

# Boston Housing Prices Project

In [ ]:

```
# Importing Libraries
```

In [1]:

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

In [2]:

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

Out[2]:

	CRIM	ZN	INDUS	CHAS	NOX	RN	AGE	DIS	RED	TAX	PTRATIO	BK	LSTA
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.9
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.1
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.0
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.9
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.3
...	...	...	...	...	...	...	...	...	...	...	...	...	.
501	0.06263	0.0	11.93	0	0.573	6.593	69.1	2.4786	1	273	21.0	391.99	9.6
502	0.04527	0.0	11.93	0	0.573	6.120	76.7	2.2875	1	273	21.0	396.90	9.0
503	0.06076	0.0	11.93	0	0.573	6.976	91.0	2.1675	1	273	21.0	396.90	5.6
504	0.10959	0.0	11.93	0	0.573	6.794	89.3	2.3889	1	273	21.0	393.45	6.4
505	0.04741	0.0	11.93	0	0.573	6.030	80.8	2.5050	1	273	21.0	396.90	7.8

506 rows × 14 columns



In [7]:

```
df.head(15)
```

Out[7]:

	CRIM	ZN	INDUS	CHAS	NOX	RN	AGE	DIS	RED	TAX	PTRATIO	BK	LSTAT
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.9
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.1
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.0
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.9
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.3
5	0.02985	0.0	2.18	0	0.458	6.430	58.7	6.0622	3	222	18.7	394.12	5.2
6	0.08829	12.5	7.87	0	0.524	6.012	66.6	5.5605	5	311	15.2	395.60	12.4
7	0.14455	12.5	7.87	0	0.524	6.172	96.1	5.9505	5	311	15.2	396.90	19.1
8	0.21124	12.5	7.87	0	0.524	5.631	100.0	6.0821	5	311	15.2	386.63	29.9
9	0.17004	12.5	7.87	0	0.524	6.004	85.9	6.5921	5	311	15.2	386.71	17.1
10	0.22489	12.5	7.87	0	0.524	6.377	94.3	6.3467	5	311	15.2	392.52	20.4
11	0.11747	12.5	7.87	0	0.524	6.009	82.9	6.2267	5	311	15.2	396.90	13.2
12	0.09378	12.5	7.87	0	0.524	5.889	39.0	5.4509	5	311	15.2	390.50	15.7
13	0.62976	0.0	8.14	0	0.538	5.949	61.8	4.7075	4	307	21.0	396.90	8.2
14	0.63796	0.0	8.14	0	0.538	6.096	84.5	4.4619	4	307	21.0	380.02	10.2

In [4]:

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

Out[4]:

```
CRIM      0
ZN         0
INDUS      0
CHAS       0
NOX        0
RN         0
AGE        0
DIS        0
RED        0
TAX        0
PTRATIO    0
BK         0
LSTAT      0
MEDV       0
dtype: int64
```

In [5]:

```
df.dtypes
```

Out[5]:

```
CRIM      float64
ZN        float64
INDUS     float64
CHAS      int64
NOX       float64
RN        float64
AGE       float64
DIS       float64
RED       int64
TAX       int64
PTRATIO   float64
BK        float64
LSTAT     float64
MEDV     float64
dtype: object
```

In [6]:

```
df.shape
```

Out[6]:

(506, 14)

In [8]:

```
df.describe()
```

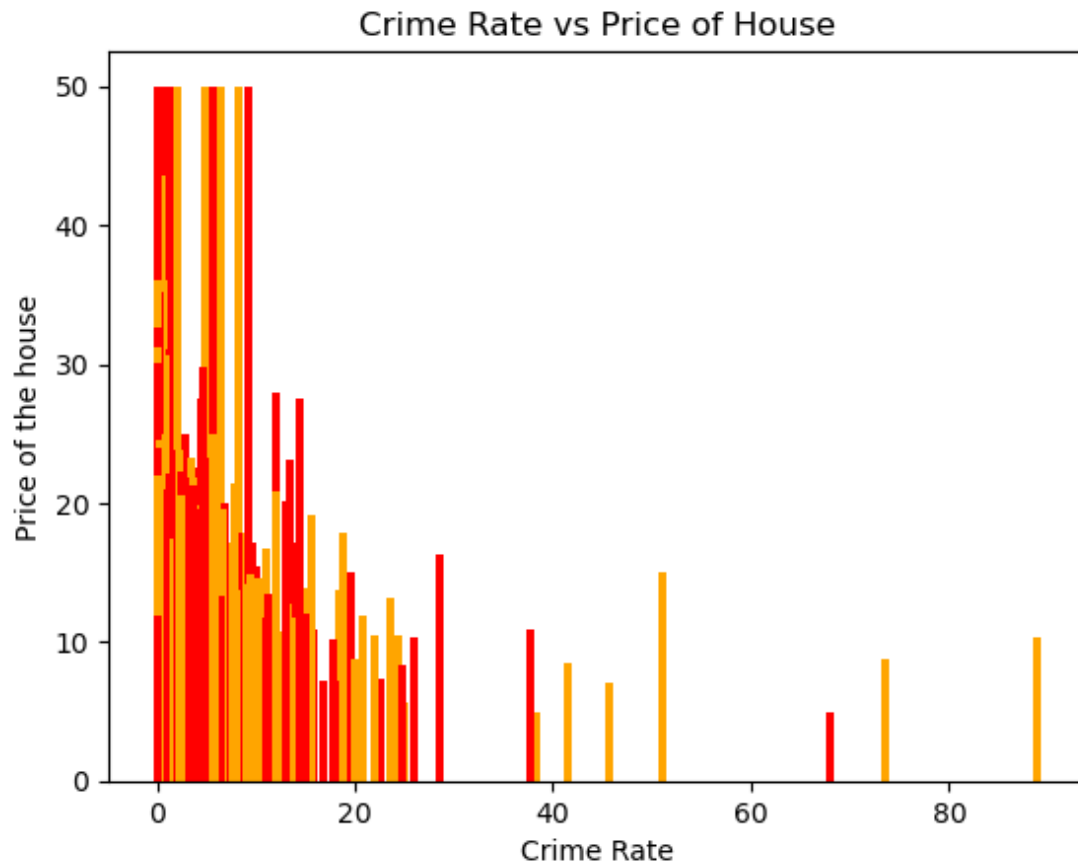
Out[8]:

	M	ZN	INDUS	CHAS	NOX	RN	AGE	DIS	RED
count	506	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	24	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407
std	15	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259
min	20	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000
25%	15	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000
50%	10	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000
75%	33	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000
max	30	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000

when crime rate increase the Price of Houses is Down continuously

In [9]:

```
plt.bar(df.CRIM, df.MEDV, color=['orange', 'red'])  
plt.xlabel('Crime Rate')  
plt.ylabel('Price of the house')  
plt.title('Crime Rate vs Price of House')  
plt.show()
```



## observation

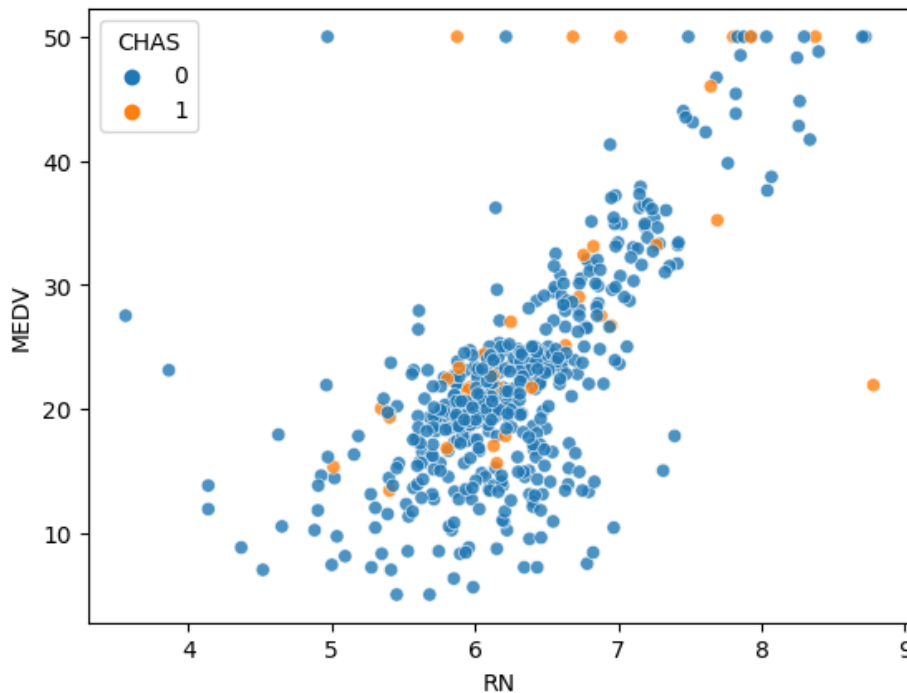
When the crime rate increases in a particular area, it can lead to a decrease in the desirability of that area, and as a result, the demand for housing in that area can decrease. When demand for housing decreases, sellers may have to lower their prices in order to attract buyers.

**When lands are closer to Charles River the Price of the land will be increase and land are further away from the river the cost will be down**

In [10]:

```
sns.scatterplot(y='MEDV', x='RN', data=df, alpha=0.8, hue='CHAS')  
plt.suptitle('plots showing MEDV and Room Relationship based on Charles River Dummy variable')  
plt.show()
```

plots showing MEDV and Room Relationship based on Charles River Dummy variable



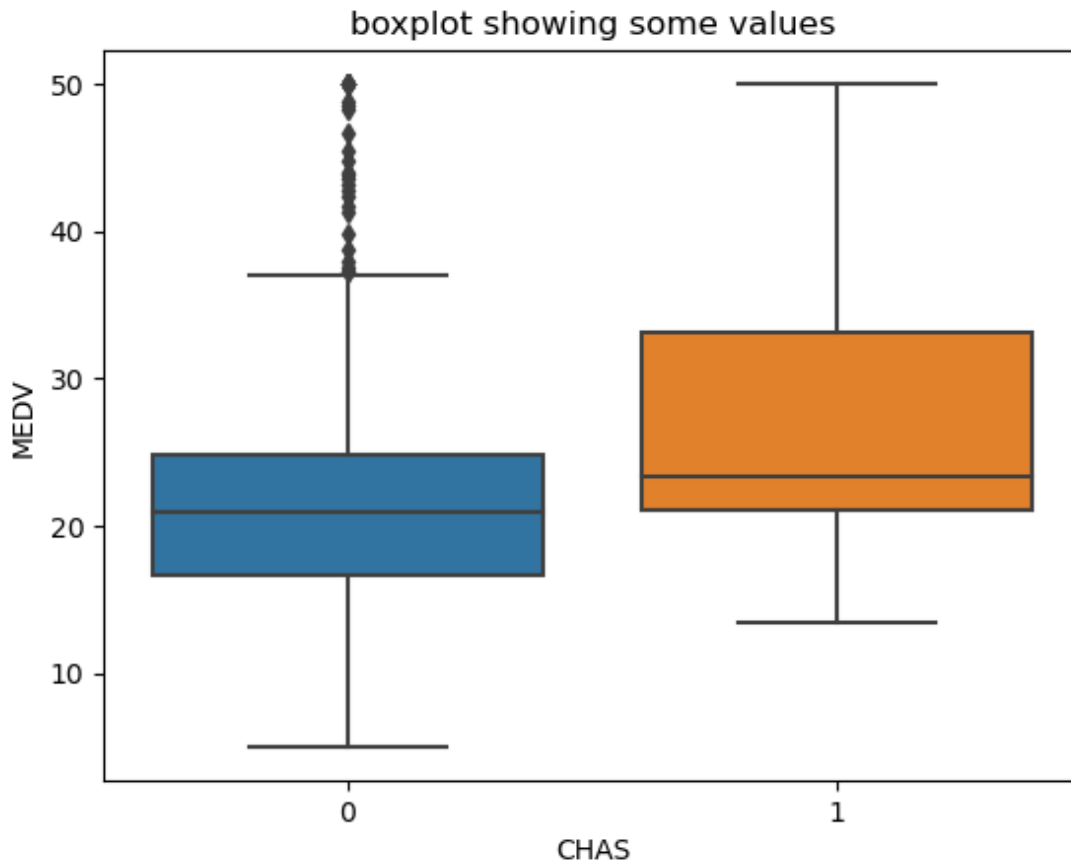
## observation

In the Boston area. The land near the river is considered prime Location because of the view of the river and proximity to water-based activities in this land there are sufficient water for daily life activity. Therefore, properties close to the Charles River tend to be more more expensive as compared to land which is further away from Charles River

**When lands are closer to Charles River the Price of the land will be increase and land are further away from the river the cost will be down using boxplot**

In [6]:

```
sns.boxplot(x= 'CHAS',y='MEDV',data= df )  
plt.title('boxplot showing some values' )  
plt.show()
```



## observation

Price of houses closer to Charles River are found to be higher in general with higher value of 1st Quantile Median and 3rd Quantile Even the min or max values are higher if the house is located in closer of Charles River

Number of Outlier are found to be unusually high in case of when the houses are further away from Charles River this could be affect the predictability of pricing which is further away from the Charles River

## Location wise Tax Distribution

In [4]:

```
sns.histplot(data=df, x='TAX')  
plt.xlabel('TAX values')  
plt.ylabel('Sqr feet')  
plt.title('Distribution of TAX in Boston Housing Dataset')  
plt.show()
```



## observation

1 Location-wise tax distribution refers to the way in which property taxes are distributed across different geographic locations or regions. Property taxes are typically assessed by local governments

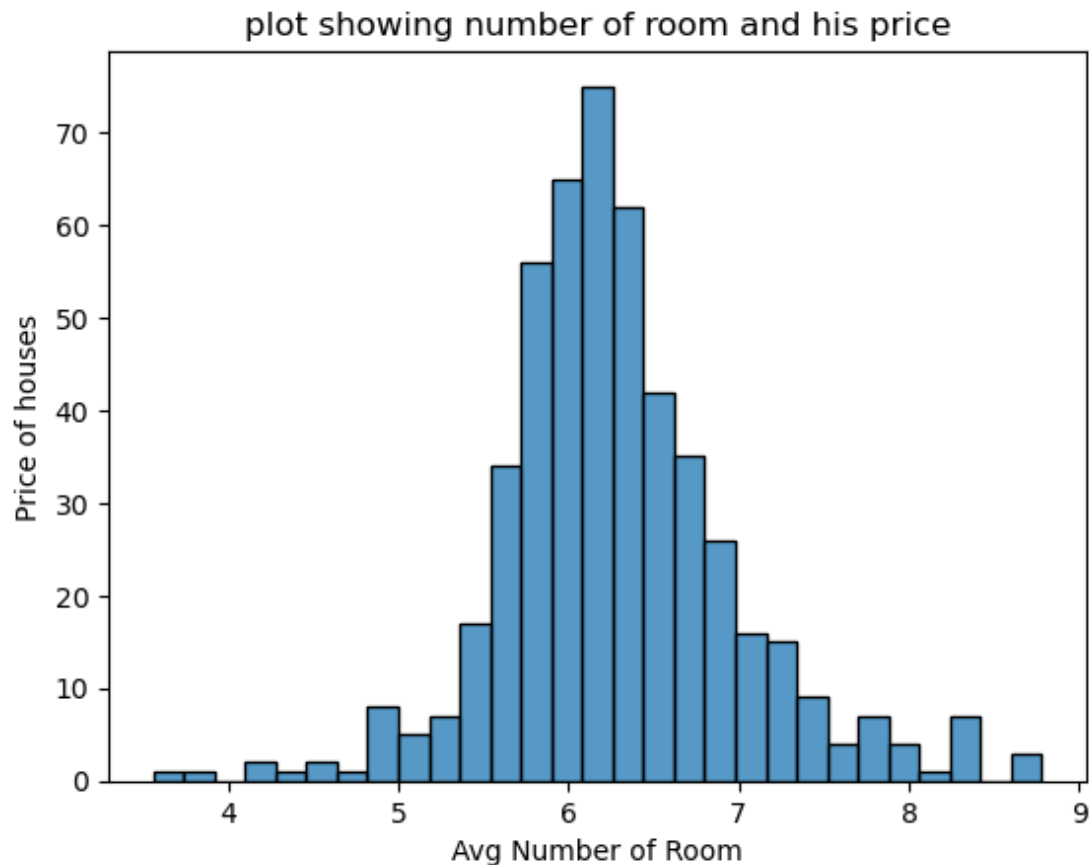
2 For example, areas with higher property values may have higher tax rates in order to generate more revenue for local governments.

3 Therefore Taxes are Totally depended on the Location

**The Avg Number of Rooms are Increasing the price of the house is also increasing**

In [13]:

```
sns.histplot(data=df, x='RN')  
plt.xlabel('Avg Number of Room')  
plt.ylabel('Price of houses')  
plt.title('plot showing number of room and his price')  
plt.show()
```



## observation

1 there is a positive correlation between the number of rooms in a house and its price.

2 the fact that larger houses with more rooms generally have more square footage, which can increase the overall value of the property.

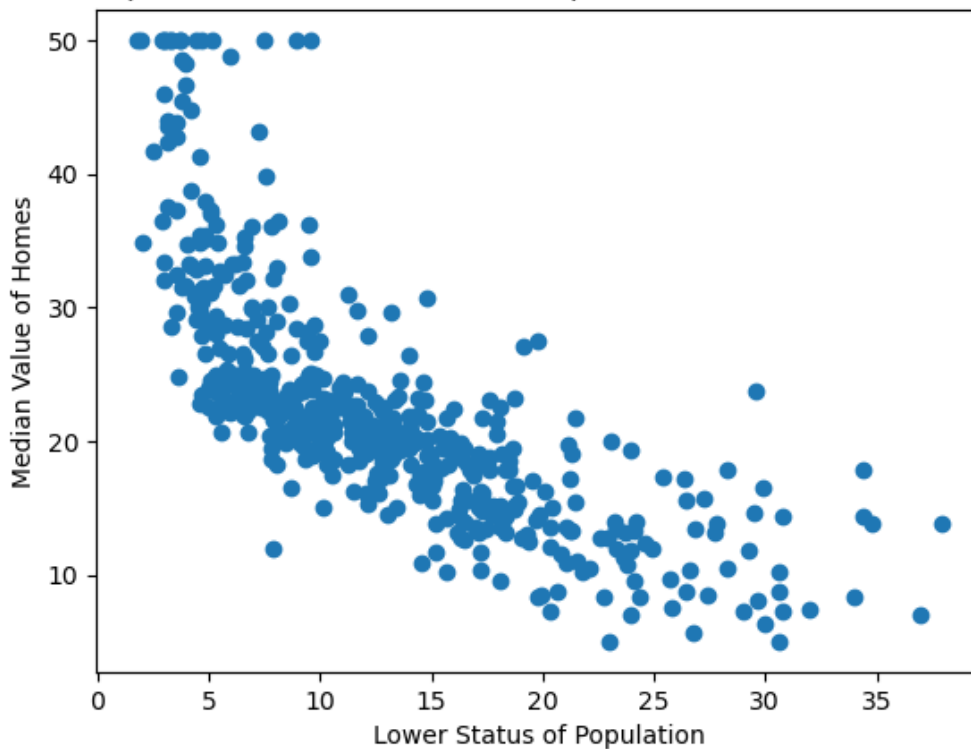
**The median value of homes tends to decrease as the lower status of the population increases**



In [13]:

```
plt.scatter(df[ 'LSTAT'], df[ 'MEDV'])  
  
plt.xlabel ('Lower Status of Population')  
plt.ylabel('Median Value of Homes')  
plt.title('Relationship between Lower Status of Population and Median Value of Homes')  
  
plt.show()
```

Relationship between Lower Status of Population and Median Value of Homes



## observation

1 The column LSTAT represents the percentage of lower status of the population in a given area, while MEDV represents the median value of owner-occupied homes in thousands of dollars.

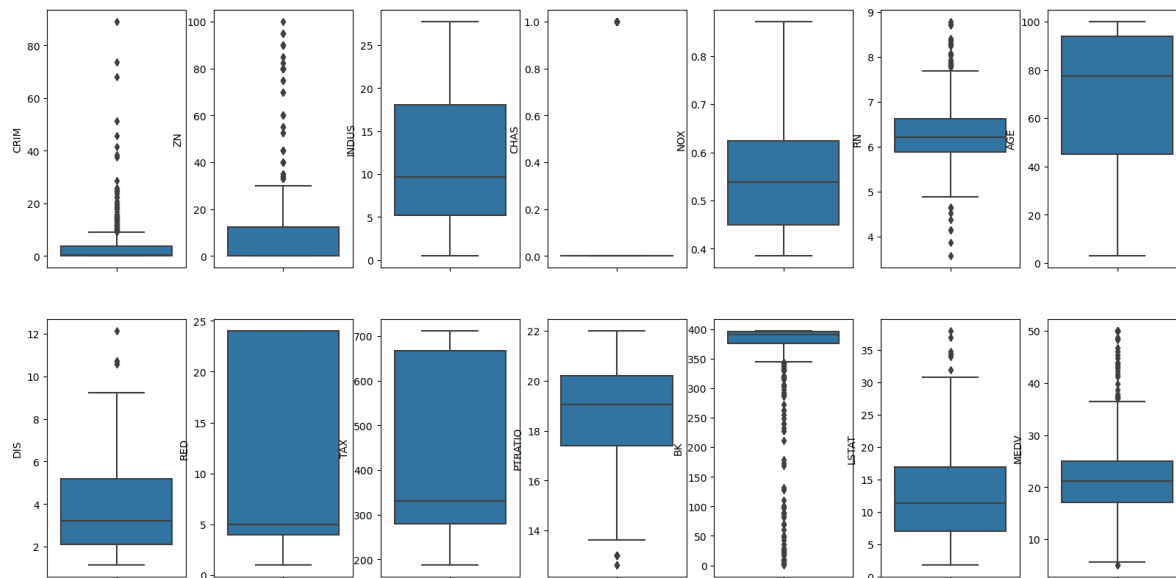
2 There is a negative correlation between LSTAT and MEDV.

3 This negative correlation between LSTAT and MEDV can be explained by a variety of factors. Areas with a higher percentage of lower status population may have lower income levels, which can make it more difficult for residents to afford higher- priced homes. Additionally, areas with higher poverty rates may also have higher crime rates, worse school systems, and less desirable living conditions, all of which can negatively impact home values.

## Checking Outliers

In [14]:

```
fig, ax = plt.subplots(ncols=7, nrows=2, figsize=(20,10))
index = 0
ax = ax.flatten()
for col in df.items():
    sns.boxplot(y=col[0], data=df, ax=ax[index])
    index += 1
```



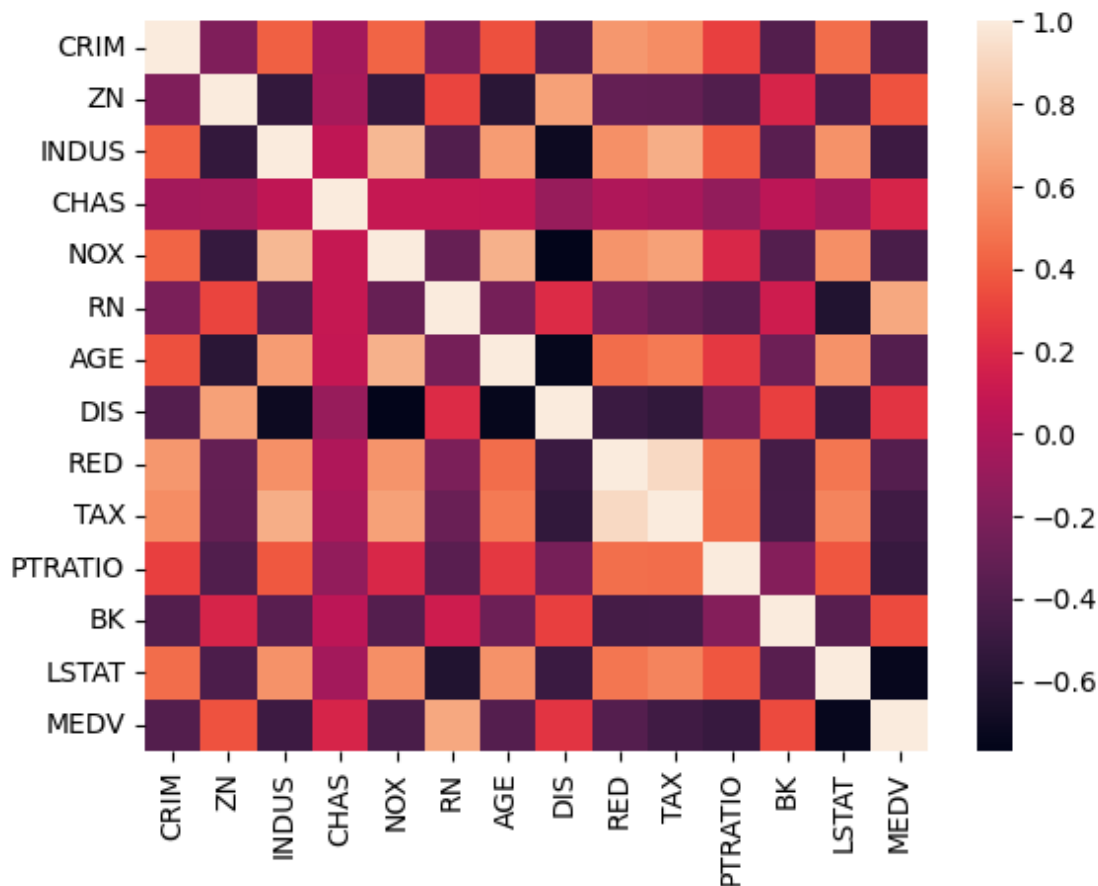
## Checking Correlation

In [15]:

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

Out[15]:

&lt;Axes: &gt;



## Conclusion

1 There is a negative correlation between the crime rate and the median value of homes. This means that as the crime rate increases, the median value of homes tends to decrease.

2 Homes that are located closer to the Charles River tend to have a higher median value than those located further away.

3 There is a negative correlation between the median value of homes and the percentage of the lower status of the population. This means that as the percentage of lower status population increases, the median value of homes tends to decrease.

4 The Avg Number of Rooms are Increasing the price of the house is also increasing Because there are sufficient space for the buyer buyer give lots of money to the land owner and wants to good facility in the house

In [ ]:

In [ ]: