In [2]:
```
from sklearn.datasets import load_boston
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
```

```
C:\Users\yashm\anaconda3\lib\importlib\_bootstrap.py:219: RuntimeWarning: numpy.ufunc size changed, may indicate binary
incompatibility. Expected 192 from C header, got 216 from PyObject
  return f(*args, **kwds)
```

In [3]:
```
boston = load_boston()
```

In [4]:
```
boston
```

Out[4]:
```
{'data': array([[6.3200e-03, 1.8000e+01, 2.3100e+00, ..., 1.5300e+01, 3.9690e+02,
         4.9800e+00],
        [2.7310e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9690e+02,
         9.1400e+00],
        [2.7290e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9283e+02,
         4.0300e+00],
        ...,
        [6.0760e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
         5.6400e+00],
        [1.0959e-01, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9345e+02,
         6.4800e+00],
        [4.7410e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
         7.8800e+00]]),
 'target': array([24. , 21.6, 34.7, 33.4, 36.2, 28.7, 22.9, 27.1, 16.5, 18.9, 15. ,
        18.9, 21.7, 20.4, 18.2, 19.9, 23.1, 17.5, 20.2, 18.2, 13.6, 19.6,
        15.2, 14.5, 15.6, 13.9, 16.6, 14.8, 18.4, 21. , 12.7, 14.5, 13.2,
        13.1, 13.5, 18.9, 20. , 21. , 24.7, 30.8, 34.9, 26.6, 25.3, 24.7,
        21.2, 19.3, 20. , 16.6, 14.4, 19.4, 19.7, 20.5, 25. , 23.4, 18.9,
        35.4, 24.7, 31.6, 23.3, 19.6, 18.7, 16. , 22.2, 25. , 33. , 23.5,
```

In [10]:
```
data = pd.DataFrame(boston.data,columns = boston.feature_names)
```

In [11]:
```
data
```

Out[11]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.90	9.14
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33
...	...	...	...	...	...	...	...	...	...	...	...	...	...
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	391.99	9.67
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0	396.90	9.08
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	396.90	5.64
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	393.45	6.48
505	0.04741	0.0	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0	396.90	7.88

506 rows × 13 columns

In [12]:
```
data['Target']  = boston.target
```

In [13]:
```
data.head()
```

Out[13]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	Target
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	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	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33	36.2

In [14]:
```
data.shape
```

Out[14]:
```
(506, 14)
```

In [15]:
```
data.isna().sum()
```

Out[15]:
```
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
Target     0
dtype: int64
```

In [16]:
```
data.describe()
```

Out[16]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.00
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.455534	356.67
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164946	91.29
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000	0.32
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400000	375.37
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050000	391.44
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200000	396.22
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000	396.90

In [23]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

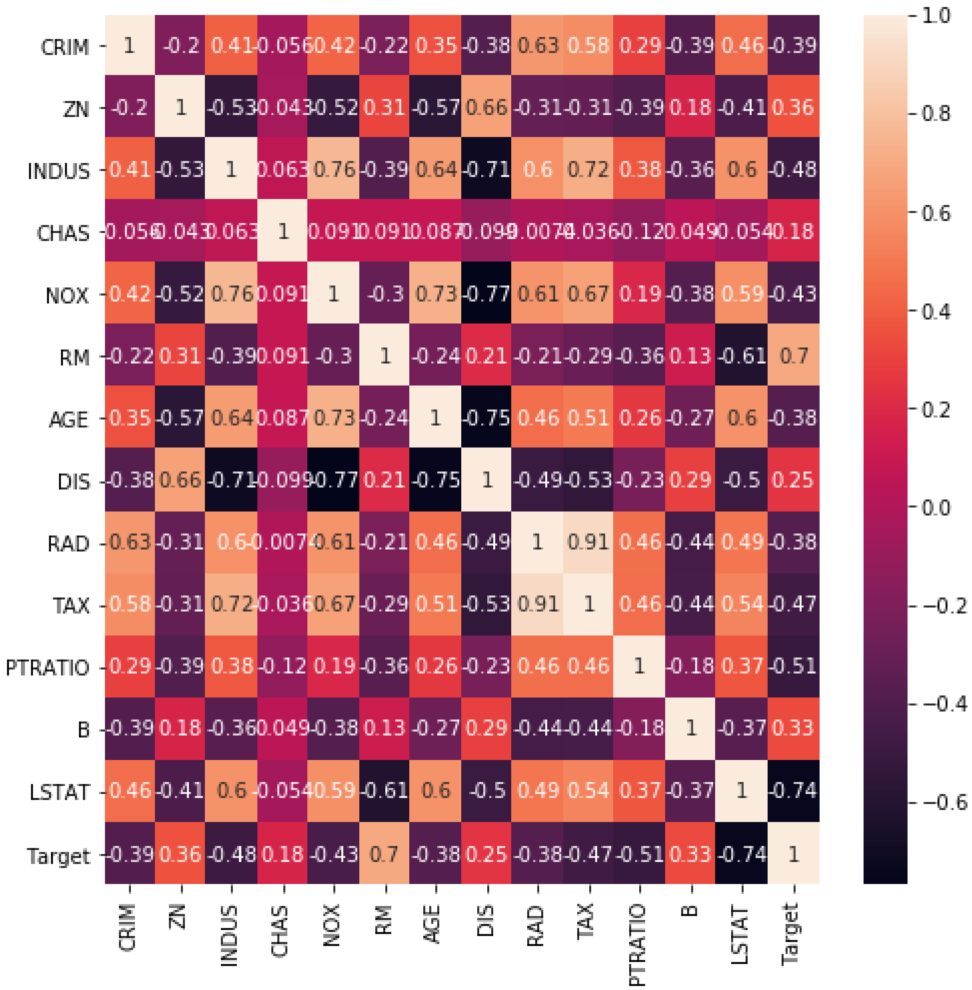
In [24]:
```
data.corr()
```

Out[24]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
CRIM	1.000000	-0.200469	0.406583	-0.055892	0.420972	-0.219247	0.352734	-0.379670	0.625505	0.582764	0.289946	-0.385064	0.455621
ZN	-0.200469	1.000000	-0.533828	-0.042697	-0.516604	0.311991	-0.569537	0.664408	-0.311948	-0.314563	-0.391679	0.175520	-0.412995
INDUS	0.406583	-0.533828	1.000000	0.062938	0.763651	-0.391676	0.644779	-0.708027	0.595129	0.720760	0.383248	-0.356977	0.603800
CHAS	-0.055892	-0.042697	0.062938	1.000000	0.091203	0.091251	0.086518	-0.099176	-0.007368	-0.035587	-0.121515	0.048788	-0.053929
NOX	0.420972	-0.516604	0.763651	0.091203	1.000000	-0.302188	0.731470	-0.769230	0.611441	0.668023	0.188933	-0.380051	0.590879
RM	-0.219247	0.311991	-0.391676	0.091251	-0.302188	1.000000	-0.240265	0.205246	-0.209847	-0.292048	-0.355501	0.128069	-0.613808
AGE	0.352734	-0.569537	0.644779	0.086518	0.731470	-0.240265	1.000000	-0.747881	0.456022	0.506456	0.261515	-0.273534	0.602339
DIS	-0.379670	0.664408	-0.708027	-0.099176	-0.769230	0.205246	-0.747881	1.000000	-0.494588	-0.534432	-0.232471	0.291512	-0.496996
RAD	0.625505	-0.311948	0.595129	-0.007368	0.611441	-0.209847	0.456022	-0.494588	1.000000	0.910228	0.464741	-0.444413	0.488676
TAX	0.582764	-0.314563	0.720760	-0.035587	0.668023	-0.292048	0.506456	-0.534432	0.910228	1.000000	0.460853	-0.441808	0.543993
PTRATIO	0.289946	-0.391679	0.383248	-0.121515	0.188933	-0.355501	0.261515	-0.232471	0.464741	0.460853	1.000000	-0.177383	0.374044
B	-0.385064	0.175520	-0.356977	0.048788	-0.380051	0.128069	-0.273534	0.291512	-0.444413	-0.441808	-0.177383	1.000000	-0.366087
LSTAT	0.455621	-0.412995	0.603800	-0.053929	0.590879	-0.613808	0.602339	-0.496996	0.488676	0.543993	0.374044	-0.366087	1.000000
Target	-0.388305	0.360445	-0.483725	0.175260	-0.427321	0.695360	-0.376955	0.249929	-0.381626	-0.468536	-0.507787	0.333461	-0.737663

In [27]:
```
fig, ax = plt.subplots(figsize = (8,8))
sns.heatmap(data.corr(),annot = True)
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x1a952763a08>



In [28]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [31]:
```
X = data.drop('Target',1)
vif_df = pd.DataFrame()
```

In [32]:
```
vif_df['features']  = X.columns
```

In [33]:
```
vif_df["vif"] =  [variance_inflation_factor(X.values,i) for i in range(len(X.columns))]
```

In [37]:
```
vif_df[vif_df['vif']<5]
```

Out[37]:

	features	vif
0	CRIM	2.100373
1	ZN	2.844013
3	CHAS	1.152952

In [38]:
```
vif_df
```

Out[38]:

	features	vif
0	CRIM	2.100373
1	ZN	2.844013
2	INDUS	14.485758
3	CHAS	1.152952
4	NOX	73.894947
5	RM	77.948283
6	AGE	21.386850
7	DIS	14.699652
8	RAD	15.167725
9	TAX	61.227274
10	PTRATIO	85.029547
11	B	20.104943
12	LSTAT	11.102025

In [39]:
```
data.head()
```

Out[39]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	Target
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.90	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	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396.90	5.33	36.2

In [40]:
```
from sklearn.model_selection import train_test_split as tts
```

In [41]:
```
X,y = data.drop('Target',axis =1),data['Target']
```

In [48]:
```
X_train,x_test,y_train,y_test = tts(X,y,random_state = 0)
```

In [49]:
```
lm = LinearRegression()
```

In [50]:
```
lm.fit(X_train,y_train)
```

Out[50]:
```
LinearRegression()
```

In [51]:
```
lm.coef_
```

Out[51]:
```
array([-1.17735289e-01,  4.40174969e-02, -5.76814314e-03,  2.39341594e+00,
       -1.55894211e+01,  3.76896770e+00, -7.03517828e-03, -1.43495641e+00,
        2.40081086e-01, -1.12972810e-02, -9.85546732e-01,  8.44443453e-03,
       -4.99116797e-01])
```

In [52]:
```
lm.intercept_
```

Out[52]:
```
36.93325545711977
```

In [53]:
```
data['Target'].mean()
```

Out[53]:
```
22.532806324110698
```

Evaluation for regression

In [55]:
```
from sklearn.metrics import r2_score,mean_squared_error,mean_absolute_error
```

In [56]:
```
y_pred = lm.predict(x_test)
```

In [58]:
```
r2_score(y_pred,y_test)
```

Out[58]: 0.4967900069591097

In [59]:
```
mean_squared_error(y_pred,y_test) # (1/n)*sum((y-ypred)^2)
```

Out[59]: 29.7822450923024

In [60]:
```
mean_absolute_error(y_pred,y_test) # (1/n)*sum(|(y-ypred)|)
```

Out[60]: 3.668330148135725

In [62]:
```
100*mean_absolute_error(y_pred,y_test)/data['Target'].mean()
```

Out[62]: 16.27995241857875

In [73]:
```
y_pred_tr = lm.predict(X_train)
r2_score(y_pred_tr,y_train)
```

Out[73]: 0.7009105753444579

Polynomial Regression

f(x) => o(3)

polynomial of x with order 3:

f(x) = m1x + m2x^2 + m3x^3 + c

In [64]:
```
from sklearn.preprocessing import PolynomialFeatures
```

In [67]:
```
poly = PolynomialFeatures(degree = 4)
X_poly = poly.fit_transform(X)
```

In [71]:
```
X_poly.shape
```

Out[71]: (506, 2380)

In [74]:
```
lm.fit(X_poly,y)
```

Out[74]: LinearRegression()

In [77]:
```
lm.score(X_poly,y)
```

Out[77]: 1.0

In [78]:
```
mean_squared_error(lm.predict(X_poly),y)
```

Out[78]: 2.524152532226545e-19

In [ ]:
```

```