Data Science Masters :Assignment 20

Problem:

Build the linear regression model using scikit learn in boston data to predict 'Price' based on other dependent variable.

Solution:

In [142]:

```
# Import the required Libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns

%matplotlib inline

# Load the Boston Housing DataSet from scikit-learn
from sklearn.datasets import load_boston
boston_dataset = load_boston()

# boston_dataset is a dictionary
# let's check what it contains
boston_dataset.keys()

# Load the data into pandas dataframe
bos = pd.DataFrame(boston_dataset.data, columns=boston_dataset.feature_names)

# The target values is missing from the data. Create a new column of target values and add it to dataframe
bos['MEDV'] = boston_dataset.target
bos.head(2)
```

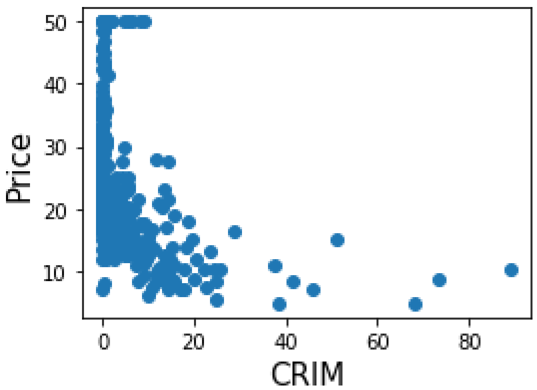
Out[142]:

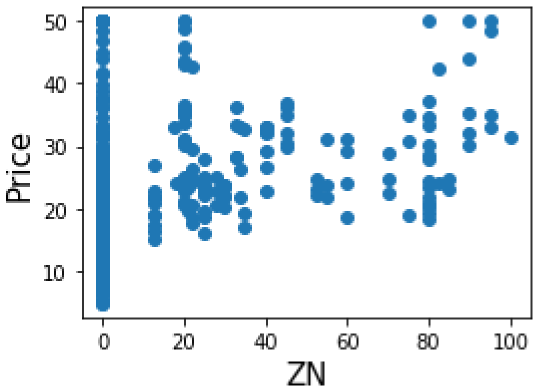
	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.9	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.9	9.14	21.6

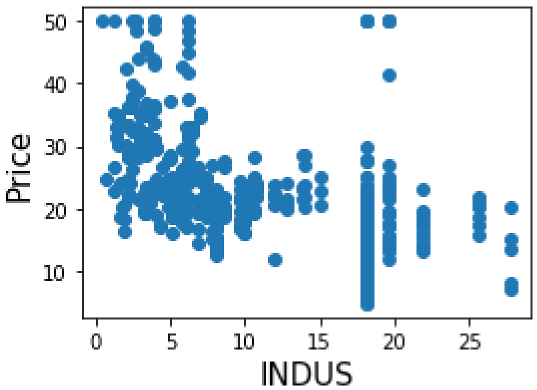
In [143]:
```
# Date Pre Processing
bos.isnull().sum()  # No missing values found in the dataset
```

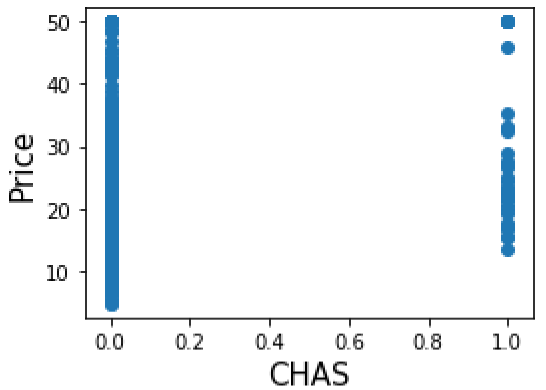
Out[143]:
```
CRIM       0
ZN         0
INDUS      0
CHAS       0
NOX        0
RM         0
AGE        0
DIS        0
RAD        0
TAX        0
PTRATIO    0
B          0
LSTAT      0
MEDV       0
dtype: int64
```

