





Harness Upstream Geophysical and Petrophysical Data with AI Workflows

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Module 08

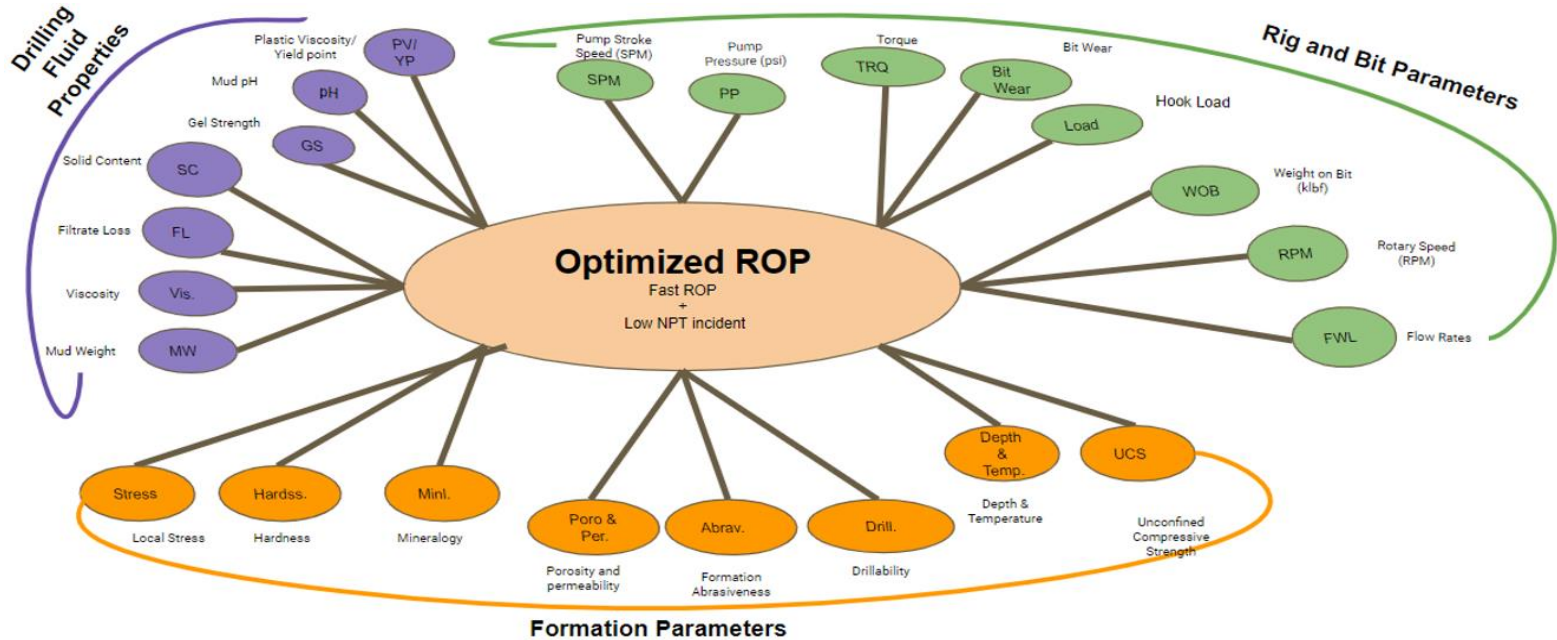
Case Studies: Drilling Program & Completion Study and Virtual Assistant for Fluids and Lithology

LEARNING OBJECTIVES

- GOAL01: Case Studies – Drilling and Completion in Unconventional Reservoirs
- GOAL02: Case Studies – Fluids and Lithology Virtual Assistant

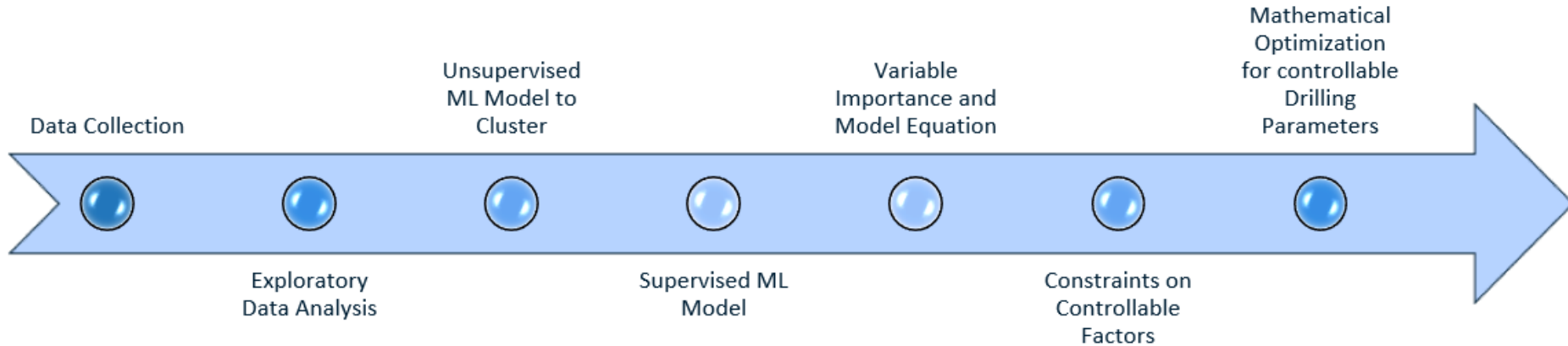
Case Studies

Drilling Optimization Process Workflow



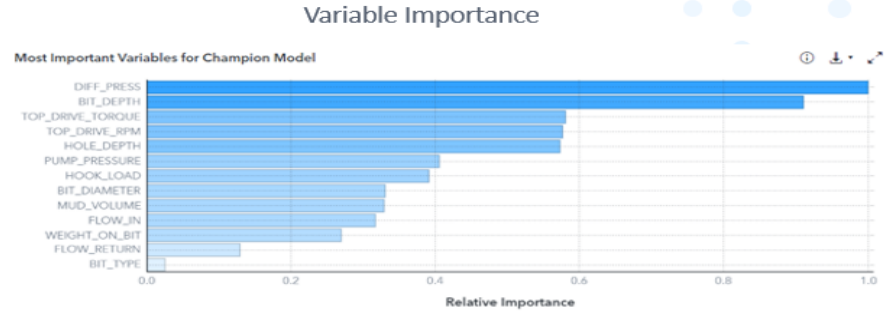
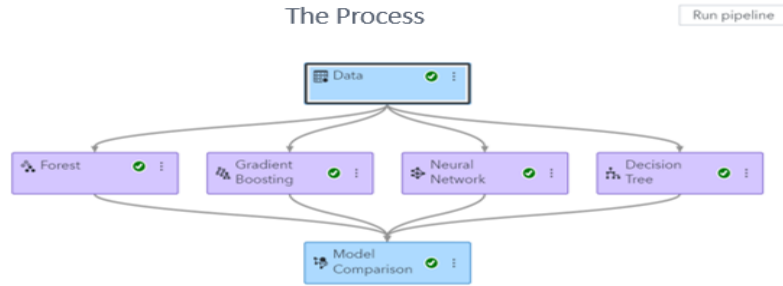
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Drilling Optimization Process Workflow

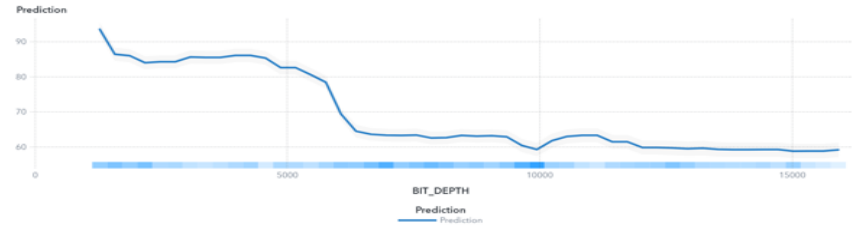
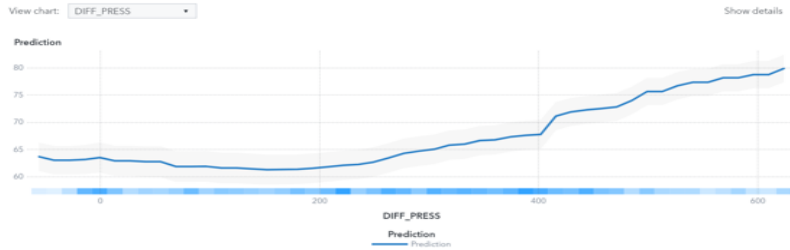


Case Studies

Drilling Optimization Process Workflow



Explainable AI



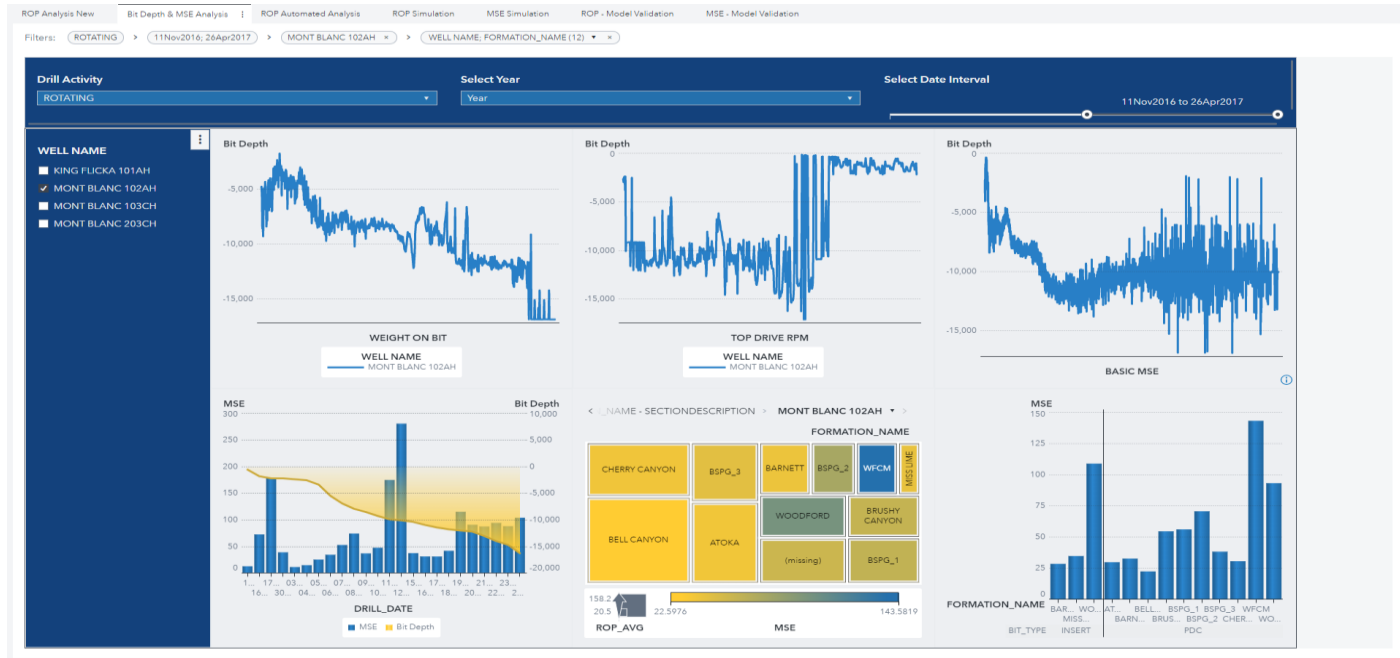
Case Studies

Drilling Optimization Process Workflow



Case Studies

Drilling Optimization Process Workflow



Case Studies

Drilling Optimization Process Workflow

Business Goal

- Optimize ROP while managing cost, NPT, HSE

Challenge

- Complex multivariate problem – rock properties, Force on bit, bit type, drilling speed, unforeseen drilling hazards, mud properties.
- Real-time decision making required
- Human-only decision making is very difficult
- Mistakes can cost equipment, time, cost and human life.

Solution:

AI models provides real-time intelligent assistant with prescriptive analytics:

- Real-time drilling surveillance
- Real-time optimization of drilling parameters for max cost-effective ROP, better well integrity
- Continuous Prediction of bit wear, depth-to-failure, etc.
- Optimal operating conditions for equipment, e.g., mud motors, early warning of instability and failure.

Business Benefits Seen:

- Reduce NPT by ~55%
- Increase ROP by ~75%
- Reduced Cost by ~\$15M/Annually predicting drilling reliability issues/failures
- Maximum Reservoir Contact

Sensor data in real-time & Static

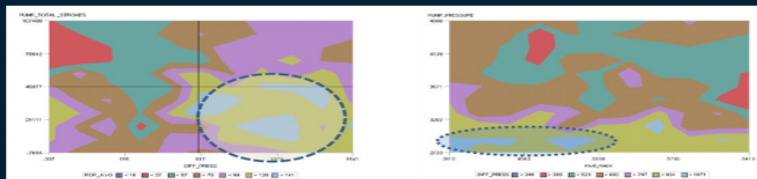
Data Integration
Data Exploration
Data Pre-Processing

Test & Score ML/DL model
Run Simulations
Select Optimum Model

Generalize & Operationalize Optimum Model

Real-time Drilling Optimization/Advisory Prescription Model

- Bit Mode
- Tool face Gravity
- Mud properties
- Torque
- WOB
- RPM
- HMSE
- Hook Load



AI Model Types

- Classification
- SVM
- GB
- GTB
- ANN
- ML/DL



Case Studies

Lithology-Fluids Pattern Recognition

- Well Logs best suited for Lithofacies Classification?
- Classify Lithofacies based on Supervised Learning
 - Support Vector Machine
 - Gradient Tree Boosting
 - Artificial Neural Network
 - Random Forest
- Predicting Stratigraphic Units from Well Logs

Case Studies

Lithology-Fluids Pattern Recognition

Manual interpretation of lithofacies from wireline log data is traditionally performed by an expert, can be subject to biases, and is substantially laborious and time-consuming for large datasets.

Automating the facies classification process using machine learning is a potentially intuitive and efficient way to facilitate facies interpretation based on large-volume data. An expert traditionally performs manual interpretation of lithofacies from wireline log data.

The input parameters used to train AI models include LWD, MWD, Drilling Data, Gas Components data.

Data will be from multiple reservoirs, fields, formations, wells

Data would be for more than 75 wells.

Actual Lithology and fluid tags would be identified and used as the target variable.

Additional Derived variables would be created that would be able to explain the lithology facies better.

Different classes of lithology facies and fluid-type relationships will be modeled.

The automated Machine Learning process to predict field pattern type recognition

The AI assistant will suggest the best approach to follow to the domain experts.

Provide workflow automation that reduces work time and raises efficiency with real-time interpretation.

Multi-Well Log
Analysis

Lithology
Characterization

Automated Lithology
Classification

Lithology
Classification Model

Case Studies

Lithology-Fluids Pattern Recognition

Typical Input Data: Facies-Fluids: *Feature Engineering*

Table 1 - LWD Curves

Logs While Drilling (LWD)	Gas Components	Drilling Params.
Gamma Ray	Total Gas (TG)	Weight on Bit (WOB)
Resistivity Shallow	Methane (C1)	Rate of Penetration (ROP)
Resistivity Deep	Ethane (C2)	
Neutron	Propane (C3)	
Density	IsoButane (iC4)	
	NormalButane (nC4)	
	IsoPentane (iC5)	
	NormalPentane (nC5)	

Table 2 - Derived Features

Derived	Formula
LHR	$C1+C2/C3+iC4+nC4+iC5+nC5$
CH	$iC4+nC4+iC5+nC5/C3$
WH	$C2+C3+iC4+nC4+iC5+nC5/C1+C2+C3+iC4+nC4+iC5+nC5$
C1/C2	$C1/C2$
C1/C3	$C1/C3$
C2/C3	$C2/C3$
%C1	$(C1/C1+C2+C3+iC4+nC4+iC5+nC5)*100$
%C2	$(C2/C1+C2+C3+iC4+nC4+iC5+nC5)*100$
%C3	$(C3/C1+C2+C3+iC4+nC4+iC5+nC5)*100$
%C4	$(iC4+nC4/C1+C2+C3+iC4+nC4+iC5+nC5)*100$
%C5	$(iC5+nC5/C1+C2+C3+iC4+nC4+iC5+nC5)*100$



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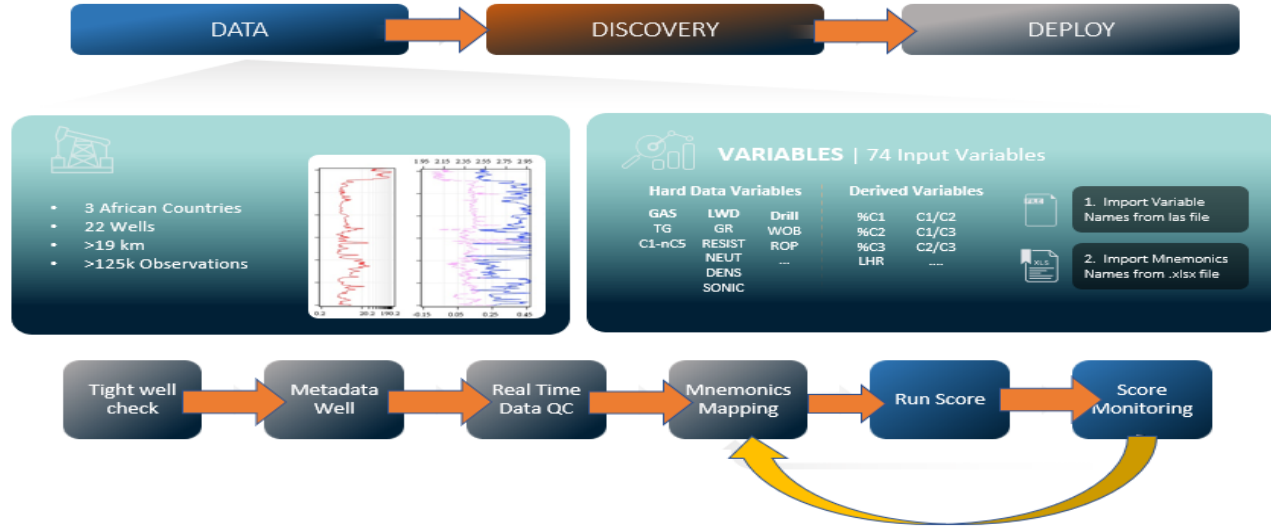
Artificial Intelligence and Machine Learning Techniques Provide Operations Geologists With an Automated and Reliable Lithology-Fluid Pattern Recognition Assistant: A Case History in a Clastic Reservoir in West Africa

Davide Baldini and Luca Piazza, ENI SpA; Luca Barbarotti, SAS Institute

Case Studies

Lithology-Fluids Pattern Recognition

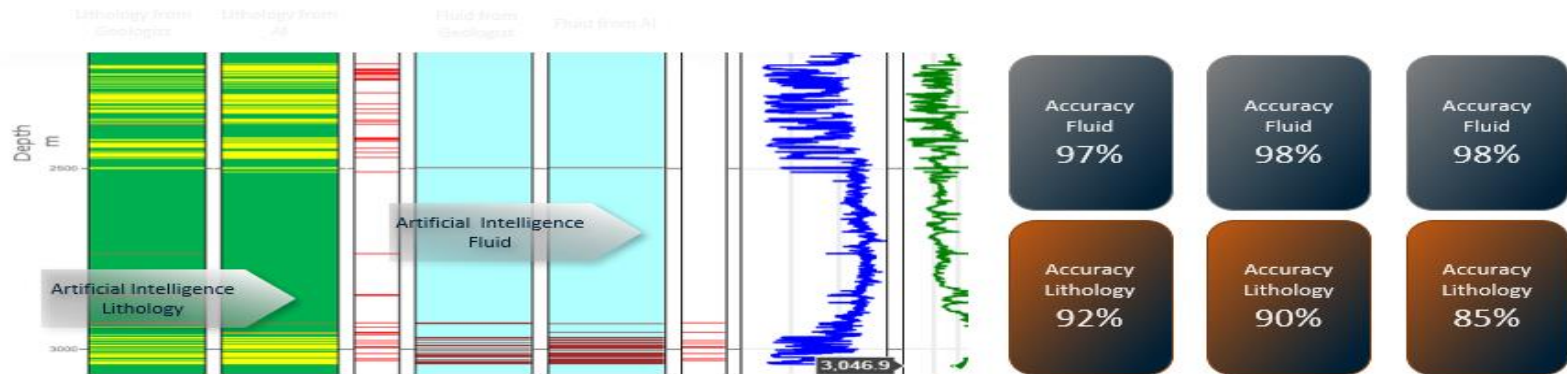
Fluid and rock identification from well log analysis – LWD and MWD



Case Studies

Lithology-Fluids Pattern Recognition

Fluid and rock identification from well log analysis – LWD and MWD



Module 09
**Case Studies: Time-Series Analysis and Production
Forecasting**

MODULE 09

This Module introduces the six principles of forecasting in a time-series dataset.

We shall implement these principles in the case study to optimize production data collected in a brownfield.

The SEMMA process takes on a journey to analyze temporal data using several time-series statistical and machine-learning methods. The well, reservoir, and field production forecasting uses spatial and temporal data to optimize the re-engineering of a brownfield.

We shall show the use of both supervised and unsupervised techniques. And we shall introduce a deep neural network architecture called a Recurrent Neural Network for time-series analysis. RNNs are discussed in Module 05.



