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Harness Upstream Geophysical and Petrophysical Data with AI Workflows

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Module 08

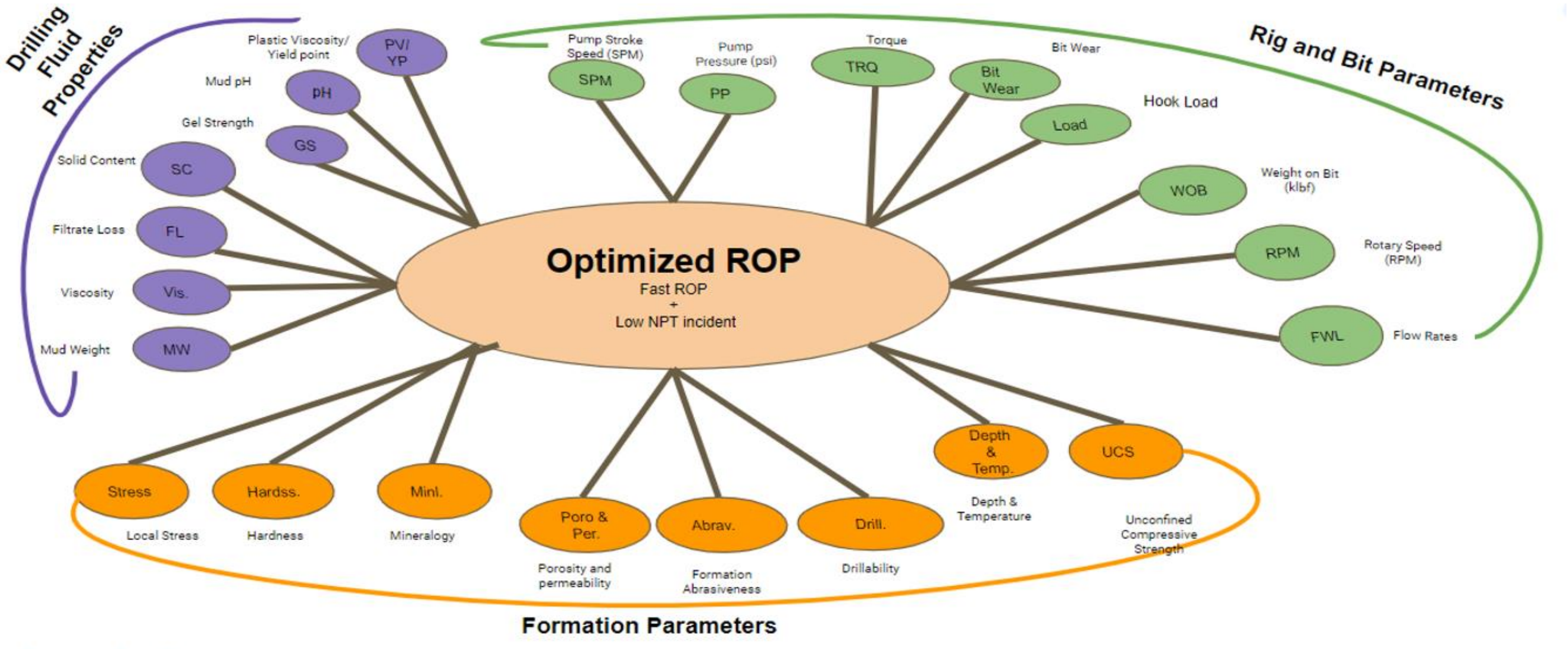
Case Studies: Drilling Program & Completion Study and Virtual Assistant for Fluids and Lithology

LEARNING OBJECTIVES

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

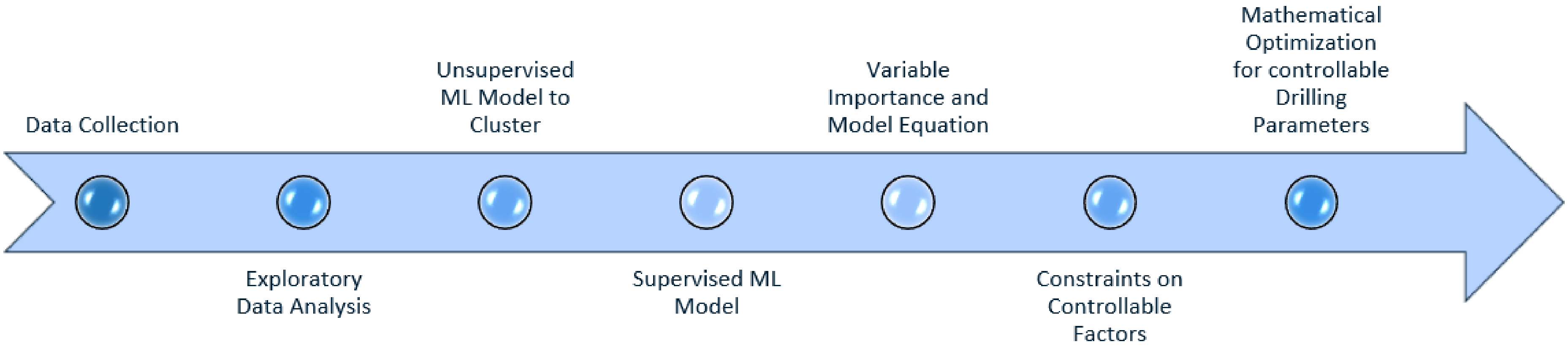
Case Studies

Drilling Optimization Process Workflow



Case Studies

Drilling Optimization Process Workflow

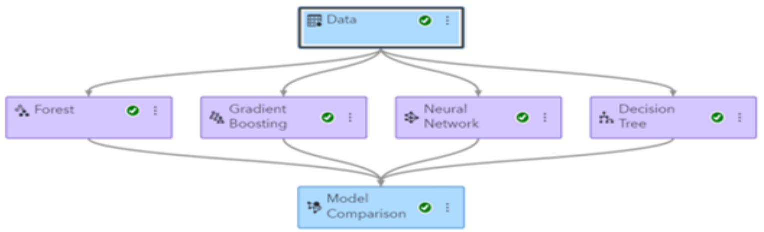


Case Studies

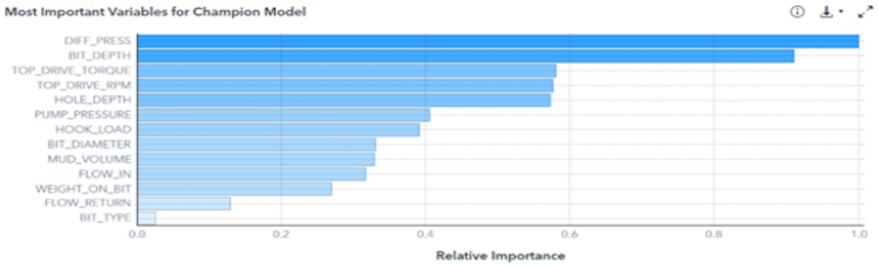
Drilling Optimization Process Workflow

The Process

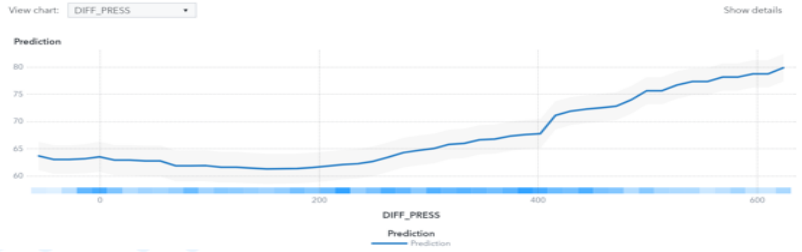
Run pipeline

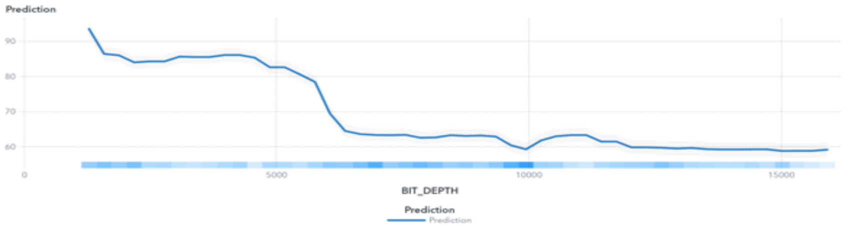


Variable Importance



Explainable AI



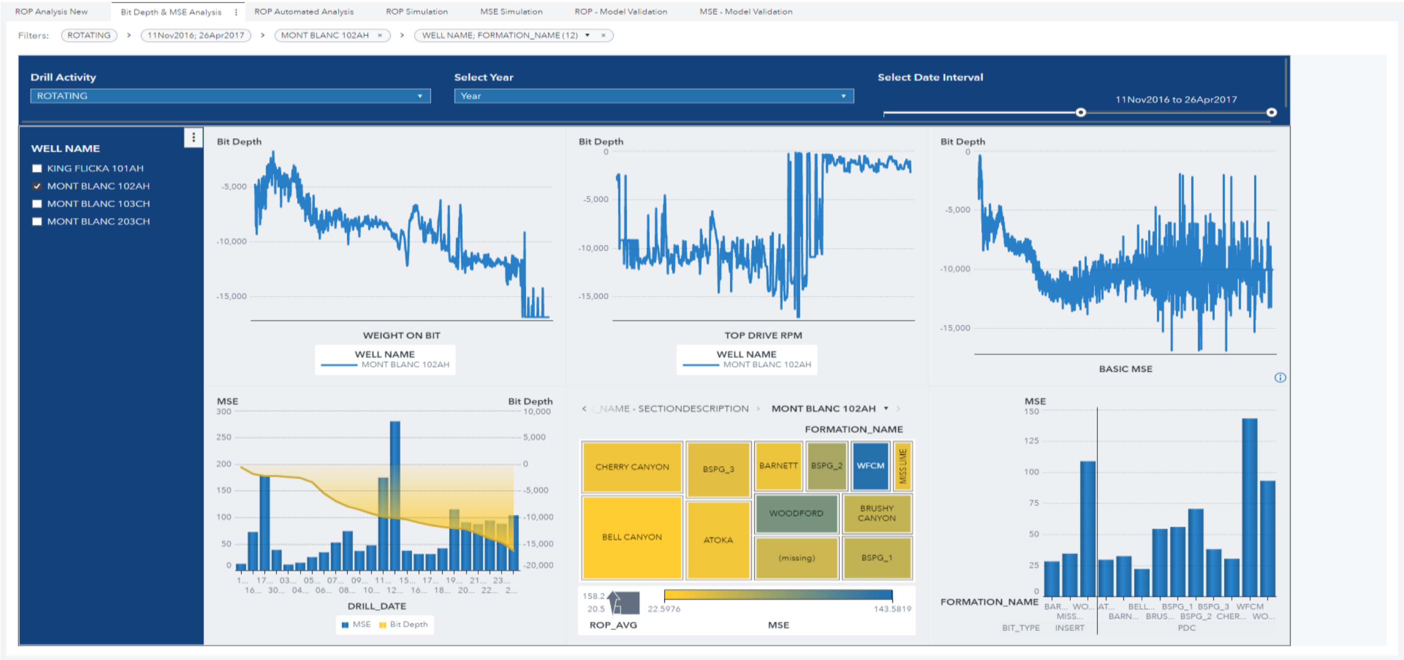


Case Studies

Drilling Optimization Process Workflow

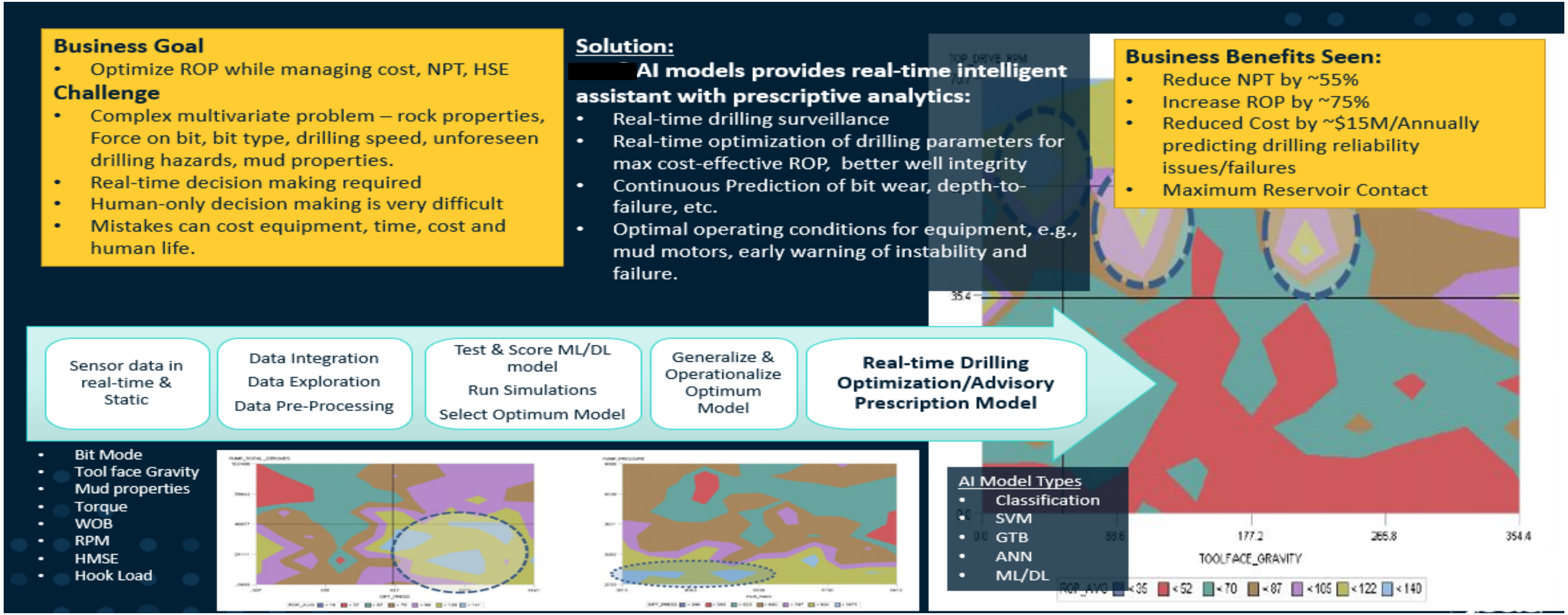
Case Studies

Drilling Optimization Process Workflow



Case Studies

Drilling Optimization Process Workflow



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.

Multi-Well Log Analysis

Lithology Characteristization

Automated Lithology Classification

Lithology Classification Model

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.

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	Forumla
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

IPTC International Petroleum Technology Conference

IPTC-19701-MS

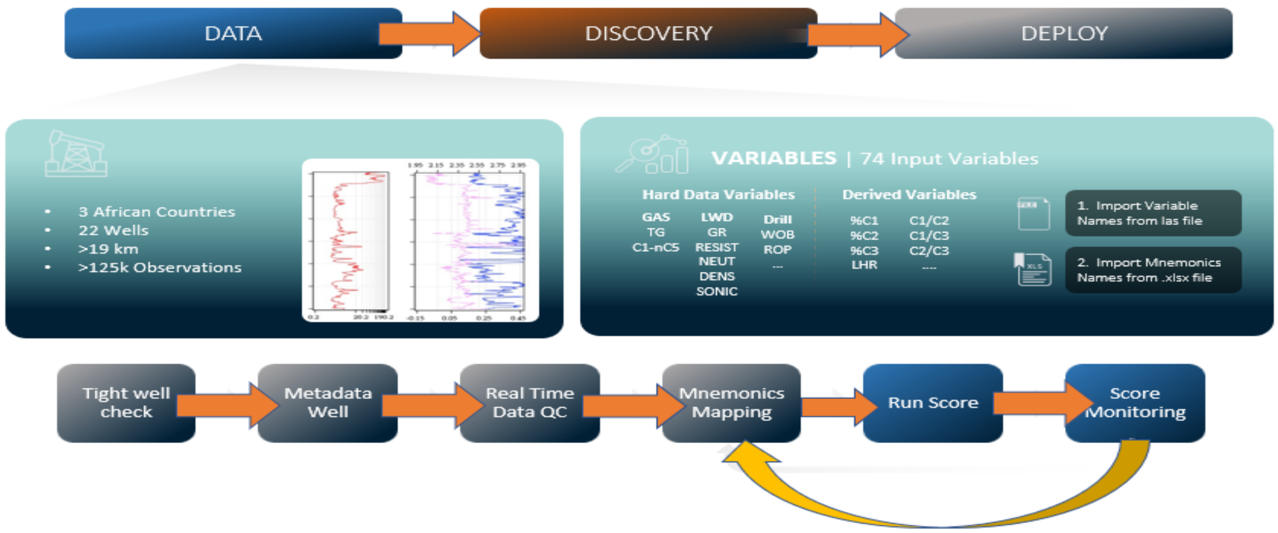
Artificial Intelligence and Machine Learning Techniques Provide Operations Geologists With an Automated and Reliable Lithology-Fluid Pattern Recognition Assistant: A Case History in a Clastic Reservoir in West Africa

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

Case Studies

Lithology-Fluids Pattern Recognition

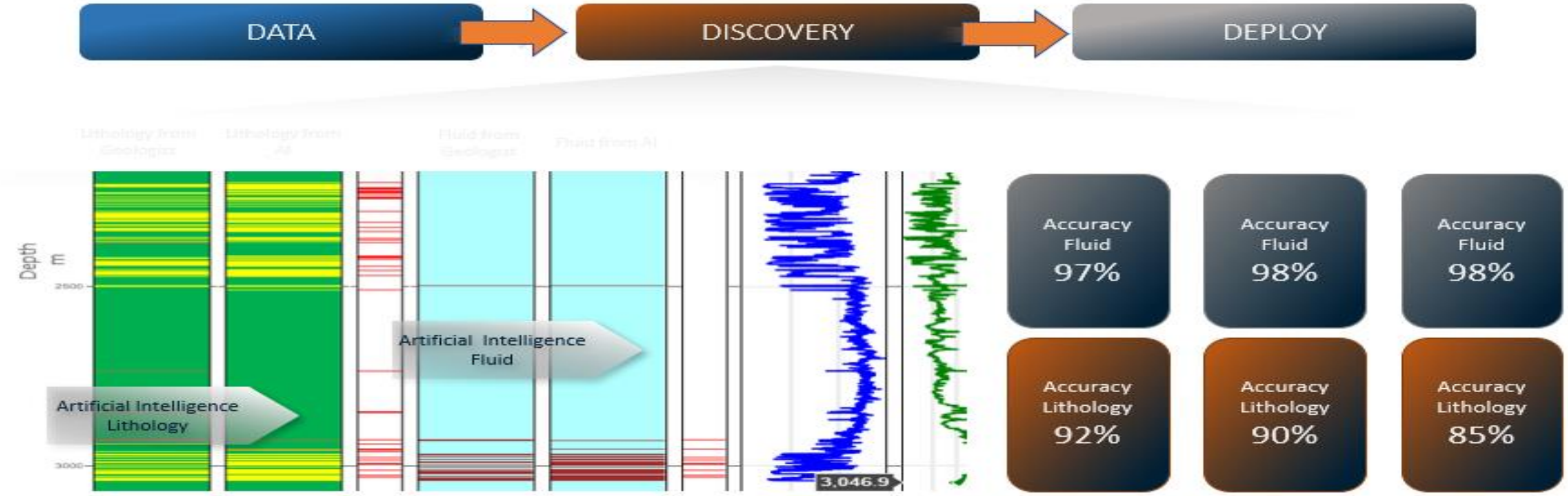
Fluid and rock identification from well log analysis – LWD and MWD



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.

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