

# Badge-4 Lab-4 [SVM]

**Out date:** Aug 10, 2022

**Due date:** Aug 14 at 11:59PM

## Submission

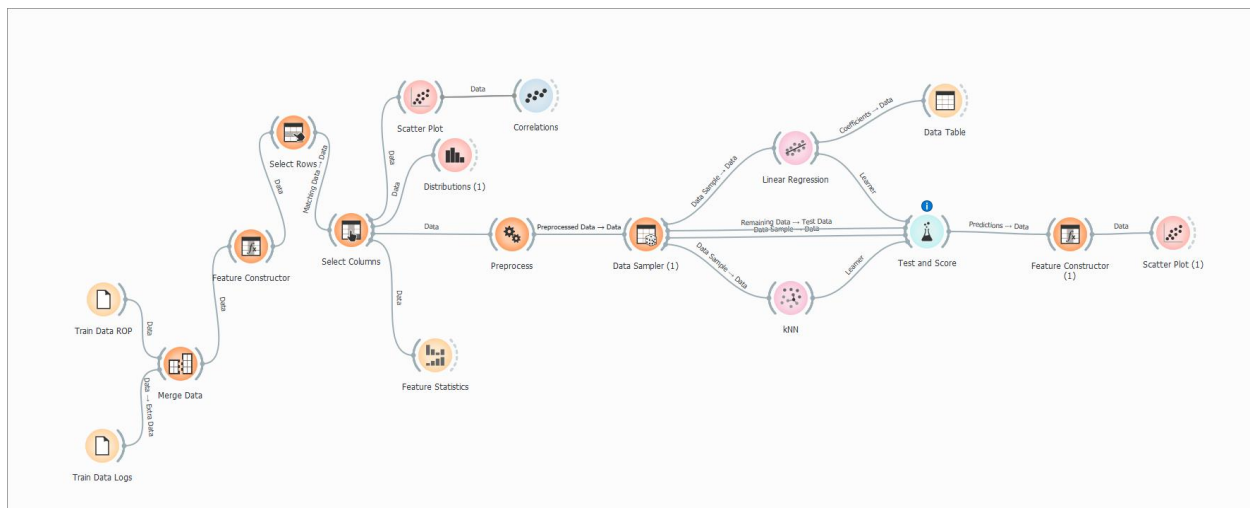
1. Prepare your solution in Orange and save the workspace for Problem 1 (e.g., Lab-4\_SVM\_LastName.ows) **[20 points]**
2. Complete the tables given below and save the file (e.g., Lab-4\_SVM\_LastName.docx). **[80 points]**
3. Upload the files to the Canvas.

## Objective(s):

To apply SVM algorithm for a regression problem and compare its performance with other machine learning algorithms.

**Data:** Please download the following files from Canvas to complete your assignment:

1. [Badge3\\_Lab4\\_start.ows](#) file with the starting pipeline as shown below:



2. [TrainData.csv](#) containing the following features:

File: TrainData.csv

Info

6576 instance(s)  
10 feature(s) (no missing values)  
Data has no target variable.  
0 meta attribute(s)

Columns (Double click to edit)

	Name	Type	Role	Values
1	ID	N numeric	meta	
2	Rop	N numeric	target	
3	Wob	N numeric	feature	
4	Hookload	N numeric	feature	
5	TempOut	N numeric	feature	
6	TempIn	N numeric	feature	
7	PumpPres	N numeric	feature	
8	SurfTorq	N numeric	feature	
9	Rpm	N numeric	feature	
10	FlowIn	N numeric	feature	

3. [\*TrainData\\_formationevaluation.csv\*](#) is an optional dataset available to you for use and it contains the following features. Since drilling involves penetrating subsurface rocks, considering one or more of these features may help in improving your model performance.

File: TrainData\_formationevaluation.csv

Info

6576 instance(s)  
5 feature(s) (no missing values)  
Data has no target variable.  
0 meta attribute(s)

Columns (Double click to edit)

	Name	Type	Role
1	ID	N numeric	meta
2	GR	N numeric	feature
3	DEEP_RES	N numeric	feature
4	DENS	N numeric	feature
5	SP	N numeric	feature

Drilling diagnostics predictor variables:

WOB- Weight applied to the drill bit in kilopounds (k-lbs)

Hookload – Total weight of the suspended drill string in kilopounds (k-lbs)

TempOut and TempIn- Temperature of the drilling fluid going in and coming out in degF

PumpPres: Pressure exerted by the surface pump when pumping drilling fluid (mud) downhole, in psi.

RPM- Rotations per minute – Speed at which the drill string is rotated at surface

SurfTorq – Torque as a result of the drill string rotation, in psi

FlowIn – Flow rate at which the drilling fluid is pumped downhole, in gallons per minute

Optional formation evaluation predictor variables:

Gamma Ray(GR), Density of the formation (DENS), Resistivity of the formation (DEEP\_RES) and Spontaneous Potential (SP)

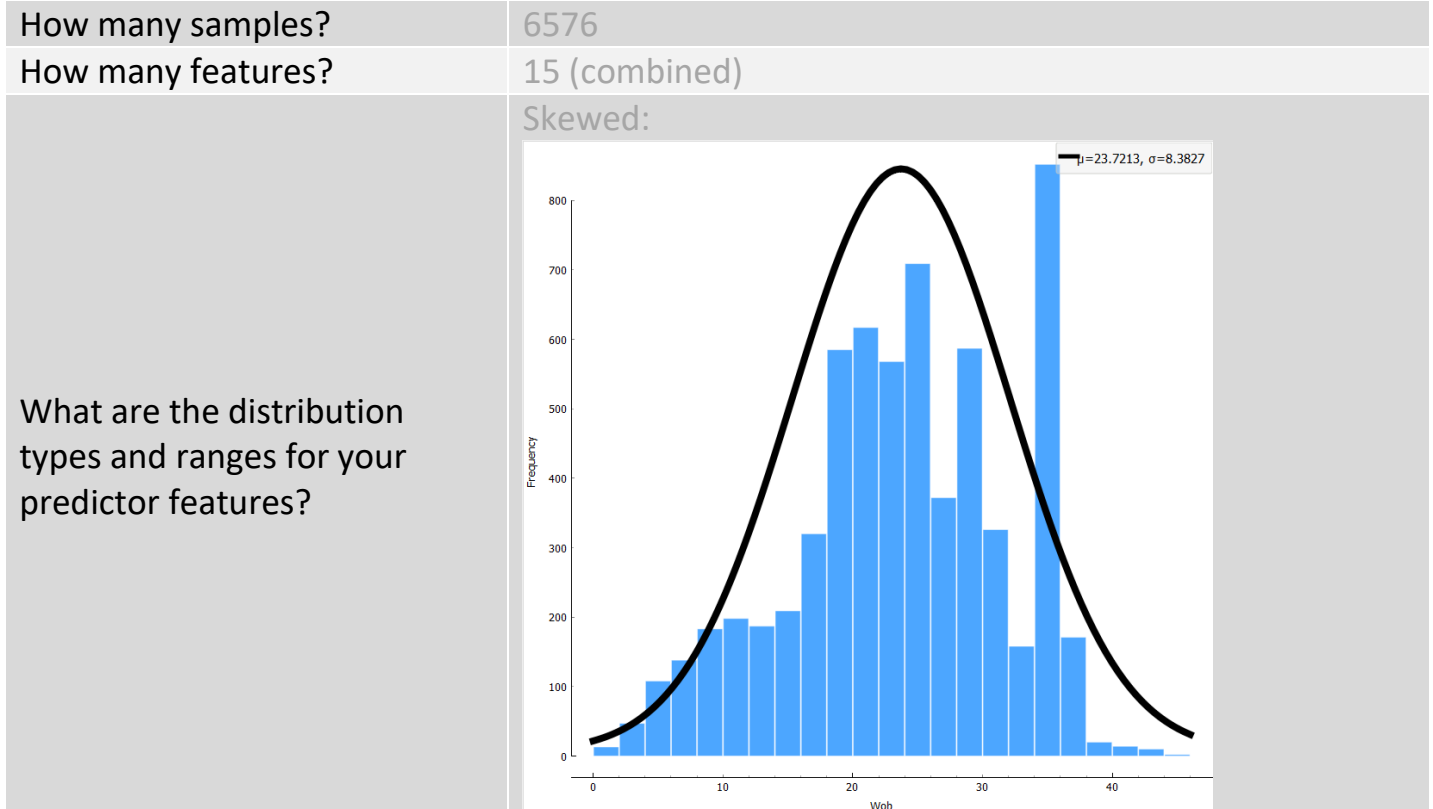
**Target variable:** Rate of Penetration (ROP) in feet/hour, a measure of how fast the drilling has progressed.

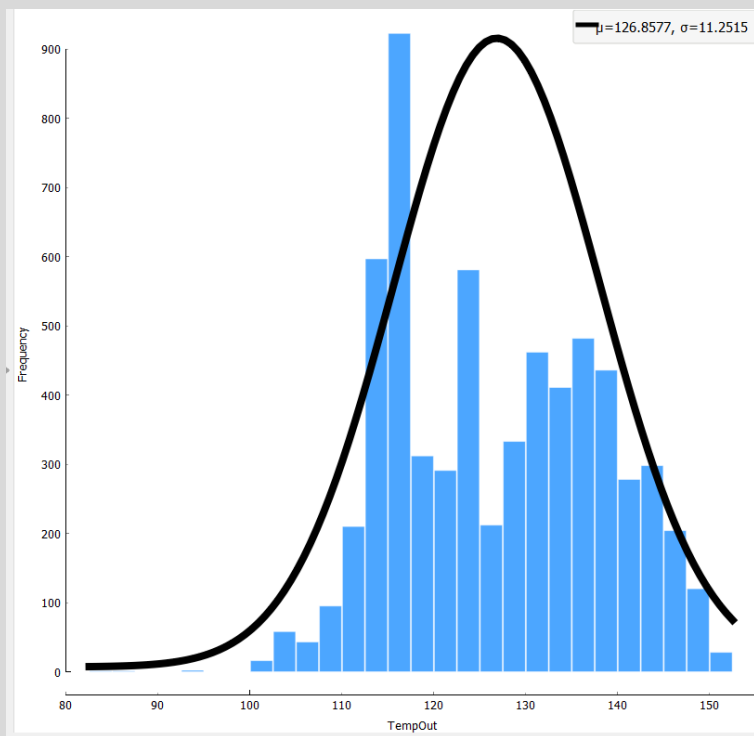
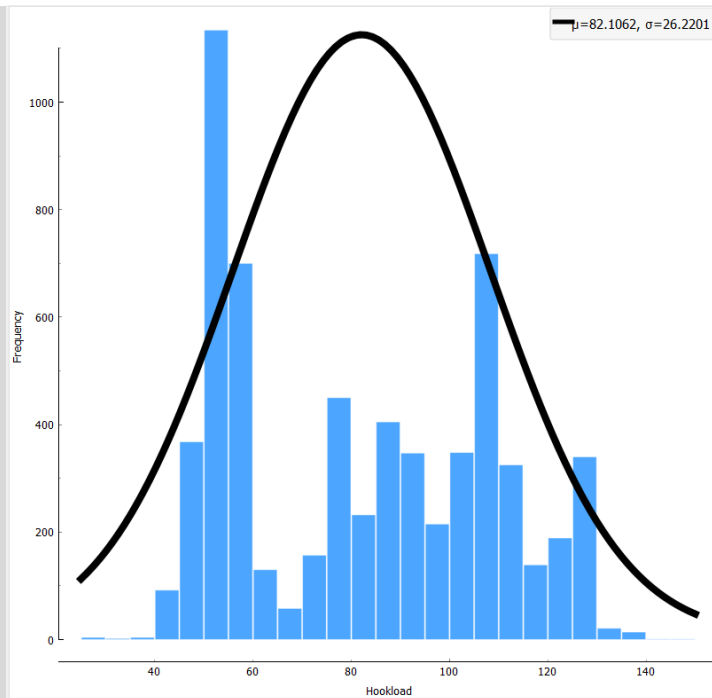
Reference:

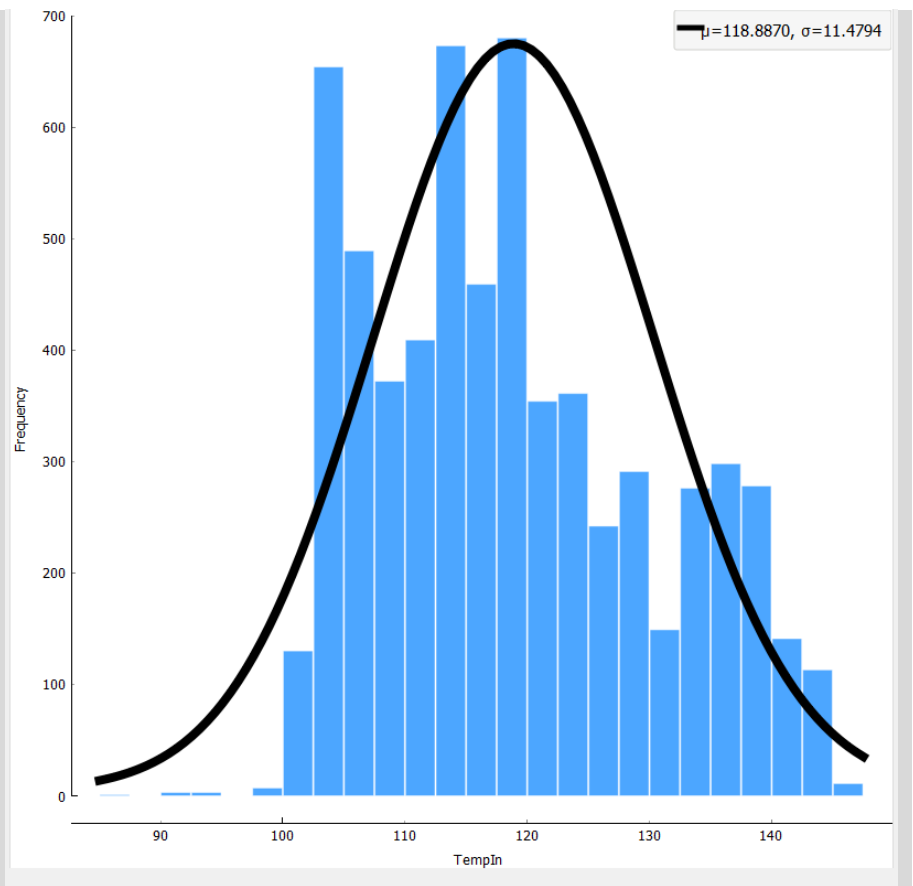
<https://gdr.openei.org/submissions/1113> (data)

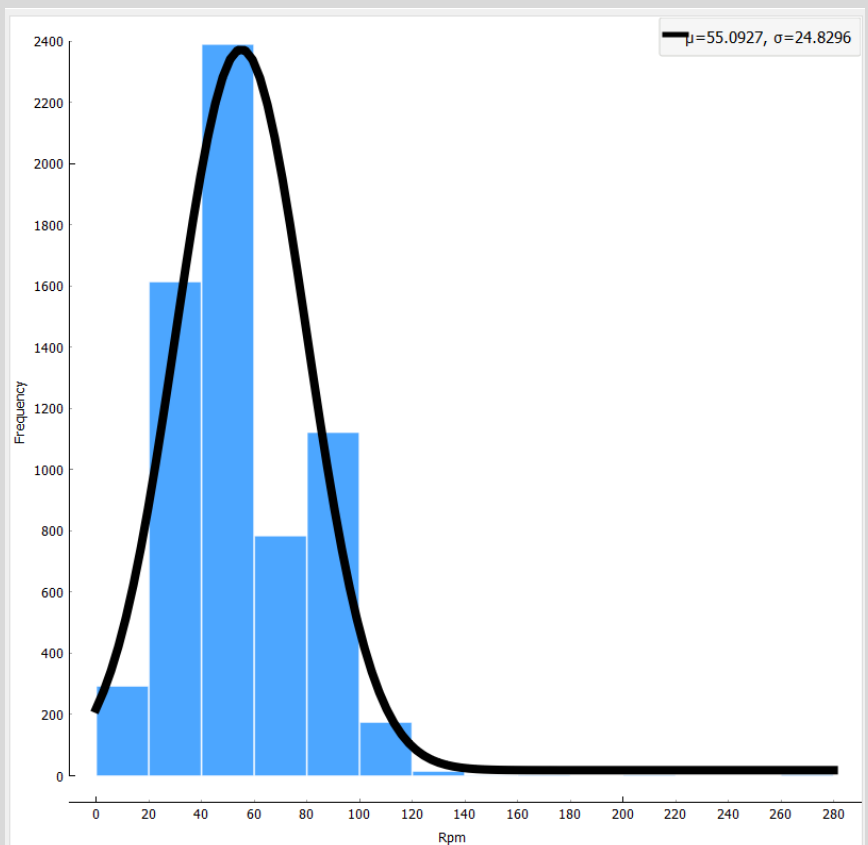
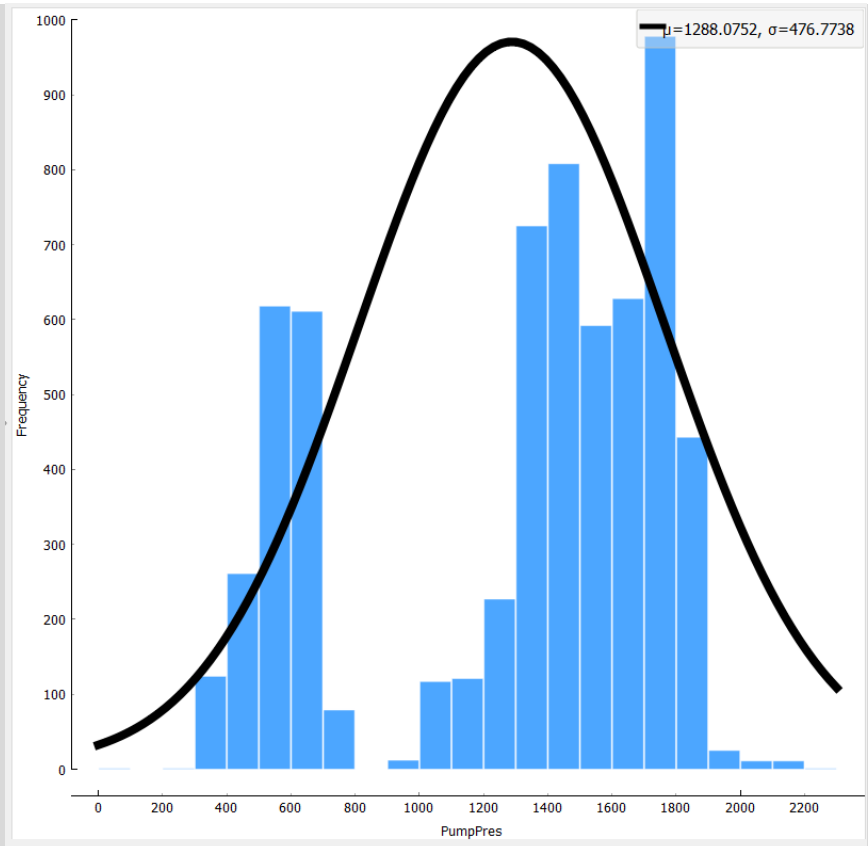
[https://www.youtube.com/watch?v=guFiQ87tg\\_s](https://www.youtube.com/watch?v=guFiQ87tg_s) (a video about the oil well drilling process)

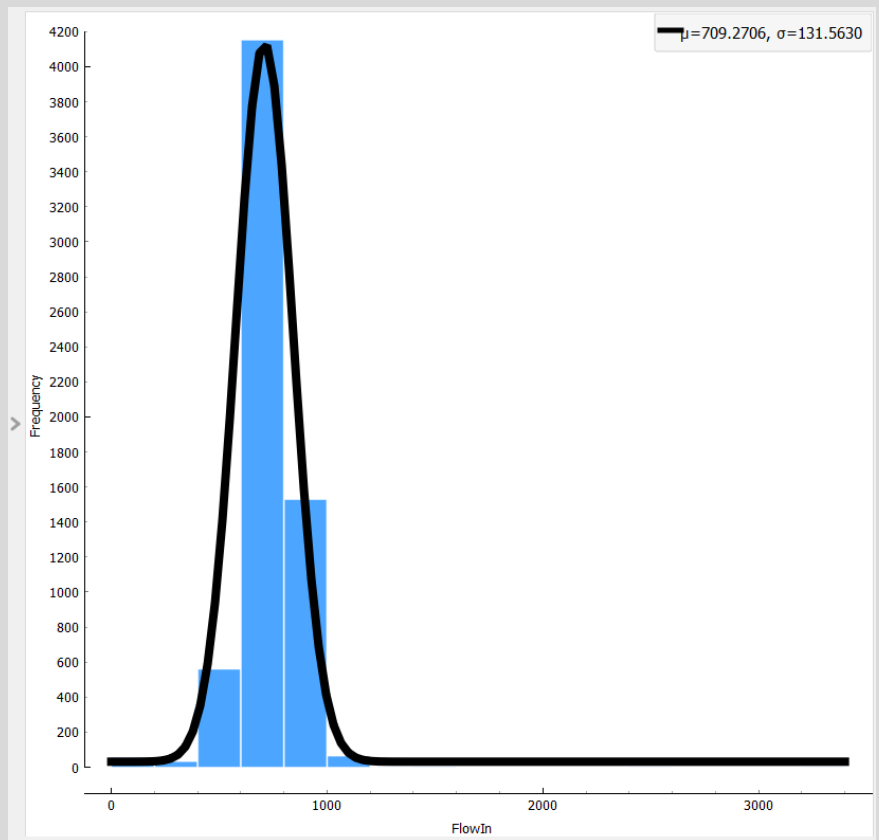
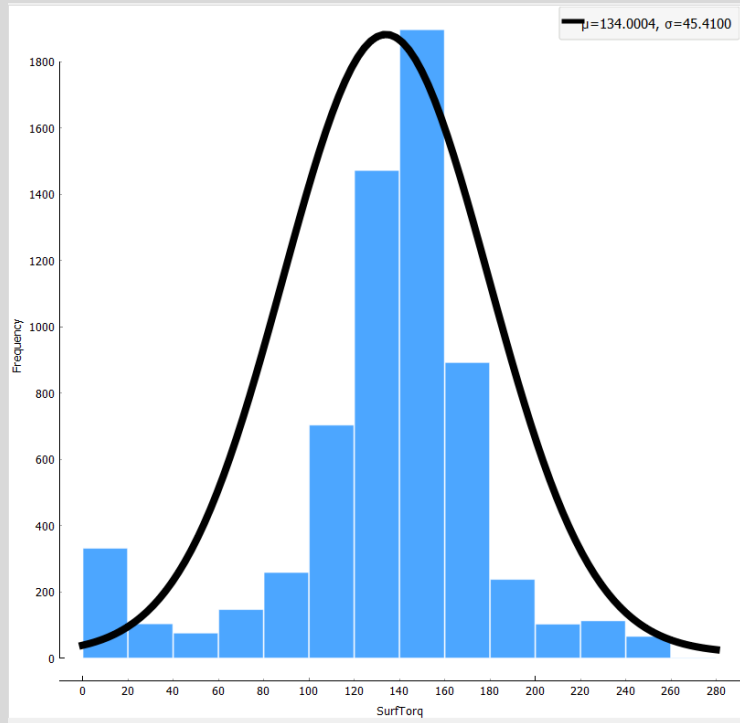
1. Open the *Badge3\_Lab4\_start.ows* file using Orange.
2. Inspect the **entire** pipeline: **(15 points)**





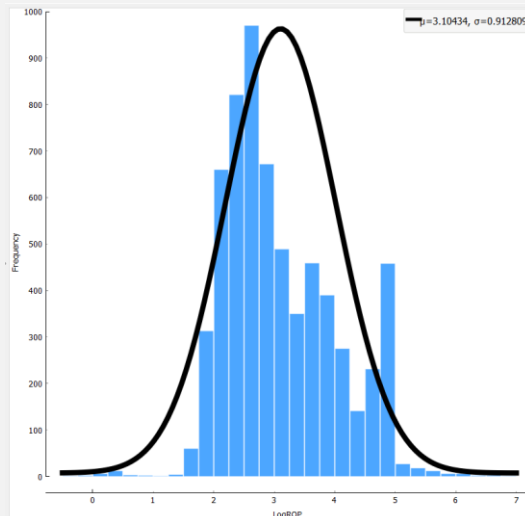






What is your target variable?  
 What is the distribution type and range for the target variable?  
 Do you see the need for a variable transformation?

Rate of Penetration (ROP) in feet/hour, a measure of how fast the drilling has progressed.



No, seems already has log and looks normal

Use the Scatter Plot and Correlations widget to understand the relationship between the target variable and predictors.

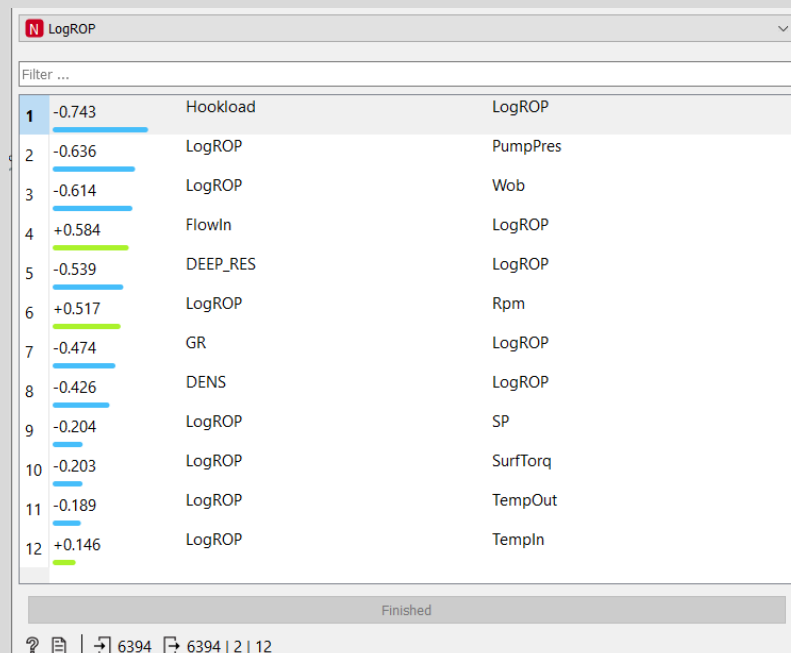
Comment on the relationships, predictors you think will have the biggest impact on predicting the target variable.

Not all of the predictors follow the r line, but very concentrated on one area.

Top 3 below will have the most negative correlation

FlowIn would have the most positive correlation

Up to 8 rank have strong correlations

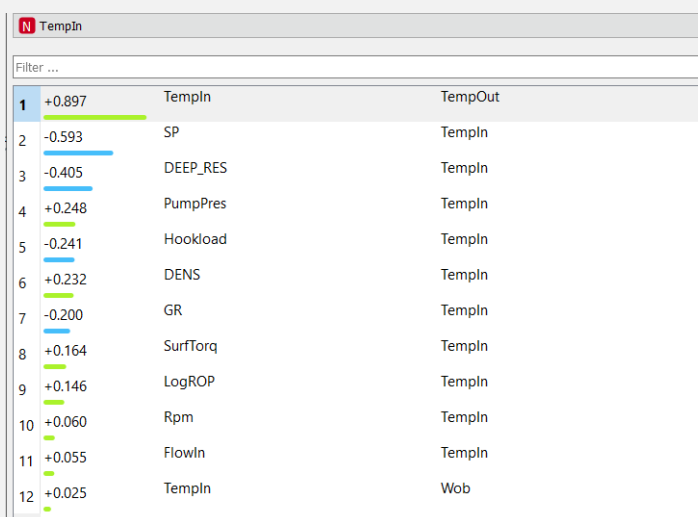
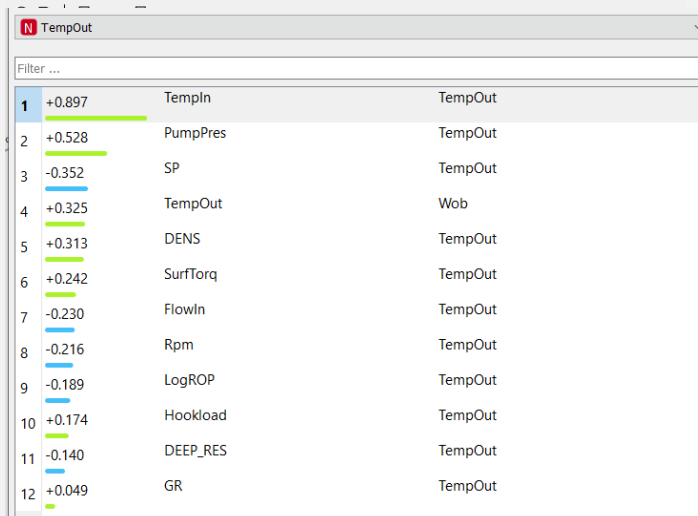
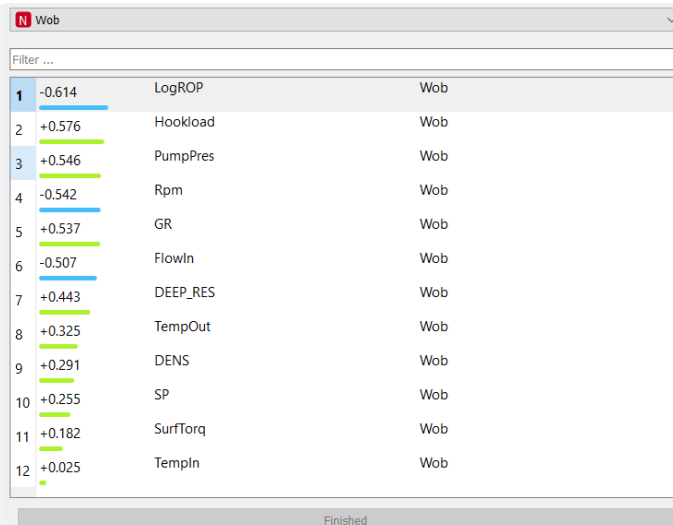




What do you think about the correlation between predictors?

Identify predictors with moderate to strong correlations.

Explain how would you consider this when selecting variables for your model training.



Hookload		
Filter ...		
1	-0.743	Hookload
2	+0.628	DEEP_RES
3	+0.594	Hookload
4	-0.591	FlowIn
5	+0.576	Hookload
6	-0.566	Hookload
7	+0.537	GR
8	+0.520	Hookload
9	-0.241	Hookload
10	+0.174	Hookload
11	+0.138	DENS
12	+0.133	Hookload

SurfTorq		
Filter ...		
1	+0.262	PumpPres
2	+0.242	SurfTorq
3	-0.207	FlowIn
4	-0.203	LogROP
5	+0.182	SurfTorq
6	+0.179	GR
7	+0.164	SurfTorq
8	+0.133	Hookload
9	+0.093	DENS
10	+0.072	DEEP_RES
11	+0.050	Rpm
12	-0.045	SP

Rpm		
Filter ...		
1	-0.647	PumpPres
2	-0.566	Hookload
3	-0.542	Rpm
4	+0.528	FlowIn
5	+0.517	LogROP
6	-0.379	GR
7	-0.358	DEEP_RES
8	-0.216	Rpm
9	-0.125	Rpm
10	+0.060	Rpm
11	+0.050	Rpm
12	+0.013	DENS

N FlowIn			
Filter ...			
1	-0.591	FlowIn	Hookload
2	+0.584	FlowIn	LogROP
3	-0.547	FlowIn	PumpPres
4	+0.528	FlowIn	Rpm
5	-0.507	FlowIn	Wob
6	-0.491	FlowIn	GR
7	-0.421	DEEP_RES	FlowIn
8	-0.230	FlowIn	TempOut
9	-0.207	FlowIn	SurfTorq
10	-0.167	FlowIn	SP
11	-0.085	DENS	FlowIn
12	+0.055	FlowIn	Templn

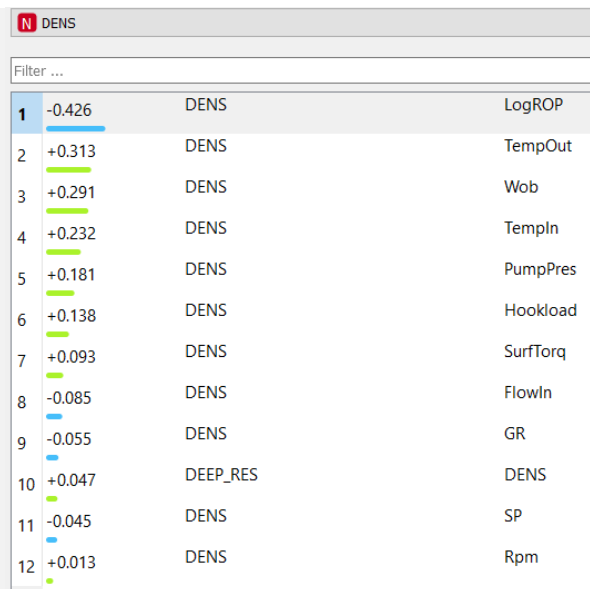
Correlations - Orange			
Pearson correlation			
N PumpPres			
Filter ...			
1	-0.647	PumpPres	Rpm
2	-0.636	LogROP	PumpPres
3	+0.594	Hookload	PumpPres
4	-0.547	FlowIn	PumpPres
5	+0.546	PumpPres	Wob
6	+0.528	PumpPres	TempOut
7	+0.358	GR	PumpPres
8	+0.321	DEEP_RES	PumpPres
9	+0.262	PumpPres	SurfTorq
10	+0.248	PumpPres	Templn
11	+0.181	DENS	PumpPres
12	-0.174	PumpPres	SP

Finished

6394 | 2 | 12

N GR			
Filter ...			
1	+0.537	GR	Hookload
2	+0.537	GR	Wob
3	+0.504	DEEP_RES	GR
4	-0.491	FlowIn	GR
5	-0.474	GR	LogROP
6	-0.379	GR	Rpm
7	+0.358	GR	PumpPres
8	+0.309	GR	SP
9	-0.200	GR	Templn
10	+0.179	GR	SurfTorq
11	-0.055	DENS	GR
12	+0.049	GR	TempOut

N DEEP_RES			
Filter ...			
1	+0.628	DEEP_RES	Hookload
2	-0.539	DEEP_RES	LogROP
3	+0.504	DEEP_RES	GR
4	+0.443	DEEP_RES	Wob
5	+0.441	DEEP_RES	SP
6	-0.421	DEEP_RES	FlowIn
7	-0.405	DEEP_RES	Templn
8	-0.358	DEEP_RES	Rpm
9	+0.321	DEEP_RES	PumpPres
10	-0.140	DEEP_RES	TempOut
11	+0.072	DEEP_RES	SurfTorq
12	+0.047	DEEP_RES	DENS



So based on above of predictors, each will have their own correlation that they are strong to and can be unique. The stronger correlations will definitely have impacts when we are selecting the variables.

Hint: Can you drill with zero WOB?

The original merge data, the an anomalous of ROP (target) is that:

Mean	Median	Dispersion	Min.	Max.	Missing
42.4851	18.08	1.8347	0.71	2977.91	0 (0%)

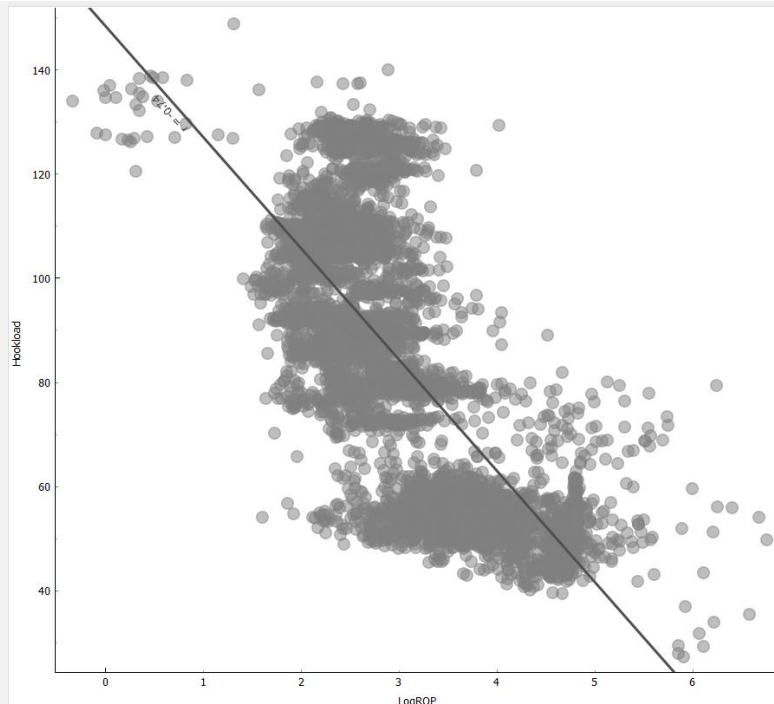
You cannot drill 2977 ft/hr

You cannot have 0.00 WOB as min

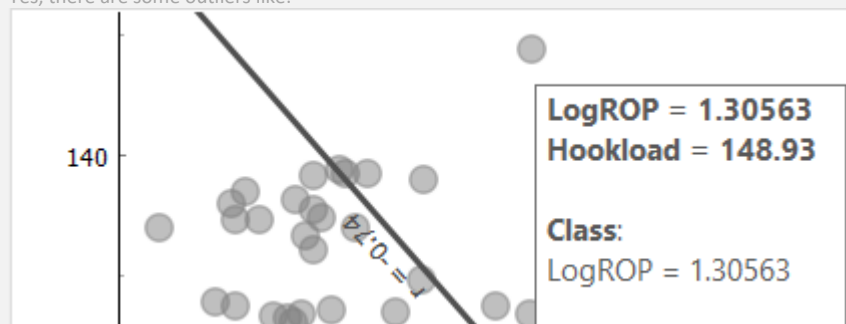
Do you see any anomalous data instances? If yes, what % of the dataset is affected and how would you deal with this anomaly?

Consider the Scatter plot between your strongest predictor and target variable.

Do you see any outliers? How would you deal with the outliers?



Yes, there are some outliers like:



Remove one obvious outlier by filtering out ROP > 2900, transforming the variable like log...

3. Add **Random Forest** trainer to the pipeline with parameters as shown below:

Random Forest

Name

Random Forest

Basic Properties

Number of trees: 50

☒ Number of attributes considered at each split: 3

☒ Replicable training

Growth Control

☐ Limit depth of individual trees: 20

☐ Do not split subsets smaller than: 2

4. Complete the table below based on **cross validation (5-fold)** on your training data using metrics from Evaluation Results in the **Test and Score** widget. (30 points)

Model	RMSE	MAE	R <sup>2</sup>
kNN	0.269	0.180	0.914
Linear Regression	0.433	0.326	0.778
Random Forest	0.251	0.168	0.926

5. Add **SVM (RBF)** trainer to the pipeline and tune model using following parameters.

SVM

Name: SVM

SVM Type:

- ☒ SVM
  - Cost (C): 0.10
  - Regression loss epsilon (ε): 0.10
- ☐ ν-SVM
  - Regression cost (C): 1.00
  - Complexity bound (ν): 0.50

Kernel:

- ☐ Linear
- ☐ Polynomial
- ☒ RBF
  - Kernel:  $\exp(-\gamma \|x-y\|^2)$
  - γ: auto
- ☐ Sigmoid

Optimization Parameters:

- Numerical tolerance: 0.0010
- ☒ Iteration limit: 250
- ☒ Apply Automatically

5116

SVM Parameters	R <sup>2</sup>
C=0.1, Loss=0.1	0.646
C=0.1, Loss=0.5	0.828
C=0.1, Loss=1	0.694
C=0.5, Loss=0.1	0.731
C=0.5, Loss=0.5	0.866
C=0.5, Loss=1	0.751
C=1, Loss=0.1	0.675
<b>C=1, Loss=0.5</b>	<b>0.870</b>
C=1, Loss=1	0.763

C=10, Loss=0.1	0.643
C=10, Loss=0.5	0.834
C=10, Loss=1	0.750

6. Set **SVM** parameters to the best performing model from the above table and complete the table below with **Sampling** as **Cross Validation, 10 folds**:

Model	RMSE	MAE	R <sup>2</sup>
kNN	0.269	0.180	0.914
Linear Regression	0.433	0.326	0.778
Random Forest	0.251	0.168	0.926
SVM	0.332	0.257	0.870

Complete the table for **Test on test data**:

Model	RMSE	MAE	R <sup>2</sup>
kNN	0.271	0.184	0.907
Linear Regression	0.432	0.327	0.763
Random Forest	0.239	0.167	0.927
SVM	0.325	0.256	0.866