

# Comparative Assessment of Cloud-based Machine Learning Models in Production Engineering

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## 1. Background

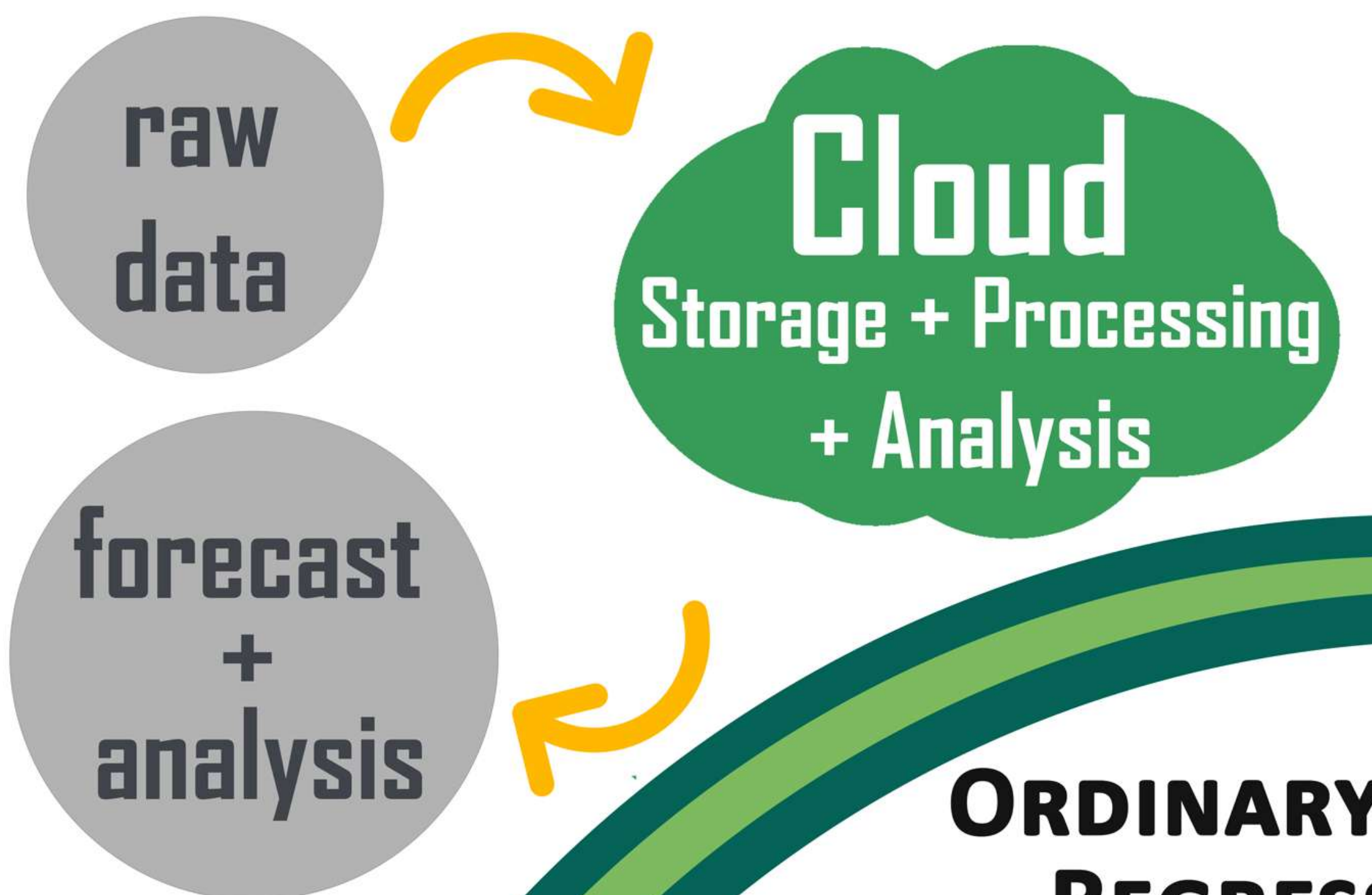
- Large field data-sets are fed into commercial cloud services to obtain accurate forecasting or analysis.
- Raw data can be uploaded onto cloud services by users, or live data can be used instead.
- Cloud services perform a multitude of tasks including **Storage, Processing** and **Analysis**.
- Cloud services have **multiple** machine-learning models which can be deployed for **specific insights**.



