In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_boston
```

In [2]:

```
ds=load_boston()
```

```
In [3]:
```

```
ds
```

```
Out[3]:
```

```
{'data': array([[6.3200e-03, 1.8000e+01, 2.3100e+00, ..., 1.5300e+01, 3.96
90e+02,
         4.9800e+00],
        [2.7310e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9690e+02,
         9.1400e+00],
        [2.7290e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9283e+02,
         4.0300e+00],
        ...,
        [6.0760e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
         5.6400e+00],
        [1.0959e-01, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9345e+02,
         6.4800e+00],
        [4.7410e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
         7.8800e+00]]),
 'target': array([24. , 21.6, 34.7, 33.4, 36.2, 28.7, 22.9, 27.1, 16.5, 1
8.9, 15. ,
        18.9, 21.7, 20.4, 18.2, 19.9, 23.1, 17.5, 20.2, 18.2, 13.6, 19.6,
        15.2, 14.5, 15.6, 13.9, 16.6, 14.8, 18.4, 21. , 12.7, 14.5, 13.2,
        13.1, 13.5, 18.9, 20. , 21. , 24.7, 30.8, 34.9, 26.6, 25.3, 24.7,
        21.2, 19.3, 20. , 16.6, 14.4, 19.4, 19.7, 20.5, 25. , 23.4, 18.9,
        35.4, 24.7, 31.6, 23.3, 19.6, 18.7, 16. , 22.2, 25. , 33. , 23.5,
        19.4, 22. , 17.4, 20.9, 24.2, 21.7, 22.8, 23.4, 24.1, 21.4, 20. ,
        20.8, 21.2, 20.3, 28. , 23.9, 24.8, 22.9, 23.9, 26.6, 22.5, 22.2,
        23.6, 28.7, 22.6, 22. , 22.9, 25. , 20.6, 28.4, 21.4, 38.7, 43.8,
        33.2, 27.5, 26.5, 18.6, 19.3, 20.1, 19.5, 19.5, 20.4, 19.8, 19.4,
        21.7, 22.8, 18.8, 18.7, 18.5, 18.3, 21.2, 19.2, 20.4, 19.3, 22. ,
        20.3, 20.5, 17.3, 18.8, 21.4, 15.7, 16.2, 18. , 14.3, 19.2, 19.6,
        23. , 18.4, 15.6, 18.1, 17.4, 17.1, 13.3, 17.8, 14. , 14.4, 13.4,
        15.6, 11.8, 13.8, 15.6, 14.6, 17.8, 15.4, 21.5, 19.6, 15.3, 19.4,
        17. , 15.6, 13.1, 41.3, 24.3, 23.3, 27. , 50. , 50. , 50. , 22.7,
        25. , 50. , 23.8, 23.8, 22.3, 17.4, 19.1, 23.1, 23.6, 22.6, 29.4,
        23.2, 24.6, 29.9, 37.2, 39.8, 36.2, 37.9, 32.5, 26.4, 29.6, 50. ,
        32. , 29.8, 34.9, 37. , 30.5, 36.4, 31.1, 29.1, 50. , 33.3, 30.3,
        34.6, 34.9, 32.9, 24.1, 42.3, 48.5, 50. , 22.6, 24.4, 22.5, 24.4,
        20. , 21.7, 19.3, 22.4, 28.1, 23.7, 25. , 23.3, 28.7, 21.5, 23. ,
        26.7, 21.7, 27.5, 30.1, 44.8, 50. , 37.6, 31.6, 46.7, 31.5, 24.3,
        31.7, 41.7, 48.3, 29. , 24. , 25.1, 31.5, 23.7, 23.3, 22. , 20.1,
        22.2, 23.7, 17.6, 18.5, 24.3, 20.5, 24.5, 26.2, 24.4, 24.8, 29.6,
        42.8, 21.9, 20.9, 44. , 50. , 36. , 30.1, 33.8, 43.1, 48.8, 31. ,
        36.5, 22.8, 30.7, 50. , 43.5, 20.7, 21.1, 25.2, 24.4, 35.2, 32.4,
        32. , 33.2, 33.1, 29.1, 35.1, 45.4, 35.4, 46. , 50. , 32.2, 22. ,
        20.1, 23.2, 22.3, 24.8, 28.5, 37.3, 27.9, 23.9, 21.7, 28.6, 27.1,
        20.3, 22.5, 29. , 24.8, 22. , 26.4, 33.1, 36.1, 28.4, 33.4, 28.2,
        22.8, 20.3, 16.1, 22.1, 19.4, 21.6, 23.8, 16.2, 17.8, 19.8, 23.1,
        21. , 23.8, 23.1, 20.4, 18.5, 25. , 24.6, 23. , 22.2, 19.3, 22.6,
        19.8, 17.1, 19.4, 22.2, 20.7, 21.1, 19.5, 18.5, 20.6, 19. , 18.7,
        32.7, 16.5, 23.9, 31.2, 17.5, 17.2, 23.1, 24.5, 26.6, 22.9, 24.1,
        18.6, 30.1, 18.2, 20.6, 17.8, 21.7, 22.7, 22.6, 25. , 19.9, 20.8,
        16.8, 21.9, 27.5, 21.9, 23.1, 50. , 50. , 50. , 50. , 50. , 13.8,
        13.8, 15. , 13.9, 13.3, 13.1, 10.2, 10.4, 10.9, 11.3, 12.3,  8.8,
         7.2, 10.5,  7.4, 10.2, 11.5, 15.1, 23.2,  9.7, 13.8, 12.7, 13.1,
        12.5,  8.5,  5. ,  6.3,  5.6,  7.2, 12.1,  8.3,  8.5,  5. , 11.9,
        27.9, 17.2, 27.5, 15. , 17.2, 17.9, 16.3,  7. ,  7.2,  7.5, 10.4,
         8.8,  8.4, 16.7, 14.2, 20.8, 13.4, 11.7,  8.3, 10.2, 10.9, 11. ,
         9.5, 14.5, 14.1, 16.1, 14.3, 11.7, 13.4,  9.6,  8.7,  8.4, 12.8,
        10.5, 17.1, 18.4, 15.4, 10.8, 11.8, 14.9, 12.6, 14.1, 13. , 13.4,
        15.2, 16.1, 17.8, 14.9, 14.1, 12.7, 13.5, 14.9, 20. , 16.4, 17.7,
        19.5, 20.2, 21.4, 19.9, 19. , 19.1, 19.1, 20.1, 19.9, 19.6, 23.2,
        29.8, 13.8, 13.3, 16.7, 12. , 14.6, 21.4, 23. , 23.7, 25. , 21.8,
        20.6, 21.2, 19.1, 20.6, 15.2,  7. ,  8.1, 13.6, 20.1, 21.8, 24.5,
        23.1, 19.7, 18.3, 21.2, 17.5, 16.8, 22.4, 20.6, 23.9, 22. , 11.
9]),
 'feature_names': array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AG
E', 'DIS', 'RAD',
        'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7'),
 'DESCR': ".. _boston_dataset:\n\nBoston house prices dataset\n-----------
----------------\n\n**Data Set Characteristics:**  \n\n    :Number of Inst
ances: 506 \n\n    :Number of Attributes: 13 numeric/categorical predictiv
e. Median Value (attribute 14) is usually the target.\n\n    :Attribute In
formation (in order):\n        - CRIM     per capita crime rate by town\n
- ZN       proportion of residential land zoned for lots over 25,000 sq.f
t.\n        - INDUS    proportion of non-retail business acres per town\n
- CHAS     Charles River dummy variable (= 1 if tract bounds river; 0 othe
rwise)\n        - NOX      nitric oxides concentration (parts per 10 milli
on)\n        - RM       average number of rooms per dwelling\n        - AG
E      proportion of owner-occupied units built prior to 1940\n        - D
IS      weighted distances to five Boston employment centres\n        - RA
D      index of accessibility to radial highways\n        - TAX      full-
value property-tax rate per $10,000\n        - PTRATIO  pupil-teacher rati
o by town\n        - B        1000(Bk - 0.63)^2 where Bk is the proportion
of blacks by town\n        - LSTAT    % lower status of the population\n
- MEDV     Median value of owner-occupied homes in $1000's\n\n    :Missing
Attribute Values: None\n\n    :Creator: Harrison, D. and Rubinfeld, D.L.\n
\nThis is a copy of UCI ML housing dataset.\nhttps://archive.ics.uci.edu/m
l/machine-learning-databases/housing/\n\n\nThis dataset was taken from the
StatLib library which is maintained at Carnegie Mellon University.\n\nThe
Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic\npric
es and the demand for clean air', J. Environ. Economics & Management,\nvo
l.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostic
s\n...', Wiley, 1980.   N.B. Various transformations are used in the table
on\npages 244-261 of the latter.\n\nThe Boston house-price data has been u
sed in many machine learning papers that address regression\nproblems.
\n     \n.. topic:: References\n\n   - Belsley, Kuh & Welsch, 'Regression
diagnostics: Identifying Influential Data and Sources of Collinearity', Wi
ley, 1980. 244-261.\n   - Quinlan,R. (1993). Combining Instance-Based and
Model-Based Learning. In Proceedings on the Tenth International Conference
of Machine Learning, 236-243, University of Massachusetts, Amherst. Morgan
Kaufmann.\n",
 'filename': 'C:\\Users\\fambareen\\Anaconda3\\lib\\site-packages\\sklearn
\\datasets\\data\\boston_house_prices.csv'}
```

In [ ]:

