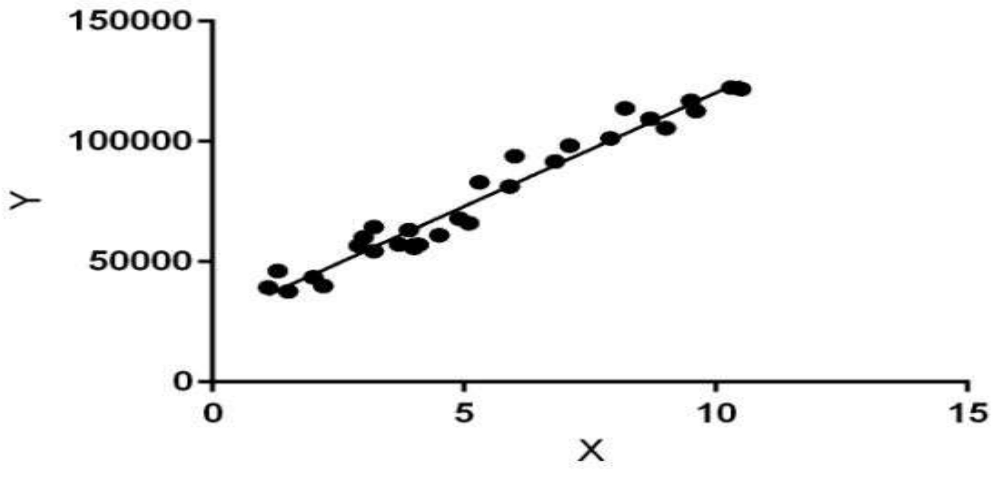
Experiment No. 1
Analyze the Boston Housing dataset and apply appropriate Regression Technique
Date of Performance:
Date of Submission:

Aim: Analyze the Boston Housing dataset and apply appropriate Regression Technique.

Objective: Ablility to perform various feature engineering tasks, apply linear regression on the given dataset and minimise the error.

Theory:

Linear Regression is a machine learning algorithm based on supervised learning. It performs a regression task. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between variables and forecasting. Different regression models differ based on – the kind of relationship between dependent and independent variables they are considering, and the number of independent variables getting used.



Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). So, this regression technique finds out a linear relationship between x (input) and y(output). Hence, the name is Linear Regression.

In the figure above, X (input) is the work experience and Y (output) is the salary of a person. The regression line is the best fit line for our model.

Dataset:

The Boston Housing Dataset

The Boston Housing Dataset is a derived from information collected by the U.S. Census Service concerning housing in the area of Boston MA. The following describes the dataset columns:

CRIM - per capita crime rate by town
ZN - proportion of residential land zoned for lots over 25,000 sq.ft.
INDUS - proportion of non-retail business acres per town.
CHAS - Charles River dummy variable (1 if tract bounds river; 0 otherwise)
NOX - nitric oxides concentration (parts per 10 million)
RM - average number of rooms per dwelling
AGE - proportion of owner-occupied units built prior to 1940
DIS - weighted distances to five Boston employment centres
RAD - index of accessibility to radial highways
TAX - full-value property-tax rate per $10,000
PTRATIO - pupil-teacher ratio by town
B - 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town
LSTAT - % lower status of the population
MEDV - Median value of owner-occupied homes in $1000's

Code:

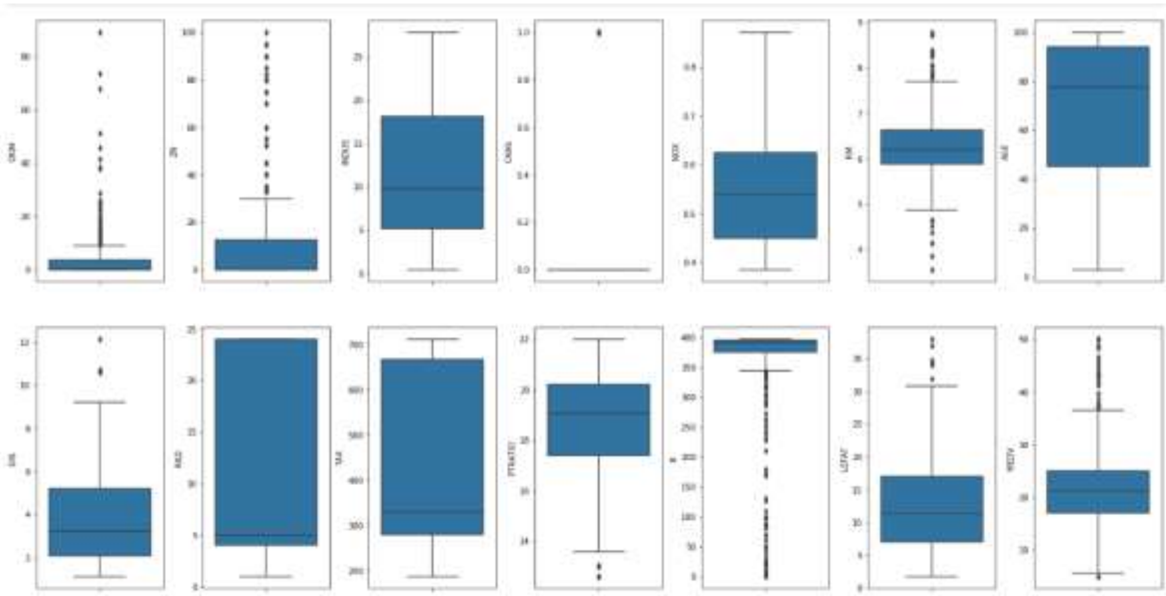
```
import numpy as np
import pandas as pd
import os
print(os.listdir("../input"))
from pandas import read_csv
column_names = ['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX', 'PTRATIO', 'B', 'LSTAT', 'MEDV']
data=read_csv('../input/housing.csv',header=None,delimiter=r"\s+",names=column_names)
print(data.head(5))
```

```
['housing.csv']
      CRIM    ZN  INDUS  CHAS    NOX     RM   AGE     DIS  RAD    TAX  \
0  0.00632  18.0   2.31     0  0.538  6.575  65.2  4.0900    1  296.0
1  0.02731   0.0   7.07     0  0.469  6.421  78.9  4.9671    2  242.0
2  0.02729   0.0   7.07     0  0.469  7.185  61.1  4.9671    2  242.0
3  0.03237   0.0   2.18     0  0.458  6.998  45.8  6.0622    3  222.0
4  0.06905   0.0   2.18     0  0.458  7.147  54.2  6.0622    3  222.0

   PTRATIO       B  LSTAT  MEDV
0     15.3  396.90   4.98  24.0
1     17.8  396.90   9.14  21.6
2     17.8  392.83   4.03  34.7
3     18.7  394.63   2.94  33.4
4     18.7  396.90   5.33  36.2
```

```
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats
fig, axs = plt.subplots(ncols=7, nrows=2, figsize=(20, 10))
index = 0
```

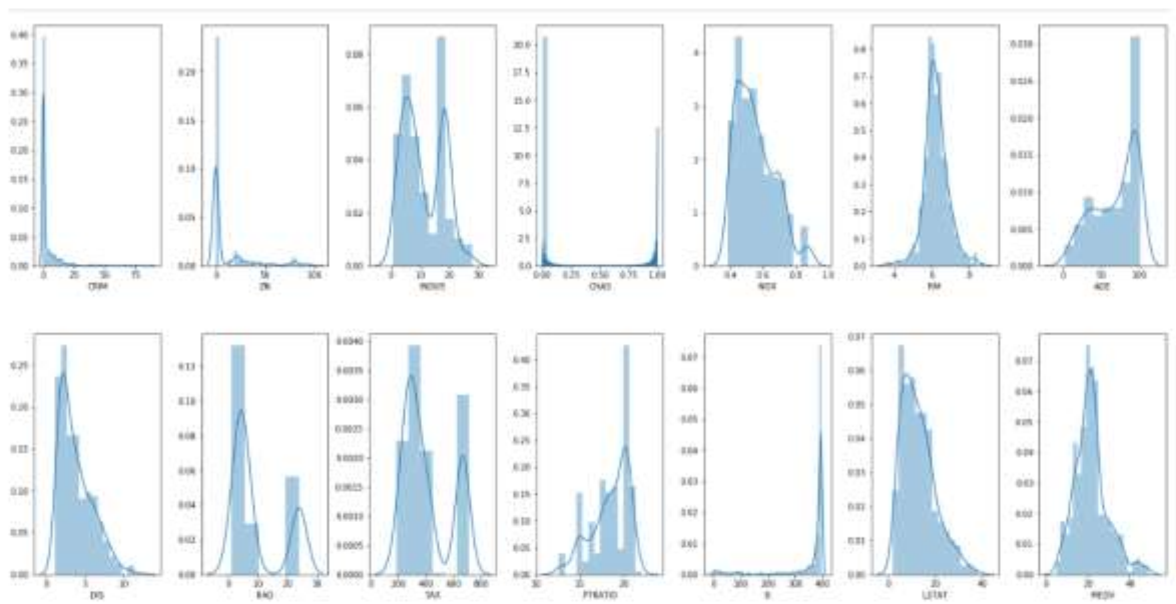
```
axs = axs.flatten()
for k,v in data.items():
   sns.boxplot(y=k, data=data, ax=axs[index])
   index += 1
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=5.0)
```



```
for k, v in data.items():
   q1 = v.quantile(0.25)
   q3 = v.quantile(0.75)
   irq = q3 - q1
   v_col = v[(v <= q1 - 1.5 * irq) | (v >= q3 + 1.5 * irq)]
   perc = np.shape(v_col)[0] * 100.0 / np.shape(data)[0]
   print("Column %s outliers = %.2f%%" % (k, perc))
```

```
data = data[~(data['MEDV'] >= 50.0)]
print(np.shape(data))

fig, axs = plt.subplots(ncols=7, nrows=2, figsize=(20, 10))
index = 0
axs = axs.flatten()
for k,v in data.items():
    sns.distplot(v, ax=axs[index])
    index += 1
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=5.0)
```



```
plt.figure(figsize=(20, 10))
sns.heatmap(data.corr().abs(),  annot=True)
```


CRIM
ZN
INDUS
CHAS
NOX
RM
AGE
DIS
RAD
TAX
PTRATIO
B
LSTAT
MEDV
1.0
0.8
0.6
0.4
0.2

```
from sklearn import preprocessing
min_max_scaler = preprocessing.MinMaxScaler()
column_sels = ['LSTAT', 'INDUS', 'NOX', 'PTRATIO', 'RM', 'TAX', 'DIS', 'AGE']
x = data.loc[:,column_sels]
y = data['MEDV']
x=pd.DataFrame(data=min_max_scaler.fit_transform(x), columns=column_sels)
fig, axs = plt.subplots(ncols=4, nrows=2, figsize=(20, 10))
index = 0
axs = axs.flatten()
for i, k in enumerate(column_sels):
    sns.regplot(y=y, x=x[k], ax=axs[i])
plt.tight_layout(pad=0.4, w_pad=0.5, h_pad=5.0)
y =  np.log1p(y)
for col in x.columns:
    if np.abs(x[col].skew()) > 0.3:
        x[col] = np.log1p(x[col])
from sklearn import datasets, linear_model
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
import numpy as np
l_regression = linear_model.LinearRegression()
kf = KFold(n_splits=10)
min_max_scaler = preprocessing.MinMaxScaler()
```

```
x_scaled = min_max_scaler.fit_transform(x)
scores=cross_val_score(l_regression,x_scaled,y,cv=kf,scoring='neg_mean_squa
red_error')
print("MSE: %0.2f (+/- %0.2f)" % (scores.mean(), scores.std()))
MSE: -0.04 (+/- 0.04)
```

Conclusion:

Features have been chosen to develop the model:

1. CRIM - Per capita crime rate by town
2. CHAS - Charles River dummy variable (1 if tract bounds river; else 0)
3. NOX - Nitric oxides concentration (parts per 10 million)
4. RM - Average number of rooms per dwelling
5. DIS - weighted distances to five Boston employment centres
6. RAD - Index of accessibility to radial highways
7. TAX - Full-value property-tax rate per $10,000
8. PTRATIO - Pupil-teacher ratio by town
9. LSTAT - Lower status of the population

Mean Squared Error calculated

- Calculated Mean Squared Error : 0.04 (+/- 0.04)
- The Mean Squared Error measures how close a regression line is to a set of data points.
- Lesser the Mean Squared Error refers to Smaller is the error and Better the estimator.