Dat Analytics - Housing Data

In [1]:
```
#importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
## TO remove warning from notebook
import warnings
warnings.filterwarnings(action='ignore')
import seaborn as sns
```

In [2]:
```
df = pd.read_csv("housing_data.csv")
df
```

Out[2]:

	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	296	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	242	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	242	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	222	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	222	18.7	396.90	NaN	36.2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1	273	21.0	391.99	NaN	22.4
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1	273	21.0	396.90	9.08	20.6
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1	273	21.0	396.90	5.64	23.9
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1	273	21.0	393.45	6.48	22.0
505	0.04741	0.0	11.93	0.0	0.573	6.030	NaN	2.5050	1	273	21.0	396.90	7.88	11.9

506 rows × 14 columns

In [3]:
```
df.columns
```

Out[3]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT', 'MEDV'],
      dtype='object')
```

In [4]:
```
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
```

In [5]:
```
## Check Null  values
```

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
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
```

In [7]:
```
nc = [feature for feature in df.columns if df[feature].dtype != 'O']
nc
```

Out[7]:
```
['CRIM',
 'ZN',
 'INDUS',
 'CHAS',
 'NOX',
 'RM',
 'AGE',
 'DIS',
 'RAD',
 'TAX',
 'PTRATIO',
 'B',
 'LSTAT',
 'MEDV']
```

In [8]:
```
for i in nc:
    df[i].fillna(df[i].median(),inplace = True)
```

In [9]:
```
df
```

Out[9]:

	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	296	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	242	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	242	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	222	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	222	18.7	396.90	11.43	36.2
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1	273	21.0	391.99	11.43	22.4
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1	273	21.0	396.90	9.08	20.6
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1	273	21.0	396.90	5.64	23.9

504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1	273	21.0	393.45	6.48	22.0
505	0.04741	0.0	11.93	0.0	0.573	6.030	76.8	2.5050	1	273	21.0	396.90	7.88	11.9

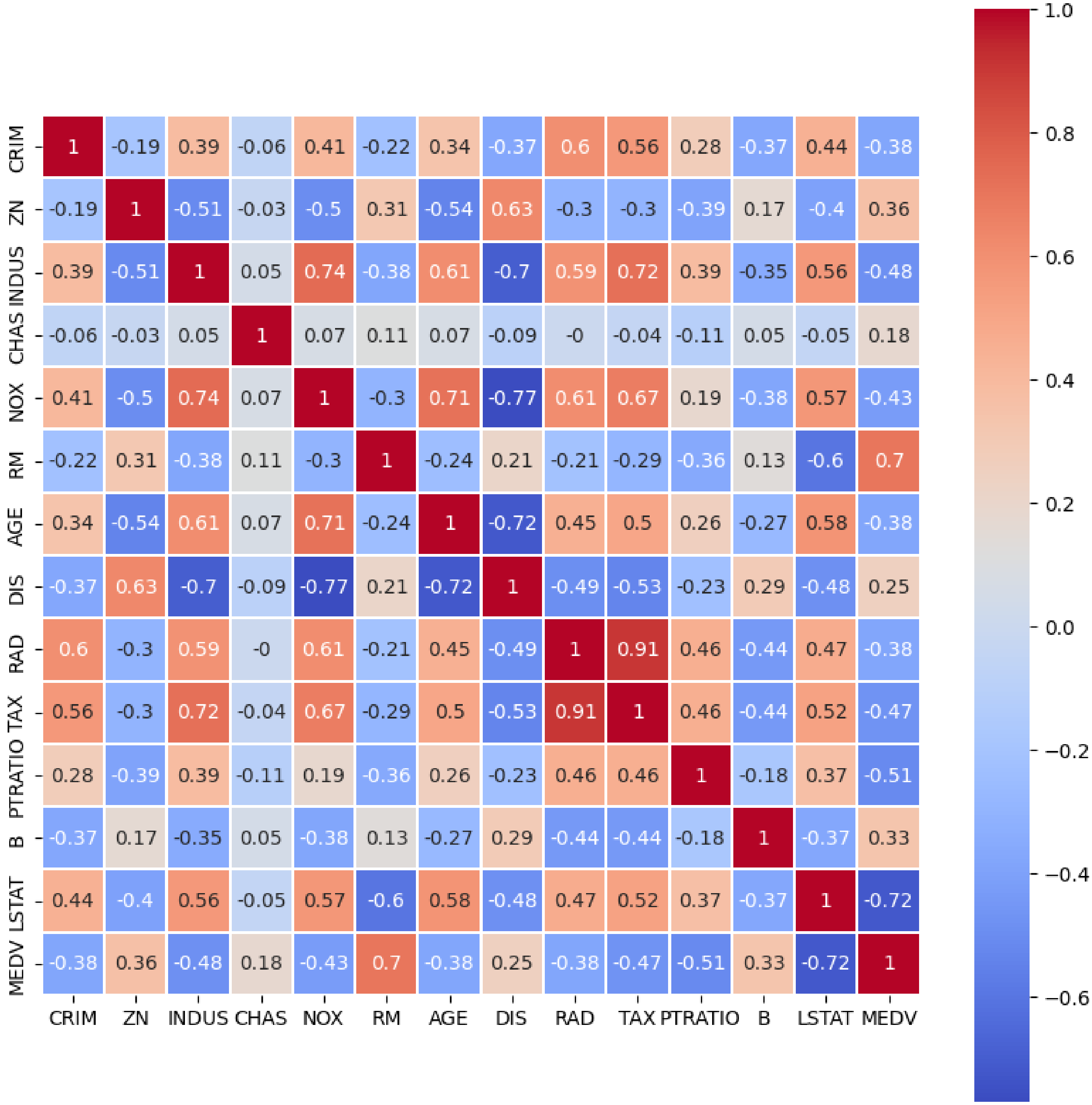
506 rows × 14 columns

Feature Selection

Heat Map

In [74]:
```
plt.figure(figsize=(10,10))
sns.heatmap(data=df.corr().round(2), annot=True, cmap='coolwarm',linewidths=0.2,square=T
```

Out[74]:
```
<Axes: >
```



In [11]:
```
df1 = df[['RM','LSTAT','TAX','PTRATIO','MEDV']]
```

In [12]:
```
df1
```

Out[12]:

	RM	LSTAT	TAX	PTRATIO	MEDV
0	6.575	4.98	296	15.3	24.0
1	6.421	9.14	242	17.8	21.6
2	7.185	4.03	242	17.8	34.7
3	6.998	2.94	222	18.7	33.4
4	7.147	11.43	222	18.7	36.2
...	...	...	...	...	...
501	6.593	11.43	273	21.0	22.4
502	6.120	9.08	273	21.0	20.6
503	6.976	5.64	273	21.0	23.9
504	6.794	6.48	273	21.0	22.0
505	6.030	7.88	273	21.0	11.9

506 rows × 5 columns

In [13]:
```
df1.head()
```

Out[13]:

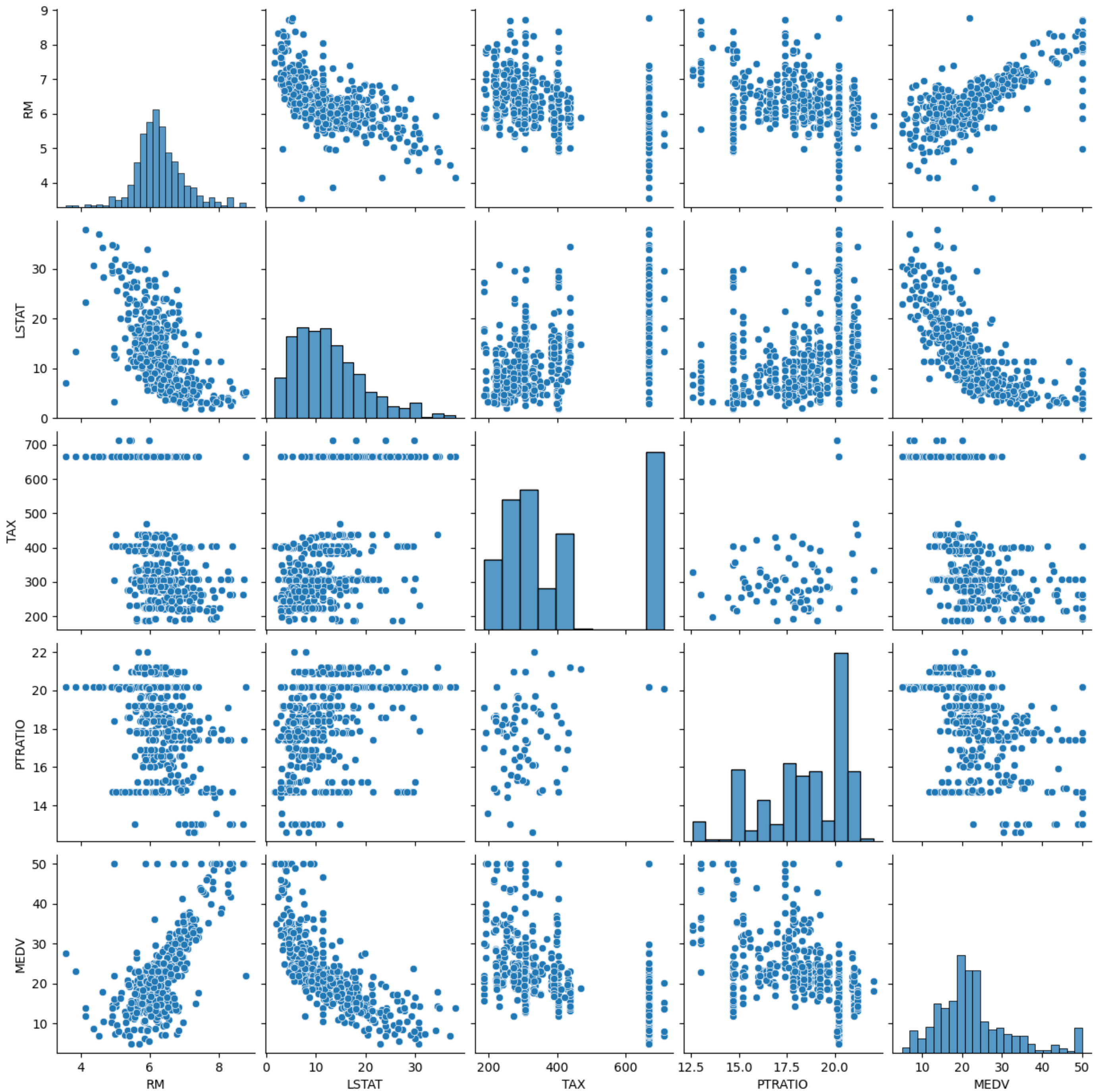
	RM	LSTAT	TAX	PTRATIO	MEDV
0	6.575	4.98	296	15.3	24.0
1	6.421	9.14	242	17.8	21.6
2	7.185	4.03	242	17.8	34.7
3	6.998	2.94	222	18.7	33.4
4	7.147	11.43	222	18.7	36.2

Pair Plot

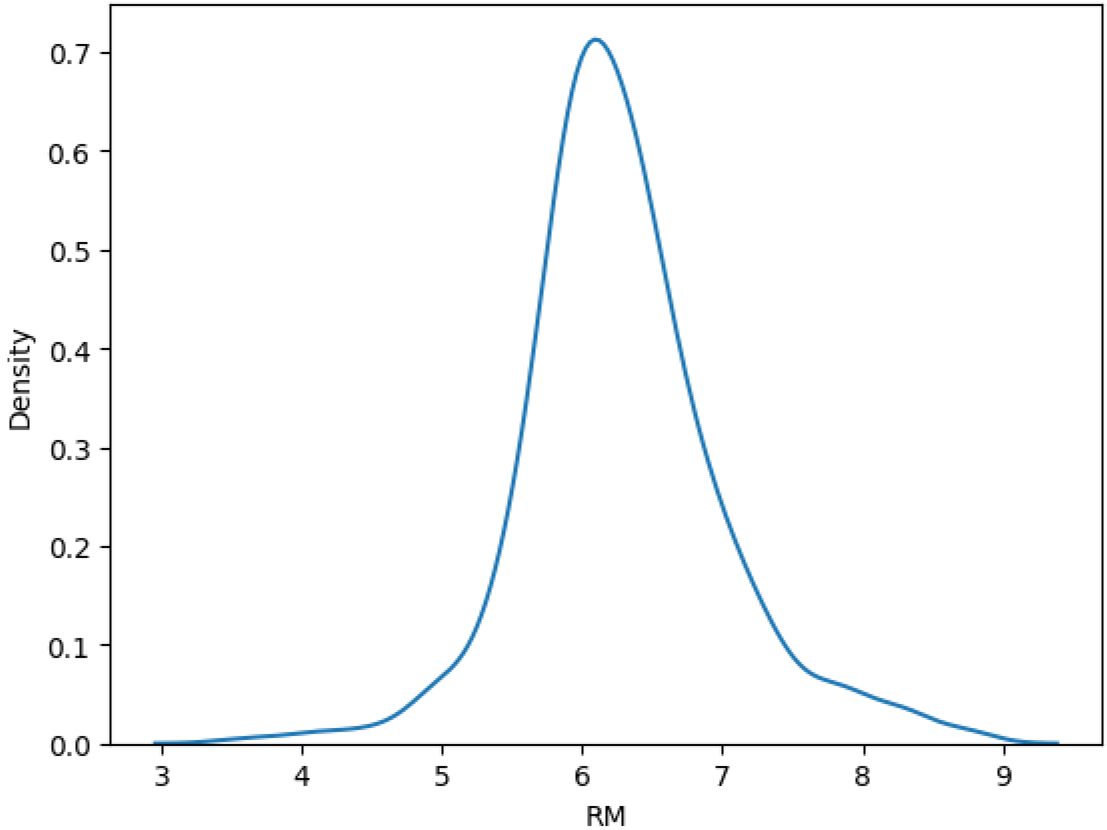
In [77]:
```
plt.figure(figsize=(0.1,0.1))
sns.pairplot(df1)
plt.plot()
```

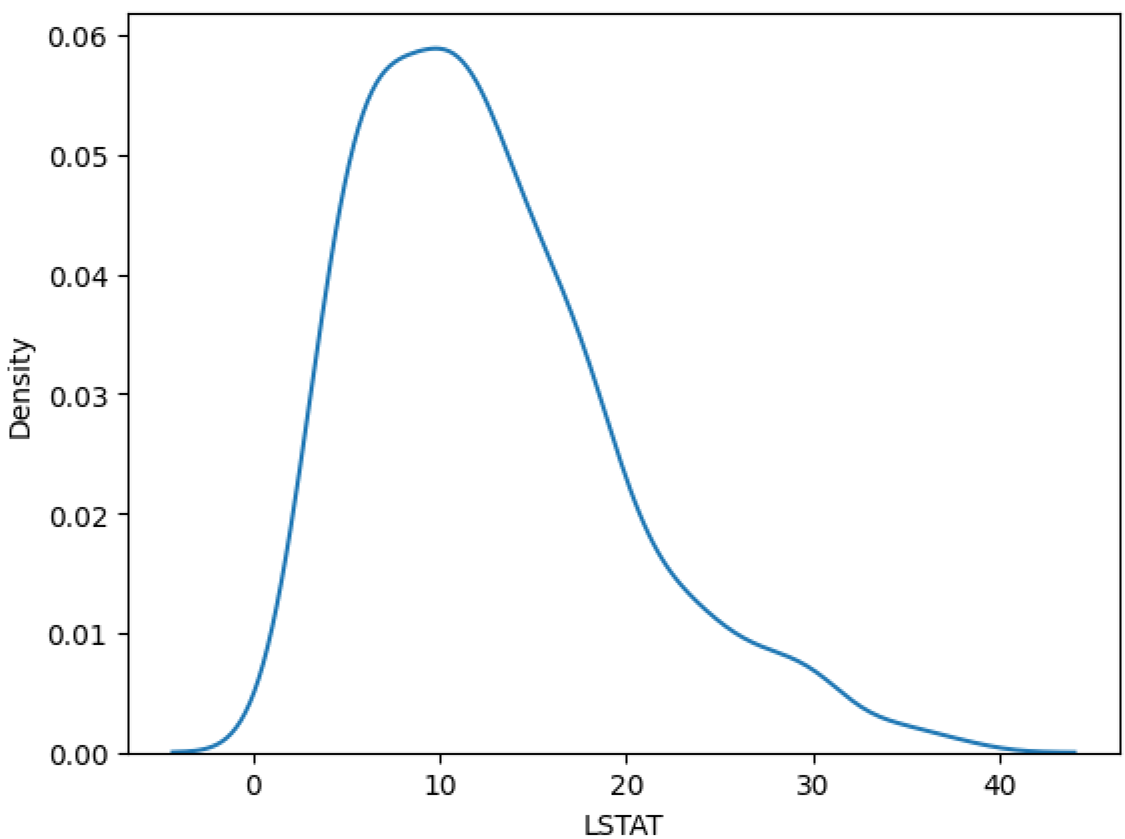
Out[77]:
```
[]
```

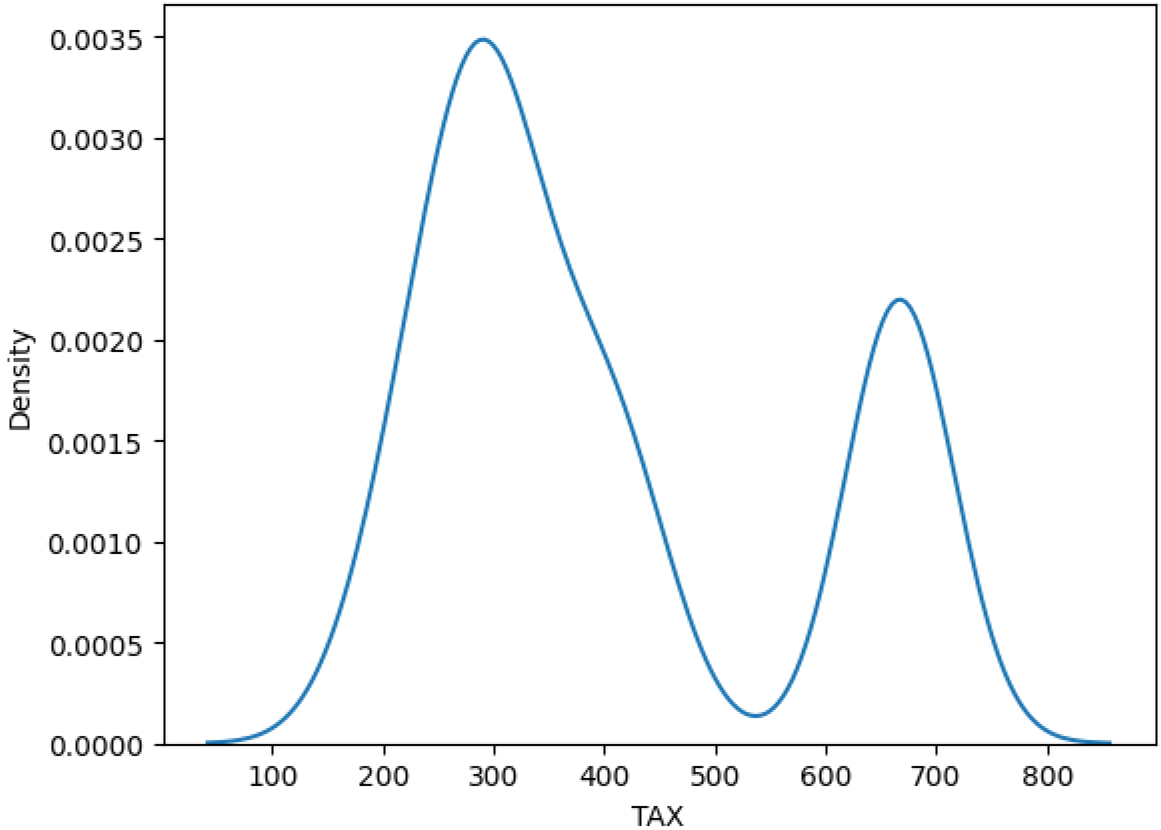
```
<Figure size 10x10 with 0 Axes>
```

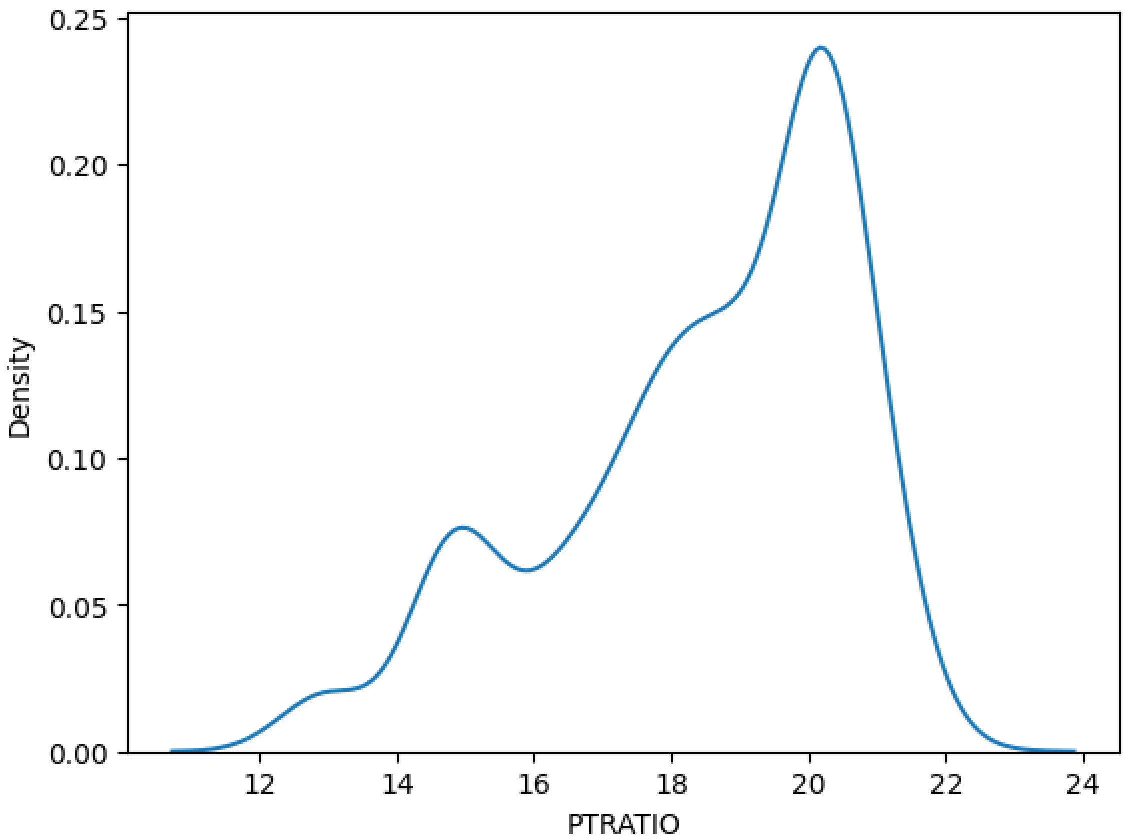


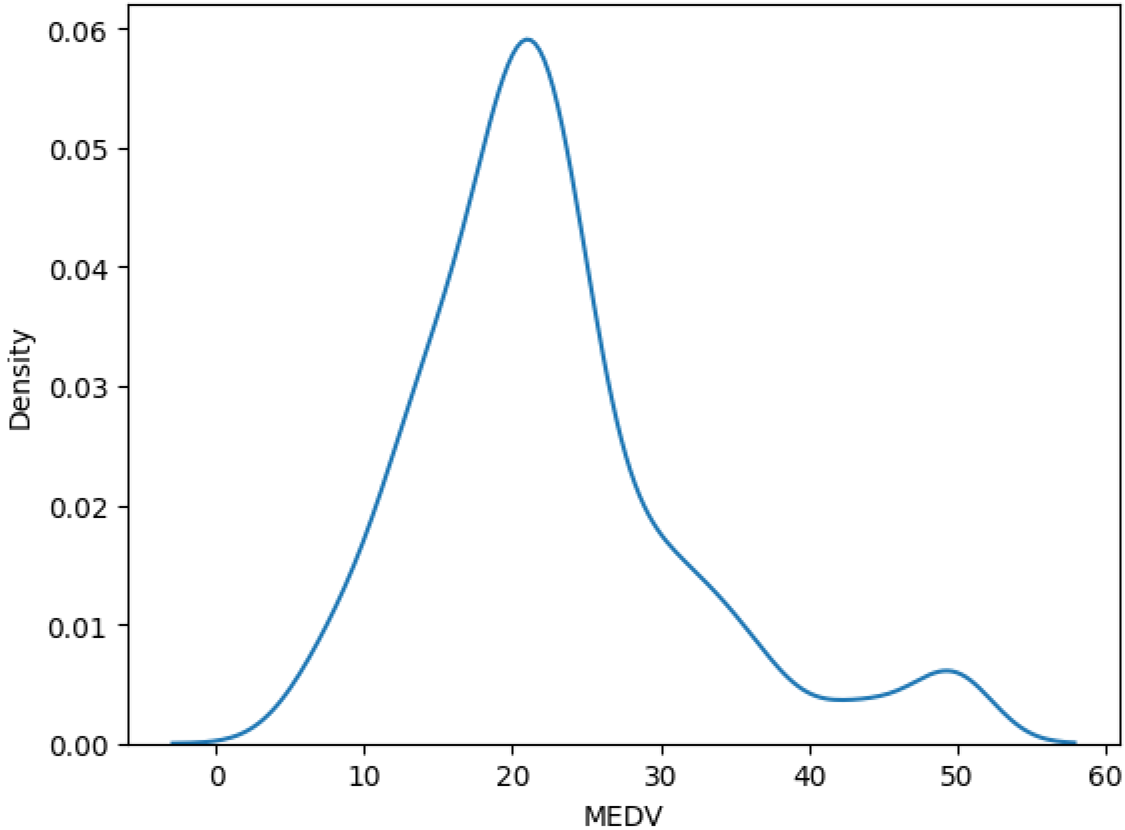
In [15]:
```
for i in df1.columns:
    sns.kdeplot(df1[i])
    plt.show()
```


0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Density
3
4
5
6
7
8
9
RM


0.06
0.05
0.04
0.03
0.02
0.01
0.00
Density
0
10
20
30
40
LSTAT


0.0035
0.0030
0.0025
0.0020
0.0015
0.0010
0.0005
0.0000
Density
100
200
300
400
500
600
700
800
TAX


0.25
0.20
0.15
0.10
0.05
0.00
Density
12
14
16
18
20
22
24
PTRATIO



In [16]:
```
df1.describe().round(2)
```

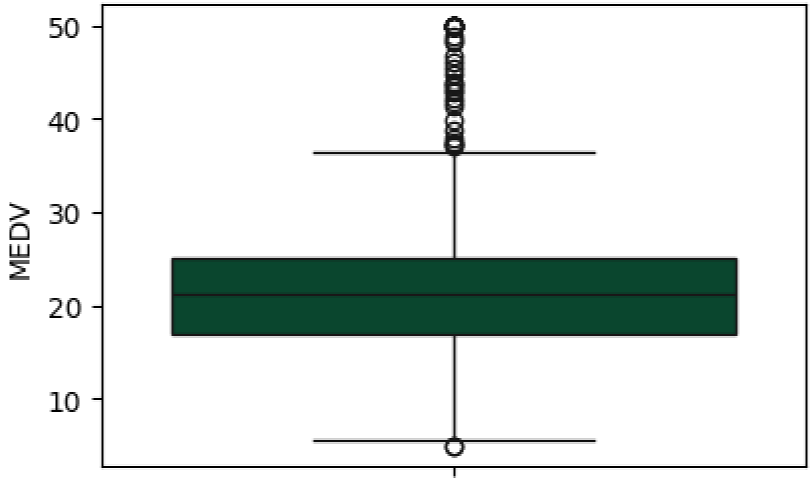
Out[16]:

	RM	LSTAT	TAX	PTRATIO	MEDV
count	506.00	506.00	506.00	506.00	506.00
mean	6.28	12.66	408.24	18.46	22.53
std	0.70	7.02	168.54	2.16	9.20
min	3.56	1.73	187.00	12.60	5.00
25%	5.89	7.23	279.00	17.40	17.02
50%	6.21	11.43	330.00	19.05	21.20
75%	6.62	16.57	666.00	20.20	25.00
max	8.78	37.97	711.00	22.00	50.00

In [17]:
```
## Univariant Analysis
```

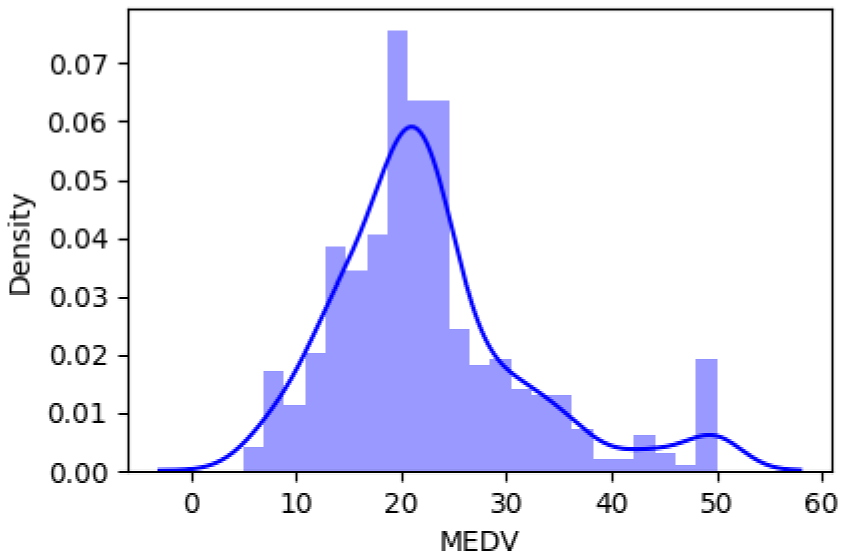
In [18]:
```
plt.figure(figsize=(10,3))
plt.subplot(1,2,1)
sns.boxplot(df1.MEDV,color='#005030')
```

Out[18]: <Axes: ylabel='MEDV'>



In [19]:
```
plt.figure(figsize=(10,3))
plt.title("Distribution Plot of MEDV")
plt.subplot(1,2,1)
sns.distplot(df1.MEDV,color='blue')
```

Out[19]: `<Axes: xlabel='MEDV', ylabel='Density'>`



In [20]:
```
# ## Handle Outliers I+Using IQR
# for col in df1.columns:
#     Q1 = df1[col].quantile(0.25)
#     Q3 = df1[col].quantile(0.75)
#     IQR = Q3-Q1
#     lb = Q1 - 1.5*IQR
#     ub = Q3 + 1.5*IQR
```

In [20]:

In [21]:
```
desc = df1.describe().round(2)
```

In [22]:
```
MEDV_Q3 = desc['MEDV']['75%']
MEDV_Q1 = desc['MEDV']['25%']
MEDV_IQR = MEDV_Q3-MEDV_Q1

MEDV_lb = MEDV_Q1-1.5*MEDV_IQR
MEDV_ub = MEDV_Q3+1.5*MEDV_IQR
```

In [23]:
```
df1[df1['MEDV']<MEDV_lb]
```

Out[23]:

	RM	LSTAT	TAX	PTRATIO	MEDV
398	5.453	30.59	666	20.2	5.0
405	5.683	22.98	666	20.2	5.0

In [24]:

```
df1[df1['MEDV']>MEDV_ub].sort_values(by=['MEDV','RM'])
```

Out[24]:

	RM	LSTAT	TAX	PTRATIO	MEDV
190	6.951	5.10	398	15.2	37.0
179	6.980	5.04	193	17.8	37.2
291	7.148	3.56	245	19.2	37.3
226	8.040	11.43	307	17.4	37.6
182	7.155	4.82	193	17.8	37.9
97	8.069	4.21	276	18.0	38.7
180	7.765	7.56	193	17.8	39.8
157	6.943	4.59	403	14.7	41.3
232	8.337	2.47	307	17.4	41.7
202	7.610	3.11	348	14.7	42.3
253	8.259	3.54	330	19.1	42.8
261	7.520	7.26	264	13.0	43.1
268	7.470	3.16	264	13.0	43.5
98	7.820	3.57	276	18.0	43.8
256	7.454	3.11	244	15.9	44.0
224	8.266	4.14	307	17.4	44.8
280	7.820	3.76	216	14.9	45.4
282	7.645	3.01	216	14.9	46.0
228	7.686	11.43	307	17.4	46.7
233	8.247	3.95	307	17.4	48.3
203	7.853	3.81	224	14.7	48.5
262	8.398	5.91	264	13.0	48.8
368	4.970	3.26	666	20.2	50.0
372	5.875	8.88	666	20.2	50.0
371	6.216	9.53	666	20.2	50.0
369	6.683	3.73	666	20.2	50.0
370	7.016	2.96	666	20.2	50.0
161	7.489	1.73	403	14.7	50.0
162	7.802	1.92	403	14.7	50.0
186	7.831	4.45	193	17.8	50.0
195	7.875	2.97	255	14.4	50.0
283	7.923	3.16	198	13.6	50.0
166	7.929	3.70	403	14.7	50.0
204	8.034	2.88	224	14.7	50.0

267	8.297	7.44	264	13.0	50.0
163	8.375	3.32	403	14.7	50.0
257	8.704	5.12	264	13.0	50.0
225	8.725	4.63	307	17.4	50.0

- With the observation when MEDV = 50 there is variation in values of RM . hence remove entries

In [25]:
```
df1.shape
```
Out[25]:
```
(506, 5)
```

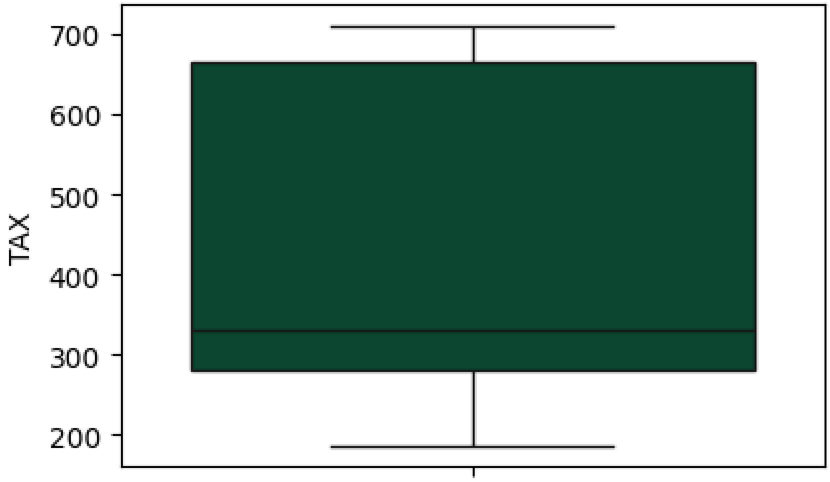
In [26]:
```
df2=df1[df1['MEDV']<50].sort_values(by=['MEDV','RM'])
df2
```
Out[26]:

	RM	LSTAT	TAX	PTRATIO	MEDV
398	5.453	30.59	666	20.2	5.0
405	5.683	22.98	666	20.2	5.0
400	5.987	26.77	666	20.2	5.6
399	5.852	29.97	666	20.2	6.3
414	4.519	36.98	666	20.2	7.0
...	...	...	...	...	...
282	7.645	3.01	216	14.9	46.0
228	7.686	11.43	307	17.4	46.7
233	8.247	3.95	307	17.4	48.3
203	7.853	3.81	224	14.7	48.5
262	8.398	5.91	264	13.0	48.8

490 rows × 5 columns

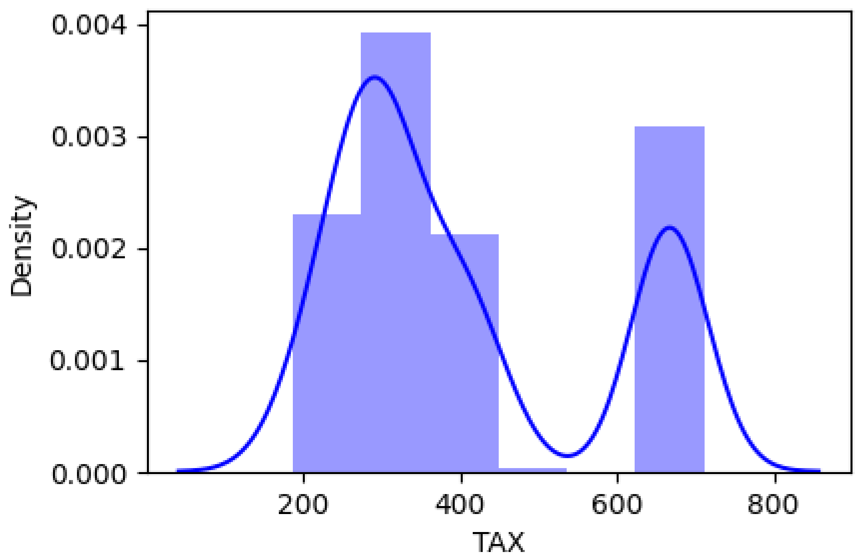
In [27]:
```
### Now we are observing for feature TAX
```

In [28]:
```
plt.figure(figsize=(10,3))
plt.title("BOXPLOT of TAX")
plt.subplot(1,2,1)
sns.boxplot(df2.TAX,color='#005030')
```
Out[28]:
```
<Axes: ylabel='TAX'>
```

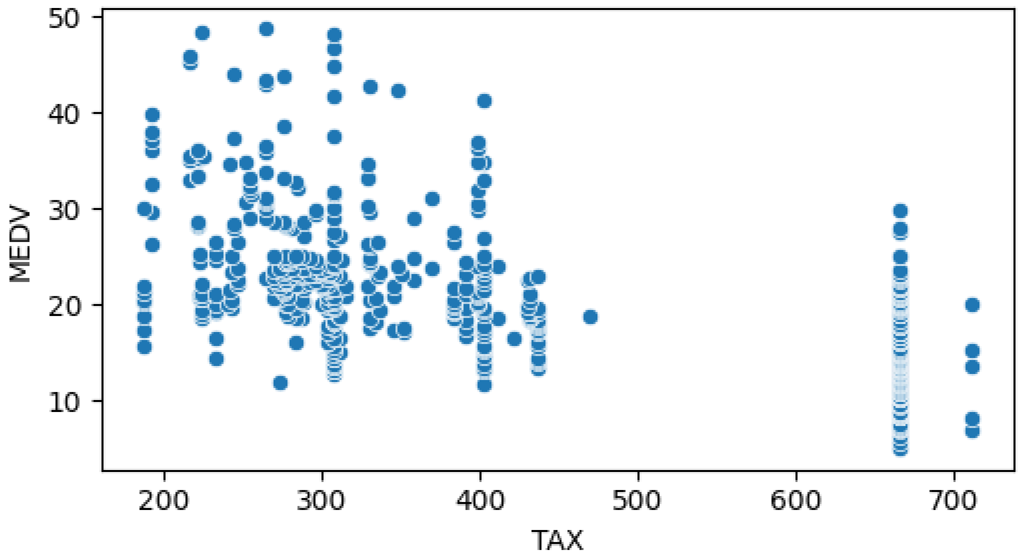


In [29]:
```
plt.figure(figsize=(10,3))
plt.title("Distribution Plot of MEDV")
plt.subplot(1,2,1)
sns.distplot(df2.TAX,color='blue')
```

Out[29]: <Axes: xlabel='TAX', ylabel='Density'>



In [30]:
```
plt.figure(figsize=(20,3))
plt.title("Scatter plot of TAV v/s MEDV")
plt.subplot(1,3,3)
sns.scatterplot(x=df2.TAX,y=df2.MEDV)
plt.show()
```



In [31]:
```
temp_df = df2[df1['TAX']>600].sort_values(by=['MEDV','RM'])
temp_df.shape
```

Out[31]:
```
(132, 5)
```

In [32]:
```
temp_df.describe()
```

Out[32]:

	RM	LSTAT	TAX	PTRATIO	MEDV
count	132.000000	132.000000	132.000000	132.000000	132.000000
mean	6.000689	18.828864	667.704545	20.196212	14.994697
std	0.712621	6.590380	8.623365	0.019163	5.405825
min	3.561000	5.290000	666.000000	20.100000	5.000000
25%	5.674250	14.175000	666.000000	20.200000	10.900000
50%	6.139500	17.910000	666.000000	20.200000	14.100000
75%	6.407250	23.052500	666.000000	20.200000	19.200000
max	8.780000	37.970000	711.000000	20.200000	29.800000

In [33]:
```
temp_df
```

Out[33]:

	RM	LSTAT	TAX	PTRATIO	MEDV
398	5.453	30.59	666	20.2	5.0
405	5.683	22.98	666	20.2	5.0
400	5.987	26.77	666	20.2	5.6
399	5.852	29.97	666	20.2	6.3
414	4.519	36.98	666	20.2	7.0
...	...	...	...	...	...
482	7.061	7.01	666	20.2	25.0
365	3.561	7.12	666	20.2	27.5
409	6.852	19.78	666	20.2	27.5
407	5.608	11.43	666	20.2	27.9
473	6.980	11.43	666	20.2	29.8

132 rows × 5 columns

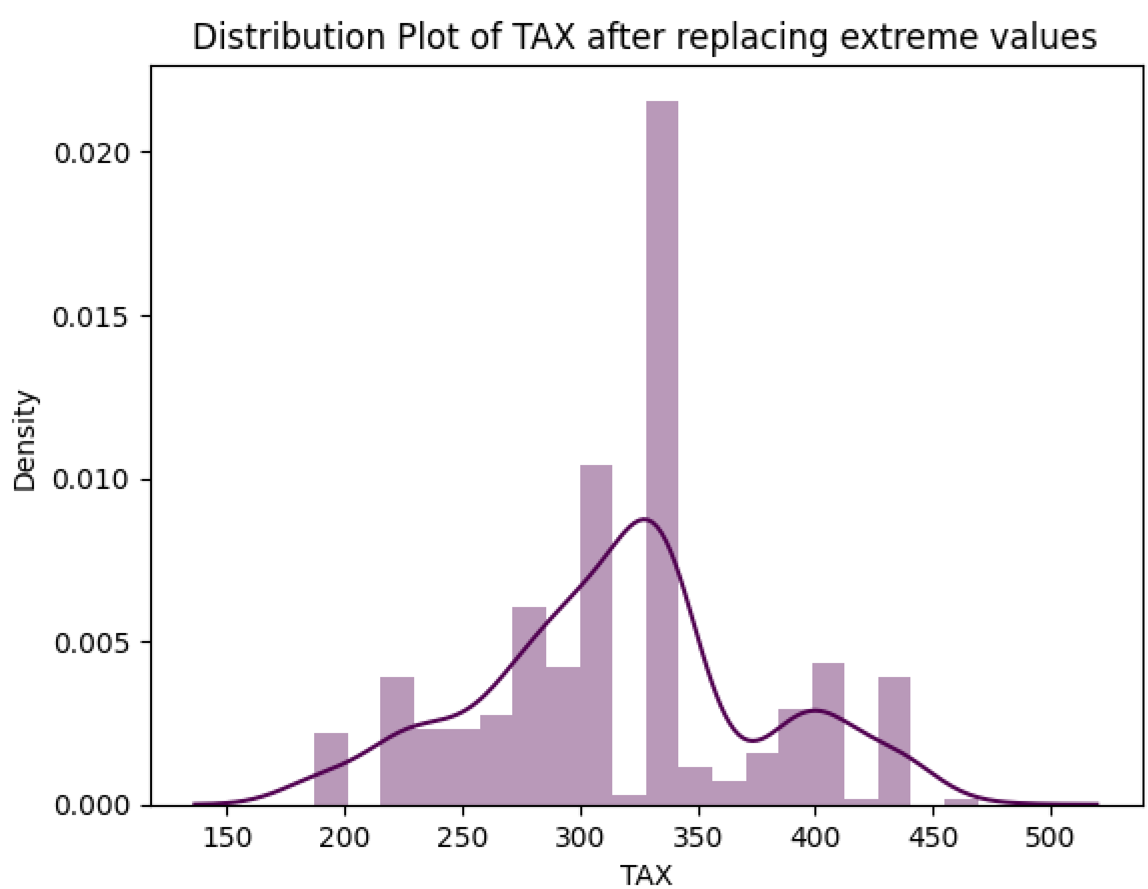
In [34]:
```
## Performing Imputation for TAX as some unusual values have been observed
TAX_10 = df2[(df2['TAX']<600) & (df2['LSTAT']>=0) & (df2['LSTAT']<10)]['TAX'].mean()
TAX_20 = df2[(df2['TAX']<600) & (df2['LSTAT']>=10) & (df2['LSTAT']<20)]['TAX'].mean()
TAX_30 = df2[(df2['TAX']<600) & (df2['LSTAT']>=20) & (df2['LSTAT']<30)]['TAX'].mean()
TAX_40 = df2[(df2['TAX']<600) & (df2['LSTAT']>=30)]['TAX'].mean()

indexes = list(df2.index)
for i in indexes:
    if df2['TAX'][i] > 600:
        if (0 <= df2['LSTAT'][i] < 10):
            df2.at[i,'TAX'] = TAX_10
        elif (10 <= df2['LSTAT'][i] < 20):
            df2.at[i,'TAX'] = TAX_20
        elif (20 <= df2['LSTAT'][i] < 30):
            df2.at[i,'TAX'] = TAX_30
        elif (df2['LSTAT'][i] >30):
            df2.at[i,'TAX'] = TAX_40

print('Values imputed successfully')
```

```
Values imputed successfully
```

In [35]:
```
## To whether values imputed  or not
df2[df2['TAX']>600]['TAX'].count()
```

Out[35]:
```
0
```

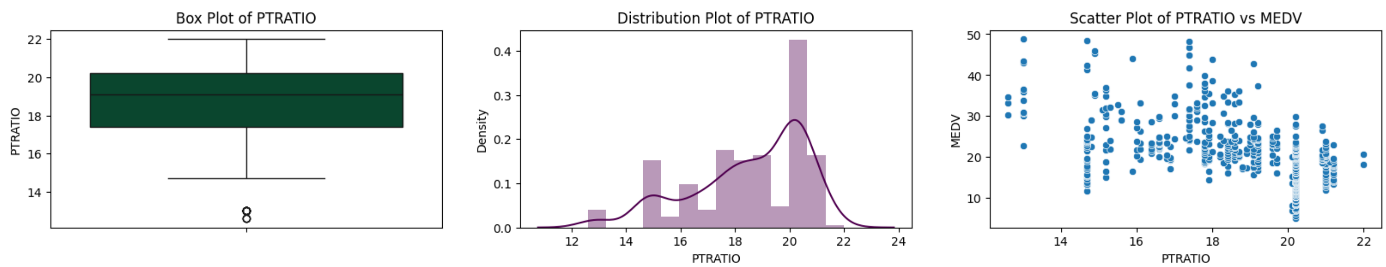
In [36]:
```
sns.distplot(a=df2.TAX,color='#500050')
plt.title('Distribution Plot of TAX after replacing extreme values')
plt.show()
```



In [37]:
```
## Now observing for feature PTRATIO
```

In [38]:

```
plt.figure(figsize=(20,3))

plt.subplot(1,3,1)
sns.boxplot(df2.PTRATIO,color='#005030')
plt.title('Box Plot of PTRATIO')

plt.subplot(1,3,2)
sns.distplot(a=df2.PTRATIO,color='#500050')
plt.title('Distribution Plot of PTRATIO')

plt.subplot(1,3,3)
sns.scatterplot(x=df2.PTRATIO,y=df2.MEDV)
plt.title('Scatter Plot of PTRATIO vs MEDV')

plt.show()
```



In [39]:

```
## By observing distplot we can conclude that PTRATIO is not
## normally distributed
```

In [40]:

```
df2[df2['PTRATIO']<14].sort_values(by=['LSTAT','MEDV'])
```

Out[40]:

	RM	LSTAT	TAX	PTRATIO	MEDV
268	7.470	3.16	264.0	13.0	43.5
196	7.287	4.08	329.0	12.6	33.3
262	8.398	5.91	264.0	13.0	48.8
198	7.274	6.62	329.0	12.6	34.6
259	6.842	6.90	264.0	13.0	30.1
261	7.520	7.26	264.0	13.0	43.1
258	7.333	7.79	264.0	13.0	36.0
264	7.206	8.10	264.0	13.0	36.5
197	7.107	8.61	329.0	12.6	30.3
260	7.203	9.59	264.0	13.0	33.8
265	5.560	10.45	264.0	13.0	22.8
263	7.327	11.25	264.0	13.0	31.0
266	7.014	14.79	264.0	13.0	30.7

In [41]:

```
## No unusual observation in abovve data
```

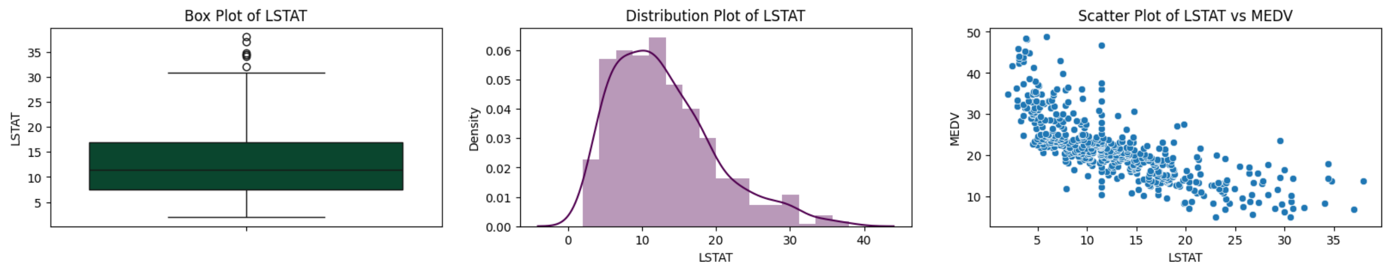
In [42]:

```
## Now check for LSTAT
```

In [43]:

```
plt.figure(figsize=(20,3))

plt.subplot(1,3,1)
sns.boxplot(df2.LSTAT,color='#005030')
```

```
plt.title('Box Plot of LSTAT')

plt.subplot(1,3,2)
sns.distplot(a=df2.LSTAT,color='#500050')
plt.title('Distribution Plot of LSTAT')

plt.subplot(1,3,3)
sns.scatterplot(x=df2.LSTAT,y=df2.MEDV)
plt.title('Scatter Plot of LSTAT vs MEDV')

plt.show()
```



In [44]:
```
## Right Skwed data but  normally distributed
```

In [45]:
```
LSTAT_Q3 = desc['LSTAT']['75%']
LSTAT_Q1 = desc['LSTAT']['25%']
LSTAT_IQR = LSTAT_Q3 - LSTAT_Q1
LSTAT_UV = LSTAT_Q3 + 1.5*LSTAT_IQR
LSTAT_LV = LSTAT_Q1 - 1.5*LSTAT_IQR

df2[df2['LSTAT']>LSTAT_UV].sort_values(by='LSTAT')
```

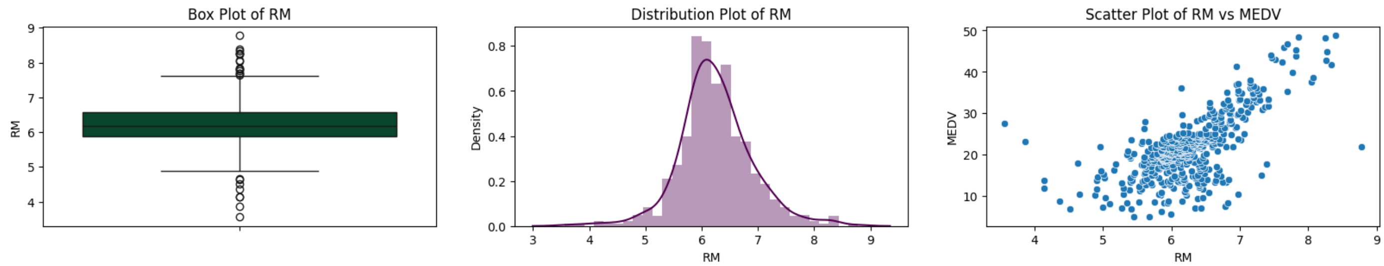
Out[45]:

	RM	LSTAT	TAX	PTRATIO	MEDV
398	5.453	30.59	335.0	20.2	5.0
388	4.880	30.62	335.0	20.2	10.2
384	4.368	30.63	335.0	20.2	8.8
385	5.277	30.81	335.0	20.2	7.2
48	5.399	30.81	233.0	17.9	14.4
387	5.000	31.99	335.0	20.2	7.4
438	5.935	34.02	335.0	20.2	8.4
412	4.628	34.37	335.0	20.2	17.9
141	5.019	34.41	437.0	21.2	14.4
373	4.906	34.77	335.0	20.2	13.8
414	4.519	36.98	335.0	20.2	7.0
374	4.138	37.97	335.0	20.2	13.8

In [46]:
```
## Checking the feature RM
```

In [47]:
```
plt.figure(figsize=(20,3))

plt.subplot(1,3,1)
sns.boxplot(df2.RM,color='#005030')
plt.title('Box Plot of RM')

plt.subplot(1,3,2)
sns.distplot(a=df2.RM,color='#500050')
```

```
plt.title('Distribution Plot of RM')

plt.subplot(1,3,3)
sns.scatterplot(x=df2.RM,y=df2.MEDV)
plt.title('Scatter Plot of RM vs MEDV')

plt.show()
```



In [48]:
```
RM_Q3 = desc['RM']['75%']
RM_Q1 = desc['RM']['25%']
RM_IQR = RM_Q3 - RM_Q1
RM_UV = RM_Q3 + 1.5*RM_IQR
RM_LV = RM_Q1 - 1.5*RM_IQR

df2[df2['RM']<RM_LV].sort_values(by=['RM','MEDV'])
```

Out[48]:

	RM	LSTAT	TAX	PTRATIO	MEDV
365	3.561	7.12	294.139785	20.2	27.5
367	3.863	13.33	330.770270	20.2	23.1
406	4.138	23.34	338.636364	20.2	11.9
374	4.138	37.97	335.000000	20.2	13.8
384	4.368	30.63	335.000000	20.2	8.8
414	4.519	36.98	335.000000	20.2	7.0
412	4.628	34.37	335.000000	20.2	17.9
386	4.652	28.28	338.636364	20.2	10.5

In [49]:
```
print(f'Shape of dataset before removing data points: {df2.shape}')
df3 = df2.drop(axis=0,index=[365,367])
print(f'Shape of dataset before removing data points: {df3.shape}')
```

```
Shape of dataset before removing data points: (490, 5)
Shape of dataset before removing data points: (488, 5)
```

In [50]:
```
df3[df3['RM']>RM_UV].sort_values(by=['RM','MEDV'])
```

Out[50]:

	RM	LSTAT	TAX	PTRATIO	MEDV
180	7.765	7.56	193.000000	17.8	39.8
98	7.820	3.57	276.000000	18.0	43.8
280	7.820	3.76	216.000000	14.9	45.4
203	7.853	3.81	224.000000	14.7	48.5
226	8.040	11.43	307.000000	17.4	37.6
97	8.069	4.21	276.000000	18.0	38.7
233	8.247	3.95	307.000000	17.4	48.3
253	8.259	3.54	330.000000	19.1	42.8

224	8.266	4.14	307.000000	17.4	44.8
232	8.337	2.47	307.000000	17.4	41.7
262	8.398	5.91	264.000000	13.0	48.8
364	8.780	5.29	294.139785	20.2	21.9

In [51]:
```
print(f'Shape of dataset before removing data points: {df3.shape}')
df3 = df3.drop(axis=0,index=[364])
print(f'Shape of dataset before removing data points: {df3.shape}')
```

```
Shape of dataset before removing data points: (488, 5)
Shape of dataset before removing data points: (487, 5)
```

SPLITTING THE DATA

In [52]:
```
#Now will split our dataset into Dependent variable and Independent variable

X = df3.iloc[:,0:4].values
y = df3.iloc[:,-1:].values
```

In [53]:
```
print(f"Shape of Dependent Variable X = {X.shape}")
print(f"Shape of Independent Variable y = {y.shape}")
```

```
Shape of Dependent Variable X = (487, 4)
Shape of Independent Variable y = (487, 1)
```

FEATURE SCALING

In [54]:
```
def FeatureScaling(X):

    mean = np.mean(X,axis=0)
    std = np.std(X,axis=0)
    for i in range(X.shape[1]):
        X[:,i] = (X[:,i]-mean[i])/std[i]

    return X
```

In [55]:
```
X = FeatureScaling(X)
```

In [56]:
```
m,n = X.shape
X = np.append(arr=np.ones((m,1)),values=X,axis=1)
```

Train the data

In [57]:
```
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 = 42)

print(f"Shape of X_train = {X_train.shape}")
print(f"Shape of X_test = {X_test.shape}")
print(f"Shape of y_train = {y_train.shape}")
print(f"Shape of y_test = {y_test.shape}")
```

```
Shape of X_train = (389, 5)
Shape of X_test = (98, 5)
Shape of y_train = (389, 1)
Shape of y_test = (98, 1)
```

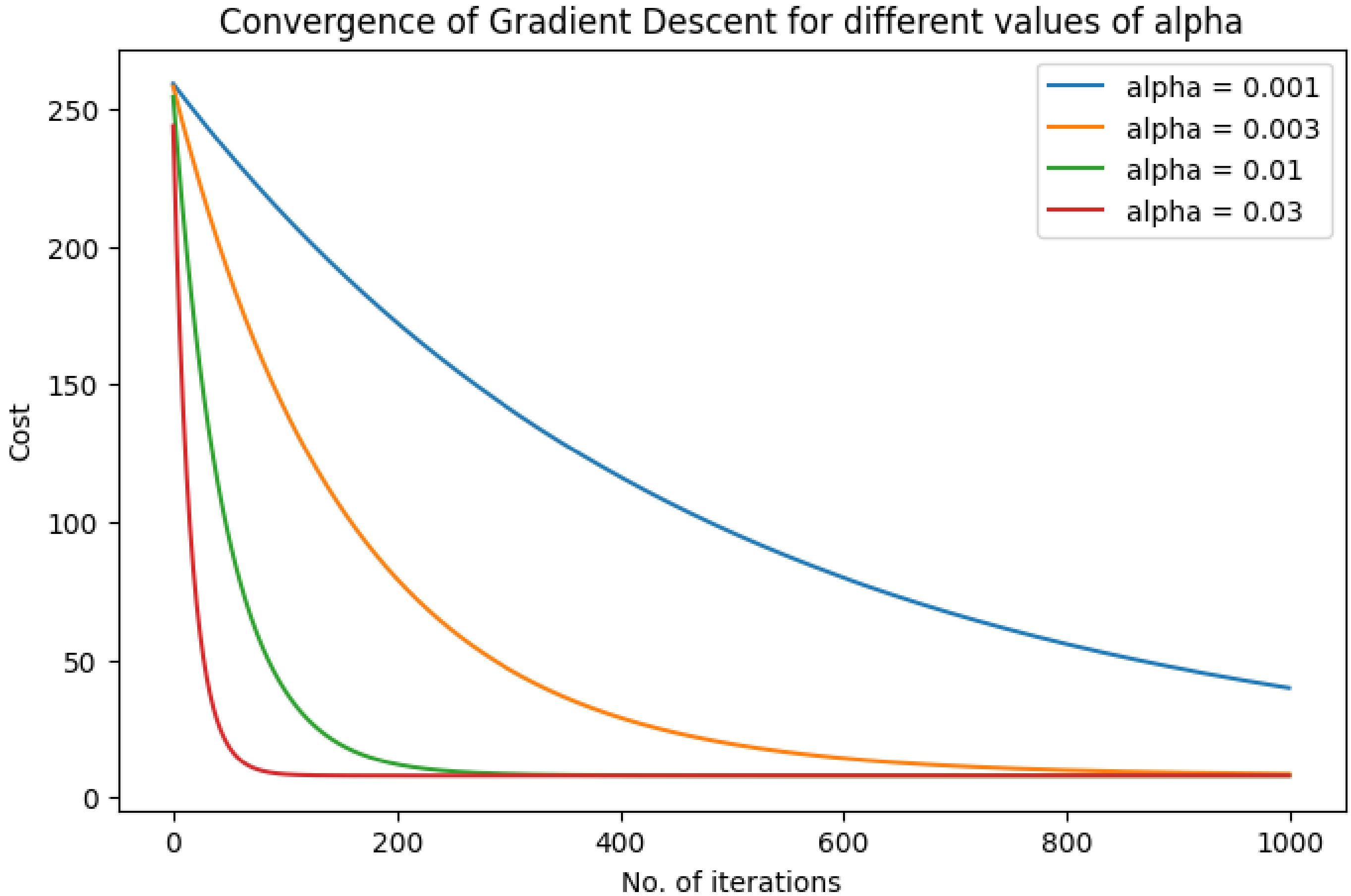
Multiple Linear Regression Model

In [58]:
```
def ComputeCost(X,y,theta):

    m=X.shape[0] #number of data points in the set
    J = (1/(2*m)) * np.sum((X.dot(theta) - y)**2)
    return J
```

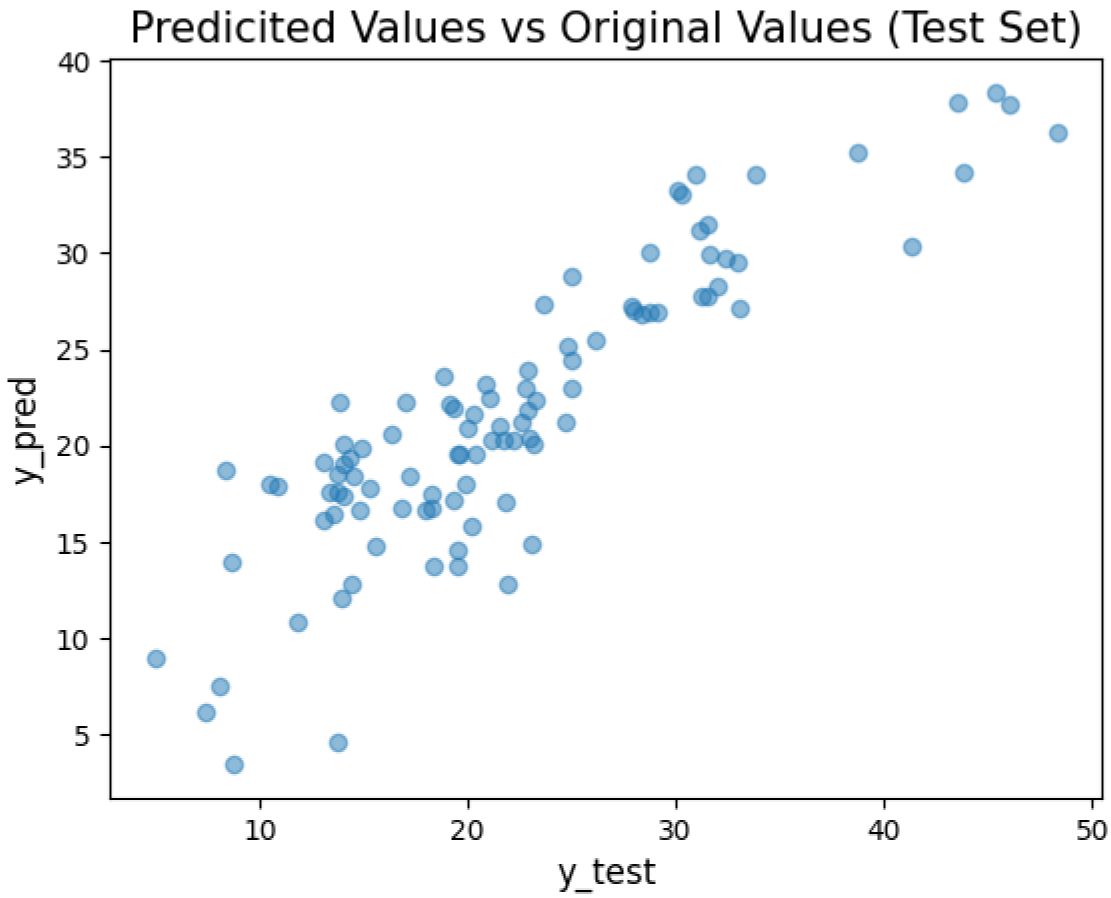
In [59]:
```
#Gradient Descent Algorithm to minimize the Cost and find best parameters in order to ge

def GradientDescent(X,y,theta,alpha,no_of_iters):
    m=X.shape[0]
    J_Cost = []
    for i in range(no_of_iters):
        error = np.dot(X.transpose(),(X.dot(theta)-y))
        theta = theta - alpha * (1/m) * error
        J_Cost.append(ComputeCost(X,y,theta))

    return theta, np.array(J_Cost)
```

In [60]:
```
iters = 1000

alpha1 = 0.001
theta1 = np.zeros((X_train.shape[1],1))
theta1, J_Costs1 = GradientDescent(X_train,y_train,theta1,alpha1,iters)

alpha2 = 0.003
theta2 = np.zeros((X_train.shape[1],1))
theta2, J_Costs2 = GradientDescent(X_train,y_train,theta2,alpha2,iters)

alpha3 = 0.01
theta3 = np.zeros((X_train.shape[1],1))
theta3, J_Costs3 = GradientDescent(X_train,y_train,theta3,alpha3,iters)

alpha4 = 0.03
theta4 = np.zeros((X_train.shape[1],1))
theta4, J_Costs4 = GradientDescent(X_train,y_train,theta4,alpha4,iters)
```

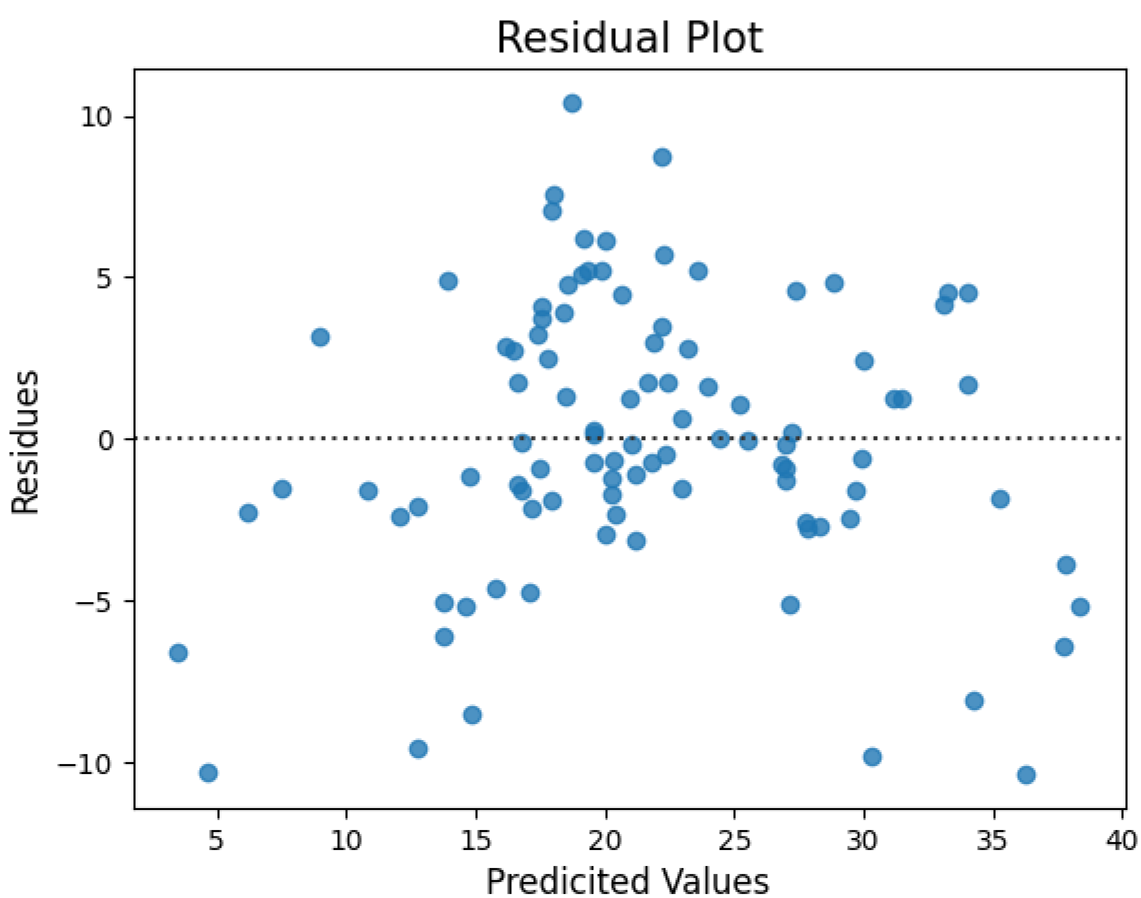
In [61]:
```
plt.figure(figsize=(8,5))
plt.plot(J_Costs1,label = 'alpha = 0.001')
plt.plot(J_Costs2,label = 'alpha = 0.003')
plt.plot(J_Costs3,label = 'alpha = 0.01')
plt.plot(J_Costs4,label = 'alpha = 0.03')
plt.title('Convergence of Gradient Descent for different values of alpha')
plt.xlabel('No. of iterations')
plt.ylabel('Cost')
plt.legend()
plt.show()
```



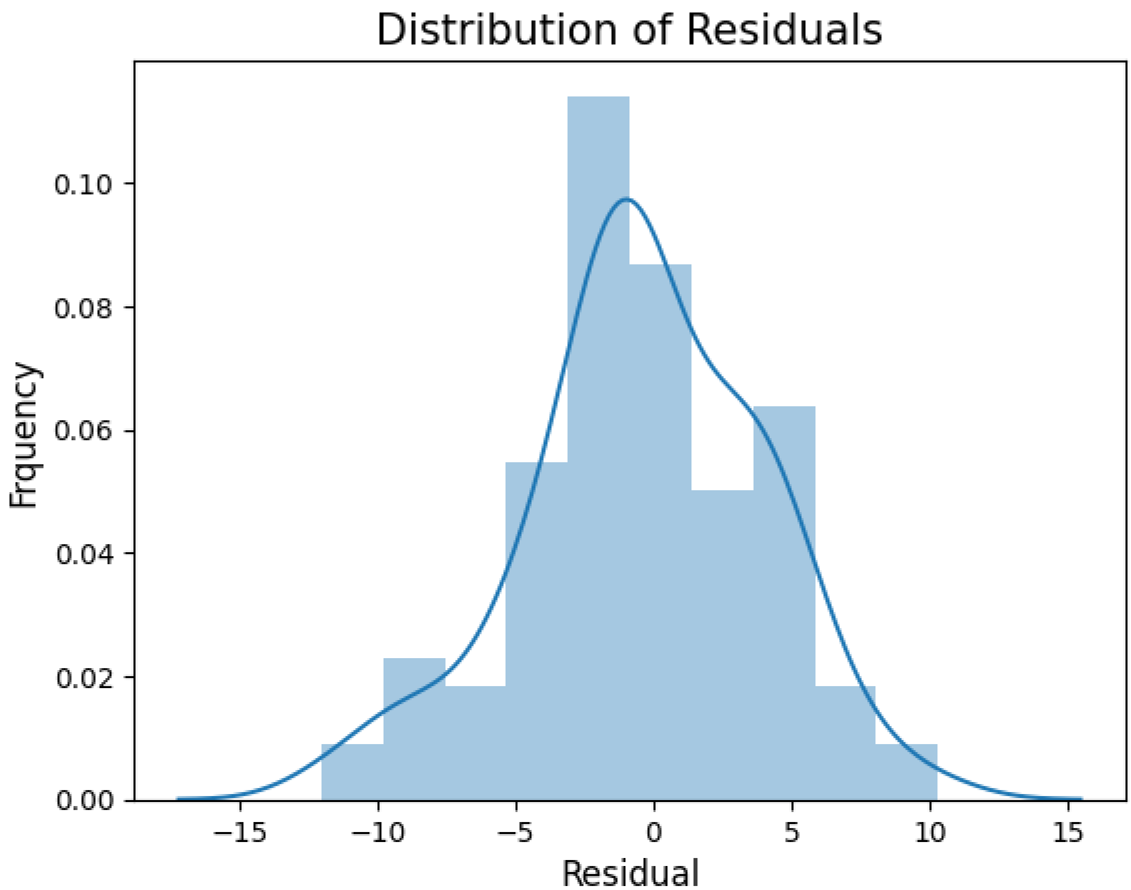
In [62]:
```
theta4
```
Out[62]:
```
array([[21.54687154],
       [ 3.13762495],
       [-2.59944591],
       [-1.09593223],
       [-2.08103859]])
```
In [63]:
```
def Predict(X,theta):
    y_pred = X.dot(theta)
    return y_pred
```
In [64]:
```
y_pred = Predict(X_test,theta4)
y_pred[:5]
```
Out[64]:
```
array([[17.54791827],
       [23.17808358],
       [29.7161842 ],
       [20.04954155],
       [26.79459549]])
```
In [65]:
```
plt.scatter(x=y_test,y=y_pred,alpha=0.5)
plt.xlabel('y_test',size=12)
plt.ylabel('y_pred',size=12)
plt.title('Predicited Values vs Original Values (Test Set)',size=15)
plt.show()
```



In [66]:
```
sns.residplot(x=y_pred,y=(y_pred-y_test))
plt.xlabel('Predicited Values',size=12)
plt.ylabel("Residues",size=12)
plt.title('Residual Plot',size=15)
plt.show()
```



In [67]:
```
sns.distplot(y_pred-y_test)
plt.xlabel('Residual',size=12)
plt.ylabel('Frquency',size=12)
plt.title('Distribution of Residuals',size=15)
plt.show()
```



EVALUATION

In [68]:
```
from sklearn import metrics
r2= metrics.r2_score(y_test,y_pred)
N,p = X_test.shape
adj_r2 = 1-((1-r2)*(N-1))/(N-p-1)
print(f'R^2 = {r2}')
print(f'Adjusted R^2 = {adj_r2}')
```

```
R^2 = 0.7729424445651353
Adjusted R^2 = 0.7606023600306318
```

In [69]:
```
from sklearn import metrics
mse = metrics.mean_squared_error(y_test,y_pred)
mae = metrics.mean_absolute_error(y_test,y_pred)
rmse = np.sqrt(metrics.mean_squared_error(y_test,y_pred))
print(f'Mean Squared Error: {mse}',f'Mean Absolute Error: {mae}',f'Root Mean Squared Err
```

```
Mean Squared Error: 18.50526831362888
Mean Absolute Error: 3.3478420556094606
Root Mean Squared Error: 4.301775018946119
```

Model Interpretation

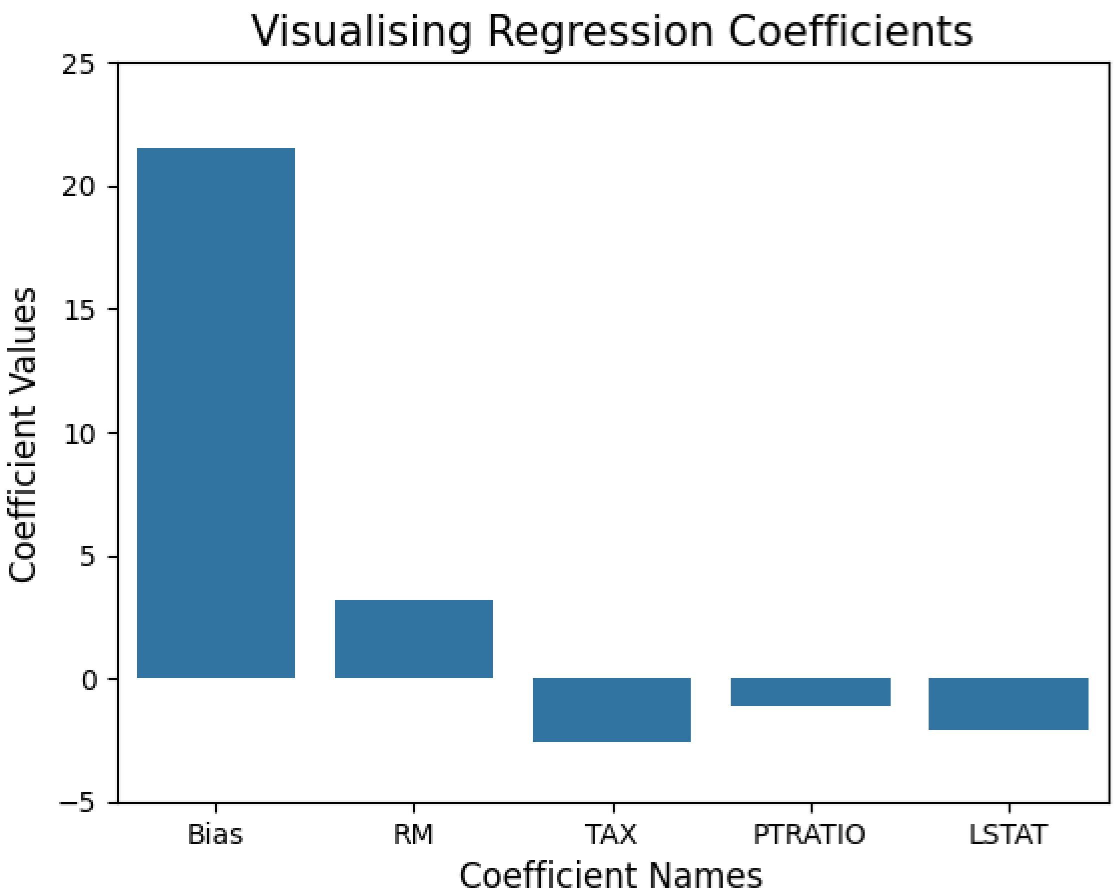
In [70]:
```
#coefficients of regression model
coeff=np.array([y for x in theta4 for y in x]).round(2)
features=['Bias','RM','TAX','PTRATIO','LSTAT']
```

```python
eqn = 'MEDV = '
for f,c in zip(features,coeff):
    eqn+=f" + ({c} * {f})";

print(eqn)
```

```
MEDV =  + (21.55 * Bias) + (3.14 * RM) + (-2.6 * TAX) + (-1.1 * PTRATIO) + (-2.08 * LSTA
T)
```

In [71]:

```python
sns.barplot(x=features,y=coeff)
plt.ylim([-5,25])
plt.xlabel('Coefficient Names',size=12)
plt.ylabel('Coefficient Values',size=12)
plt.title('Visualising Regression Coefficients',size=15)
plt.show()
```



In [71]: