In [1]:
```
#importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

#importing libraries for machine learning
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.metrics import r2_score
```

In [2]:
```
#importing the dataset
df = pd.read_csv('C:/Users/DELL/OneDrive/Desktop/DATA SCIENCE COURSE (Datase
```

In [23]:
```
df.head()
```

Out[23]:

	crim	zn	indus	chas	nox	rm	age	dis	rad	tax	ptratio	black	lstat	medv
0	0.15876	0.0	10.81	0	0.413	5.961	17.5	5.2873	4	305	19.2	376.94	9.88	21.7
1	0.10328	25.0	5.13	0	0.453	5.927	47.2	6.9320	8	284	19.7	396.90	9.22	19.6
2	0.34940	0.0	9.90	0	0.544	5.972	76.7	3.1025	4	304	18.4	396.24	9.97	20.3
3	2.73397	0.0	19.58	0	0.871	5.597	94.9	1.5257	5	403	14.7	351.85	21.45	15.4
4	0.04337	21.0	5.64	0	0.439	6.115	63.0	6.8147	4	243	16.8	393.97	9.43	20.5

In [4]:
```
df.shape
```

Out[4]: (404, 14)

In [5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 404 entries, 0 to 403
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   crim     404 non-null    float64
 1   zn       404 non-null    float64
 2   indus    404 non-null    float64
 3   chas     404 non-null    int64  
 4   nox      404 non-null    float64
 5   rm       404 non-null    float64
 6   age      404 non-null    float64
 7   dis      404 non-null    float64
 8   rad      404 non-null    int64  
 9   tax      404 non-null    int64  
 10  ptratio  404 non-null    float64
 11  black    404 non-null    float64
 12  lstat    404 non-null    float64
 13  medv     404 non-null    float64
dtypes: float64(11), int64(3)
memory usage: 44.3 KB
```

In [24]:
```
df.isna().sum()
```

Out[24]:
```
crim       0
zn         0
indus      0
chas       0
nox        0
rm         0
age        0
dis        0
rad        0
tax        0
ptratio    0
black      0
lstat      0
medv       0
dtype: int64
```

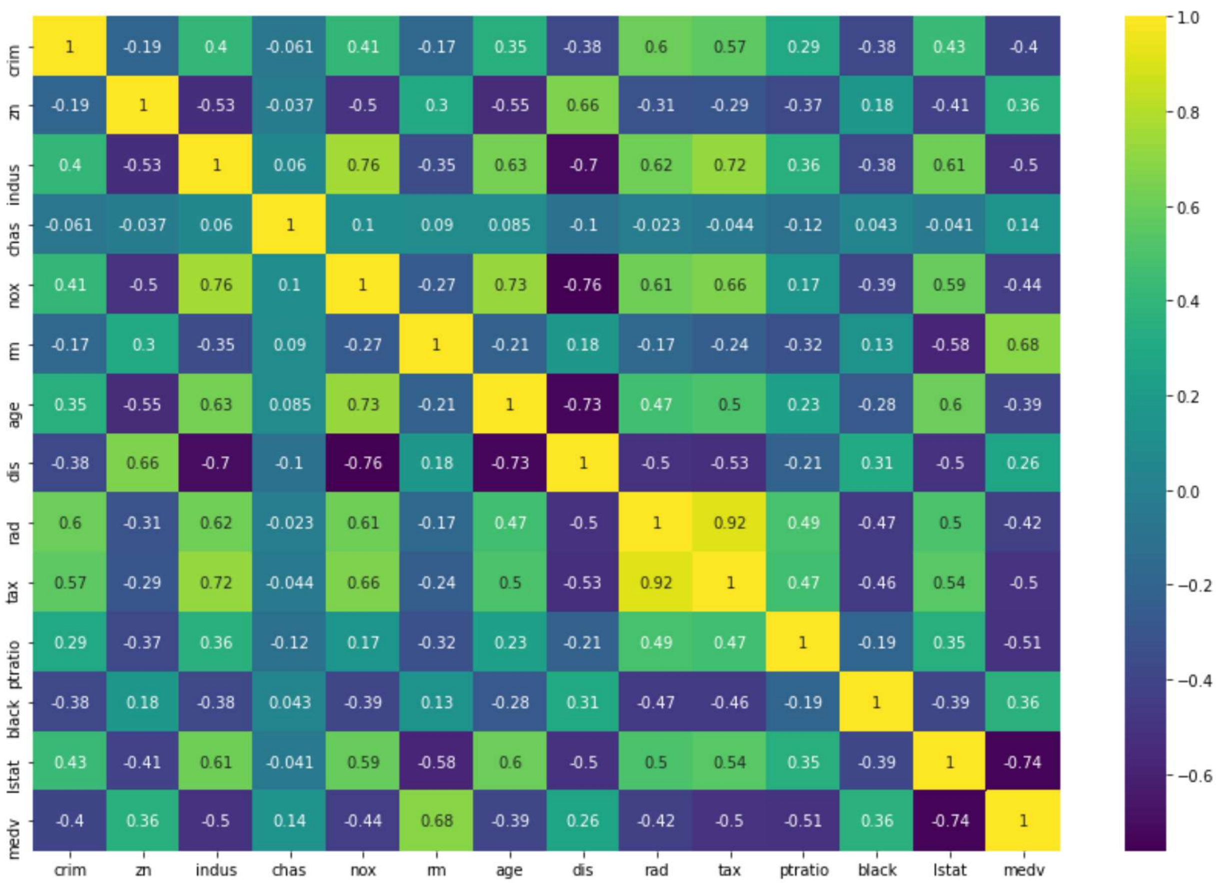
In [6]:
```
df.describe()
```

Out[6]:

	crim	zn	indus	chas	nox	rm	age	
count	404.000000	404.000000	404.000000	404.000000	404.000000	404.00000	404.000000	404.000
mean	3.730912	10.509901	11.189901	0.069307	0.556710	6.30145	68.601733	3.799
std	8.943922	22.053733	6.814909	0.254290	0.117321	0.67583	28.066143	2.109
min	0.006320	0.000000	0.460000	0.000000	0.392000	3.56100	2.900000	1.169
25%	0.082382	0.000000	5.190000	0.000000	0.453000	5.90275	45.800000	2.087
50%	0.253715	0.000000	9.795000	0.000000	0.538000	6.23050	76.600000	3.207
75%	4.053158	12.500000	18.100000	0.000000	0.631000	6.62925	94.150000	5.222
max	88.976200	95.000000	27.740000	1.000000	0.871000	8.78000	100.000000	12.126

In [22]:
```
plt.figure(figsize = (15,10))
correlation = df.corr()
sns.heatmap(correlation , annot = True , cmap = 'viridis')
```

Out[22]: <AxesSubplot:>



In [ ]:
```

```

Splitting the dataframe into training and testing data

In [10]:
```
#assigning independent variables to x and dependent variable or response var
x = df[['crim', 'zn', 'indus', 'chas', 'nox', 'rm', 'age', 'dis', 'rad', 'ta
y = df['medv']
```

In [11]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3)
```

In [25]:
```
print("Dimension of x_train :",x_train.shape)
print("Dimension of x_test :",x_test.shape)
print("Dimension of y_train :",y_train.shape)
print("Dimension of y_test :",y_test.shape)
```

```
Dimension of x_train : (282, 13)
Dimension of x_test : (122, 13)
Dimension of y_train : (282,)
Dimension of y_test : (122,)
```

Building a Linear Regression Model

In [12]:
```
lm = LinearRegression()
reg = lm.fit(x_train,y_train)
```

In [13]:
```
predictions = lm.predict(x_test)
```

In [14]:
```
predictions
```

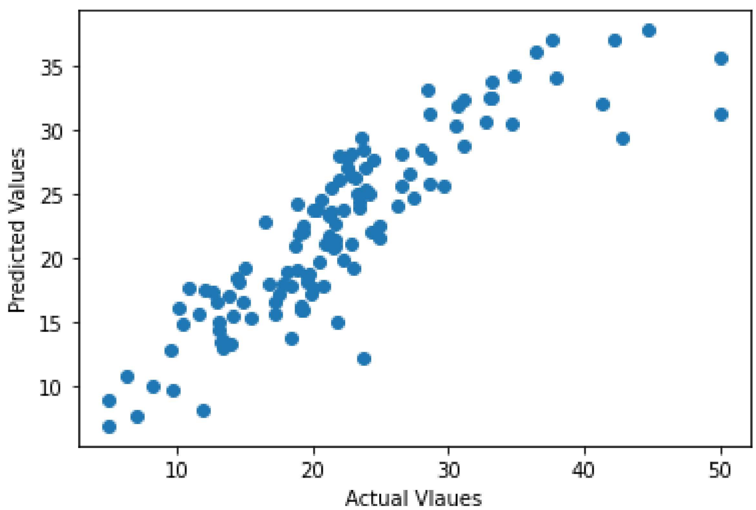
Out[14]:
```
array([20.91378468, 21.86576533, 23.72286085, 15.43379467, 22.50179969,
       18.12823755, 17.10769135, 25.62052683, 19.75938076, 26.24959121,
       16.51174583, 14.99090162, 28.47088781, 16.04536552,  7.58942277,
       18.75984464, 18.03090961, 23.55248909, 27.96337224, 32.47073528,
       36.93411706, 23.80771545, 21.06115435, 21.59470343, 28.46430294,
       21.331082  , 16.50699046, 12.2394018 , 26.01740713, 16.49366542,
       33.7509393 , 23.4741521 , 25.40520818, 14.36407566, 25.03689012,
       23.22570717,  6.88700416, 31.9978947 , 26.96038018, 13.62767967,
       27.73024658, 17.70414795, 20.82012421,  9.64675216, 32.48215302,
       26.5497374 , 15.61803454, 17.72587664, 29.41580429, 27.0848801 ,
       13.26602854, 19.24382327,  8.86144774, 31.17546825, 23.96354024,
       10.07192289, 19.73880545, 25.32485777, 28.04267791, 18.43856465,
       17.62281739, 34.22031643, 22.63785753, 20.88214578, 24.6371908 ,
       32.2884916 , 19.10075826, 15.62376286, 25.71608493, 18.63863745,
       24.53422976, 13.73775297, 30.38159601, 30.529498  , 10.73025935,
       36.07486065, 37.74803058, 17.10737644, 27.7335233 , 28.65636976,
       31.29159947, 29.39221347, 23.80481197, 36.93536117,  8.08409603,
       24.91456329, 31.78254417, 18.94538985, 25.21229133, 13.46174133,
       30.2795401 , 14.90137942, 22.86848684, 18.17696309, 27.65227873,
       28.14800401, 17.08945754, 14.97114672, 34.0545077 , 15.95524151,
       24.01345436, 17.86410648, 12.93790828, 17.45462697, 33.18000907,
       35.67417978, 15.96896026, 25.58363583, 21.010364  , 24.21655606,
       22.00359187, 26.37398592, 17.35003145, 17.99822953, 22.53445835,
       16.17855705, 12.83894521, 21.67662422, 15.23288805, 24.3069439 ,
       19.15136612, 22.08567355])
```

In [15]:
```
y_test
```

Out[15]:
```
297    21.7
110    19.0
2      20.3
312    14.1
263    25.0
       ...
240    21.2
3      15.4
211    23.4
236    15.0
150    24.4
Name: medv, Length: 122, dtype: float64
```

In [26]:
```
plt.scatter(y_test,predictions)
plt.xlabel('Actual Vlaues')
plt.ylabel('Predicted Values')
```

Out[26]:
```
Text(0, 0.5, 'Predicted Values')
```



The scatter plot shows a high correlation between predicted and actual values

In [17]:
```
print('MAE:', metrics.mean_absolute_error(y_test, predictions))
print('MSE:', metrics.mean_squared_error(y_test, predictions))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, predictions)))
```

```
MAE: 2.9398539889900737
MSE: 16.803042496936982
RMSE: 4.099151436204447
```

In [19]:
```
coefficients = pd.DataFrame(lm.coef_,x.columns)
coefficients.columns = ['coefficients']
coefficients
```

Out[19]:

	coefficients
crim	-0.087497
zn	0.042785
indus	-0.079213
chas	1.144681
nox	-15.059968
rm	3.559057
age	-0.004544
dis	-1.496255
rad	0.250453
tax	-0.011919
ptratio	-0.913969
black	0.007732
lstat	-0.491359

From the above table it can be inferred that chas, nox, rm, dis, ptratio, lstat highly affects the house price

In [20]:
```
yhat = reg.predict(x)
```

In [21]:
```
r2 = r2_score(y,yhat)
print("R-Squared =",r2)
```

```
R-Squared = 0.7483983231686366
```

R^2 value is 0.74 which means the model explains about 74% of the variation in our dependent variables