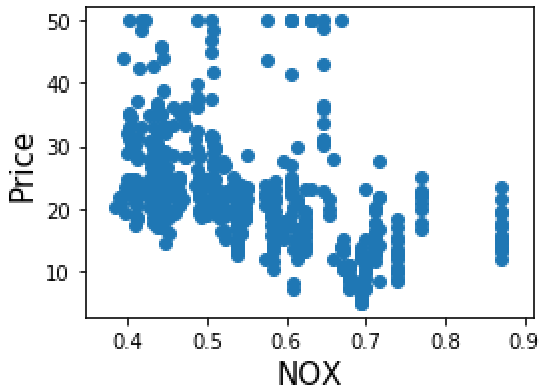
In [144]:
```
# Data Visualization thru Scatter plots to study the relationship b/w target and predictor variables
for index, feature_name in enumerate(boston_dataset.feature_names):
    plt.figure(figsize=(4, 3))
    plt.scatter(boston_dataset.data[:, index], boston_dataset.target)
    plt.ylabel('Price', size=15)
    plt.xlabel(feature_name, size=15)
    plt.tight_layout()
```

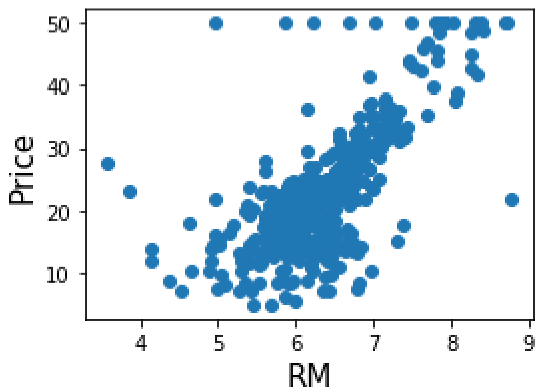

Price
CRIM
0
20
40
60
80
10
20
30
40
50

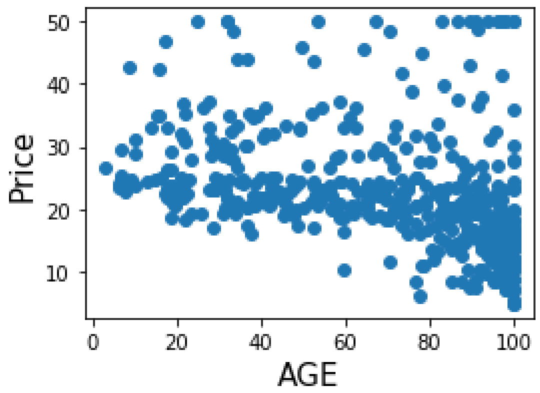

Price
ZN
0
20
40
60
80
100
10
20
30
40
50

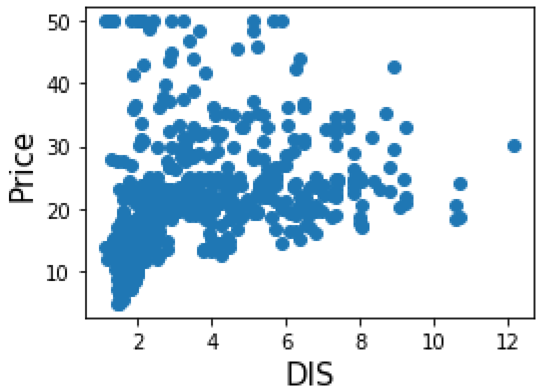

Price
INDUS
0
5
10
15
20
25
10
20
30
40
50

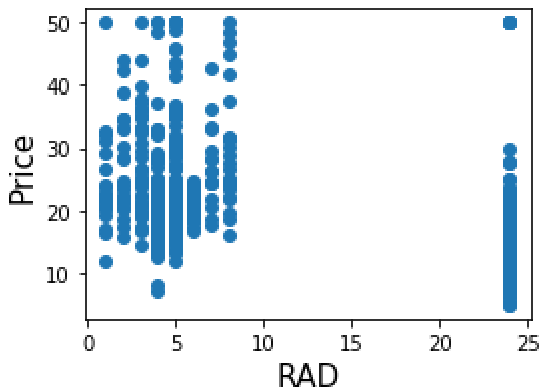

Price
CHAS

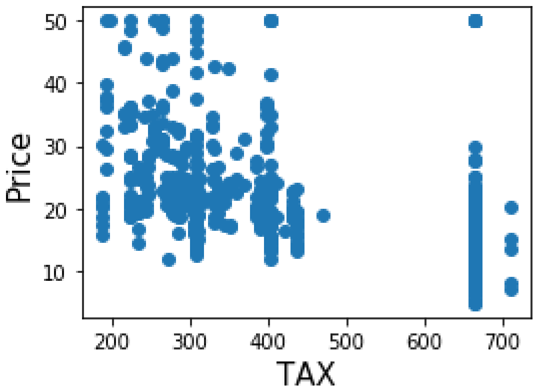

Price
NOX

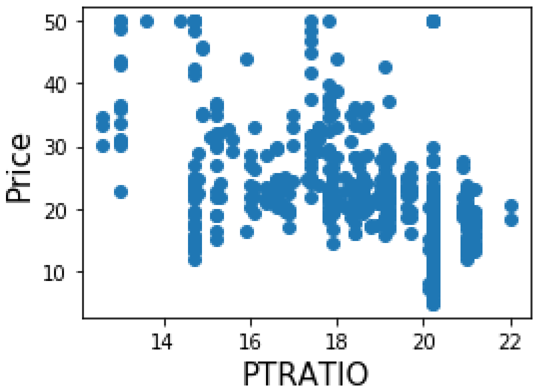

Price
RM

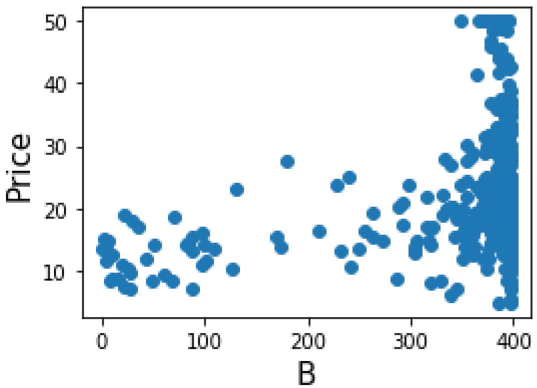

Price
AGE

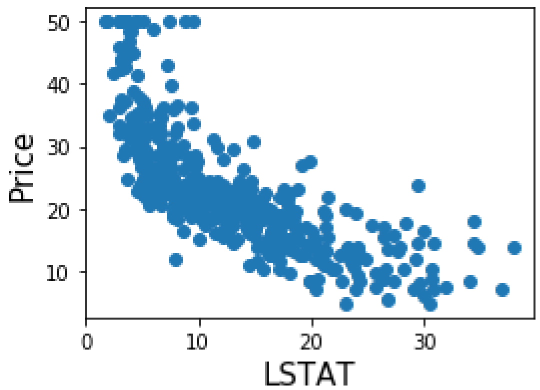

Price
DIS


Price
RAD


Price
TAX
10
20
30
40
50
200
300
400
500
600
700


Price
PTRATIO
10
20
30
40
50
14
16
18
20
22


Price
B
10
20
30
40
50
0
100
200
300
400



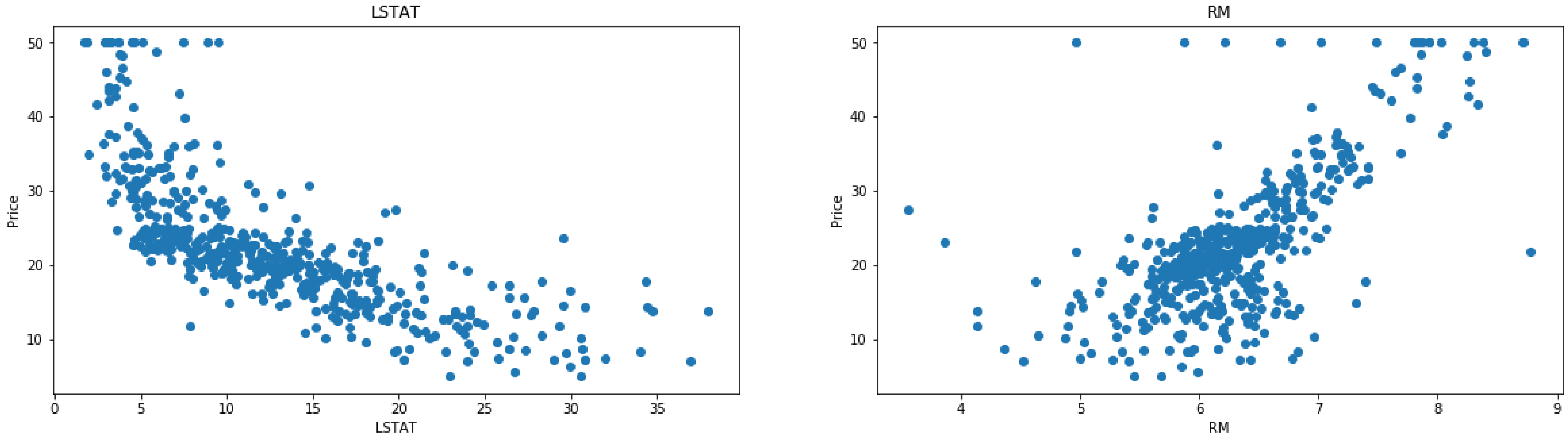
Price
LSTAT
50
40
30
20
10
0
10
20
30

In [155]:
```python
# Correlation matrix
# compute the pair wise correlation for all columns
correlation_matrix = bos.corr().round(2)
# use the heatmap function from seaborn to plot the correlation matrix
fig, ax = plt.subplots(figsize=(10,8))        # Sample figsize in inches
sns.heatmap(data=correlation_matrix, annot=True, linewidths=.5, ax=ax)
```

Out[155]: <matplotlib.axes._subplots.AxesSubplot at 0x1f404e8d860>

In [146]:

```
# Observations
# From the above coorelation plot we can see that MEDV is strongly correlated to LSTAT, RM

plt.figure(figsize=(20, 5))

features = ['LSTAT', 'RM']
target = bos['MEDV']

for i, col in enumerate(features):
    plt.subplot(1, len(features) , i+1)
    x = bos[col]
    y = target
    plt.scatter(x, y, marker='o')
    plt.title(col)
    plt.xlabel(col)
    plt.ylabel('Price')
```



In [147]:

```
# Prepare the data for training
X = pd.DataFrame(boston_dataset.data, columns=boston_dataset.feature_names)
Y = pd.DataFrame(boston_dataset.target)

# Split the data into training and testing sets
from sklearn.model_selection import train_test_split

# splits the training and test data set in 80% : 20%
# assign random_state to any value.This ensures consistency.
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size = 0.2, random_state=8)
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(404, 13)
(102, 13)
(404, 1)
(102, 1)
```

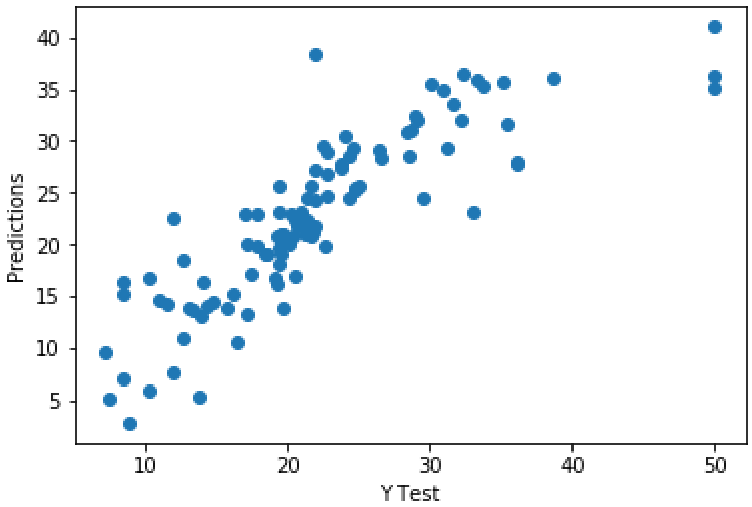
In [148]:

```
from sklearn import linear_model,metrics
lm = linear_model.LinearRegression()
model = lm.fit(X_train,y_train)

print('Cooefficients :\n',lm.coef_)
# variance score: 1 means perfect prediction
print('Variance score (R2 score): {}'.format(lm.score(X_test, y_test)))
```

```
Cooefficients :
 [[-1.10076971e-01  5.18341557e-02  1.47403635e-02  2.51379056e+00
  -1.49662742e+01  3.92758142e+00 -4.57455922e-03 -1.51880342e+00
   2.86533167e-01 -1.12074638e-02 -9.35054169e-01  8.42310515e-03
  -5.60927991e-01]]
Variance score (R2 score): 0.7081348459510759
```

In [149]:
```
#Predicting Test Data
predictions = lm.predict(X_test)

plt.scatter(y_test,predictions)
plt.xlabel('Y Test')
plt.ylabel('Predictions')
```

Out[149]: `Text(0,0.5,'Predictions')`



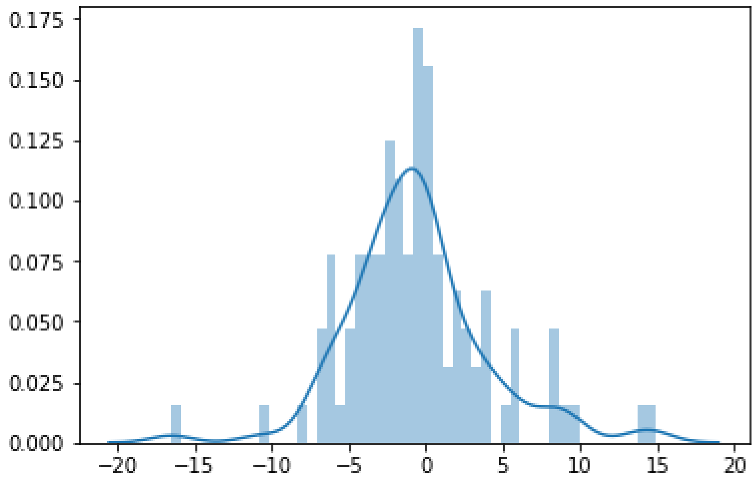
In [150]:
```
# Evaluating the Model
from sklearn import metrics
print('MSE: ',metrics.mean_squared_error(y_test,predictions))
print('RMSE: ',np.sqrt(metrics.mean_squared_error(y_test,predictions)))
```

```
MSE:  21.62548657267114
RMSE:  4.650321125757999
```

In [151]:
```
# Residual Histogram
sns.distplot((y_test-predictions),bins=50)
```

```
C:\Users\mkarthikeyan\AppData\Local\Continuum\anaconda3\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarning: The 'normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

Out[151]: <matplotlib.axes._subplots.AxesSubplot at 0x1f404d7b6a0>



Conclusion

In [152]:
```
# regression coefficients
coeff_df = pd.DataFrame(lm.coef_, columns=X.columns)
coeff_df
```

Out[152]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LST
0	-0.110077	0.051834	0.01474	2.513791	-14.966274	3.927581	-0.004575	-1.518803	0.286533	-0.011207	-0.935054	0.008423	-0.560

In [156]:

```
# Comparison b/w predicted and actual y values in test data set...Looks acceptable results...
df = pd.DataFrame(y_test[0])
df.columns = ['ActualY']
df['PredictedY']=predictions
df.head(100)
```

Out[156]:

	ActualY	PredictedY
337	18.5	19.159865
30	12.7	10.954195
364	21.9	38.413819
240	22.0	27.179487
162	50.0	41.021555
181	36.2	27.726664
8	16.5	10.527713
274	32.4	36.395810
177	24.6	29.252249
370	50.0	35.072998
25	13.9	13.178303
406	11.9	7.685844
127	16.2	15.251174
96	21.4	24.542799
455	14.1	16.394547
308	22.8	28.929814
463	20.2	22.944595
338	20.6	22.286110
12	21.7	20.800669
404	8.5	7.162371
50	19.7	20.959531
56	24.7	25.231675
0	24.0	30.446446

	ActualY	PredictedY
231	31.7	33.491364
295	28.6	28.462301
306	33.4	35.809341
387	7.4	5.154644
27	14.8	14.505834
165	25.0	25.677559
154	17.0	22.986407
...	...	...
126	15.7	13.927109
302	26.4	29.083984
305	28.4	30.895930
194	29.1	32.007152
120	22.0	21.811737
272	24.4	28.607290
298	22.5	29.508700
68	17.4	17.148002
496	19.7	13.816242
153	19.4	18.048952
33	13.1	13.949880
388	10.2	6.003410
397	8.5	16.356949
453	17.8	22.851445
107	20.4	20.734500

	ActualY	PredictedY
89	28.7	31.102260
419	8.4	15.130758
211	19.3	16.096448
111	22.8	26.756154
55	35.4	31.617588
59	19.6	20.980792
78	21.2	21.083410
344	31.2	29.226275
273	35.2	35.597169
442	18.4	19.048718
4	36.2	28.030334
37	21.0	23.204374
72	22.8	24.699832
312	19.4	23.217279
435	13.4	13.742199

100 rows × 2 columns