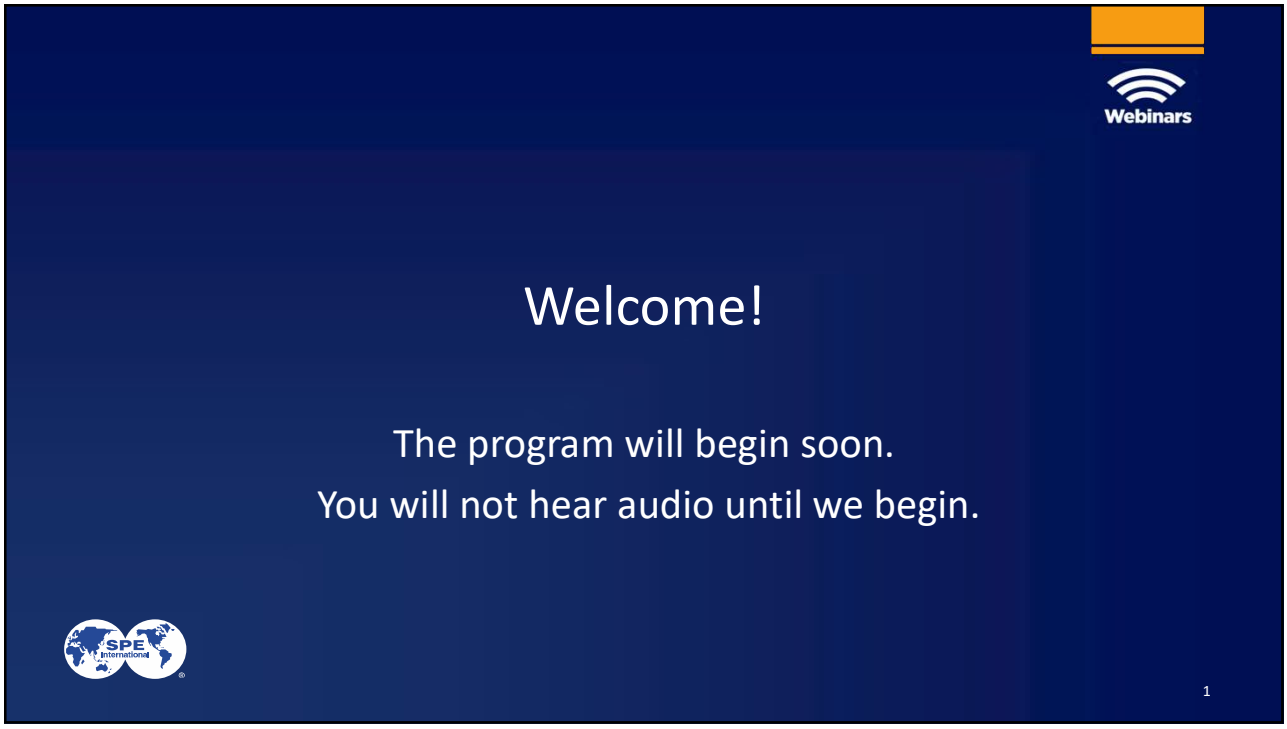
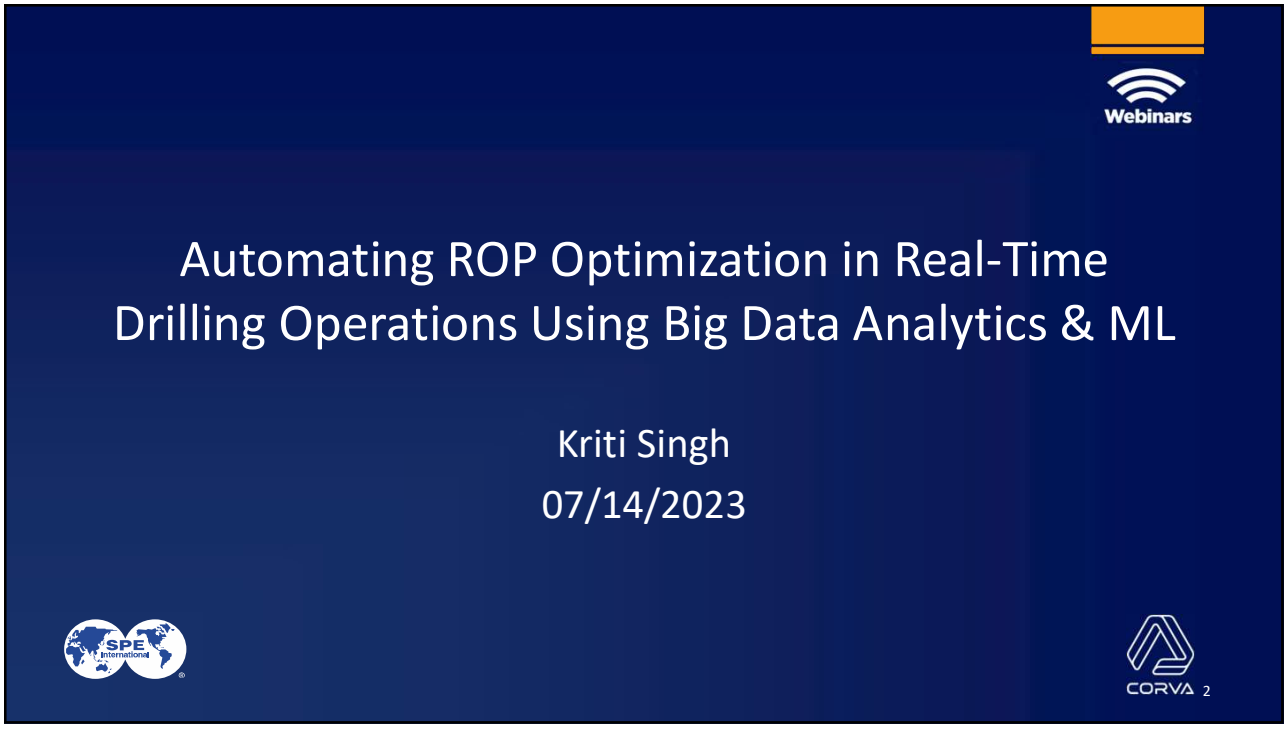

Webinars
Welcome!
The program will begin soon.
You will not hear audio until we begin.
SPE International
1

1


Webinars
Automating ROP Optimization in Real-Time Drilling Operations Using Big Data Analytics & ML
Kriti Singh
07/14/2023
SPE International
CORVA
2

2

DUPTS – Drilling Uncertainty Prediction

Webinars

connect.spe.org/dupts/home

DUPTS holds

+ 2,000 members distributed globally

Covering

NOC, IOC
Service company members and Academia

Roadmap

Data and Modeling
Diagnostics and Forecasting

DUPTS provides international multi-disciplinary forum for technical discussion and a consensus-based arena related to drilling uncertainty & prediction, which focuses mainly on artificial intelligence, machine learning and data science solutions supporting drilling, planning and execution challenges.

SPE International
Drilling Uncertainty Prediction Technical Section

3

3

DUPTS – Drilling Uncertainty Prediction

Webinars

connect.spe.org/dupts/home

Technical Webinars

Conducted by international experts

We take part in special events

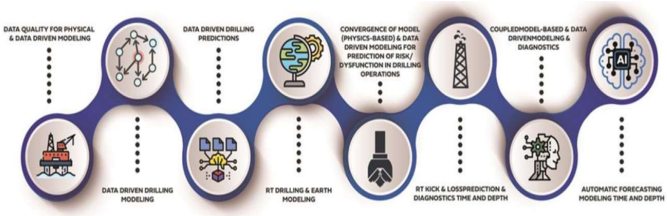
Ámsterdam Energy Summit 2023
Technical programs around the world

Student Competition

Computer Vision 2022
Drilling Data Competition 2021

SPE International
Drilling Uncertainty Prediction Technical Section

DUPTS – ROADMAP



- ✓ Clarifying existing challenges in drilling domain.
- ✓ Pointing education resources.
- ✓ Stimulating the community to share knowledge and collaborate in this area.
- ✓ Spread the awareness about AI, ML and data science.

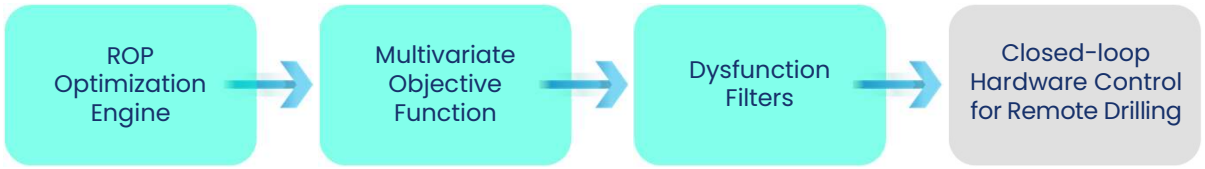
4

4

Agenda

- Introduction
- Review of the ML model used for ROP prediction
- Semi-automated machine learning pipeline for model training
- Review of SPE publications
  - Field test results
  - ROP Optimizer
  - Automated calibration factor
- Summary
- What's next?

Rotary Automation Milestones

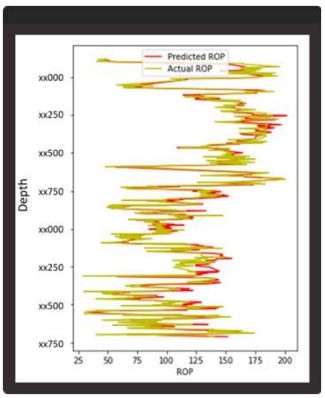


6

6

Review - Machine Learning Model Published in URTeC 2019 - 343

Feature	Weights (%)
Differential Pressure	52.74
Surface Torque	19.05
Lagged MSE	14.19
Surface Weight on Bit	6.76
Lagged Surface RPM	4.61
Lagged Surface Torque	0.15

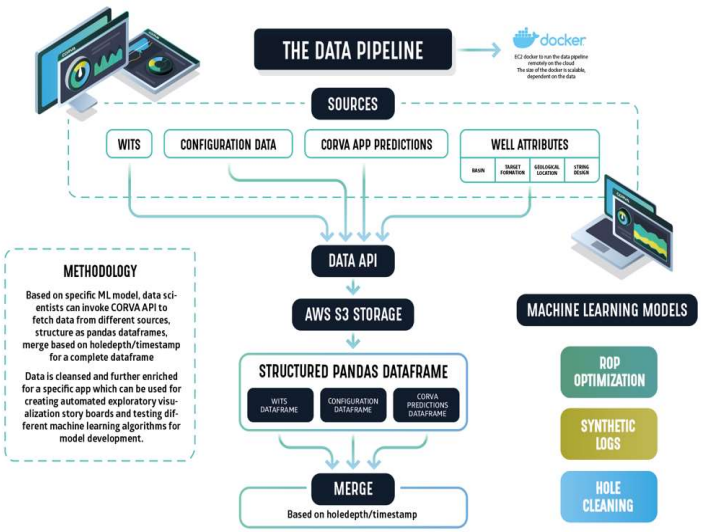


MAPE on blind wells < 15%

7

Input Parameters

- WITSML data
- BHA data
- Survey data
- Mud data
- Corva Engineering calculations



8

8

Input Parameters

Engineered Features are added:

- Bit Hydraulic Horsepower per Square Inch
- Bit Run Distance
  - Proxy for bit wear
- Lagged Features
  - Lagged MSE is a proxy for formation strength

ML Model Inputs
Bit hydraulic horsepower per square inch
Bit run distance
Bit size
Bit total flow area
Differential pressure
Hole depth
Hook load
Lagged differential pressure
Lagged MSE
Lagged mud flow rate
Lagged TDRPM
Lagged rotary torque
Mud density
Mud flow rate
Mud plastic viscosity
Mud yield point
Rotary RPM (TDRPM)
Rotary torque
Standpipe pressure
Weight on bit

Current working model is a Multi-Variate Regression Model

9

9

Semi-Automated ML Model Trainer

Webinars

Asset Selector

- Filter assets by Company/Basin/ Rig/Target Formation
- Map visualization of asset location

Asset Downloader

- Parallel downloading of training data
- Automatic and standardized cleaning process
- Automatic combination of training data into one dataset
- Reduction of download time from 20 to 1 day.

Model Trainer

- Exploratory data analysis
- Ability to train multiple models to evaluate the best performer
- Ability to edit/add/remove features

Model Evaluator

- Evaluation on new (blind) data
- Export results of all wells into tabular form for easy comparison
- Once approved, model is pushed to BETA for further testing

10

10

Asset Selector

1.5.2.2. Basin filter

[37]:
```
basins = filtered_assets['basin'].unique()
basins = basins[basins != None]
basins.sort()
basins_SM = ipywidgets.SelectMultiple(
    options=basins,
    value=(),
    rows=20,
    description='Basins:',
    disabled=False
)
basins_SM
```

Basins:
- Marietta Basin
- Alberta
- Anadarko
- Appalachia
- Ardmore
- Bakken
- Cold Lake
- Delaware
- Delaware-Permian
- Eagle Ford

1.5.2.3. Formation filter

[49]:
```
formations = filtered_assets['target_formation'].unique()
formations = formations[formations != None]
formations.sort()
formation_SM = ipywidgets.SelectMultiple(
    options=formations,
    value=[],
    rows=10,
    description='Formations:',
    disabled=False
)
formation_SM
```

Formations:
- DEAN
- Dean Sand
- JO MILL
- Jo Mill
- LOWER SPRABERRY MFS
- LOWER SPRABERRY SHALE
- Lower Spraberry
- Lower Spraberry Sand
- Lower Spraberry Shale
- MIDDLE SPRABERRY

11

11

Asset Downloader

	overall	asset_id	wits	configurations	predictions	hydraulics
0	False	[redacted]	False	False	False	False
1	False	[redacted]	False	False	False	False

1.6. EC2 Invocation

1.6.1. Setup Template

```
[28]: num_instances = len(asset_ids) // 1
      num_instances

[30]: 2

[31]: template = {
          "ec2_type": "t3.2xlarge",
          # If you want to load a branch use this format: "--branch fix/my_fix git@github.com:corva-ai/automated_ml_pipeline.git"
      #   "git_repository": "git@github.com:corva-ai/automated_ml_pipeline.git",
          "git_repository": "--branch feature/additional_wits_channels_for_AD_development git@github.com:corva-ai/automated_ml_pipeline.git",
          "handler_module": "src.asset_downloader.downloader.ec2_handler",
          "handler_function": "ec2_handler",
          "instance_count": num_instances,
          "environment_variables": {
              "s3_bucket_name":"corva-ai",
              "API_ROOT_URL":"https://api.corva.ai",
              "APP_ENV":"production",
              "APP_NAME":"AutomatedML",
              "LOGGING_LEVEL":"INFO",
              "LOGGING_ASSET_ID":"all",
              **SagemakerOperation.get_secure_environment_variables(),
          }
      }
```

Following environment variables loaded from Sagemaker tags: ['APP_NAME', 'API_KEY', 's3_bucket_name', 'API_ROOT_URL']

1.6.2. EC2 Runner

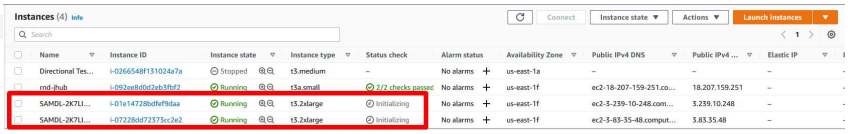
Instantiate the ec2 runner and setup based on the template above

```
[32]: ec2_runner = Ec2Runner(template)
      ec2_runner

[32]: <src.asset_downloader.downloader.ec2_runner.Ec2Runner at 0x7f61ada1ffd0>
```

1.6.3. Start EC2 instances

Check here Link



Model Trainer Example

	model	train_time	r2	mape
8	(DecisionTreeRegressor(max_features='auto', ra...	24.140379	0.98796	2.429
10	(DecisionTreeRegressor(random_state=630921809)...	2.459478	0.98263	2.525
11	HistGradientBoostingRegressor()	0.656610	0.87770	11.322
12	(StandardScaler(), MLPRegressor(early_stopping...	50.434030	0.85330	12.281
13	(StandardScaler(), MLPRegressor(early_stopping...	27.811588	0.83591	13.263
9	([DecisionTreeRegressor(criterion='friedman_ms...	7.984549	0.79532	15.355
7	(StandardScaler(), LinearSVR())	0.125731	0.67238	19.745
5	Ridge()	0.013557	0.67500	19.854
0	LinearRegression()	0.010579	0.67500	19.856
1	(StandardScaler(), LinearRegression())	0.017687	0.67500	19.856
3	BayesianRidge()	0.014784	0.67500	19.861
2	ARDRegression()	0.016585	0.67070	19.899
4	ElasticNet()	0.048342	0.65831	20.213
6	RANSACRegressor()	0.229651	0.51986	23.228

Model Evaluator

	MAPE [-15, 15]	1.5 Sigma Error Bounds [-20, 20]	ROP Trend Similarity [0.6, 1.0]	[INFO] Median Under-prediction [-5, inf]	[INFO] Median Over-prediction [-inf, 5]	[INFO] Actual-vs-Predicted Slope [0.5, 1.5]	[INFO] Actual-vs-Predicted Intercept [-200, 200]	[INFO] Actual-vs-Predicted R2 [0.5, 1]	[INFO] ROP Distribution Similarity [0.8, 1.0]	Overall
53436232	4.600000	[-15.8, 16.2]	0.940000	0.200000	0.200000	0.890000	17.000000	0.890000	0.990000	Figure
Average	4.600000	nan	0.940000	0.200000	0.200000	0.890000	17.000000	0.890000	0.990000	nan
Median	4.600000	nan	0.940000	0.200000	0.200000	0.890000	17.000000	0.890000	0.990000	nan

Deployer

```
display(HBox([from_dd, to_dd]))
display(load_btn)

display(HBox([from_tree, to_tree]))

display(from_path_txt)
display(to_path_txt)
display(deploy_btn)

display(output)
```

From: alpha To: qa

Load

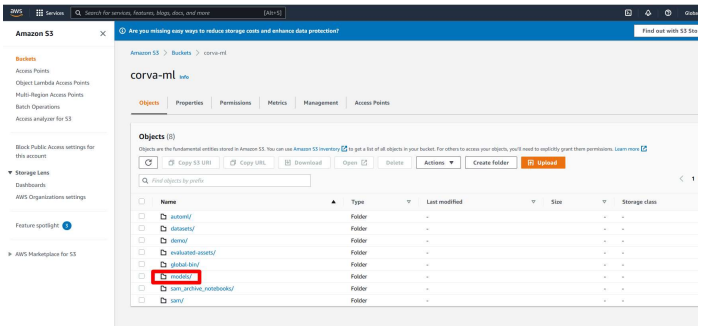
qa
staging
production

Error displaying widget: model not found

From Prefix: Folder to copy from

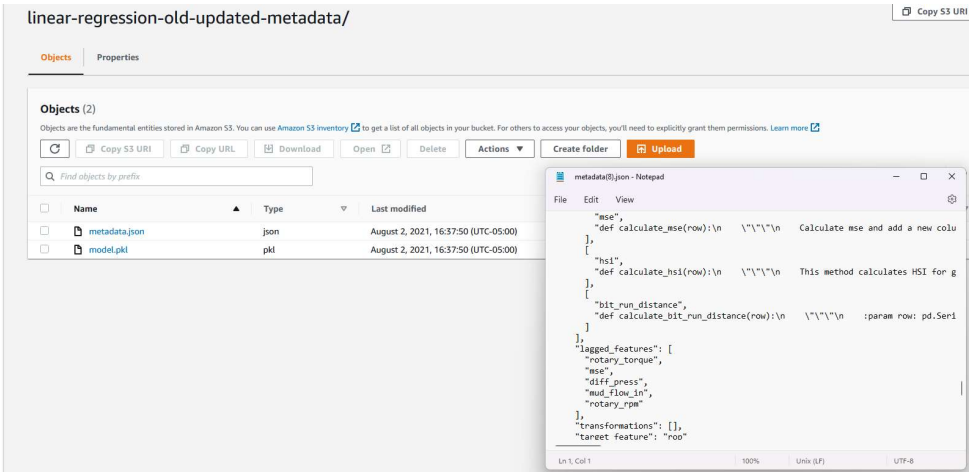
To Prefix: Folder to copy to

Deploy



15

Model Execution



Review – Field Test Results Published in SPE/IADC 2021-204043

- Wolfcamp A
- Same Gamma Ray
- Same BHA
- Same Bit Size

17

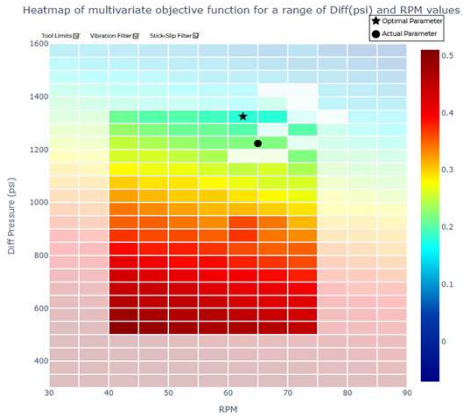
Review – ROP Optimizer Presented in SPE/IADC 2022-208751

$$multivariate\ objective = w_{ROP}\left(1 - \frac{ROP}{N_{ROP}}\right) + w_{MSE}\frac{MSE}{N_{MSE}} + w_{RT}\frac{RT}{N_{RT}}$$

Where:

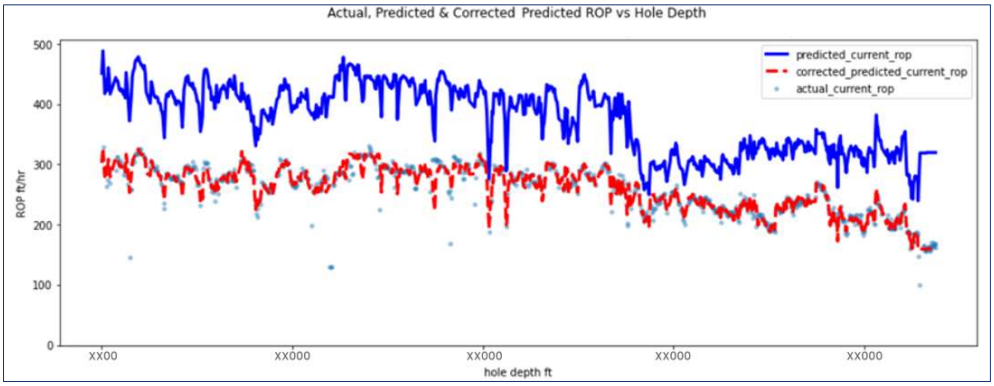
w_i	User specified weight for each component
N_i	Normalization factor for each component
ROP	Rate Of Penetration
MSE	Mechanical Specific Energy
RT	Rotational Tendency

- **Filters**:
- Vibration
- Torsional Severity Ratio
- Parameter Limits



18

Review – Automated Calibration Factor Presented in SPE/IADC 2023-212568



The corrected ROP prediction after applying calibration matches the actual ROP values

19

19

Field Test Results - Accelerate RIG Uptake

Observed improved rig compliance. The actual ROP response was very close to the predicted values

Summary

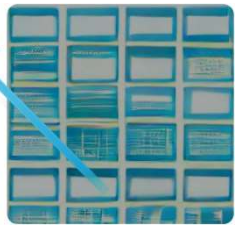
Real-time ROP prediction using ML

Identify the optimal set for drilling parameters

Reduce cost per foot of drilling

Reduce hazards by leveraging RT data (e.g. vibration)

Augments Driller's Capability: Reduces driller's fatigue by automatically picking the optimal drilling parameters



RT comparison with offset wells data

21

21

What's next?

- Closed loop automation
- Strategic partnership with a major rig contractor
- Directly control the AutoDriller setpoints using cloud -> cloud -> HMI connection
- Closed loop field testing with major Oil & Gas operators

22


Webinars
SPE Webinars are Sponsored by:
SPE
SPE Foundation
23

23