Mercedes-Benz Greener Manufacturing

1. BUSINESS PROBLEM

1.1 DESCRIPTION

Since the first automobile, the Benz Patent Motor Car in 1886, Mercedes-Benz has stood for important automotive innovations. These include, for example, the passenger safety cell with crumple zone, the airbag and intelligent assistance systems. Mercedes-Benz applies for nearly 2000 patents per year, making the brand the European leader among premium car makers. Daimler's Mercedes-Benz cars are leaders in the premium car industry. With a huge selection of features and options, customers can choose the customized Mercedes-Benz of their dreams.

To ensure the safety and reliability of each and every unique car configuration before they hit the road, Daimler's engineers have developed a robust testing system. But, optimizing the speed of their testing system for so many possible feature combinations is complex and time-consuming without a powerful algorithmic approach. As one of the world's biggest manufacturers of premium cars, safety and efficiency are paramount on Daimler's production lines.

1.2 SOURCES

DATA SOURCE: https://www.kaggle.com/c/mercedes-benz-greener-manufacturing/data (https://www.kaggle.com/c/mercedes-benz-greener-manufacturing/data)

RESEARCH PAPER: https://medium.com/@williamkoehrsen/capstone-project-mercedes-benz-greener-manufacturing-competition-4798153e2476 (https://medium.com/@williamkoehrsen/capstone-project-mercedes-benz-greener-manufacturing-competition-4798153e2476)

1.3 Real World / Business Objectives and Constraints

1. Accurately predict the time taken on the test bench.
2. Incorrect prediction could affect production line.
3. No strict latency contraints.

2. Machine Learning Overview

2.1 DATA OVERVIEW

This dataset contains an anonymized set of variables, each representing a custom feature in a Mercedes car. For example, a variable could be 4WD, added air suspension, or a head-up display.

The ground truth is labeled 'y' and represents the time (in seconds) that the car took to pass testing for each variable.

File descriptions Variables with letters are categorical. Variables with 0/1 are binary values.

train.csv - the training set test.csv - the test set, you must predict the 'y' variable for the 'ID's in this file sample_submission.csv - a sample submission file in the correct format

2.2 TYPE OF PROBLEM

This is a regression problem since we need to predict the time in seconds as to how long the vehicle stays on the text bench.

2.3 PERFOMANCE METRICS

The metric to be optimized for is the coefficient of determination. The coefficient of determination, denoted R2 or r2 and pronounced "R squared", is the proportion of the variance in the dependent variable that is predictable from the independent variable(s).

3. Exploratory Data Analysis

In [1]:
```
!pip3 install --force-reinstall mlxtend==0.16.0
```

```
Collecting mlxtend==0.16.0
  Using cached https://files.pythonhosted.org/packages/c0/ca/54fe0ae783ce81a467710d1c5fb41cfca075121139b483
27b807020dc40c/mlxtend-0.16.0-py2.py3-none-any.whl (https://files.pythonhosted.org/packages/c0/ca/54fe0ae78
3ce81a467710d1c5fb41cfca075121139b48327b807020dc40c/mlxtend-0.16.0-py2.py3-none-any.whl)
Collecting pandas>=0.17.1 (from mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/d8/69/987bc87788077f933213f4c2cded964f3b345fb14c0ec7
ce943ce0800acf/pandas-0.25.2-cp35-cp35m-manylinux1_x86_64.whl (https://files.pythonhosted.org/packages/d8/6
9/987bc87788077f933213f4c2cded964f3b345fb14c0ec7ce943ce0800acf/pandas-0.25.2-cp35-cp35m-manylinux1_x86_64.w
hl)
Collecting scipy>=0.17 (from mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/7a/0e/3781e028d62a8422244582abd8f084e631429702676058
7c85607f687bf3/scipy-1.3.1-cp35-cp35m-manylinux1_x86_64.whl (https://files.pythonhosted.org/packages/7a/0e/
3781e028d62a8422244582abd8f084e6314297026760587c85607f687bf3/scipy-1.3.1-cp35-cp35m-manylinux1_x86_64.whl)
Collecting setuptools (from mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/6a/9a/50fadfd53ec909e4399b67c74cc7f4e883488035cfcdb9
0b685758fa8b34/setuptools-41.4.0-py2.py3-none-any.whl (https://files.pythonhosted.org/packages/6a/9a/50fadf
d53ec909e4399b67c74cc7f4e883488035cfcdb90b685758fa8b34/setuptools-41.4.0-py2.py3-none-any.whl)
Collecting numpy>=1.10.4 (from mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/5e/f8/82a8a6ed446b58aa718b2744b265983783a2c84098a73d
b6d0b78a573e25/numpy-1.17.3-cp35-cp35m-manylinux1_x86_64.whl (https://files.pythonhosted.org/packages/5e/f
8/82a8a6ed446b58aa718b2744b265983783a2c84098a73db6d0b78a573e25/numpy-1.17.3-cp35-cp35m-manylinux1_x86_64.wh
l)
Collecting matplotlib>=1.5.1 (from mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/89/61/465fb3bfba684b0f53b5c4829c3c89e86e6fe9fdcdfda9
3e38f1788090f0/matplotlib-3.0.3-cp35-cp35m-manylinux1_x86_64.whl (https://files.pythonhosted.org/packages/8
9/61/465fb3bfba684b0f53b5c4829c3c89e86e6fe9fdcdfda93e38f1788090f0/matplotlib-3.0.3-cp35-cp35m-manylinux1_x8
6_64.whl)
Collecting scikit-learn>=0.18 (from mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/1f/af/e3c3cd6f61093830059138624dbd26d938d6da1caeec5a
eabe772b916069/scikit_learn-0.21.3-cp35-cp35m-manylinux1_x86_64.whl (https://files.pythonhosted.org/package
s/1f/af/e3c3cd6f61093830059138624dbd26d938d6da1caeec5aeabe772b916069/scikit_learn-0.21.3-cp35-cp35m-manylin
ux1_x86_64.whl)
Collecting pytz>=2017.2 (from pandas>=0.17.1->mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/e7/f9/f0b53f88060247251bf481fa6ea62cd0d25bf1b11a8788
8e53ce5b7c8ad2/pytz-2019.3-py2.py3-none-any.whl (https://files.pythonhosted.org/packages/e7/f9/f0b53f880602
47251bf481fa6ea62cd0d25bf1b11a87888e53ce5b7c8ad2/pytz-2019.3-py2.py3-none-any.whl)
Collecting python-dateutil>=2.6.1 (from pandas>=0.17.1->mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/41/17/c62faccbfbd163c7f57f3844689e3a78bae1f403648a6a
fb1d0866d87fbb/python_dateutil-2.8.0-py2.py3-none-any.whl (https://files.pythonhosted.org/packages/41/17/c6
2faccbfbd163c7f57f3844689e3a78bae1f403648a6afb1d0866d87fbb/python_dateutil-2.8.0-py2.py3-none-any.whl)
Collecting pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 (from matplotlib>=1.5.1->mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/11/fa/0160cd525c62d7abd076a070ff02b2b94de589f1a97897
74f17d7c54058e/pyparsing-2.4.2-py2.py3-none-any.whl (https://files.pythonhosted.org/packages/11/fa/0160cd52
5c62d7abd076a070ff02b2b94de589f1a9789774f17d7c54058e/pyparsing-2.4.2-py2.py3-none-any.whl)
Collecting cycler>=0.10 (from matplotlib>=1.5.1->mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/f7/d2/e07d3ebb2bd7af696440ce7e754c59dd546ffe1bbe732c
8ab68b9c834e61/cycler-0.10.0-py2.py3-none-any.whl (https://files.pythonhosted.org/packages/f7/d2/e07d3ebb2b
d7af696440ce7e754c59dd546ffe1bbe732c8ab68b9c834e61/cycler-0.10.0-py2.py3-none-any.whl)
Collecting kiwisolver>=1.0.1 (from matplotlib>=1.5.1->mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/ee/18/4cd2e84c6aff0c6a50479118083d20b9e676e5175a913c
0ea76d700fc244/kiwisolver-1.1.0-cp35-cp35m-manylinux1_x86_64.whl (https://files.pythonhosted.org/packages/e
e/18/4cd2e84c6aff0c6a50479118083d20b9e676e5175a913c0ea76d700fc244/kiwisolver-1.1.0-cp35-cp35m-manylinux1_x8
6_64.whl)
Collecting joblib>=0.11 (from scikit-learn>=0.18->mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/8f/42/155696f85f344c066e17af287359c9786b436b1bf86029
bb3411283274f3/joblib-0.14.0-py2.py3-none-any.whl (https://files.pythonhosted.org/packages/8f/42/155696f85f
344c066e17af287359c9786b436b1bf86029bb3411283274f3/joblib-0.14.0-py2.py3-none-any.whl)
Collecting six>=1.5 (from python-dateutil>=2.6.1->pandas>=0.17.1->mlxtend==0.16.0)
  Using cached https://files.pythonhosted.org/packages/73/fb/00a976f728d0d1fecfe898238ce23f502a721c0ac0ecfe
db80e0d88c64e9/six-1.12.0-py2.py3-none-any.whl (https://files.pythonhosted.org/packages/73/fb/00a976f728d0d
1fecfe898238ce23f502a721c0ac0ecfedb80e0d88c64e9/six-1.12.0-py2.py3-none-any.whl)
Installing collected packages: numpy, pytz, six, python-dateutil, pandas, scipy, setuptools, pyparsing, cyc
ler, kiwisolver, matplotlib, joblib, scikit-learn, mlxtend
Successfully installed cycler-0.10.0 joblib-0.14.0 kiwisolver-1.1.0 matplotlib-3.0.3 mlxtend-0.16.0 numpy-
1.17.3 pandas-0.25.2 pyparsing-2.4.2 python-dateutil-2.8.0 pytz-2019.3 scikit-learn-0.21.3 scipy-1.3.1 setu
ptools-41.4.0 six-1.12.0
```

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
import mlxtend
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.metrics import r2_score
from sklearn.decomposition import PCA, FastICA
from sklearn.linear_model import SGDRegressor
import warnings
warnings.filterwarnings('ignore')
from sklearn import neighbors
from sklearn.metrics import mean_squared_error
from math import sqrt
import matplotlib.pyplot as plt
from sklearn.linear_model import Ridge
from sklearn import linear_model
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
from prettytable import PrettyTable
from sklearn.random_projection import GaussianRandomProjection
from sklearn.random_projection import SparseRandomProjection
import xgboost as xgb
from sklearn.linear_model import ElasticNet
from sklearn.model_selection import StratifiedKFold
from mlxtend.regressor import StackingRegressor
from mlxtend.data import boston_housing_data
```

In [54]:
```
train_df=pd.read_csv("train.csv")
```

In [92]:
```
test_df=pd.read_csv("test.csv")
```

In [36]:
```
print("Train shape : ", train_df.shape)
print("Test shape : ", test_df.shape)
```

```
Train shape :  (4209, 378)
Test shape :  (4209, 377)
```

In [37]:
```
train_df.head()
```

Out[37]:

	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378	X379	X380	X382	X383	X384	X385
0	0	130.81	k	v	at	a	d	u	j	o	...	0	0	1	0	0	0	0	0	0	0
1	6	88.53	k	t	av	e	d	y	l	o	...	1	0	0	0	0	0	0	0	0	0
2	7	76.26	az	w	n	c	d	x	j	x	...	0	0	0	0	0	0	1	0	0	0
3	9	80.62	az	t	n	f	d	x	l	e	...	0	0	0	0	0	0	0	0	0	0
4	13	78.02	az	v	n	f	d	h	d	n	...	0	0	0	0	0	0	0	0	0	0

5 rows × 378 columns

In [38]:
```
test_df.head()
```

Out[38]:

	ID	X0	X1	X2	X3	X4	X5	X6	X8	X10	...	X375	X376	X377	X378	X379	X380	X382	X383	X384	X385
0	1	az	v	n	f	d	t	a	w	0	...	0	0	0	1	0	0	0	0	0	0
1	2	t	b	ai	a	d	b	g	y	0	...	0	0	1	0	0	0	0	0	0	0
2	3	az	v	as	f	d	a	j	j	0	...	0	0	0	1	0	0	0	0	0	0
3	4	az	l	n	f	d	z	l	n	0	...	0	0	0	1	0	0	0	0	0	0
4	5	w	s	as	c	d	y	i	m	0	...	1	0	0	0	0	0	0	0	0	0

5 rows × 377 columns

We can see that the data consists of 4208 rows with each row having a y value which is the time in seconds.

In [39]:
```
train_df.describe()
```

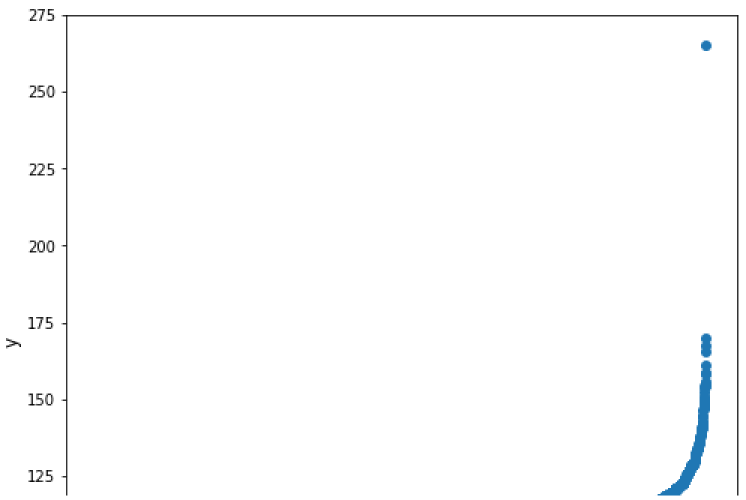
Out[39]:

	ID	y	X10	X11	X12	X13	X14	X15	X16	X17
count	4209.000000	4209.000000	4209.000000	4209.0	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000	4209.000000
mean	4205.960798	100.669318	0.013305	0.0	0.075077	0.057971	0.428130	0.000475	0.002613	0.007603
std	2437.608688	12.679381	0.114590	0.0	0.263547	0.233716	0.494867	0.021796	0.051061	0.086872
min	0.000000	72.110000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	2095.000000	90.820000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50%	4220.000000	99.150000	0.000000	0.0	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	6314.000000	109.010000	0.000000	0.0	0.000000	0.000000	1.000000	0.000000	0.000000	0.000000
max	8417.000000	265.320000	1.000000	0.0	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000

8 rows × 370 columns

3.1 Analysis of 'y'

In [40]:
```
plt.figure(figsize=(8,8))
plt.scatter(range(train_df.shape[0]), np.sort(train_df.y.values))
plt.xlabel('Index', fontsize=12)
plt.ylabel('y', fontsize=12)
plt.show()
```



We can see that the mean value of y is 100.66 seconds. We can see that there is one outlier and all the other values are less than 180.

In [41]:
```
train_df[train_df.y >= 180]
```

Out[41]:

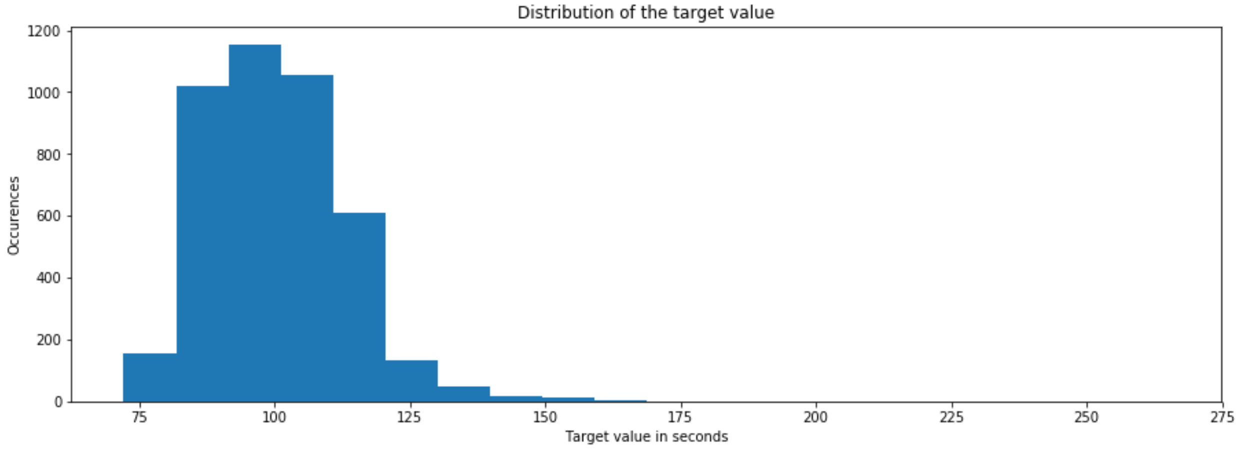
	ID	y	X0	X1	X2	X3	X4	X5	X6	X8	...	X375	X376	X377	X378	X379	X380	X382	X383	X384	X385
883	1770	265.32	y	r	ai	f	d	ag	l	t	...	0	0	0	0	0	0	0	0	0	0

1 rows × 378 columns

In [42]:
```
y_train = train_df['y'].values
plt.figure(figsize=(15, 5))
plt.hist(y_train, bins=20)
plt.xlabel('Target value in seconds')
plt.ylabel('Occurences')
plt.title('Distribution of the target value')

print('min: {} max: {} mean: {} std: {}'.format(min(y_train), max(y_train), y_train.mean(), y_train.std()))
```

```
min: 72.11 max: 265.32 mean: 100.66931812782134 std: 12.6778749695168
```



3.2 Analysis of Features

In [43]:
```
data_type = train_df.dtypes.reset_index()
data_type.columns = ["Count", "Column Type"]
data_type.groupby("Column Type").aggregate('count').reset_index()
```

Out[43]:

	Column Type	Count
0	int64	369
1	float64	1
2	object	8

We can see that there are 378 columns of which 369 are integers and 8 are objects. Also there are a few features which consist of all 0 or 1 values which do not add any value to the model.

In [44]:
```
data_type.iloc[:15,:]
```

Out[44]:

	Count	Column Type
0	ID	int64
1	y	float64
2	X0	object
3	X1	object
4	X2	object
5	X3	object
6	X4	object
7	X5	object
8	X6	object
9	X8	object
10	X10	int64

X0 to X8 are the categorical objects while the others are binary.

In [60]:
```
no_variation = []
for feature in train_df:
    if max(train_df[feature]) == min(train_df[feature]):
        print(feature)
        no_variation.append(feature)
```

```
X11
X93
X107
X233
X235
X268
X289
X290
X293
X297
X330
X347
```

4. Data Cleaning

Convert categorical variable to dummy variable

In [93]:
```
train_df=pd.get_dummies(train_df)
test_df=pd.get_dummies(test_df)
```

Removing Outliers

In [57]:
```
train_df = train_df[train_df.y < 180]
```

Drop features with no Variation and ID column.

In [61]:
```
train_df = train_df.drop(no_variation,1)
```

In [94]:
```
del train_df['ID']
del test_df['ID']
```

In [50]:
```
train_df.head()
```

Out[50]:

	y	X10	X12	X13	X14	X15	X16	X17	X18	X19	...	X8_p	X8_q	X8_r	X8_s	X8_t	X8_u	X8_v	X8_w	X8_x	X8_y
0	130.81	0	0	1	0	0	0	0	1	0	...	0	0	0	0	0	0	0	0	0	0
1	88.53	0	0	0	0	0	0	0	1	0	...	0	0	0	0	0	0	0	0	0	0
2	76.26	0	0	0	0	0	0	1	0	0	...	0	0	0	0	0	0	0	0	1	0
3	80.62	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	78.02	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 552 columns

Save target y values in an array

In [63]:
```
y=np.array(train_df['y'])
```

In [52]:
```
train_df, test_df=train_df.align(test_df, join='inner',axis=1)
```

In [53]:
```
test_df.head()
```

Out[53]:

	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	...	X8_p	X8_q	X8_r	X8_s	X8_t	X8_u	X8_v	X8_w	X8_x	X8_y
0	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	1	0	0
1	0	0	0	0	0	0	0	0	1	0	...	0	0	0	0	0	0	0	0	0	1
2	0	0	0	1	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0
4	0	0	0	1	0	0	0	0	0	0	...	0	0	0	0	0	0	0	0	0	0

5 rows × 541 columns

5. Machine Learning Models

5.1 Baseline Linear Regression Model

In [64]:
```
x_train, x_test, y_train, y_test = train_test_split(train_df, y, test_size=0.2, random_state=42)
```

In [55]:
```
regressor = LinearRegression()
regressor.fit(x_train, y_train)
```

Out[55]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [56]:
```
y_pred=regressor.predict(x_test)
```

In [57]:
```
r2_score(y_test,y_pred)
```

Out[57]:
```
-2.273738906805264e+23
```

Lets try to add PCA as well to help improve performance

In [58]:
```
pca = PCA(n_components=140, random_state=42)
pca2_results_train = pca.fit_transform(train_df)
pca2_results_test = pca.transform(test_df)
```

In [59]:
```
for i in range(1, 140+1):
    train_df['pca_' + str(i)] = pca2_results_train[:,i-1]
    test_df['pca_' + str(i)] = pca2_results_test[:, i-1]
```

In [60]:
```
train_df.head()
```

Out[60]:

	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	...	pca_131	pca_132	pca_133	pca_134	pca_135	pca_136	pca_13
0	0	0	1	0	0	0	0	1	0	0	...	0.547548	-0.294746	0.266133	0.111302	-0.062792	-0.169481	0.01428
1	0	0	0	0	0	0	0	1	0	0	...	0.009837	0.072340	-0.095669	0.093936	0.085435	-0.342695	0.27818
2	0	0	0	0	0	0	1	0	0	0	...	-0.653037	-0.069716	0.112751	-0.032921	-0.038133	-0.206149	-0.59570
3	0	0	0	0	0	0	0	0	0	0	...	0.094094	-0.227754	0.115279	0.036104	-0.239833	-0.119930	-0.03090
4	0	0	0	0	0	0	0	0	0	0	...	0.227805	-0.035984	0.106756	-0.036217	-0.091140	-0.019108	-0.19370

5 rows × 681 columns

Repeat the above experiment.

In [61]:
```
x_train, x_test, y_train, y_test = train_test_split(train_df, y, test_size=0.2, random_state=42)
```

In [62]:
```
regressor = LinearRegression()
regressor.fit(x_train, y_train)
```

Out[62]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [63]:
```
y_pred=regressor.predict(x_test)
```

In [64]:
```
r2_score(y_test,y_pred)
```

Out[64]:
```
-3.3769758800474546e+22
```

https://www.kaggle.com/frednavruzov/baselines-to-start-with-lb-0-56?scriptVersionId=1208832 (https://www.kaggle.com/frednavruzov/baselines-to-start-with-lb-0-56?scriptVersionId=1208832) ICA is also an useful feature to boost performance.

In [65]:
```
ica = FastICA(n_components=140, random_state=42)
ica2_results_train = ica.fit_transform(train_df)
ica2_results_test = ica.transform(test_df)
```

In [66]:
```
train_df['ica_' + str(i)] = ica2_results_train[:,i-1]
test_df['ica_' + str(i)] = ica2_results_test[:, i-1]
```

In [67]:
```
train_df.head()
```

Out[67]:

	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	...	pca_132	pca_133	pca_134	pca_135	pca_136	pca_137	pca_13
0	0	0	1	0	0	0	0	1	0	0	...	-0.294746	0.266133	0.111302	-0.062792	-0.169481	0.014283	-0.47292
1	0	0	0	0	0	0	0	1	0	0	...	0.072340	-0.095669	0.093936	0.085435	-0.342695	0.278186	0.14556
2	0	0	0	0	0	0	1	0	0	0	...	-0.069716	0.112751	-0.032921	-0.038133	-0.206149	-0.595703	-0.56971
3	0	0	0	0	0	0	0	0	0	0	...	-0.227754	0.115279	0.036104	-0.239833	-0.119930	-0.030907	-0.18245
4	0	0	0	0	0	0	0	0	0	0	...	-0.035984	0.106756	-0.036217	-0.091140	-0.019108	-0.193708	-0.21173

5 rows × 682 columns

Lets try a Linear Regressor model with the engineered features.

In [68]:
```
x_train, x_test, y_train, y_test = train_test_split(train_df, y, test_size=0.2, random_state=42)
```

In [69]:
```
regressor = LinearRegression()
regressor.fit(x_train, y_train)
```

Out[69]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [70]:
```
y_pred=regressor.predict(x_test)
```

In [71]:
```
r2_score(y_test,y_pred)
```

Out[71]:
```
-2.379771955112134e+22
```

We can observe a significant improvement with these features.

In [73]:
```
import pickle
train_df.to_pickle('train_df.pickle')
pd.DataFrame(y).to_csv("labels.csv",index=False)
test_df.to_pickle('test_df.pickle')
```

5.2 SGD Regressor

In [3]:
```
import pickle
train_df=pd.read_pickle('train_df.pickle')
y=pd.read_csv("labels.csv")
test_df=pd.read_pickle('test_df.pickle')
```

In [75]:
```
y.head()
```

Out[75]:

	0
0	130.81
1	88.53
2	76.26
3	80.62
4	78.02

In [4]:
```
x_train, x_test, y_train, y_test = train_test_split(train_df, y, test_size=0.2, random_state=42)
```

In [22]:
```
regressor=SGDRegressor()
```

In [23]:
```
param_grid = {
    'alpha': 10.0 ** -np.arange(1, 5),
    'loss': ['squared_loss', 'huber', 'epsilon_insensitive'],
    'penalty': ['l2', 'l1'],
    'learning_rate': ['constant', 'optimal', 'invscaling'],
}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
```

```
Fitting 3 folds for each of 72 candidates, totalling 216 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:    1.4s
[Parallel(n_jobs=-1)]: Done 185 out of 216 | elapsed:   28.2s remaining:    4.7s
[Parallel(n_jobs=-1)]: Done 216 out of 216 | elapsed:   42.5s finished
```

Out[23]:
```
GridSearchCV(cv='warn', error_score='raise-deprecating',
             estimator=SGDRegressor(alpha=0.0001, average=False,
                                    early_stopping=False, epsilon=0.1,
                                    eta0=0.01, fit_intercept=True,
                                    l1_ratio=0.15, learning_rate='invscaling',
                                    loss='squared_loss', max_iter=1000,
                                    n_iter_no_change=5, penalty='l2',
                                    power_t=0.25, random_state=None,
                                    shuffle=True, tol=0.001,
                                    validation_fraction=0.1, verbose=0,
                                    warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'alpha': array([0.1   , 0.01  , 0.001 , 0.0001]),
                         'learning_rate': ['constant', 'optimal', 'invscaling'],
                         'loss': ['squared_loss', 'huber',
                                  'epsilon_insensitive'],
                         'penalty': ['l2', 'l1']},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=1)
```

In [24]:
```
print (clf.best_params_)
```

```
{'penalty': 'l2', 'loss': 'epsilon_insensitive', 'alpha': 0.001, 'learning_rate': 'constant'}
```

In [25]:
```
regressor = SGDRegressor(alpha =0.001 , loss='epsilon_insensitive', penalty="l2", learning_rate= 'constant' )

regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

In [26]:
```
r2_score(y_test,y_pred)
```

Out[26]:
```
0.5437364331529582
```

5.3 KNN Regressor

In [75]:
```
import pickle
train_df=pd.read_pickle('train_df.pickle')
y=pd.read_csv("labels.csv")
test_df=pd.read_pickle('test_df.pickle')
```

In [76]:
```
x_train, x_test, y_train, y_test = train_test_split(train_df, y, test_size=0.2, random_state=42)
```

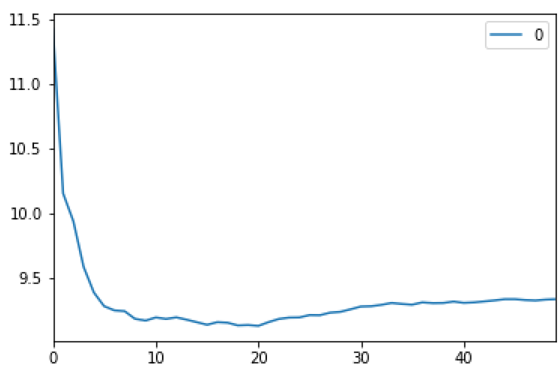
In [93]:
```
rmse_val=[]
for K in range(50):
    K = K+1
    model = neighbors.KNeighborsRegressor(n_neighbors = K, n_jobs=-1)

    model.fit(x_train, y_train)  #fit the model
    pred=model.predict(x_test) #make prediction on test set
    error = sqrt(mean_squared_error(y_test,pred)) #calculate rmse
    rmse_val.append(error) #store rmse values
    print('RMSE value for k= ' , K , 'is:', error)
```

```
RMSE value for k=  1 is: 11.423217777592235
RMSE value for k=  2 is: 10.15514260014187
RMSE value for k=  3 is: 9.939645194643909
RMSE value for k=  4 is: 9.586655936546617
RMSE value for k=  5 is: 9.38867481080732
RMSE value for k=  6 is: 9.282406792478184
RMSE value for k=  7 is: 9.249977652398808
RMSE value for k=  8 is: 9.243881653085783
RMSE value for k=  9 is: 9.185255325065578
RMSE value for k=  10 is: 9.170845979505378
RMSE value for k=  11 is: 9.195320729327923
RMSE value for k=  12 is: 9.183902697021049
RMSE value for k=  13 is: 9.19600947808431
RMSE value for k=  14 is: 9.178025428385684
RMSE value for k=  15 is: 9.1584640883524
RMSE value for k=  16 is: 9.138762061691319
RMSE value for k=  17 is: 9.158982465831066
RMSE value for k=  18 is: 9.154543398137204
RMSE value for k=  19 is: 9.133658164606384
```

In [94]:
```
curve = pd.DataFrame(rmse_val) #elbow curve
curve.plot()
```

Out[94]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7efbe535c278>
```



We reach our elbow point when k=20.

In [95]:
```python
model = neighbors.KNeighborsRegressor(n_neighbors = 20, n_jobs=-1)
model.fit(x_train, y_train)  #fit the model
y_pred=model.predict(x_test)
```

In [96]:
```python
r2_score(y_test,y_pred)
```

Out[96]:
```
0.4679711642059091
```

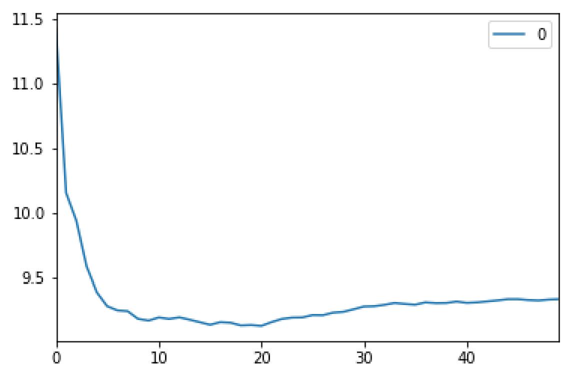
In [93]:
```python
rmse_val=[]
for K in range(50):
    K = K+1
    model = neighbors.KNeighborsRegressor(n_neighbors = K, n_jobs=-1)

    model.fit(x_train, y_train)  #fit the model
    pred=model.predict(x_test) #make prediction on test set
    error = sqrt(mean_squared_error(y_test,pred)) #calculate rmse
    rmse_val.append(error) #store rmse values
    print('RMSE value for k= ' , K , 'is:', error)
```

```
RMSE value for k=  1 is: 11.423217777592235
RMSE value for k=  2 is: 10.15514260014187
RMSE value for k=  3 is: 9.939645194643909
RMSE value for k=  4 is: 9.586655936546617
RMSE value for k=  5 is: 9.38867481080732
RMSE value for k=  6 is: 9.282406792478184
RMSE value for k=  7 is: 9.249977652398808
RMSE value for k=  8 is: 9.243881653085783
RMSE value for k=  9 is: 9.185255325065578
RMSE value for k=  10 is: 9.170845979505378
RMSE value for k=  11 is: 9.195320729327923
RMSE value for k=  12 is: 9.183902697021049
RMSE value for k=  13 is: 9.19600947808431
RMSE value for k=  14 is: 9.178025428385684
RMSE value for k=  15 is: 9.1584640883524
RMSE value for k=  16 is: 9.138762061691319
RMSE value for k=  17 is: 9.158982465831066
RMSE value for k=  18 is: 9.154543398137204
RMSE value for k=  19 is: 9.133658164606384
```

In [94]:
```python
curve = pd.DataFrame(rmse_val) #elbow curve
curve.plot()
```

Out[94]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7efbe535c278>
```



We reach our elbow point when k=20.

In [95]:
```python
model = neighbors.KNeighborsRegressor(n_neighbors = 20, n_jobs=-1)
model.fit(x_train, y_train)  #fit the model
y_pred=model.predict(x_test)
```

In [96]:
```python
r2_score(y_test,y_pred)
```

Out[96]:
```
0.4679711642059091
```


5.4 Linear Regression Models

Ridge Regressor

In [28]:
```
regressor = Ridge()
param_grid = {
    'alpha': 10.0 ** -np.arange(1, 5),
    'normalize': ['True', 'False']
}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 out of  24 | elapsed:    1.6s remaining:    0.5s
[Parallel(n_jobs=-1)]: Done  24 out of  24 | elapsed:    1.7s finished

{'alpha': 0.1, 'normalize': 'True'}
```

In [30]:
```
regressor = Ridge(alpha= 0.1, normalize= 'True')
regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

In [31]:
```
r2_score(y_test,y_pred)
```

Out[31]:
```
0.5354907508243725
```

Lasso Regressor

In [77]:
```
regressor = linear_model.Lasso()
param_grid = {
    'alpha': 10.0 ** -np.arange(1, 5),
    'normalize': ['True', 'False']
}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 out of  24 | elapsed:    4.9s remaining:    1.6s
[Parallel(n_jobs=-1)]: Done  24 out of  24 | elapsed:    5.6s finished

{'normalize': 'True', 'alpha': 0.01}
```

In [80]:
```
regressor = linear_model.Lasso(alpha= 0.01, normalize= 'True')
regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

In [81]:
```
r2_score(y_test,y_pred)
```

Out[81]:
```
0.5609292598255868
```

5.5 Decision Tree Regression Models

In [82]:
```
regressor = DecisionTreeRegressor()
param_grid = {
    'max_depth': [3, 50],
    'min_samples_split' : np.linspace(0.1, 1.0, 10),
    'min_samples_leaf' : np.linspace(0.1, 0.5, 5)

}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:    2.0s
[Parallel(n_jobs=-1)]: Done 168 tasks      | elapsed:    3.3s

{'min_samples_split': 0.4, 'max_depth': 50, 'min_samples_leaf': 0.1}

[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:    4.2s finished
```

In [83]:
```
regressor = DecisionTreeRegressor(max_depth= 50, min_samples_split= 0.4, min_samples_leaf=0.1)
regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

In [84]:
```
r2_score(y_test,y_pred)
```

Out[84]:
```
0.4428141304492136
```

5.6 Support Vector Regression

In [53]:
```
regressor = SVR()
param_grid = {
    'kernel': ['rbf','linear'],
    'C' : [0.001, 0.01, 0.1, 1, 10],
    'gamma' : [0.001, 0.01, 0.1, 1]

}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 40 candidates, totalling 120 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:   20.9s
[Parallel(n_jobs=-1)]: Done 120 out of 120 | elapsed:  1.8min finished

{'C': 0.1, 'gamma': 0.001, 'kernel': 'linear'}
```

In [48]:
```
regressor = SVR(kernel= "linear", C= 0.1, gamma=0.001)
regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

In [49]:
```
r2_score(y_test,y_pred)
```

Out[49]:
```
0.5269127775904145
```

5.7 XGB Regression

In [107]:
```
regressor = xgb.XGBRegressor()
param_grid = {
    'n_estimators': [30,50,60,75,100],
    'max_depth':[1,2,3,5],
    'learning_rate':10.0 ** -np.arange(1, 5)

}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 80 candidates, totalling 240 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:    3.1s
[Parallel(n_jobs=-1)]: Done 168 tasks      | elapsed:   41.8s
[Parallel(n_jobs=-1)]: Done 240 out of 240 | elapsed:  1.0min finished

[14:12:07] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor o
f reg:squarederror.
{'n_estimators': 60, 'max_depth': 2, 'learning_rate': 0.1}
```

In [108]:
```
regressor = xgb.XGBRegressor(n_estimators= 60, max_depth= 2, learning_rate=0.1)
regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

```
[14:12:29] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor o
f reg:squarederror.
```

In [109]:
```
r2_score(y_test,y_pred)
```

Out[109]:
```
0.566196544447676
```

Observations

In [115]:
```
x = PrettyTable()

x.field_names = ["Regressor Used", "r2 Score"]

x.add_row(["Base Linear Regression Model", -2.37])
x.add_row(["SGD Regressor", 0.54])
x.add_row(["KNN Regressor", 0.467])
x.add_row(["Ridge Regressor", 0.53])
x.add_row(["Lasso Regressor", 0.56])
x.add_row(["Decision Tree Regressor", 0.44])
x.add_row(["Support Vector Regressor", 0.526])
x.add_row(["XGB Regressor", 0.566])

print(x)
```

```
+------------------------------+----------+
|        Regressor Used        | r2 Score |
+------------------------------+----------+
| Base Linear Regression Model |  -2.37   |
|        SGD Regressor         |   0.54   |
|        KNN Regressor         |  0.467   |
|       Ridge Regressor        |   0.53   |
|       Lasso Regressor        |   0.56   |
|   Decision Tree Regressor    |   0.44   |
|   Support Vector Regressor   |  0.526   |
|        XGB Regressor         |  0.566   |
+------------------------------+----------+
```

1. We added features of PCA and ICA to our preprocessed data.
2. We tried several different ML regressor models.
3. Linear Lasso regresor worked the best for us with a r2 score of 0.56.

Lets try to further improve the r2 score with some feature engineering if possible.

6. Feature Engineering to improve performance

Lets try to incorcporate GRP and SRP to see if it improves performance.

In [10]:
```
#https://nbviewer.jupyter.org/github/jovsa/mercedes-benz-greener-manufacturing/blob/master/mercedes-benz-gree
grp = GaussianRandomProjection(n_components=140, eps=0.1, random_state=42)
grp_results_train = grp.fit_transform(x_train)
grp_results_test = grp.transform(x_test)

# # SRP
srp = SparseRandomProjection(n_components=140, dense_output=True, random_state=42)
srp_results_train = srp.fit_transform(x_train)
srp_results_test = srp.transform(x_test)

for i in range(1, 140+1):
    x_train['grp_' + str(i)] = grp_results_train[:,i-1]
    x_test['grp_' + str(i)] = grp_results_test[:, i-1]

    x_train['srp_' + str(i)] = srp_results_train[:,i-1]
    x_test['srp_' + str(i)] = srp_results_test[:, i-1]
```

In [111]:
```
x_train.head()
```

Out[111]:

	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	...	grp_136	srp_136	grp_137	srp_137	grp_138	srp_138	grp
3830	0	0	0	0	0	0	0	0	0	1	...	-0.809910	-0.218930	-0.674410	0.876364	-0.111975	-0.730458	-0.03
152	0	0	0	0	0	0	0	0	0	0	...	-1.126888	-0.241439	-0.366262	-0.234665	-0.664250	-0.218271	0.45
1557	0	0	0	1	0	0	0	0	0	0	...	0.614183	0.047490	0.854856	0.462912	0.602624	0.347911	-0.00
2358	0	1	0	0	0	0	0	0	0	0	...	0.708187	-0.472972	-0.130035	1.218877	-0.668759	0.214921	0.03
1316	0	0	0	0	0	0	0	0	0	0	...	-0.345911	-0.066179	0.722259	0.388007	-1.069088	0.873102	-0.74

5 rows × 962 columns

Lets try the top performing models previously to observe any improvement.

6.1 Lasso Regressor

In [65]:
```
regressor = linear_model.Lasso()
param_grid = {
    'alpha': 10.0 ** -np.arange(1, 5),
    'normalize': ['True', 'False']
}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 out of  24 | elapsed:    6.4s remaining:    2.1s
[Parallel(n_jobs=-1)]: Done  24 out of  24 | elapsed:    7.4s finished

{'alpha': 0.01, 'normalize': 'True'}
```

In [66]:
```
regressor = linear_model.Lasso(alpha= 0.01, normalize= 'True')
regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

In [67]:
```
r2_score(y_test,y_pred)
```

Out[67]:
```
0.5559869736318757
```

6.2 Support Vector Regressor

In [68]:
```
regressor = SVR()
param_grid = {
    'kernel': ['rbf','linear'],
    'C' : [0.001, 0.01, 0.1, 1, 10],
    'gamma' : [0.001, 0.01, 0.1, 1]

}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 40 candidates, totalling 120 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:   29.4s
[Parallel(n_jobs=-1)]: Done 120 out of 120 | elapsed:  7.7min finished

{'C': 0.1, 'gamma': 0.001, 'kernel': 'linear'}
```

In [69]:
```
regressor = SVR(kernel= "linear", C= 0.1, gamma=0.001)
regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

In [70]:
```
r2_score(y_test,y_pred)
```

Out[70]:
```
0.5302678575364022
```

6.3 SGD Regressor

In [72]:
```
regressor=SGDRegressor()
```

In [73]:
```
param_grid = {
    'alpha': 10.0 ** -np.arange(1, 5),
    'loss': ['squared_loss', 'huber', 'epsilon_insensitive'],
    'penalty': ['l2', 'l1'],
    'learning_rate': ['constant', 'optimal', 'invscaling'],
}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 72 candidates, totalling 216 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:    3.4s
[Parallel(n_jobs=-1)]: Done 168 tasks      | elapsed:   27.5s
[Parallel(n_jobs=-1)]: Done 216 out of 216 | elapsed:   39.5s finished

{'penalty': 'l2', 'loss': 'huber', 'alpha': 0.001, 'learning_rate': 'optimal'}
```

In [92]:
```
regressor = SGDRegressor(alpha =0.001 , loss='huber', penalty="l2", learning_rate= 'optimal' )

regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

In [93]:
```
r2_score(y_test,y_pred)
```

Out[93]:
```
0.523286031475242
```

6.4 XGB Regression

In [107]:
```
regressor = xgb.XGBRegressor()
param_grid = {
    'n_estimators': [30,50,60,75,100],
    'max_depth':[1,2,3,5],
    'learning_rate':10.0 ** -np.arange(1, 5)

}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 80 candidates, totalling 240 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:    3.1s
[Parallel(n_jobs=-1)]: Done 168 tasks      | elapsed:   41.8s
[Parallel(n_jobs=-1)]: Done 240 out of 240 | elapsed:  1.0min finished

[14:12:07] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor o
f reg:squarederror.
{'n_estimators': 60, 'max_depth': 2, 'learning_rate': 0.1}
```

In [112]:
```
regressor = xgb.XGBRegressor(n_estimators= 60, max_depth= 2, learning_rate=0.1)
regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

```
[14:13:05] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor o
f reg:squarederror.
```

In [113]:
```
r2_score(y_test,y_pred)
```

Out[113]:
```
0.5614055957811037
```

Observations

In [114]:
```
x = PrettyTable()

print("Feature Engineered Models")
x.field_names = ["Regressor Used", "r2 Score"]

x.add_row(["Lasso Regressor", 0.55])
x.add_row(["Support Vector Regressor", 0.53])
x.add_row(["SGD Regressor", 0.52])
x.add_row(["XGB Regressor", 0.561])


print(x)
```

```
Feature Engineered Models
+--------------------------+----------+
|      Regressor Used      | r2 Score |
+--------------------------+----------+
|     Lasso Regressor      |   0.55   |
| Support Vector Regressor |   0.53   |
|      SGD Regressor       |   0.52   |
|      XGB Regressor       |  0.561   |
+--------------------------+----------+
```

1. We added extra features such as GRP and SRP.
2. The improve in performance was negligible so we try to ad some more features.

Feature Engineering based on Combining features

In [5]:
```
train_df['X314_plus_X315'] = train_df.apply(lambda row: row.X314 + row.X315, axis=1)
test_df['X314_plus_X315'] = test_df.apply(lambda row: row.X314 + row.X315, axis=1)
```

In [6]:
```
train_df['X118_plus_X314'] = train_df.apply(lambda row: row.X118 + row.X314, axis=1)
test_df['X118_plus_X314'] = test_df.apply(lambda row: row.X118 + row.X314, axis=1)
```

We combined 2 features based on the end product having a coorealtion with y.

In [151]:
```
train_df.head()
```

Out[151]:

	X10	X12	X13	X14	X15	X16	X17	X18	X19	X20	...	pca_135	pca_136	pca_137	pca_138	pca_139	pca_140	ica_14
0	0	0	1	0	0	0	0	1	0	0	...	-0.062792	-0.169481	0.014283	-0.472926	0.120114	-0.011677	-0.00020
1	0	0	0	0	0	0	0	1	0	0	...	0.085435	-0.342695	0.278186	0.145561	0.371188	0.511744	0.02026
2	0	0	0	0	0	0	1	0	0	0	...	-0.038133	-0.206149	-0.595703	-0.569718	0.354165	0.057655	-0.00606
3	0	0	0	0	0	0	0	0	0	0	...	-0.239833	-0.119930	-0.030907	-0.182453	-0.222312	0.306198	-0.00094
4	0	0	0	0	0	0	0	0	0	0	...	-0.091140	-0.019108	-0.193708	-0.211739	0.176596	0.041106	-0.00292

5 rows × 685 columns

Lets rerun the previous models with the new features added.

Lasso Regressor

In [173]:
```
regressor = linear_model.Lasso()
param_grid = {
    'alpha': 10.0 ** -np.arange(1, 5),
    'normalize': ['True', 'False']
}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 out of  24 | elapsed:    5.9s remaining:    2.0s
[Parallel(n_jobs=-1)]: Done  24 out of  24 | elapsed:    6.9s finished

{'alpha': 0.01, 'normalize': 'True'}
```

In [191]:
```
regressor = linear_model.Lasso(alpha= 0.01, normalize= 'True')
regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

In [192]:
```
r2_score(y_test,y_pred)
```

Out[192]:
```
0.561978964563808
```

Support Vector Regressor

In [174]:
```
regressor = SVR()
param_grid = {
    'kernel': ['rbf','linear'],
    'C' : [0.001, 0.01, 0.1, 1, 10],
    'gamma' : [0.001, 0.01, 0.1, 1]

}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 40 candidates, totalling 120 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:   30.0s
[Parallel(n_jobs=-1)]: Done 120 out of 120 | elapsed:  3.6min finished

{'C': 0.1, 'gamma': 0.001, 'kernel': 'linear'}
```

In [193]:
```
regressor = SVR(kernel= "linear", C= 0.1, gamma=0.001)
regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

In [194]:
```
r2_score(y_test,y_pred)
```

Out[194]:
```
0.5277247152246309
```

SGD Regressor

In [197]:
```
regressor=SGDRegressor()
```

In [198]:
```
param_grid = {
    'alpha': 10.0 ** -np.arange(1, 5),
    'loss': ['squared_loss', 'huber', 'epsilon_insensitive'],
    'penalty': ['l2', 'l1'],
    'learning_rate': ['constant', 'optimal', 'invscaling'],
}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 72 candidates, totalling 216 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:    2.5s
[Parallel(n_jobs=-1)]: Done 185 out of 216 | elapsed:   34.0s remaining:    5.7s
[Parallel(n_jobs=-1)]: Done 216 out of 216 | elapsed:   47.0s finished

{'penalty': 'l2', 'loss': 'huber', 'alpha': 0.0001, 'learning_rate': 'optimal'}
```

In [199]:
```
regressor = SGDRegressor(alpha =0.0001 , loss='huber', penalty="l2", learning_rate= 'optimal' )

regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

In [200]:
```
r2_score(y_test,y_pred)
```

Out[200]:
```
0.5441650745213811
```

XGB Regression

In [177]:
```
regressor = xgb.XGBRegressor()
param_grid = {
    'n_estimators': [30,50,60,75,100],
    'max_depth':[1,2,3,5],
    'learning_rate':10.0 ** -np.arange(1, 5)

}
clf = GridSearchCV(regressor, param_grid, verbose=1,n_jobs=-1)
clf.fit(x_train, y_train)
print (clf.best_params_)
```

```
Fitting 3 folds for each of 80 candidates, totalling 240 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done  18 tasks      | elapsed:    5.7s
[Parallel(n_jobs=-1)]: Done 168 tasks      | elapsed:  1.3min
[Parallel(n_jobs=-1)]: Done 240 out of 240 | elapsed:  1.9min finished

[16:21:40] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor o
f reg:squarederror.
{'n_estimators': 50, 'max_depth': 2, 'learning_rate': 0.1}
```

In [213]:
```
regressor = xgb.XGBRegressor(n_estimators= 50, max_depth= 2, learning_rate=0.1)
regressor.fit(x_train, y_train)
y_pred=regressor.predict(x_test)
```

```
[16:48:43] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor o
f reg:squarederror.
```

In [214]:
```
r2_score(y_test,y_pred)
```

Out[214]:
```
0.5613813759288654
```

Observations

In [234]:
```
x = PrettyTable()

print("Feature Engineered Models")
x.field_names = ["Regressor Used", "r2 Score"]

x.add_row(["Lasso Regressor", 0.561])
x.add_row(["Support Vector Regressor", 0.527])
x.add_row(["SGD Regressor", 0.544])
x.add_row(["XGB Regressor", 0.561])


print(x)
```

```
Feature Engineered Models
+--------------------------+----------+
|      Regressor Used      | r2 Score |
+--------------------------+----------+
|     Lasso Regressor      |  0.561   |
| Support Vector Regressor |  0.527   |
|      SGD Regressor       |  0.544   |
|      XGB Regressor       |  0.561   |
+--------------------------+----------+
```

7. Stacking Models

7.1 XBG Regressor as Meta Regressor

In [29]:
```
#http://rasbt.github.io/mlxtend/user_guide/regressor/StackingRegressor/

lr = linear_model.Lasso(alpha= 0.01, normalize= 'True')
sgd = SGDRegressor(alpha =0.0001 , loss='huber', penalty="l2", learning_rate= 'optimal' )
svr = SVR(kernel= "linear", C= 0.1, gamma=0.001)
xgb = xgb.XGBRegressor(n_estimators= 50, max_depth= 2, learning_rate=0.1)

stregr = StackingRegressor(regressors=[lr, sgd, svr],
                           meta_regressor=xgb)
```

In [30]:
```
stregr.fit(x_train, y_train)
y_pred=stregr.predict(x_test)
```

```
[16:47:20] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor o
f reg:squarederror.
```

In [31]:
```
r2_score(y_test,y_pred)
```

Out[31]:
```
0.5687538035261528
```

7.2 SVR Regressor as Meta Regressor

In [39]:
```
#http://rasbt.github.io/mlxtend/user_guide/regressor/StackingRegressor/

lr = linear_model.Lasso(alpha= 0.01, normalize= 'True')
sgd = SGDRegressor(alpha =0.0001 , loss='huber', penalty="l2", learning_rate= 'optimal' )
svr = SVR(kernel= "linear", C= 0.1, gamma=0.001)
xgb = xgb.XGBRegressor(n_estimators= 50, max_depth= 2, learning_rate=0.1)

stregr = StackingRegressor(regressors=[lr, xgb, sgd],
                           meta_regressor=svr)
```

In [40]:
```
stregr.fit(x_train, y_train)
y_pred=stregr.predict(x_test)
```

```
[16:50:04] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor o
f reg:squarederror.
```

In [41]:
```
r2_score(y_test,y_pred)
```

Out[41]:
```
0.5293541254864508
```

7.3 Linear Regressor Regressor as Meta Regressor

In [7]:
```
#http://rasbt.github.io/mlxtend/user_guide/regressor/StackingRegressor/

lr = linear_model.Lasso(alpha= 0.01, normalize= 'True')
sgd = SGDRegressor(alpha =0.0001 , loss='huber', penalty="l2", learning_rate= 'optimal' )
svr = SVR(kernel= "linear", C= 0.1, gamma=0.001)
xgb = xgb.XGBRegressor(n_estimators= 50, max_depth= 2, learning_rate=0.1)

stregr = StackingRegressor(regressors=[svr, xgb, sgd],
                           meta_regressor=lr)
```

In [8]:
```
stregr.fit(x_train, y_train)
y_pred=stregr.predict(x_test)
```

```
[06:10:14] WARNING: /workspace/src/objective/regression_obj.cu:152: reg:linear is now deprecated in favor o
f reg:squarederror.
```

In [9]:
```
r2_score(y_test,y_pred)
```

Out[9]:
```
0.5725816674474449
```

Observations

In [10]:
```
x = PrettyTable()

print("Stacked Models")
x.field_names = ["Meta Regressor Used", "r2 Score"]

x.add_row(["Lasso Regressor", 0.5725])
x.add_row(["Support Vector Regressor", 0.5293])
x.add_row(["XGB Regressor", 0.5687])


print(x)
```

```
Stacked Models
+--------------------------+----------+
|   Meta Regressor Used    | r2 Score |
+--------------------------+----------+
|     Lasso Regressor      |  0.5725  |
| Support Vector Regressor |  0.5293  |
|      XGB Regressor       |  0.5687  |
+--------------------------+----------+
```

Using stacked models with Lasso regressor as the meta regressor, gave us the best performond model so fat with a r2 score of 0.5725.

CONCLUSION

1. The data consists of 4209 rows with 377 features.
2. We separated the y label into a different data set and used the train data to train our models.
3. We tried different regression models before and after adding a few engineered features.
4. The stacked model with a lasso regressor as the meta regressor gave us the best performance with a r2 score of 0.5725.

In [ ]: