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Machine Learning Applications for Optimizing Real-Time Drilling and Hydraulic Fracturing

Yuxing Ben



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Outline

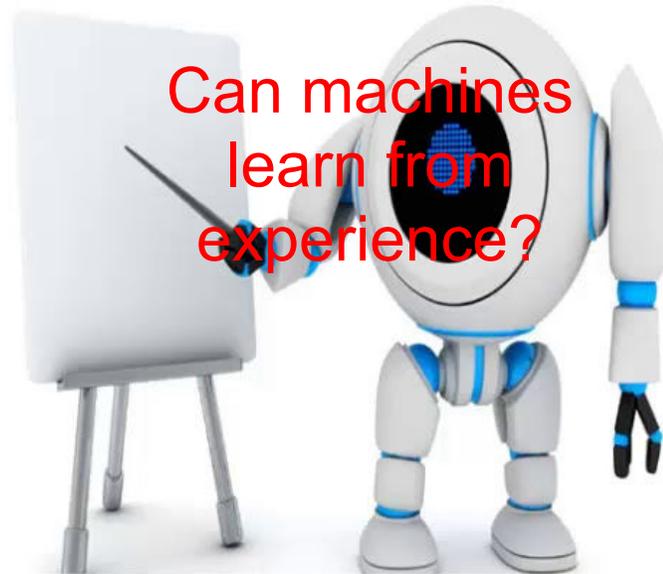
- Background
 - What is Machine Learning (ML)
 - Types of Machine Learning
- Application Cases
 - Development and Deployment of Real-Time Drilling State Identification with ML
 - Real-Time Hydraulic Fracturing (HF) Pressure Prediction with ML
 - Real-Time HF Cost Optimization with ML and Model Predictive Control
- Takeaways and Future Development

What is Machine Learning?

Learn From Experience



Learn From **Data**
Experience



Can machines
learn from
experience?

Follow Instructions

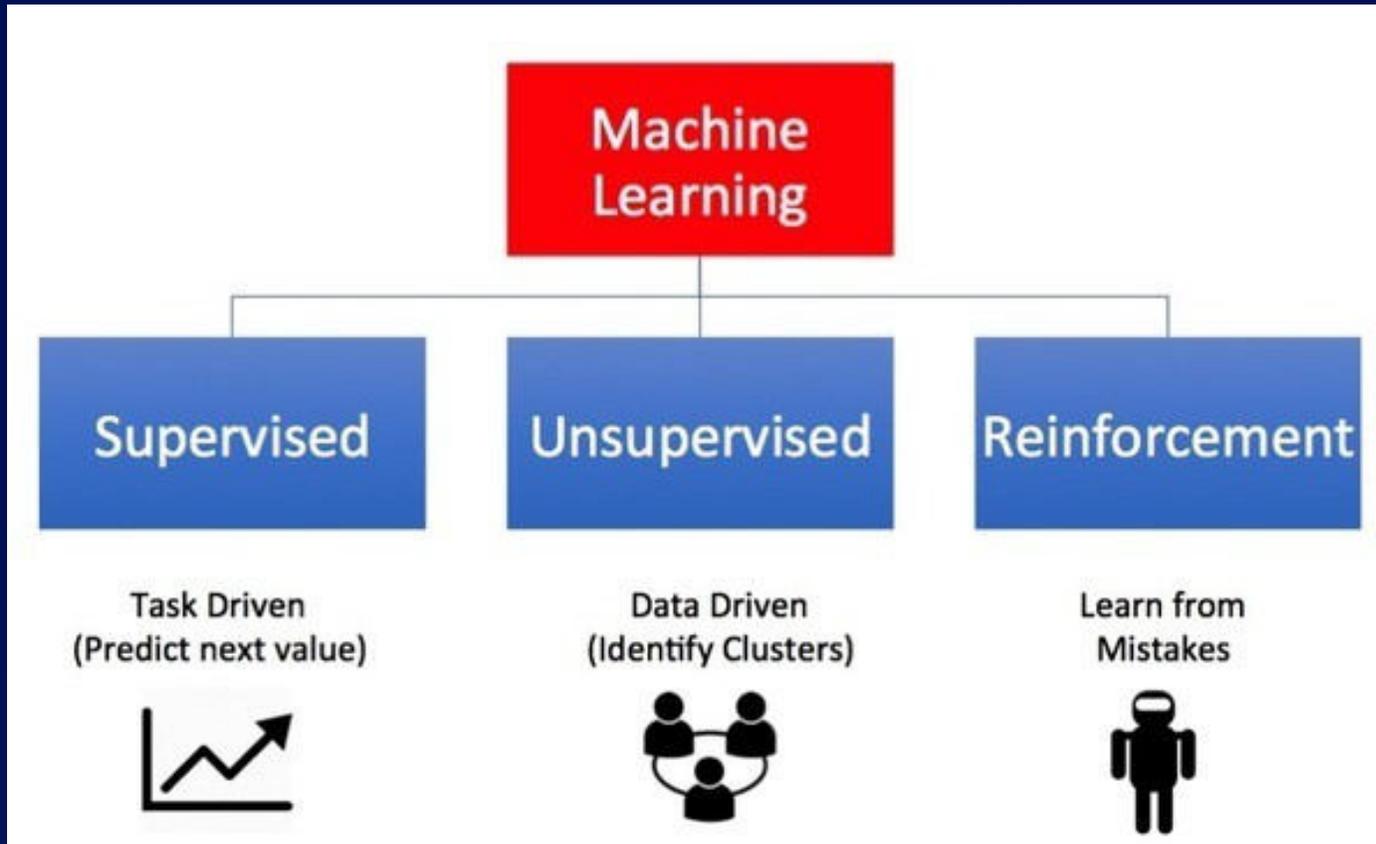


Image captured from https://www.youtube.com/watch?v=2QgyH29x0_M

What is Machine Learning?

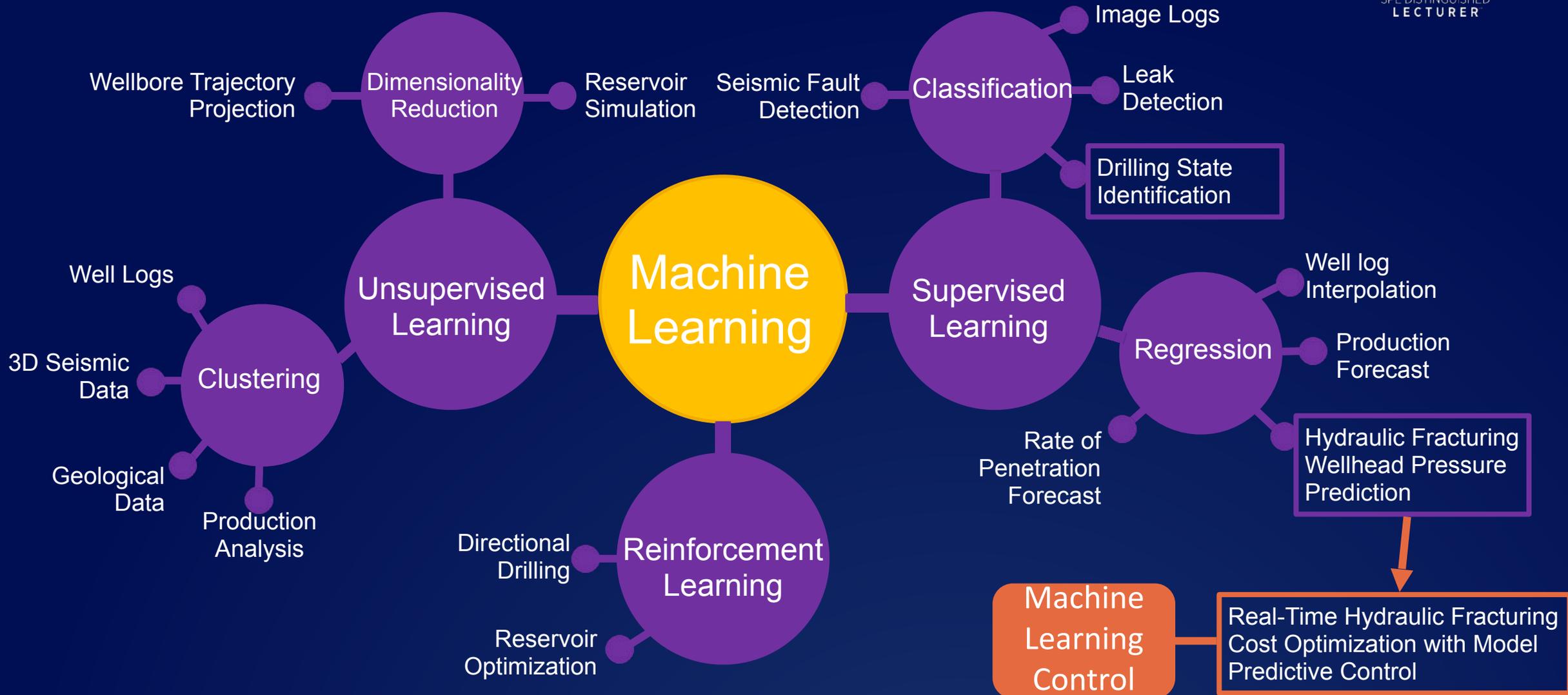
- “Machine learning (ML) is a field of study that gives computers the ability to learn without being explicitly programmed.” (Arthur Samuel, IBM, 1959)
 - The problem cannot be solved by “If Then” statements.
 - Machine-learning programs adjust themselves in response to the data they’re exposed to. (<https://skymind.ai/>)
- “The field of machine learning is concerned with the question of how to construct computer programs that automatically improve with experience.” (Tom Mitchell, Carnegie Mellon University, 1997)
- ML is one of the ways we expect to achieve Artificial Intelligence (AI).

Types of Machine Learning



<https://towardsdatascience.com/what-are-the-types-of-machine-learning-e2b9e5d1756f> by Hunter Heidenreich

Machine Learning in Oil and Gas



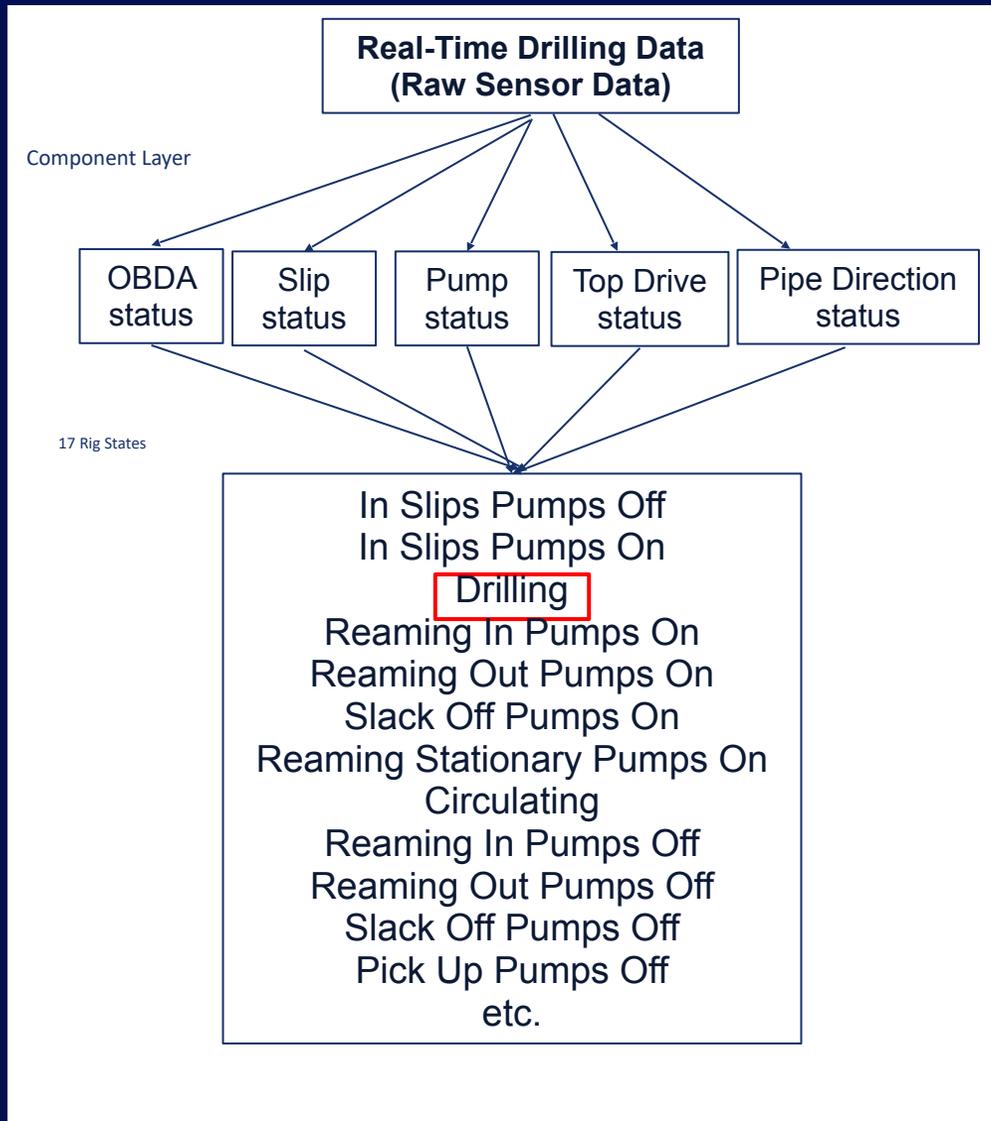
Why Build a Real-Time Drilling Platform?

