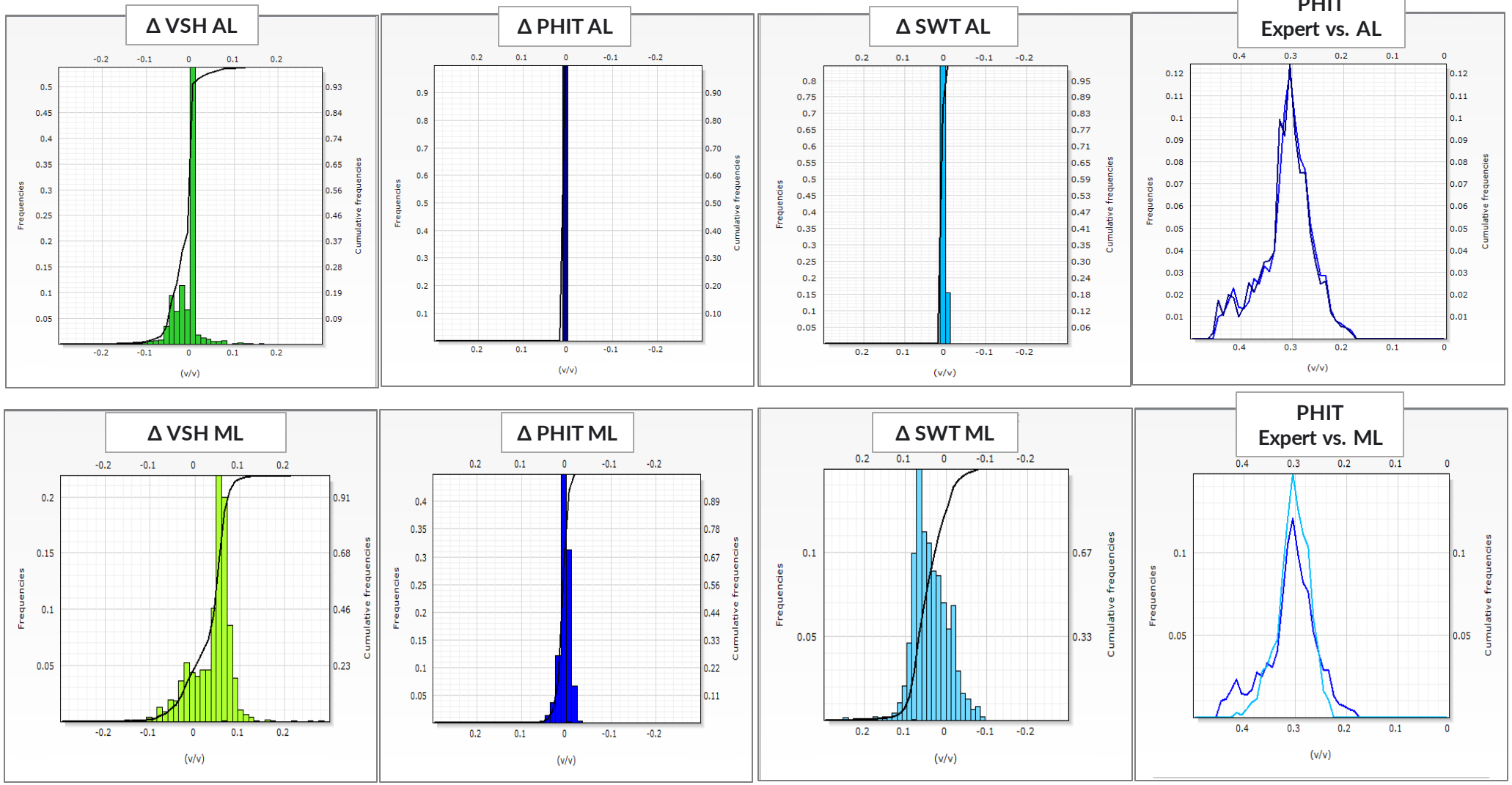
SWT in the Reservoir Zones Expert vs. AL

Legend:
VSH – Shale Volume
PHIT – Total Porosity
SWT – Total Water Saturation
NEUR. NET. – Neural Networks Interpretation (ML)

Comparing Augmented Learning and Neural Networks

Augmented Learning

Machine Learning



Future Potential

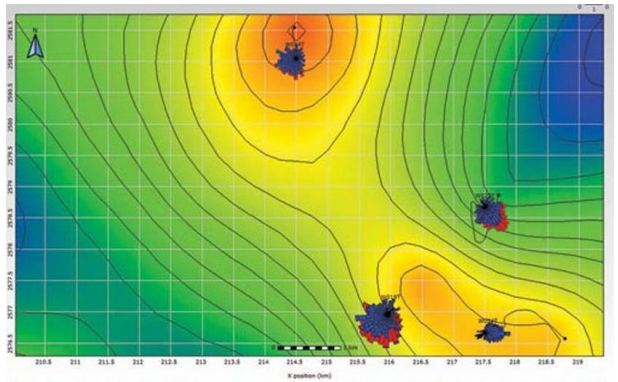
Collaborating to improve the application

Improvements to make the system more intelligent:

- **Pattern recognition** - find the most similar wellbores and zones to the target zone
- **Uncertainties** in the input parameters – weight the parameters based on their confidence
- **Data analytics tools** to evaluate the accuracy of the automated interpretation

Taking the application into use

- **Scaling up** semi-automated interpretation to more fields and reservoir types
- Creating a **consistent interpretation** dataset for regional studies
- **Screening tool** for exploration



Collaboration

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Conclusions and Benefits

High quality of auto CPIs

- Auto CPIs reproduce expert-interpretation of blind test wells (VSH, PHIT, SWT) to a very large extend

Automation

- Increase in productivity and using more data when interpreting new wells

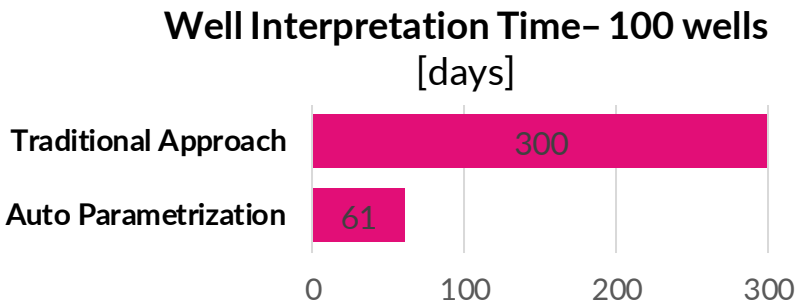
Consistent regional interpretation

- Building a consistent dataset of CPIs including overburden and underburden formations

Knowledge Management

- The more expert knowledge you ingest, the more intelligent it gets - reduced overall uncertainty of the model

300 % ↑ in productivity



THANK YOU!

Questions?

Get in touch:

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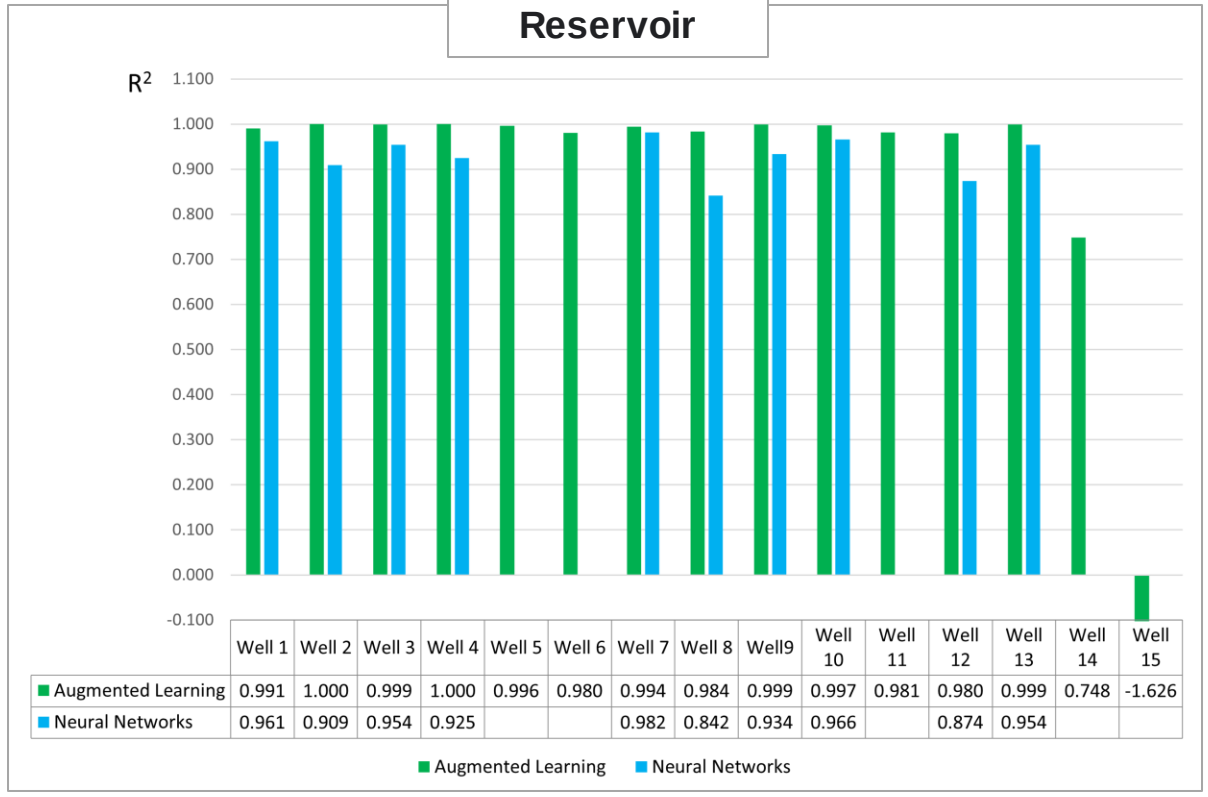
Results: R^2 Score – Coefficient of Determination

PHIT R^2 Score - Reservoir

	Well 1	Well 2	Well 3	Well 4	Well 5	Well 6	Well 7	Well 8	Well9	Well 10	Well 11	Well 12	Well 13	Well 14	Well 15
Augmented Learning	0.999	0.995	0.999	0.999	0.999	0.996	1.000	0.999	0.999	1.000	0.455	0.981	0.983	0.987	0.997
Neural Networks	0.952	0.918	0.901	0.852			0.848	0.865	0.778	0.925		0.343	0.617		

Augmented Learning Neural Networks

SWT R^2 Score - Reservoir



	Well 1	Well 2	Well 3	Well 4	Well 5	Well 6	Well 7	Well 8	Well9	Well 10	Well 11	Well 12	Well 13	Well 14	Well 15
Augmented Learning	0.991	1.000	0.999	1.000	0.996	0.980	0.994	0.984	0.999	0.997	0.981	0.980	0.999	0.748	-1.626
Neural Networks	0.961	0.909	0.954	0.925			0.982	0.842	0.934	0.966		0.874	0.954		

Augmented Learning Neural Networks