In [112]:

```
import warnings
warnings.filterwarnings("ignore")
from sklearn.datasets import load_boston
from random import seed
from random import randrange
from csv import reader
from math import sqrt
from sklearn import preprocessing
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from prettytable import PrettyTable
from sklearn.linear_model import SGDRegressor
from sklearn import preprocessing
from sklearn.metrics import mean_squared_error
```

In [113]:

```
A = load_boston()
X = load_boston().data
Y = load_boston().target
```

In [114]:

```
A.keys()
```

Out[114]:

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

In [115]:

```python
print(A.DESCR)
```

```
.. _boston_dataset:

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

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Value
(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 25,0
00 sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds rive
r; 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 1940
        - DIS      weighted distances to five Boston employment centres
        - 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 blacks
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/


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

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnost
ics
...', Wiley, 1980.   N.B. Various transformations are used in the table on
pages 244-261 of the latter.

The Boston house-price data has been used in many machine learning papers
that address regression
problems.

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influenti
al Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - 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.
```

In [116]:

```
data = pd.DataFrame(X)
#Assigning feature-names to colums of data frame
data.columns = A.feature_names
data.head()
```

Out[116]:

	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

In [117]:

```
#Adding the target column Price to the data frame
data['Price'] = Y
data.head()
```

Out[117]:

	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

In [118]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   CRIM     506 non-null    float64
 1   ZN       506 non-null    float64
 2   INDUS    506 non-null    float64
 3   CHAS     506 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      506 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    float64
 9   TAX      506 non-null    float64
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    506 non-null    float64
 13  Price    506 non-null    float64
dtypes: float64(14)
memory usage: 55.5 KB
```

In [119]:

```
data.describe()
```

Out[119]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000

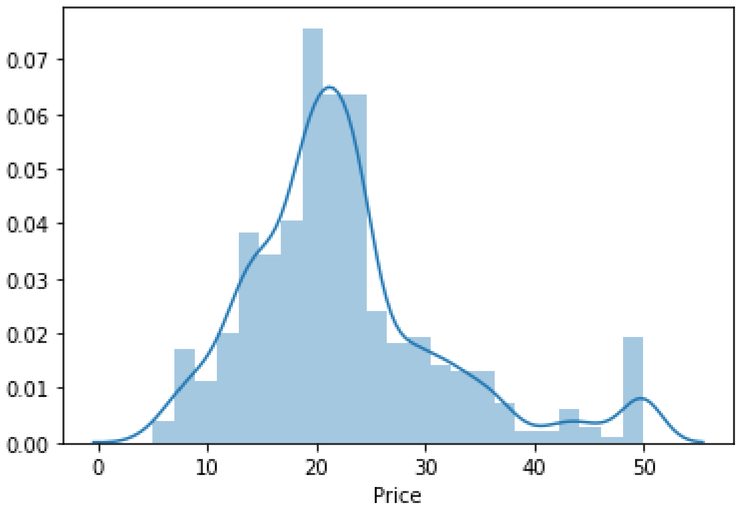
Plotting on the boston housing data set

In [120]:

```
sns.distplot(data['Price'])
```

Out[120]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x223ae05fe88>
```



In [121]:

```
#Splitting whole data into train and test

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=3)

# applying column standardization on train and test data

scaler = preprocessing.StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test=scaler.transform(X_test)

df_train=pd.DataFrame(X_train)
df_train['Price']=y_train
df_train.head()
```

Out[121]:

	0	1	2	3	4	5	6	7	
0	0.062687	-0.476211	1.024013	-0.281546	1.862698	-0.243926	0.472420	-0.611027	1.6
1	1.614536	-0.476211	1.024013	-0.281546	0.983540	-3.128541	1.143780	-1.262686	1.6
2	-0.392880	-0.476211	-1.206774	-0.281546	-0.938540	2.251982	-1.121610	-0.142692	-0.8
3	-0.377619	0.431835	-0.609844	3.551814	-0.774775	2.063473	-0.586677	0.271119	-0.7
4	-0.394475	-0.476211	-1.155441	-0.281546	-0.809252	0.079022	-1.828872	0.673913	-0.6

In [132]:

```
#Custom function for SGD

# Data Sampling reference : https://statinfer.com/104-3-1-data-sampling-in-python/


def Custom_SGD(data,stepsize,n_iterations,k):

    r = stepsize
    w , b = np.zeros(shape=(1,13)) , 0

    for i in range(0,n_iterations):

        d = data.sample(k)

        y=np.array(d['Price'])
        x=np.array(d.drop('Price',axis=1))

        w1 , b1 = np.zeros(shape=(1,13)), 0

        for j in range(k):

            w1 = w1 + (-2)*x[j]*(y[j]-(np.dot(w,x[j])+b))
            b1 = b1 + (-2)*(y[j]-(np.dot(w,x[j])+b))

        w = (w - r * (w1/k))
        b = (b - r * (b1/k))

        #r=r/2

    print(w)
    print(b)
    return w,b
```

In [123]:

```
w,b = Custom_SGD(df_train,1,100,20)
```

```
[[ 13.64189485   5.46896198  -4.50078501   2.84367127 -14.03093828
   18.51957488   9.77737059   4.93121118   4.09254251   1.68075172
   12.34277982 -16.23023763  -5.8219613 ]]
[17.32384135]
```

In [124]:

```
#prediction on x_test
# Reference for numpy as scalar : https://www.geeksforgeeks.org/numpy-asscalar-in-pytho
n/

y_pred=[]

for i in range(len(X_test)):

    val=np.dot(w,X_test[i])+b  #val= wTx+b

    y_pred.append(np.asscalar(val))
```

In [125]:

```
#Scatter plot of actual price vs predicted price

plt.scatter(y_test,y_pred)
plt.xlabel('Actual price')
plt.ylabel('Predictd price')
plt.title('Actual price vs Predicted price')
plt.show()
```

In [158]:

```
MSE_1=mean_squared_error(y_test,y_pred)
print('mean squared error =',MSE_1)
```

```
mean squared error = 976.1616968737734
```

Trying with different parameter values in custom SGD

Model 2

In [127]:

```
w2,b2 = Custom_SGD(df_train,1,400,25)
```

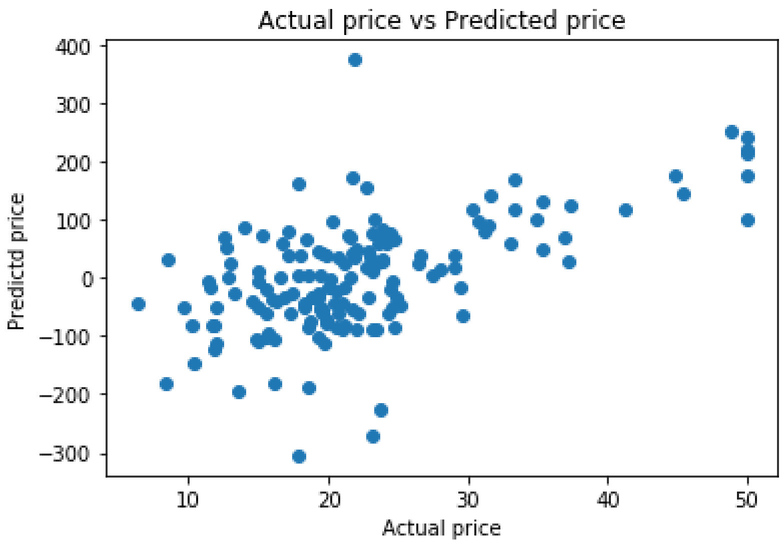
```
[[ 28.77978703  29.98667992  13.70710378  25.13581497  11.05078756
   61.3726718   22.91756199  -1.18272017   4.07524358  11.40748835
  -11.00286476  51.31245485 -19.22053076]]
[0.85227994]
```

In [129]:

```
#prediction on x_test
# Reference for numpy as scalar : https://www.geeksforgeeks.org/numpy-asscalar-in-pytho
n/

y_pred_2=[]

for i in range(len(X_test)):

    val=np.dot(w2,X_test[i])+b2  #val= wTx+b

    y_pred_2.append(np.asscalar(val))
```

In [130]:

```
#Scatter plot of actual price vs predicted price

plt.scatter(y_test,y_pred_2)
plt.xlabel('Actual price')
plt.ylabel('Predictd price')
plt.title('Actual price vs Predicted price')
plt.show()
```



In [148]:

```
MSE_2=mean_squared_error(y_test,y_pred_2)
print('mean squared error =',MSE_2)
```

```
mean squared error = 9173.138607410328
```

Model 3

When R(stepsize/Learning rate) is constant we are able to see low error

In [133]:

```
w3,b3 = Custom_SGD(df_train,0.01,800,30)
```

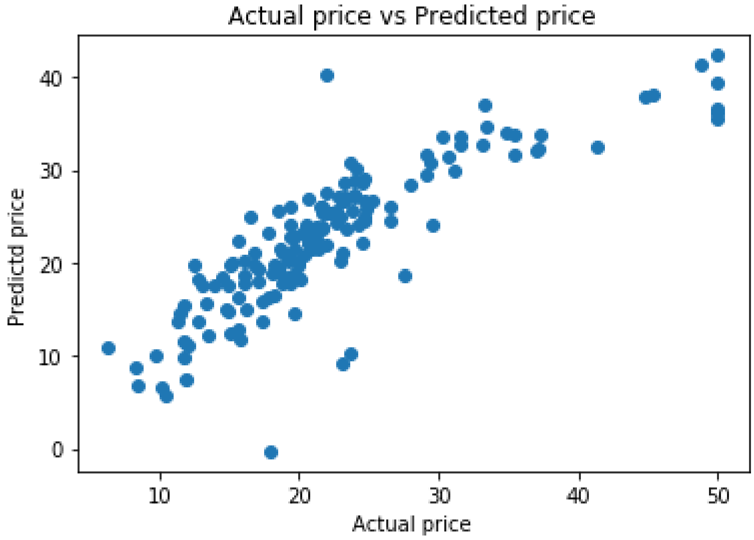
```
[[-1.17675394e+00  9.03298492e-01 -5.78189077e-01  1.24875673e+00
  -1.21827941e+00  2.69109997e+00  7.47084791e-04 -2.36305980e+00
   1.70187392e+00 -6.85670219e-01 -1.95490543e+00  1.16832279e+00
  -3.69279217e+00]]
[22.74554409]
```

In [134]:

```
#prediction on x_test
# Reference for numpy as scalar : https://www.geeksforgeeks.org/numpy-asscalar-in-pytho
n/

y_pred_3=[]

for i in range(len(X_test)):

    val=np.dot(w3,X_test[i])+b3  #val= wTx+b

    y_pred_3.append(np.asscalar(val))
```

In [135]:

```
#Scatter plot of actual price vs predicted price

plt.scatter(y_test,y_pred_3)
plt.xlabel('Actual price')
plt.ylabel('Predictd price')
plt.title('Actual price vs Predicted price')
plt.show()
```



In [149]:

```
MSE_3=mean_squared_error(y_test,y_pred_3)
print('mean squared error =',MSE_3)
```

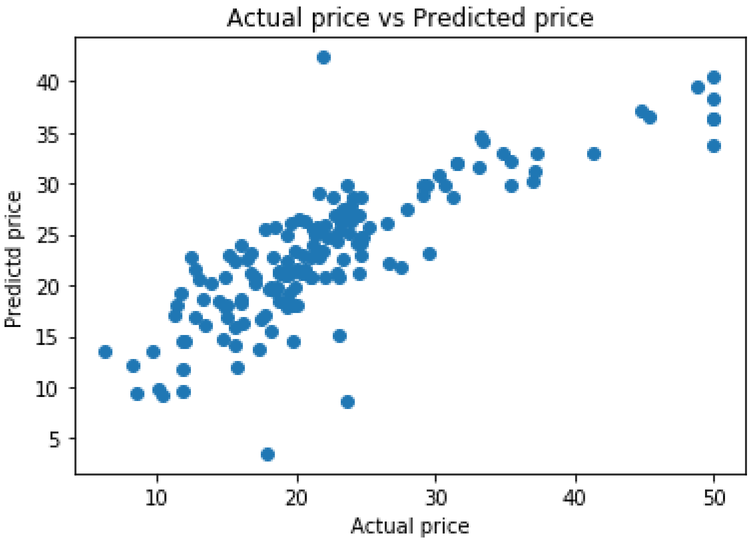
```
mean squared error = 23.185837117659656
```

In [140]:

```
#SGD regression sklearn implementation

LR =SGDRegressor(learning_rate='constant',penalty=None,max_iter=100)
LR.fit(X_train,y_train)
y_pred_sgd=LR.predict(X_test)
```

In [141]:

```
#Scatter plot of actual price vs predicted price

plt.scatter(y_test,y_pred_sgd)
plt.xlabel('Actual price')
plt.ylabel('Predictd price')
plt.title('Actual price vs Predicted price')
plt.show()
```



In [142]:

```
MSE_lr=mean_squared_error(y_test,y_pred_sgd)
print('mean squared error =',MSE_lr)
```

```
mean squared error = 26.897098413583674
```

In [145]:

```
from prettytable import PrettyTable

pt = PrettyTable()
pt.field_names=['Weight_custom_SGD ','Weight_sklearn_SGD']

weight_sgd=LR.coef_
for i in range(13):
    pt.add_row([w[0][i],weight_sgd[i]])
print(pt)
```

```
+--------------------+---------------------+
|  Weight_custom_SGD  |  Weight_sklearn_SGD  |
+--------------------+---------------------+
|  13.641894852414767 | -1.2907264860048555  |
|  5.468961980326554  |  1.0745731947801327  |
|  -4.500785013661613 | -0.20019601672410214 |
|  2.8436712737018475 |  1.2008571022301076  |
|  -14.03093828140941 | -1.3310653335268143  |
|  18.519574878008658 |  2.1864383617609713  |
|  9.777370590575368  | 0.31596517537045643  |
|  4.931211177611487  | -2.8380250422948268  |
|  4.092542508197102  |  3.021292909131984   |
|  1.680751723142019  |  -0.719226272778815  |
|  12.342779821634979 | -1.6899433204167493  |
| -16.230237630069563 |  1.0023769950687802  |
|  -5.821961297405411 |  -4.237564588141838  |
+--------------------+---------------------+
```

In [159]:

```
from prettytable import PrettyTable

pt = PrettyTable()
pt.field_names=['SGD','MSE']
pt.add_row(['Custom 1',MSE_1])
pt.add_row(['Custom 2',MSE_2])
pt.add_row(['Custom 3 with constant R',MSE_3])
pt.add_row(['Standard SKlearn SGD',MSE_lr])
print(pt)
```

```
+--------------------------+--------------------+
|           SGD            |        MSE         |
+--------------------------+--------------------+
|         Custom 1         | 976.1616968737734  |
|         Custom 2         | 9173.138607410328  |
| Custom 3 with constant R | 23.185837117659656 |
|   Standard SKlearn SGD   | 26.897098413583674 |
+--------------------------+--------------------+
```

Observations:

1. We Initially split the data and standardized the values in order to bring the values under same scale
2. Implemented a Custom SGD function for Linear Regression
3. Considering the necessary parameters build mutilple models to attain best MSE value
4. Changing the Iterations and batch size, we can observe a huge change in the MSE value
5. With constant R(stepsize/learning rate) and other parameters, we acquired a good MSE when compared to the actual standard SKlearn SGD

In [ ]:

```

```