```
```

In [4]:

```
ds_1 = pd.DataFrame(ds.data)
```

In [41]:

```
ds_1
```

Out[41]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
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	4.98
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	9.14
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	4.03
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	2.94
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	5.33
...	...	...	...	...	...	...	...	...	...	...	...	...	...
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	391.99	9.67
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0	396.90	9.08
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	396.90	5.64
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	393.45	6.48
505	0.04741	0.0	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0	396.90	7.88

506 rows × 13 columns

In [4]:

```
ds_1.head()
```

Out[4]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
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	4.98
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	9.14
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	4.03
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	2.94
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	5.33

In [43]:

```
ds_1.keys()
```

Out[43]:

```
RangeIndex(start=0, stop=13, step=1)
```

In [31]:

```
print(ds_1.keys())
```

```
RangeIndex(start=0, stop=13, step=1)
```

In [5]:

```
ds_1.columns= ds.feature_names
```

In [45]:

```
ds_1.head()
```

Out[45]:

	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	4
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	9
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	4
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	2
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	5

In [6]:

```
ds_1["Price"]=ds.target
```

In [47]:

```
ds_1.head()
```

Out[47]:

	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	4
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	9
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	4
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	2
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	5

In [7]:

```
X=ds_1.iloc[:, :-1]
y=ds_1.iloc[:, -1]
```

In [8]:

```
X
```

Out[8]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B
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
...	...	...	...	...	...	...	...	...	...	...	...	...
501	0.06263	0.0	11.93	0.0	0.573	6.593	69.1	2.4786	1.0	273.0	21.0	391.99
502	0.04527	0.0	11.93	0.0	0.573	6.120	76.7	2.2875	1.0	273.0	21.0	396.90
503	0.06076	0.0	11.93	0.0	0.573	6.976	91.0	2.1675	1.0	273.0	21.0	396.90
504	0.10959	0.0	11.93	0.0	0.573	6.794	89.3	2.3889	1.0	273.0	21.0	393.45
505	0.04741	0.0	11.93	0.0	0.573	6.030	80.8	2.5050	1.0	273.0	21.0	396.90

506 rows × 13 columns

In [9]:

```
y
```

Out[9]:

```
0      24.0
1      21.6
2      34.7
3      33.4
4      36.2
       ...
501    22.4
502    20.6
503    23.9
504    22.0
505    11.9
Name: Price, Length: 506, dtype: float64
```

In [49]:

```
#Linear Regression
from sklearn.model_selection import cross_val_score
from sklearn.linear_model  import LinearRegression
```

In [50]:

```
lr = LinearRegression()
```

In [51]:

```
#Mean Square Error
mse=cross_val_score(lr, X,y, scoring='neg_mean_squared_error', cv=5)
```

In [52]:

```
mse
```

Out[52]:

```
array([-12.46030057, -26.04862111, -33.07413798, -80.76237112,
       -33.31360656])
```

In [14]:

```
mean_mse= np.mean(mse)
```

In [15]:

```
mean_mse
```

Out[15]:

```
-37.13180746769922
```

In [16]:

```
#Ridge Regression
from sklearn.linear_model import Ridge
from sklearn.model_selection import GridSearchCV
r=Ridge()
```

In [17]:

```
parameters={'alpha':[1e-15, 1e-10, 1e-8, 1e-3, 1e-2, 1,5,10,20,30,35,40,45,50,55,100]}
ridge_regressor=GridSearchCV(r,parameters,scoring='neg_mean_squared_error',cv=5)
```

In [18]:

```
ridge_regressor.fit(X,y)
```

Out[18]:

```
GridSearchCV(cv=5, estimator=Ridge(),
             param_grid={'alpha': [1e-15, 1e-10, 1e-08, 0.001, 0.01, 1, 5, 1
0,
                                   20, 30, 35, 40, 45, 50, 55, 100]},
             scoring='neg_mean_squared_error')
```

In [19]:

```
ridge_regressor.best_params_
```

Out[19]:

```
{'alpha': 100}
```

In [20]:

```
ridge_regressor.best_score_
```

Out[20]:

```
-29.905701947540372
```

In [21]:

```
#Lasso Regression
from sklearn.linear_model import Lasso
from sklearn.model_selection import GridSearchCV
ls =Lasso()
```

In [25]:

```
parameters ={'alpha' :[1e-15, 1e-10, 1e-8, 1e-3, 1e-2, 1,5,10,20,30,35,40,45,50,55,100]}
ls.fit(X,y)
```

Out[25]:

```
Lasso()
```

In [39]:

```
coef = print(ls.sparse_coef_)
```

```
  (0, 0)	-0.06343729004514066
  (0, 1)	0.04916466550764739
  (0, 5)	0.9498106999845143
  (0, 6)	0.020909514944737546
  (0, 7)	-0.6687900023707882
  (0, 8)	0.26420643097453383
  (0, 9)	-0.015211589791634 73
  (0, 10)	-0.7229663585199505
  (0, 11)	0.008247033485494 21
  (0, 12)	-0.7611145367697878
```

In [31]:

```
print(ls.score)
```

```
<bound method RegressorMixin.score of Lasso()>
```

In [40]:

```
ls.get_params
```

Out[40]:

```
<bound method BaseEstimator.get_params of Lasso()>
```

In [45]:

```
#Train test split
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test =train_test_split(X,y, test_size=0.3, random_state=0)
```

In [60]:

```
predict_lasso = ls.predict(X_test)
```

In [56]:

```

```

In [61]:

```
predict_Ridge = ridge_regressor.predict(X_test)
```

In [62]:

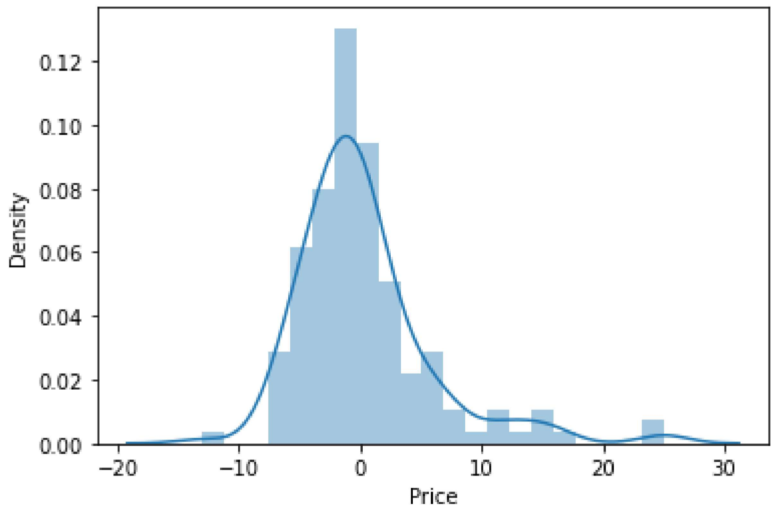
```
import seaborn as sns
```

In [66]:

```
plt = sns.distplot(y_test-predict_lasso)
plt.show()
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-66-7ecd39d605b0> in <module>
      1 plt = sns.distplot(y_test-predict_lasso)
----> 2 plt.show()

AttributeError: 'AxesSubplot' object has no attribute 'show'
```



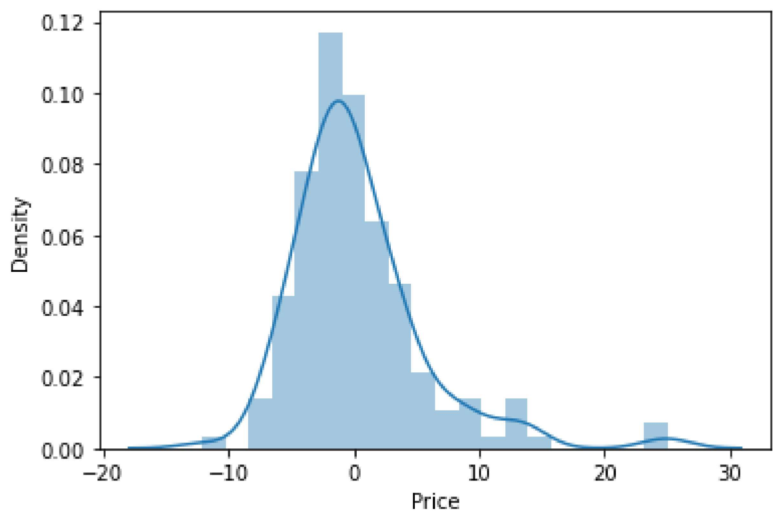
In [67]:

```
import seaborn as sns
sns.distplot(y_test-predict_Ridge)
```

```
C:\Users\fambareen\Anaconda3\lib\site-packages\seaborn\distributions.py:255
1: FutureWarning: `distplot` is a deprecated function and will be removed in
a future version. Please adapt your code to use either `displot` (a figure-l
evel function with similar flexibility) or `histplot` (an axes-level functio
n for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[67]:

```
<AxesSubplot:xlabel='Price', ylabel='Density'>
```



In [ ]: