Business Problem

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. Hence, Daimler has challenged to reduce the time that cars spend on the test bench. The Objective of the Case Study is to optimize the testing process in a greener way i.e. reducing the testing time with lower carbon dioxide emissions without reducing Daimler's standards on safety and efficiency.

ML Formulation

We can pose this problem as a regression problem to predict the testing time by selecting some important features from the dataset to tackle the curse of dimensionality.

In order to know how our ML model is performing better, We will develop a baseline or random model and we will compare our models with the baseline model, to get a knowledge where our model stands.

Performance Metric

The metric we will use to evaluate our models is - R^2

Why R^2 as metric?

What is R^2

It is the amount of the variation in the output dependent attribute which is predictable from the input independent variable. It is used to check how well-observed results are reproduced by the model, depending on the ratio of total deviation of results described by the model

Interpretation -

Assume R2 = 0.68 It can be referred that 68% of the changeability of the dependent output attribute can be explained by the model while the remaining 32 % of the variability is still unaccounted for.

R-squared = 1 - (SSres / SStot)

SSres is the sum of squares of the residual errors.

SStot is the total sum of the errors.

which means we scale our simple MSE based on the difference of actual values from their mean.

R^2 is a convenient rescaling of MSE that is unit invariant.

It is also very interpretable as -

The best possible score is 1 which is obtained when the predicted values are the same as the actual values.

R^2 with value 0 means the model is same as simple mean model.

Negative value of R² mean that the model is worse than simple mean model.

Why?

MSE or MAE penalizes the large prediction errors hence the sum of errors can become very large and interpreting it won't be trivial.

Whereas, R^2 is a scale-free score i.e. irrespective of the values being small or large, the value of R square will be less than one or in worst cases just greater than 1.



```
In [1]:
```

```
'''importing dependencies'''
import pandas as pd
import warnings
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import os
from xgboost import XGBRegressor
from tqdm import tqdm
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion matrix
import plotly.offline as offline
import plotly.graph_objs as go
offline.init_notebook_mode()
from collections import Counter
warnings.filterwarnings('ignore')
sns.set()
```

Reading the data

```
In [2]:
```

```
data = pd.read_csv('downloads/trainwa.csv')
data.head()
```

Out[2]:

	ID	у	X0	X1	X2	Х3	X4	X5	X6	X8	 X375	X376	X377	X378	X379	X380	X382	X383	X384	X385
0	0	130.81	k	٧	at	а	d	u	j	0	 0	0	1	0	0	0	0	0	0	0
1	6	88.53	k	t	av	е	d	У	- 1	О	 1	0	0	0	0	0	0	0	0	0
2	7	76.26	az	w	n	С	d	х	j	х	 0	0	0	0	0	0	1	0	0	0
3	9	80.62	az	t	n	f	d	x	- 1	е	 0	0	0	0	0	0	0	0	0	0
4	13	78.02	az	٧	n	f	d	h	d	n	 0	0	0	0	0	0	0	0	0	0

5 rows × 378 columns

Knowing the data

Data Shape

```
In [3]:
```

```
print("Train Data Shape : = ", data.shape)
Train Data Shape : = (4209, 378)
```

Detail View of Train Data

In [4]:

```
data.describe()
```

Out[4]:

	ID	у	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 ID	12.679381 y	0.114 <u>5</u> 90 X10	X11	0.263 <u>54</u> 7 X12	0.233716 X13	0.494867 X14	0.021796 X15	0.051061 X16	0.086872 X17
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

Checking for null values in the Data

```
In [5]:
```

```
print("Number of missing values in Train data: ",data.isnull().sum().sum())
```

Number of missing values in Train data: 0

Checking for duplicate values in the Data

In [6]:

```
print(len(data[data.duplicated()]))
```

0

Analyzing the Prediction Column 'y'

In [7]:

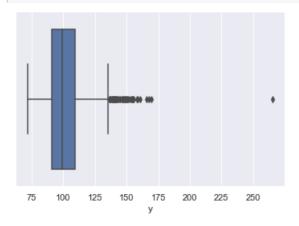
```
y = data['y']
y.describe()
```

Out[7]:

```
4209.000000
count
mean
        100.669318
          12.679381
std
          72.110000
min
25%
          90.820000
          99.150000
50%
75%
         109.010000
         265.320000
Name: y, dtype: float64
```

In [8]:

```
ax = sns.boxplot(data['y'])
```



Observations

- 1. The dataset does not have null values.
- 2. The dataset does not have duplicate values.
- 3. The Prediction column y has some outlier points

We will first remove these outlier points then we will know the features

Knowing the percentiles to decide the threshold to remove the outliers

```
In [9]
```

```
print("Listing all percentiles for training time: ")
print("100: ", np.percentile(data.y,100))
print("99.9: ", np.percentile(data.y,99.9))
print("99.8: ", np.percentile(data.y,99.8))
print("99.7: ", np.percentile(data.y,99.7))
print("99.6: ", np.percentile(data.y,99.6))
print("99.5: ", np.percentile(data.y,99.5))
print("99: ", np.percentile(data.y,99))
Listing all percentiles for training time:
100: 265.32
99.9: 160.38328000000087
99.8: 154.6869599999994
99.7: 151.4276800000003
99.6: 149.037439999998
99.5: 146.2304000000006
99: 137.4304
```

Observations -

We can see from 99.7 percentile onwards the y value is increasing drastically. We decide the threshold as 99.7

Removing Noise

```
In [10]:
```

```
threshold = np.percentile(data.y,99.7)
outlliers = data[data['y']>=threshold]
data.drop(data[data['y']>=threshold].index, inplace = True)
```

Data Shape after removing noise

```
In [11]:
data.shape
Out[11]:
(4196, 378)
In [12]:
Outlliers.head()
Out[12]:
```

	ID	у	X0	X1	X2	Х3	X4	X5	X6	X8	 X375	X376	X377	X378	X379	X380	X382	X383	X384	X385
342	681	169.91	aa	1	ak	f	d	i	С	d	 0	0	0	0	0	0	0	0	0	0

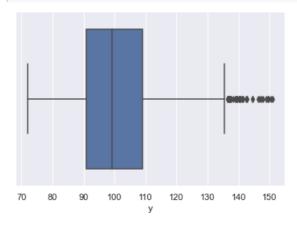
4	129	836 ID	154.87 y	ak X0	x1	ae X2	x3 ^f	$\mathbf{x_4}^{d}$	x ^d	ХĞ	8X	 X375	X376	x37 7	X378	X379	X380	X382	X383	X384	X385
			265.32																		
8	889	1784	158.53	aj	1	as	f	d	ag	k	е	 0	0	0	0	0	0	0	0	0	0
10	060	2111	154.43	W	٧	r	С	d	ag	d	q	 1	0	0	0	0	0	0	0	0	0

5 rows × 378 columns

Box-Plot of y after removing noise

In [13]:

```
ax = sns.boxplot(data['y'])
```



Observations

1. The dataset looks more cleaner now.

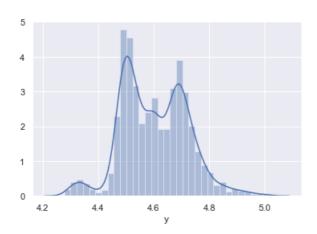
Log Transformation Distribution of target

In [14]:

```
sns.distplot(np.log(data['y']))
```

Out[14]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fa66abcb8e0>



Log Transformation Distribution of target variable in outlier data

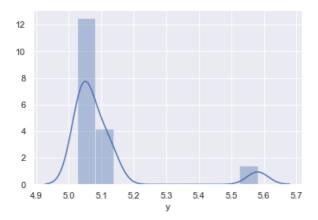
In [15]:

sns.distplot(np.log(outlliers['v']))

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Out[15]:

<matplotlib.axes._subplots.AxesSubplot at 0x7fa66a203640>



Observations

- 1. Most of the y values lie between 80 and 140.
- 2. Only a bunch of values are greater than 150.
- 3. Few values are less than 80.

Selecting important features for EDA

Building a simple XGBoost Model to get Feature Importances

```
In [16]:
```

```
y = data['y']
x = data.drop(columns = ['ID','y'], axis = 1)
#x = x.drop('id')
x.shape, y.shape
cols = x.columns
```

```
In [17]:
```

```
x_cat = data.loc[:,'X0':'X8']
x_num = data.loc[:,'X10':]
```

In [18]:

```
from sklearn.preprocessing import LabelEncoder
enc = LabelEncoder()
for i in x_cat.columns:
    x_cat[i] = enc.fit_transform(x_cat[i])
```

In [19]:

```
x = pd.DataFrame(np.hstack((x_cat,x_num)), columns = cols)
```

In [20]:

```
x.head()
```

Out[20]:

```
      X0
      X1
      X2
      X3
      X4
      X5
      X6
      X8
      X10
      X11
      ...
      X375
      X376
      X377
      X378
      X379
      X380
      X382
      X383
      X384
      X385

      0
      32
      23
      17
      0
      3
      24
      9
      14
      0
      0
      ...
      0
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      1
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```

```
1 X9 X1 X2 X3 X4 X5 X6 X8 X10 X11 ... X375 X376 X377 X378 X378 X380 X382 X383 X384 X385
                        23
                                 0 ...
2 20 24 34
            2
               3
                  27
                      9
                             0
                                             0
                                                                                  0
           5 3 27 11 4
                                 0 ...
                                                                                  0
3 20 21 34
                             0
                                            0
                                0 ... 0
4 20 23 34 5 3 12 3 13
                             0
                                            0
                                                 0
                                                      0
                                                           0
                                                               0
                                                                    0
                                                                         0
                                                                             0
                                                                                  0
```

5 rows × 376 columns

```
In [21]:
```

```
model = XGBRegressor(n_estimators=100, learning_rate = 0.1,n_jobs = -1)
model.fit(x,y)
```

Out[21]:

In [22]:

```
imp = pd.DataFrame()
imp['columns'] = x.columns
imp['importances'] = model.feature_importances_[0]
result = imp.sort_values(by = 'importances')[:10]
```

Top 10 important features with importances

```
In [23]:
```

```
result
```

Out[23]:

	columns	importances
0	X0	0.000737
255	X263	0.000737
254	X262	0.000737
253	X261	0.000737
252	X260	0.000737
251	X259	0.000737
250	X258	0.000737
249	X257	0.000737
248	X256	0.000737
247	X255	0.000737

In [24]:

```
print("The Top 10 important features are : ", list(result['columns']))

The Top 10 important features are : ['X0', 'X263', 'X262', 'X261', 'X260', 'X259', 'X258', 'X257', 'X256', 'X255']
```

EDA for important Features

Knowing important features

```
In [25]:
```

```
imp_features = list(result['columns'])
imp_data = pd.DataFrame()
for i in imp_features:
    imp_data[i] = x[i]
```

In [26]:

```
#plotting categorical columns
fig, ax = plt.subplots(5, 2, figsize=(20, 20))
for variable, subplot in zip(imp_data.columns, ax.flatten()):
      sns.countplot(imp data[variable], ax=subplot)
   300
                                                                              3000
   250
 1 200
8 ...
                                                                             2000
   150
   100
      0 1 2 3 4 5 6 7 8 9 1011121314151617181920212223242526272829303132333435363738394041424344454
                                                                                                                 X263
  4000
                                                                              2000
  3000
8 2000
                                                                               1000
  1000
    0
                                    X262
                                                                                                                 X261
  4000
                                                                               4000
  3000
§ 2000
                                                                             9 2000
    0
                                    X260
                                                                                                                 X259
  4000
                                                                               4000
E 2000
                                                                             8 2000
  1000
                                                                               1000
                                    X258
                                                                                                                 X257
  4000
  3000
                                                                               3000
2000
                                                                             5 2000
                                                                               1000
```

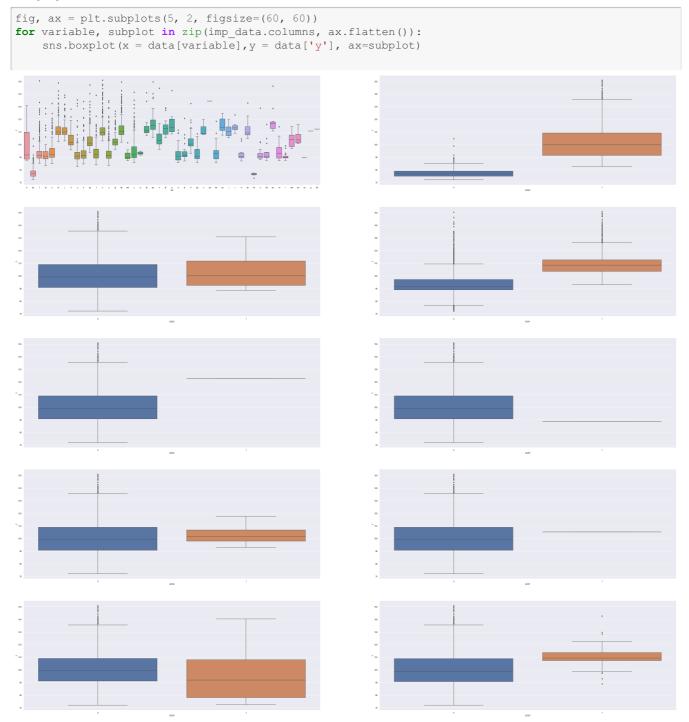
Observations -

- 1. The Categorical Feature X0 has well distributed Categories.
- 2. For the binary features X261 and X263 have significant values of 1 while the rest have mostly 0 values, which means tey are sparse.

Univariate Analysis for Important features

Box - Plot

In [27]:



Observations -

- 1. For binary features X263, X261, X255, X260, X259 the testing time is distinguishable according to the 0 and 1 value.
- 1. For X0 the percentiles for all the categories is distinguishable so we can interpret the testing time according to category.
- 1. For X263, 0 value indicates testing time less than 85 and 1 value indicates testing time between 80 and 130.
- 1. For X261, 0 value indicates testing time between 75 and 110 and 1 value indicates testing time between 100 and 130.

In [28]:

```
fig, ax = plt.subplots(5, 2, figsize=(60, 60))
sns.lineplot(x = data[variable],y = data['y'], ax=subplot)
```

Observations -

- 1. Line Plot is very interpretable for X0 which has many categories, while for binary features this does not give better information than Box-Plot.
- 1. For X0 we can conclude that, category 'aa' results in testing time greater than 130 while categories 'az' and 'bc' result in less than 80. The rest lie between 80 and 130.

```
In [ ]:
```

In []:

Co - relation of features

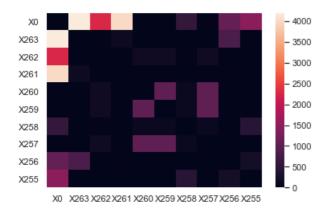
Chi Squared Test

```
In [29]:
```

```
import scipy.stats as stats
rows = imp_data.columns
col = imp data.columns
chi2 matrix = pd.DataFrame(columns = col, index = rows)
p_matrix = pd.DataFrame(columns = col, index = rows)
lesser correlated cols = []
for i in imp_features:
   for j in imp_features:
        if i != j:
            table = pd.crosstab(imp_data[i],imp_data[j])
            #Observed value
            obs_val = table.values
            chi2,p,dof,exp = stats.chi2_contingency(table)
            chi2 matrix[i][j] = chi2
            p_{matrix[i][j]} = p
            if p>=0.05:
                if (j,i) not in lesser correlated cols:
                    lesser_correlated_cols.append((i,j))
chi2 matrix = chi2 matrix.fillna(0)
print("The less realated column pairs are : ")
print(lesser correlated cols)
print("The heatmap for chi square values : ")
print(sns.heatmap(chi2_matrix))
The less realated column pairs are :
```

```
The less realated column pairs are:
[('X0', 'X260'), ('X0', 'X259'), ('X0', 'X257'), ('X263', 'X262'), ('X263', 'X258'), ('X263', 'X25
5'), ('X262', 'X261'), ('X262', 'X256'), ('X262', 'X255'), ('X261', 'X260'), ('X261', 'X259'), ('X
261', 'X257'), ('X261', 'X255'), ('X260', 'X256'), ('X259', 'X256'), ('X258', 'X256'), ('X257', 'X
256')]
The heatmap for chi square values:
```

The heatmap for chi square values: AxesSubplot(0.125,0.125;0.62x0.755)



In [30]:

```
p_matrix = p_matrix.fillna(1)
print("The P-value matrix is :")
print(sns.heatmap(p_matrix))
```

```
The P-value matrix is: AxesSubplot(0.125,0.125;0.62x0.755)
```





Observations -

1. The pair of less related features are :

```
 ('X0', 'X260'), ('X0', 'X259'), ('X0', 'X257'), ('X263', 'X262'), ('X263', 'X258'), ('X263', 'X255'), ('X262', 'X261'), ('X262', 'X256'), ('X262', 'X255'), ('X261', 'X259'), ('X261', 'X259'), ('X261', 'X255'), ('X260', 'X256'), ('X259', 'X256'), ('X258', 'X256'), ('X257', 'X256')
```

1. The above pairs are decided on the basis of p-value, the null hypothesis that the features are not related is accepted.

Now lets see how these lesser corelated column pairs impact the target together

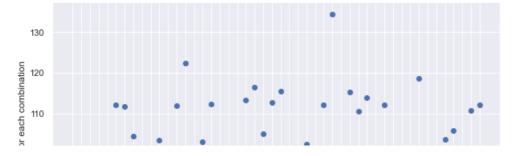
Feature Pairs with XO

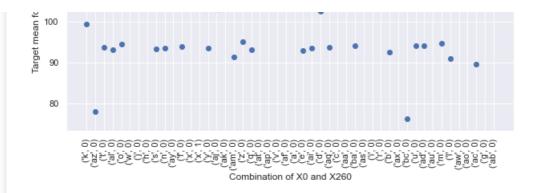
In [31]:

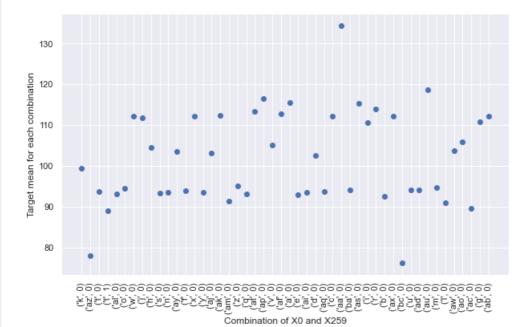
In [32]:

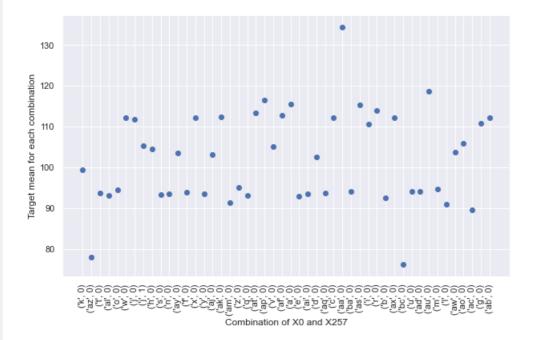
```
for i in lesser_correlated_cols[:3]:
    ans = mean_with_category(i)
    x_plot = ans.keys()
    y_plot = ans.values()

plt.figure(figsize=(10, 6))
    plt.scatter([str(a) for a in x_plot], y_plot)
    plt.xticks(rotation='vertical')
    plt.xlabel("Combination of "+i[0]+ " and "+i[1])
    plt.ylabel("Target mean for each combination")
```









Observations -

1. For the combination X0 with X260, X259, X257, the category 'aa' and value 0 has highest testing time mean and 'bc' and 0 has lowest.

Binary-Binary features

In [33]:

```
fig, ax = plt.subplots(14, 1, figsize=(5, 40))
for i ,subplot in zip(lesser_correlated_cols[3:], ax.flatten()):
    ans = mean_with_category(i)
    x_plot = ans.keys()
    y_plot = ans.values()
    subplot.scatter([str(a) for a in x_plot], y_plot)
    subplot.set_title("Combination of "+i[0]+ " and "+i[1]+" VS testing Time")
    fig.tight_layout(pad=3.0)
```

Combination of X263 and X262 VS testing Time 105 100 95 90 85 80 (1, 1) (1, 0) (0, 0)

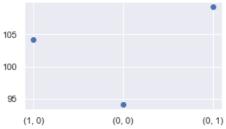
Combination of X263 and X258 VS testing Time



Combination of X263 and X255 VS testing Time



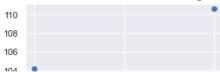
Combination of X262 and X261 VS testing Time



Combination of X262 and X256 VS testing Time



Combination of X262 and X255 VS testing Time



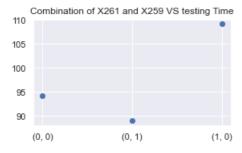


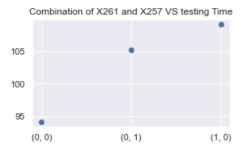


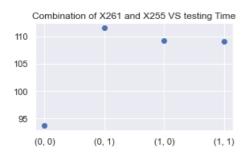
(1, 0)

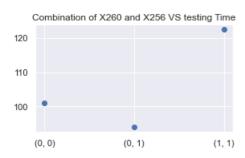
(1, 1)

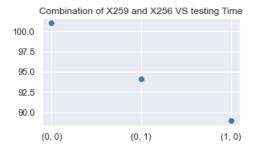
(0, 0)



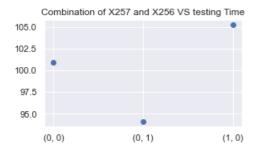








Combination of X258 and X256 VS testing Time 102 100 98 96 94 (0, 0) (0, 1) (1, 0)



Observations -

1. For X263 and X262,

if both have 0 values the average testing time is less than 80. if X263 has 1 and X262 has 0, the average testing time is more than 100. if both have value 1, the average testing time is more than 105.

1. For X263 and X258,

if both have 0 values the average testing time is less than 80. if X263 has 1 and X258 has 0, the average testing time is close to 100. if both have value 1, the average testing time is more than 100.

1. For X263 and X255,

if both have 0 values the average testing time is less than 80. if X263 has 1 and X255 has 0, the average testing time is close to 100. if both have value 1, the average testing time is more than 110.

1. For X262 and X261,

if both have 0 values the average testing time is less than 95. if X262 has 1 and X261 has 0, the average testing time is close to 105. if X262 has 0 and X261 has 1, the average testing time is more than 105.

1. For X262 and X256,

if both have 0 values the average testing time is close to 101. if X262 has 1 and X256 has 0, the average testing time is close to 104. if X262 has 0 and X261 has 1, the average testing time is more than 94.

1. For X262 and X255,

if both have 0 values the average testing time is close to 100. if X262 has 1 and X255 has 0, the average testing time is close to 104. if X262 has 0 and X255 has 1, the average testing time is more than 110.

1. For X261 and X260,

if both have 0 values the average testing time is less than 100. if X261 has 1 and X260 has 0, the average testing time is close to 110. if both have value 1, the average testing time is more than 120.

1. For X261 and X259.

if both have 0 values the average testing time is close to 95. if X261 has 0 and X259 has 1, the average testing time is less than 90. if X261 has 1 and X259 has 0, the average testing time is close to 110.

1. For X261 and X257,

if both have 0 values the average testing time is close to 95. if X261 has 0 and X257 has 1, the average testing time is less than 105. if X261 has 1 and X257 has 0, the average testing time is close to 110.

1. For X261 and X255,

if both have 0 values the average testing time is close to 95. if X261 has 0 and X255 has 1, the average testing time is more than 110. if X261 has 1 and X257 has 0, the average testing time is close to 110. if both have value 1, the average testing time is close to 110.

1. For X260 and X256,

if both have 0 values the average testing time is close to 100. if X260 has 0 and X256 has 1, the average testing time is less than 100. if both have value 1, the average testing time is more than 120.

1. For X259 and X256.

if both have 0 values the average testing time is close to 100. if X259 has 0 and X256 has 1, the average testing time is close to 94. if X259 has 1 and X256 has 0, the average testing time is more than 120.

1. For X258 and X256,

if both have 0 values the average testing time is close to 101. if X258 has 0 and X256 has 1, the average testing time is close to 94. if X258 has 1 and X256 has 0, the average testing time is more than 102.

1. For X257 and X256,

if both have 0 values the average testing time is close to 101. if X257 has 0 and X256 has 1, the average testing time is close to 94. if X257 has 1 and X256 has 0, the average testing time is more than 105.

EDA - Conclusion

- 1. There are no null and duplicate values in the data.
- 2. Categorical features seem to hold more information as they are more widely present and also account for testing time geater than 130 and less than 80. Also they give information about for testing time between 80 and 130
- 3. The numerical features are either 0 or 1 with most of the values being 0.
- 4. The most important features are 'X0', 'X263', 'X262', 'X261', 'X260', 'X259', 'X258', 'X257', 'X256', 'X255'
- 5. The prediction column y has most values between 80 and 150.

Feature Engineering

```
In [34]:
```

```
# split into train test sets
from sklearn.model_selection import train_test_split
y = data['y']
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random_state=1)
print("Done")
```

Done

Baseline model

model which outputs mean

```
In [35]:
```

```
y_pred_value = y_train.mean()
y_pred = []
for i in range(0,len(y_test)):
    y_pred.append(y_pred_value)
```

```
In [36]:
```

```
from sklearn.metrics import r2_score
```

```
score = rz_score(y_test, y_prea)
print(score)
-0.002042687819177935
In [ ]:
In [ ]:
In [37]:
x.head()
Out[37]:
  X0 X1 X2 X3 X4 X5 X6 X8 X10 X11 ... X375 X376 X377 X378 X379 X380 X382 X383 X384 X385
1 32 21 19
             4 3 28 11 14
                                   0 ...
                                          1
                                               Λ
                                                    0
                                                         Λ
                                                              Λ
                                                                   n
                                                                       Λ
                                                                                 0
                                                                                      0
                              0
                                                                            n
                                   0 ...
2 20 24 34
             2
                3 27
                      9 23
                              0
                                          0
                                               0
                                                    0
                                                         0
                                                              0
                                                                                      0
3 20 21 34 5 3 27 11 4
                              0
                                   0 ...
                                          0
                                               0
                                                    0
                                                         0
                                                             0
                                                                  0
                                                                       0
                                                                            0
                                                                                      0
                                                                                 0
                                  0 ... 0 0
4 20 23 34 5 3 12 3 13
                              0
5 rows × 376 columns
In [38]:
# split into train test sets
y = data['y']
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random_state=1)
print("Done")
Done
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(X train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
In [40]:
 #train autoencoder for regression with no compression in the bottleneck layer
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import LeakyReLU
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.utils import plot model
from matplotlib import pyplot
from keras import backend as K
In [41]:
n inputs = x.shape[1]
```

In [42]:

```
# define encoder
input_data = Input(shape=(n_inputs,))
#encoder level 1
encoder = Dense(n inputs*2)(input data)
encoder = BatchNormalization() (encoder)
encoder = LeakyReLU()(encoder)
# define bottleneck
n bottleneck = n inputs
bottleneck = Dense(n_bottleneck)(encoder)
# decoder level 2
decoder = Dense(n_inputs*2) (bottleneck)
decoder = BatchNormalization()(decoder)
decoder = LeakyReLU()(decoder)
# output layer
output = Dense(n inputs, activation='linear')(decoder)
# define autoencoder model
model = Model(inputs=input data, outputs=output)
# compile autoencoder model
model.compile(optimizer='adam', loss='mse')
```

In [43]:

model.summary()

Model: "model"

Layer (type) 	Output Shape	Param #
input_1 (InputLayer)	[(None, 376)]	0
dense (Dense)	(None, 752)	283504
oatch_normalization (BatchNo	(None, 752)	3008
leaky_re_lu (LeakyReLU)	(None, 752)	0
dense_1 (Dense)	(None, 376)	283128
dense_2 (Dense)	(None, 752)	283504
oatch_normalization_1 (Batch	(None, 752)	3008
leaky_re_lu_1 (LeakyReLU)	(None, 752)	0
dense_3 (Dense)	(None, 376)	283128
Total params: 1,139,280 Trainable params: 1,136,272		

In [44]:

Non-trainable params: 3,008

```
# plot the autoencoder
plot_model(model, 'autoencoder.png', show_shapes=True)

# fit the autoencoder model to reconstruct input
history = model.fit(X_train, y_train, epochs=400, batch_size=16, verbose=2, validation_data=(X_test,y_test))
# plot loss
pyplot.plot(history.history['loss'], label='train')
pyplot.plot(history.history['val_loss'], label='test')
pyplot.legend()
pyplot.show()
# define an encoder model (without the decoder)
encoder = Model(inputs=input_data, outputs=bottleneck)
plot_model(encoder, 'encoder.png', show_shapes=True)
# save the encoder to file
encoder.save('encoder.h5')
```

('Failed to import pydot. You must 'pip install pydot' and install graphyiz

```
(https://graphviz.gitlab.io/download/), ', 'for `pydotprint` to work.')
Epoch 1/400
176/176 - 3s - loss: 5499.0928 - val_loss: 1826.5393
Epoch 2/400
176/176 - 1s - loss: 422.9340 - val loss: 391.2757
Epoch 3/400
176/176 - 1s - loss: 133.7853 - val loss: 194.6954
Epoch 4/400
176/176 - 1s - loss: 106.5347 - val loss: 88.7789
Epoch 5/400
176/176 - 1s - loss: 106.5038 - val_loss: 99.2424
Epoch 6/400
176/176 - 1s - loss: 100.0545 - val loss: 164.7752
Epoch 7/400
176/176 - 1s - loss: 90.8175 - val loss: 103.7822
Epoch 8/400
176/176 - 1s - loss: 84.8220 - val_loss: 92.4677
Epoch 9/400
176/176 - 1s - loss: 82.8022 - val loss: 128.8290
Epoch 10/400
176/176 - 1s - loss: 88.1136 - val loss: 93.5977
Epoch 11/400
176/176 - 1s - loss: 82.5877 - val loss: 81.1296
Epoch 12/400
176/176 - 1s - loss: 76.0784 - val loss: 85.6597
Epoch 13/400
176/176 - 1s - loss: 78.2701 - val loss: 72.4152
Epoch 14/400
176/176 - 1s - loss: 79.6855 - val loss: 72.8835
Epoch 15/400
176/176 - 1s - loss: 74.8075 - val loss: 74.6937
Epoch 16/400
176/176 - 1s - loss: 68.1959 - val_loss: 66.9120
Epoch 17/400
176/176 - 1s - loss: 69.8392 - val loss: 79.9594
Epoch 18/400
176/176 - 1s - loss: 70.8375 - val loss: 76.1121
Epoch 19/400
176/176 - 2s - loss: 70.6452 - val loss: 76.6279
Epoch 20/400
176/176 - 2s - loss: 68.7051 - val loss: 70.2009
Epoch 21/400
176/176 - 2s - loss: 65.8434 - val_loss: 75.0868
Epoch 22/400
176/176 - 2s - loss: 66.7507 - val loss: 65.8429
Epoch 23/400
176/176 - 1s - loss: 65.5383 - val_loss: 70.0330
Epoch 24/400
176/176 - 2s - loss: 65.2324 - val loss: 75.0619
Epoch 25/400
176/176 - 1s - loss: 65.7619 - val loss: 75.8300
Epoch 26/400
176/176 - 1s - loss: 64.8737 - val loss: 74.5101
Epoch 27/400
176/176 - 2s - loss: 66.2497 - val_loss: 66.1449
Epoch 28/400
176/176 - 1s - loss: 61.2127 - val loss: 74.3116
Epoch 29/400
176/176 - 1s - loss: 63.1190 - val loss: 73.6189
Epoch 30/400
176/176 - 2s - loss: 65.7285 - val loss: 96.1582
Epoch 31/400
176/176 - 2s - loss: 62.6298 - val_loss: 72.1713
Epoch 32/400
176/176 - 2s - loss: 60.6657 - val loss: 77.7556
Epoch 33/400
176/176 - 2s - loss: 62.9241 - val loss: 68.8074
Epoch 34/400
176/176 - 2s - loss: 62.9711 - val_loss: 68.9775
Epoch 35/400
176/176 - 2s - loss: 59.9610 - val loss: 74.4107
Epoch 36/400
176/176 - 2s - loss: 61.3350 - val_loss: 86.2266
Epoch 37/400
176/176 - 2s - loss: 58.2212 - val_loss: 76.8918
Epoch 38/400
176/176 - 1s - loss: 56.9443 - val loss: 68.5377
```

```
_____
                              var 1000. 00.00,,
Epoch 39/400
176/176 - 1s - loss: 60.5161 - val loss: 84.7164
Epoch 40/400
176/176 - 1s - loss: 57.7570 - val loss: 68.3400
Epoch 41/400
176/176 - 2s - loss: 58.8814 - val loss: 81.0477
Epoch 42/400
176/176 - 2s - loss: 57.2878 - val loss: 76.2670
Epoch 43/400
176/176 - 2s - loss: 54.8938 - val loss: 69.1802
Epoch 44/400
176/176 - 2s - loss: 58.0282 - val_loss: 84.9829
Epoch 45/400
176/176 - 2s - loss: 56.5856 - val_loss: 80.8975
Epoch 46/400
176/176 - 2s - loss: 53.3907 - val loss: 72.7264
Epoch 47/400
176/176 - 1s - loss: 54.5113 - val loss: 86.7194
Epoch 48/400
176/176 - 2s - loss: 54.6124 - val_loss: 66.3194
Epoch 49/400
176/176 - 2s - loss: 54.5340 - val loss: 67.7091
Epoch 50/400
176/176 - 2s - loss: 53.2115 - val loss: 73.5927
Epoch 51/400
176/176 - 2s - loss: 52.1238 - val_loss: 71.7823
Epoch 52/400
176/176 - 2s - loss: 53.4635 - val loss: 97.1081
Epoch 53/400
176/176 - 1s - loss: 54.1837 - val_loss: 68.5108
Epoch 54/400
176/176 - 1s - loss: 54.2739 - val loss: 66.4236
Epoch 55/400
176/176 - 1s - loss: 55.0513 - val_loss: 69.6937
Epoch 56/400
176/176 - 1s - loss: 52.5711 - val loss: 81.7859
Epoch 57/400
176/176 - 1s - loss: 54.8904 - val loss: 75.9867
Epoch 58/400
176/176 - 2s - loss: 52.0961 - val loss: 98.8686
Epoch 59/400
176/176 - 2s - loss: 53.4520 - val loss: 74.7452
Epoch 60/400
176/176 - 2s - loss: 52.7307 - val loss: 69.3547
Epoch 61/400
176/176 - 2s - loss: 51.4843 - val loss: 76.7101
Epoch 62/400
176/176 - 1s - loss: 51.2800 - val_loss: 69.2934
Epoch 63/400
176/176 - 1s - loss: 51.7591 - val_loss: 73.5051
Epoch 64/400
176/176 - 2s - loss: 50.8940 - val loss: 69.4393
Epoch 65/400
176/176 - 2s - loss: 52.2141 - val loss: 69.5699
Epoch 66/400
176/176 - 2s - loss: 51.0712 - val loss: 80.3294
Epoch 67/400
176/176 - 1s - loss: 52.2058 - val loss: 70.1714
Epoch 68/400
176/176 - 1s - loss: 49.1044 - val_loss: 69.8486
Epoch 69/400
176/176 - 2s - loss: 50.4404 - val loss: 96.3290
Epoch 70/400
176/176 - 2s - loss: 47.4721 - val_loss: 70.7383
Epoch 71/400
176/176 - 2s - loss: 47.6107 - val loss: 70.6391
Epoch 72/400
176/176 - 1s - loss: 49.1079 - val loss: 78.2389
Epoch 73/400
176/176 - 2s - loss: 49.7241 - val loss: 69.7560
Epoch 74/400
176/176 - 2s - loss: 50.0472 - val_loss: 100.3777
Epoch 75/400
176/176 - 2s - loss: 48.2729 - val loss: 76.0493
Epoch 76/400
176/176 - 2s - loss: 49.5903 - val loss: 73.7908
Enoch 77/400
```

```
Thocii 11/400
176/176 - 2s - loss: 50.1444 - val_loss: 69.7101
Epoch 78/400
176/176 - 2s - loss: 47.6211 - val loss: 69.6636
Epoch 79/400
176/176 - 2s - loss: 46.8562 - val loss: 70.6914
Epoch 80/400
176/176 - 2s - loss: 49.3114 - val loss: 75.9259
Epoch 81/400
176/176 - 2s - loss: 46.6632 - val loss: 84.2512
Epoch 82/400
176/176 - 2s - loss: 48.5955 - val loss: 81.8557
Epoch 83/400
176/176 - 2s - loss: 47.8074 - val loss: 70.3463
Epoch 84/400
176/176 - 2s - loss: 47.3706 - val loss: 74.1677
Epoch 85/400
176/176 - 2s - loss: 47.3961 - val loss: 75.6681
Epoch 86/400
176/176 - 1s - loss: 46.1290 - val loss: 71.4274
Epoch 87/400
176/176 - 2s - loss: 48.0312 - val loss: 77.7676
Epoch 88/400
176/176 - 1s - loss: 47.7145 - val loss: 71.8181
Epoch 89/400
176/176 - 1s - loss: 47.0475 - val loss: 72.4865
Epoch 90/400
176/176 - 1s - loss: 46.4600 - val loss: 70.9406
Epoch 91/400
176/176 - 1s - loss: 44.2532 - val_loss: 72.1382
Epoch 92/400
176/176 - 1s - loss: 45.9137 - val loss: 69.8645
Epoch 93/400
176/176 - 1s - loss: 44.8460 - val loss: 71.5068
Epoch 94/400
176/176 - 1s - loss: 46.4233 - val loss: 89.4306
Epoch 95/400
176/176 - 2s - loss: 44.3616 - val_loss: 76.4762
Epoch 96/400
176/176 - 2s - loss: 47.1931 - val loss: 78.4553
Epoch 97/400
176/176 - 2s - loss: 45.6001 - val loss: 73.3102
Epoch 98/400
176/176 - 1s - loss: 44.1569 - val loss: 70.1398
Epoch 99/400
176/176 - 2s - loss: 44.0157 - val_loss: 70.5667
Epoch 100/400
176/176 - 2s - loss: 44.1801 - val loss: 72.3570
Epoch 101/400
176/176 - 1s - loss: 43.1739 - val loss: 71.0491
Epoch 102/400
176/176 - 1s - loss: 43.5431 - val_loss: 71.3291
Epoch 103/400
176/176 - 1s - loss: 43.7190 - val loss: 67.7769
Epoch 104/400
176/176 - 1s - loss: 42.9169 - val loss: 73.9759
Epoch 105/400
176/176 - 1s - loss: 44.9072 - val loss: 73.2137
Epoch 106/400
176/176 - 1s - loss: 44.4389 - val loss: 72.0213
Epoch 107/400
176/176 - 2s - loss: 45.2041 - val loss: 115.4611
Epoch 108/400
176/176 - 2s - loss: 44.4686 - val loss: 79.0440
Epoch 109/400
176/176 - 1s - loss: 44.5816 - val_loss: 94.7577
Epoch 110/400
176/176 - 1s - loss: 42.6605 - val_loss: 71.8696
Epoch 111/400
176/176 - 2s - loss: 42.3586 - val loss: 77.9566
Epoch 112/400
176/176 - 2s - loss: 42.8234 - val loss: 70.3982
Epoch 113/400
176/176 - 2s - loss: 44.0534 - val_loss: 69.7192
Epoch 114/400
176/176 - 1s - loss: 42.7242 - val_loss: 79.7198
Epoch 115/400
176/176 - 10 - 1000 AR RADO - TOOL 1000 75 2020
```

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1/0/1/0 - 15 - 1055. 43.3432 - Val_1055. /3.2323
Epoch 116/400
176/176 - 1s - loss: 44.7026 - val_loss: 70.6786
Epoch 117/400
176/176 - 1s - loss: 40.3295 - val loss: 72.5420
Epoch 118/400
176/176 - 2s - loss: 41.7095 - val loss: 76.0517
Epoch 119/400
176/176 - 1s - loss: 41.4533 - val loss: 76.0074
Epoch 120/400
176/176 - 2s - loss: 42.7494 - val loss: 81.4865
Epoch 121/400
176/176 - 2s - loss: 42.9156 - val loss: 73.0981
Epoch 122/400
176/176 - 2s - loss: 43.4649 - val loss: 73.1937
Epoch 123/400
176/176 - 2s - loss: 42.5243 - val_loss: 77.2516
Epoch 124/400
176/176 - 1s - loss: 41.3700 - val_loss: 78.2918
Epoch 125/400
176/176 - 1s - loss: 42.2446 - val loss: 75.7171
Epoch 126/400
176/176 - 1s - loss: 40.5677 - val loss: 74.2784
Epoch 127/400
176/176 - 1s - loss: 40.8233 - val_loss: 70.9316
Epoch 128/400
176/176 - 2s - loss: 41.8471 - val loss: 84.5435
Epoch 129/400
176/176 - 2s - loss: 40.2313 - val loss: 76.5672
Epoch 130/400
176/176 - 1s - loss: 41.4740 - val loss: 74.1562
Epoch 131/400
176/176 - 2s - loss: 40.3366 - val_loss: 86.9290
Epoch 132/400
176/176 - 2s - loss: 42.7090 - val_loss: 72.3119
Epoch 133/400
176/176 - 2s - loss: 42.9966 - val loss: 70.6961
Epoch 134/400
176/176 - 2s - loss: 41.2937 - val loss: 79.9082
Epoch 135/400
176/176 - 2s - loss: 41.0696 - val_loss: 73.8363
Epoch 136/400
176/176 - 2s - loss: 42.9793 - val loss: 73.7382
Epoch 137/400
176/176 - 1s - loss: 42.5368 - val loss: 69.0523
Epoch 138/400
176/176 - 1s - loss: 40.1117 - val_loss: 73.8824
Epoch 139/400
176/176 - 2s - loss: 40.7774 - val loss: 69.0042
Epoch 140/400
176/176 - 2s - loss: 41.0509 - val loss: 69.2200
Epoch 141/400
176/176 - 2s - loss: 38.3438 - val loss: 70.4052
Epoch 142/400
176/176 - 2s - loss: 40.0507 - val loss: 71.5636
Epoch 143/400
176/176 - 2s - loss: 39.3088 - val loss: 80.3238
Epoch 144/400
176/176 - 2s - loss: 40.9407 - val loss: 72.5842
Epoch 145/400
176/176 - 2s - loss: 39.7627 - val_loss: 79.4307
Epoch 146/400
176/176 - 2s - loss: 39.5249 - val_loss: 73.1918
Epoch 147/400
176/176 - 2s - loss: 40.9066 - val loss: 75.2320
Epoch 148/400
176/176 - 2s - loss: 39.5795 - val loss: 71.3494
Epoch 149/400
176/176 - 2s - loss: 41.2543 - val loss: 70.9091
Epoch 150/400
176/176 - 2s - loss: 39.8834 - val loss: 79.1727
Epoch 151/400
176/176 - 1s - loss: 39.1067 - val loss: 77.6904
Epoch 152/400
176/176 - 2s - loss: 39.0470 - val loss: 73.6002
Epoch 153/400
176/176 - 1s - loss: 39.8822 - val_loss: 78.8301
Enach 15///00
```

```
FDOCII TO4/400
176/176 - 1s - loss: 39.2833 - val loss: 73.7295
Epoch 155/400
176/176 - 2s - loss: 40.4391 - val_loss: 71.4960
Epoch 156/400
176/176 - 1s - loss: 40.0136 - val_loss: 75.5244
Epoch 157/400
176/176 - 1s - loss: 38.7439 - val loss: 83.7063
Epoch 158/400
176/176 - 1s - loss: 39.8912 - val loss: 74.8859
Epoch 159/400
176/176 - 1s - loss: 37.6503 - val loss: 82.7705
Epoch 160/400
176/176 - 2s - loss: 38.6661 - val loss: 75.3175
Epoch 161/400
176/176 - 1s - loss: 38.5554 - val loss: 74.6078
Epoch 162/400
176/176 - 1s - loss: 38.1169 - val loss: 73.9857
Epoch 163/400
176/176 - 1s - loss: 41.2674 - val_loss: 73.9493
Epoch 164/400
176/176 - 2s - loss: 38.0883 - val loss: 75.5907
Epoch 165/400
176/176 - 2s - loss: 39.0672 - val loss: 72.2326
Epoch 166/400
176/176 - 2s - loss: 38.2700 - val loss: 74.8087
Epoch 167/400
176/176 - 2s - loss: 39.9395 - val loss: 76.7045
Epoch 168/400
176/176 - 2s - loss: 36.7781 - val loss: 72.2839
Epoch 169/400
176/176 - 2s - loss: 37.7477 - val loss: 73.0197
Epoch 170/400
176/176 - 1s - loss: 39.4674 - val_loss: 73.2275
Epoch 171/400
176/176 - 1s - loss: 37.6219 - val loss: 73.5224
Epoch 172/400
176/176 - 1s - loss: 38.5473 - val loss: 77.6256
Epoch 173/400
176/176 - 1s - loss: 38.4783 - val loss: 73.6294
Epoch 174/400
176/176 - 1s - loss: 37.7623 - val_loss: 77.3915
Epoch 175/400
176/176 - 1s - loss: 39.4547 - val loss: 72.7528
Epoch 176/400
176/176 - 2s - loss: 38.4913 - val loss: 71.6550
Epoch 177/400
176/176 - 2s - loss: 37.5861 - val_loss: 73.1824
Epoch 178/400
176/176 - 2s - loss: 37.1741 - val_loss: 72.0115
Epoch 179/400
176/176 - 1s - loss: 36.5765 - val_loss: 74.4579
Epoch 180/400
176/176 - 1s - loss: 37.1536 - val loss: 75.2929
Epoch 181/400
176/176 - 1s - loss: 38.8787 - val loss: 73.1412
Epoch 182/400
176/176 - 1s - loss: 36.8764 - val loss: 80.0059
Epoch 183/400
176/176 - 2s - loss: 37.2026 - val loss: 99.5892
Epoch 184/400
176/176 - 2s - loss: 37.8607 - val loss: 74.6229
Epoch 185/400
176/176 - 2s - loss: 35.9972 - val_loss: 75.9495
Epoch 186/400
176/176 - 2s - loss: 38.0483 - val loss: 75.6715
Epoch 187/400
176/176 - 1s - loss: 37.7373 - val loss: 78.9413
Epoch 188/400
176/176 - 2s - loss: 36.8910 - val loss: 75.2199
Epoch 189/400
176/176 - 1s - loss: 36.5872 - val_loss: 74.4051
Epoch 190/400
176/176 - 1s - loss: 37.6495 - val loss: 75.0209
Epoch 191/400
176/176 - 2s - loss: 38.1606 - val loss: 77.1153
Epoch 192/400
```

```
Epoch 193/400
176/176 - 1s - loss: 37.9695 - val loss: 79.2579
Epoch 194/400
176/176 - 1s - loss: 37.9605 - val loss: 74.8661
Epoch 195/400
176/176 - 1s - loss: 36.6880 - val_loss: 79.2404
Epoch 196/400
176/176 - 1s - loss: 37.6131 - val loss: 85.9251
Epoch 197/400
176/176 - 1s - loss: 36.7191 - val loss: 73.4023
Epoch 198/400
176/176 - 1s - loss: 36.2469 - val loss: 72.7060
Epoch 199/400
176/176 - 1s - loss: 35.5827 - val_loss: 79.9430
Epoch 200/400
176/176 - 1s - loss: 36.2927 - val loss: 78.2766
Epoch 201/400
176/176 - 1s - loss: 35.9062 - val loss: 76.6085
Epoch 202/400
176/176 - 1s - loss: 35.0304 - val loss: 79.1186
Epoch 203/400
176/176 - 2s - loss: 36.6377 - val_loss: 72.0735
Epoch 204/400
176/176 - 1s - loss: 37.4170 - val loss: 72.2780
Epoch 205/400
176/176 - 2s - loss: 36.9788 - val loss: 87.4624
Epoch 206/400
176/176 - 1s - loss: 35.9530 - val loss: 75.5042
Epoch 207/400
176/176 - 2s - loss: 35.2597 - val loss: 76.0645
Epoch 208/400
176/176 - 1s - loss: 36.6005 - val loss: 73.0535
Epoch 209/400
176/176 - 2s - loss: 34.9531 - val loss: 72.1466
Epoch 210/400
176/176 - 1s - loss: 34.4998 - val_loss: 88.3679
Epoch 211/400
176/176 - 1s - loss: 34.9375 - val loss: 71.7683
Epoch 212/400
176/176 - 1s - loss: 36.7127 - val loss: 90.3684
Epoch 213/400
176/176 - 1s - loss: 36.4936 - val_loss: 70.9737
Epoch 214/400
176/176 - 1s - loss: 35.5509 - val loss: 78.3897
Epoch 215/400
176/176 - 1s - loss: 35.0383 - val loss: 73.7384
Epoch 216/400
176/176 - 1s - loss: 35.4438 - val loss: 71.8860
Epoch 217/400
176/176 - 2s - loss: 34.8358 - val_loss: 72.6873
Epoch 218/400
176/176 - 2s - loss: 37.7358 - val loss: 85.1001
Epoch 219/400
176/176 - 2s - loss: 34.5646 - val loss: 72.8228
Epoch 220/400
176/176 - 2s - loss: 35.7835 - val_loss: 79.1234
Epoch 221/400
176/176 - 2s - loss: 36.3326 - val_loss: 80.5708
Epoch 222/400
176/176 - 1s - loss: 36.7242 - val loss: 76.8412
Epoch 223/400
176/176 - 2s - loss: 35.8849 - val loss: 76.0899
Epoch 224/400
176/176 - 2s - loss: 36.7013 - val loss: 72.3019
Epoch 225/400
176/176 - 2s - loss: 35.1019 - val_loss: 74.7658
Epoch 226/400
176/176 - 2s - loss: 33.3039 - val loss: 70.9419
Epoch 227/400
176/176 - 2s - loss: 36.4513 - val loss: 77.6647
Epoch 228/400
176/176 - 2s - loss: 33.1491 - val loss: 71.9657
Epoch 229/400
176/176 - 2s - loss: 34.9525 - val loss: 75.7952
Epoch 230/400
176/176 - 2s - loss: 34.1068 - val loss: 75.2301
```

1/6/1/6 - IS - 10SS: 3/.U05U - Val 10SS: /3.453/

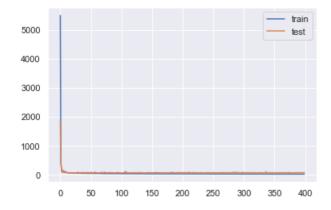
```
Epoch 231/400
176/176 - 1s - loss: 33.1462 - val loss: 76.3310
Epoch 232/400
176/176 - 1s - loss: 35.9665 - val loss: 78.5925
Epoch 233/400
176/176 - 1s - loss: 35.2663 - val loss: 76.5972
Epoch 234/400
176/176 - 1s - loss: 34.4851 - val_loss: 74.7185
Epoch 235/400
176/176 - 1s - loss: 37.1037 - val_loss: 72.6755
Epoch 236/400
176/176 - 2s - loss: 35.0229 - val loss: 74.4079
Epoch 237/400
176/176 - 2s - loss: 33.2192 - val loss: 70.5984
Epoch 238/400
176/176 - 2s - loss: 34.8407 - val loss: 72.2998
Epoch 239/400
176/176 - 2s - loss: 33.0130 - val loss: 73.6929
Epoch 240/400
176/176 - 1s - loss: 34.9152 - val_loss: 76.1458
Epoch 241/400
176/176 - 1s - loss: 36.7966 - val loss: 82.6680
Epoch 242/400
176/176 - 1s - loss: 35.2473 - val_loss: 76.0237
Epoch 243/400
176/176 - 1s - loss: 32.1315 - val loss: 79.9937
Epoch 244/400
176/176 - 2s - loss: 34.1305 - val loss: 78.1944
Epoch 245/400
176/176 - 2s - loss: 34.9625 - val loss: 71.9832
Epoch 246/400
176/176 - 2s - loss: 34.0084 - val loss: 77.7942
Epoch 247/400
176/176 - 2s - loss: 33.2884 - val loss: 73.2565
Epoch 248/400
176/176 - 2s - loss: 33.8622 - val loss: 72.2278
Epoch 249/400
176/176 - 2s - loss: 34.4497 - val_loss: 74.2774
Epoch 250/400
176/176 - 2s - loss: 33.3307 - val loss: 72.0307
Epoch 251/400
176/176 - 2s - loss: 32.8144 - val loss: 85.4721
Epoch 252/400
176/176 - 1s - loss: 33.4107 - val loss: 71.5661
Epoch 253/400
176/176 - 1s - loss: 34.1140 - val_loss: 78.3422
Epoch 254/400
176/176 - 1s - loss: 33.4270 - val loss: 75.4869
Epoch 255/400
176/176 - 1s - loss: 34.1697 - val loss: 72.0176
Epoch 256/400
176/176 - 1s - loss: 33.3299 - val_loss: 76.4766
Epoch 257/400
176/176 - 2s - loss: 33.7922 - val_loss: 73.4611
Epoch 258/400
176/176 - 2s - loss: 32.8450 - val loss: 77.0736
Epoch 259/400
176/176 - 2s - loss: 31.7463 - val loss: 76.3922
Epoch 260/400
176/176 - 2s - loss: 32.4095 - val loss: 76.6776
Epoch 261/400
176/176 - 2s - loss: 34.0251 - val loss: 74.7458
Epoch 262/400
176/176 - 2s - loss: 33.6038 - val_loss: 73.0118
Epoch 263/400
176/176 - 2s - loss: 30.4197 - val loss: 77.0520
Epoch 264/400
176/176 - 2s - loss: 33.4008 - val loss: 73.2791
Epoch 265/400
176/176 - 2s - loss: 33.7199 - val loss: 73.9358
Epoch 266/400
176/176 - 1s - loss: 33.2749 - val loss: 87.7678
Epoch 267/400
176/176 - 1s - loss: 34.3428 - val loss: 76.8553
Epoch 268/400
176/176 - 2s - loss: 33.5765 - val_loss: 77.1879
Epoch 269/400
                     . . . . . .
```

```
176/176 - 2s - loss: 32.9146 - val loss: 75.0721
Epoch 270/400
176/176 - 2s - loss: 34.2702 - val loss: 75.6055
Epoch 271/400
176/176 - 2s - loss: 33.6392 - val_loss: 73.0568
Epoch 272/400
176/176 - 2s - loss: 32.6657 - val_loss: 80.1733
Epoch 273/400
176/176 - 2s - loss: 33.3614 - val loss: 74.5138
Epoch 274/400
176/176 - 2s - loss: 33.0479 - val loss: 73.6188
Epoch 275/400
176/176 - 1s - loss: 33.7294 - val loss: 71.8412
Epoch 276/400
176/176 - 2s - loss: 31.4378 - val loss: 83.2375
Epoch 277/400
176/176 - 2s - loss: 32.7230 - val loss: 77.3573
Epoch 278/400
176/176 - 1s - loss: 34.4467 - val loss: 74.4060
Epoch 279/400
176/176 - 2s - loss: 31.7374 - val_loss: 76.6179
Epoch 280/400
176/176 - 2s - loss: 32.0174 - val loss: 77.4170
Epoch 281/400
176/176 - 2s - loss: 32.1911 - val loss: 78.0881
Epoch 282/400
176/176 - 2s - loss: 32.2001 - val_loss: 77.5577
Epoch 283/400
176/176 - 2s - loss: 32.9292 - val loss: 90.0914
Epoch 284/400
176/176 - 2s - loss: 34.2033 - val loss: 70.1018
Epoch 285/400
176/176 - 2s - loss: 31.6988 - val_loss: 75.9812
Epoch 286/400
176/176 - 2s - loss: 33.8524 - val_loss: 95.5078
Epoch 287/400
176/176 - 2s - loss: 33.5633 - val loss: 95.2012
Epoch 288/400
176/176 - 2s - loss: 31.8574 - val loss: 71.6039
Epoch 289/400
176/176 - 2s - loss: 32.8924 - val loss: 86.2127
Epoch 290/400
176/176 - 1s - loss: 32.3214 - val loss: 87.0471
Epoch 291/400
176/176 - 1s - loss: 32.8245 - val loss: 78.1744
Epoch 292/400
176/176 - 1s - loss: 32.1466 - val loss: 73.3320
Epoch 293/400
176/176 - 2s - loss: 31.9461 - val_loss: 76.3347
Epoch 294/400
176/176 - 1s - loss: 33.3875 - val_loss: 80.0905
Epoch 295/400
176/176 - 1s - loss: 32.0325 - val loss: 71.7802
Epoch 296/400
176/176 - 1s - loss: 29.8512 - val_loss: 75.3915
Epoch 297/400
176/176 - 1s - loss: 30.3108 - val loss: 76.4246
Epoch 298/400
176/176 - 1s - loss: 30.1642 - val loss: 75.7130
Epoch 299/400
176/176 - 1s - loss: 30.3259 - val loss: 93.3852
Epoch 300/400
176/176 - 1s - loss: 33.0983 - val loss: 73.9966
Epoch 301/400
176/176 - 1s - loss: 33.8358 - val loss: 84.4772
Epoch 302/400
176/176 - 1s - loss: 32.6685 - val loss: 70.6843
Epoch 303/400
176/176 - 2s - loss: 30.9637 - val loss: 75.9548
Epoch 304/400
176/176 - 1s - loss: 30.3543 - val_loss: 72.6787
Epoch 305/400
176/176 - 1s - loss: 31.6203 - val loss: 74.8412
Epoch 306/400
176/176 - 1s - loss: 31.9061 - val loss: 75.1914
Epoch 307/400
176/176 - 1s - loss: 30.3028 - val loss: 83.8828
```

```
Epoch 308/400
176/176 - 2s - loss: 31.1076 - val loss: 74.2560
Epoch 309/400
176/176 - 2s - loss: 32.0953 - val loss: 77.1800
Epoch 310/400
176/176 - 2s - loss: 30.7334 - val_loss: 74.3671
Epoch 311/400
176/176 - 1s - loss: 31.7907 - val loss: 71.4913
Epoch 312/400
176/176 - 1s - loss: 30.5630 - val loss: 77.6507
Epoch 313/400
176/176 - 1s - loss: 31.0626 - val loss: 81.4490
Epoch 314/400
176/176 - 1s - loss: 30.7659 - val loss: 85.2107
Epoch 315/400
176/176 - 1s - loss: 31.8239 - val loss: 71.9903
Epoch 316/400
176/176 - 1s - loss: 31.5599 - val loss: 69.8480
Epoch 317/400
176/176 - 2s - loss: 32.5166 - val loss: 70.6072
Epoch 318/400
176/176 - 2s - loss: 30.2911 - val_loss: 75.8833
Epoch 319/400
176/176 - 1s - loss: 30.8746 - val loss: 81.3253
Epoch 320/400
176/176 - 2s - loss: 31.3071 - val loss: 74.7825
Epoch 321/400
176/176 - 2s - loss: 30.4705 - val loss: 74.4348
Epoch 322/400
176/176 - 2s - loss: 30.8644 - val loss: 70.3873
Epoch 323/400
176/176 - 2s - loss: 29.9974 - val loss: 72.8805
Epoch 324/400
176/176 - 2s - loss: 30.7602 - val loss: 75.8659
Epoch 325/400
176/176 - 2s - loss: 31.2430 - val_loss: 74.5988
Epoch 326/400
176/176 - 1s - loss: 30.5551 - val loss: 75.5245
Epoch 327/400
176/176 - 2s - loss: 30.3881 - val loss: 78.9752
Epoch 328/400
176/176 - 2s - loss: 31.5809 - val loss: 78.6183
Epoch 329/400
176/176 - 2s - loss: 30.4139 - val loss: 78.7944
Epoch 330/400
176/176 - 1s - loss: 30.5994 - val loss: 76.9351
Epoch 331/400
176/176 - 2s - loss: 31.3348 - val loss: 81.2462
Epoch 332/400
176/176 - 2s - loss: 29.3209 - val_loss: 72.5476
Epoch 333/400
176/176 - 1s - loss: 29.5907 - val_loss: 75.4488
Epoch 334/400
176/176 - 1s - loss: 29.6908 - val loss: 75.0651
Epoch 335/400
176/176 - 2s - loss: 30.6860 - val loss: 73.2232
Epoch 336/400
176/176 - 2s - loss: 29.2031 - val_loss: 73.7189
Epoch 337/400
176/176 - 2s - loss: 29.0096 - val loss: 108.5419
Epoch 338/400
176/176 - 2s - loss: 29.6752 - val loss: 76.9124
Epoch 339/400
176/176 - 1s - loss: 30.0419 - val loss: 76.1593
Epoch 340/400
176/176 - 2s - loss: 30.7494 - val_loss: 75.1866
Epoch 341/400
176/176 - 2s - loss: 30.0602 - val loss: 78.7228
Epoch 342/400
176/176 - 2s - loss: 29.0066 - val loss: 75.8863
Epoch 343/400
176/176 - 1s - loss: 29.4396 - val loss: 73.4764
Epoch 344/400
176/176 - 1s - loss: 30.6552 - val loss: 74.2472
Epoch 345/400
176/176 - 1s - loss: 29.3349 - val loss: 73.6597
Epoch 346/400
```

```
176/176 - 1s - loss: 31.0770 - val loss: 78.9724
Epoch 347/400
176/176 - 1s - loss: 30.2400 - val loss: 76.6946
Epoch 348/400
176/176 - 1s - loss: 30.5301 - val loss: 68.9275
Epoch 349/400
176/176 - 1s - loss: 28.5551 - val loss: 72.0549
Epoch 350/400
176/176 - 1s - loss: 30.6016 - val_loss: 76.7853
Epoch 351/400
176/176 - 1s - loss: 29.4519 - val_loss: 80.3212
Epoch 352/400
176/176 - 1s - loss: 29.9399 - val loss: 76.6044
Epoch 353/400
176/176 - 2s - loss: 28.0644 - val loss: 75.3617
Epoch 354/400
176/176 - 1s - loss: 31.4846 - val loss: 75.2439
Epoch 355/400
176/176 - 1s - loss: 28.6634 - val loss: 80.0869
Epoch 356/400
176/176 - 1s - loss: 29.8296 - val loss: 74.4235
Epoch 357/400
176/176 - 1s - loss: 30.5101 - val_loss: 76.2021
Epoch 358/400
176/176 - 1s - loss: 28.7483 - val loss: 77.9865
Epoch 359/400
176/176 - 1s - loss: 30.1102 - val loss: 71.4483
Epoch 360/400
176/176 - 1s - loss: 29.0026 - val loss: 74.4442
Epoch 361/400
176/176 - 1s - loss: 29.6333 - val loss: 76.2279
Epoch 362/400
176/176 - 2s - loss: 28.7602 - val loss: 82.9859
Epoch 363/400
176/176 - 2s - loss: 27.8475 - val loss: 70.7980
Epoch 364/400
176/176 - 1s - loss: 30.1193 - val_loss: 72.7172
Epoch 365/400
176/176 - 1s - loss: 30.2034 - val_loss: 72.0500
Epoch 366/400
176/176 - 1s - loss: 29.0643 - val loss: 74.8982
Epoch 367/400
176/176 - 1s - loss: 29.8525 - val loss: 83.8622
Epoch 368/400
176/176 - 1s - loss: 27.9630 - val_loss: 77.9593
Epoch 369/400
176/176 - 1s - loss: 28.0144 - val loss: 76.9533
Epoch 370/400
176/176 - 1s - loss: 28.5126 - val loss: 76.9640
Epoch 371/400
176/176 - 1s - loss: 31.4024 - val loss: 68.2840
Epoch 372/400
176/176 - 2s - loss: 29.6269 - val_loss: 73.6603
Epoch 373/400
176/176 - 1s - loss: 28.9449 - val_loss: 72.1174
Epoch 374/400
176/176 - 1s - loss: 29.3474 - val loss: 88.4905
Epoch 375/400
176/176 - 1s - loss: 29.5241 - val_loss: 74.6628
Epoch 376/400
176/176 - 1s - loss: 28.1063 - val loss: 69.8975
Epoch 377/400
176/176 - 1s - loss: 28.2611 - val loss: 79.4127
Epoch 378/400
176/176 - 1s - loss: 28.3519 - val loss: 71.3558
Epoch 379/400
176/176 - 1s - loss: 28.9158 - val_loss: 74.1024
Epoch 380/400
176/176 - 1s - loss: 29.2656 - val loss: 73.8958
Epoch 381/400
176/176 - 1s - loss: 28.4899 - val loss: 74.9737
Epoch 382/400
176/176 - 1s - loss: 28.5299 - val_loss: 71.8360
Epoch 383/400
176/176 - 1s - loss: 28.6185 - val_loss: 75.7301
Epoch 384/400
176/176 - 1s - loss: 27.7710 - val loss: 76.3501
```

```
Epoch 385/400
176/176 - 2s - loss: 29.0874 - val loss: 72.7840
Epoch 386/400
176/176 - 1s - loss: 29.3795 - val loss: 70.3512
Epoch 387/400
176/176 - 1s - loss: 28.2418 - val loss: 72.5651
Epoch 388/400
176/176 - 1s - loss: 28.6041 - val loss: 85.1789
Epoch 389/400
176/176 - 1s - loss: 27.6295 - val_loss: 73.5796
Epoch 390/400
176/176 - 2s - loss: 29.7335 - val loss: 75.8557
Epoch 391/400
176/176 - 2s - loss: 27.8086 - val loss: 77.2627
Epoch 392/400
176/176 - 2s - loss: 28.9726 - val loss: 76.2319
Epoch 393/400
176/176 - 2s - loss: 28.2413 - val loss: 69.9003
Epoch 394/400
176/176 - 1s - loss: 27.4743 - val loss: 71.7077
Epoch 395/400
176/176 - 1s - loss: 28.5333 - val loss: 81.6068
Epoch 396/400
176/176 - 1s - loss: 27.3425 - val_loss: 78.5002
Epoch 397/400
176/176 - 3s - loss: 28.5365 - val_loss: 75.9045
Epoch 398/400
176/176 - 2s - loss: 28.7745 - val_loss: 75.7964
Epoch 399/400
176/176 - 2s - loss: 28.4715 - val loss: 71.8274
Epoch 400/400
176/176 - 2s - loss: 29.0769 - val loss: 93.3401
```



('Failed to import pydot. You must `pip install pydot` and install graphviz (https://graphviz.gitlab.io/download/), ', 'for `pydotprint` to work.')

In [45]:

```
from tensorflow.keras.models import load_model
# load the model from file
encoder = load_model('encoder.h5')
```

WARNING:tensorflow:No training configuration found in the save file, so the model was *not* compiled. Compile it manually.

In [46]:

```
X_train_encode = encoder.predict(X_train)
# encode the test data
X_test_encode = encoder.predict(X_test)
```

In [47]:

```
X_train_encode.shape
```

Random XGBoost Model with encoded Features

```
In [48]:
```

```
reg = XGBRegressor(n_estimators=100, learning_rate = 0.1)
reg.fit(X_train_encode, y_train)
y_pred = reg.predict(X_test_encode)
score = r2_score(y_test, y_pred)
print(score)
```

0.44974943013321533

Observation -

The Random XGBoost Model with encoded features produces better r2 than Simple mean model

Some Other Feature Engg Techniques

PCA Features

```
In [49]:
```

```
from sklearn.decomposition import PCA
#taking top 10 components
components = 10
pca = PCA(n components=components, random state=420)
x pca = pd.DataFrame(pca.fit transform(x num))
print(x pca.shape)
print(x pca.head())
(4196, 10)
                                  2
                                              3
                                                                                 6
0 0.749079 2.255215 1.016952 0.929835 1.388466 0.044720 0.608854
1 -0.216276 1.103237 -0.832779 -0.670249 0.243599 0.037451 1.199850
2 -0.888967 2.978889 0.269069 2.570786 -0.994356 3.279242 -0.877726
3 -0.509223 2.445044 -0.645017 2.985013 -1.728502 3.132381 0.108157
4 \ -0.488367 \ \ 2.236544 \ -0.787629 \ \ 3.193679 \ -2.052340 \ \ 3.167224 \ -0.091210
           7
                       8
0 -0.929240 0.200321 -0.730352
1 -0.563451 -0.083035 0.459006
2 0.533689 -0.939597 -0.102745
3 0.017575 -1.028170 0.260647
4 0.125130 -1.729599 -0.344936
```

SVD

In [50]:

```
# get the matrix factors
U, S, VT = np.linalg.svd(x_num,full_matrices=1)
# calculating the aspect ratio b
m = x_num.shape[1]
n = x_num.shape[0]
b = m/n

#taking w_b from table corresponding to b
w_b = 1.6089
# getting the median singular value
```

```
ymed = np.median(S)

# finding the Hard threshold
cutoff = w_b * ymed
print("The Hard Threshold for Truncation = ",cutoff)
# get the number of components
r = np.max(np.where(S > cutoff))
print("Number of total components to be selected = ",r)
```

The Hard Threshold for Truncation = 3.8431396016312185 Number of total components to be selected = 152

In [51]:

```
from sklearn.decomposition import TruncatedSVD
n_comp = r

tsvd = TruncatedSVD(n_components=r, random_state=420)
x_svd= tsvd.fit_transform(x_num)

print(x_svd.shape)
```

(4196, 152)

Different Models

XGBoost

```
In [52]:
    results = []
```

Feature Set - 1

Auto - Encoded Features + XGBoost

```
In [53]:
```

```
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.33, random_state=1)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33)
print("Done")
```

Done

In [54]:

```
X_train_encode = encoder.predict(X_train)
# encode the test data
X_test_encode = encoder.predict(X_test)
#
X_cv_encode = encoder.predict(X_cv)
```

In [55]:

```
X_train_encode.shape
```

Out[55]:

(1883, 376)

Tn [56]:

_______. from sklearn.metrics import r2_score learning_rate = [0.0001, 0.001, 0.01, 0.1, 0.2, 0.3] $n_{estimators} = [5, 10, 50, 75, 100, 200]$ auc_train = [] auc_cv = [] plot rate,plot estim = [],[] for i in learning rate: for j in n estimators: clf = XGBRegressor(learning_rate = i, n_estimators = j,verbosity = 0,n_jobs = -1) clf.fit(X_train_encode ,y_train) y_train_pred = clf.predict(X_train_encode) y_cv_pred = clf.predict(X_cv_encode) auc_train.append(r2_score(y_train,y_train_pred)) auc_cv.append(r2_score(y_cv,y_cv_pred)) plot_rate.append(i)

In [57]:

plot_estim.append(j)

In [58]:

```
model = XGBRegressor(n_estimators=50, learning_rate =0.1)
model.fit(X_train_encode,y_train)
y_te = model.predict(X_test_encode)
score1 = r2_score(y_test, y_te)
results.append(score1)
print("Test Score for 1st feature set : ", score1)
```

Test Score for 1st feature set : 0.4783789326440554

```
In [ ]:
In [ ]:
Feature Set - 2
Auto - Encoded Features + PCA + XGBoost
In [59]:
X_train_Set2, X_test_Set2, y_train, y_test = train_test_split(x_pca, y, test_size=0.33, random_stat
X_train_Set2, X_cv_Set2, y_train, y_cv = train_test_split(X_train_Set2, y_train, test_size=0.33)
print("Done")
Done
In [60]:
X train Set2.shape
Out[60]:
(1883, 10)
In [61]:
X train Set2 = pd.DataFrame(np.hstack((X train encode, X train Set2)))
X cv Set2 = pd.DataFrame(np.hstack((X cv encode, X cv Set2)))
X test Set2 = pd.DataFrame(np.hstack((X test encode, X test Set2)))
print(X train Set2.shape, X test Set2.shape, X cv Set2.shape)
(1883, 386) (1385, 386) (928, 386)
In [62]:
from sklearn.metrics import r2_score
learning_rate = [0.0001, 0.001, 0.01, 0.1, 0.2, 0.3]
n estimators = [5,10,50,75,100,200]
score train = []
score cv = []
plot_rate,plot_estim = [],[]
for i in learning rate:
    for j in n_estimators:
        #scaling the positive weight to tackle imbalanced data
        clf = XGBRegressor(learning rate = i, n estimators = j,verbosity = 0,n jobs = -1)
        clf.fit(X_train_Set2 ,y_train)
        y_train_pred = clf.predict(X_train_Set2)
        y_cv_pred = clf.predict(X_cv_Set2)
        score_train.append(r2_score(y_train,y_train_pred))
       score_cv.append(r2_score(y_cv,y_cv_pred))
       plot rate.append(i)
       plot estim.append(j)
In [63]:
#plotting the auc corresponding to different hyper parameter permutations to understand
```

trace1 = go.Scatter3d(x=plot_estim,y=plot_rate,z=score_train, name = 'train')

data = [trace1, trace2]

trace2 = go.Scatter3d(x=plot estim,y=plot rate,z=score cv, name = 'Cross validation')

```
In [64]:
```

```
model = XGBRegressor(n_estimators=75, learning_rate =0.1)
model.fit(X_train_Set2,y_train)
y_te = model.predict(X_test_Set2)
score2 = r2_score(y_test, y_te)
results.append(score2)
print("Test Score for 2nd feature set : ", score2)
```

Test Score for 2nd feature set : 0.49980931503390214

```
In [ ]:
```

In []:

Feature Set - 3

PCA + SVD + XGBoost

```
In [65]:
```

```
X_Set3 = pd.DataFrame(np.hstack((x_pca,x_svd)))
print(X_Set3.shape)
```

(4196, 162)

In [66]:

```
X_train_Set3, X_test_Set3, y_train, y_test = train_test_split(X_Set3, y, test_size=0.33, random_sta
te=1)
X_train_Set3, X_cv_Set3, y_train, y_cv = train_test_split(X_train_Set3, y_train, test_size=0.33)
print("Done")
```

Done

In [67]:

```
print(X_train_Set3.shape,X_test_Set3.shape,X_cv_Set3.shape)
```

(1883, 162) (1385, 162) (928, 162)

In [68]:

```
from sklearn.metrics import r2_score
learning_rate = [0.0001, 0.001, 0.01, 0.1, 0.2, 0.3]
n estimators = [5,10,50,75,100,200]
score_train = []
score_cv = []
plot_rate,plot_estim = [],[]
for i in learning rate:
    for j in n estimators:
       #scaling the positive weight to tackle imbalanced data
       clf = XGBRegressor(learning rate = i, n estimators = j,verbosity = 0,n jobs = -1)
       clf.fit(X_train_Set3 ,y_train)
       y train pred = clf.predict(X train Set3)
        y cv pred = clf.predict(X cv Set3)
       score_train.append(r2_score(y_train,y_train_pred))
       score cv.append(r2 score(y cv,y cv pred))
       plot_rate.append(i)
       plot estim.append(j)
```

In [69]:

```
In [70]:
```

```
model = XGBRegressor(n_estimators=50, learning_rate =0.1)
model.fit(X_train_Set3,y_train)
y_te = model.predict(X_test_Set3)
score3 = r2_score(y_test, y_te)
results.append(score3)
print("Test Score for 3rd feature set : ", score3)
```

Test Score for 3rd feature set : 0.5168185624963257

Feature Set - 4

Label Encoded Categorical features + original Binary Features + PCA + SVD + XGBoost

```
In [71]:
```

```
X_Set4 = pd.DataFrame(np.hstack((x,x_pca,x_svd)))
print(X_Set4.shape)
```

(4196, 538)

In [72]:

```
X_train_Set4, X_test_Set4, y_train, y_test = train_test_split(X_Set4, y, test_size=0.33, random_sta
te=1)
X_train_Set4, X_cv_Set4, y_train, y_cv = train_test_split(X_train_Set4, y_train, test_size=0.33)
print("Done")
```

Done

In [73]:

```
print(X_train_Set4.shape,X_test_Set4.shape,X_cv_Set4.shape)
```

(1883, 538) (1385, 538) (928, 538)

In [74]:

```
from sklearn.metrics import r2 score
learning_rate = [0.0001, 0.001, 0.01, 0.1, 0.2, 0.3]
n estimators = [5,10,50,75,100,200]
score_train = []
score cv = []
plot rate,plot estim = [],[]
for i in learning_rate:
    for j in n estimators:
        clf = XGBRegressor(learning_rate = i, n_estimators = j,verbosity = 0,n_jobs = -1)
       clf.fit(X_train_Set4 ,y_train)
       y train pred = clf.predict(X train Set4)
       y_cv_pred = clf.predict(X_cv_Set4)
       score_train.append(r2_score(y_train,y_train_pred))
       score_cv.append(r2_score(y_cv,y_cv_pred))
        plot_rate.append(i)
        plot estim.append(j)
```

```
In [75]:
```

In [76]:

```
model = XGBRegressor(n_estimators=50, learning_rate =0.1)
model.fit(X_train_Set4,y_train)
y_te = model.predict(X_test_Set4)
score4 = r2_score(y_test, y_te)
results.append(score4)
print("Test Score for 4th feature set : ", score4)
```

Test Score for 3rd feature set : 0.5854359536270364

In []:

Feature Set - 5

Label Encoded Categorical features + original Binary Features + SVD + XGBoost

```
In [77]:
```

```
X_Set5 = pd.DataFrame(np.hstack((x,x_svd)))
print(X_Set5.shape)
```

```
(4196, 528)
```

In [78]:

```
X_train_Set5, X_test_Set5, y_train, y_test = train_test_split(X_Set5, y, test_size=0.33, random_sta
te=1)
X_train_Set5, X_cv_Set5, y_train, y_cv = train_test_split(X_train_Set5, y_train, test_size=0.33)
print("Done")
```

Done

In [79]:

```
print(X_train_Set5.shape,X_test_Set5.shape,X_cv_Set5.shape)

(1883, 528) (1385, 528) (928, 528)
```

In [80]:

```
from sklearn.metrics import r2_score
learning rate = [0.0001, 0.001, 0.01, 0.1, 0.2, 0.3]
n estimators = [5,10,50,75,100,200]
score train = []
score cv = []
plot_rate,plot_estim = [],[]
for i in learning rate:
    for j in n estimators:
       clf = XGBRegressor(learning_rate = i, n_estimators = j,verbosity = 0,n_jobs = -1)
       clf.fit(X_train_Set5 ,y_train)
       y_train_pred = clf.predict(X_train_Set5)
       y_cv_pred = clf.predict(X_cv_Set5)
       score_train.append(r2_score(y_train,y_train_pred))
       score_cv.append(r2_score(y_cv,y_cv_pred))
       plot rate.append(i)
       plot estim.append(j)
```

In [81]:

```
model = XGBRegressor(n estimators=50, learning rate =0.1)
model.fit(X_train_Set5,y_train)
y te = model.predict(X test Set5)
score5 = r2_score(y_test, y_te)
results.append(score5)
print("Test Score for 5th feature set : ", score5)
Test Score for 3rd feature set : 0.5858048821103229
Linear Regression
With Feature Set - 4
In [84]:
{\bf from \ sklearn.linear\_model \ import \ LinearRegression}
X_Set4 = pd.DataFrame(np.hstack((x,x_pca,x_svd)))
print(X Set4.shape)
(4196, 538)
In [85]:
X_train_LR_Set4, X_test_LR_Set4, y_train, y_test = train_test_split(X_Set4, y, test_size=0.33, rand
om state=1)
print("Done")
Done
In [88]:
lr = LinearRegression()
lr.fit(X_train_LR_Set4,y_train)
y pred = lr.predict(X test LR Set4)
score6 = r2_score(y_test,y_pred)
print('R_2 Error on test : ', score6)
R 2 Error on test : -6.05298153727229e+19
In [ ]:
```

With Feature Set - 5

```
In [89]:
```

In [82]:

```
X_Set5 = pd.DataFrame(np.hstack((x,x_svd)))
print(X_Set5.shape)
```

```
(4196, 528)
In [90]:
X_train_LR_Set5, X_test_LR_Set5, y_train, y_test = train_test_split(X_Set5, y, test_size=0.33, rand
om state=1)
print("Done")
Done
In [91]:
lr = LinearRegression()
lr.fit(X train LR Set5, y train)
y pred = lr.predict(X test LR Set5)
score7 = r2_score(y_test,y_pred)
print('R_2 Error on test : ', score7)
R_2 Error on test : -9.760415548410465e+19
In [ ]:
Random Forest
With Feature Set - 4
In [227]:
X Set4 = pd.DataFrame(np.hstack((x,x pca,x svd)))
print(X Set4.shape)
(4196, 538)
In [228]:
X train RF Set4, X test RF Set4, y train, y test = train test split(X Set4, y, test size=0.33, rand
om state=1)
X_train_RF_Set4, X_cv_RF_Set4, y_train, y_cv = train_test_split(X_train_RF_Set4, y_train,
test size=0.33)
print("Done")
Done
In [229]:
from sklearn.ensemble import RandomForestRegressor
max_depth = [5, 10, 15, 20, 25, 40]
n_{estimators} = [5, 10, 50, 75, 100, 200]
score_train = []
score cv = []
plot_dep,plot_estim = [],[]
```

```
from sklearn.ensemble import RandomForestRegressor
max_depth = [5, 10, 15,20, 25, 40]
n_estimators = [5,10,50,75,100,200]
score_train = []
score_cv = []
plot_dep,plot_estim = [],[]
for i in max_depth:
    for j in _estimators:
        clf = RandomForestRegressor(max_depth = i, n_estimators = j, verbose = 0,n_jobs = -1)
        clf.fit(X_train_RF_Set4 ,y_train)
        y_train_pred = clf.predict(X_train_RF_Set4)
        y_cv_pred = clf.predict(X_cv_RF_Set4)
        score_train.append(r2_score(y_train,y_train_pred))
        score_cv.append(r2_score(y_cv,y_cv_pred))
        plot_dep.append(i)
        plot_estim.append(j)
```

```
In [230]:
```

In [231]:

```
model = RandomForestRegressor(n_estimators=200, max_depth =5)
model.fit(X_train_RF_Set4,y_train)
y_te = model.predict(X_test_RF_Set4)
score8 = r2_score(y_test, y_te)
print("Test Score for 4th feature set : ", score8)
```

Test Score for 4th feature set : 0.5919103348411419

With Feature Set - 5

```
In [206]:
```

```
X_Set5 = pd.DataFrame(np.hstack((x,x_svd)))
print(X_Set5.shape)
```

(4196, 528)

In [207]:

```
X_train_RF_Set5, X_test_RF_Set5, y_train, y_test = train_test_split(X_Set5, y, test_size=0.33, rand
om_state=1)
X_train_RF_Set5, X_cv_RF_Set5, y_train, y_cv = train_test_split(X_train_RF_Set5, y_train,
test_size=0.33)
print("Done")
```

```
princ( Done /
```

Done

In [208]:

```
max_depth = [5, 10, 15,20, 25, 40]
n_estimators = [5,10,50,75,100,200]
score_train = []
score_cv = []
plot_dep,plot_estim = [],[]
for i in max_depth:
    for j in n_estimators:
        clf = RandomForestRegressor(max_depth = i, n_estimators = j, verbose = 0,n_jobs = -1)
        clf.fit(X_train_RF_Set5 ,y_train)
        y_train_pred = clf.predict(X_train_RF_Set5)
        y_cv_pred = clf.predict(X_cv_RF_Set5)
        score_train.append(r2_score(y_train,y_train_pred))
        score_cv.append(r2_score(y_cv,y_cv_pred))
        plot_dep.append(i)
        plot_estim.append(j)
```

In [209]:

In [213]:

```
model = RandomForestRegressor(n_estimators=200, max_depth =5)
model.fit(X_train_RF_Set5,y_train)
y_te = model.predict(X_test_RF_Set5)
```

```
score9 = r2_score(y_test, y_te)
print("Test Score for 4th feature set : ", score9)

Test Score for 4th feature set : 0.5977776730961734
```

MLP

With Feature Set - 4

```
In [138]:
```

```
from keras.models import Sequential
from keras.utils import np_utils
from keras.layers.core import Dense, Activation, Dropout
from keras.layers import BatchNormalization
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.callbacks import ModelCheckpoint
import tensorflow as tf
import datetime
```

In [153]:

```
from keras import backend as K
"""Custom R2 Score"""
def rsquared(y_true, y_pred):
    from keras import backend as K
    SS_res = K.sum(K.square( y_true-y_pred ))
    SS_tot = K.sum(K.square( y_true - K.mean(y_true) ) )
    return ( 1 - SS_res/(SS_tot + K.epsilon()) )
```

In [154]:

```
X_Set4 = pd.DataFrame(np.hstack((x,x_pca,x_svd)))
print(X_Set4.shape)
```

(4196, 538)

In [155]:

```
X_train_MLP_Set4, X_test_MLP_Set4, y_train, y_test = train_test_split(X_Set4, y, test_size=0.33, ra
ndom_state=1)
print("Done")
```

Done

In [170]:

```
input_dim = X_train_MLP_Set4.shape[1]

# The Input Layer :
model = Sequential()
model.add(Dense(128,kernel_initializer='normal', input_dim=input_dim, activation='relu'))

# The Hidden Layers :
model.add(Dense(256, kernel_initializer='normal',activation='relu'))
model.add(Dense(256, kernel_initializer='normal',activation='relu'))
model.add(Dense(256, kernel_initializer='normal',activation='relu'))
model.add(Dense(256, kernel_initializer='normal',activation='relu'))
model.add(Dense(256, kernel_initializer='normal',activation='relu'))
# The Output Layer :
model.add(Dense(1, kernel_initializer='normal',activation='linear'))

model.compile(loss='mean_squared_error', optimizer='adam', metrics=[rsquared])
model.summary()
```

Model: "sequential 16"

Layer (type)	Output Shape	Param #
dense_124 (Dense)	(None, 128)	68992
dense_125 (Dense)	(None, 256)	33024
dense_126 (Dense)	(None, 256)	65792
dense_127 (Dense)	(None, 256)	65792
dropout_11 (Dropout)	(None, 256)	0
dense_128 (Dense)	(None, 256)	65792
dense_129 (Dense)	(None, 256)	65792
dense_130 (Dense)	(None, 1)	257

Total params: 365,441 Trainable params: 365,441 Non-trainable params: 0

```
In [171]:
filepath="/tmp/checkpoint"
checkpoint = ModelCheckpoint (filepath=filepath, monitor='val rsquared', verbose=1, save best only=T
rue, mode='max')
optimizer = tf.keras.optimizers.Adam(0.01)
#time = datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
log dir= "logs/fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard callback = tf.keras.callbacks.TensorBoard(log dir=log dir,histogram freq=1, write graph
=True,write grads=True)
callbacks list = [checkpoint,tensorboard callback]
model.fit(X train MLP Set4,y train,epochs=200, validation data=(X test MLP Set4,y test), batch size
=1000, callbacks=callbacks list)
WARNING:tensorflow:`write grads` will be ignored in TensorFlow 2.0 for the `TensorBoard` Callback.
loss: 9970.0342 - val rsquared: -71.6742
Epoch 00001: val_rsquared improved from -inf to -71.67418, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 2/200
oss: 8989.9873 - val rsquared: -64.5589
Epoch 00002: val rsquared improved from -71.67418 to -64.55894, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 3/200
oss: 5360.4272 - val rsquared: -38.1855
Epoch 00003: val rsquared improved from -64.55894 to -38.18546, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 4/200
oss: 842.4279 - val_rsquared: -5.0031
Epoch 00004: val rsquared improved from -38.18546 to -5.00307, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
oss: 852.6474 - val rsquared: -5.0748
Epoch 00005: val rsquared did not improve from -5.00307
Epoch 6/200
```

```
3/3 [=========== ] - 0s 75ms/step - loss: 710.5410 - rsquared: -3.9172 -
val loss: 1131.0057 - val rsquared: -7.3391
Epoch 00006: val rsquared did not improve from -5.00307
Epoch 7/200
val loss: 1376.0593 - val rsquared: -9.1267
Epoch 00007: val rsquared did not improve from -5.00307
Epoch 8/200
3/3 [========== ] - 0s 84ms/step - loss: 1213.2979 - rsquared: -7.4892 -
val loss: 375.1458 - val rsquared: -1.7568
Epoch 00008: val rsquared improved from -5.00307 to -1.75680, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 9/200
val loss: 805.6639 - val rsquared: -4.7317
Epoch 00009: val rsquared did not improve from -1.75680
Epoch 10/200
val_loss: 312.0695 - val_rsquared: -1.2193
Epoch 00010: val_rsquared improved from -1.75680 to -1.21927, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 11/200
val loss: 397.1273 - val rsquared: -1.9160
Epoch 00011: val rsquared did not improve from -1.21927
Epoch 12/200
val loss: 362.2863 - val rsquared: -1.6574
Epoch 00012: val_rsquared did not improve from -1.21927
val_loss: 182.8946 - val_rsquared: -0.2953
Epoch 00013: val rsquared improved from -1.21927 to -0.29532, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 14/200
val loss: 269.5939 - val rsquared: -0.9046
Epoch 00014: val rsquared did not improve from -0.29532
Epoch 15/200
3/3 [============= - 0s 64ms/step - loss: 252.0918 - rsquared: -0.7132 -
val loss: 147.0453 - val rsquared: -0.0523
Epoch 00015: val_rsquared improved from -0.29532 to -0.05230, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 16/200
3/3 [============= ] - 0s 69ms/step - loss: 187.0069 - rsquared: -0.2790 -
val loss: 189.0066 - val rsquared: -0.3669
Epoch 00016: val_rsquared did not improve from -0.05230
Epoch 17/200
val loss: 116.7072 - val rsquared: 0.1796
Epoch 00017: val rsquared improved from -0.05230 to 0.17963, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 18/200
val loss: 149.3207 - val rsquared: -0.0453
Epoch 00018: val_rsquared did not improve from 0.17963
Epoch 19/200
val loss: 102.9286 - val rsquared: 0.2799
Epoch 00019: val rsquared improved from 0.17963 to 0.27992, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 20/200
3/3 [=========== ] - 0s 61ms/step - loss: 131.1961 - rsquared: 0.0973 -
```

```
val loss: 113.8689 - val rsquared: 0.1970
Epoch 00020: val_rsquared did not improve from 0.27992
Epoch 21/200
3/3 [=========== ] - 0s 60ms/step - loss: 128.9985 - rsquared: 0.1057 -
val loss: 95.4064 - val rsquared: 0.3405
Epoch 00021: val rsquared improved from 0.27992 to 0.34051, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 22/200
3/3 [========= ] - 0s 67ms/step - loss: 113.0565 - rsquared: 0.2238 -
val loss: 93.4564 - val rsquared: 0.3549
Epoch 00022: val rsquared improved from 0.34051 to 0.35492, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 23/200
3/3 [========= ] - 0s 84ms/step - loss: 104.0866 - rsquared: 0.2847 -
val loss: 89.4747 - val rsquared: 0.3800
Epoch 00023: val rsquared improved from 0.35492 to 0.37998, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 24/200
val loss: 81.4669 - val rsquared: 0.4394
Epoch 00024: val rsquared improved from 0.37998 to 0.43936, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 25/200
83.3247 - val rsquared: 0.4274
Epoch 00025: val rsquared did not improve from 0.43936
Epoch 26/200
76.9323 - val rsquared: 0.4727
Epoch 00026: val rsquared improved from 0.43936 to 0.47265, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 27/200
77.8089 - val rsquared: 0.4662
Epoch 00027: val rsquared did not improve from 0.47265
Epoch 28/200
76.4617 - val rsquared: 0.4778
Epoch 00028: val rsquared improved from 0.47265 to 0.47776, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 29/200
74.2161 - val rsquared: 0.4936
Epoch 00029: val rsquared improved from 0.47776 to 0.49362, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 30/200
75.4038 - val rsquared: 0.4843
Epoch 00030: val rsquared did not improve from 0.49362
Epoch 31/200
73.5344 - val rsquared: 0.4990
Epoch 00031: val rsquared improved from 0.49362 to 0.49899, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 32/200
72.3219 - val rsquared: 0.5071
Epoch 00032: val rsquared improved from 0.49899 to 0.50707, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 33/200
3/3 [============ 0.4545 - val loss: 80.6965 - rsquared: 0.4545 - val loss:
71.9376 - val_rsquared: 0.5097
Epoch 00033: val rsquared improved from 0.50707 to 0.50970, saving model to /tmp/checkpoint
```

```
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 34/200
71.0064 - val rsquared: 0.5169
Epoch 00034: val rsquared improved from 0.50970 to 0.51689, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 35/200
70.4507 - val_rsquared: 0.5208
Epoch 00035: val rsquared improved from 0.51689 to 0.52078, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 36/200
70.1320 - val rsquared: 0.5227
Epoch 00036: val rsquared improved from 0.52078 to 0.52275, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 37/200
69.5968 - val rsquared: 0.5266
Epoch 00037: val rsquared improved from 0.52275 to 0.52661, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 38/200
69.6498 - val rsquared: 0.5259
Epoch 00038: val rsquared did not improve from 0.52661
Epoch 39/200
68.7835 - val rsquared: 0.5324
Epoch 00039: val rsquared improved from 0.52661 to 0.53238, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 40/200
69.1991 - val rsquared: 0.5291
Epoch 00040: val rsquared did not improve from 0.53238
Epoch 41/200
68.5306 - val rsquared: 0.5339
Epoch 00041: val rsquared improved from 0.53238 to 0.53387, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 42/200
68.3718 - val rsquared: 0.5350
Epoch 00042: val rsquared improved from 0.53387 to 0.53499, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 43/200
3/3 [========== 0.5071 - val loss: 71.1604 - rsquared: 0.5071 - val loss:
68.6292 - val_rsquared: 0.5330
Epoch 00043: val rsquared did not improve from 0.53499
Epoch 44/200
67.8660 - val rsquared: 0.5386
Epoch 00044: val rsquared improved from 0.53499 to 0.53857, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 45/200
68.9349 - val rsquared: 0.5309
Epoch 00045: val_rsquared did not improve from 0.53857
Epoch 46/200
67.8376 - val rsquared: 0.5390
Epoch 00046: val rsquared improved from 0.53857 to 0.53900, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 47/200
```

3/3 [=========== 0.5407 - val loss: 67.7787 - rsquared: 0.5407 - val loss:

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69.1060 - val rsquared: 0.5297
Epoch 00047: val rsquared did not improve from 0.53900
Epoch 48/200
67.0180 - val rsquared: 0.5450
Epoch 00048: val rsquared improved from 0.53900 to 0.54501, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 49/200
68.2759 - val rsquared: 0.5358
Epoch 00049: val rsquared did not improve from 0.54501
Epoch 50/200
67.7525 - val rsquared: 0.5399
Epoch 00050: val_rsquared did not improve from 0.54501
Epoch 51/200
67.9638 - val rsquared: 0.5383
Epoch 00051: val_rsquared did not improve from 0.54501
Epoch 52/200
67.4911 - val_rsquared: 0.5417
Epoch 00052: val rsquared did not improve from 0.54501
Epoch 53/200
3/3 [========== 0.5655 - val loss:
69.0038 - val rsquared: 0.5309
Epoch 00053: val rsquared did not improve from 0.54501
Epoch 54/200
70.7501 - val rsquared: 0.5183
Epoch 00054: val rsquared did not improve from 0.54501
Epoch 55/200
3/3 [============= ] - 0s 65ms/step - loss: 65.8908 - rsquared: 0.5541 - val_loss:
66.5192 - val rsquared: 0.5491
Epoch 00055: val rsquared improved from 0.54501 to 0.54913, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 56/200
69.8151 - val rsquared: 0.5247
Epoch 00056: val rsquared did not improve from 0.54913
Epoch 57/200
68.7004 - val_rsquared: 0.5327
Epoch 00057: val rsquared did not improve from 0.54913
Epoch 58/200
67.0625 - val rsquared: 0.5447
Epoch 00058: val rsquared did not improve from 0.54913
3/3 [========== 0.5595 - val loss: 64.2548 - rsquared: 0.5595 - val loss:
70.2925 - val rsquared: 0.5210
Epoch 00059: val rsquared did not improve from 0.54913
Epoch 60/200
66.7742 - val rsquared: 0.5467
Epoch 00060: val rsquared did not improve from 0.54913
Epoch 61/200
67.1131 - val rsquared: 0.5444
Epoch 00061: val rsquared did not improve from 0.54913
Epoch 62/200
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67.0458 - val rsquared: 0.5448
Epoch 00062: val rsquared did not improve from 0.54913
68.1583 - val rsquared: 0.5362
Epoch 00063: val_rsquared did not improve from 0.54913
Epoch 64/200
77.1320 - val_rsquared: 0.4703
Epoch 00064: val rsquared did not improve from 0.54913
Epoch 65/200
65.1900 - val rsquared: 0.5575
Epoch 00065: val rsquared improved from 0.54913 to 0.55745, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 66/200
74.8183 - val rsquared: 0.4872
Epoch 00066: val rsquared did not improve from 0.55745
Epoch 67/200
3/3 [========== 0.5877 - val loss: 61.7245 - rsquared: 0.5877 - val loss:
71.4546 - val_rsquared: 0.5117
Epoch 00067: val rsquared did not improve from 0.55745
Epoch 68/200
65.8219 - val rsquared: 0.5531
Epoch 00068: val rsquared did not improve from 0.55745
Epoch 69/200
80.1174 - val rsquared: 0.4490
Epoch 00069: val rsquared did not improve from 0.55745
Epoch 70/200
65.0544 - val rsquared: 0.5586
Epoch 00070: val rsquared improved from 0.55745 to 0.55857, saving model to /tmp/checkpoint
INFO:tensorflow:Assets written to: /tmp/checkpoint/assets
Epoch 71/200
79.1400 - val rsquared: 0.4560
Epoch 00071: val rsquared did not improve from 0.55857
Epoch 72/200
67.7525 - val rsquared: 0.5391
Epoch 00072: val rsquared did not improve from 0.55857
Epoch 73/200
69.5335 - val rsquared: 0.5261
Epoch 00073: val rsquared did not improve from 0.55857
Epoch 74/200
val loss: 78.5204 - val rsquared: 0.4604
Epoch 00074: val rsquared did not improve from 0.55857
Epoch 75/200
65.1455 - val rsquared: 0.5580
Epoch 00075: val rsquared did not improve from 0.55857
Epoch 76/200
3/3 [========================== - Os 89ms/step - loss: 59.1641 - rsquared: 0.5894 - val loss:
77.8923 - val rsquared: 0.4655
Epoch 00076: val rsquared did not improve from 0.55857
Epoch 77/200
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67.4149 - val rsquared: 0.5415
Epoch 00077: val rsquared did not improve from 0.55857
Epoch 78/200
74.3124 - val rsquared: 0.4915
Epoch 00078: val rsquared did not improve from 0.55857
Epoch 79/200
3/3 [=========: 0.5956 - val loss: 59.2638 - rsquared: 0.5956 - val loss:
72.5151 - val rsquared: 0.5046
Epoch 00079: val rsquared did not improve from 0.55857
Epoch 80/200
3/3 [============ ] - 0s 112ms/step - loss: 58.0894 - rsquared: 0.6013 -
val loss: 67.6984 - val rsquared: 0.5395
Epoch 00080: val rsquared did not improve from 0.55857
Epoch 81/200
3/3 [=========== 0.6053 - val loss: 56.1943 - rsquared: 0.6053 - val loss:
75.2134 - val rsquared: 0.4851
Epoch 00081: val rsquared did not improve from 0.55857
Epoch 82/200
70.6613 - val rsquared: 0.5180
Epoch 00082: val_rsquared did not improve from 0.55857
Epoch 83/200
72.7045 - val rsquared: 0.5033
Epoch 00083: val rsquared did not improve from 0.55857
Epoch 84/200
3/3 [========== 0.6202 - val loss: 55.6942 - rsquared: 0.6202 - val loss:
76.4739 - val rsquared: 0.4759
Epoch 00084: val rsquared did not improve from 0.55857
Epoch 85/200
68.3054 - val rsquared: 0.5350
Epoch 00085: val rsquared did not improve from 0.55857
Epoch 86/200
78.0263 - val rsquared: 0.4650
Epoch 00086: val rsquared did not improve from 0.55857
Epoch 87/200
          3/3 [======
72.6334 - val rsquared: 0.5043
Epoch 00087: val rsquared did not improve from 0.55857
72.4031 - val rsquared: 0.5060
Epoch 00088: val_rsquared did not improve from 0.55857
Epoch 89/200
75.6621 - val rsquared: 0.4822
Epoch 00089: val rsquared did not improve from 0.55857
Epoch 90/200
67.8651 - val_rsquared: 0.5388
Epoch 00090: val rsquared did not improve from 0.55857
Epoch 91/200
82.4200 - val_rsquared: 0.4342
Epoch 00091: val rsquared did not improve from 0.55857
Epoch 92/200
72.3376 - val rsquared: 0.5072
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Epoch 00092: val_rsquared did not improve from 0.55857
Epoch 93/200
3/3 [=========: 0.6320 - val loss: 53.7121 - rsquared: 0.6320 - val loss:
71.8829 - val_rsquared: 0.5105
Epoch 00093: val rsquared did not improve from 0.55857
Epoch 94/200
3/3 [=========== 0.6327 - val loss: 53.9575 - rsquared: 0.6327 - val loss:
78.1009 - val rsquared: 0.4655
Epoch 00094: val_rsquared did not improve from 0.55857
Epoch 95/200
70.7946 - val rsquared: 0.5187
Epoch 00095: val rsquared did not improve from 0.55857
Epoch 96/200
3/3 [========== 0.6200 - val loss: 55.6678 - rsquared: 0.6200 - val loss:
71.0826 - val rsquared: 0.5161
Epoch 00096: val rsquared did not improve from 0.55857
Epoch 97/200
76.7842 - val rsquared: 0.4748
Epoch 00097: val_rsquared did not improve from 0.55857
Epoch 98/200
72.4915 - val rsquared: 0.5056
Epoch 00098: val rsquared did not improve from 0.55857
Epoch 99/200
3/3 [============ 0.6286 - val loss: 55.2208 - rsquared: 0.6286 - val loss:
79.3060 - val_rsquared: 0.4563
Epoch 00099: val rsquared did not improve from 0.55857
Epoch 100/200
3/3 [============ 0.6312 - val loss:
79.8149 - val rsquared: 0.4526
Epoch 00100: val rsquared did not improve from 0.55857
Epoch 101/200
69.8191 - val rsquared: 0.5248
Epoch 00101: val rsquared did not improve from 0.55857
Epoch 102/200
74.1511 - val rsquared: 0.4938
Epoch 00102: val rsquared did not improve from 0.55857
Epoch 103/200
3/3 [============ 0.6428 - val loss: 51.1717 - rsquared: 0.6428 - val loss:
77.2919 - val rsquared: 0.4718
Epoch 00103: val_rsquared did not improve from 0.55857
Epoch 104/200
3/3 [========== 0.6504 - val loss: 51.0362 - rsquared: 0.6504 - val loss:
74.8077 - val_rsquared: 0.4902
Epoch 00104: val_rsquared did not improve from 0.55857
Epoch 105/200
77.8782 - val rsquared: 0.4682
Epoch 00105: val rsquared did not improve from 0.55857
Epoch 106/200
81.8952 - val rsquared: 0.4390
Epoch 00106: val rsquared did not improve from 0.55857
Epoch 107/200
73.0498 - val rsquared: 0.5032
Epoch 00107: val rsquared did not improve from 0.55857
Epoch 108/200
```

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76.2555 - val rsquared: 0.4804
Epoch 00108: val rsquared did not improve from 0.55857
Epoch 109/200
74.8916 - val rsquared: 0.4907
Epoch 00109: val rsquared did not improve from 0.55857
Epoch 110/200
79.2534 - val rsquared: 0.4593
Epoch 00110: val rsquared did not improve from 0.55857
Epoch 111/200
74.7931 - val rsquared: 0.4916
Epoch 00111: val rsquared did not improve from 0.55857
Epoch 112/200
73.8821 - val rsquared: 0.4989
Epoch 00112: val rsquared did not improve from 0.55857
Epoch 113/200
77.2740 - val rsquared: 0.4742
Epoch 00113: val_rsquared did not improve from 0.55857
Epoch 114/200
78.1639 - val rsquared: 0.4676
Epoch 00114: val rsquared did not improve from 0.55857
Epoch 115/200
3/3 [========== 0.6581 - val loss: 49.3940 - rsquared: 0.6581 - val loss:
71.8377 - val rsquared: 0.5126
Epoch 00115: val rsquared did not improve from 0.55857
Epoch 116/200
84.5959 - val rsquared: 0.4206
Epoch 00116: val rsquared did not improve from 0.55857
Epoch 117/200
71.0078 - val rsquared: 0.5192
Epoch 00117: val rsquared did not improve from 0.55857
Epoch 118/200
74.2935 - val rsquared: 0.4963
Epoch 00118: val_rsquared did not improve from 0.55857
Epoch 119/200
val loss: 83.7192 - val rsquared: 0.4288
Epoch 00119: val_rsquared did not improve from 0.55857
Epoch 120/200
85.2839 - val_rsquared: 0.4176
Epoch 00120: val rsquared did not improve from 0.55857
Epoch 121/200
76.4137 - val rsquared: 0.4815
Epoch 00121: val rsquared did not improve from 0.55857
Epoch 122/200
85.8734 - val rsquared: 0.4134
Epoch 00122: val rsquared did not improve from 0.55857
Epoch 123/200
```

79.0272 - val rsquared: 0.4627

```
Epoch 00123: val_rsquared did not improve from 0.55857
Epoch 124/200
3/3 [========== 0.69ms/step - loss: 46.8006 - rsquared: 0.6733 - val loss:
69.7140 - val_rsquared: 0.5297
Epoch 00124: val rsquared did not improve from 0.55857
Epoch 125/200
3/3 [=========== 0.6648 - val loss: 48.3959 - rsquared: 0.6648 - val loss:
80.4410 - val rsquared: 0.4527
Epoch 00125: val rsquared did not improve from 0.55857
Epoch 126/200
87.4756 - val rsquared: 0.4013
Epoch 00126: val rsquared did not improve from 0.55857
Epoch 127/200
73.6424 - val rsquared: 0.5004
Epoch 00127: val rsquared did not improve from 0.55857
Epoch 128/200
75.9006 - val rsquared: 0.4841
Epoch 00128: val rsquared did not improve from 0.55857
Epoch 129/200
91.3664 - val rsquared: 0.3730
Epoch 00129: val rsquared did not improve from 0.55857
Epoch 130/200
84.9563 - val rsquared: 0.4204
Epoch 00130: val rsquared did not improve from 0.55857
Epoch 131/200
75.0424 - val rsquared: 0.4919
Epoch 00131: val rsquared did not improve from 0.55857
Epoch 132/200
86.7497 - val rsquared: 0.4079
Epoch 00132: val rsquared did not improve from 0.55857
Epoch 133/200
80.3070 - val rsquared: 0.4542
Epoch 00133: val rsquared did not improve from 0.55857
Epoch 134/200
82.8414 - val rsquared: 0.4361
Epoch 00134: val rsquared did not improve from 0.55857
Epoch 135/200
3/3 [========== 0.6665 - val loss: 48.6565 - rsquared: 0.6665 - val loss:
95.2016 - val_rsquared: 0.3466
Epoch 00135: val rsquared did not improve from 0.55857
Epoch 136/200
3/3 [========== 0.66ms/step - loss: 46.1335 - rsquared: 0.6852 - val loss:
76.2901 - val rsquared: 0.4823
Epoch 00136: val rsquared did not improve from 0.55857
Epoch 137/200
82.9736 - val rsquared: 0.4337
Epoch 00137: val rsquared did not improve from 0.55857
Epoch 138/200
89.2286 - val rsquared: 0.3892
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Epoch 00138: val rsquared did not improve from 0.55857

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Epoch 139/200
74.0043 - val rsquared: 0.4989
Epoch 00139: val rsquared did not improve from 0.55857
Epoch 140/200
3/3 [========== 0.66ms/step - loss: 47.3584 - rsquared: 0.6728 - val loss:
80.5739 - val rsquared: 0.4524
Epoch 00140: val rsquared did not improve from 0.55857
Epoch 141/200
101.1057 - val rsquared: 0.3047
Epoch 00141: val rsquared did not improve from 0.55857
Epoch 142/200
82.7865 - val rsquared: 0.4376
Epoch 00142: val rsquared did not improve from 0.55857
78.4658 - val rsquared: 0.4683
Epoch 00143: val rsquared did not improve from 0.55857
Epoch 144/200
82.8297 - val rsquared: 0.4366
Epoch 00144: val_rsquared did not improve from 0.55857
Epoch 145/200
3/3 [========== ] - 0s 102ms/step - loss: 45.2890 - rsquared: 0.6879 -
val_loss: 89.3104 - val_rsquared: 0.3900
Epoch 00145: val rsquared did not improve from 0.55857
Epoch 146/200
96.1804 - val rsquared: 0.3407
Epoch 00146: val rsquared did not improve from 0.55857
Epoch 147/200
92.5646 - val rsquared: 0.3672
Epoch 00147: val rsquared did not improve from 0.55857
Epoch 148/200
74.8287 - val rsquared: 0.4953
Epoch 00148: val rsquared did not improve from 0.55857
Epoch 149/200
76.5572 - val rsquared: 0.4833
Epoch 00149: val rsquared did not improve from 0.55857
Epoch 150/200
99.8910 - val_rsquared: 0.3149
Epoch 00150: val rsquared did not improve from 0.55857
Epoch 151/200
3/3 [============ 0.6698 - val loss: 47.6372 - rsquared: 0.6698 - val loss:
82.1617 - val_rsquared: 0.4419
Epoch 00151: val rsquared did not improve from 0.55857
Epoch 152/200
3/3 [========== 0.7010 - val loss: 43.8164 - rsquared: 0.7010 - val loss:
76.4029 - val rsquared: 0.4826
Epoch 00152: val rsquared did not improve from 0.55857
Epoch 153/200
3/3 [=========== 0.7001 - val loss: 43.7410 - rsquared: 0.7001 - val loss:
98.3576 - val_rsquared: 0.3251
Epoch 00153: val rsquared did not improve from 0.55857
Epoch 154/200
```

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1 00 00M0/000P 1000. 10.1101 104Matem. 0.7010 Val_1000.
91.5270 - val rsquared: 0.3756
Epoch 00154: val rsquared did not improve from 0.55857
Epoch 155/200
80.9335 - val rsquared: 0.4528
Epoch 00155: val rsquared did not improve from 0.55857
Epoch 156/200
90.0024 - val rsquared: 0.3872
Epoch 00156: val rsquared did not improve from 0.55857
Epoch 157/200
91.6177 - val rsquared: 0.3751
Epoch 00157: val rsquared did not improve from 0.55857
Epoch 158/200
86.7724 - val rsquared: 0.4105
Epoch 00158: val rsquared did not improve from 0.55857
Epoch 159/200
81.9646 - val rsquared: 0.4454
Epoch 00159: val rsquared did not improve from 0.55857
Epoch 160/200
81.5969 - val_rsquared: 0.4479
Epoch 00160: val rsquared did not improve from 0.55857
Epoch 161/200
88.7645 - val rsquared: 0.3961
Epoch 00161: val rsquared did not improve from 0.55857
Epoch 162/200
3/3 [=========== 0.7150 - val loss: 41.6320 - rsquared: 0.7150 - val loss:
91.8355 - val rsquared: 0.3737
Epoch 00162: val rsquared did not improve from 0.55857
Epoch 163/200
85.0970 - val rsquared: 0.4229
Epoch 00163: val rsquared did not improve from 0.55857
Epoch 164/200
87.7767 - val_rsquared: 0.4045
Epoch 00164: val_rsquared did not improve from 0.55857
Epoch 165/200
89.0937 - val rsquared: 0.3955
Epoch 00165: val_rsquared did not improve from 0.55857
Epoch 166/200
3/3 [========== 0.7105 - val_loss: 42.1718 - rsquared: 0.7105 - val_loss:
96.5374 - val_rsquared: 0.3419
Epoch 00166: val_rsquared did not improve from 0.55857
Epoch 167/200
85.8999 - val rsquared: 0.4187
Epoch 00167: val rsquared did not improve from 0.55857
Epoch 168/200
86.9287 - val rsquared: 0.4110
Epoch 00168: val rsquared did not improve from 0.55857
Epoch 169/200
```

96.2006 - val rsquared: 0.3434

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Epoch 00169: val_rsquared did not improve from 0.55857
Epoch 170/200
91.8136 - val_rsquared: 0.3762
Epoch 00170: val rsquared did not improve from 0.55857
Epoch 171/200
98.4182 - val rsquared: 0.3293
Epoch 00171: val rsquared did not improve from 0.55857
Epoch 172/200
96.8621 - val rsquared: 0.3404
Epoch 00172: val rsquared did not improve from 0.55857
Epoch 173/200
3/3 [============ 0.7188 - val loss: 41.1149 - rsquared: 0.7188 - val loss:
94.7509 - val rsquared: 0.3546
Epoch 00173: val_rsquared did not improve from 0.55857
Epoch 174/200
3/3 [============ 0.73ms/step - loss: 37.8668 - rsquared: 0.7351 - val loss:
80.9984 - val rsquared: 0.4535
Epoch 00174: val rsquared did not improve from 0.55857
Epoch 175/200
88.2593 - val rsquared: 0.4014
Epoch 00175: val rsquared did not improve from 0.55857
Epoch 176/200
3/3 [============ 0.7333 - val loss: 38.9921 - rsquared: 0.7333 - val loss:
97.8620 - val_rsquared: 0.3329
Epoch 00176: val rsquared did not improve from 0.55857
Epoch 177/200
103.0694 - val rsquared: 0.2950
Epoch 00177: val rsquared did not improve from 0.55857
Epoch 178/200
97.3295 - val rsquared: 0.3356
Epoch 00178: val rsquared did not improve from 0.55857
Epoch 179/200
89.5533 - val rsquared: 0.3927
Epoch 00179: val_rsquared did not improve from 0.55857
Epoch 180/200
3/3 [=========== ] - 0s 64ms/step - loss: 37.8009 - rsquared: 0.7349 - val loss:
88.4306 - val rsquared: 0.4016
Epoch 00180: val rsquared did not improve from 0.55857
Epoch 181/200
92.2603 - val_rsquared: 0.3746
Epoch 00181: val rsquared did not improve from 0.55857
Epoch 182/200
3/3 [============ ] - 0s 79ms/step - loss: 39.4529 - rsquared: 0.7296 - val loss:
100.1925 - val rsquared: 0.3169
Epoch 00182: val rsquared did not improve from 0.55857
Epoch 183/200
3/3 [=========== 0.7413 - val loss: 37.5067 - rsquared: 0.7413 - val loss:
96.7032 - val rsquared: 0.3417
Epoch 00183: val rsquared did not improve from 0.55857
Epoch 184/200
89.5015 - val rsquared: 0.3946
Epoch 00184: val rsquared did not improve from 0.55857
Fnoch 185/200
```

```
FPUCII TOU/ZUU
val loss: 94.6274 - val rsquared: 0.3591
Epoch 00185: val rsquared did not improve from 0.55857
Epoch 186/200
102.6150 - val rsquared: 0.3020
Epoch 00186: val rsquared did not improve from 0.55857
Epoch 187/200
99.3175 - val rsquared: 0.3254
Epoch 00187: val rsquared did not improve from 0.55857
Epoch 188/200
103.5989 - val rsquared: 0.2947
Epoch 00188: val_rsquared did not improve from 0.55857
Epoch 189/200
103.3889 - val rsquared: 0.2966
Epoch 00189: val_rsquared did not improve from 0.55857
Epoch 190/200
3/3 [=========== 0.7388 - val loss:
101.8172 - val rsquared: 0.3075
Epoch 00190: val rsquared did not improve from 0.55857
Epoch 191/200
3/3 [============ 0.7368 - val loss: 37.9822 - rsquared: 0.7368 - val loss:
95.0816 - val_rsquared: 0.3555
Epoch 00191: val rsquared did not improve from 0.55857
Epoch 192/200
3/3 [============ 0.7373 - val loss: 38.5661 - rsquared: 0.7373 - val loss:
103.3661 - val rsquared: 0.2968
Epoch 00192: val rsquared did not improve from 0.55857
Epoch 193/200
3/3 [=========== 0.7469 - val loss: 36.5188 - rsquared: 0.7469 - val loss:
97.9688 - val rsquared: 0.3355
Epoch 00193: val rsquared did not improve from 0.55857
Epoch 194/200
3/3 [=========== 0.7393 - val loss: 37.4633 - rsquared: 0.7393 - val loss:
98.8919 - val rsquared: 0.3280
Epoch 00194: val rsquared did not improve from 0.55857
Epoch 195/200
val loss: 114.5364 - val rsquared: 0.2159
Epoch 00195: val_rsquared did not improve from 0.55857
Epoch 196/200
112.1199 - val rsquared: 0.2340
Epoch 00196: val rsquared did not improve from 0.55857
Epoch 197/200
3/3 [========== 0.7335 - val loss: 38.6595 - rsquared: 0.7335 - val loss:
92.2749 - val_rsquared: 0.3765
Epoch 00197: val_rsquared did not improve from 0.55857
Epoch 198/200
84.5297 - val rsquared: 0.4332
Epoch 00198: val rsquared did not improve from 0.55857
Epoch 199/200
91.2670 - val rsquared: 0.3845
Epoch 00199: val rsquared did not improve from 0.55857
Epoch 200/200
```

101 1644 **** ********** 0 2120

```
Epoch 00200: val_rsquared did not improve from 0.55857

Out[171]:
<tensorflow.python.keras.callbacks.History at 0x7fa63dcbcdf0>

In [214]:

score10 = 0.5587
```

With Feature Set - 5

```
In [177]:
```

```
X_Set5 = pd.DataFrame(np.hstack((x,x_svd)))
print(X_Set5.shape)
(4196, 528)
```

In [178]:

```
X_train_MLP_Set5, X_test_MLP_Set5, y_train, y_test = train_test_split(X_Set5, y, test_size=0.33, ra
ndom_state=1)
print("Done")
```

Done

In [179]:

```
input_dim = X_train_MLP_Set5.shape[1]

# The Input Layer :
model = Sequential()
model.add(Dense(128,kernel_initializer='normal', input_dim=input_dim, activation='relu'))

# The Hidden Layers :
model.add(Dense(256, kernel_initializer='normal',activation='relu'))
model.add(Dense(256, kernel_initializer='normal',activation='relu'))
model.add(Dense(256, kernel_initializer='normal',activation='relu'))
model.add(Dense(256, kernel_initializer='normal',activation='relu'))
model.add(Dense(256, kernel_initializer='normal',activation='relu'))
# The Output Layer :
model.add(Dense(1, kernel_initializer='normal',activation='linear'))

model.compile(loss='mean_squared_error', optimizer='adam', metrics=[rsquared])
model.summary()
```

Model: "sequential_17"

Layer (type)	Output Shape	Param #
dense_131 (Dense)	(None, 128)	67712
dense_132 (Dense)	(None, 256)	33024
dense_133 (Dense)	(None, 256)	65792
dense_134 (Dense)	(None, 256)	65792
dropout_12 (Dropout)	(None, 256)	0
dense_135 (Dense)	(None, 256)	65792
dense_136 (Dense)	(None, 256)	65792
dense_137 (Dense)	(None, 1)	257

```
Total params: 364,161
Trainable params: 364,161
Non-trainable params: 0
```

In [180]:

T 1 00000

```
filepath="/tmp/checkpoint2"
checkpoint = ModelCheckpoint(filepath=filepath, monitor='val rsquared', verbose=1, save best only=T
rue, mode='max')
optimizer = tf.keras.optimizers.Adam(0.01)
#time = datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
log dir= "logs/fit/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard callback = tf.keras.callbacks.TensorBoard(log dir=log dir,histogram freq=1, write graph
=True, write grads=True)
callbacks list = [checkpoint,tensorboard callback]
=1000, callbacks=callbacks list)
WARNING:tensorflow:`write grads` will be ignored in TensorFlow 2.0 for the `TensorBoard` Callback.
Epoch 1/200
loss: 9756.2100 - val rsquared: -70.1243
Epoch 00001: val rsquared improved from -inf to -70.12425, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 2/200
oss: 8004.1074 - val rsquared: -57.4111
Epoch 00002: val rsquared improved from -70.12425 to -57.41114, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 3/200
oss: 2582.0291 - val rsquared: -17.9900
Epoch 00003: val rsquared improved from -57.41114 to -17.98996, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 4/200
oss: 2828.3259 - val rsquared: -19.1378
Epoch 00004: val rsquared did not improve from -17.98996
Epoch 5/200
oss: 498.8972 - val rsquared: -2.6868
Epoch 00005: val_rsquared improved from -17.98996 to -2.68678, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 6/200
          3/3 [======
val loss: 1433.2096 - val rsquared: -9.5800
Epoch 00006: val rsquared did not improve from -2.68678
Epoch 7/200
val_loss: 785.8000 - val_rsquared: -4.8199
Epoch 00007: val_rsquared did not improve from -2.68678
Epoch 8/200
val loss: 498.0602 - val rsquared: -2.5393
Epoch 00008: val rsquared improved from -2.68678 to -2.53931, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 9/200
val loss: 617.5739 - val rsquared: -3.3761
```

1 11 1 1 1 6 0 50001

```
Epoch UUUU9: val rsquared did not improve from -2.53931
Epoch 10/200
val loss: 335.7969 - val rsquared: -1.4705
Epoch 00010: val rsquared improved from -2.53931 to -1.47054, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 11/200
val_loss: 459.4618 - val_rsquared: -2.3916
Epoch 00011: val rsquared did not improve from -1.47054
Epoch 12/200
3/3 [============= - 0s 64ms/step - loss: 453.0011 - rsquared: -1.9873 -
val loss: 209.4948 - val rsquared: -0.5093
Epoch 00012: val rsquared improved from -1.47054 to -0.50927, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 13/200
3/3 [============= - 0s 61ms/step - loss: 263.0817 - rsquared: -0.7956 -
val_loss: 314.5125 - val_rsquared: -1.2218
Epoch 00013: val rsquared did not improve from -0.50927
Epoch 14/200
val loss: 164.8149 - val rsquared: -0.1794
Epoch 00014: val rsquared improved from -0.50927 to -0.17938, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 15/200
val loss: 208.0563 - val rsquared: -0.5108
Epoch 00015: val rsquared did not improve from -0.17938
Epoch 16/200
3/3 [===========] - 0s 63ms/step - loss: 224.0285 - rsquared: -0.5184 -
val loss: 129.4624 - val rsquared: 0.0857
Epoch 00016: val rsquared improved from -0.17938 to 0.08568, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 17/200
val_loss: 154.3812 - val_rsquared: -0.0846
Epoch 00017: val rsquared did not improve from 0.08568
Epoch 18/200
3/3 [============= ] - 0s 64ms/step - loss: 160.9762 - rsquared: -0.1201 -
val loss: 115.4702 - val rsquared: 0.1845
Epoch 00018: val rsquared improved from 0.08568 to 0.18454, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 19/200
3/3 [========= ] - 0s 61ms/step - loss: 144.8060 - rsquared: 0.0071 -
val_loss: 115.1973 - val_rsquared: 0.1866
Epoch 00019: val rsquared improved from 0.18454 to 0.18661, saving model to /tmp/checkpoint2
INFO:tensorflow: Assets written to: /tmp/checkpoint2/assets
Epoch 20/200
val loss: 110.0284 - val rsquared: 0.2310
Epoch 00020: val rsquared improved from 0.18661 to 0.23098, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 21/200
val loss: 96.5357 - val rsquared: 0.3271
Epoch 00021: val_rsquared improved from 0.23098 to 0.32712, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 22/200
3/3 [============== ] - 0s 68ms/step - loss: 111.2948 - rsquared: 0.2363 -
val loss: 98.7842 - val rsquared: 0.3093
Epoch 00022: val rsquared did not improve from 0.32712
Epoch 23/200
3/3 [=========== ] - 0s 66ms/step - loss: 111.5426 - rsquared: 0.2299 -
val loss: 89.7993 - val rsquared: 0.3761
```

```
Epoch 00023: val rsquared improved from 0.32712 to 0.37615, saving model to /tmp/checkpoint2
INFO:tensorflow: Assets written to: /tmp/checkpoint2/assets
Epoch 24/200
val loss: 88.0242 - val rsquared: 0.3892
Epoch 00024: val_rsquared improved from 0.37615 to 0.38923, saving model to /\text{tmp/checkpoint2}
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 25/200
val loss: 85.9408 - val rsquared: 0.4041
Epoch 00025: val rsquared improved from 0.38923 to 0.40413, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 26/200
82.7151 - val rsquared: 0.4290
Epoch 00026: val rsquared improved from 0.40413 to 0.42899, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 27/200
80.5978 - val rsquared: 0.4447
Epoch 00027: val rsquared improved from 0.42899 to 0.44467, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 28/200
3/3 [============ 0.3689 - val loss: 91.7069 - rsquared: 0.3689 - val loss:
79.6083 - val rsquared: 0.4522
Epoch 00028: val rsquared improved from 0.44467 to 0.45220, saving model to /tmp/checkpoint2
INFO:tensorflow: Assets written to: /tmp/checkpoint2/assets
Epoch 29/200
78.2499 - val rsquared: 0.4632
Epoch 00029: val_rsquared improved from 0.45220 to 0.46316, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 30/200
77.2031 - val rsquared: 0.4708
Epoch 00030: val rsquared improved from 0.46316 to 0.47084, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 31/200
76.3970 - val rsquared: 0.4770
Epoch 00031: val rsquared improved from 0.47084 to 0.47699, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 32/200
3/3 [========== 0.4354 - val loss: 81.8454 - rsquared: 0.4354 - val loss:
75.7652 - val rsquared: 0.4814
Epoch 00032: val rsquared improved from 0.47699 to 0.48145, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 33/200
75.0990 - val rsquared: 0.4863
Epoch 00033: val_rsquared improved from 0.48145 to 0.48629, saving model to / tmp/checkpoint2
INFO:tensorflow: Assets written to: /tmp/checkpoint2/assets
Epoch 34/200
74.6045 - val_rsquared: 0.4900
Epoch 00034: val_rsquared improved from 0.48629 to 0.49004, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 35/200
73.8529 - val rsquared: 0.4958
Epoch 00035: val_rsquared improved from 0.49004 to 0.49577, saving model to /\text{tmp/checkpoint2}
INFO:tensorflow: Assets written to: /tmp/checkpoint2/assets
Epoch 36/200
```

```
73.8401 - val rsquared: 0.4952
Epoch 00036: val_rsquared did not improve from 0.49577
72.8288 - val rsquared: 0.5023
Epoch 00037: val rsquared improved from 0.49577 to 0.50225, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 38/200
72.6703 - val rsquared: 0.5026
Epoch 00038: val_rsquared improved from 0.50225 to 0.50257, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 39/200
3/3 [======
           =============== ] - 0s 84ms/step - loss: 80.7671 - rsquared: 0.4459 - val loss:
72.1722 - val rsquared: 0.5060
Epoch 00039: val rsquared improved from 0.50257 to 0.50603, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 40/200
72.3239 - val rsquared: 0.5049
Epoch 00040: val rsquared did not improve from 0.50603
Epoch 41/200
71.4928 - val rsquared: 0.5113
Epoch 00041: val rsquared improved from 0.50603 to 0.51130, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 42/200
71.4189 - val rsquared: 0.5113
Epoch 00042: val rsquared did not improve from 0.51130
Epoch 43/200
70.7068 - val rsquared: 0.5159
Epoch 00043: val rsquared improved from 0.51130 to 0.51585, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 44/200
70.4935 - val rsquared: 0.5168
Epoch 00044: val rsquared improved from 0.51585 to 0.51675, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 45/200
3/3 [========== 0.5198 - val loss: 70.3921 - rsquared: 0.5198 - val loss:
70.5366 - val_rsquared: 0.5161
Epoch 00045: val rsquared did not improve from 0.51675
Epoch 46/200
70.0920 - val rsquared: 0.5194
Epoch 00046: val rsquared improved from 0.51675 to 0.51941, saving model to /\text{tmp/checkpoint2}
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 47/200
69.0915 - val rsquared: 0.5270
Epoch 00047: val rsquared improved from 0.51941 to 0.52698, saving model to /tmp/checkpoint2
INFO:tensorflow: Assets written to: /tmp/checkpoint2/assets
Epoch 48/200
3/3 [============ ] - 0s 58ms/step - loss: 70.4326 - rsquared: 0.5105 - val_loss:
71.4922 - val_rsquared: 0.5090
Epoch 00048: val rsquared did not improve from 0.52698
Epoch 49/200
3/3 [========== 0.5122 - val loss: 71.3697 - rsquared: 0.5122 - val loss:
68.8644 - val rsquared: 0.5287
Epoch 00049: val rsquared improved from 0.52698 to 0.52871, saving model to /tmp/checkpoint2
```

INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets

```
Epoch 50/200
74.7543 - val rsquared: 0.4844
Epoch 00050: val rsquared did not improve from 0.52871
Epoch 51/200
69.0619 - val rsquared: 0.5270
Epoch 00051: val rsquared did not improve from 0.52871
Epoch 52/200
75.3992 - val rsquared: 0.4790
Epoch 00052: val rsquared did not improve from 0.52871
Epoch 53/200
68.2077 - val rsquared: 0.5320
Epoch 00053: val rsquared improved from 0.52871 to 0.53202, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 54/200
76.0041 - val rsquared: 0.4737
Epoch 00054: val rsquared did not improve from 0.53202
Epoch 55/200
67.8792 - val rsquared: 0.5341
Epoch 00055: val rsquared improved from 0.53202 to 0.53405, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 56/200
73.9734 - val rsquared: 0.4890
Epoch 00056: val rsquared did not improve from 0.53405
Epoch 57/200
67.6415 - val rsquared: 0.5363
Epoch 00057: val_rsquared improved from 0.53405 to 0.53627, saving model to /\text{tmp/checkpoint2}
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 58/200
71.8457 - val rsquared: 0.5054
Epoch 00058: val rsquared did not improve from 0.53627
Epoch 59/200
67.4676 - val rsquared: 0.5378
Epoch 00059: val_rsquared improved from 0.53627 to 0.53778, saving model to /\text{tmp/checkpoint2}
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 60/200
70.8118 - val rsquared: 0.5130
Epoch 00060: val rsquared did not improve from 0.53778
Epoch 61/200
69.3310 - val rsquared: 0.5235
Epoch 00061: val rsquared did not improve from 0.53778
Epoch 62/200
69.5181 - val_rsquared: 0.5221
Epoch 00062: val rsquared did not improve from 0.53778
Epoch 63/200
3/3 [=============== ] - Os 102ms/step - loss: 64.7873 - rsquared: 0.5569 -
val_loss: 71.2141 - val_rsquared: 0.5099
Epoch 00063: val rsquared did not improve from 0.53778
Epoch 64/200
```

68.7566 - val rsquared: 0.5286

```
Epoch 00064: val_rsquared did not improve from 0.53778
Epoch 65/200
71.6643 - val rsquared: 0.5074
Epoch 00065: val_rsquared did not improve from 0.53778
67.8015 - val_rsquared: 0.5354
Epoch 00066: val rsquared did not improve from 0.53778
Epoch 67/200
3/3 [============ 0.5587 - val loss: 62.6915 - rsquared: 0.5587 - val loss:
71.9556 - val rsquared: 0.5043
Epoch 00067: val rsquared did not improve from 0.53778
Epoch 68/200
67.9391 - val rsquared: 0.5331
Epoch 00068: val rsquared did not improve from 0.53778
Epoch 69/200
71.8466 - val rsquared: 0.5045
Epoch 00069: val rsquared did not improve from 0.53778
Epoch 70/200
3/3 [=========== 0.6063 - val loss: 59.0770 - rsquared: 0.6063 - val loss:
69.3957 - val rsquared: 0.5226
Epoch 00070: val rsquared did not improve from 0.53778
Epoch 71/200
70.2096 - val rsquared: 0.5167
Epoch 00071: val rsquared did not improve from 0.53778
Epoch 72/200
67.2373 - val_rsquared: 0.5386
Epoch 00072: val rsquared improved from 0.53778 to 0.53856, saving model to /tmp/checkpoint2
INFO:tensorflow:Assets written to: /tmp/checkpoint2/assets
Epoch 73/200
3/3 [========== 0.5730 - val loss: 62.8202 - rsquared: 0.5730 - val loss:
72.3569 - val rsquared: 0.5007
Epoch 00073: val rsquared did not improve from 0.53856
Epoch 74/200
71.3760 - val rsquared: 0.5083
Epoch 00074: val rsquared did not improve from 0.53856
Epoch 75/200
3/3 [========== 0.5943 - val loss: 59.4301 - rsquared: 0.5943 - val loss:
68.9405 - val_rsquared: 0.5265
Epoch 00075: val rsquared did not improve from 0.53856
Epoch 76/200
69.9777 - val rsquared: 0.5194
Epoch 00076: val rsquared did not improve from 0.53856
Epoch 77/200
69.6021 - val rsquared: 0.5225
Epoch 00077: val rsquared did not improve from 0.53856
Epoch 78/200
71.9532 - val rsquared: 0.5050
Epoch 00078: val_rsquared did not improve from 0.53856
Epoch 79/200
71.8070 - val rsquared: 0.5055
```

```
Epoch 00079: val rsquared did not improve from 0.53856
Epoch 80/200
68.3922 - val rsquared: 0.5306
Epoch 00080: val rsquared did not improve from 0.53856
Epoch 81/200
val loss: 73.2566 - val rsquared: 0.4955
Epoch 00081: val rsquared did not improve from 0.53856
Epoch 82/200
3/3 [============ 0.6067 - val loss: 58.0794 - rsquared: 0.6067 - val loss:
72.7973 - val_rsquared: 0.4996
Epoch 00082: val rsquared did not improve from 0.53856
68.8117 - val rsquared: 0.5288
Epoch 00083: val rsquared did not improve from 0.53856
Epoch 84/200
3/3 [=========== 0.6067 - val loss: 56.2570 - rsquared: 0.6067 - val loss:
72.1400 - val_rsquared: 0.5039
Epoch 00084: val_rsquared did not improve from 0.53856
Epoch 85/200
77.3433 - val rsquared: 0.4667
Epoch 00085: val rsquared did not improve from 0.53856
Epoch 86/200
70.8468 - val rsquared: 0.5145
Epoch 00086: val rsquared did not improve from 0.53856
Epoch 87/200
76.9284 - val rsquared: 0.4696
Epoch 00087: val_rsquared did not improve from 0.53856
Epoch 88/200
76.0167 - val rsquared: 0.4766
Epoch 00088: val_rsquared did not improve from 0.53856
Epoch 89/200
70.3056 - val rsquared: 0.5184
Epoch 00089: val rsquared did not improve from 0.53856
Epoch 90/200
73.1342 - val_rsquared: 0.4983
Epoch 00090: val_rsquared did not improve from 0.53856
Epoch 91/200
81.6685 - val rsquared: 0.4359
Epoch 00091: val rsquared did not improve from 0.53856
Epoch 92/200
78.9322 - val rsquared: 0.4552
Epoch 00092: val rsquared did not improve from 0.53856
Epoch 93/200
67.7202 - val rsquared: 0.5366
Epoch 00093: val rsquared did not improve from 0.53856
3/3 [============ 0.6205 - val loss: 55.3028 - rsquared: 0.6205 - val loss:
78.2793 - val rsquared: 0.4605
Epoch 00094: val_rsquared did not improve from 0.53856
Epoch 95/200
```

```
88.9948 - val rsquared: 0.3824
Epoch 00095: val rsquared did not improve from 0.53856
Epoch 96/200
67.6363 - val rsquared: 0.5374
Epoch 00096: val rsquared did not improve from 0.53856
Epoch 97/200
72.5770 - val rsquared: 0.5013
Epoch 00097: val_rsquared did not improve from 0.53856
89.4280 - val rsquared: 0.3788
Epoch 00098: val rsquared did not improve from 0.53856
Epoch 99/200
67.2236 - val rsquared: 0.5397
Epoch 00099: val rsquared improved from 0.53856 to 0.53969, saving model to /tmp/checkpoint2
INFO:tensorflow: Assets written to: /tmp/checkpoint2/assets
Epoch 100/200
84.5866 - val rsquared: 0.4143
Epoch 00100: val_rsquared did not improve from 0.53969
Epoch 101/200
83.0296 - val_rsquared: 0.4260
Epoch 00101: val rsquared did not improve from 0.53969
Epoch 102/200
72.7112 - val rsquared: 0.5010
Epoch 00102: val_rsquared did not improve from 0.53969
Epoch 103/200
86.5635 - val rsquared: 0.4005
Epoch 00103: val rsquared did not improve from 0.53969
Epoch 104/200
86.8937 - val rsquared: 0.3990
Epoch 00104: val rsquared did not improve from 0.53969
Epoch 105/200
69.3262 - val rsquared: 0.5264
Epoch 00105: val rsquared did not improve from 0.53969
Epoch 106/200
3/3 [========= ] - 0s 113ms/step - loss: 52.0305 - rsquared: 0.6424 -
val loss: 82.1705 - val rsquared: 0.4334
Epoch 00106: val rsquared did not improve from 0.53969
Epoch 107/200
3/3 [=========== 0.6526 - val loss: 49.3686 - rsquared: 0.6526 - val loss:
79.4275 - val rsquared: 0.4533
Epoch 00107: val rsquared did not improve from 0.53969
Epoch 108/200
73.5621 - val rsquared: 0.4965
Epoch 00108: val rsquared did not improve from 0.53969
Epoch 109/200
3/3 [============= ] - 0s 67ms/step - loss: 48.7434 - rsquared: 0.6562 - val loss:
76.8162 - val rsquared: 0.4729
Epoch 00109: val rsquared did not improve from 0.53969
Epoch 110/200
3/3 [========= ] - 0s 102ms/step - loss: 50.9564 - rsquared: 0.6447 -
```

```
val loss: 80.0590 - val rsquared: 0.4487
Epoch 00110: val rsquared did not improve from 0.53969
Epoch 111/200
87.2218 - val rsquared: 0.3966
Epoch 00111: val rsquared did not improve from 0.53969
Epoch 112/200
3/3 [=========: 0.6701 - val loss: 47.8052 - rsquared: 0.6701 - val loss:
71.2139 - val rsquared: 0.5131
Epoch 00112: val rsquared did not improve from 0.53969
Epoch 113/200
80.2733 - val rsquared: 0.4476
Epoch 00113: val rsquared did not improve from 0.53969
Epoch 114/200
87.4570 - val rsquared: 0.3960
Epoch 00114: val rsquared did not improve from 0.53969
Epoch 115/200
91.0872 - val rsquared: 0.3699
Epoch 00115: val_rsquared did not improve from 0.53969
Epoch 116/200
72.5323 - val rsquared: 0.5042
Epoch 00116: val rsquared did not improve from 0.53969
Epoch 117/200
3/3 [========== 0.6541 - val loss: 50.2324 - rsquared: 0.6541 - val loss:
86.6257 - val rsquared: 0.4028
Epoch 00117: val rsquared did not improve from 0.53969
Epoch 118/200
82.4244 - val rsquared: 0.4331
Epoch 00118: val rsquared did not improve from 0.53969
Epoch 119/200
3/3 [============ 0.6679 - val loss: 48.1473 - rsquared: 0.6679 - val loss:
71.8875 - val rsquared: 0.5084
Epoch 00119: val rsquared did not improve from 0.53969
Epoch 120/200
3/3 [======
          83.3800 - val rsquared: 0.4247
Epoch 00120: val rsquared did not improve from 0.53969
Epoch 121/200
82.9033 - val rsquared: 0.4282
Epoch 00121: val_rsquared did not improve from 0.53969
Epoch 122/200
73.1227 - val rsquared: 0.4986
Epoch 00122: val rsquared did not improve from 0.53969
Epoch 123/200
3/3 [========== 0.6624 - val loss: 48.5529 - rsquared: 0.6624 - val loss:
76.0466 - val_rsquared: 0.4784
Epoch 00123: val rsquared did not improve from 0.53969
Epoch 124/200
90.1360 - val_rsquared: 0.3781
Epoch 00124: val rsquared did not improve from 0.53969
Epoch 125/200
83.5692 - val rsquared: 0.4260
```

```
Epoch 00125: val_rsquared did not improve from 0.53969
Epoch 126/200
3/3 [=========: 0.6660 - val loss: 48.8686 - rsquared: 0.6660 - val loss:
82.0059 - val_rsquared: 0.4376
Epoch 00126: val rsquared did not improve from 0.53969
Epoch 127/200
3/3 [=========== 0.64ms/step - loss: 49.5645 - rsquared: 0.6573 - val loss:
84.6544 - val rsquared: 0.4181
Epoch 00127: val_rsquared did not improve from 0.53969
Epoch 128/200
88.7015 - val rsquared: 0.3883
Epoch 00128: val rsquared did not improve from 0.53969
Epoch 129/200
83.9302 - val rsquared: 0.4228
Epoch 00129: val rsquared did not improve from 0.53969
Epoch 130/200
loss: 49.3301 - rsquared: 0.6678 - val loss: 82.9012 - val_rsquared: 0.4301
Epoch 00130: val_rsquared did not improve from 0.53969
Epoch 131/200
84.6411 - val rsquared: 0.4180
Epoch 00131: val rsquared did not improve from 0.53969
Epoch 132/200
3/3 [============ 0.65ms/step - loss: 45.8757 - rsquared: 0.6822 - val loss:
90.1682 - val_rsquared: 0.3785
Epoch 00132: val rsquared did not improve from 0.53969
Epoch 133/200
3/3 [=========== 0.6674 - val loss: 49.6857 - rsquared: 0.6674 - val loss:
92.1388 - val rsquared: 0.3637
Epoch 00133: val rsquared did not improve from 0.53969
Epoch 134/200
80.8116 - val rsquared: 0.4453
Epoch 00134: val rsquared did not improve from 0.53969
Epoch 135/200
87.9854 - val rsquared: 0.3934
Epoch 00135: val rsquared did not improve from 0.53969
Epoch 136/200
96.9019 - val rsquared: 0.3281
Epoch 00136: val_rsquared did not improve from 0.53969
Epoch 137/200
3/3 [========== 0.64ms/step - loss: 47.0181 - rsquared: 0.6732 - val loss:
83.8929 - val_rsquared: 0.4228
Epoch 00137: val rsquared did not improve from 0.53969
Epoch 138/200
3/3 [============ 0.65ms/step - loss: 45.9871 - rsquared: 0.6751 - val loss:
74.7960 - val rsquared: 0.4887
Epoch 00138: val rsquared did not improve from 0.53969
Epoch 139/200
83.8910 - val rsquared: 0.4214
Epoch 00139: val rsquared did not improve from 0.53969
Epoch 140/200
100.4094 - val rsquared: 0.3003
Epoch 00140: val rsquared did not improve from 0.53969
Epoch 141/200
```

```
3/3 [============ ] - 0s 80ms/step - loss: 45.6307 - rsquared: 0.6785 - val loss:
83.3491 - val rsquared: 0.4261
Epoch 00141: val rsquared did not improve from 0.53969
Epoch 142/200
84.1785 - val rsquared: 0.4214
Epoch 00142: val rsquared did not improve from 0.53969
Epoch 143/200
88.4691 - val rsquared: 0.3906
Epoch 00143: val rsquared did not improve from 0.53969
Epoch 144/200
101.5430 - val rsquared: 0.2964
Epoch 00144: val rsquared did not improve from 0.53969
Epoch 145/200
3/3 [======
         =========] - 0s 76ms/step - loss: 47.1522 - rsquared: 0.6734 - val_loss:
90.8139 - val rsquared: 0.3756
Epoch 00145: val rsquared did not improve from 0.53969
Epoch 146/200
89.2050 - val rsquared: 0.3859
Epoch 00146: val_rsquared did not improve from 0.53969
Epoch 147/200
98.1981 - val rsquared: 0.3187
Epoch 00147: val rsquared did not improve from 0.53969
Epoch 148/200
3/3 [========== 0.63ms/step - loss: 46.6770 - rsquared: 0.6789 - val loss:
91.5471 - val rsquared: 0.3675
Epoch 00148: val rsquared did not improve from 0.53969
Epoch 149/200
87.2931 - val rsquared: 0.3988
Epoch 00149: val rsquared did not improve from 0.53969
Epoch 150/200
83.6271 - val rsquared: 0.4258
Epoch 00150: val rsquared did not improve from 0.53969
Epoch 151/200
108.4963 - val rsquared: 0.2444
Epoch 00151: val rsquared did not improve from 0.53969
Epoch 152/200
102.9463 - val_rsquared: 0.2861
Epoch 00152: val_rsquared did not improve from 0.53969
Epoch 153/200
3/3 [============ ] - 0s 76ms/step - loss: 45.5970 - rsquared: 0.6848 - val loss:
81.0736 - val_rsquared: 0.4465
Epoch 00153: val rsquared did not improve from 0.53969
Epoch 154/200
80.3773 - val rsquared: 0.4494
Epoch 00154: val rsquared did not improve from 0.53969
Epoch 155/200
100.8352 - val rsquared: 0.2985
Epoch 00155: val rsquared did not improve from 0.53969
Epoch 156/200
```

101.1413 - val rsquared: 0.2975

```
Epoch 00156: val rsquared did not improve from 0.53969
Epoch 157/200
3/3 [==========: 0.6996 - val loss: 43.5085 - rsquared: 0.6996 - val loss:
102.5588 - val_rsquared: 0.2881
Epoch 00157: val rsquared did not improve from 0.53969
Epoch 158/200
3/3 [========== 0.68ms/step - loss: 45.1255 - rsquared: 0.6867 - val loss:
83.4762 - val rsquared: 0.4269
Epoch 00158: val rsquared did not improve from 0.53969
Epoch 159/200
85.7464 - val rsquared: 0.4098
Epoch 00159: val rsquared did not improve from 0.53969
Epoch 160/200
3/3 [============ 0.7000 - val loss: 44.4027 - rsquared: 0.7000 - val loss:
100.2592 - val rsquared: 0.3057
Epoch 00160: val rsquared did not improve from 0.53969
Epoch 161/200
104.2024 - val rsquared: 0.2773
Epoch 00161: val rsquared did not improve from 0.53969
Epoch 162/200
3/3 [============ 0.7081 - val loss: 42.5162 - rsquared: 0.7081 - val loss:
94.6722 - val rsquared: 0.3464
Epoch 00162: val rsquared did not improve from 0.53969
Epoch 163/200
89.1959 - val rsquared: 0.3852
Epoch 00163: val rsquared did not improve from 0.53969
Epoch 164/200
95.4777 - val rsquared: 0.3391
Epoch 00164: val rsquared did not improve from 0.53969
Epoch 165/200
3/3 [=========== ] - 0s 112ms/step - loss: 44.0883 - rsquared: 0.6947 -
val loss: 104.5227 - val rsquared: 0.2734
Epoch 00165: val rsquared did not improve from 0.53969
Epoch 166/200
106.6308 - val rsquared: 0.2589
Epoch 00166: val rsquared did not improve from 0.53969
Epoch 167/200
98.9396 - val rsquared: 0.3146
Epoch 00167: val rsquared did not improve from 0.53969
Epoch 168/200
3/3 [=========== 0.7181 - val loss: 40.6389 - rsquared: 0.7181 - val loss:
90.2194 - val_rsquared: 0.3772
Epoch 00168: val rsquared did not improve from 0.53969
Epoch 169/200
3/3 [========== 0.7072 - val loss: 42.2517 - rsquared: 0.7072 - val loss:
85.0897 - val rsquared: 0.4150
Epoch 00169: val rsquared did not improve from 0.53969
Epoch 170/200
85.1683 - val rsquared: 0.4149
Epoch 00170: val rsquared did not improve from 0.53969
Epoch 171/200
113.5731 - val rsquared: 0.2070
```

Epoch 00171: val rsquared did not improve from 0.53969

```
Epoch 172/200
116.7531 - val_rsquared: 0.1835
Epoch 00172: val rsquared did not improve from 0.53969
Epoch 173/200
116.8704 - val rsquared: 0.1823
Epoch 00173: val rsquared did not improve from 0.53969
Epoch 174/200
103.4597 - val rsquared: 0.2816
Epoch 00174: val rsquared did not improve from 0.53969
Epoch 175/200
89.9147 - val rsquared: 0.3810
Epoch 00175: val rsquared did not improve from 0.53969
93.2107 - val rsquared: 0.3562
Epoch 00176: val rsquared did not improve from 0.53969
Epoch 177/200
95.4100 - val rsquared: 0.3394
Epoch 00177: val_rsquared did not improve from 0.53969
Epoch 178/200
130.0516 - val_rsquared: 0.0880
Epoch 00178: val rsquared did not improve from 0.53969
Epoch 179/200
125.9213 - val rsquared: 0.1192
Epoch 00179: val rsquared did not improve from 0.53969
Epoch 180/200
102.8483 - val rsquared: 0.2863
Epoch 00180: val rsquared did not improve from 0.53969
Epoch 181/200
92.3802 - val rsquared: 0.3622
Epoch 00181: val rsquared did not improve from 0.53969
Epoch 182/200
3/3 [============ ] - 0s 72ms/step - loss: 41.1700 - rsquared: 0.7180 - val loss:
95.1402 - val rsquared: 0.3421
Epoch 00182: val rsquared did not improve from 0.53969
Epoch 183/200
100.4846 - val_rsquared: 0.3034
Epoch 00183: val_rsquared did not improve from 0.53969
Epoch 184/200
3/3 [============ 0.7131 - val loss: 42.3769 - rsquared: 0.7131 - val loss:
106.7722 - val_rsquared: 0.2577
Epoch 00184: val rsquared did not improve from 0.53969
Epoch 185/200
132.3289 - val rsquared: 0.0704
Epoch 00185: val rsquared did not improve from 0.53969
Epoch 186/200
127.9638 - val rsquared: 0.1026
Epoch 00186: val rsquared did not improve from 0.53969
Epoch 187/200
```

```
118.0099 - val rsquared: 0.1762
Epoch 00187: val rsquared did not improve from 0.53969
Epoch 188/200
101.3739 - val rsquared: 0.2974
Epoch 00188: val rsquared did not improve from 0.53969
Epoch 189/200
108.7451 - val rsquared: 0.2427
Epoch 00189: val rsquared did not improve from 0.53969
Epoch 190/200
121.6437 - val rsquared: 0.1481
Epoch 00190: val rsquared did not improve from 0.53969
Epoch 191/200
108.2384 - val rsquared: 0.2461
Epoch 00191: val_rsquared did not improve from 0.53969
Epoch 192/200
94.6782 - val rsquared: 0.3452
Epoch 00192: val rsquared did not improve from 0.53969
Epoch 193/200
3/3 [========== ] - 0s 114ms/step - loss: 40.7619 - rsquared: 0.7224 -
val_loss: 97.3004 - val_rsquared: 0.3257
Epoch 00193: val rsquared did not improve from 0.53969
Epoch 194/200
111.7724 - val rsquared: 0.2202
Epoch 00194: val rsquared did not improve from 0.53969
Epoch 195/200
112.8108 - val rsquared: 0.2129
Epoch 00195: val rsquared did not improve from 0.53969
Epoch 196/200
125.7706 - val rsquared: 0.1184
Epoch 00196: val rsquared did not improve from 0.53969
Epoch 197/200
132.7331 - val rsquared: 0.0680
Epoch 00197: val_rsquared did not improve from 0.53969
Epoch 198/200
134.7598 - val rsquared: 0.0537
Epoch 00198: val rsquared did not improve from 0.53969
Epoch 199/200
3/3 [========= 0.7304 - val loss: 40.2247 - rsquared: 0.7304 - val loss:
122.4880 - val_rsquared: 0.1436
Epoch 00199: val rsquared did not improve from 0.53969
Epoch 200/200
101.6148 - val rsquared: 0.2959
Epoch 00200: val rsquared did not improve from 0.53969
Out[180]:
<tensorflow.python.keras.callbacks.History at 0x7fa6284a9c40>
```

In [215]:

11 0 50000

1 00 05m0/000p 1000. 12.7070 104aa10a. 0.7001 7a1_1000.

Decision Tree

```
In [216]:
```

```
from sklearn.tree import DecisionTreeRegressor
```

With Feature Set - 4

```
In [217]:
```

```
X_Set4 = pd.DataFrame(np.hstack((x,x_pca,x_svd)))
print(X_Set4.shape)

(4196, 538)
```

In [218]:

```
X_train_DT_Set4, X_test_DT_Set4, y_train, y_test = train_test_split(X_Set4, y, test_size=0.33, rand
om_state=1)
X_train_DT_Set4, X_cv_DT_Set4, y_train, y_cv = train_test_split(X_train_DT_Set4, y_train,
test_size=0.33)
print("Done")
```

Done

In [219]:

```
max_depth = [1,5,10,50]
samples_split = [5,10,100,500]
score_train = []
score_cv = []
plot_dep,plot_sample = [],[]
for i in max_depth:
    for j in samples_split:
        clf = DecisionTreeRegressor(max_depth = i, min_samples_split = j)
        clf.fit(X_train_DT_Set4 ,y_train)
        y_train_pred = clf.predict(X_train_DT_Set4)
        y_cv_pred = clf.predict(X_cv_DT_Set4)
        score_train.append(r2_score(y_train,y_train_pred))
        score_cv.append(r2_score(y_cv,y_cv_pred))
        plot_dep.append(i)
        plot_sample.append(j)
```

In [220]:

In [221]:

```
model = DecisionTreeRegressor(max_depth =5, min_samples_split =500 )
model.fit(X_train_DT_Set4,y_train)
y_te = model.predict(X_test_DT_Set4)
score12 = r2_score(y_test, y_te)
print("Test Score for 4th feature set : ", score12)
```

Test Score for 4th feature set : 0.5833543142557482

With Feature Set - 5

```
In [222]:
```

```
X_Set5 = pd.DataFrame(np.hstack((x,x_svd)))
print(X_Set5.shape)
```

(4196, 528)

In [223]:

```
X_train_DT_Set5, X_test_DT_Set5, y_train, y_test = train_test_split(X_Set5, y, test_size=0.33, rand
om_state=1)
X_train_DT_Set5, X_cv_DT_Set5, y_train, y_cv = train_test_split(X_train_DT_Set5, y_train,
test_size=0.33)
print("Done")
```

Done

In [224]:

In [225]:

In [226]:

```
model = DecisionTreeRegressor(max_depth =10, min_samples_split =500 )
model.fit(X_train_DT_Set5,y_train)
y_te = model.predict(X_test_DT_Set5)
score13 = r2_score(y_test, y_te)
print("Test Score for 4th feature set : ", score13)
```

Test Score for 4th feature set : 0.6021492704025679

Concluding Results of different Models

In [232]:

```
['Label - Encoded Features + SVD','MLP', score11],
               ['Label - Encoded Features + PCA + SVD', 'Decision Tree', score12],
               ['Label - Encoded Features + SVD', 'Decision Tree', score13]],
              headers=['Features', 'Model','R2_Score'], tablefmt='orgtbl'))
                                             | R2 Score |
| Features
                                  | Model
| Auto - Encoded Features
                                                    0.478379
                                  | XGBoost
                                                    0.499809
                             | XGBoost
| Auto - Encoded Features + PCA
| PCA + SVD
                                   | XGBoost
                                                        0.516819
                                                     0.585436
| Label - Encoded Features + PCA + SVD | XGBoost
| Label - Encoded Features + SVD | XGBoost
                                                    0.585805
| Label - Encoded Features + PCA + SVD | Linear Regression | -6.05298e+19 |
| Label - Encoded Features + SVD | Linear Regression | -9.76042e+19 |
| Label - Encoded Features + PCA + SVD | Random Forest |
                                                        0.59191
| Label - Encoded Features + SVD | Random Forest
                                                     0.597778
| Label - Encoded Features + PCA + SVD | MLP
                                                     0.5587
| Label - Encoded Features + SVD | MLP
                                                     0.53969
Building Final Model
In [233]:
enc = LabelEncoder()
for i in x cat.columns:
 x cat[i] = enc.fit transform(x cat[i])
In [234]:
test data = pd.read csv('downloads/testwa.csv')
In [235]:
test cat = test data.loc[:,'X0':'X8']
test_num = test_data.loc[:,'X10':]
In [236]:
for i in x cat.columns:
   test_cat[i] = enc.fit_transform(test_cat[i])
In [237]:
test_svd = tsvd.transform(test_num)
test = pd.DataFrame(np.hstack((test_cat,test_num,test_svd)))
print(test.shape)
(4209, 528)
In [239]:
X final = pd.DataFrame(np.hstack((x,x svd)))
print(X final.shape)
(4196, 528)
X_train_final, X_cv_final, y_train, y_cv = train_test_split(X_final, y, test_size=0.33)
print("Done")
```

Done

In [241]:

```
max_depth = [5, 10, 15,20, 25, 40]
n_estimators = [5,10,50,75,100,200]
score_train = []
score_cv = []
plot_dep,plot_estim = [],[]
for i in max_depth:
    for j in n_estimators:
        clf = RandomForestRegressor(max_depth = i, n_estimators = j, verbose = 0,n_jobs = -1)
        clf.fit(X_train_final ,y_train)
        y_train_pred = clf.predict(X_train_final)
        y_cv_pred = clf.predict(X_cv_final)
        score_train.append(r2_score(y_train,y_train_pred))
        score_cv.append(r2_score(y_cv,y_cv_pred))
        plot_dep.append(i)
        plot_estim.append(j)
```

In [243]:

In [244]:

```
model = RandomForestRegressor(n_estimators=200, max_depth =5)
model.fit(X_train_final,y_train)
y_pred = model.predict(test)
```