In [1]:
```python
from sklearn.datasets import load_boston
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error
boston = load_boston()
```

In [2]:
```python
print(boston.data.shape)
```

```
(506, 13)
```

In [3]:
```python
print(boston.feature_names)
```

```
['CRIM' 'ZN' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATIO'
 'B' 'LSTAT']
```

In [4]:
```python
print(boston.target)
```

```
[24.  21.6 34.7 33.4 36.2 28.7 22.9 27.1 16.5 18.9 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]
```

In [5]:
```python
print(boston.DESCR)
```

```
Boston House Prices dataset
===========================

Notes
------
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 25,000 sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds river; 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.
http://archive.ics.uci.edu/ml/datasets/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. 'Hedonic
prices and the demand for clean air', J. Environ. Economics & Management,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagnostics
...', 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.

**References**

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influential Data and Sources of Collinearity', Wiley, 198
0. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings on the Tenth International Confe
rence of Machine Learning, 236-243, University of Massachusetts, Amherst. Morgan Kaufmann.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing)
```

In [6]:
```python
import pandas as pd

bos = pd.DataFrame(boston.data)
print(bos.head())
```

```
         0     1     2    3      4      5     6       7    8      9    10  \
0  0.00632  18.0  2.31  0.0  0.538  6.575  65.2  4.0900  1.0  296.0  15.3
1  0.02731   0.0  7.07  0.0  0.469  6.421  78.9  4.9671  2.0  242.0  17.8
2  0.02729   0.0  7.07  0.0  0.469  7.185  61.1  4.9671  2.0  242.0  17.8
3  0.03237   0.0  2.18  0.0  0.458  6.998  45.8  6.0622  3.0  222.0  18.7
4  0.06905   0.0  2.18  0.0  0.458  7.147  54.2  6.0622  3.0  222.0  18.7

       11    12
0  396.90  4.98
1  396.90  9.14
2  392.83  4.03
3  394.63  2.94
4  396.90  5.33
```

In [7]:
```python
bos['PRICE'] = boston.target
bos=bos.sample(506)
X = bos.drop('PRICE', axis = 1)
Y = bos['PRICE']
```

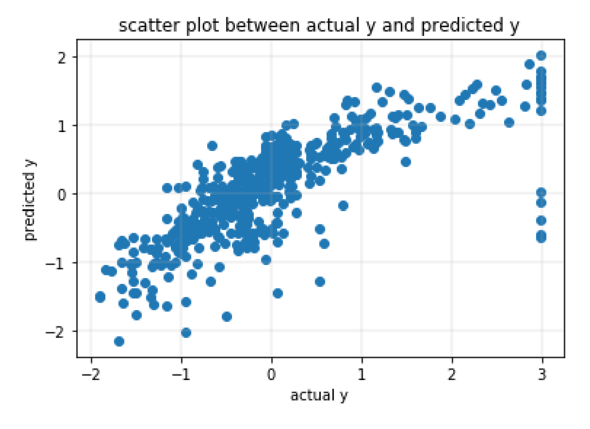
In [8]:
```python
print(bos.head())
```

```
           0     1      2    3      4      5      6       7     8      9  \
5    0.02985   0.0   2.18  0.0  0.458  6.430   58.7  6.0622   3.0  222.0
258  0.66351  20.0   3.97  0.0  0.647  7.333  100.0  1.8946   5.0  264.0
486  5.69175   0.0  18.10  0.0  0.583  6.114   79.8  3.5459  24.0  666.0
189  0.08370  45.0   3.44  0.0  0.437  7.185   38.9  4.5667   5.0  398.0
158  1.34284   0.0  19.58  0.0  0.605  6.066  100.0  1.7573   5.0  403.0

       10      11     12  PRICE
5    18.7  394.12   5.21   28.7
258  13.0  383.29   7.79   36.0
486  20.2  392.68  14.98   19.1
189  15.2  396.90   5.39   34.9
158  14.7  353.89   6.43   24.3
```

In [9]:
```python
# applying column standardization on train and test data
from sklearn.preprocessing import StandardScaler
s=StandardScaler()
X_data=s.fit_transform(np.array(X))
Y_data=s.fit_transform(np.array(Y).reshape(-1,1))
```

Applying manual SGD on Boston Dataset

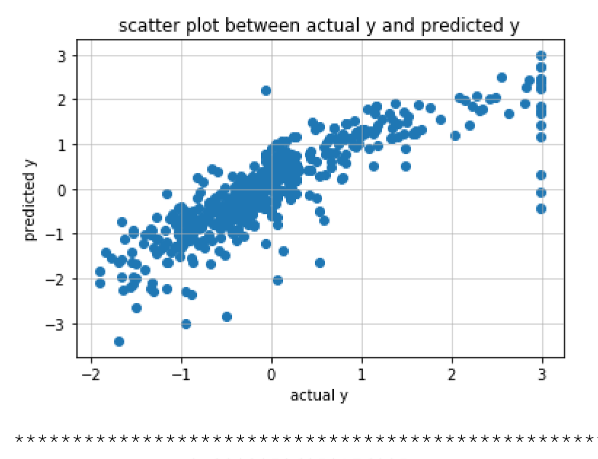
In [28]:
```python
wj_plus1=np.zeros(shape=(1,13))
bj_plus1=0
n=1
r=0.01
n_iter=1000
while(n<=n_iter):
    wj=wj_plus1
    bj=bj_plus1
    w_=np.zeros(shape=(1,13))
    b_=0


    for i in range(10):  # for getting the derivatives using sgd with k=10
            y_curr=np.dot(wj,X_data[i])+bj
            w_ = w_ + X_data[i] * (Y_data[i] - y_curr)
            b_ = b_ + (Y_data[i]-y_curr)

    wj_plus1=(wj-r*(w_ * (-2/X_data.shape[0])))
    bj_plus1=(bj-r*(b_ * (-2/X_data.shape[0])))
    n=n+1

y_pred=[]
for i in range(len(X_data)):
    y=np.asscalar(np.dot(wj_plus1,X_data[i])+bj_plus1)
    y_pred.append(y)


plt.scatter(Y_data,y_pred)
plt.grid(b=True, linewidth=0.3)
plt.title('scatter plot between actual y and predicted y')
plt.xlabel('actual y')
plt.ylabel('predicted y')
plt.show()
print('*************************************************************')



manual_error=mean_squared_error(Y_data,y_pred)
print('error=',manual_error)
```




```
*************************************************************
error= 0.3965411555102916
```

Applying sklearn SGD on boston dataset

In [34]:
```python
import seaborn as sns
import numpy as np
from sklearn.linear_model import SGDRegressor
max_iter=1
clf=SGDRegressor(alpha=0.0001, penalty=None, learning_rate='constant', eta0=0.01, power_t=0.25,max_iter=max_iter)
clf.fit(X_data, Y_data.ravel())
y_pred=clf.predict(X_data)

#scatter plot
plt.scatter(Y_data,y_pred)
plt.title('scatter plot between actual y and predicted y')
plt.xlabel('actual y')
plt.ylabel('predicted y')
plt.grid(b=True, linewidth=0.5)
plt.show()
print('*************************************************************')

#kdeplot


sgd_error=mean_squared_error(Y_data,y_pred)
print('mean sq error=', sgd_error)
print('Maximum number of iteration=', max_iter)
```




```
*************************************************************
mean sq error= 0.30988526850176085
Maximum number of iteration= 1
```

From both above manual and sklearn SGD implementations, we can observe that as we increase the number of iterations upto 1000 the error value comes close to sklearn SGD error.But after 1000 iterations, the manual SGD error increases as the number of iterations increases.

In [ ]:
```python
# code source:https://medium.com/@haydar_ai/learning-data-science-day-9-linear-regression-on-boston-housing-dataset-cd62a8077
5ef
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt

lm = LinearRegression()
lm.fit(X_train, Y_train)

Y_pred = lm.predict(X_test)

plt.scatter(Y_test, Y_pred)
plt.xlabel("Prices: $Y_i$")
plt.ylabel("Predicted prices: $\hat{Y}_i$")
plt.title("Prices vs Predicted prices: $Y_i$ vs $\hat{Y}_i$")
plt.show()
```

In [ ]:
```python
delta_y = Y_test - Y_pred;

import seaborn as sns;
import numpy as np;
sns.set_style('whitegrid')
sns.kdeplot(np.array(delta_y), bw=0.5)
plt.show()
```

In [ ]:
```python
sns.set_style('whitegrid')
sns.kdeplot(np.array(Y_pred), bw=0.5)
plt.show()
```

In [ ]:
```python
# Make a prediction with coefficients
def predict(row, coefficients):
    yhat = coefficients[0]
    for i in range(len(row)-1):
        yhat += coefficients[i + 1] * row[i]
    return yhat
```

In [ ]:
```python
# Estimate linear regression coefficients using stochastic gradient descent
def coefficients_sgd(train, l_rate, n_epoch):
    coef = [0.0 for i in range(len(train[0]))]
    for epoch in range(n_epoch):
        for row in train:
            yhat = predict(row, coef)
            error = yhat - row[-1]
            coef[0] = coef[0] - l_rate * error
            for i in range(len(row)-1):
                coef[i + 1] = coef[i + 1] - l_rate * error * row[i]
            # print(l_rate, n_epoch, error)
    return coef
```

In [ ]:
```python
# Linear Regression Algorithm With Stochastic Gradient Descent
def linear_regression_sgd(train, test, l_rate, n_epoch):
    predictions = list()
    coef = coefficients_sgd(train, l_rate, n_epoch)
    for row in test:
        yhat = predict(row, coef)
        predictions.append(yhat)
    return(predictions)
```