To improve drilling efficiency and optimization through real-time monitoring and automation

- Engineers and field crews have multiple conflicting priorities
 - ❖ Minimize wellbore tortuosity
 - ❖ Drill the lateral in the zone
 - ❖ Drive efficient, repeatable performance
- Practical priorities tend to outrank optimization efforts
- Asset teams are asking for automated, real-time analysis tools to:
 - ❖ Enable fast, data-driven decisions
 - ❖ Deliver repeatable workflows
 - ❖ Lay a foundation for future technological advancements

(Ben, Y et al. URTEC-2019-253)

Drilling Data Analytics

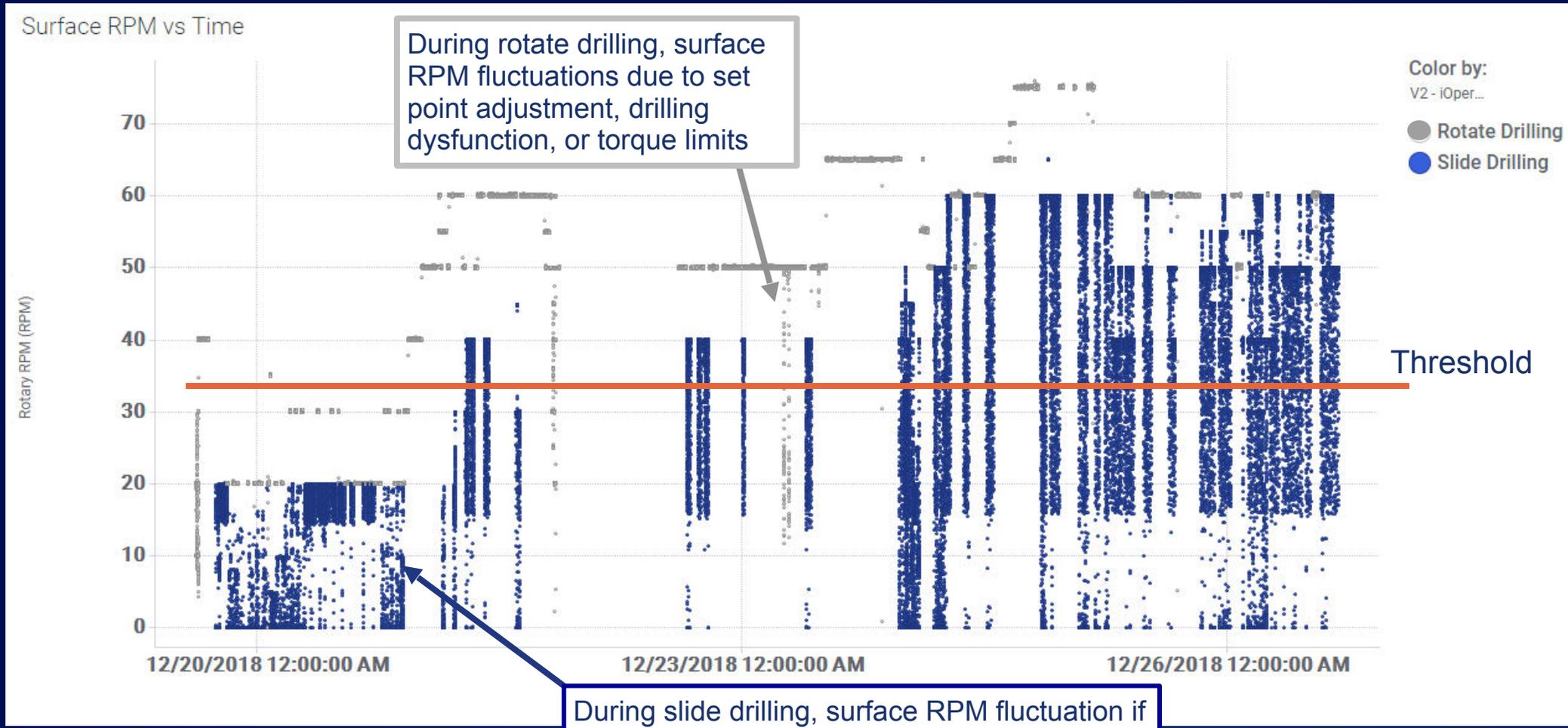


- Starts with second-by-second data
- Component layer uses rules to classify the status of major rig system
- Apply a second set of rules to determine a rig state
- Accuracy is extremely high except for Drilling because:
 - mud motor is used and “rocking” is used during sliding (SPE 87162)
 - must be further classified into rotate or slide drilling

Note: OBDA (if bit is on bottom and drilling ahead)



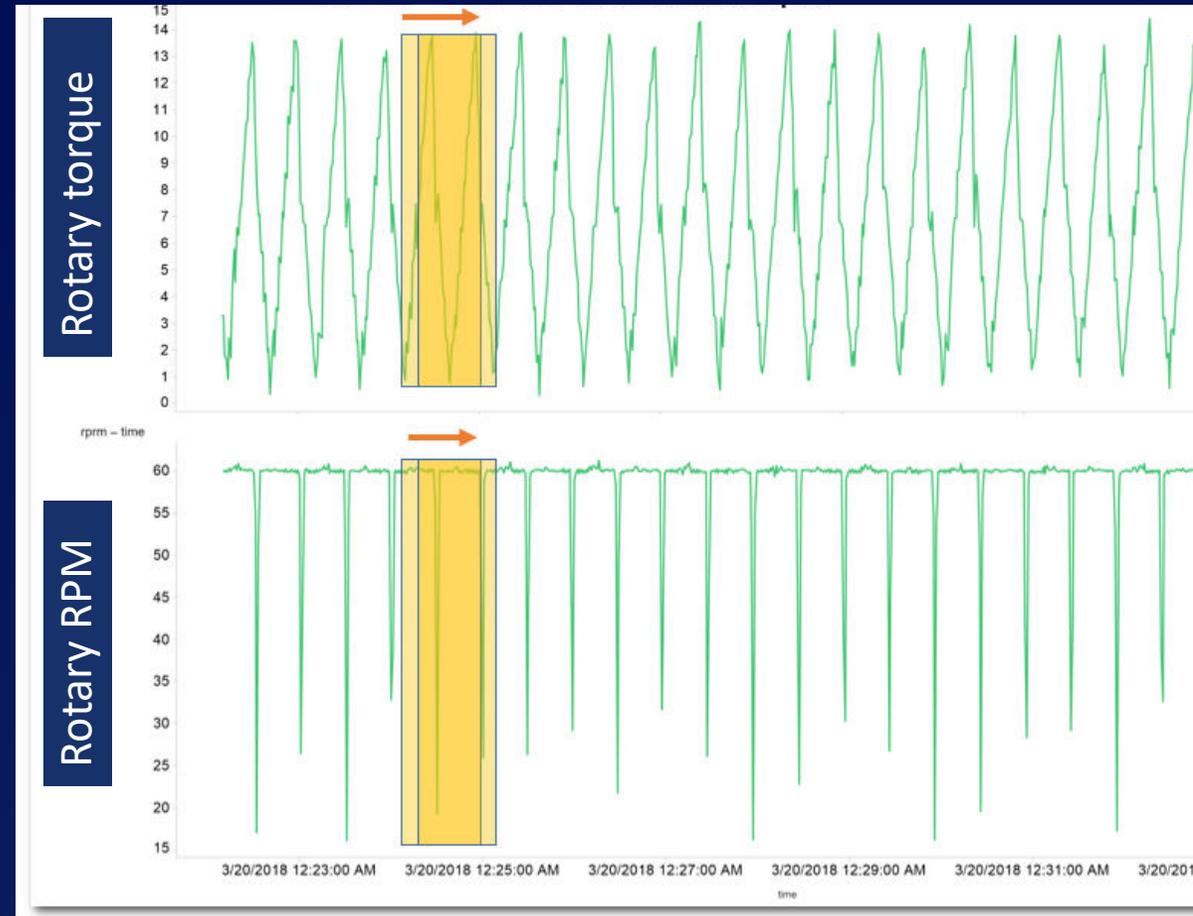
Threshold Rules Do Not Reliably Distinguish Rotate/Slide Drilling



Solution: Convert Drilling Time Series into a One-Dimensional Image Classification Problem

Moving window to look back 20 seconds

- Feature Selection
 - RPM and torque
 - Well section (vertical, curve, lateral)
- Labeled 10 wells from the Delaware Basin and 12 wells from DJ Basin
 - About 11,000,000 rows of data



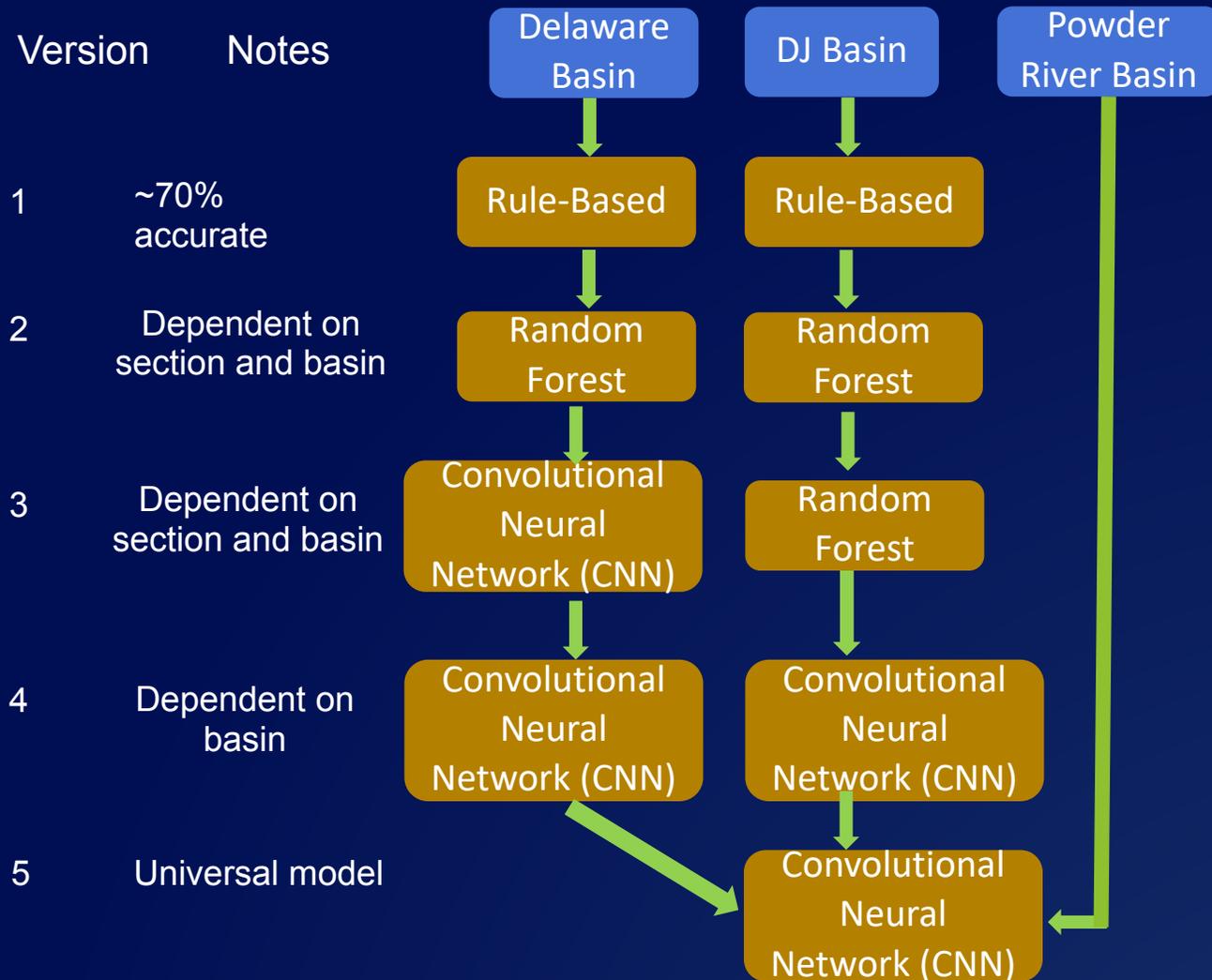
Results from Three Different Classification Machine Learning Approaches

- Random forest
- Convolutional Neural Network (CNN)
- Hybrid Recurrent Neural Network (RNN)+Convolutional Neural Network(CNN)

Test Well	Random Forest	CNN	Hybrid RNN + CNN
Well No 1	99.8%	99.5%	99.4%
Well No 2	99.5%	99.9%	99.7%
Well No 3	99.3%	99.8%	99.9%
Well No 4	99.8%	99.5%	99.3%
Well No 5	97.2%	99.2%	98.7%
Well No 6	99.96%	99.9%	99.9%
Well No 7	89.3%	99.9%	99.9%
Well No 8	99.9%	99.9%	99.9%
Well No 9	86.7%	98.7%	99.1%
Well No 10	99.8%	99.8%	99.8%

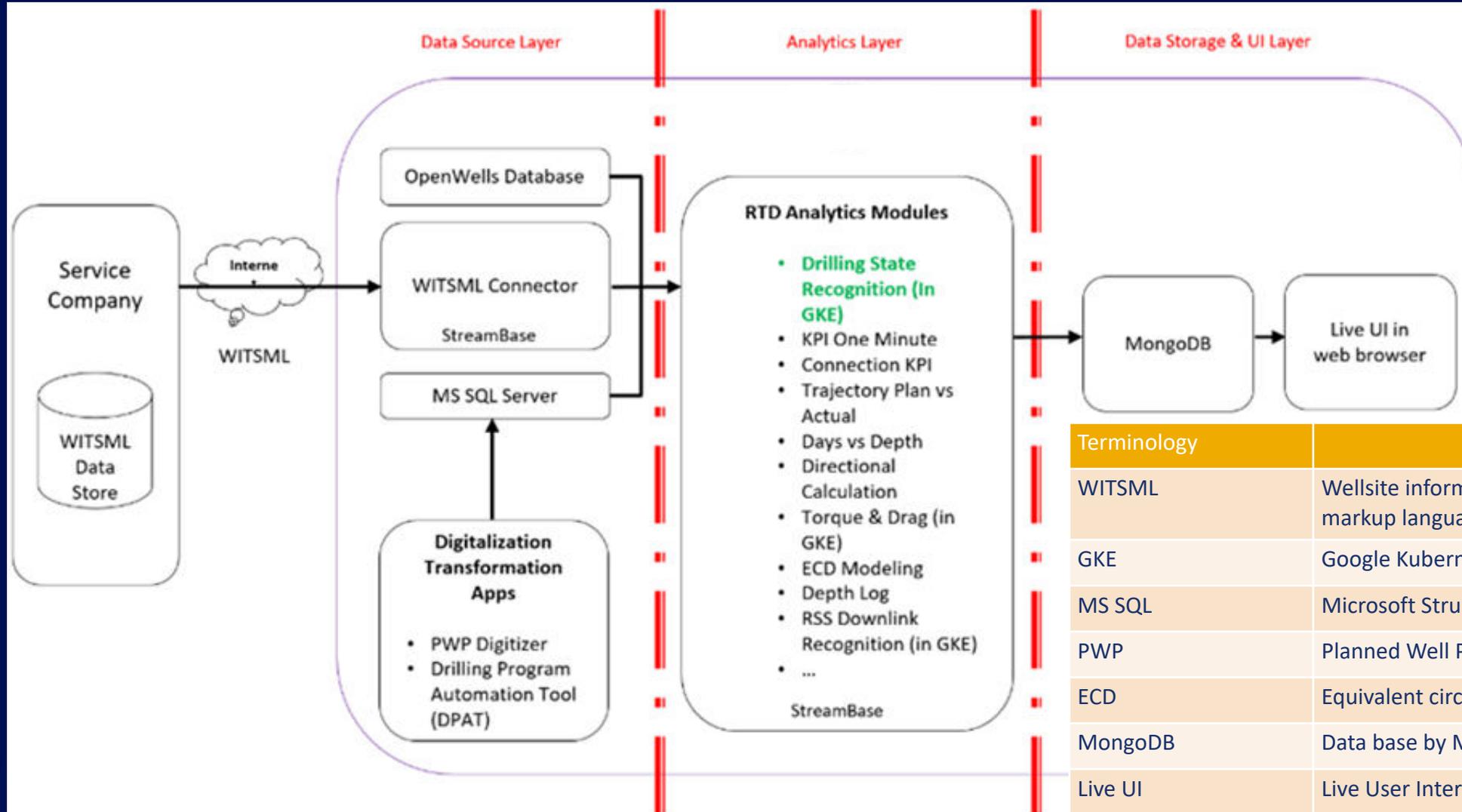
Delaware Basin

Deployment and Lessons Learned



- Version 1 deployed before 7/2018
- Version 2 deployed 12/2018
- Lessons Learned
 - Wellbore section (vertical, curve, lateral) are not always available
 - Accuracy in production was lower than expected
- Model Evolution
 - Removed model dependency on wellbore section
 - Added more training data and developed a universal model
- Version 5 deployed 4/2019

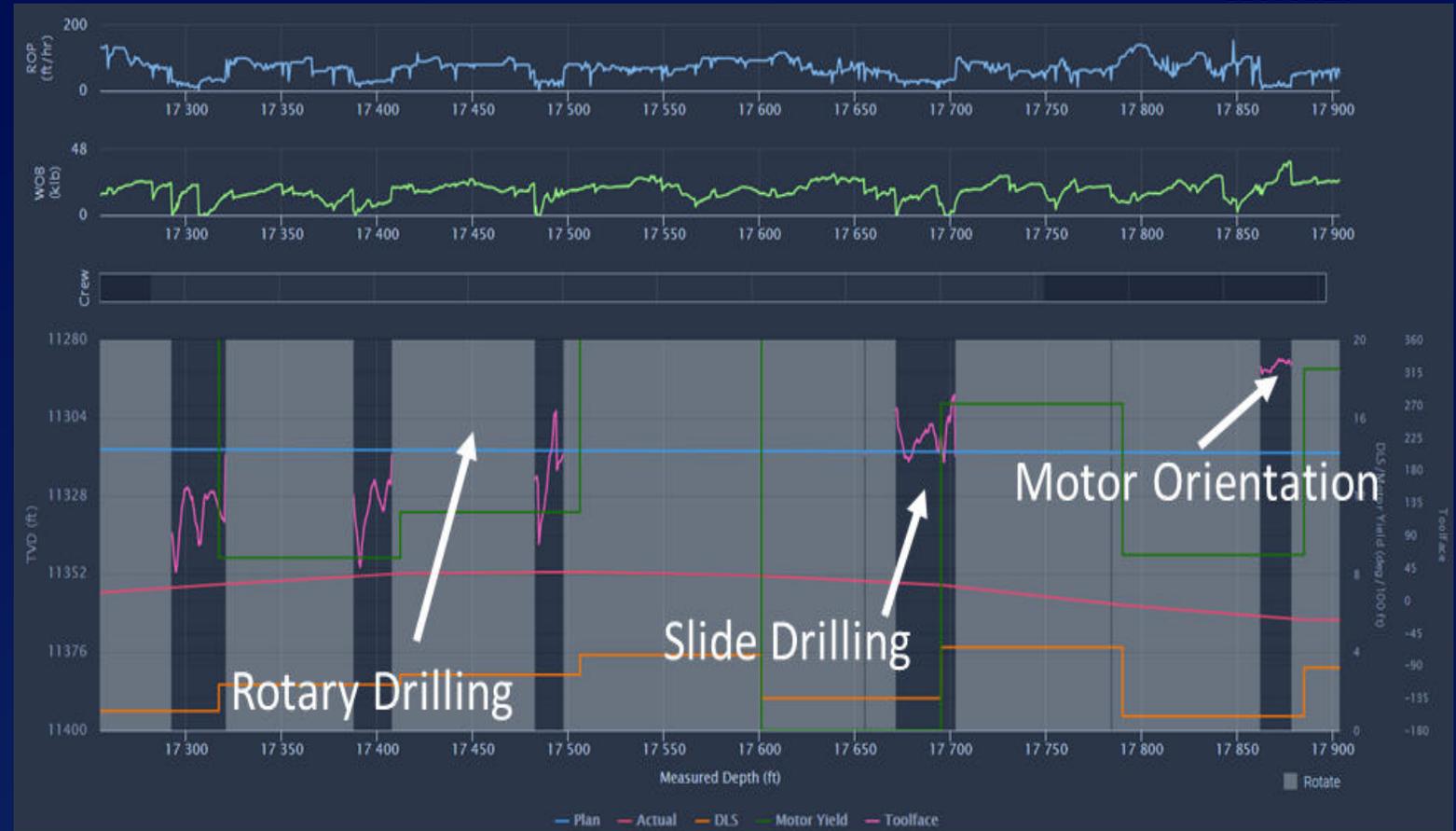
Architecture of the Real-Time Drilling System



Terminology	
WITSML	Wellsite information transfer standard markup language
GKE	Google Kubernetes Engine
MS SQL	Microsoft Structured Query Language
PWP	Planned Well Path
ECD	Equivalent circulating density
MongoDB	Data base by Mongo DB Inc
Live UI	Live User Interface

Application and Use Cases

- Directional Analysis
 - Accurate rotate/slide detection allows visualization of motor orientation (toolface) while sliding
 - Can compare slide performance to surveys and drilling parameters to diagnose problems and optimization opportunities



- Rotary drilling is represented by the gray colored stripes;
- Slide drilling is represented by the black colored strips;
- The motor orientation is represented by the pink line

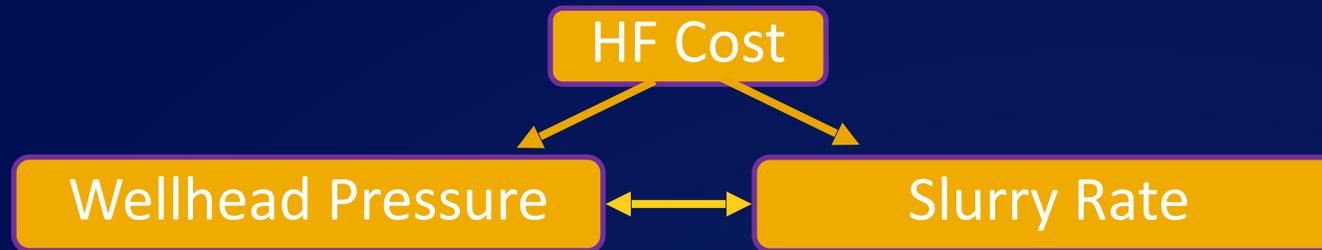
Application and Use Cases, continued

- KPI
 - Pad-level analysis shown across six wells
 - Rapidly compare slide/rotate footage percentages
 - Analyze drilling rates (ROP) between rotate and slide drilling between wells



Why Do We Need Real-Time Hydraulic Fracturing (HF)?

- HF costs twice as much as drilling for onshore wells



(Ben, Y et al. SPE 199699, 2020)

- If we can predict wellhead pressure, we can
 - Prevent screen-out
 - Optimize HF cost in real time by adjusting the pumping schedule
 - Help completion engineers make better decisions in real time

Why Data-Driven Model?

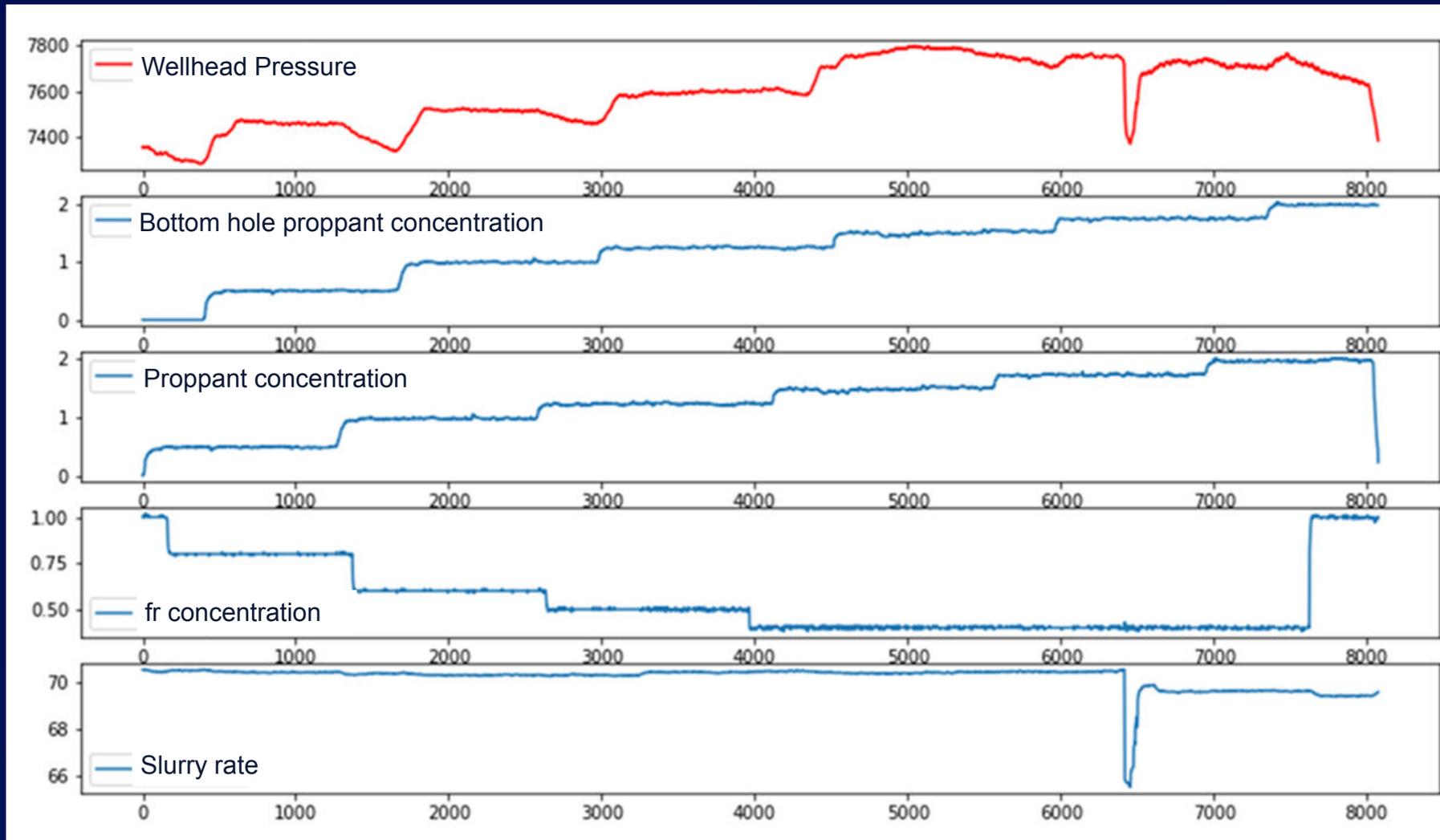
- Wellhead pressure includes the following contributions:

$$\text{WHTP} = \text{BHFP} - P_{\text{hydrostatic}} + P_{\text{pipefriction}} + P_{\text{perforation}} + P_{\text{nwb}}$$

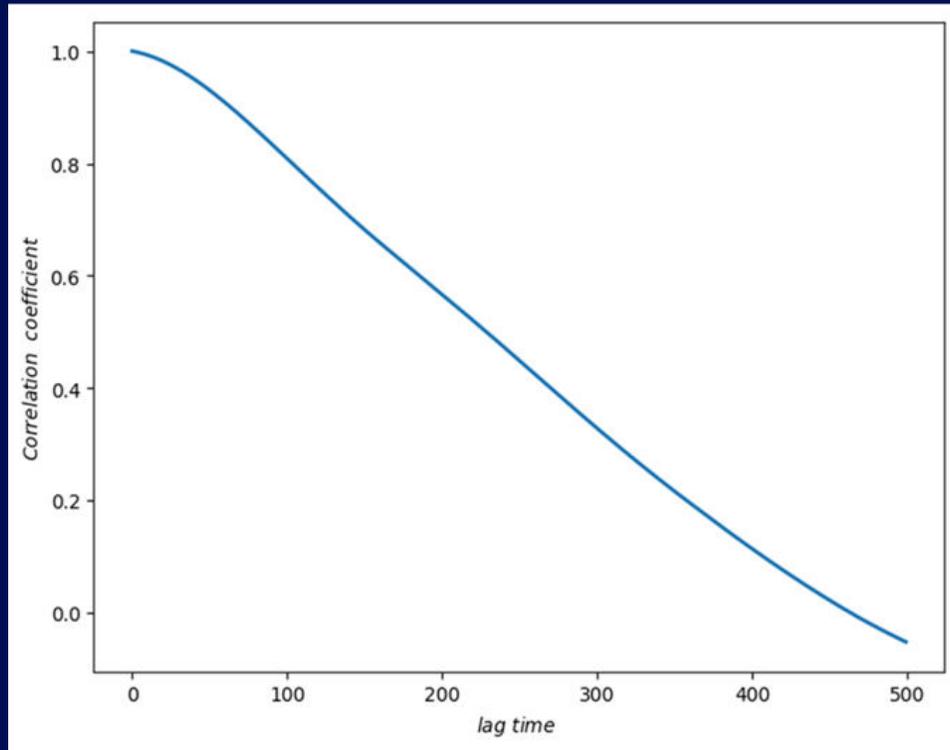
Wellhead treating pressure Bottomhole fracturing pressure Near-wellbore pressure

- Physics-based model
 - Make assumptions
 - Cannot simulate each of the contributions very well, such as the near-wellbore tortuosity

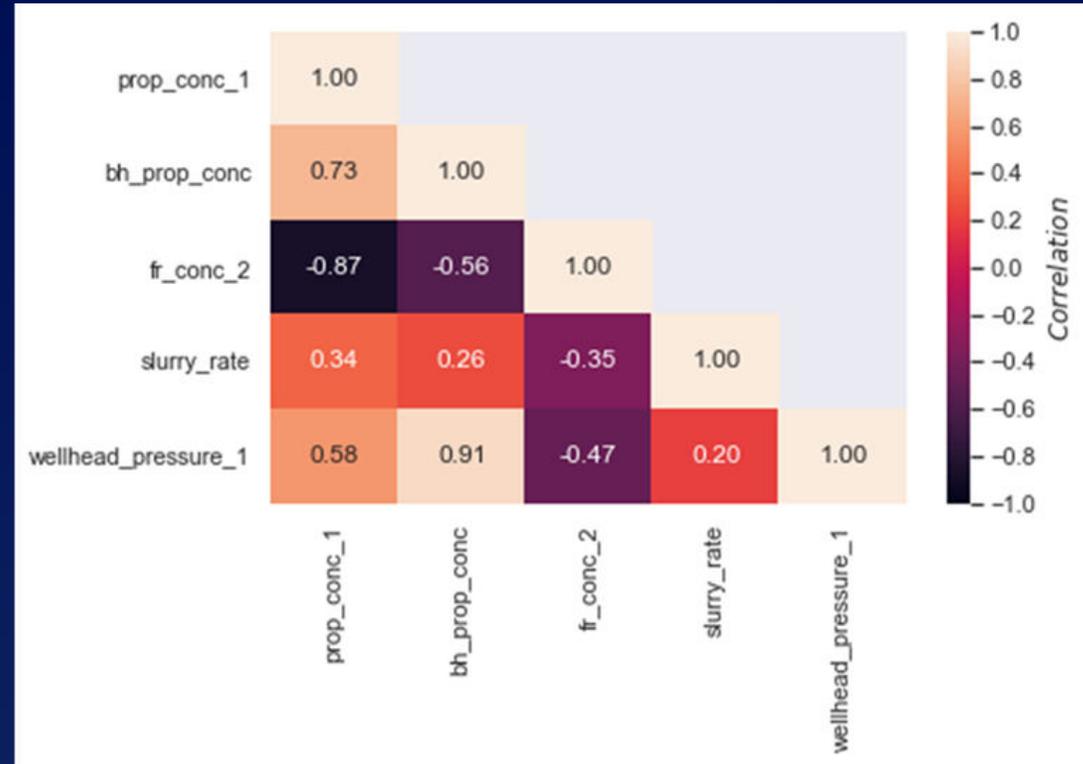
Data Visualization Shows Strong Correlation Between Wellhead Pressure and Proppant Concentration



Data Analysis Shows Strong Correlation of Wellhead Pressure to Its History and Proppant Concentration

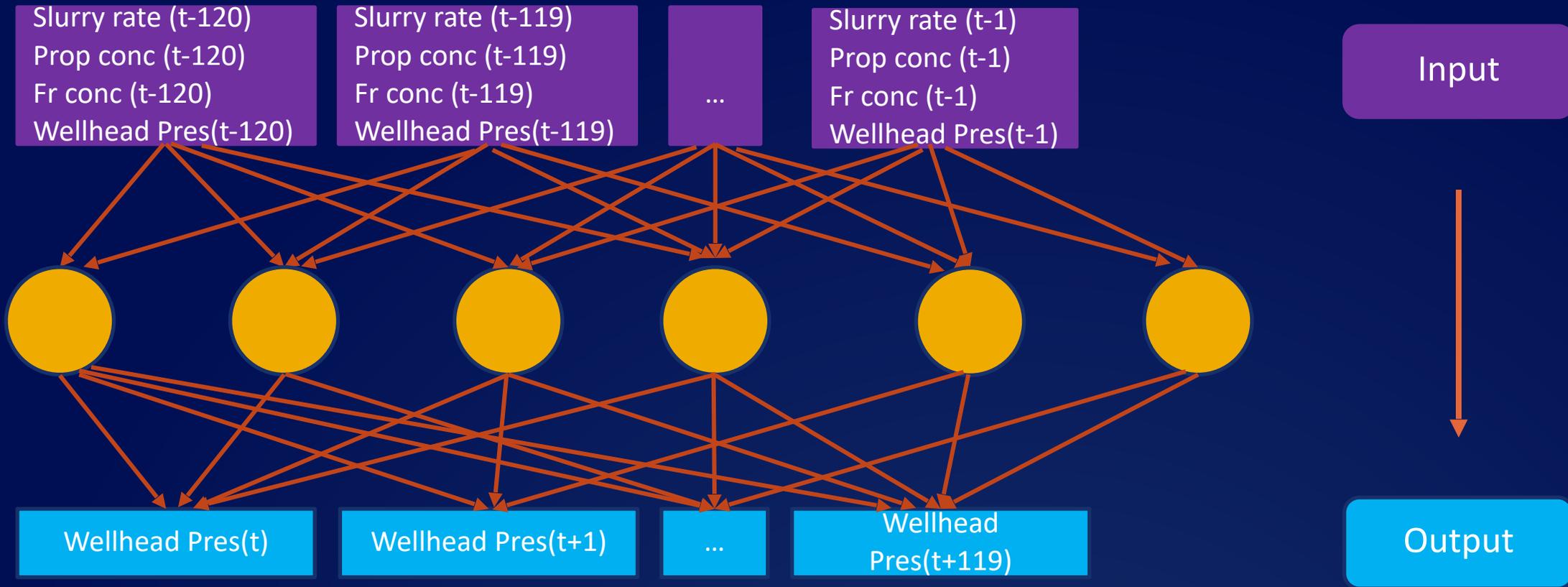


Autocorrelation coefficients show wellhead pressure depends on its past values.



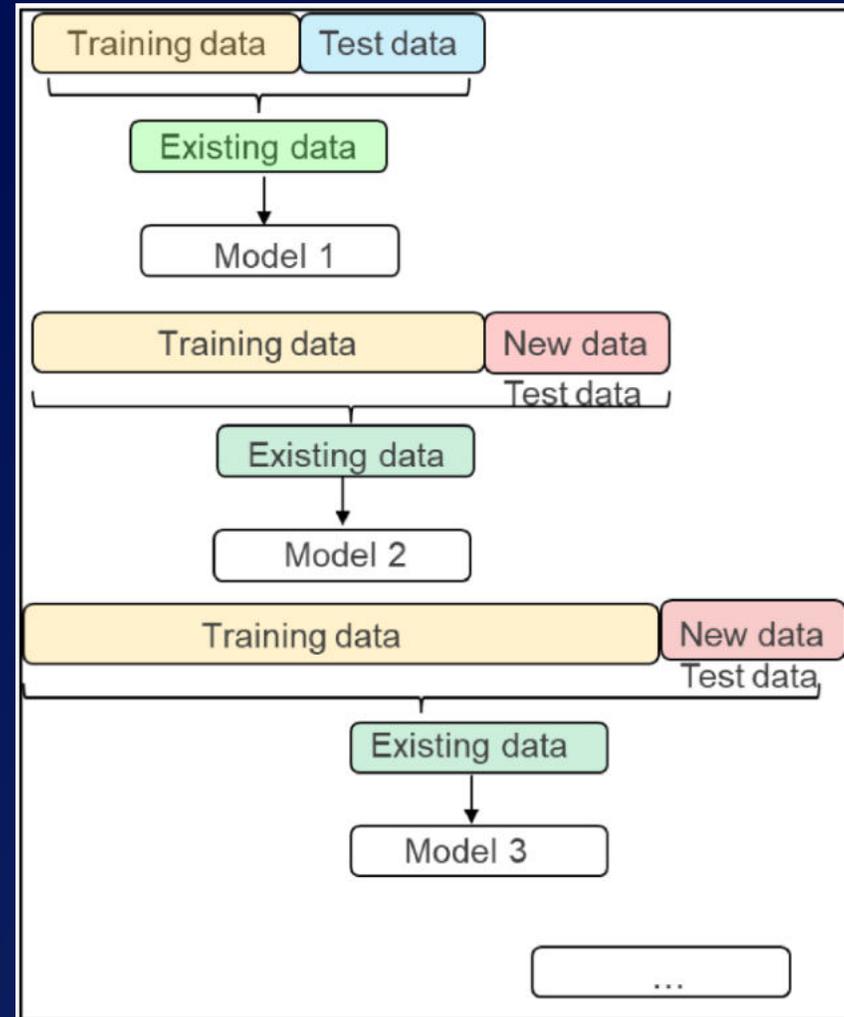
Pearson correlation coefficients shown in the colored map summarize the strength of the linear relationship between variables

Wellhead Prediction by Neural Network

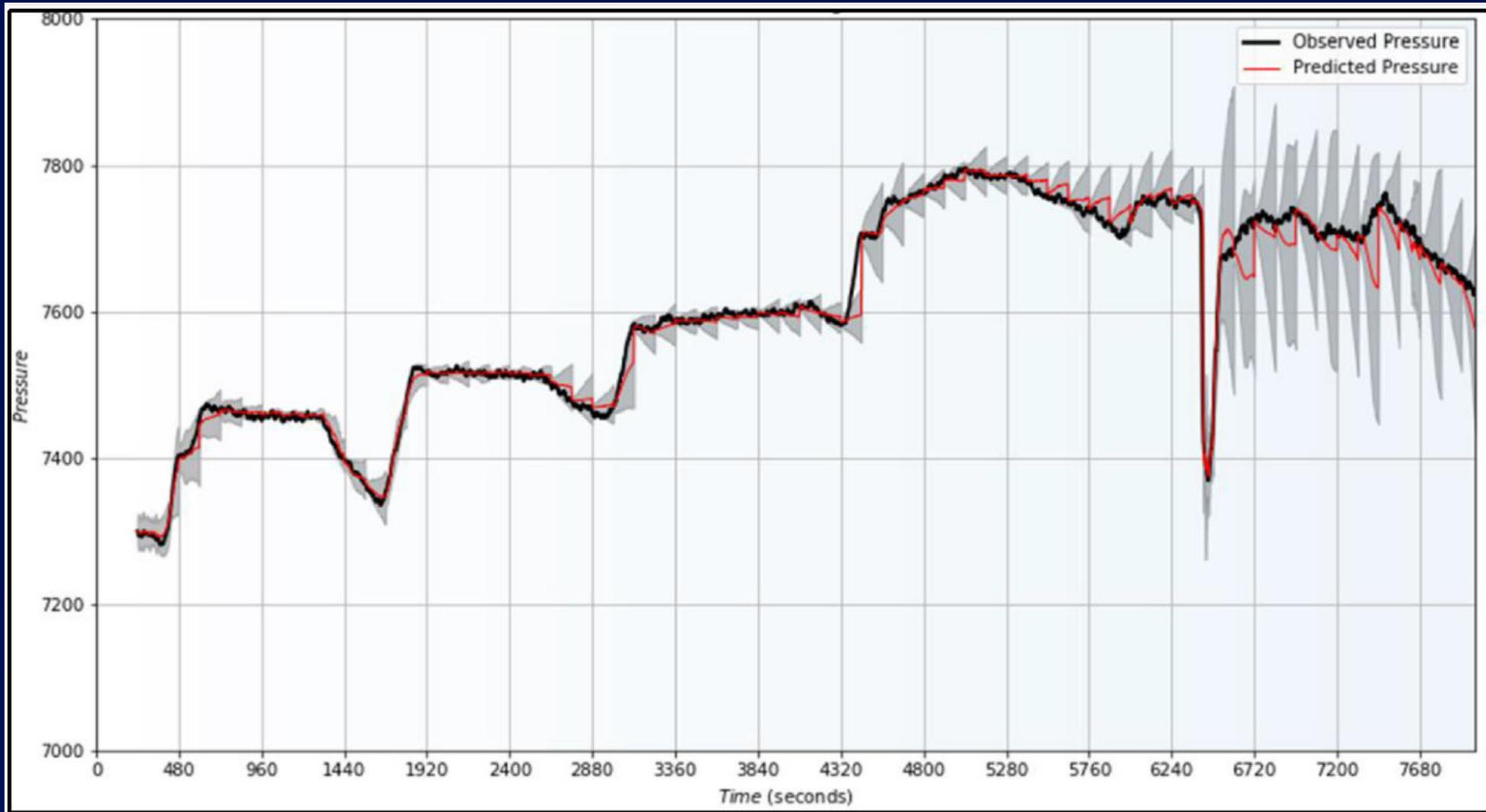


Apply Continuous Learning to Real-Time Wellhead Pressure Forecasts for Better Accuracy

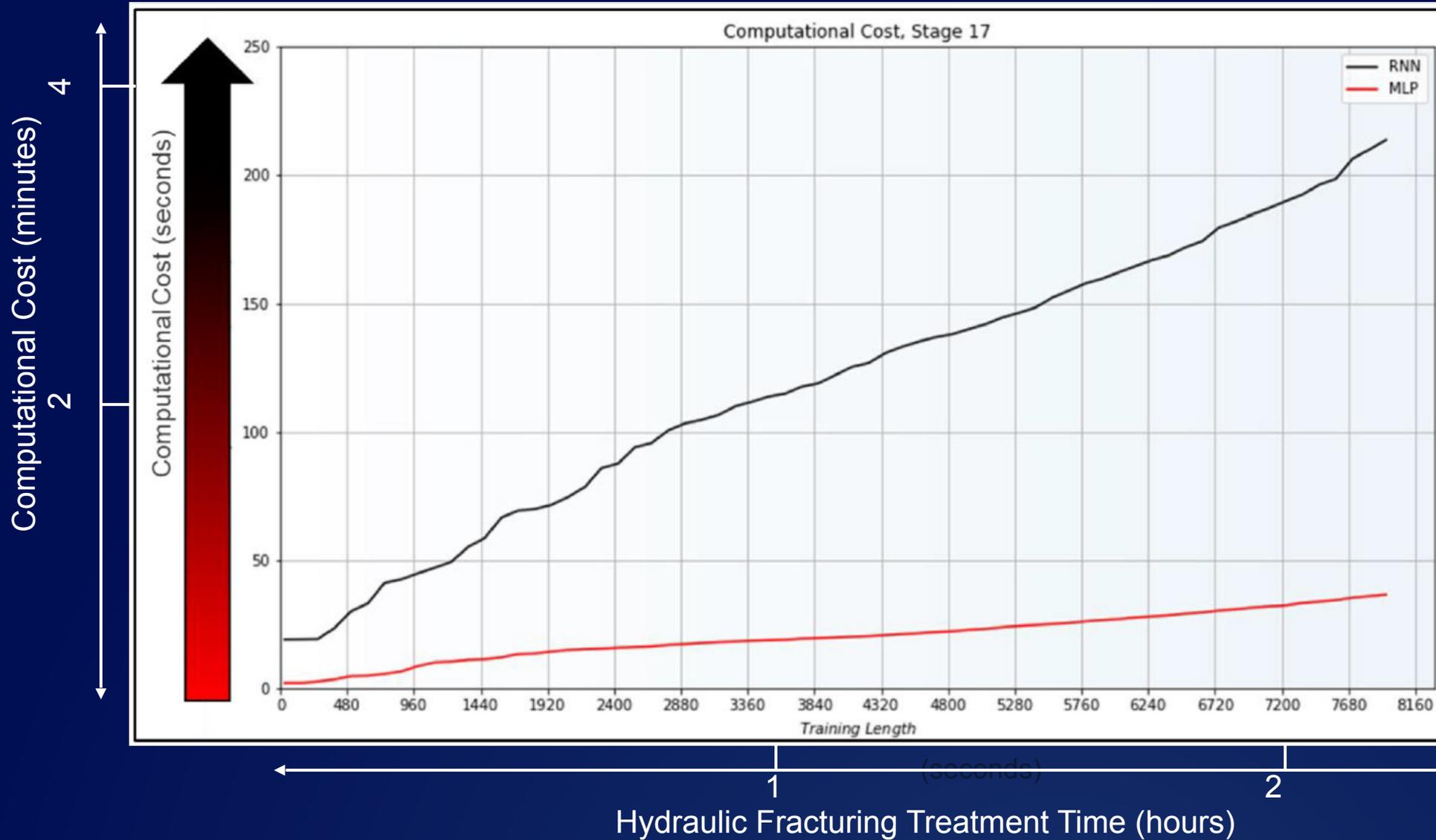
Time



Neural Network Forecasting Errors Are Shown by the Uncertainty Cones with Grey Shapes

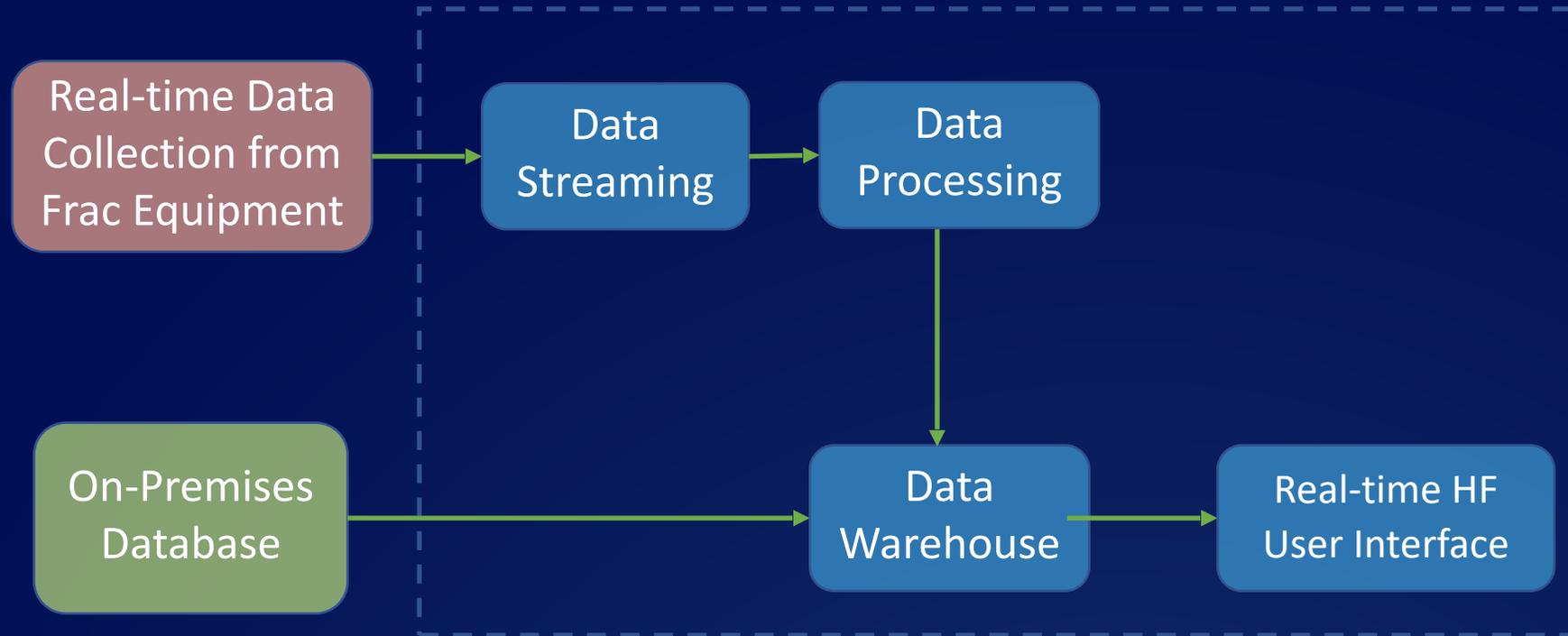


Computation Is Fast Enough for Real-Time Forecasting



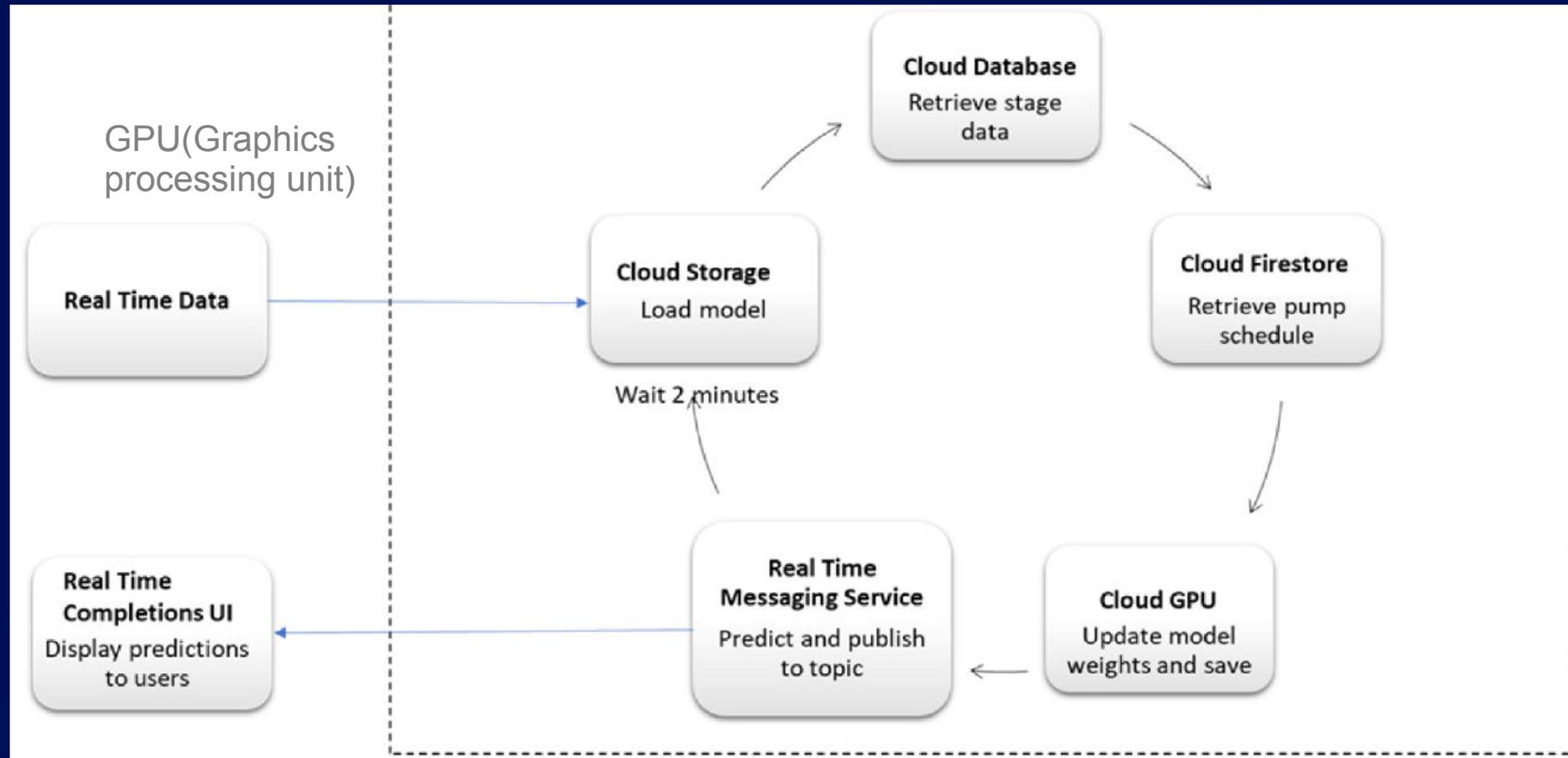
RNN (Recurrent Neural Network)
MLP (Multi-layer perceptron)

Real-Time Data Streaming on a Cloud Platform



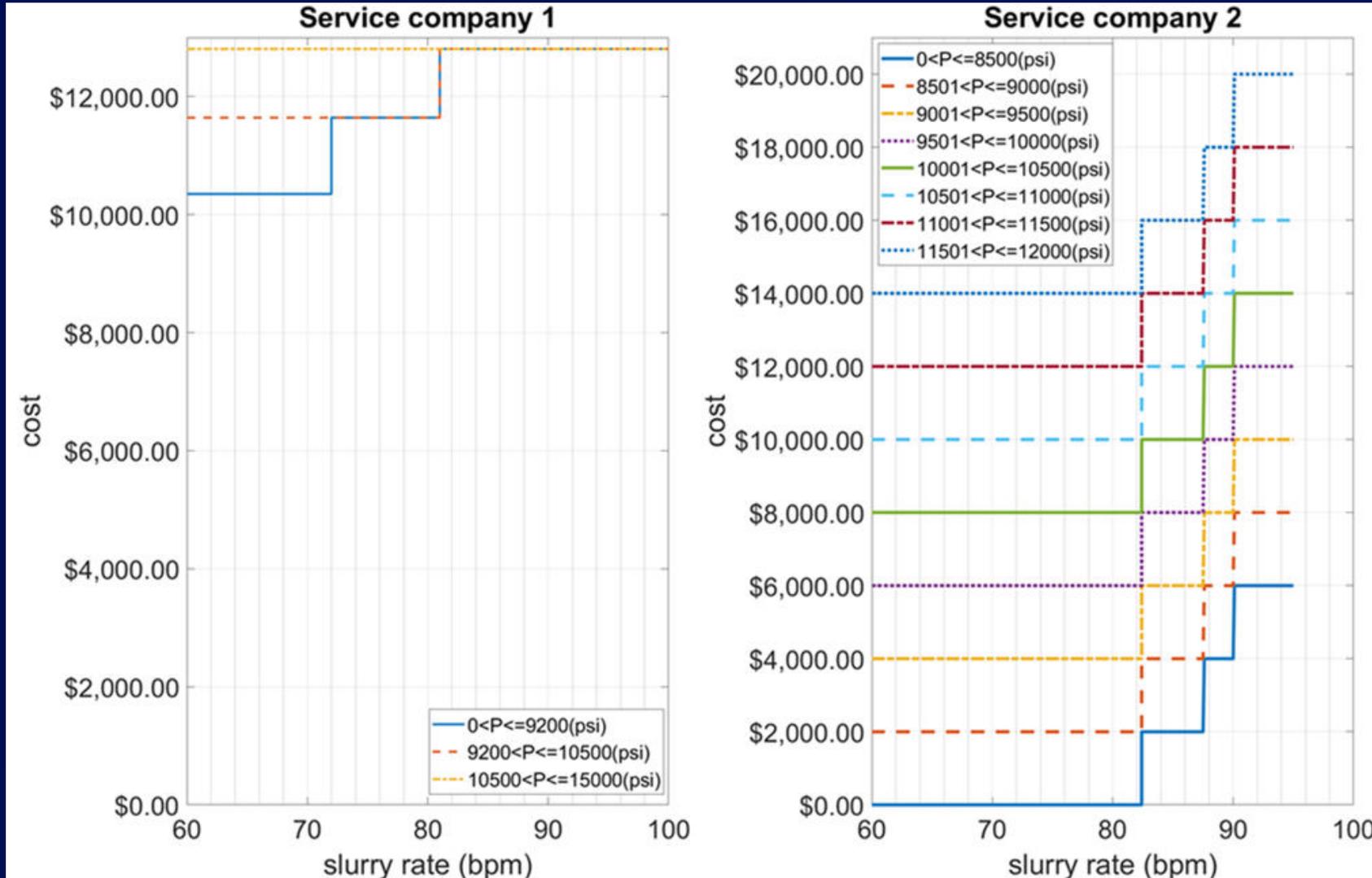
This can be realized by any cloud platform by leveraging the cloud functionality.

Deploy Continuous Learning Model on the Cloud



(cloud.google.com; azure.microsoft.com; aws.amazon.com)

Hydraulic Fracturing Cost Remains the Same When Slurry Rate and Pressure Are in a Certain Range



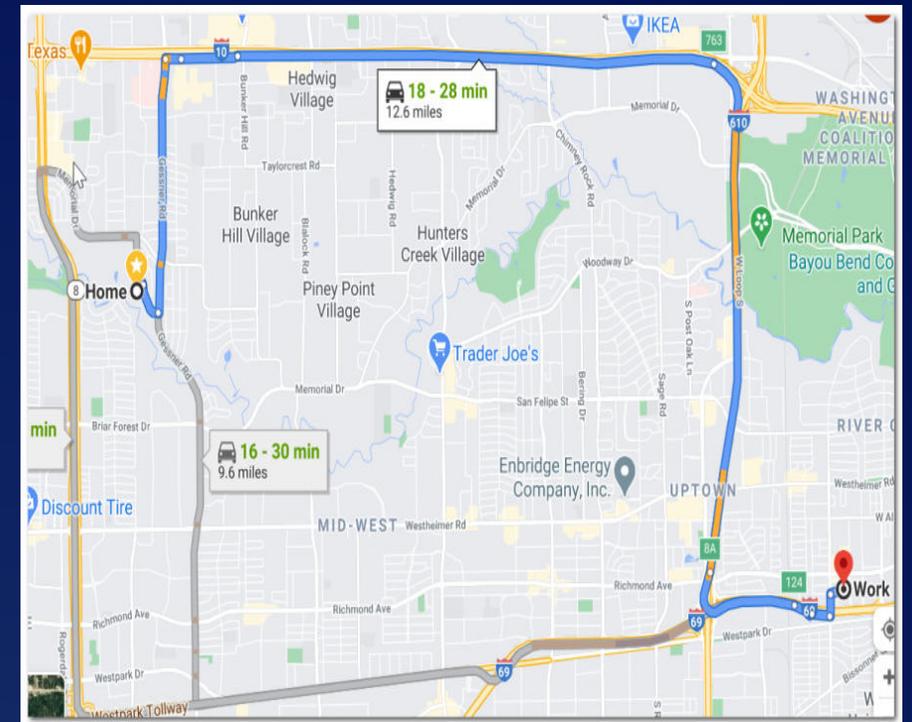
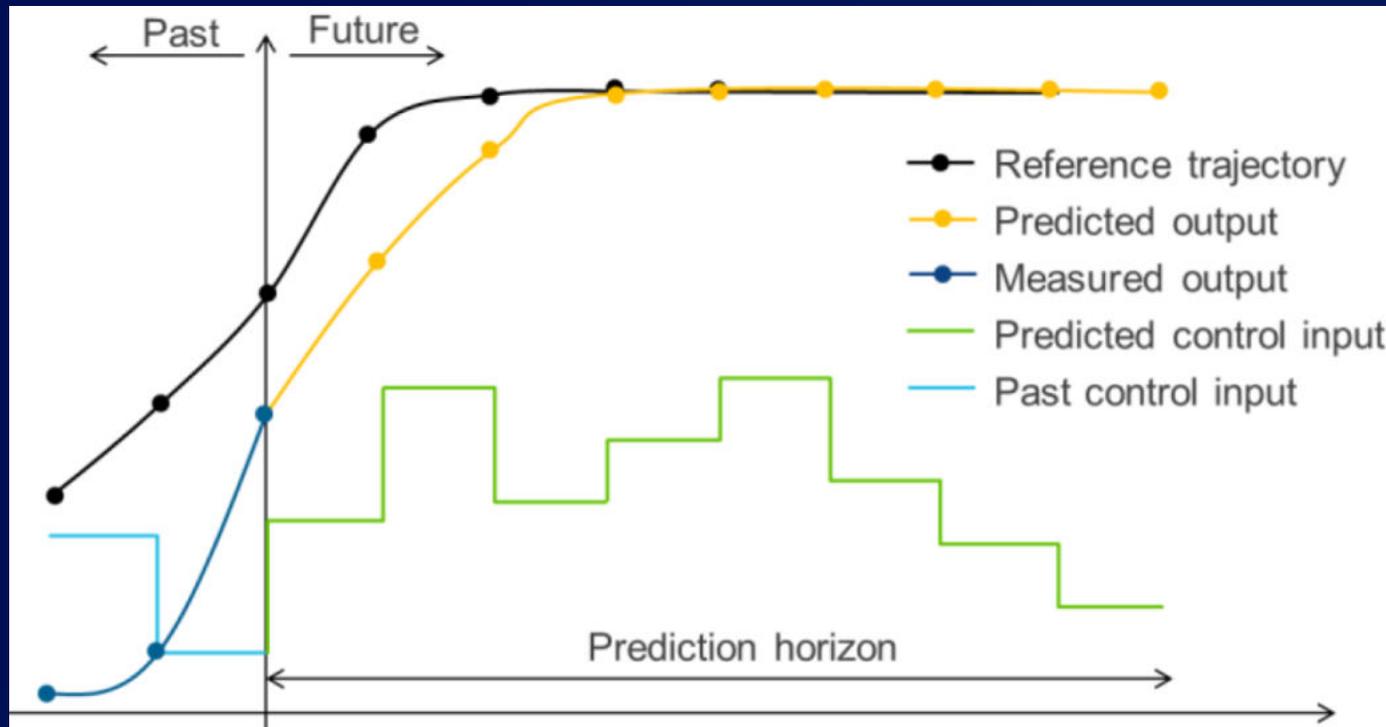
Can we adjust pumping schedule to save completion costs on the hydraulic horsepower?

Ben, Y et al. SPE 199688, 2020. [Reported by Drilling contractor.](#)

Optimization by Model Predictive Control

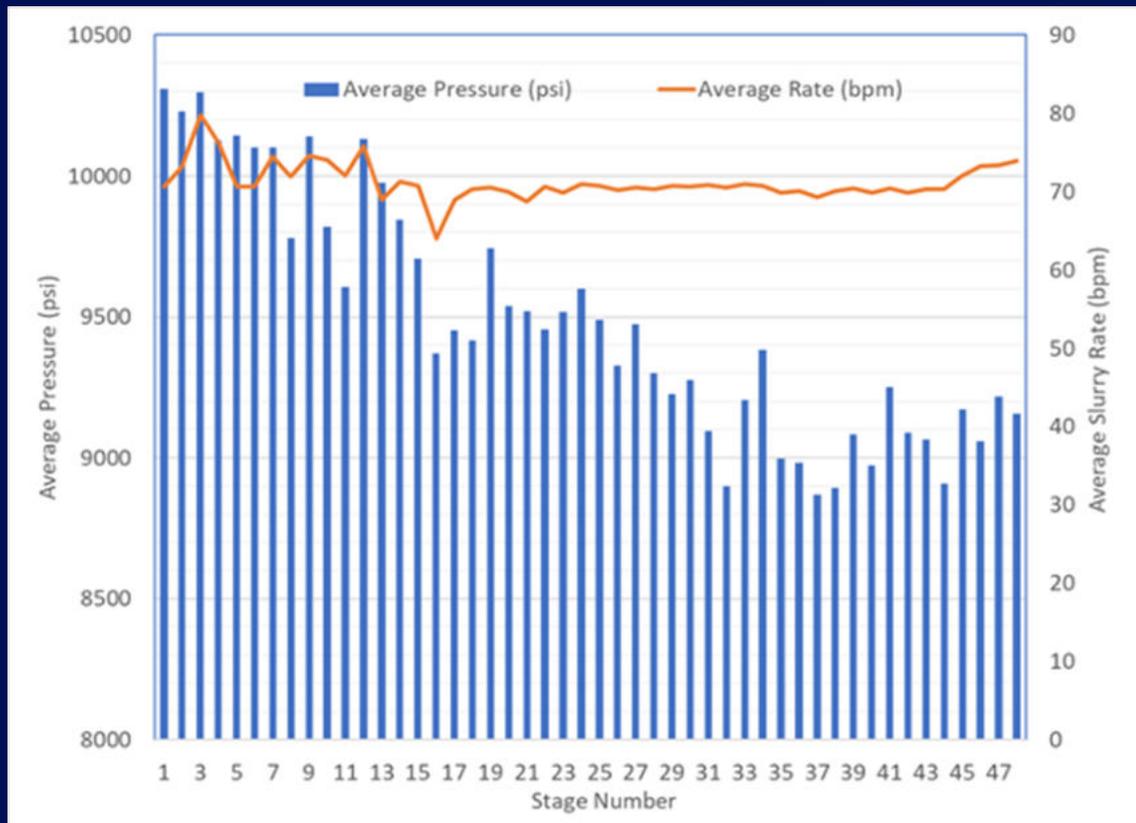
- Develop a model based on existing data and make prediction about future behavior
- Set up constraints on the wellhead pressure and slurry rate, proppant concentration, and friction reducer concentration

Driving with Google Map

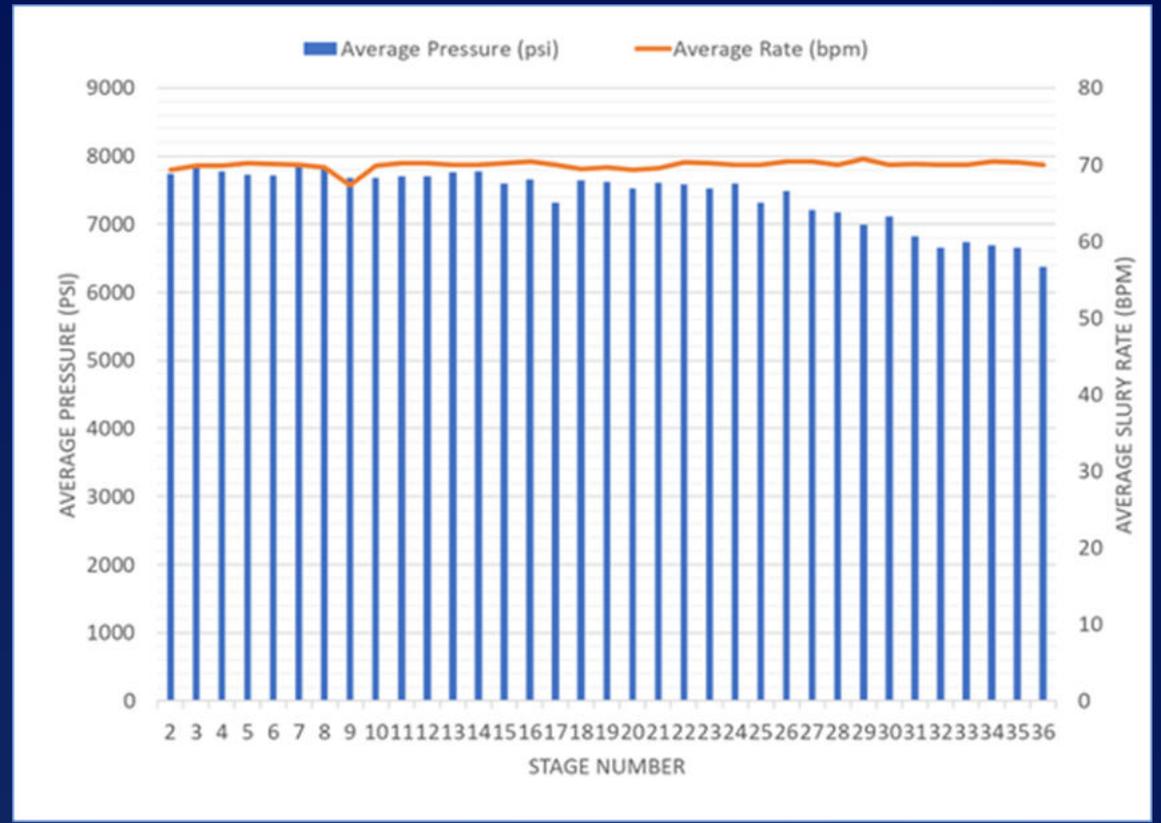


Field Case: Reducing Fr at the Heel Stages to Save Cost

- Cost of hydraulic horsepower is the same
- Average wellhead pressure decreases from toe stage to heel stage



Well No. 1



Well No. 2

Predict Wellhead Pressure with System Identification



- Basic representation:

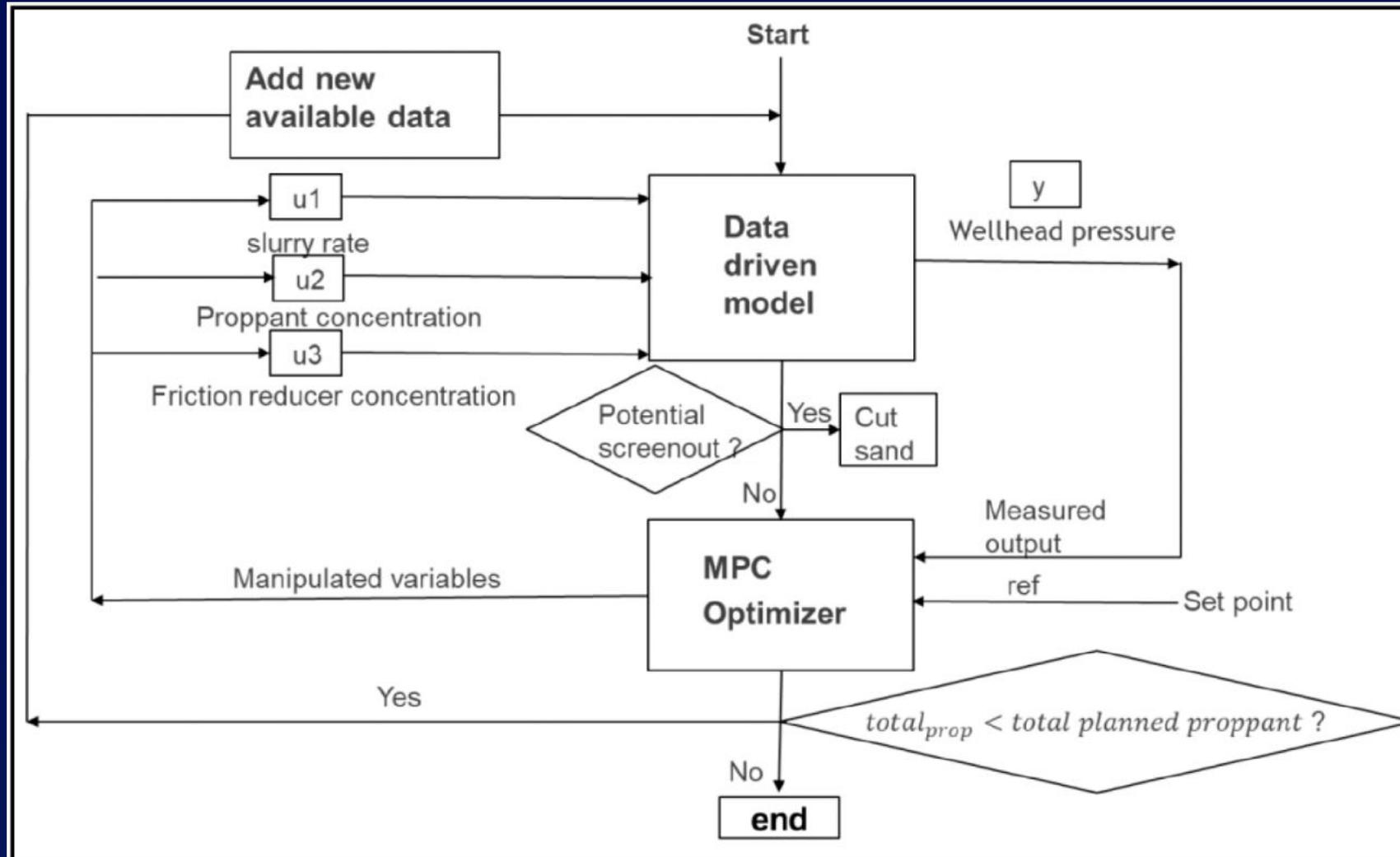
$$\frac{dx(t)}{dt} = Ax(t) + Bu(t)$$

- Focus on variables that can be adjusted in real time by a completion engineer

$x(t)$: *wellhead Pres*

$u(t)$: $\left\{ \begin{array}{l} \textit{prop conc} \\ \textit{slurry rate} \\ \textit{fr conc} \end{array} \right.$

Proposed Workflow for Model Predictive Control (MPC) to Optimize Costs

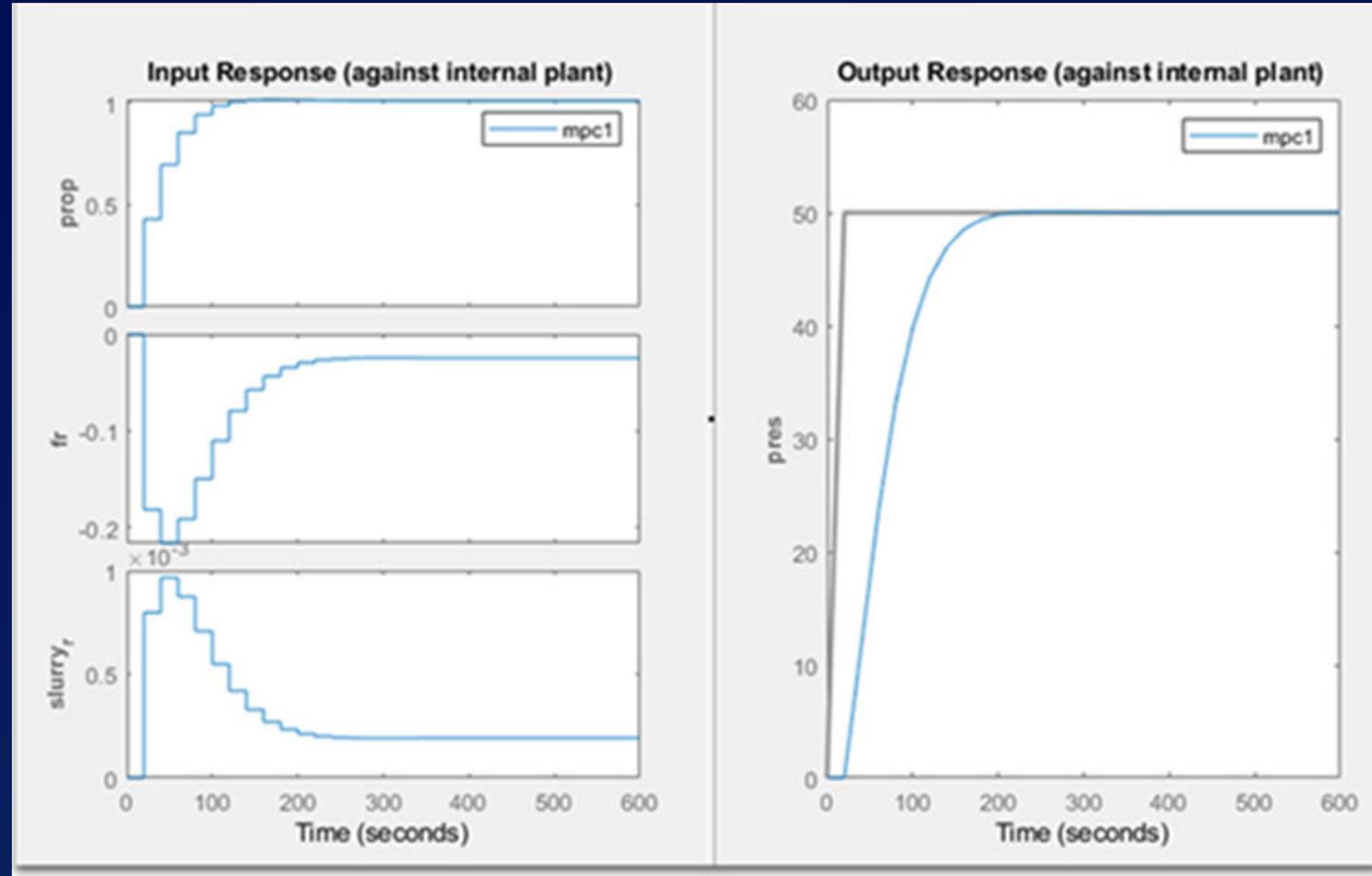


Cost Saving by Increasing Proppant Concentration and Reducing Fr

Scenario 1:

Constraint: $\Delta p = 50 \text{ psi}$

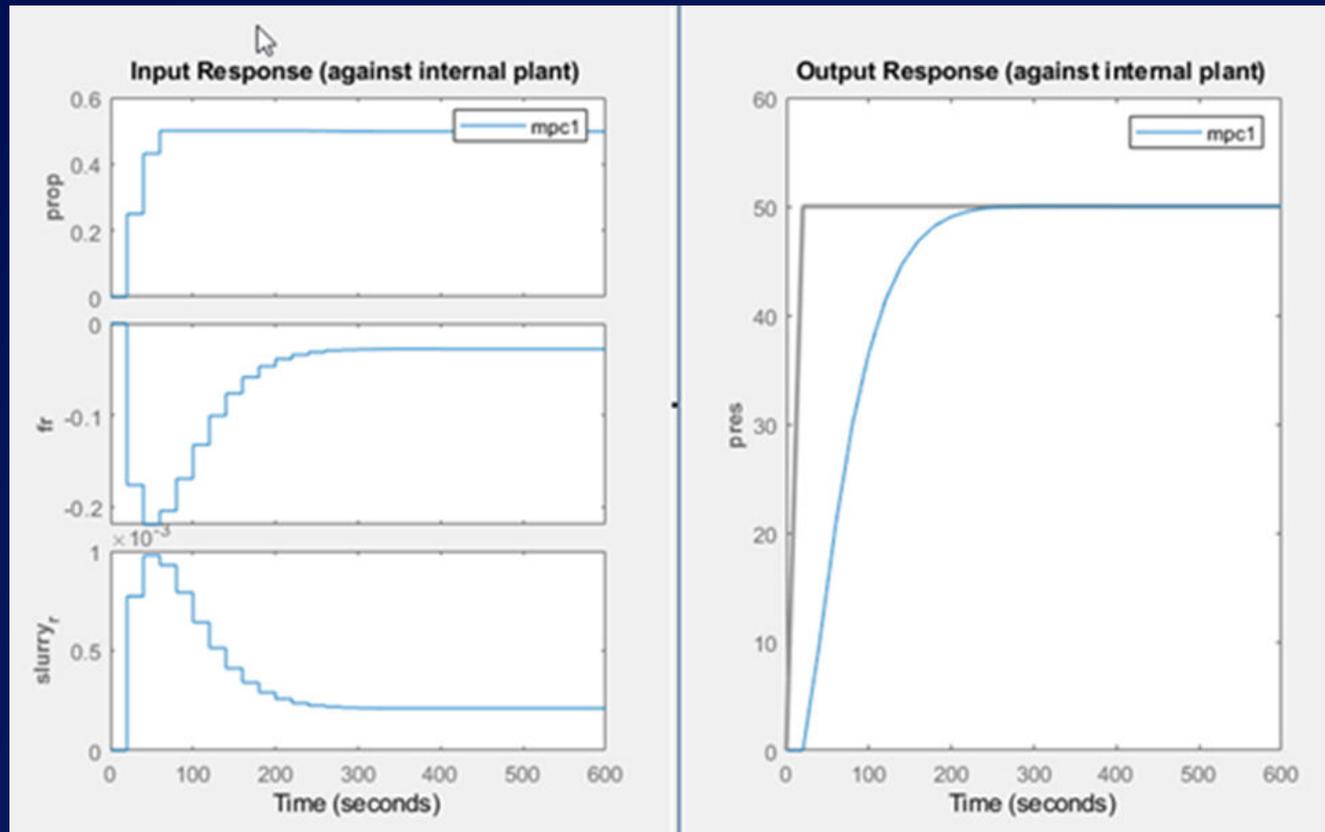
Assumption: Increasing 50 psi won't increase the cost on hydraulic horsepower



Cost Saving by Increasing Proppant Concentration and Reducing Fr

Scenario 2: Constraint: $\Delta p = 50 \text{ psi}$, $Max_{prop} = 0.5$, and $Max_{\Delta prop} = 0.25$

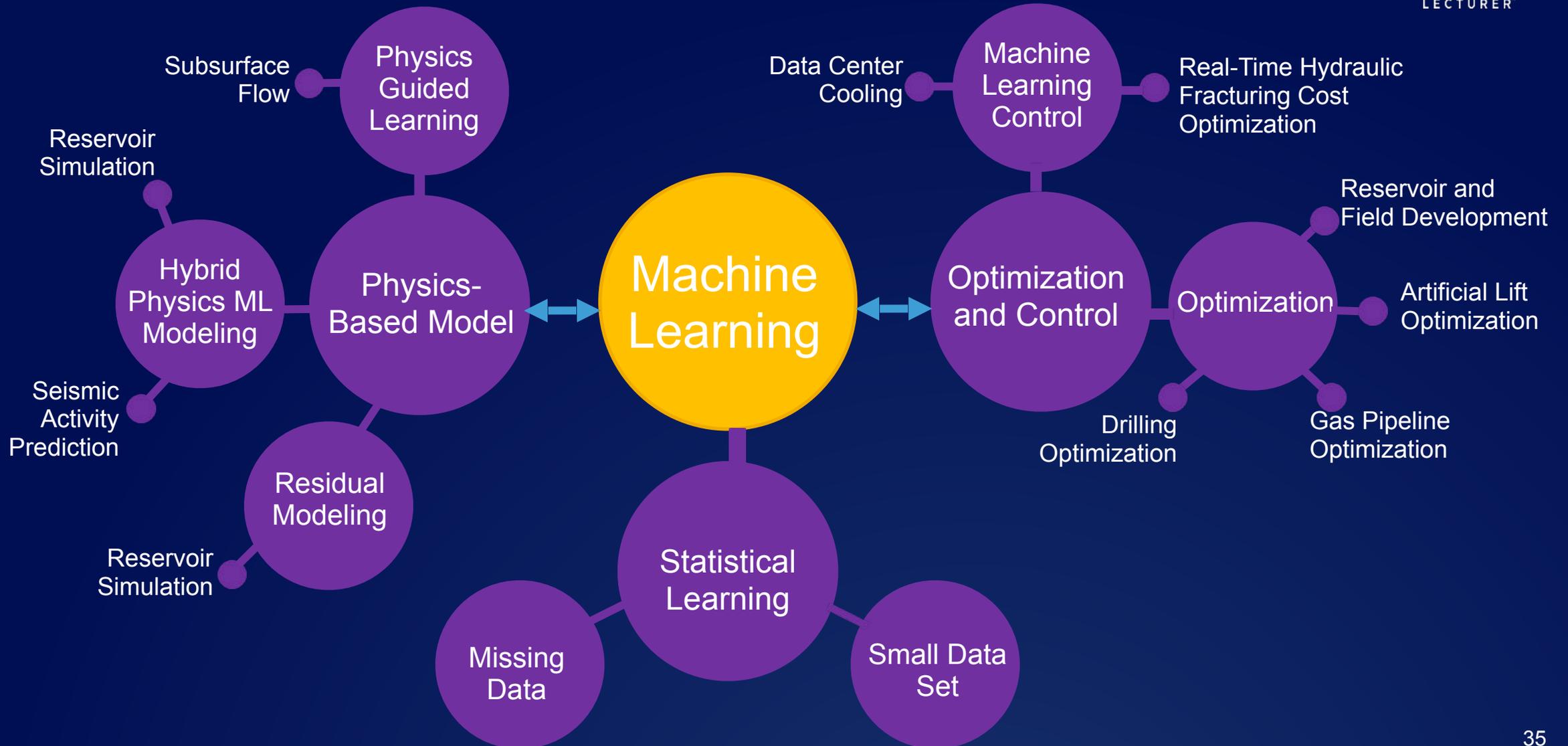
Assumption: Increasing 50 psi won't increase the cost of hydraulic horsepower



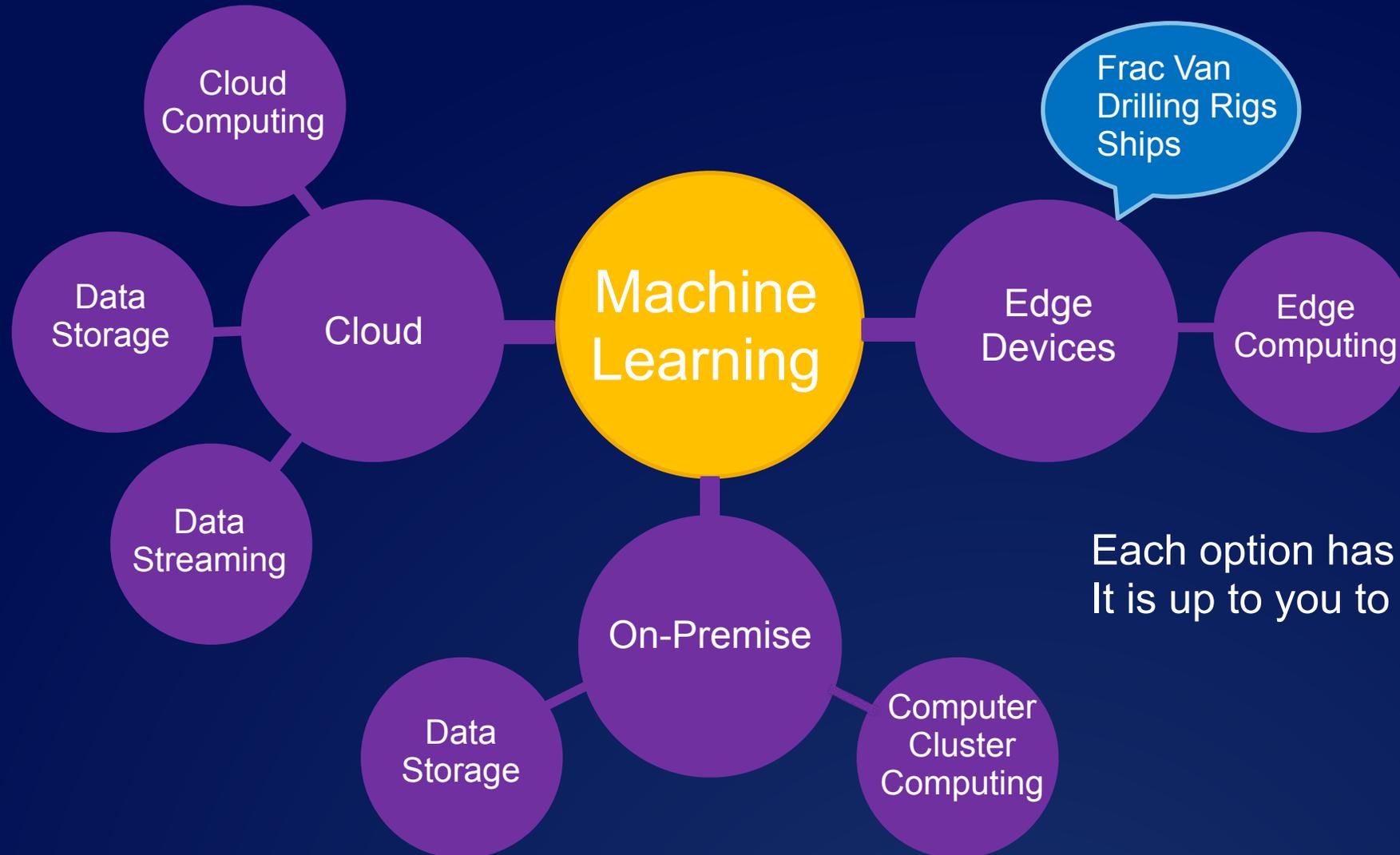
Takeaways 1: Summary of the Examples

- What have we done?
 - Developed and deployed a universal machine learning model with high accuracy for all onshore unconventional rigs in the whole company
 - Demonstrated how to use the Cloud to deploy a machine learning model that can be updated in real time
 - Developed a workflow to optimize hydraulic fracturing costs
- What have we learned?
 - Machine learning can perform much better than a rule-based model.
 - A successful machine learning application requires collaboration of data scientist, drilling/completion engineers, data engineers, and software developers.

Takeaways 2: Future Development - Algorithms



Takeaways 3: Future Development – Infrastructure



Each option has pros and cons.
It is up to you to decide!

Takeaways 4: Risks and Remedies



Risks

- Scenarios are not represented in the training data.
- In case of failure, it might be very difficult to establish responsibilities.
- 'Hidden' biases derived from the data
- Malicious adversaries can potentially attack the systems by poisoning the training data

Remedies

- ✓ Using engineering judgement
- ✓ Set up alerts in the system to identify outliers
- ✓ Establish liabilities between service companies and operators
- ✓ Collaborate with other industries to bring best practices to the oil and gas industry

([https://www.europarl.europa.eu/RegData/etudes/STUD/2019/624261/EPRS_STU\(2019\)624261_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/STUD/2019/624261/EPRS_STU(2019)624261_EN.pdf))

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