Southern Plains, AB

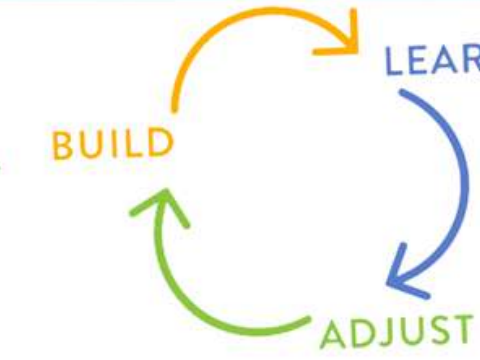
### Experimental Data Source:

- For this assessment, a sandstone reservoir with an adequate homogeneity was selected.
- Production schematic consists of a waterflood project with **135** production wells, and **28** injection wells.
- Approximately **535** unique data points in **6** distinct categories.

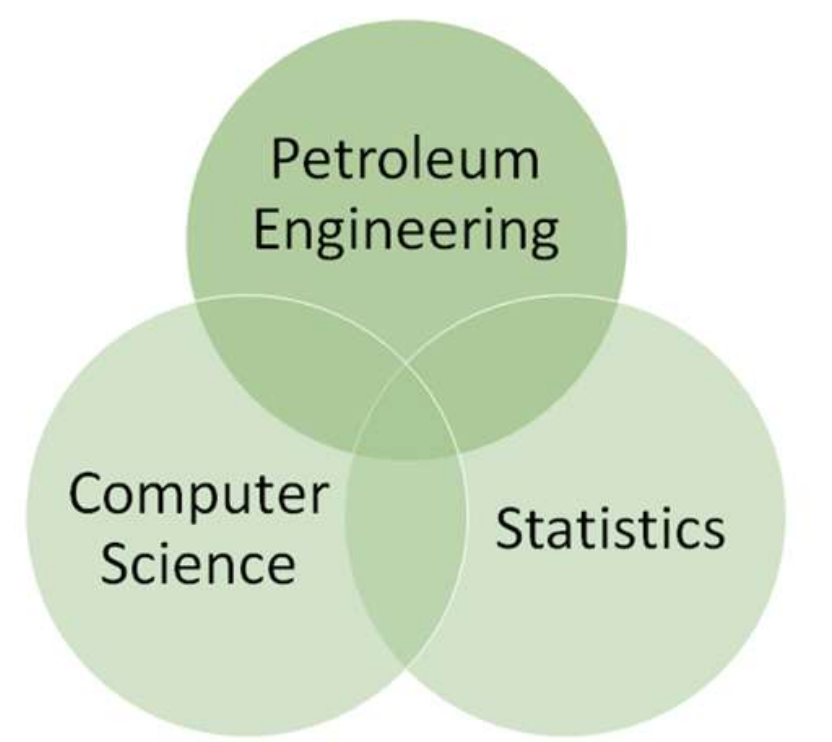


## 3. Engineering Design

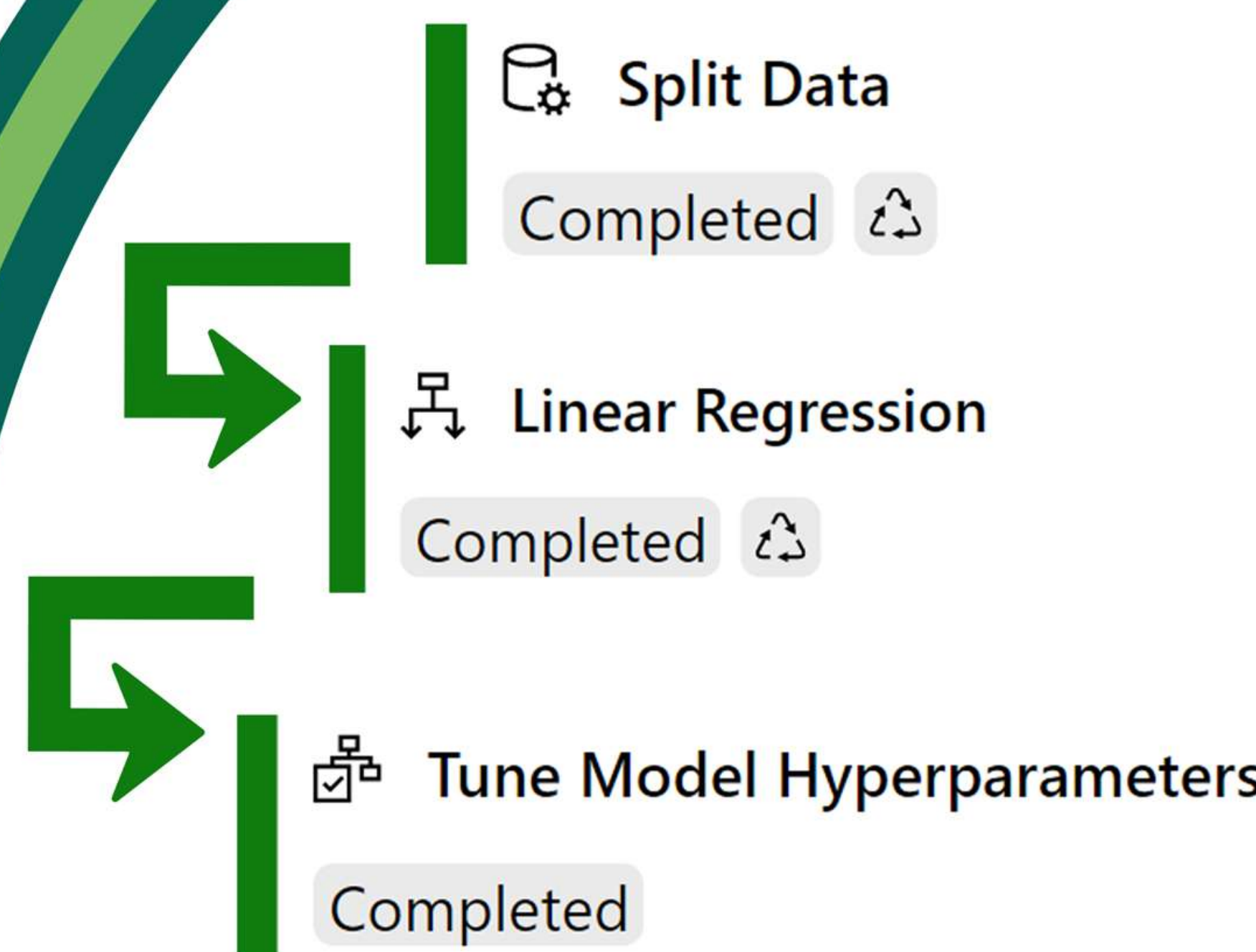
- **Data-centric Approach:** This approach is centered around **retrieving**, and/or **improving** the quality of an existing dataset — either through **filtering erroneous data**, or **enhancing training data** through use of synthetic data. Data quality is often regarded as more important than the selection and optimization of a model. For this project, specific queries were used to acquire a higher quality dataset from **AccuMap**.



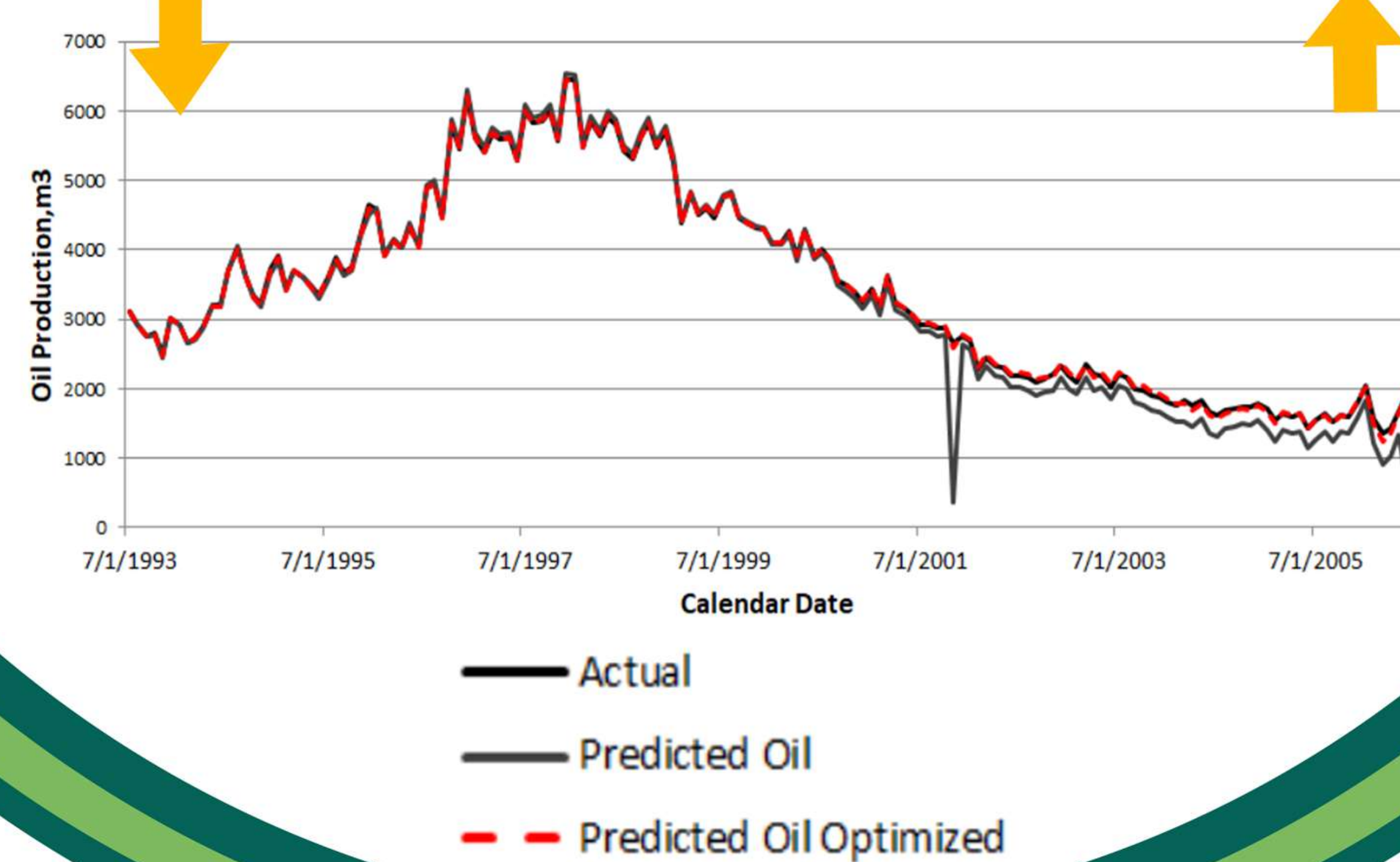
A Dual Design Approach to Maximize the Accuracy of the Models Used in this Project



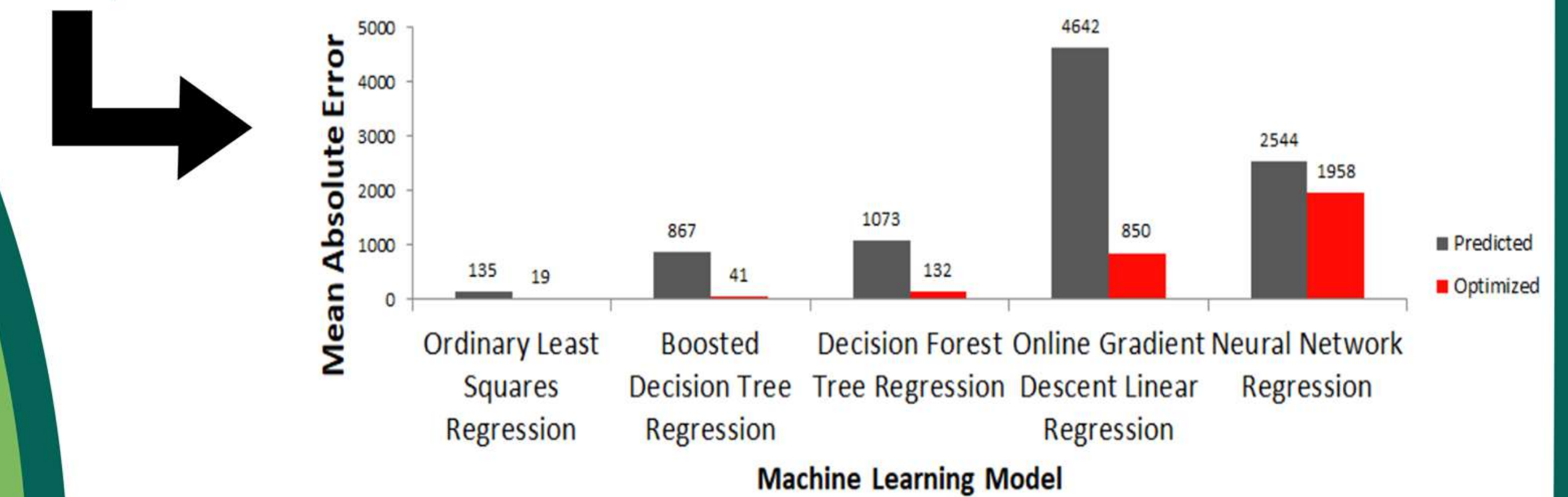
### ORDINARY LEAST SQUARE REGRESSION MODEL



<b>Mean Absolute Error</b>	
Before optimization	135.27
After optimization	18.89
Reduction in mean absolute error	↓ 86.03%
<b>Mean R<sup>2</sup> Value</b>	
Before optimization	0.967
After optimization	0.999
Increase in R <sup>2</sup> value	↑ 3.18%



- **Model-centric Approach:** An iterative, and a 'trial and error' approach for training, testing, or tuning of models. Once complete, the **optimum hyperparameters** are selected. For this assessment, hyperparameters of 5 ML models were iteratively optimized, and subsequently finalized based on the optimum error criterion.



## 2. Methodology

**20% Data Collection**

Prod ID	Month	Cum Prod	Month	Cum Prod
21459	180.7	286.2	7.1	48.6
21490	246.3	532.5	10.7	99.3
21520	362.4	894.9	12.5	71.8
21551	301.6	1196.5	9.6	81.4
21582	539	1735.5	22.6	104
21610	601.4	2336.9	27.2	131.2
21641	471.5	2808.4	16.7	147.9

- Defining inputs
- Data Ingestion
- QA/QC checks

**60% Data pre-processing**

- Formatting Data
- Cleansing Data
- Visualization & Descriptive Statistics

**20% ML Model & Assessment**

- Model training
- Fine tuning
- Cost Analysis & Assessment

## 4. Conclusions

- **Pressure depletion** decline analysis is not typically used for **waterflood applications**.
- Traditional analytical methods, such as the **Buckley-Leverett theory**, require specific reservoir properties to predict, e.g. lab analysis for water saturation values.
- **Azure Cloud Services** are capable of constructing models and computing predictions with rudimentary field data.

- Model considerations:
  - > Memory Usage
  - > CPU /GPU Usage
  - > Interpretability
  - > Predicted costs

### Buckley-Leverett Equation 1-D

$$\frac{\partial S_w}{\partial t} + \frac{\partial}{\partial x} \left( \frac{Q}{\phi A} f_w(S_w) \right) = \phi \frac{\partial S_w}{\partial x}$$

## Did you know?



In order to increase **efficiency** and **operational sustainability**, energy companies are collaborating with **Azure**, as strategic partners.



Azure solutions on **Internet of things (IoT)** delivers an intelligent edge to operators, to enhance **production** and optimize surface facilities **operation**.

## Team

