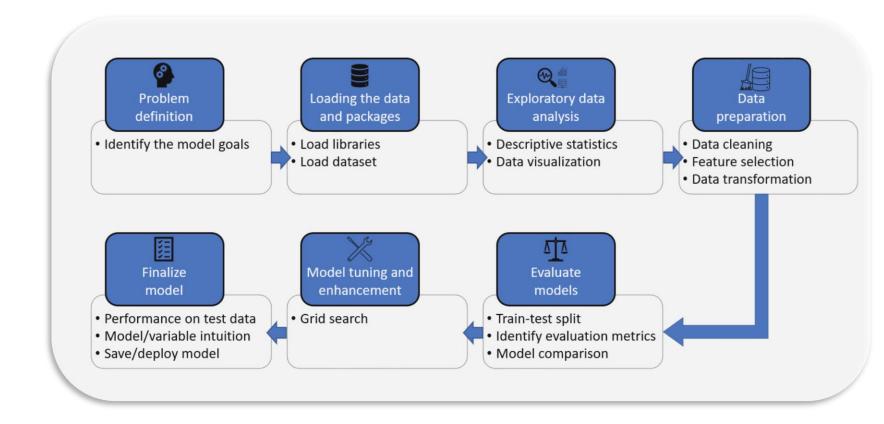
Petro.ai

Subsurface Assessment

CONTENT

- Problem Definition
- Loading data and packages
- Exploratory data analysis
- Data preparation
- Finalize model
- Model tuning and enhancements
- Evaluation models



PROBLEM DEFINITION

- The goal of the machine learning model is to predict the wells cumulative 12-month oil production.
- The model is a function that predicts y given x_1, x_2,...x_i.

•
$$y = \beta_0 + \beta_1 x_1 + ... + \beta_i x_i$$

- The target variable (y): is the cumulative 12-month oil produced.
- The input variables are: ['drainage_area', 'totalProppantByPerfLength', 'avgHzDistAnyZone', 'latitude', 'longitude', 'angleFromSHMax', 'lateralLength']



• Identify the model goals

LOADING THE DATA AND PACKAGES

• The libraries used to process and evaluate the dataset are:

Pandas – Library for data manipulation. It offers data structures to handle tables and provides tools to manipulate them.

NumPy – NumPy provides support for large, multidimensional arrays as well as a large collection of mathematical functions.

Seaborn – A library for data visualization that is based on Matplotlib. It proves a high-level of interface for drawing attractive statistical graphics.

Matplotlib – Matplotlib is a plotting library for creating 2D charts and lots.

Sklearn – Sklearn is a library offering a wide range of machine learning algorithms and utilities.

• The csv file labeled 'well_stats_Delaware' is loaded into the pandas dataframe.

```
df = pd.read_csv('../data/part2/well_stats.csv')
```

- The first few rows of the data are viewed.
 - Df.head() view the first 5 rows
 - column_list = df.columns.values.tolist() list all columns in dataframe



- Load libraries
- Load dataset

EXPLORATORY DATA ANALYSIS

- General information about the dataset is gathered and repairs are made.
- The shape of the pandas dataframe is viewed:

print(f"There are {df.shape[0]} rows and {df.shape[1]} columns in the raw well stats file.")

There are 2457 rows and 172 columns in the raw well stats file.

print(df_model.dtypes)

Column	dtype
drainage_area	Float64
totalProppant ByPerfLength	Float64
avgHzDistAnyZone	Float64
Latitude	Float64
Longitude	Float64
angleFromSHMax	int64
LateralLength	float64
prodOil12mo	float64

• The data is filtered to variables used for modeling and columns are renamed.

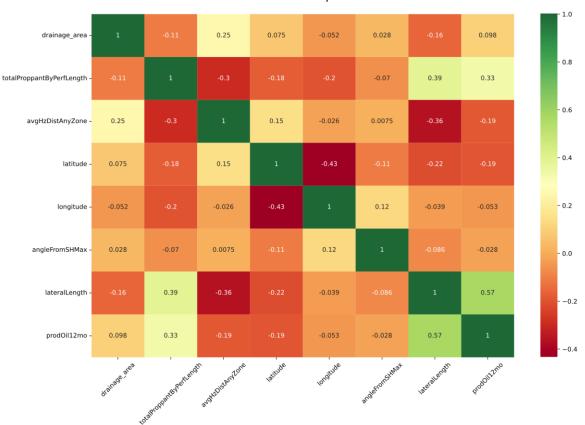
df_model = df[['drainage_area', 'totalProppantByPerfLength',
 'avgHzDistAnyZone', 'latitude', 'longitude', 'angleFromSHMax',
 'lateralLength', 'prodOil12mo']]

Plot correlation matrix as heatmap



- Descriptive statistics
- Data visualization





DATA PREPARATION

Missing data is identified and removed.

```
df_model.isna().sum()
df_model = df_model[df_model['drainage_area'] > 0].copy()
df_model = df_model.dropna(inplace=False)
```

Final dataframe included 1798 rows and 8 columns.

	drainage_area	totalProppantByPerfLength	avgHzDistAnyZone	latitude	longitude	angleFromSHMax	lateralLength	prodOil12mo
0	194838.58	2054.4040	1230.63430	36.389086	-113.386406	119	9247.0	132413.00
2	346702.40	1445.6741	2500.00000	36.371887	-113.457380	118	9163.0	185974.00
5	346830.94	458.1104	2500.00000	36.660776	-113.510260	126	4048.0	99082.00
6	342634.16	2830.5420	1471.00260	36.458529	-113.552025	110	8285.0	228579.00

- Data was Standardized and Normalized
- The target feature and variables were separated and scaled with sklearn's MinMaxScaler.

The feature range was between 0 and 1.

- Lasso and Ridge Regression were normalized.
- Elastic Net was not changed.



- Data cleaning
- Feature selection
- Data transformation

Other scalers are available:

RobustScaler() if you have outliers, this scaler will reduce the effect the influece of outliers.

StandardScaler() for relatively Normal Distribution.

Normalizer() works on the rows, not the columns.

EVALUATE MODELS

• All models were trained, tested, and split with sklearn.

• Training Size: 70%

• Test Size: 30%

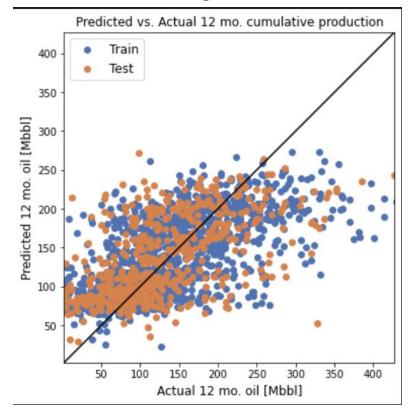
Variables	Linear	Lasso	Ridge	Elastic
Y-intercept	-0.088	-1987904.000	-884887.447	-163062.558
drainage_area	0.291	0.324	0.129	0.327
totalProppantByPerfLen gth	0.423	11.552	9.606	13.301
avgHzDistAnyZone	0.018	3.354	-4.004	3.668
latitude	-0.037	-32973.070	-30427.075	-689.219
longitude	-0.042	-27077.930	-17851.484	-549.854
angleFromSHMax	0.040	120.572	24.822	128.041
lateralLength	0.453	17.647	8.308	17.889

R_Square	Linear	Lasso (alpha=0)	Ridge (alpha =1)	Elastic
Test_r2	0.305	.305	0.278	0.299
Training_r2	0.407	0.407	0.316	0.404



- Train-test split
- Identify evaluation metrics
- Model comparison

Linear Regression

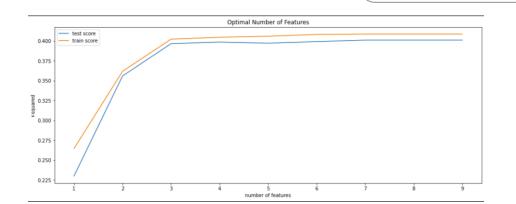


Model Tuning and Enhancement

Model tuning and enhancement

Grid search

- Tuned number of parameters for linear regression
 - folds = KFold(n_splits = 5, shuffle = True, random_state = 100)
 - hyper_params = [{'n_features_to_select': list(range(1, 10))}]
 - · specify model
 - Ir2 = LinearRegression()
 - Ir2.fit(X train, y train)
 - rfe = RFE(lr2)
 - model cv = GridSearchCV(estimator = rfe, param grid = hyper params,
 - scoring= 'r2', cv = folds, verbose = 1,return train score=True)
 - model_cv.fit(X_train, y_train)



• Tuned alpha for Lasso and Ridge Model

Both Lasso and Ridge converge to Linear Model r2

R_Square	Linear	Lasso (alpha=0.001)	Ridge (alpha =0.001)	Elastic
Test_r2	0.305	.305	.305	0.299
Training_r2	0.407	0.407	0.407	0.404

params = {'alpha': [0.0001, 0.001, 0.01, 0.05, 1.0, 5.0, 10, 50, 100]}

ridge = Ridge()

folds = 5

grid_cv_model = GridSearchCV(estimator=ridge, param_grid=params, scoring='neg_mean_absolute_error', cv=folds, return_train_score=True, verbose=1)

grid_cv_model.fit(X_train,y_train)

grid cv model.best params

Best Parameter {'alpha': 0.0001]

Finalize Model

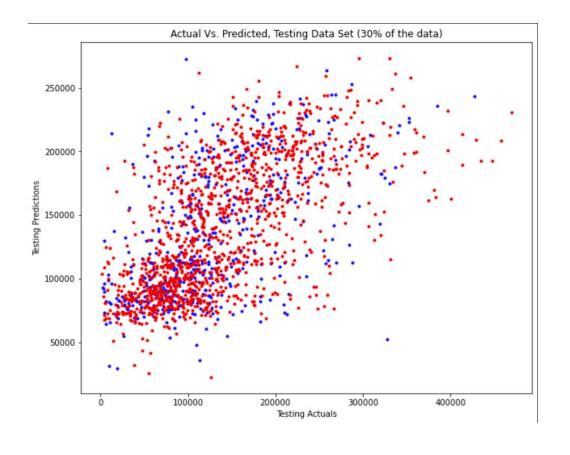
Linear model provides the best fit.

Variables	Linear	Lasso	Ridge	Elastic	
Y-intercept	-0.088	-1987904.000	-884887.447	-163062.558	
drainage_area	0.291	0.324	0.129	0.327	
totalProppantByPerfLen gth	0.423	11.552	9.606	13.301	
avgHzDistAnyZone	0.018	3.354	-4.004	3.668	
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R_Square	Linear	Lasso (alpha=0)	Ridge (alpha =1)	Elastic
Test_r2	0.305	.305	0.278	0.299
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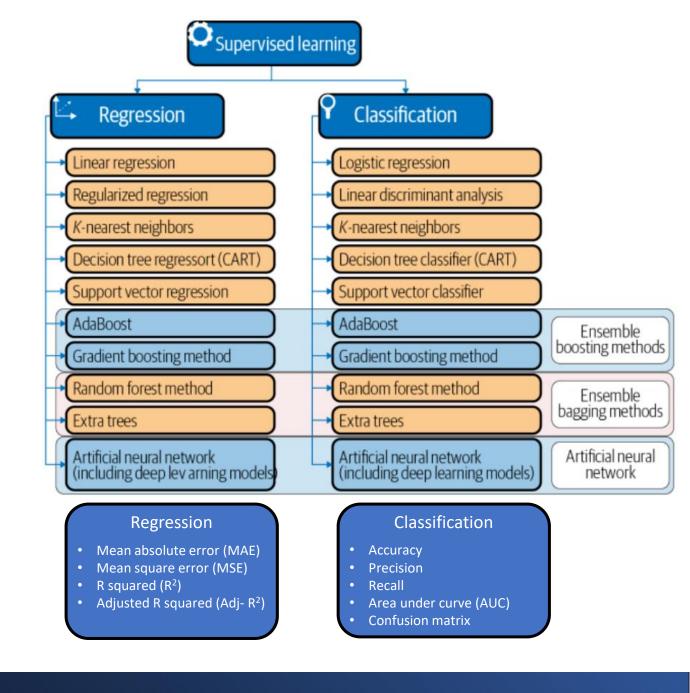
- Performance on test data
- Model/variable intuition
- Save/deploy model

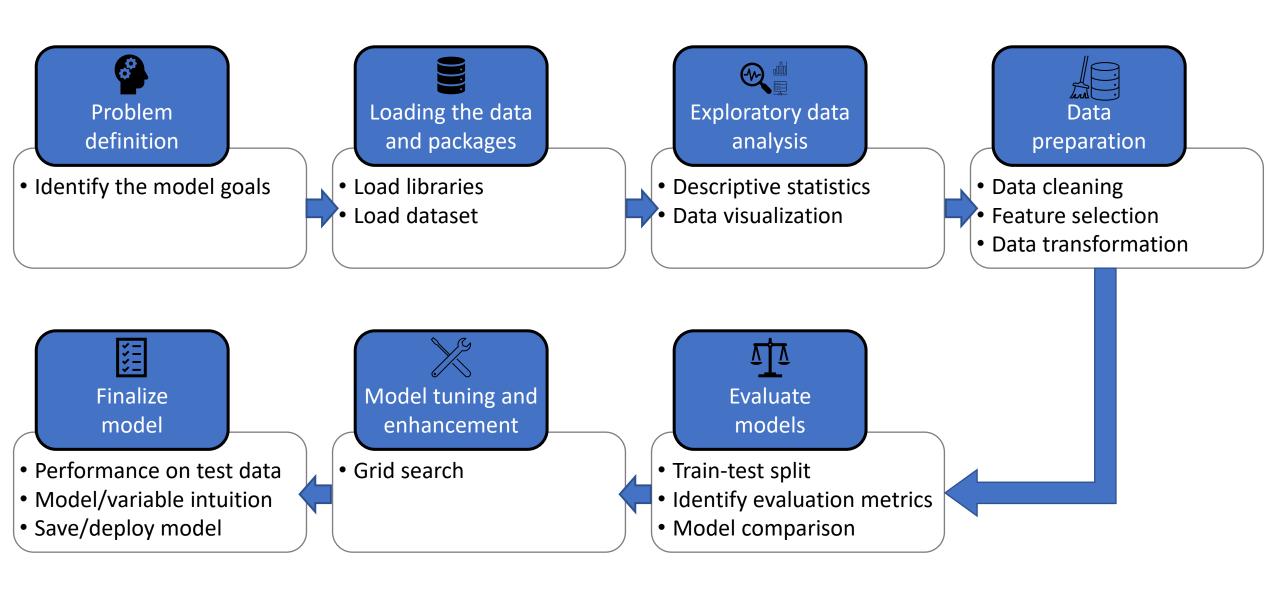


Next Steps

- Deep dive into data
- SGD (Stochastic Gradient Descent)
- K-Nearest Neighbors (KNN)
- Time series (LSTM)
- Spatial relationships

	Linear regression	Logistic regression	SVM	CART	Gradient boosting	Random forest	Artificial neural network	KNN	LDA
Simplicity	*	~	•	~	×	×	×	*	~
Training Time	~	~	×	~	×	×	×	*	~
Handle non-linearity	×	×	*	~	~	~	~	*	~
Robust to overfitting	×	×	~	×	×	~	×	*	×
Large datasets	×	×	×	~	~	~	~	×	~
Many features	×	×	*	~	~	~	*	×	~
Model interpretation	*	~	×	~	~	~	×	*	~
Feature scaling needed	×	×	~	×	×	×	×	×	×







• Identify the model goals



Loading the data and packages

- Load libraries
- Load dataset



Exploratory data analysis

- Descriptive statistics
- Data visualization



- Data cleaning
- Feature selection
- Data transformation



- Performance on test data
- Model/variable intuition
- Save/deploy model



Model tuning and enhancement

Grid search

 $\sqrt{1}$

Evaluate models

- Train-test split
- Identify evaluation metrics
- Model comparison

	Drainage_area	totalProppant ByPerfLength	avgHzDistAnyZ one	latitude	longitude	angleFrom SHMax	Lateral Length	prodOil12mo
Drainage_area	1.000000	-0.079115	0.204507	0.05661	-0.048259	0.020854	-0.091635	0.108534
totalProppant ByPerfLength	-0.079115	1.000000	-0.297495	-0.16446	-0.199341	-0.061656	0.385214	0.335033
avgHzDistAnyZone	0.204507	-0.297495	1.000000	0.15475	-0.014669	-0.010518	-0.383163	-0.218147
latitude	0.056612	-0.164460	0.154756	1.00000	-0.450329	-0.105174	-0.218155	-0.185327
longitude	-0.048259	-0.199341	-0.014669	-0.45032	1.000000	0.110571	-0.036311	-0.045839
angleFromSHMax	0.020854	-0.061656	-0.010518	-0.10517	0.110571	1.000000	-0.051407	-0.031307
LateralLength	-0.091635	0.385214	-0.383163	-0.21815	-0.036311	-0.051407	1.000000	0.588168
prodOil12mo	0.108534	0.335033	-0.218147	-0.18532	-0.045839	-0.031307	0.588168	1.000000