→ Adnaan Shaikh TYA164

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

b_data = pd.read_csv('/content/Boston.csv')
b_data
```

	Unnamed: 0	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptra
0	1	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	
1	2	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	
2	3	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	
3	4	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	
4	5	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	
501	502	0.06263	0.0	11.93	0	0.573	6.593	69.1	2.4786	1	273	:
502	503	0.04527	0.0	11.93	0	0.573	6.120	76.7	2.2875	1	273	:
503	504	0.06076	0.0	11.93	0	0.573	6.976	91.0	2.1675	1	273	:
504	505	0.10959	0.0	11.93	0	0.573	6.794	89.3	2.3889	1	273	:
505	506	0.04741	0.0	11.93	0	0.573	6.030	80.8	2.5050	1	273	:
4												•

```
b data.columns
```

```
b_data.drop('Unnamed: 0', axis=1, inplace=True)
```

```
b_data
```

crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	blac
0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.9
0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.9
0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.8
0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.6
0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.9
0.06263	0.0	11.93	0	0.573	6.593	69.1	2.4786	1	273	21.0	391.9
0.04527	0.0	11.93	0	0.573	6.120	76.7	2.2875	1	273	21.0	396.9
0.06076	0.0	11.93	0	0.573	6.976	91.0	2.1675	1	273	21.0	396.9
0.10959	0.0	11.93	0	0.573	6.794	89.3	2.3889	1	273	21.0	393.4
	0.00632 0.02731 0.02729 0.03237 0.06905 0.06263 0.04527 0.06076	0.00632 18.0 0.02731 0.0 0.02729 0.0 0.03237 0.0 0.06905 0.0 0.06263 0.0 0.04527 0.0 0.06076 0.0	0.00632 18.0 2.31 0.02731 0.0 7.07 0.02729 0.0 7.07 0.03237 0.0 2.18 0.06905 0.0 2.18 0.06263 0.0 11.93 0.06076 0.0 11.93	0.00632 18.0 2.31 0 0.02731 0.0 7.07 0 0.02729 0.0 7.07 0 0.03237 0.0 2.18 0 0.06905 0.0 2.18 0 0.06263 0.0 11.93 0 0.04527 0.0 11.93 0 0.06076 0.0 11.93 0	0.00632 18.0 2.31 0 0.538 0.02731 0.0 7.07 0 0.469 0.02729 0.0 7.07 0 0.469 0.03237 0.0 2.18 0 0.458 0.06905 0.0 2.18 0 0.458 0.06263 0.0 11.93 0 0.573 0.04527 0.0 11.93 0 0.573 0.06076 0.0 11.93 0 0.573	0.00632 18.0 2.31 0 0.538 6.575 0.02731 0.0 7.07 0 0.469 6.421 0.02729 0.0 7.07 0 0.469 7.185 0.03237 0.0 2.18 0 0.458 6.998 0.06905 0.0 2.18 0 0.458 7.147 0.06263 0.0 11.93 0 0.573 6.593 0.04527 0.0 11.93 0 0.573 6.120 0.06076 0.0 11.93 0 0.573 6.976	0.00632 18.0 2.31 0 0.538 6.575 65.2 0.02731 0.0 7.07 0 0.469 6.421 78.9 0.02729 0.0 7.07 0 0.469 7.185 61.1 0.03237 0.0 2.18 0 0.458 6.998 45.8 0.06905 0.0 2.18 0 0.458 7.147 54.2 0.06263 0.0 11.93 0 0.573 6.593 69.1 0.04527 0.0 11.93 0 0.573 6.120 76.7 0.06076 0.0 11.93 0 0.573 6.976 91.0	0.00632 18.0 2.31 0 0.538 6.575 65.2 4.0900 0.02731 0.0 7.07 0 0.469 6.421 78.9 4.9671 0.02729 0.0 7.07 0 0.469 7.185 61.1 4.9671 0.03237 0.0 2.18 0 0.458 6.998 45.8 6.0622 0.06905 0.0 2.18 0 0.458 7.147 54.2 6.0622 0.06263 0.0 11.93 0 0.573 6.593 69.1 2.4786 0.04527 0.0 11.93 0 0.573 6.120 76.7 2.2875 0.06076 0.0 11.93 0 0.573 6.976 91.0 2.1675	0.00632 18.0 2.31 0 0.538 6.575 65.2 4.0900 1 0.02731 0.0 7.07 0 0.469 6.421 78.9 4.9671 2 0.02729 0.0 7.07 0 0.469 7.185 61.1 4.9671 2 0.03237 0.0 2.18 0 0.458 6.998 45.8 6.0622 3 0.06905 0.0 2.18 0 0.458 7.147 54.2 6.0622 3 0.06263 0.0 11.93 0 0.573 6.593 69.1 2.4786 1 0.04527 0.0 11.93 0 0.573 6.120 76.7 2.2875 1 0.06076 0.0 11.93 0 0.573 6.976 91.0 2.1675 1	0.00632 18.0 2.31 0 0.538 6.575 65.2 4.0900 1 296 0.02731 0.0 7.07 0 0.469 6.421 78.9 4.9671 2 242 0.02729 0.0 7.07 0 0.469 7.185 61.1 4.9671 2 242 0.03237 0.0 2.18 0 0.458 6.998 45.8 6.0622 3 222 0.06905 0.0 2.18 0 0.458 7.147 54.2 6.0622 3 222 0.06263 0.0 11.93 0 0.573 6.593 69.1 2.4786 1 273 0.04527 0.0 11.93 0 0.573 6.120 76.7 2.2875 1 273 0.06076 0.0 11.93 0 0.573 6.976 91.0 2.1675 1 273	0.00632 18.0 2.31 0 0.538 6.575 65.2 4.0900 1 296 15.3 0.02731 0.0 7.07 0 0.469 6.421 78.9 4.9671 2 242 17.8 0.02729 0.0 7.07 0 0.469 7.185 61.1 4.9671 2 242 17.8 0.03237 0.0 2.18 0 0.458 6.998 45.8 6.0622 3 222 18.7 0.06905 0.0 2.18 0 0.458 7.147 54.2 6.0622 3 222 18.7 0.06263 0.0 11.93 0 0.573 6.593 69.1 2.4786 1 273 21.0 0.04527 0.0 11.93 0 0.573 6.120 76.7 2.2875 1 273 21.0 0.06076 0.0 11.93 0 0.573 6.976 91.0 2.1675 1 273 21.0

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	blac
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.9
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.9
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.8
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.6
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.9
501	0.06263	0.0	11.93	0	0.573	6.593	69.1	2.4786	1	273	21.0	391.9
502	0.04527	0.0	11.93	0	0.573	6.120	76.7	2.2875	1	273	21.0	396.9
503	0.06076	0.0	11.93	0	0.573	6.976	91.0	2.1675	1	273	21.0	396.9
504	0.10959	0.0	11.93	0	0.573	6.794	89.3	2.3889	1	273	21.0	393.4
505	0.04741	0.0	11.93	0	0.573	6.030	80.8	2.5050	1	273	21.0	396.9
506 rows × 14 columns												

b_data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
# Column Non-Null Count Dtype
```

```
0
     crim
              506 non-null
                               float64
 1
              506 non-null
                               float64
     zn
 2
     indus
              506 non-null
                               float64
 3
     chas
              506 non-null
                               int64
 4
              506 non-null
                               float64
     nox
 5
              506 non-null
                               float64
     rm
 6
              506 non-null
                               float64
     age
 7
                               float64
     dis
              506 non-null
                               int64
 8
              506 non-null
     rad
 9
              506 non-null
                               int64
     tax
     ptratio 506 non-null
                               float64
 10
 11
    black
              506 non-null
                               float64
 12 lstat
              506 non-null
                               float64
 13
     prices
              506 non-null
                               float64
dtypes: float64(11), int64(3)
memory usage: 55.5 KB
```

b data.isnull().sum()

```
crim
            0
            0
zn
indus
            0
            0
chas
nox
            0
            0
rm
            0
age
dis
            0
rad
            0
tax
ptratio
black
1stat
            0
prices
            0
dtype: int64
```

```
x = b_data[['crim','zn','indus','chas', 'nox', 'rm', 'age', 'dis', 'rad','tax','ptratio','bla
x = x.sum()
print(x)
```

```
crim
               0
zn
            372
indus
               0
chas
            471
nox
               0
               0
rm
               0
age
dis
               0
               0
rad
tax
               0
ptratio
               0
               0
black
1stat
               0
```

prices 0
dtype: int64

boston_data= b_data.drop(columns=['zn', 'chas'])

boston_data

	crim	indus	nox	rm	age	dis	rad	tax	ptratio	black	lstat	pr
0	0.00632	2.31	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	
1	0.02731	7.07	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	
2	0.02729	7.07	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	
3	0.03237	2.18	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	
4	0.06905	2.18	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33	
501	0.06263	11.93	0.573	6.593	69.1	2.4786	1	273	21.0	391.99	9.67	
502	0.04527	11.93	0.573	6.120	76.7	2.2875	1	273	21.0	396.90	9.08	
503	0.06076	11.93	0.573	6.976	91.0	2.1675	1	273	21.0	396.90	5.64	
504	0.10959	11.93	0.573	6.794	89.3	2.3889	1	273	21.0	393.45	6.48	
505	0.04741	11.93	0.573	6.030	80.8	2.5050	1	273	21.0	396.90	7.88	

506 rows × 12 columns

from sklearn import preprocessing

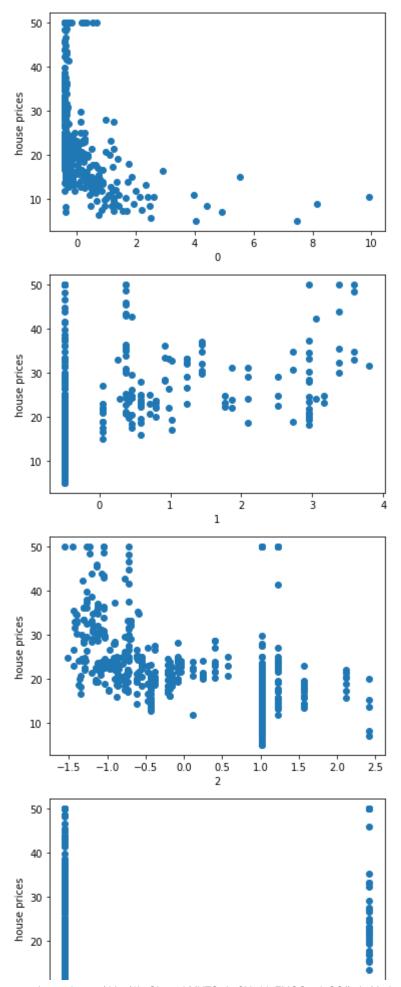
b_data

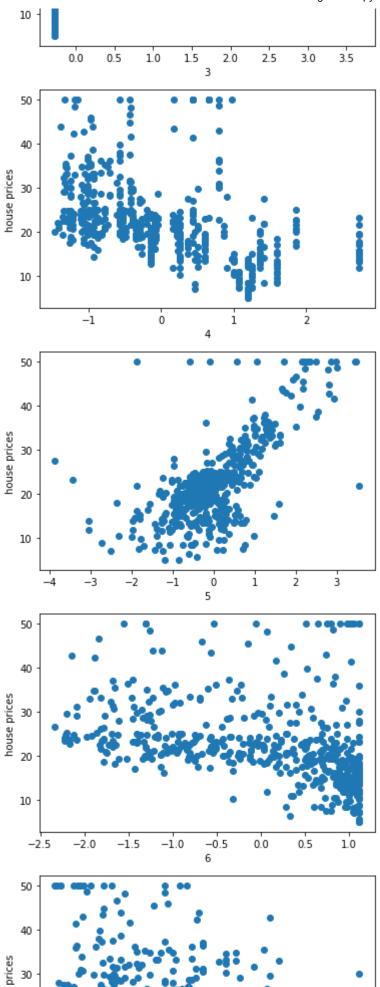
```
crim
                       indus chas
                                                                tax ptratio
                                                                              blac
                   zn
                                    nox
                                                age
                                                       dis rad
                                            rm
                                   0.538 6.575
          0.00632 18.0
                        2.31
                                                                296
                                                                             396.9
                                               65.2 4.0900
                                                                        15.3
std = preprocessing.StandardScaler()
          0 00007
y = b_data['prices']
bos = b_data.drop(['prices'], axis=1)
bos = std.fit_transform(bos)
print(bos[0])
    -0.12001342 \quad 0.1402136 \quad -0.98284286 \quad -0.66660821 \quad -1.45900038 \quad 0.44105193
     -1.0755623 ]
     504 0.10959
                   U.U TT.93
                                U U.5/3 b./94 89.3 2.3889
                                                             1 2/3
                                                                        Z1.U 393.4
boston_data = pd.DataFrame(bos)
boston data['prices'] =y
boston_data.columns = ['crim', 'indus', 'nox', 'rm', 'age', 'dis', 'rad', 'tax',
       'ptratio', 'black', 'lstat', 'prices']
b data
```

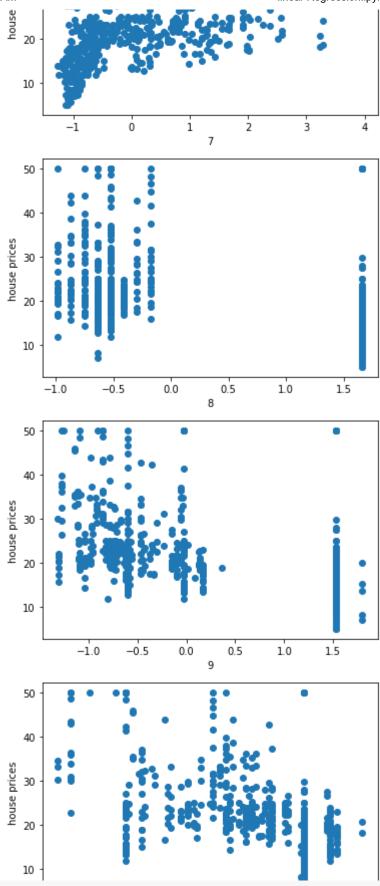
3 0 2 5 1 4 6 -0.419782 0 0.284830 -1.287909 -0.272599 -0.144217 0.413672 -0.120013 0.1401 -0.417339 -0.487722 -0.593381 -0.272599 -0.740262 0.194274 0.367166 0.557 2 -0.417342 -0.487722 -0.593381 -0.272599 1.282714 -0.265812 0.557 -0.740262 3 -0.416750 -0.487722 -1.306878 1.016303 -0.809889 -0.272599 -0.835284 1.077 4 -0.412482 -0.487722 -1.306878 -0.272599 -0.835284 1.228577 -0.511180 1.077 501 -0.413229 -0.487722 0.115738 -0.272599 0.158124 0.439316 0.018673 -0.625 -0.415249 -0.487722 0.115738 -0.272599 502 0.158124 -0.234548 0.288933 -0.716 -0.413447 -0.487722 0.115738 503 -0.272599 0.158124 0.984960 0.797449 -0.773 504 -0.407764 -0.487722 0.115738 -0.272599 0.158124 0.725672 0.736996 -0.668 -0.415000 -0.487722 -0.272599 -0.362767 505 0.115738 0.158124 0.434732 -0.613 506 rows × 14 columns

```
for i in b_data.columns:
  plt.scatter(b_data[i], b_data['prices'])
```

```
plt.xlabel(i)
plt.ylabel('house prices')
plt.show()
```







from sklearn import linear_model

Y = b_data['prices']

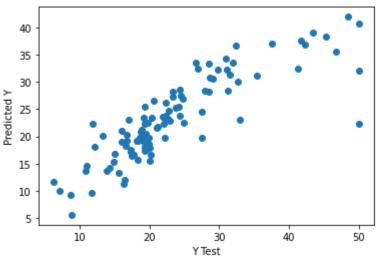
```
ν - υ_uaca·uι υρ( ρι τις , αλτο-τ)
X = np.array(X)
X.reshape(1, -1)
     array([[-0.41978194, 0.28482986, -1.2879095, ..., 1.17646583,
              0.44105193, -0.66905833]])
                                      · TAT OF THE
from sklearn.model selection import train test split
train x, test x, train y, test y = train test split(X, Y, test size=0.2, random state=4)
regr = linear model.LinearRegression()
regr.fit(train x, train y)
     LinearRegression()
      ا مد ق
             y_pred = regr.predict(test_x)
regr.score(test_x, test_y)
    0.7263451459702509
                                                  + Text
                                     + Code
This is the testing accuracy calculated as 72.58%
regr.score(train_x, train_y)
     0.7415244219726307
This is training accuracy calculated as 70.86%
        10 -
from sklearn import metrics
print('MAE:', metrics.mean absolute error(test y, y pred))
print('MSE:', metrics.mean_squared_error(test_y, y_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(test_y, y_pred)))
     MAE: 3.367790983796573
     MSE: 25.419587126821853
     RMSE: 5.041784121402051
```

Root mean squared error in this case is 4.69

```
plt.scatter(test_y,y_pred)
plt.xlabel('Y Test')
```

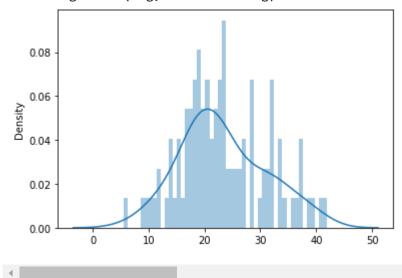
plt.ylabel('Predicted Y')

Text(0, 0.5, 'Predicted Y')



import seaborn as sns
sns.distplot(y_pred,bins=50)
plt.show()

/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarnin warnings.warn(msg, FutureWarning)



Conclusion

The model performance for the training set is 70.86% where as model performance for testing set is 72.58%.

The RMSE that is root mean squared error of the model is 4.69.

- Closing

Lets Finally create a file which contain all the independent as well as dependent variables and also the corresponding predicted values along with them.

```
y_train_pred = regr.predict(train_x)
list1 = y_train_pred.tolist() + y_pred.tolist()

output = boston_data
output['predicted_prices'] = list1
#regr.predict(X)
output.to_csv('/content/output.csv')
```

X