52.5 %

Manufacturing Waste is Landfilled

Information retrieved from: https://www.epa.gov/facts-and-figures-about-materials-waste-and-recycling/national-overview-facts-and-figures-materials

Quality Predictions In The Mining Process

ML 3253 – Group # 21 - University Of Toronto – August 2019

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AGENDA

1. Problem
2. Solution
3. Key Outcomes

Problem Statement

Predicting **% Silica (Impurity)** present in the Iron Ore concentrate

Background Process

Flotation Plant
[Physical Separation]

Iron Ore

% Silica

Other

DATASET

# of Instances	737,453
# of columns	24
Target Variable	% Silica Concentrate
Data Collection Period	20 seconds
Output Update Period	2 hours
Range	6 months
Missing Values	None
Problem Type	Supervised - Regression

Dataset retrieved from: https://www.kaggle.com/edumagalhaes/quality-prediction-in-a-mining-process

Data Preparation

Item	Approach # 1	Approach # 2
Sampling Period	20 seconds	1 hour
Outlier Detection & Removal	Z Score	Box-plots & IQR Score
Feature Selection	Manual	Semi-automatic
----------Output----------		
Total Features	6 (2 – engineered)	8 (2 – engineered)
Target Variable	1	1
# of Instances	346,000	1,817

ML Modelling Journey

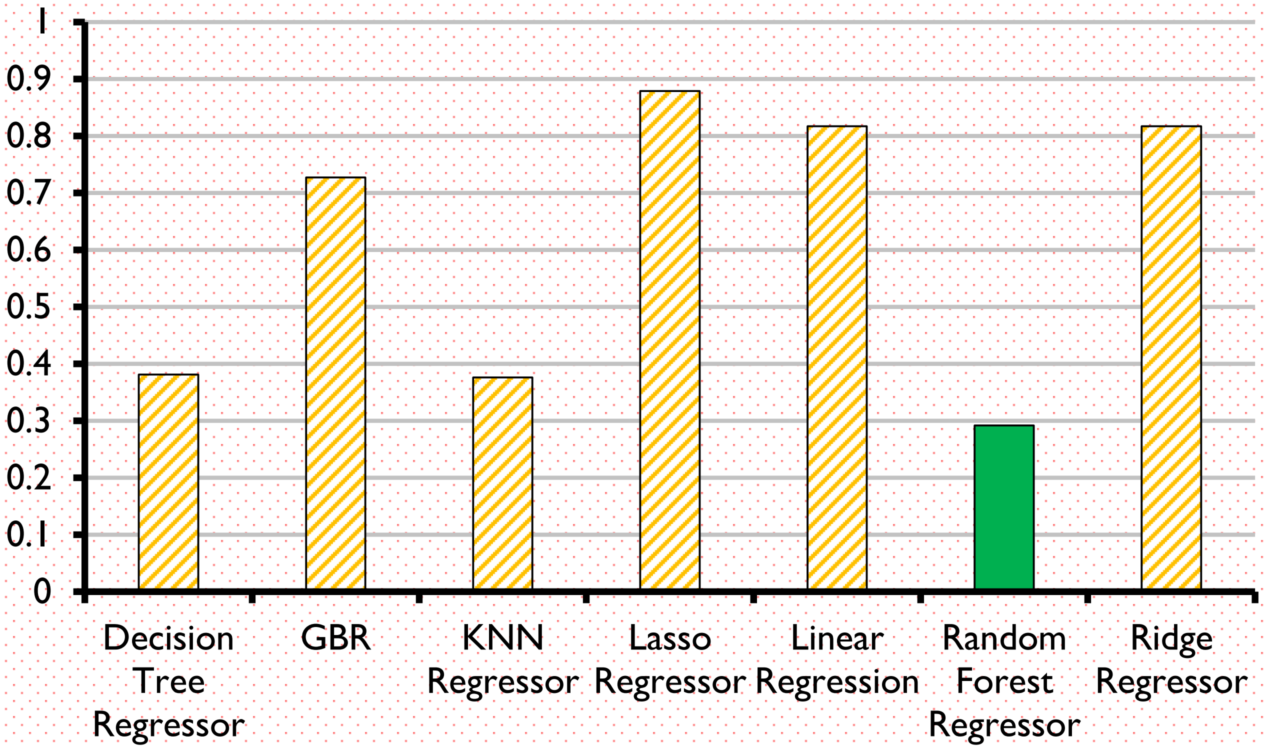
- Split Data
- Built Pipeline
- Scaling
- ML Model
- Train Model
- Evaluate Base Model
- Hyperparameter Tuning
- Re-evaluate Model
- Finalize

ML Modelling

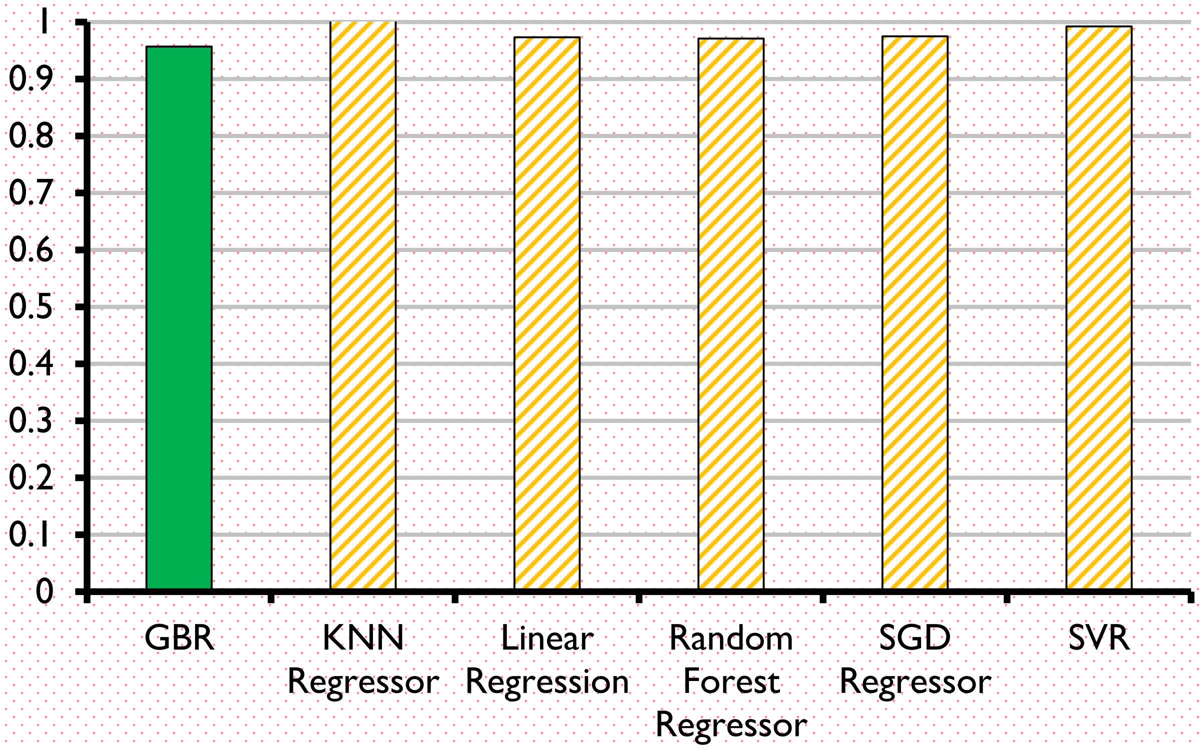
Item	Model # 1	Model # 2
Base Algorithms Used	LinearRegression,, KNeighborsRegressor, RandomForestRegressor, GradientBoostingRegressor, SGDRegressor	
Other Algorithms Used	Decision Tree Regressor, Ridge, Lasso	SVR
Scaling Data	Min_Max Scaler	Standard Scaler
Test Train Split	75% (train) - 25% (test)	70% (train) - 30% (test)
Cross Validation	K-folds 10 split	
Hyperparameter Tuning	Grid Search	
Scoring Methods	RMSE, R^2, Accuracy	

Results

Model # 1: RMSE Score



Model # 2: RMSE Score



Results

Before Tuning		
Scoring	**Model # 1 – Random Forest Regressor**	**Model # 2 – Gradient Boosting Regressor**
RMSE	0.282	0.913
R^2	0.897	0.221
Accuracy	93.64 %	62.24 %
After Tuning		
RMSE	0.282	0.907
R^2	0.908	0.232
Accuracy	93.80 %	62.89 %

Key Outcomes

Produced a generalized model that predicts % Silica (Impurity) present in the Iron Ore concentration with accuracy of:

93.80 %

Full Dataset

62.90 %

Resampled Dataset

Next Steps

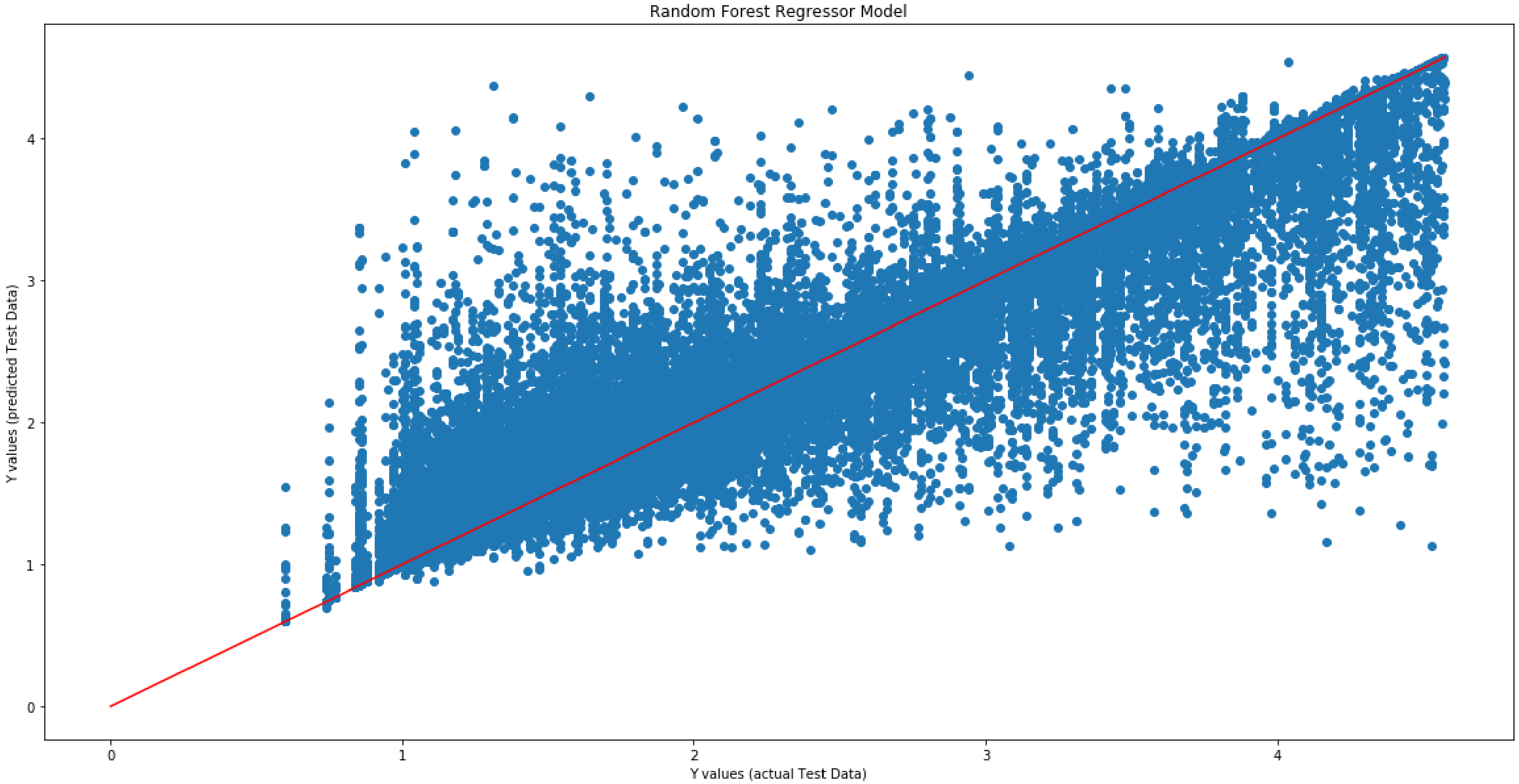
- Revisit and align on sampling period
- Consult with business to enhance the understanding of the data
- Perform in-depth hyper-parameter tuning on cloud computer (GCP, AWS, Azure)
- Experiment with different ML Packages / Libraries (Spark Mllib, TensorFlow)
- Use time series forecast to Predict Features (X) at a given time to Predict % Silica (Y)

Thank You

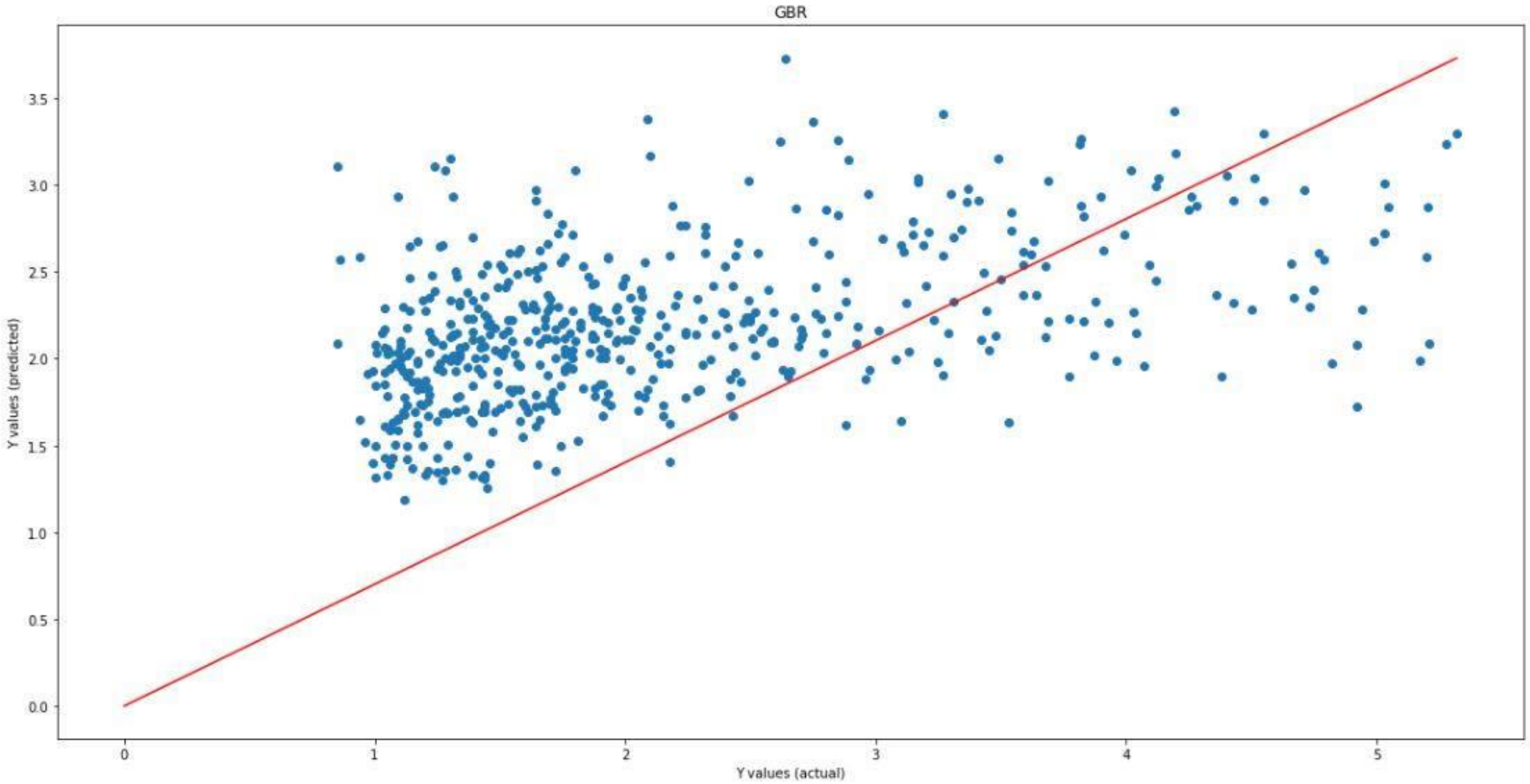
Scan me

https://github.com/nishp763/SCS-ML-3253---Final-Project.git

Appendix: Model # 1



Appendix: Model # 2



Appendix: Accuracy Function

```python
def evaluate(predictions, test_data):
    errors = abs(predictions - test_data)
    mape = 100 * np.mean(errors / test_data)
    accuracy = 100 - mape
    print('Model Performance')
    print('Average Error: {:0.4f}'.format(np.mean(errors)))
    print('Accuracy = {:0.2f}%'.format(accuracy))

    return accuracy
```

```python
base_accuracy = evaluate(y_pred, y_test)
```

```
Model Performance
Average Error: 0.1234
Accuracy = 93.64%
```