In [68]:

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python docker image: https://github.com/kaggle/docker
# For example, here's several helpful packages to load in

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the "../input/" directory.
# For example, running this (by clicking run or pressing Shift+Enter) will list the



# Any results you write to the current directory are saved as output.
```

In [69]:

```
#importing the necessary libraries such as numpy, pandas, matplotlib and seaborn
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [70]:

```
#the required data set is available in sklearn only. Hence the boston housing data .
from sklearn.datasets import load_boston
```

In [71]:

```
boston = load_boston()
```

Let us explore the dataset boston and its features

In [72]:

```
boston.keys()
# the below shows the details under the dataset. 'data' is the actual data. feature_
#target is the dependant variable which is the price of the houses. DESCR gives the
#details under the keys using 'dot' operator
```

Out[72]:

```
dict_keys(['data', 'target', 'feature_names', 'DESCR', 'filename'])
```

In [34]:

```
#the boston data has dataset, target, features, description and a filename
```

In [73]:

```
#let us check the data. the data is shown in terms of arrays.
boston.data
```

Out[73]:

```
array([[6.3200e-03, 1.8000e+01, 2.3100e+00, ..., 1.5300e+01, 3.9690e+0
2,
        4.9800e+00],
       [2.7310e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9690e+0
2,
        9.1400e+00],
       [2.7290e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9283e+0
2,
        4.0300e+00],
       ...,
       [6.0760e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+0
2,
        5.6400e+00],
       [1.0959e-01, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9345e+0
2,
        6.4800e+00],
       [4.7410e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+0
2,
        7.8800e+00]])
```

In [36]:

```
boston.feature_names
#these are the names of the columns
```

Out[36]:

```
array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RA
D',
       'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
```

In [37]:

```
#we can find the information about the data using 'DESCR'
print(boston.DESCR)
```

```
.. _boston_dataset:

Boston house prices dataset
---------------------------

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median V
alue (attribute 14) is usually the target.

    :Attribute Information (in order):
        - CRIM     per capita crime rate by town
        - ZN       proportion of residential land zoned for lots over
25,000 sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds r
iver; 0 otherwise)
        - NOX      nitric oxides concentration (parts per 10 million)
        - RM       average number of rooms per dwelling
        - AGE      proportion of owner-occupied units built prior to 1
940
        - DIS      weighted distances to five Boston employment centre
s
        - RAD      index of accessibility to radial highways
        - TAX      full-value property-tax rate per $10,000
        - PTRATIO  pupil-teacher ratio by town
        - B        1000(Bk - 0.63)^2 where Bk is the proportion of bla
ck people by town
        - LSTAT    % lower status of the population
        - MEDV     Median value of owner-occupied homes in $1000's

    :Missing Attribute Values: None

    :Creator: Harrison, D. and Rubinfeld, D.L.

This is a copy of UCI ML housing dataset.
https://archive.ics.uci.edu/ml/machine-learning-databases/housing/ (ht
tps://archive.ics.uci.edu/ml/machine-learning-databases/housing/)


This dataset was taken from the StatLib library which is maintained at
Carnegie Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedon
ic
prices and the demand for clean air', J. Environ. Economics & Manageme
nt,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diag
nostics
...', Wiley, 1980.   N.B. Various transformations are used in the tabl
e on
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning pap
```

```
ers that address regression
problems.

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influ
ential Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learn
ing. In Proceedings on the Tenth International Conference of Machine L
earning, 236-243, University of Massachusetts, Amherst. Morgan Kaufman
n.
```

Important information: The dataset contains 14 attributes. there are 506 instances(rows). there are no missing data. Further information can be gathered by converting the data in to dataframe using pandas.

In [38]:

```
#convert the data in to pandas dataframe
dfx = pd.DataFrame(boston.data, columns = boston.feature_names)
#all the independant variables/predictors are named as dfx
```

In [39]:

```
dfy = pd.DataFrame(boston.target, columns = ['target'])
#the dependant variable/outcome is the target and it is named as dfy
```

In [40]:

```
dfcombine = dfx.join(dfy)
#both the dataframes are combined and named as dfcombine
```

In [41]:

```
#let us view and examine the head of the combined dataframe
dfcombine.head()
```

Out[41]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LS
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	
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	
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	
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	
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	

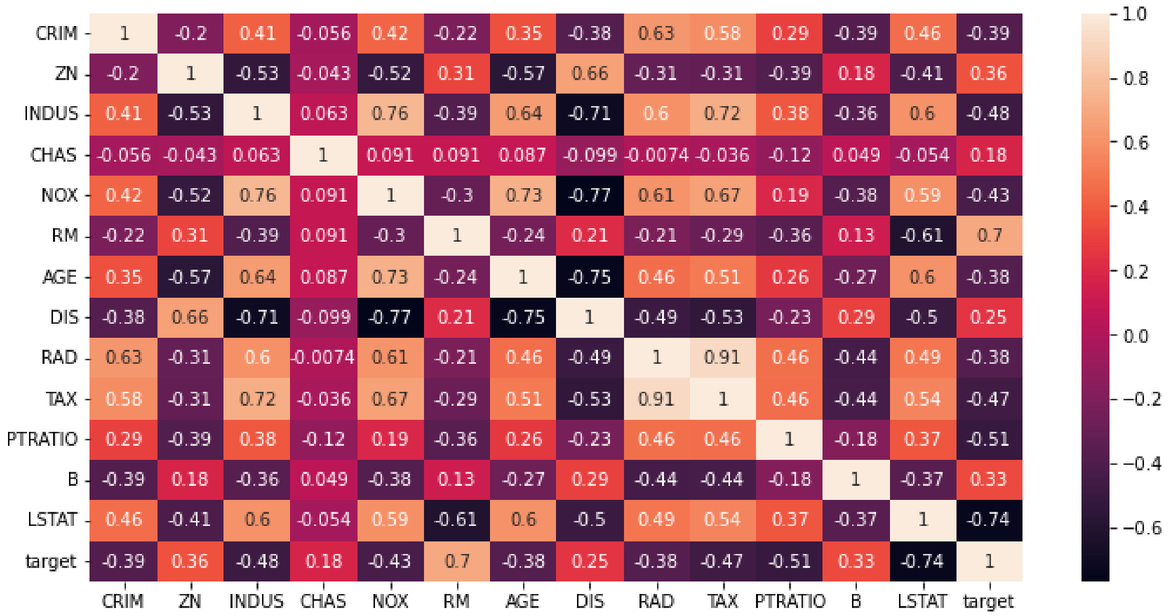
#Let us check the correlation of the features with each other and with the target

In [42]:

```
plt.figure(figsize = (12,6))
sns.heatmap(dfcombine.corr(),annot = True)
```

Out[42]:

<AxesSubplot:>



In [43]:

```
#the predictor variable such as crime, INDUS-proportion of non retail business acro
#(parts per 10 million),Age, RAD -index of accessibility to radial highways, tax, P
# LSTAT -% lower status of the population have a negative correlation on the target
#leads to the decrease in the price of the housing

#the predictor variable such as ZN-proportion of residential land zoned for lots ov
#, RM-average number of rooms per dwelling , DIS - weighted distances to five Bosto
# B - 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town, all these var
#with the target. increase in any of the bove variables leads to the increase in th
```

In [44]:

```
#to perform the train test split of the data, the train test split function is impo
from sklearn.model_selection import train_test_split
```

In [45]:

```
#the percentage of the split is taken as 30%. SO the percentage of training is 70%
X_train, X_test, y_train, y_test = train_test_split(dfx, dfy, test_size=0.3, random_
```

In [46]:

```
#the given problem is a classificaton problem. Hence linear regression is used for 
from sklearn.linear_model import LinearRegression
```

In [47]:

```
linR = LinearRegression()
```

In [48]:

```
linR.fit(X_train, y_train)
```

Out[48]:

```
LinearRegression()
```

In [49]:

```
#the target is predicted for the test dataset
predictions = linR.predict(X_test)
```

In [50]:

```
#the accuracy of the prediction is found to be 71%
linR.score(X_test,y_test)
```

Out[50]:

```
0.711226005748496
```

In [51]:

```
error = y_test - predictions
```

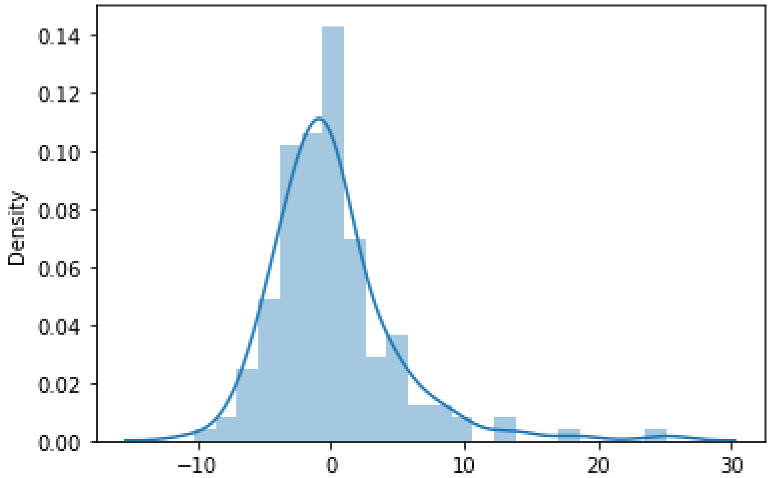
In [52]:

```
#the error is calculated for the above test predictions and a distribution plot is 
sns.distplot(error)
```

```
/home/nuke/anaconda3/lib/python3.9/site-packages/seaborn/distribution
s.py:2619: FutureWarning: `distplot` is a deprecated function and will
be removed in a future version. Please adapt your code to use either `
displot` (a figure-level function with similar flexibility) or `histpl
ot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[52]:

```
<AxesSubplot:ylabel='Density'>
```



In [53]:

```
dfx.shape
```

Out[53]:

(506, 13)

In [54]:

```
oness = np.ones((506,1),dtype = int)
dfone = pd.DataFrame(oness, columns = ['ones'])
```

In [55]:

```
dfxnew = dfone.join(dfx)
```

In [56]:

```
dfxnew.head()
```

Out[56]:

	ones	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	
0	1	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396
1	1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396
2	1	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2.0	242.0	17.8	392
3	1	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3.0	222.0	18.7	394
4	1	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3.0	222.0	18.7	396

In [62]:

```
import statsmodels.api as sm

#OrdinaryLeastSquares
```

In [63]:

```
lir_ols = sm.OLS(endog= dfy, exog = dfxnew).fit()
```

In [64]:

```
lir_ols.summary()
```

Out[64]:

OLS Regression Results

Dep. Variable:	target	**R-squared:**	0.741
Model:	OLS	**Adj. R-squared:**	0.734
Method:	Least Squares	**F-statistic:**	108.1
Date:	Tue, 26 Apr 2022	**Prob (F-statistic):**	6.72e-135
Time:	16:13:46	**Log-Likelihood:**	-1498.8
No. Observations:	506	**AIC:**	3026.
Df Residuals:	492	**BIC:**	3085.
Df Model:	13		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
ones	36.4595	5.103	7.144	0.000	26.432	46.487
CRIM	-0.1080	0.033	-3.287	0.001	-0.173	-0.043
ZN	0.0464	0.014	3.382	0.001	0.019	0.073
INDUS	0.0206	0.061	0.334	0.738	-0.100	0.141
CHAS	2.6867	0.862	3.118	0.002	0.994	4.380
NOX	-17.7666	3.820	-4.651	0.000	-25.272	-10.262
RM	3.8099	0.418	9.116	0.000	2.989	4.631
AGE	0.0007	0.013	0.052	0.958	-0.025	0.027
DIS	-1.4756	0.199	-7.398	0.000	-1.867	-1.084
RAD	0.3060	0.066	4.613	0.000	0.176	0.436
TAX	-0.0123	0.004	-3.280	0.001	-0.020	-0.005
PTRATIO	-0.9527	0.131	-7.283	0.000	-1.210	-0.696
B	0.0093	0.003	3.467	0.001	0.004	0.015
LSTAT	-0.5248	0.051	-10.347	0.000	-0.624	-0.425

Omnibus:	178.041	**Durbin-Watson:**	1.078
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	783.126
Skew:	1.521	**Prob(JB):**	8.84e-171
Kurtosis:	8.281	**Cond. No.**	1.51e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.51e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

From the statsmodels the p valuue, R value and F-value has been calculated. Considering the p-value 0.05, eliminate features which has p value more than 0.05. INDUS, AGE are those with high p-values. Which means these features are not significant in affecting the target

In [65]:

```
dfx2 = dfxnew.drop(['INDUS','AGE'], axis = 1)
```

In [66]:

```
lir_ols = sm.OLS(endog= dfy, exog = dfx2).fit()
```

In [67]:

```
lir_ols.summary()
```

Out[67]:

OLS Regression Results

Dep. Variable:	target	**R-squared:**	0.741
Model:	OLS	**Adj. R-squared:**	0.735
Method:	Least Squares	**F-statistic:**	128.2
Date:	Tue, 26 Apr 2022	**Prob (F-statistic):**	5.54e-137
Time:	16:13:53	**Log-Likelihood:**	-1498.9
No. Observations:	506	**AIC:**	3022.
Df Residuals:	494	**BIC:**	3072.
Df Model:	11		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
ones	36.3411	5.067	7.171	0.000	26.385	46.298
CRIM	-0.1084	0.033	-3.307	0.001	-0.173	-0.044
ZN	0.0458	0.014	3.390	0.001	0.019	0.072
CHAS	2.7187	0.854	3.183	0.002	1.040	4.397
NOX	-17.3760	3.535	-4.915	0.000	-24.322	-10.430
RM	3.8016	0.406	9.356	0.000	3.003	4.600
DIS	-1.4927	0.186	-8.037	0.000	-1.858	-1.128
RAD	0.2996	0.063	4.726	0.000	0.175	0.424
TAX	-0.0118	0.003	-3.493	0.001	-0.018	-0.005
PTRATIO	-0.9465	0.129	-7.334	0.000	-1.200	-0.693
B	0.0093	0.003	3.475	0.001	0.004	0.015
LSTAT	-0.5226	0.047	-11.019	0.000	-0.616	-0.429

Omnibus:	178.430	**Durbin-Watson:**	1.078
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	787.785
Skew:	1.523	**Prob(JB):**	8.60e-172
Kurtosis:	8.300	**Cond. No.**	1.47e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.47e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

In [ ]: