

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

## Finding Price

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

```
df.head(),df.tail()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1	296
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2	242
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2	242
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3	222
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3	222

	B	LSTAT	MEDV
0	396.90	4.98	24.0
1	396.90	9.14	21.6
2	392.83	4.03	34.7
3	394.63	2.94	33.4
4	396.90	NaN	36.2

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1	273
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1	273
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1	273
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1	273
505	0.04741	0.0	11.93	0.0	0.573	6.030	NaN	2.5050	1	273

	B	LSTAT	MEDV
501	391.99	NaN	22.4
502	396.90	9.08	20.6
503	396.90	5.64	23.9

```
504 393.45 6.48 22.0
505 396.90 7.88 11.9 )
```

## Checking for duplicate Data

```
df.duplicated().sum()
```

```
0
```

## Data Inforamtion

```
df.describe()
```

	CRIM	ZN	INDUS	CHAS	NOX
RM \					
count	486.000000	486.000000	486.000000	486.000000	506.000000
mean	3.611874	11.211934	11.083992	0.069959	0.554695
std	8.720192	23.388876	6.835896	0.255340	0.115878
min	0.006320	0.000000	0.460000	0.000000	0.385000
25%	0.081900	0.000000	5.190000	0.000000	0.449000
50%	0.253715	0.000000	9.690000	0.000000	0.538000
75%	3.560263	12.500000	18.100000	0.000000	0.624000
max	88.976200	100.000000	27.740000	1.000000	0.871000

	AGE	DIS	RAD	TAX	PTRATIO
B \					
count	486.000000	506.000000	506.000000	506.000000	506.000000
mean	68.518519	3.795043	9.549407	408.237154	18.455534
std	27.999513	2.105710	8.707259	168.537116	2.164946
min	2.900000	1.129600	1.000000	187.000000	12.600000
25%	45.175000	2.100175	4.000000	279.000000	17.400000
50%	76.800000	3.207450	5.000000	330.000000	19.050000
max	391.440000				

75%	93.975000	5.188425	24.000000	666.000000	20.200000
396.225000					
max	100.000000	12.126500	24.000000	711.000000	22.000000
396.900000					

	LSTAT	MEDV
count	486.000000	506.000000
mean	12.715432	22.532806
std	7.155871	9.197104
min	1.730000	5.000000
25%	7.125000	17.025000
50%	11.430000	21.200000
75%	16.955000	25.000000
max	37.970000	50.000000

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 506 entries, 0 to 505
```

```
Data columns (total 14 columns):
```

#	Column	Non-Null Count	Dtype
0	CRIM	486 non-null	float64
1	ZN	486 non-null	float64
2	INDUS	486 non-null	float64
3	CHAS	486 non-null	float64
4	NOX	506 non-null	float64
5	RM	506 non-null	float64
6	AGE	486 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	486 non-null	float64
13	MEDV	506 non-null	float64

```
dtypes: float64(12), int64(2)
```

```
memory usage: 55.5 KB
```

```
a = df.isnull().mean()
```

```
df.isnull().sum()
```

CRIM	20
ZN	20
INDUS	20
CHAS	20
NOX	0
RM	0
AGE	20

```
DIS      0
RAD      0
TAX      0
PTRATIO  0
B        0
LSTAT    20
MEDV     0
dtype: int64
```

```
# 3 percent in each column is missing
df.isnull().mean()*100
```

```
CRIM      3.952569
ZN        3.952569
INDUS     3.952569
CHAS      3.952569
NOX       0.000000
RM        0.000000
AGE       3.952569
DIS       0.000000
RAD       0.000000
TAX       0.000000
PTRATIO   0.000000
B         0.000000
LSTAT     3.952569
MEDV      0.000000
dtype: float64
```

```
#Dropping missing data
```

```
df.dropna(inplace = True)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Index: 394 entries, 0 to 504
```

```
Data columns (total 14 columns):
```

#	Column	Non-Null Count	Dtype
0	CRIM	394 non-null	float64
1	ZN	394 non-null	float64
2	INDUS	394 non-null	float64
3	CHAS	394 non-null	float64
4	NOX	394 non-null	float64
5	RM	394 non-null	float64
6	AGE	394 non-null	float64
7	DIS	394 non-null	float64
8	RAD	394 non-null	int64
9	TAX	394 non-null	int64
10	PTRATIO	394 non-null	float64
11	B	394 non-null	float64

```

12  LSTAT      394 non-null    float64
13  MEDV       394 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 46.2 KB

```

```
df.describe()
```

	CRIM	ZN	INDUS	CHAS	NOX
RM \					
count	394.000000	394.000000	394.000000	394.000000	394.000000
mean	3.690136	11.460660	11.000863	0.068528	0.553215
std	9.202423	23.954082	6.908364	0.252971	0.113112
min	0.006320	0.000000	0.460000	0.000000	0.389000
25%	0.081955	0.000000	5.130000	0.000000	0.453000
50%	0.268880	0.000000	8.560000	0.000000	0.538000
75%	3.435973	12.500000	18.100000	0.000000	0.624000
max	88.976200	100.000000	27.740000	1.000000	0.871000

	AGE	DIS	RAD	TAX	PTRATIO
B \					
count	394.000000	394.000000	394.000000	394.000000	394.000000
mean	68.932741	3.805268	9.403553	406.431472	18.537563
std	27.888705	2.098571	8.633451	168.312419	2.166460
min	2.900000	1.129600	1.000000	187.000000	12.600000
25%	45.475000	2.110100	4.000000	280.250000	17.400000
50%	77.700000	3.199200	5.000000	330.000000	19.100000
75%	94.250000	5.116700	24.000000	666.000000	20.200000
max	100.000000	12.126500	24.000000	711.000000	22.000000

	LSTAT	MEDV
count	394.000000	394.000000
mean	12.769112	22.359645
std	7.308430	9.142979
min	1.730000	5.000000

25%	7.125000	16.800000
50%	11.300000	21.050000
75%	17.117500	25.000000
max	37.970000	50.000000

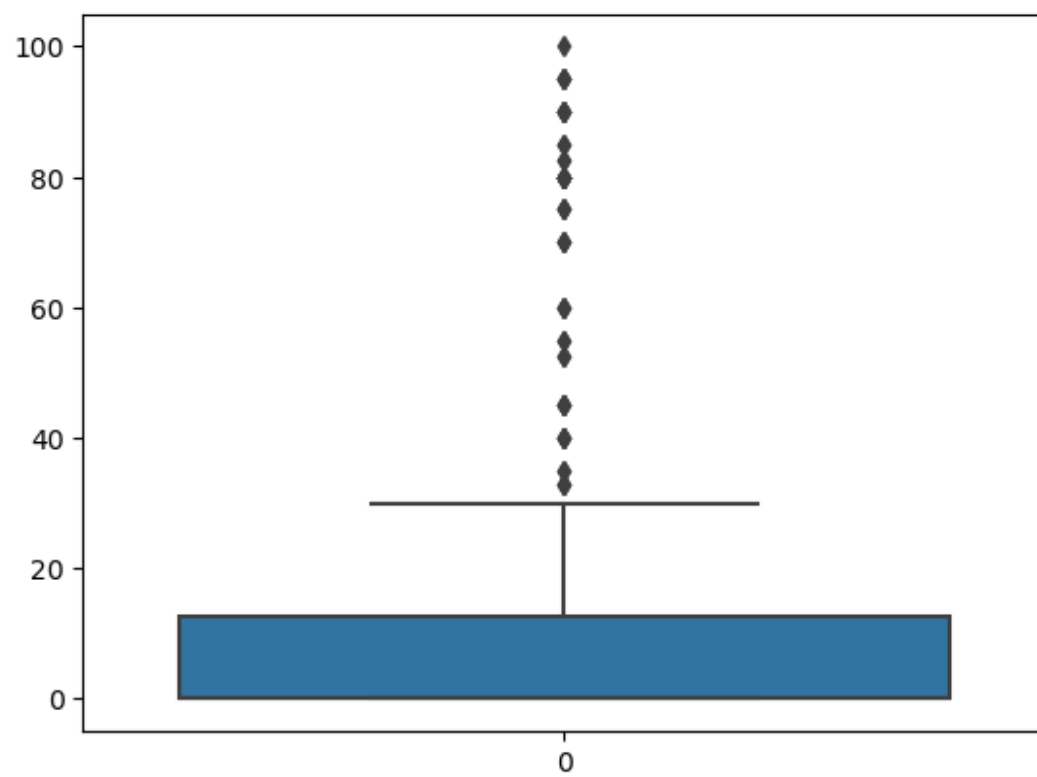
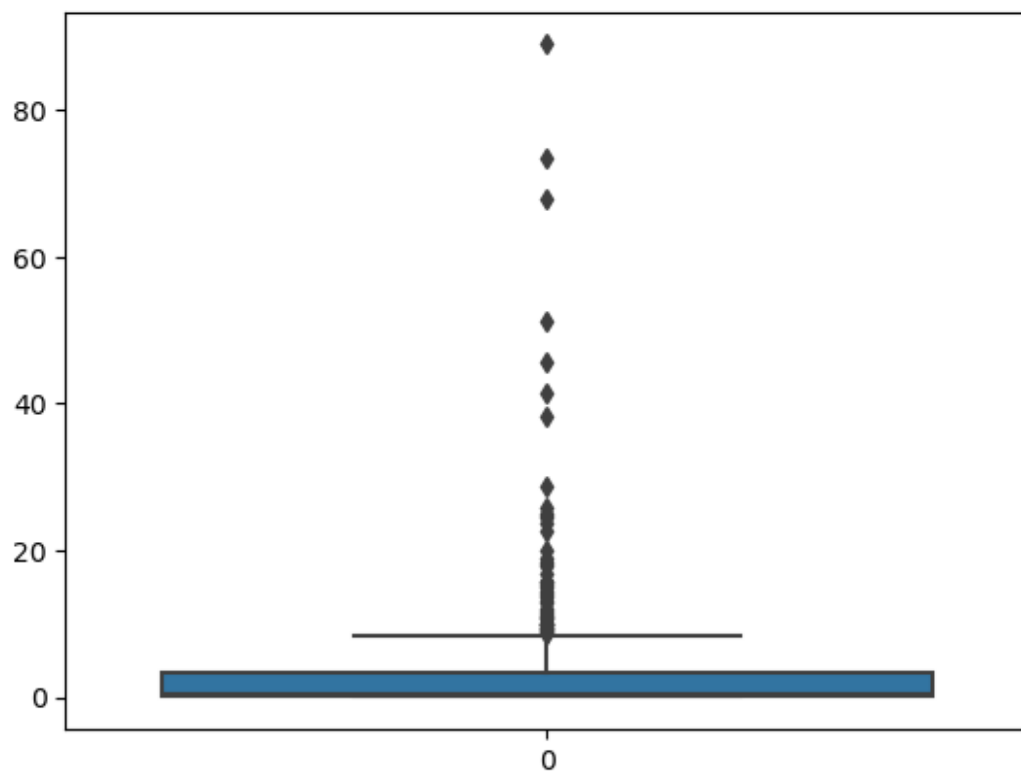
```
df.skew()
```

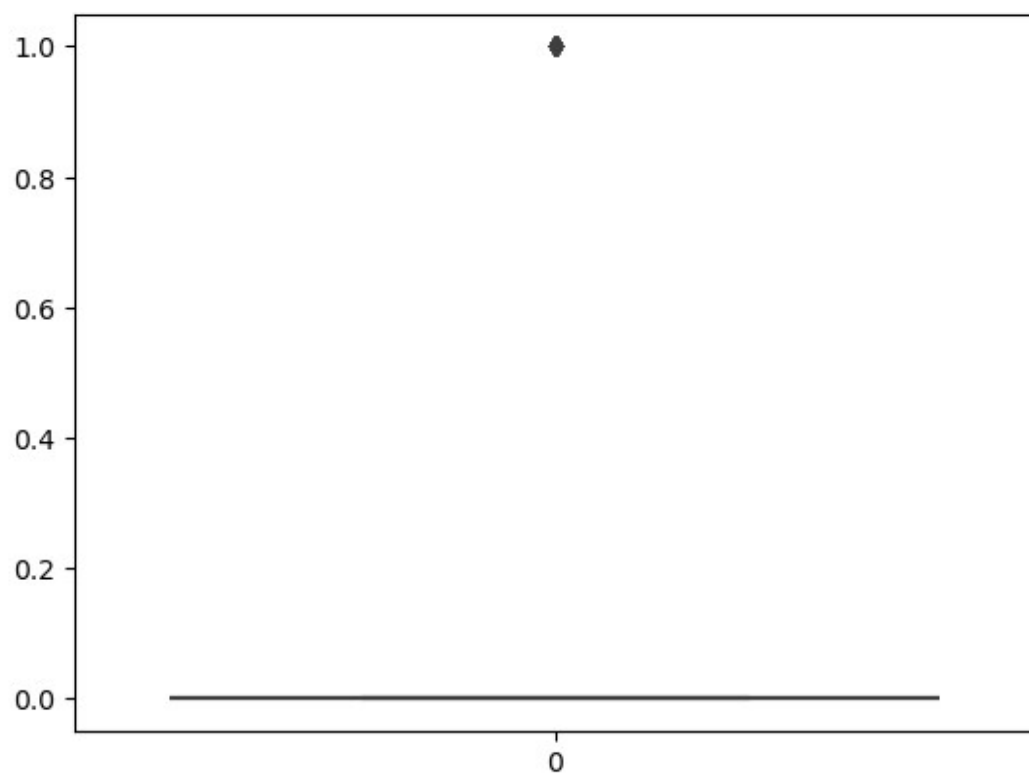
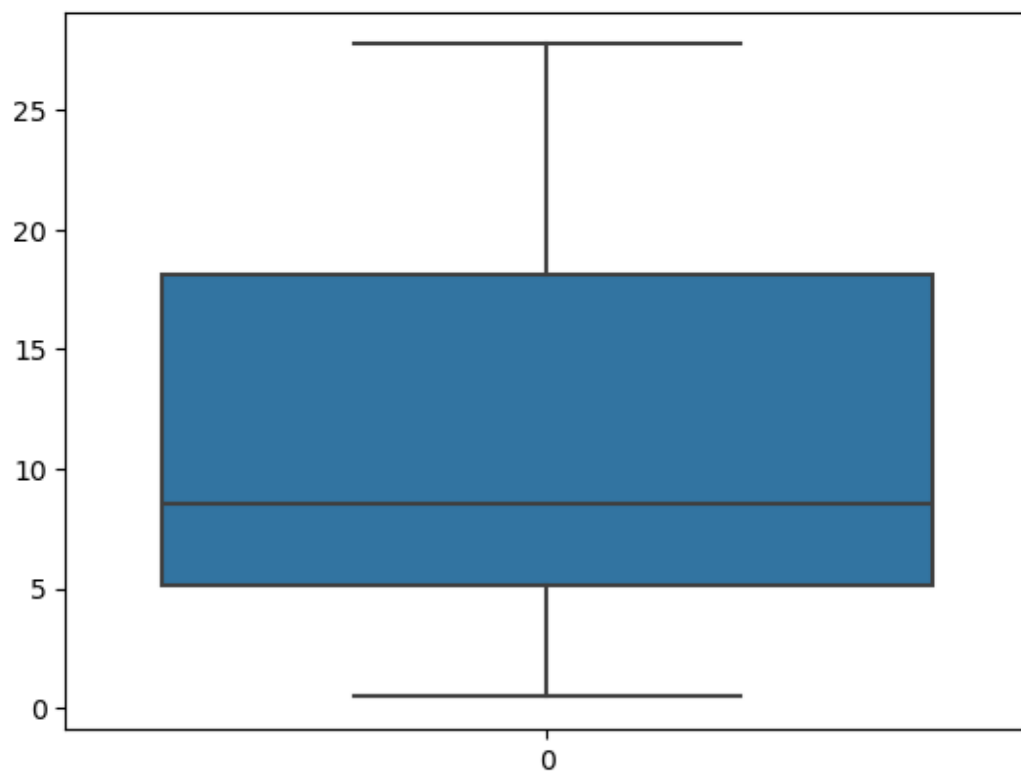
CRIM	5.256934
ZN	2.258275
INDUS	0.358792
CHAS	3.428643
NOX	0.703377
RM	0.487558
AGE	-0.594880
DIS	1.032625
RAD	1.050144
TAX	0.692876
PTRATIO	-0.884475
B	-2.987695
LSTAT	0.942665
MEDV	1.065946

dtype: float64

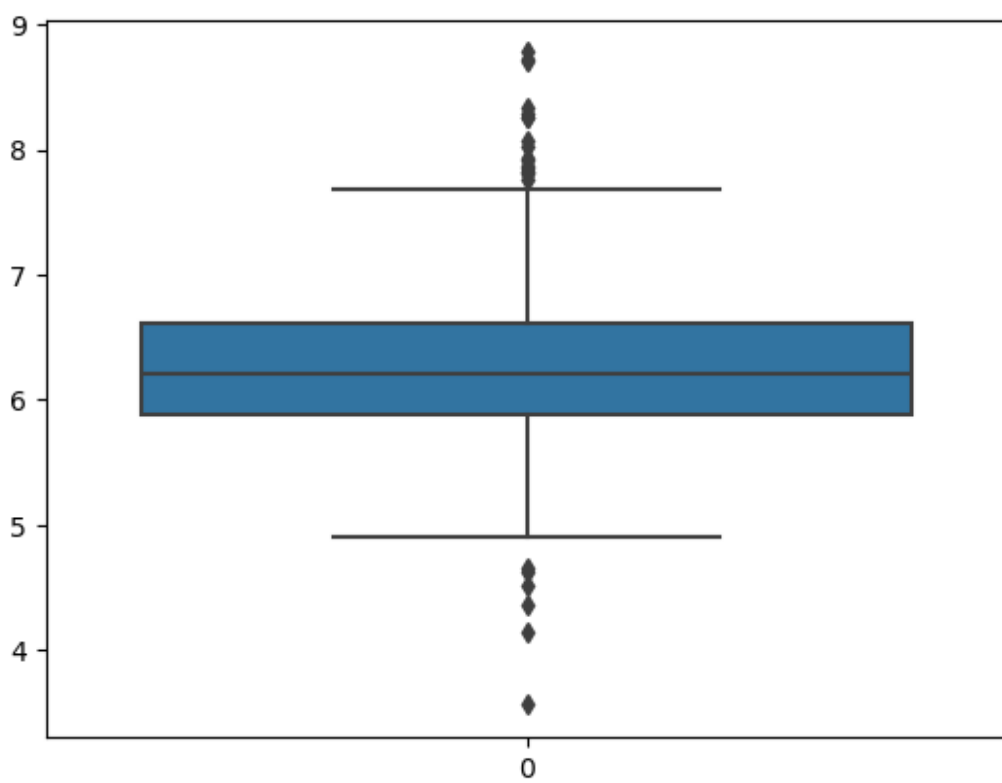
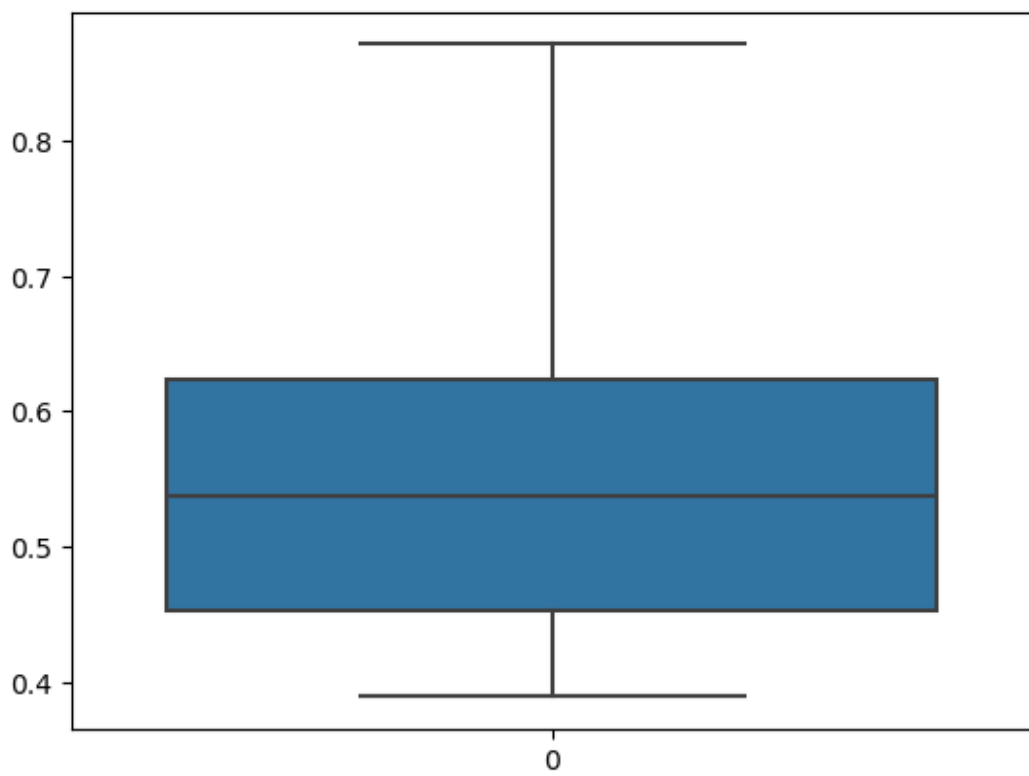
```
def boxplots(data_frame):  
    for i in data_frame:  
        sns.boxplot(df[i])  
        plt.show()
```

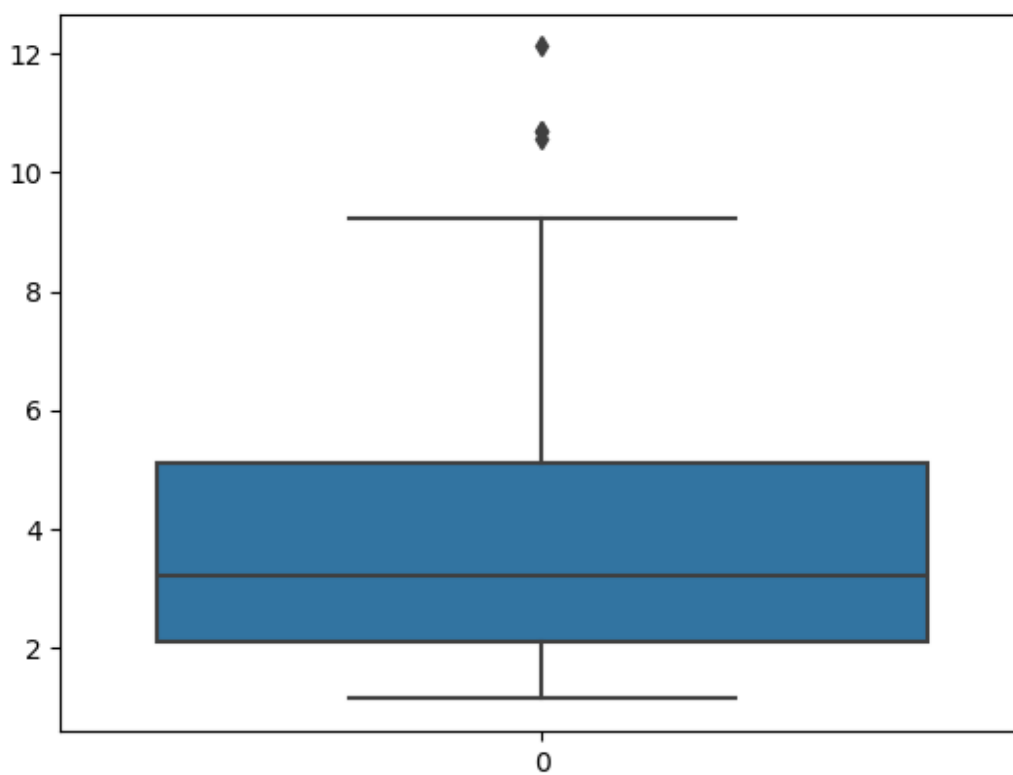
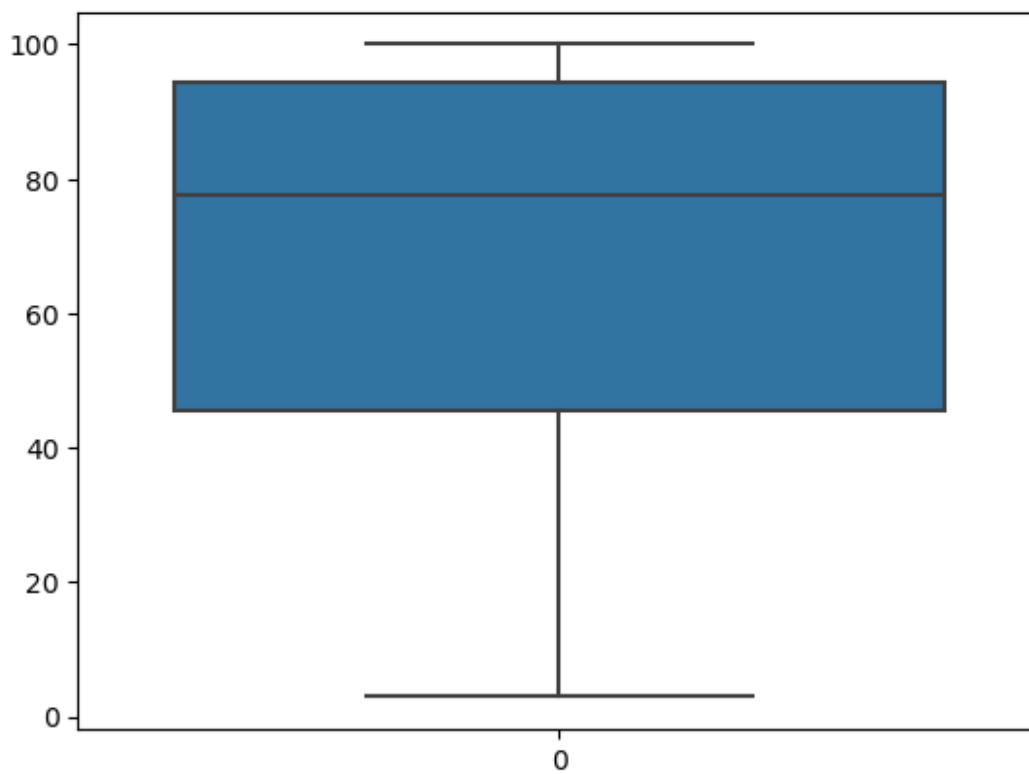
```
# boxplot of each column  
boxplots(df)
```

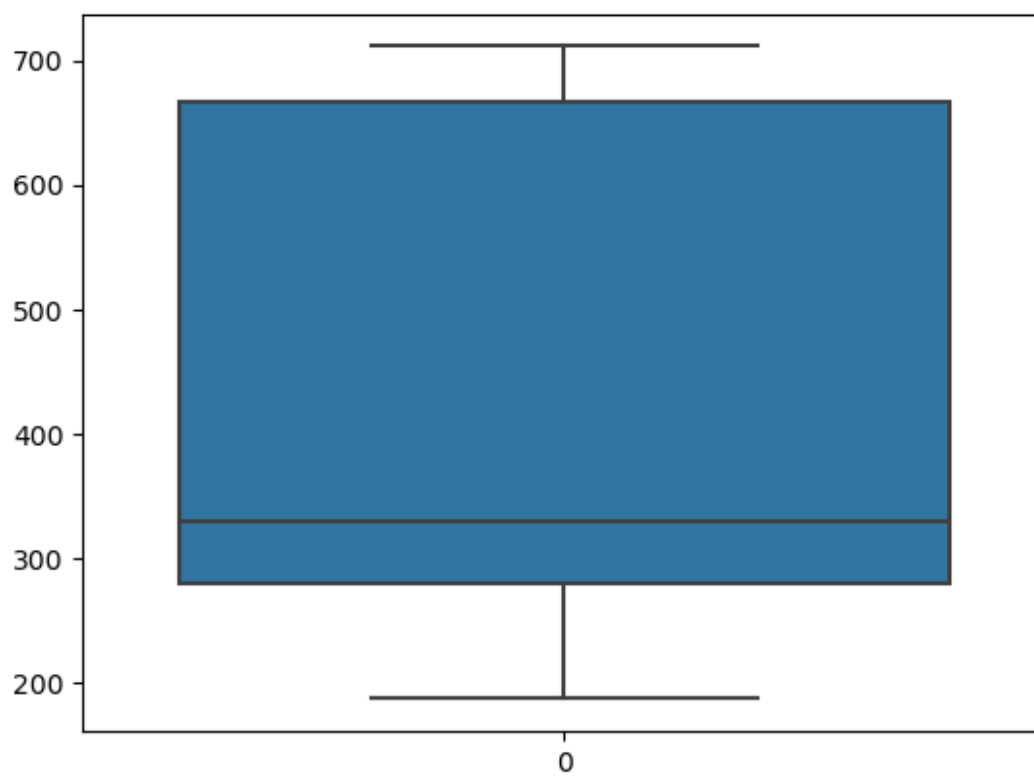
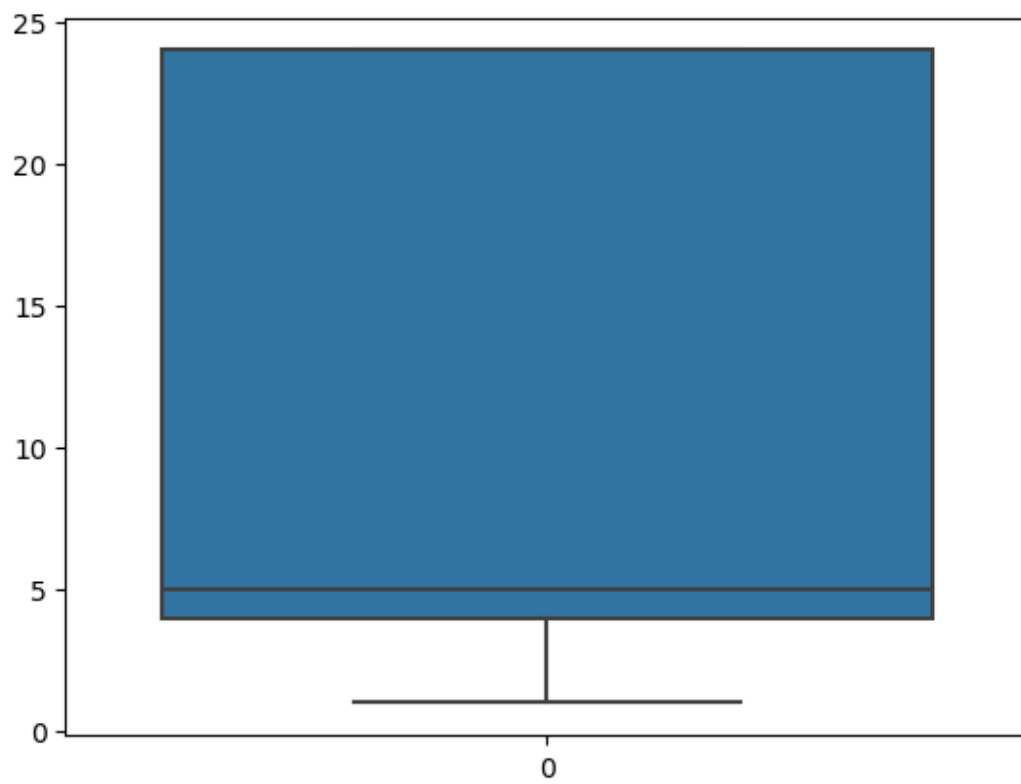


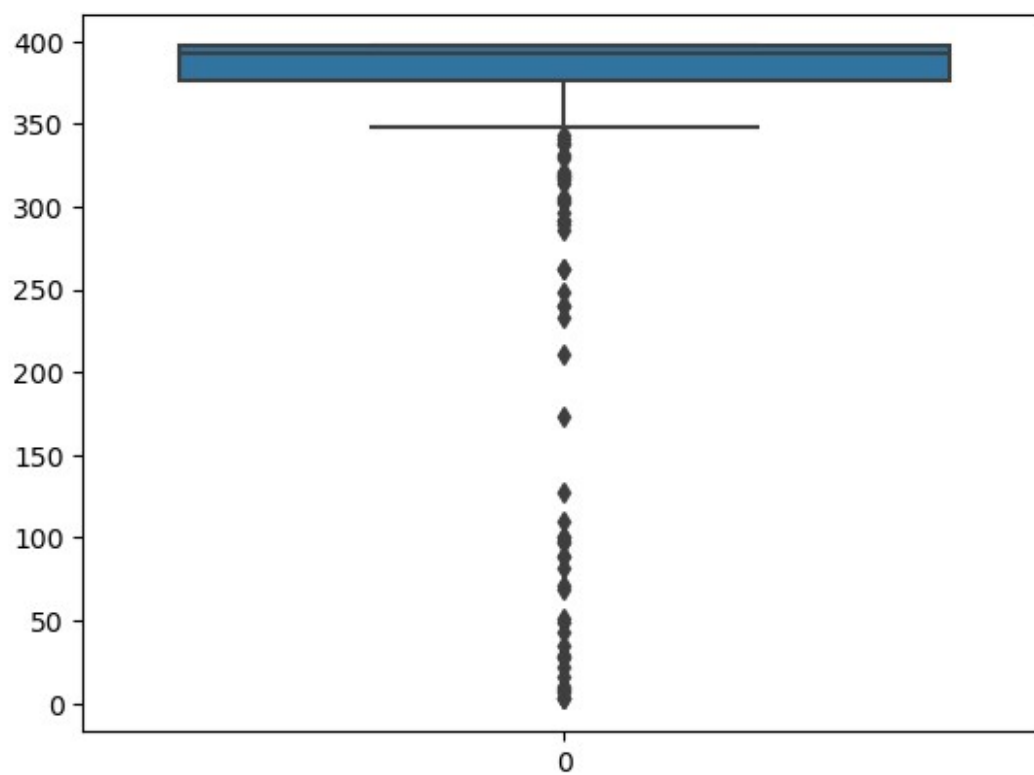
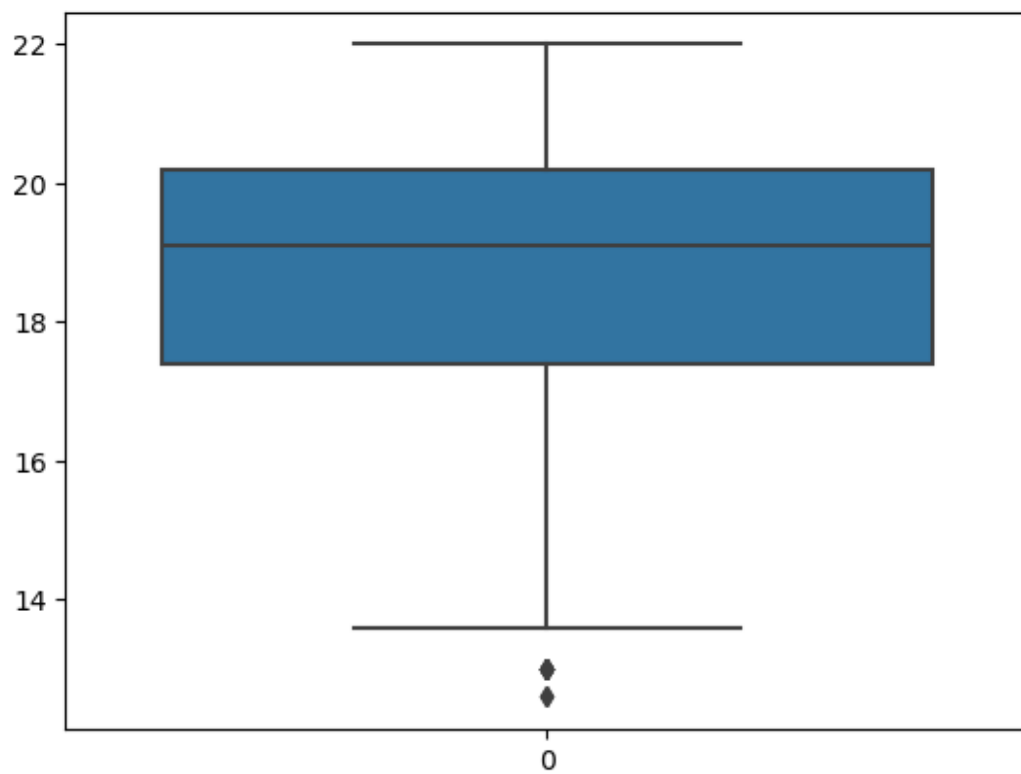


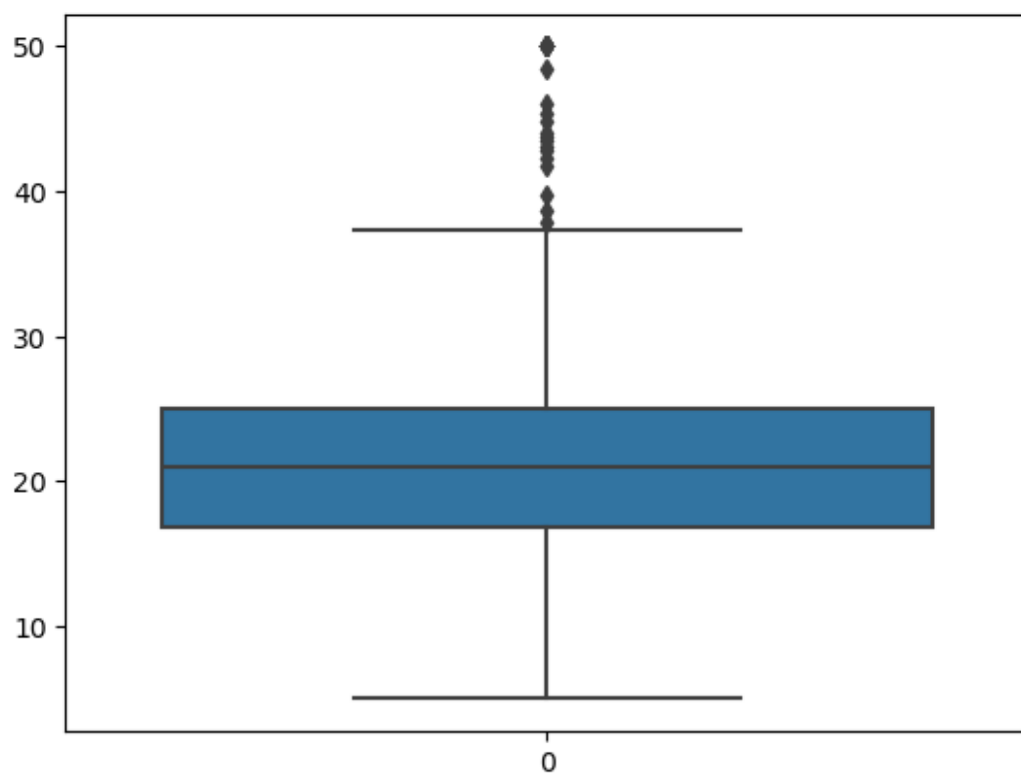
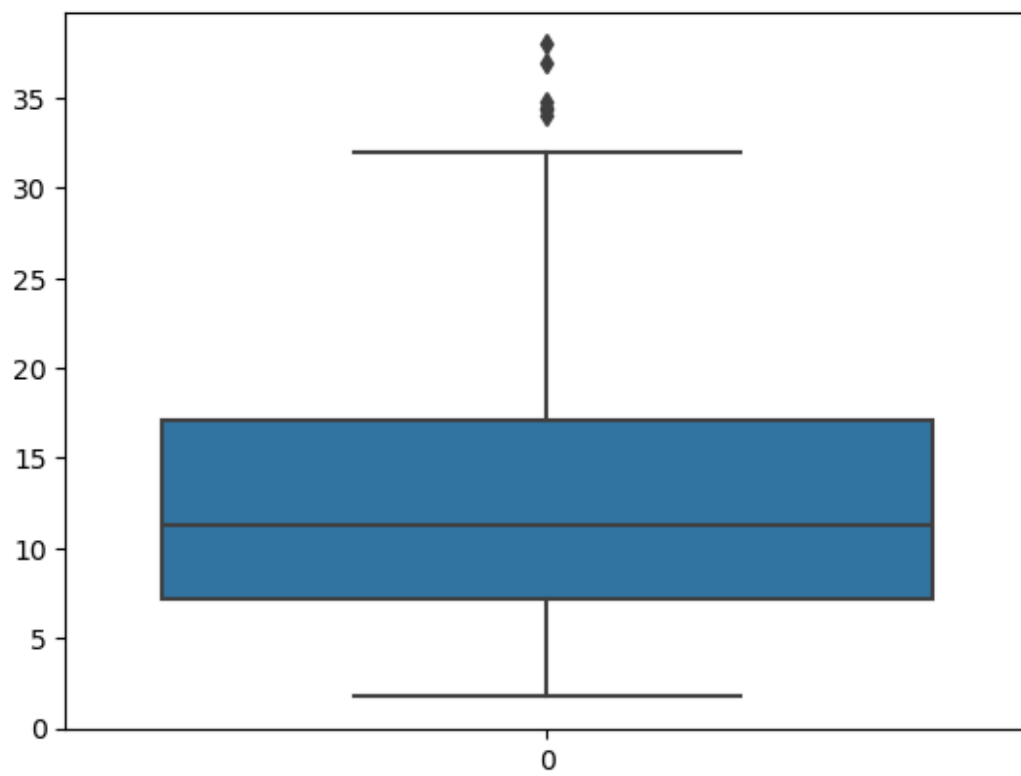












```
# correlation
```

```
corr_matrix= df.corr().round(2)
```

```
corr_matrix[corr_matrix>(0.7)]
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX
PTRATIO \										
CRIM	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
NaN										
ZN	NaN	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
NaN										
INDUS	NaN	NaN	1.00	NaN	0.76	NaN	NaN	NaN	NaN	0.73
NaN										
CHAS	NaN	NaN	NaN	1.0	NaN	NaN	NaN	NaN	NaN	NaN
NaN										
NOX	NaN	NaN	0.76	NaN	1.00	NaN	0.73	NaN	NaN	NaN
NaN										
RM	NaN	NaN	NaN	NaN	NaN	1.00	NaN	NaN	NaN	NaN
NaN										
AGE	NaN	NaN	NaN	NaN	0.73	NaN	1.00	NaN	NaN	NaN
NaN										
DIS	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	NaN	NaN
NaN										
RAD	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	0.90
NaN										
TAX	NaN	NaN	0.73	NaN	NaN	NaN	NaN	NaN	0.9	1.00
NaN										
PTRATIO	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1.0										
B	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
NaN										
LSTAT	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
NaN										
MEDV	NaN	NaN	NaN	NaN	NaN	0.72	NaN	NaN	NaN	NaN
NaN										

	B	LSTAT	MEDV
CRIM	NaN	NaN	NaN
ZN	NaN	NaN	NaN
INDUS	NaN	NaN	NaN
CHAS	NaN	NaN	NaN
NOX	NaN	NaN	NaN
RM	NaN	NaN	0.72
AGE	NaN	NaN	NaN
DIS	NaN	NaN	NaN
RAD	NaN	NaN	NaN
TAX	NaN	NaN	NaN
PTRATIO	NaN	NaN	NaN
B	1.0	NaN	NaN

LSTAT	NaN	1.0	NaN
MEDV	NaN	NaN	1.00

## Outlier Treatment

```
# Outliers = crime,zn,rm,b
```

```
df["CRIM"].describe()
```

```
count    394.000000
mean      3.690136
std       9.202423
min       0.006320
25%      0.081955
50%      0.268880
75%      3.435973
max      88.976200
```

```
Name: CRIM, dtype: float64
```

```
df["CRIM"].describe()
```

```
Q1 = 0.08
```

```
Q3 = 3.67
```

```
IQR = Q3 - Q1
```

```
Upperlimit = Q3 + 1.5*IQR
```

```
lowerlimit = Q1 - 1.5 * IQR
```

```
df["CRIM"] =
```

```
np.where(df["CRIM"]>Upperlimit,Upperlimit,np.where(df["CRIM"]<lowerlimit,lowerlimit,df["CRIM"]))
```

```
df["ZN"].describe()
```

```
count    394.000000
mean     11.460660
std      23.954082
min      0.000000
25%      0.000000
50%      0.000000
75%     12.500000
max     100.000000
```

```
Name: ZN, dtype: float64
```

```
df["ZN"].describe()
```

```
Q1 = 0.00
```

```
Q3 = 12.50
```

```
IQR = Q3 - Q1
```

```
Upperlimit = Q3 + 1.5*IQR
```

```
lowerlimit = Q1 - 1.5 * IQR
```

```
df["ZN"] =
```

```

np.where(df["ZN"]>Upperlimit,Upperlimit,np.where(df["ZN"]<lowerlimit,lowerlimit,df["ZN"]))

df["RM"].describe()

count      394.000000
mean        6.280015
std         0.697985
min         3.561000
25%         5.879250
50%         6.201500
75%         6.605500
max         8.780000
Name: RM, dtype: float64

Q1 = 5.87
Q3 = 6.60
IQR = Q3 - Q1
Upperlimit = Q3 + 1.5*IQR
lowerlimit = Q1 - 1.5 * IQR
df["RM"] =
np.where(df["RM"]>Upperlimit,Upperlimit,np.where(df["RM"]<lowerlimit,lowerlimit,df["RM"]))

df["B"].describe()

count      394.000000
mean       358.490939
std        89.283295
min         2.600000
25%        376.707500
50%        392.190000
75%        396.900000
max        396.900000
Name: B, dtype: float64

Q1 = 376.70
Q3 = 396.90
IQR = Q3 - Q1
Upperlimit = Q3 + 1.5*IQR
lowerlimit = Q1 - 1.5 * IQR
df["B"] =
np.where(df["B"]>Upperlimit,Upperlimit,np.where(df["B"]<lowerlimit,lowerlimit,df["B"]))

```

## FEATURE SCALING

```
from sklearn.preprocessing import StandardScaler
```



```
# splitting data into dependent and independent variable
x = df.drop(["MEDV"], axis = 1)
y = df["MEDV"]
```

```
scaler = StandardScaler()
x_scaler = scaler.fit_transform(x) # Scale the features
x_scaler = pd.DataFrame(x_scaler, columns=x.columns)

pd.DataFrame(x_scaler, columns = x.columns)
```

	CRIM	ZN	INDUS	CHAS	NOX	RM
AGE \						
0	-0.662816	0.948062	-1.259620	-0.271237	-0.134687	0.489673
0.134014						
1	-0.656404	-0.573816	-0.569724	-0.271237	-0.745475	0.243887
0.357849						
2	-0.656410	-0.573816	-0.569724	-0.271237	-0.745475	1.463243
0.281214						
3	-0.654858	-0.573816	-1.278462	-0.271237	-0.842847	1.164788
0.830521						
4	-0.655628	-0.573816	-1.278462	-0.271237	-0.842847	0.258251
0.367380						
..	...	...	...	...	...	...
...						
389	-0.610422	-0.573816	-0.189991	-0.271237	0.281356	-1.115919
0.163976						
390	-0.596202	-0.573816	-0.189991	-0.271237	0.281356	-0.384944
0.386570						
391	-0.650917	-0.573816	0.134666	-0.271237	0.175132	-0.236514
0.278863						
392	-0.646185	-0.573816	0.134666	-0.271237	0.175132	1.129676
0.792268						
393	-0.631268	-0.573816	0.134666	-0.271237	0.175132	0.839201
0.731233						

	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.135851	-0.974609	-0.656944	-1.496303	0.769546	-1.067126
1	0.554334	-0.858633	-0.978184	-0.340879	0.769546	-0.497196
2	0.554334	-0.858633	-0.978184	-0.340879	0.546744	-1.197278
3	1.076829	-0.742657	-1.097162	0.075073	0.645281	-1.346610
4	1.076829	-0.742657	-1.097162	0.075073	0.617362	-1.035615
..	...	...	...	...	...	...
389	-0.670530	-0.394730	-0.091800	0.306158	0.707687	0.319337
390	-0.623629	-0.394730	-0.091800	0.306158	0.769546	0.213845
391	-0.724158	-0.974609	-0.793769	1.138063	0.769546	-0.505417
392	-0.781413	-0.974609	-0.793769	1.138063	0.769546	-0.976704
393	-0.675778	-0.974609	-0.793769	1.138063	0.580685	-0.861622

```
[394 rows x 13 columns]
```

```
x_scaler.describe().round(2)
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS
RAD \								
count	394.00	394.00	394.00	394.00	394.00	394.00	394.00	394.00
mean	-0.00	-0.00	-0.00	-0.00	0.00	-0.00	-0.00	0.00
std	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
min	-0.66	-0.57	-1.53	-0.27	-1.45	-2.38	-2.37	-1.28
25%	-0.64	-0.57	-0.85	-0.27	-0.89	-0.62	-0.84	-0.81
50%	-0.58	-0.57	-0.35	-0.27	-0.13	-0.11	0.31	-0.29
75%	0.38	0.48	1.03	-0.27	0.63	0.54	0.91	0.63
max	2.10	2.07	2.43	3.69	2.81	2.28	1.12	3.97

	TAX	PTRATIO	B	LSTAT
count	394.00	394.00	394.00	394.00
mean	0.00	0.00	0.00	-0.00
std	1.00	1.00	1.00	1.00
min	-1.31	-2.74	-1.99	-1.51
25%	-0.75	-0.53	-0.34	-0.77
50%	-0.45	0.26	0.51	-0.20
75%	1.54	0.77	0.77	0.60
max	1.81	1.60	0.77	3.45

```
# VIF- Variance inflation factor > 5 - multicollinearity
```

```
x_scaler.shape
```

```
(394, 13)
```

```
from statsmodels.stats.outliers_influence import  
variance_inflation_factor
```

```
variable = x_scaler
```

```
vif = pd.DataFrame()
```

```
vif["variance inflation factor"] =  
[variance_inflation_factor(variable,i) for i in  
range(variable.shape[1])]
```

```
vif["Features"] = x.columns
```

```
vif
```

	variance inflation factor	Features
0	9.673299	CRIM
1	2.444219	ZN
2	4.078226	INDUS
3	1.070390	CHAS
4	4.513045	NOX
5	2.221245	RM
6	3.157609	AGE
7	3.875598	DIS
8	12.484269	RAD
9	8.283109	TAX
10	1.906799	PTRATIO
11	1.330136	B
12	3.498310	LSTAT

*# rad has the highest correlation factor*

```
x_scaler = x_scaler.drop("RAD", axis = 1)
```

```
x_scaler.columns
```

```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS',
      'TAX',
      'PTRATIO', 'B', 'LSTAT'],
      dtype='object')
```

```
vif = pd.DataFrame()
variable = x_scaler
vif["variance inflation factor"] =
[variance_inflation_factor(variable,i) for i in
range(variable.shape[1])]
vif["Features"] = x.columns
```

```
-----
-----
ValueError                                Traceback (most recent call
last)
```

```
Cell In[43], line 4
```

```
2 variable = x_scaler
3 vif["variance inflation factor"] =
[variance_inflation_factor(variable,i) for i in
range(variable.shape[1])]
----> 4 vif["Features"] = x.columns
```

```
File C:\ProgramData\anaconda3\Lib\site-packages\pandas\core\
frame.py:4091, in DataFrame.__setitem__(self, key, value)
```

```
4088     self._setitem_array([key], value)
4089 else:
4090     # set column
-> 4091     self._set_item(key, value)
```

```
File C:\ProgramData\anaconda3\Lib\site-packages\pandas\core\
```

```

frame.py:4300, in DataFrame._set_item(self, key, value)
  4290 def _set_item(self, key, value) -> None:
  4291     """
  4292     Add series to DataFrame in specified column.
  4293     (...)
  4298     ensure homogeneity.
  4299     """
-> 4300     value, refs = self._sanitize_column(value)
  4302     if (
  4303         key in self.columns
  4304         and value.ndim == 1
  4305         and not isinstance(value.dtype, ExtensionDtype)
  4306     ):
  4307         # broadcast across multiple columns if necessary
  4308         if not self.columns.is_unique or
isinstance(self.columns, MultiIndex):

```

```

File C:\ProgramData\anaconda3\Lib\site-packages\pandas\core\
frame.py:5039, in DataFrame._sanitize_column(self, value)
  5036     return _reindex_for_setitem(value, self.index)
  5038 if is_list_like(value):
-> 5039     com.require_length_match(value, self.index)
  5040 return sanitize_array(value, self.index, copy=True,
allow_2d=True), None

```

```

File C:\ProgramData\anaconda3\Lib\site-packages\pandas\core\
common.py:561, in require_length_match(data, index)
  557 """
  558 Check the length of data matches the length of the index.
  559 """
  560 if len(data) != len(index):
--> 561     raise ValueError(
  562         "Length of values "
  563         f"({len(data)}) "
  564         "does not match length of index "
  565         f"({len(index)})"
  566     )

```

ValueError: Length of values (13) does not match length of index (12)

```
vif["Featurers"] = x_scaler.columns
```

```
vif
```

# EDA (EXPLORATORY DATA ANALYSIS)

```
import dtale
dtale.show(df)

<IPython.lib.display.IFrame at 0x14d77dd5390>
```

## Splitting the data into Training and Testing model

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size =
0.2,random_state= 43)
```

## Building linear regression model

```
from statsmodels.regression.linear_model import OLS
import statsmodels.regression.linear_model as smf

regression = smf.OLS(endog = y_train, exog= x_train).fit()
regression.summary()
```

<class 'statsmodels.iolib.summary.Summary'>

```
"""
                                OLS Regression Results
=====
=====
Dep. Variable:                  MEDV    R-squared (uncentered):
0.961
Model:                          OLS    Adj. R-squared (uncentered):
0.960
Method:                        Least Squares    F-statistic:
577.1
Date:                          Wed, 18 Dec 2024    Prob (F-statistic):
1.64e-204
Time:                          14:30:38    Log-Likelihood:
-938.49
No. Observations:                315    AIC:
1903.
Df Residuals:                    302    BIC:
1952.
Df Model:                        13
```

Covariance Type: nonrobust

=====					
=====					
	coef	std err	t	P> t	[0.025
0.975]					
-----					
-----					
CRIM	-0.3428	0.254	-1.348	0.179	-0.843
0.158					
ZN	0.0505	0.036	1.404	0.161	-0.020
0.121					
INDUS	0.0033	0.080	0.041	0.967	-0.155
0.161					
CHAS	4.0215	1.119	3.595	0.000	1.820
6.223					
NOX	-6.8214	4.764	-1.432	0.153	-16.196
2.553					
RM	5.5628	0.546	10.186	0.000	4.488
6.638					
AGE	-0.0262	0.017	-1.510	0.132	-0.060
0.008					
DIS	-0.9999	0.233	-4.289	0.000	-1.459
-0.541					
RAD	0.2131	0.109	1.958	0.051	-0.001
0.427					
TAX	-0.0084	0.005	-1.815	0.071	-0.017
0.001					
PTRATIO	-0.7687	0.165	-4.661	0.000	-1.093
-0.444					
B	0.0460	0.012	3.689	0.000	0.021
0.071					
LSTAT	-0.3949	0.066	-6.018	0.000	-0.524
-0.266					
=====					
=====					
Omnibus:	157.385	Durbin-Watson:			
2.094					
Prob(Omnibus):	0.000	Jarque-Bera (JB):			
1113.041					
Skew:	1.946	Prob(JB):			
2.02e-242					
Kurtosis:	11.346	Cond. No.			
1.00e+04					
=====					
=====					

Notes:

[1] R<sup>2</sup> is computed without centering (uncentered) since the model does

```
not contain a constant.  
[2] Standard Errors assume that the covariance matrix of the errors is  
correctly specified.  
[3] The condition number is large, 1e+04. This might indicate that  
there are  
strong multicollinearity or other numerical problems.  
"""
```

## Approach- 2 Linear regression

```
from sklearn.linear_model import LinearRegression  
reg_model = LinearRegression()  
reg_model.fit(x_train , y_train)  
  
LinearRegression()
```

## prediction

```
y_pred = reg_model.predict(x_test)
```

## Evaluation metrics

```
from sklearn.metrics import r2_score  
  
print("Accuracy:", r2_score(y_test, y_pred))  
  
Accuracy: 0.7974958808527665  
  
sns.pairplot(df,height = 2)  
plt.show()  
  
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119:  
FutureWarning:  
  
use_inf_as_na option is deprecated and will be removed in a future  
version. Convert inf values to NaN before operating instead.  
  
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119:  
FutureWarning:  
  
use_inf_as_na option is deprecated and will be removed in a future  
version. Convert inf values to NaN before operating instead.  
  
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119:
```

FutureWarning:

use\_inf\_as\_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119:  
FutureWarning:

use\_inf\_as\_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119:  
FutureWarning:

use\_inf\_as\_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119:  
FutureWarning:

use\_inf\_as\_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119:  
FutureWarning:

use\_inf\_as\_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119:  
FutureWarning:

use\_inf\_as\_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119:  
FutureWarning:

use\_inf\_as\_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119:  
FutureWarning:

use\_inf\_as\_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119:  
FutureWarning:

use\_inf\_as\_na option is deprecated and will be removed in a future



version. Convert inf values to NaN before operating instead.

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119:  
FutureWarning:

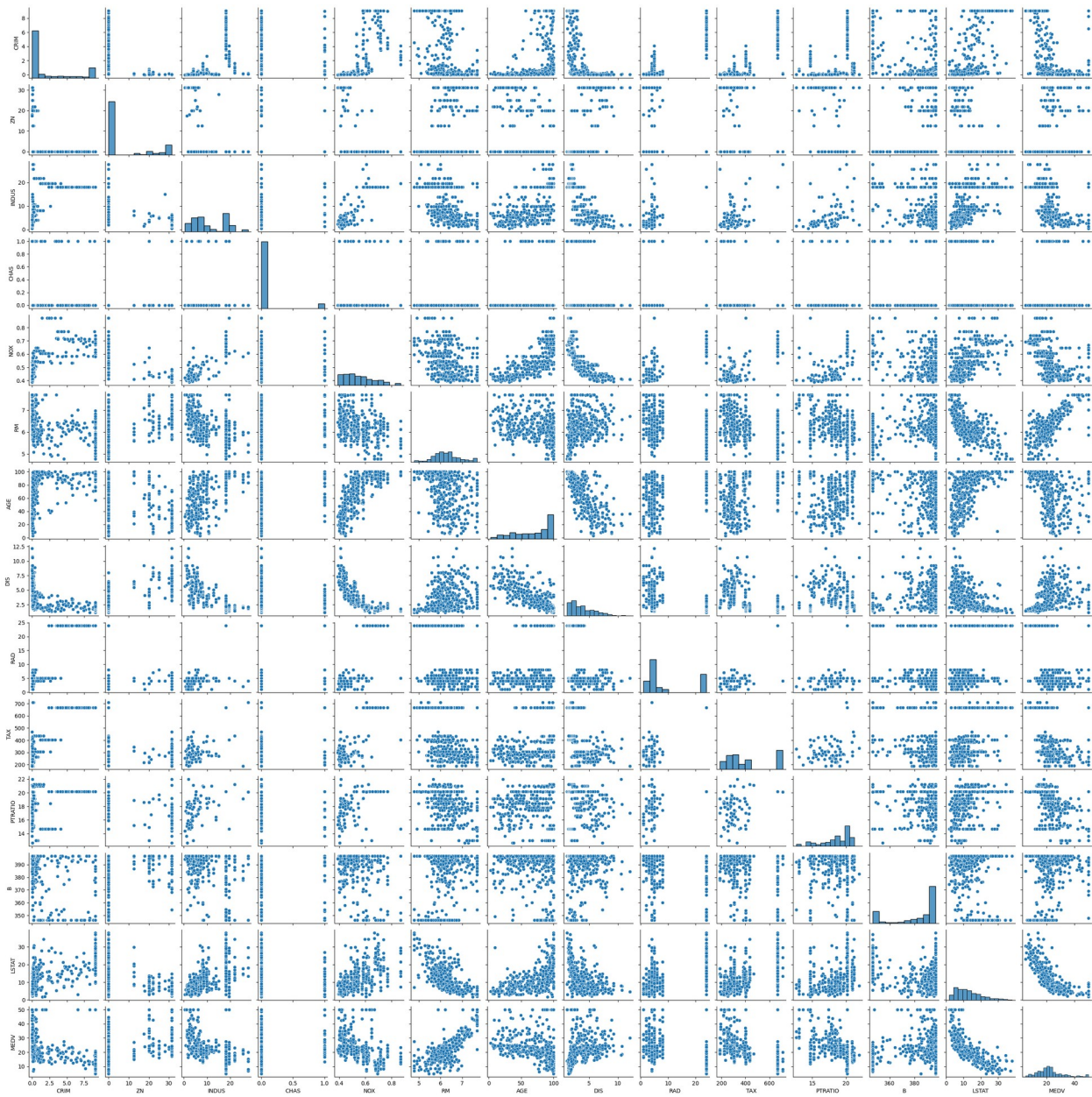
use\_inf\_as\_na option is deprecated and will be removed in a future  
version. Convert inf values to NaN before operating instead.

C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119:  
FutureWarning:

use\_inf\_as\_na option is deprecated and will be removed in a future  
version. Convert inf values to NaN before operating instead.

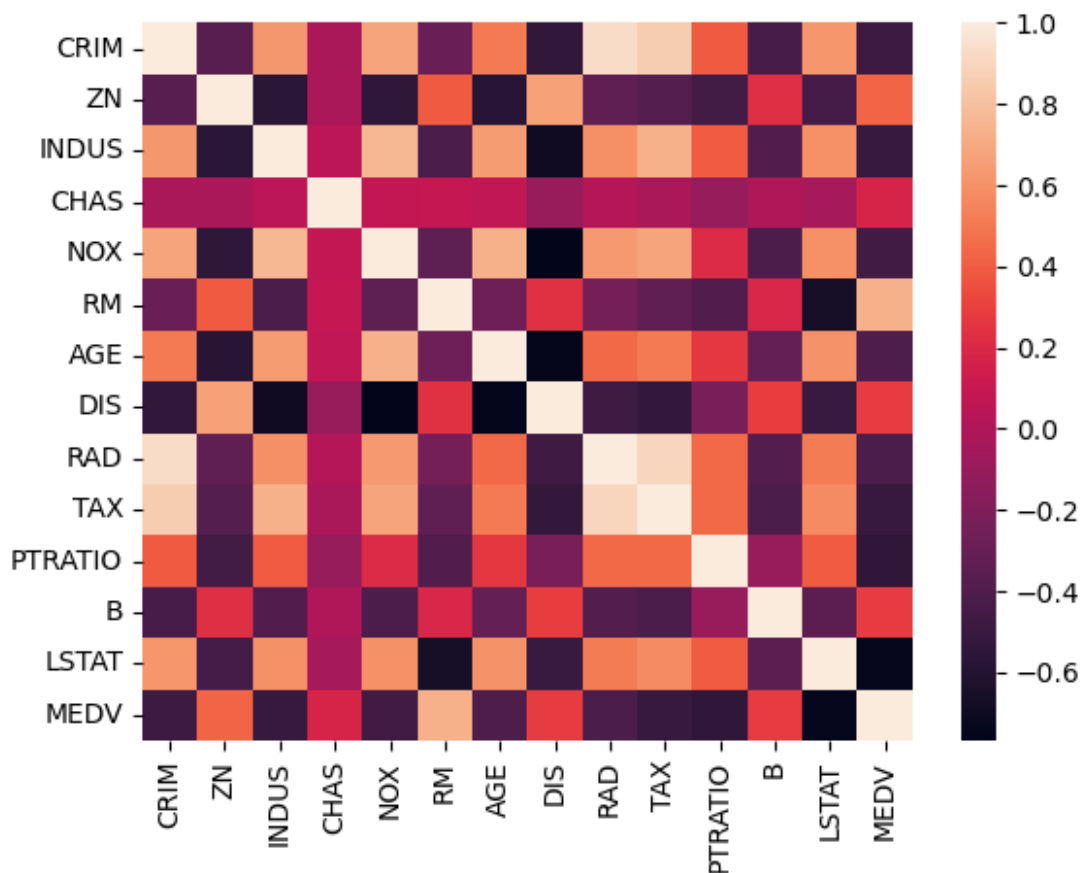
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119:  
FutureWarning:

use\_inf\_as\_na option is deprecated and will be removed in a future  
version. Convert inf values to NaN before operating instead.



```
sns.heatmap(df.corr())
```

```
<Axes: >
```



	CRIM	ZN	INDUS	CHAS	NOX	RM
AGE \						
CRIM	1.000000	-0.361225	0.623422	-0.020456	0.676892	-0.290585
0.509373						
ZN	-0.361225	1.000000	-0.573423	-0.025051	-0.547805	0.389992
0.577199						
INDUS	0.623422	-0.573423	1.000000	0.049820	0.762737	-0.420265
0.642387						
CHAS	-0.020456	-0.025051	0.049820	1.000000	0.076661	0.088389
0.072644						
NOX	0.676892	-0.547805	0.762737	0.076661	1.000000	-0.335521
0.732540						
RM	-0.290585	0.389992	-0.420265	0.088389	-0.335521	1.000000
0.265917						
AGE	0.509373	-0.577199	0.642387	0.072644	0.732540	-0.265917
1.000000						
DIS	-0.538438	0.663585	-0.696569	-0.095037	-0.768137	0.236080
0.753547						
RAD	0.925917	-0.331259	0.591944	0.014102	0.628170	-0.240004
0.443585						
TAX	0.860415	-0.378232	0.734204	-0.026513	0.679824	-0.327562

0.504472							
PTRATIO	0.389845	-0.457177	0.395691	-0.104995	0.210216	-0.397525	
0.264968							
B	-0.434958	0.227525	-0.399533	-0.007114	-0.410601	0.187988	-
0.307924							
LSTAT	0.616377	-0.449960	0.598156	-0.037113	0.593655	-0.658038	
0.601137							
MEDV	-0.479865	0.424049	-0.510829	0.173701	-0.459054	0.731312	-
0.407470							
	DIS	RAD	TAX	PTRATIO	B	LSTAT	
MEDV							
CRIM	-0.538438	0.925917	0.860415	0.389845	-0.434958	0.616377	-
0.479865							
ZN	0.663585	-0.331259	-0.378232	-0.457177	0.227525	-0.449960	
0.424049							
INDUS	-0.696569	0.591944	0.734204	0.395691	-0.399533	0.598156	-
0.510829							
CHAS	-0.095037	0.014102	-0.026513	-0.104995	-0.007114	-0.037113	
0.173701							
NOX	-0.768137	0.628170	0.679824	0.210216	-0.410601	0.593655	-
0.459054							
RM	0.236080	-0.240004	-0.327562	-0.397525	0.187988	-0.658038	
0.731312							
AGE	-0.753547	0.443585	0.504472	0.264968	-0.307924	0.601137	-
0.407470							
DIS	1.000000	-0.477075	-0.529603	-0.228840	0.287118	-0.505036	
0.279547							
RAD	-0.477075	1.000000	0.900000	0.441949	-0.384599	0.510868	-
0.416638							
TAX	-0.529603	0.900000	1.000000	0.446961	-0.420094	0.572218	-
0.508864							
PTRATIO	-0.228840	0.441949	0.446961	1.000000	-0.093122	0.395006	-
0.543809							
B	0.287118	-0.384599	-0.420094	-0.093122	1.000000	-0.340145	
0.280402							
LSTAT	-0.505036	0.510868	0.572218	0.395006	-0.340145	1.000000	-
0.743450							
MEDV	0.279547	-0.416638	-0.508864	-0.543809	0.280402	-0.743450	
1.000000							