Roll No: 31440

DSBDAL Assignment - 4

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
df=pd.read_csv("BostonHousing.csv")
```

Dataset: https://github.com/selva86/datasets/blob/master/BostonHousing.csv (https://github.com/selva86/datasets/blob/master/BostonHousing.csv)

- 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 oxide concentration (parts per 10 million)
- RM: Average number of rooms per house
- AGE: Proportion of owner-occupied units built prior to 1940
- DIS: Weighted distances to five Boston employment centers
- RAD: Index of accessibility to radial highways
- TAX: Full-value property tax rate per 10,000 dollars
- PTRATIO: Pupil-teacher ratio by town
- B: $1000(Bk — 0.63)^2$, where Bk is the proportion of [people of African American descent] by town
- LSTAT: Percentage of lower status of the population
- MEDV: Median value of owner-occupied homes in 1000s dollars

In [3]:

```
df.head()
```

Out[3]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	lstat	med
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33	36.

In [4]:

```
data=df
data.rename(columns = {'medv':'Price'},inplace=True)
```

In [5]:

```
data
```

Out[5]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	b	lstat	Pr
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	2
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	2
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	3
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	3
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33	3
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
501	0.06263	0.0	11.93	0	0.573	6.593	69.1	2.4786	1	273	21.0	391.99	9.67	2
502	0.04527	0.0	11.93	0	0.573	6.120	76.7	2.2875	1	273	21.0	396.90	9.08	2
503	0.06076	0.0	11.93	0	0.573	6.976	91.0	2.1675	1	273	21.0	396.90	5.64	2
504	0.10959	0.0	11.93	0	0.573	6.794	89.3	2.3889	1	273	21.0	393.45	6.48	2
505	0.04741	0.0	11.93	0	0.573	6.030	80.8	2.5050	1	273	21.0	396.90	7.88	1

506 rows × 14 columns

In [6]:

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

In [7]:

```
data.shape
```

Out[7]:

```
(506, 14)
```

In [8]:

```
data.describe().T
```

Out[8]:

	count	mean	std	min	25%	50%	75%	max
crim	506.0	3.613524	8.601545	0.00632	0.082045	0.25651	3.677083	88.9762
zn	506.0	11.363636	23.322453	0.00000	0.000000	0.00000	12.500000	100.0000
indus	506.0	11.136779	6.860353	0.46000	5.190000	9.69000	18.100000	27.7400
chas	506.0	0.069170	0.253994	0.00000	0.000000	0.00000	0.000000	1.0000
nox	506.0	0.554695	0.115878	0.38500	0.449000	0.53800	0.624000	0.8710
rm	506.0	6.284634	0.702617	3.56100	5.885500	6.20850	6.623500	8.7800
age	506.0	68.574901	28.148861	2.90000	45.025000	77.50000	94.075000	100.0000
dis	506.0	3.795043	2.105710	1.12960	2.100175	3.20745	5.188425	12.1265
rad	506.0	9.549407	8.707259	1.00000	4.000000	5.00000	24.000000	24.0000
tax	506.0	408.237154	168.537116	187.00000	279.000000	330.00000	666.000000	711.0000
ptratio	506.0	18.455534	2.164946	12.60000	17.400000	19.05000	20.200000	22.0000
b	506.0	356.674032	91.294864	0.32000	375.377500	391.44000	396.225000	396.9000
lstat	506.0	12.653063	7.141062	1.73000	6.950000	11.36000	16.955000	37.9700
Price	506.0	22.532806	9.197104	5.00000	17.025000	21.20000	25.000000	50.0000

In [9]:

```
data.dtypes
```

Out[9]:

```
crim       float64
zn         float64
indus      float64
chas         int64
nox        float64
rm         float64
age        float64
dis        float64
rad          int64
tax          int64
ptratio    float64
b          float64
lstat      float64
Price      float64
dtype: object
```

In [10]:

```
data.isnull().sum()
```

Out[10]:

```
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
Price      0
dtype: int64
```

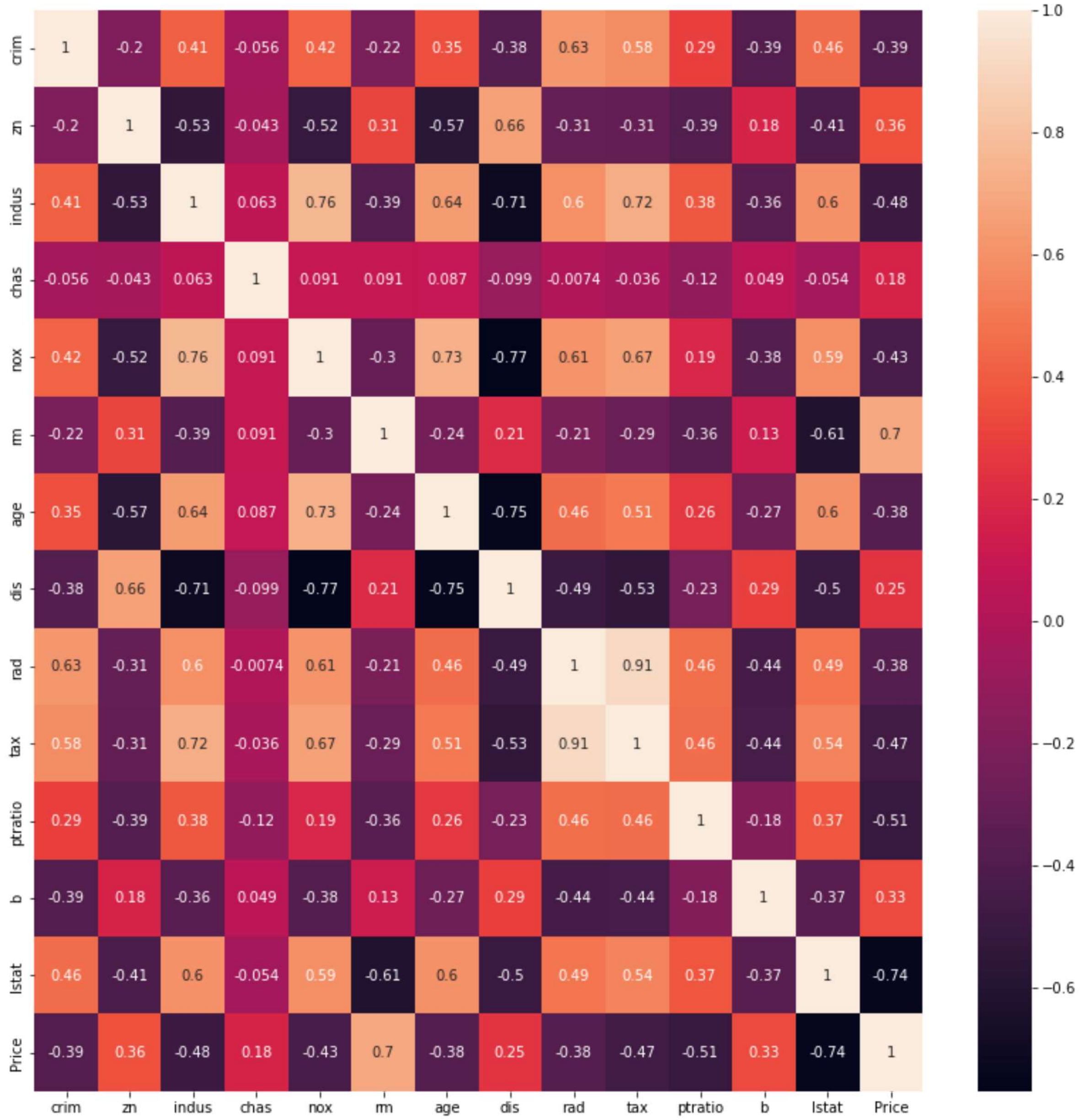
Visualizations

In [11]:

```
# Plotting a heatmap for the correlation matrix
fig = plt.figure(figsize=(14,14))
ax = fig.add_subplot(111)
sns.heatmap(data.corr(),annot=True)
```

Out[11]:

<AxesSubplot:>



Observations:

- As **medv** is the target variable we llok for correlation of other variables with medv
- We can see that **medv** has a high positive correlation with **rm** and a high negative correlation with **lstat**
- We choose **lstat**,**indus** and **ptratio** from negative correlation, **rm** ,**zn**,**dis**

In [12]:

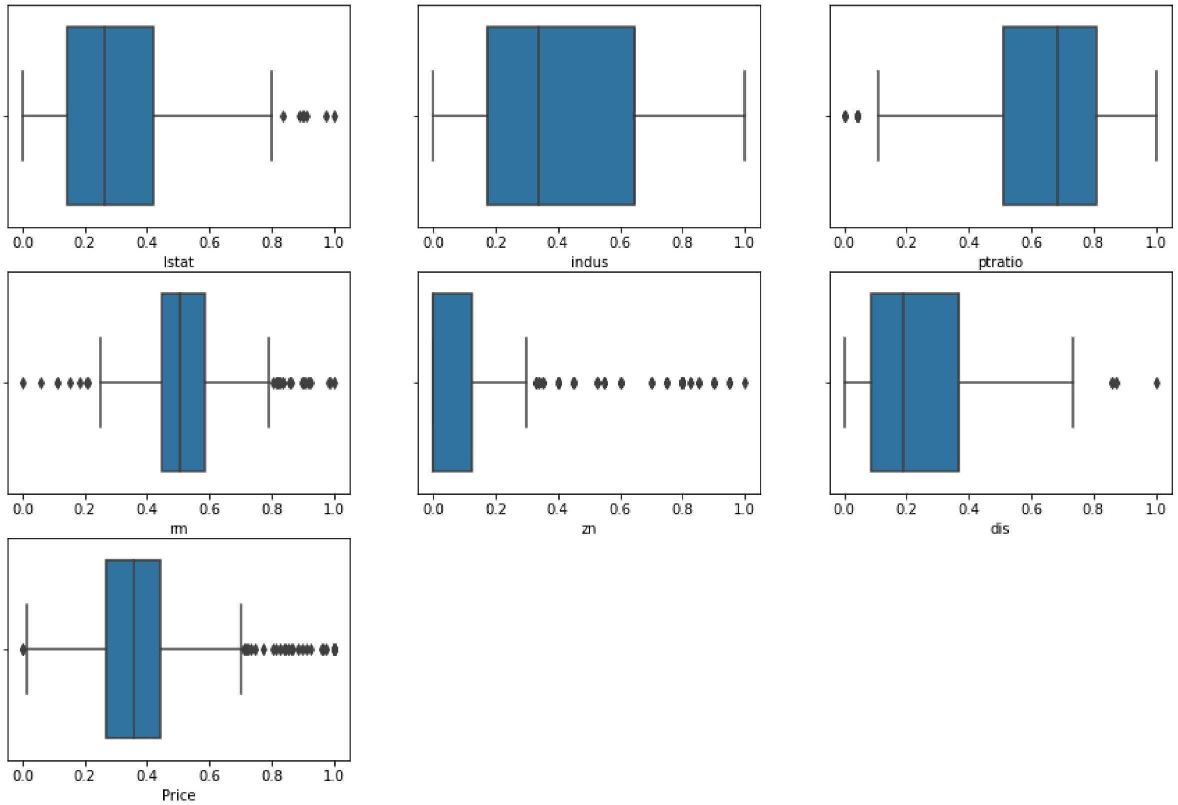
```
cols=['lstat','indus','ptratio','rm','zn','dis','Price'];
```

In [13]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
scaler.fit(data[cols])
data[cols] = scaler.transform(df[cols])
```

In [14]:

```
def boxplot():
    #plt.subplot(total rows,total columns,plot number)
    plt.figure(figsize=(15,10))
    t=1
    for i in cols:
        plt.subplot(3,3,t)
        t+=1
        sns.boxplot(data[i])
boxplot()
```



In [15]:

```
#removing of outliers
for i in cols:
    Q1=data[i].quantile(0.25)
    Q3=data[i].quantile(0.75)
    IQR=Q3-Q1

    Lower_limit=Q1-1.5*IQR
    Upper_limit=Q3+1.5*IQR

    data=data[(data[i]>Lower_limit)&(data[i]<Upper_limit)]
```

In [16]:

```
features=data[cols[0:6]]
prices=data['Price']
```

In [17]:

```
features
```

Out[17]:

	lstat	indus	ptratio	rm	zn	dis
0	0.089680	0.067815	0.287234	0.577505	0.18	0.269203
1	0.204470	0.242302	0.553191	0.547998	0.00	0.348962
2	0.063466	0.242302	0.553191	0.694386	0.00	0.348962
3	0.033389	0.063050	0.648936	0.658555	0.00	0.448545
5	0.096026	0.063050	0.648936	0.549722	0.00	0.448545
...	...	...	...	...	...	...
501	0.219095	0.420455	0.893617	0.580954	0.00	0.122671
502	0.202815	0.420455	0.893617	0.490324	0.00	0.105293
503	0.107892	0.420455	0.893617	0.654340	0.00	0.094381
504	0.131071	0.420455	0.893617	0.619467	0.00	0.114514
505	0.169702	0.420455	0.893617	0.473079	0.00	0.125072

384 rows × 6 columns

In [18]:

```
prices
```

Out[18]:

```
0      0.422222
1      0.368889
2      0.660000
3      0.631111
5      0.526667
         ...
501    0.386667
502    0.346667
503    0.420000
504    0.377778
505    0.153333
Name: Price, Length: 384, dtype: float64
```

Splitting the training and testing data

In [19]:

```
from sklearn.model_selection import train_test_split
```

In [20]:

```
X_train, X_test, y_train, y_test = train_test_split(features, prices, test_size =0.3,random

print("X_train shape : ", X_train.shape)
print("X_test shape  : ", X_test.shape)
print("y_train shape : ", y_train.shape)
print("y_test shape  : ", y_test.shape)
```

```
X_train shape :  (268, 6)
X_test shape  :  (116, 6)
y_train shape :  (268,)
y_test shape  :  (116,)
```

Building Linear Regression Model

In [21]:

```
from sklearn.linear_model import LinearRegression
reg = LinearRegression()
reg.fit(X_train, y_train)
y_pred = reg.predict(X_test)
```

In [22]:

```
for i in y_pred:
    print(i)
```

```
0.479096917477915830
0.20872289006071099
0.22941405745642846
0.32726259903084765
0.2115975230701176
0.268426086649745
0.4351608817558603
0.2692539406595828
0.37156122858631246
0.2200359897328312
0.2830781528686386
0.385351437728073
0.24699329391946317
0.4166793525947388
0.13883993451688614
0.36171019361140344
0.36494543937468465
0.4371864374285842
0.36205582657694974
```

In [23]:

```
y_test
```

Out[23]:

```
294    0.371111
136    0.275556
237    0.588889
59     0.324444
346    0.271111
         ...
147    0.213333
216    0.406667
76     0.333333
311    0.380000
13     0.342222
Name: Price, Length: 116, dtype: float64
```

In [24]:

```
print("Training Accuracy :",reg.score(X_train,y_train))
```

```
Training Accuracy : 0.6697838363430575
```

In [25]:

```
print("Testing Accuracy :",reg.score(X_test,y_test))
```

```
Testing Accuracy : 0.6507117347605373
```

Coefficient of determination/R2 score for evaluate the performance of a linear regression model

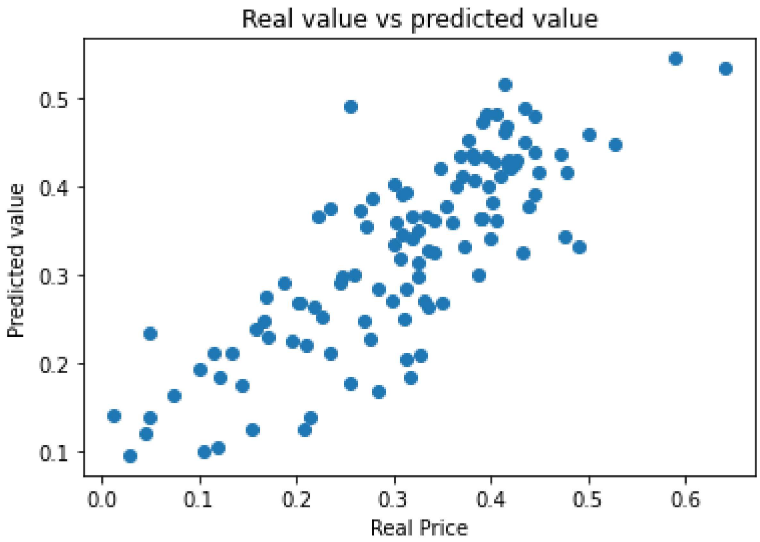
In [26]:

```
#r2 =1-sum of residual error/total sum of errors
#residual error =difference between group of observed values and arithmetical mean
from sklearn.metrics import mean_squared_error,r2_score
print("Model_accuracy :",r2_score(y_test, y_pred))
mse=mean_squared_error(y_pred, y_test)
print("Mean Squared Error :",mse)
```

```
Model_accuracy : 0.6507117347605373
Mean Squared Error : 0.005135188174742l1
```

In [28]:

```
plt.scatter(y_test, y_pred)
plt.xlabel("Real Price")
plt.ylabel("Predicted value")
plt.title("Real value vs predicted value")
plt.show()
```



In [ ]: