Linear Regression: SGD Implementation

In [1]:

```
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
from prettytable import PrettyTable
from sklearn.linear_model import SGDRegressor
from sklearn import preprocessing
from sklearn.metrics import mean_squared_error
```

In [2]:

```
from sklearn.datasets import load_boston
boston = load_boston()
```

In [3]:

```
print(boston.data.shape)
```

```
(506, 13)
```

In [4]:

```
print(boston.feature_names)
```

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

In [5]:

```
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 [6]:

```
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 C
ollinearity', Wiley, 1980. 244-261.
```

   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learning. In Proceedings on the T
enth International Conference of Machine Learning, 236-243, University of Massachusetts, Amherst.
Morgan Kaufmann.
   - many more! (see http://archive.ics.uci.edu/ml/datasets/Housing)

In [7]:

```
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 [8]:

```
bos['PRICE'] = boston.target
X = bos.drop('PRICE', axis = 1)
Y = bos['PRICE']
```

In [9]:

```
#converting to an array
X = np.asarray(X)
Y = np.asarray(Y)
```

In [10]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.33, random_state = 5)
print(X_train.shape)
print(X_test.shape)
print(Y_train.shape)
print(Y_test.shape)
```

```
(339, 13)
(167, 13)
(339,)
(167,)
```

In [11]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X_train,Y_train)
```

Out[11]:

```
StandardScaler(copy=True, with_mean=True, with_std=True)
```

In [12]:

```
X_train.shape
```

Out[12]:

```
(339, 13)
```

ciitation:#https://machinelearningmastery.com/implement-linear-regression-stochastic-gradient-descent-scratch-python/

citation: https://usermanual.wiki/Document/Stochastic20Gradient20Descent2

In [13]:

```
#Function to make prediction of y on given x
def predict_y(row, w,b):
    y_hat = b
    for i in range(len(row)):
        y_hat += w[i] * row[i]
    return y_hat
```

In [14]:

```
#SGD Function for Linear Regression

import random
def sgd(train,target, learning_rate, iterations, k):
    w = [0.0 for i in range(len(train[0]))]
    b = 0.0
    N = len(target)
    for iteration in range(iterations):
        sum_error = 0.0
        #Implementing SGD
        row_num = random.sample(range(len(train)),k)
        for i in row_num:
            row = train[i]
            row_target = target[i]
            y_hat = predict_y(row, w, b)
            error = y_hat - row_target
            sum_error += error**2
            b = b - learning_rate * error
            for i in range(len(row)):
                w[i] = w[i] - learning_rate * error * row[i]

        #learning_rate = learning_rate/2
    return w,b
```

In [15]:

```
learning_rate = 1e-6
iterations = 100000
k = 30
w,b = sgd(X_train,Y_train, learning_rate, iterations, k)
print("Wieghts")
print(w,b)
```

```
Wieghts
[-0.15972956564064322, 0.056374265488761628, -0.040405171042598602, 0.21118524249417914,
0.22810400103332118, 5.1374967587207845, -0.004222903829812062, -0.85800175666695355,
0.21244056317428303, -0.0053786497433178926, -0.30943798934764782, 0.016008929868734052, -0.438150
24732542096] 0.548974877268
```

In [16]:

```
from sklearn import linear_model
clf = linear_model.SGDRegressor(learning_rate='constant',eta0=1e-6,n_iter=100000)
clf.fit(X_train, Y_train)
w_= clf.coef_
#prediction of y on test data
pred = []
w = np.asarray(w)
b = b
for test_row in X_test:
```

```
for test_row in X_test:
    tmp = predict_y(test_row,w_,b)
    pred.append(tmp)
pred_ = np.asarray(pred)
pred_.shape
```

Out[16]:

```
(167,)
```

In [17]:

```
print('weights using sgd_regressor',w_)
```

```
weights using sgd_regressor [-0.16339922  0.04435468 -0.03911007  0.6806072   0.23837652  5.7479011
 -0.01501688 -0.98251324  0.22900914 -0.01580758 -0.50752325  0.01911708
 -0.38810629]
```

In [18]:

```
print('weights using manual sgd',w)
```

```
weights using manual sgd [ -1.59729566e-01   5.63742655e-02  -4.04051710e-02   2.11185242e-01
   2.28104001e-01   5.13749676e+00  -4.22290383e-03  -8.58001757e-01
   2.12440563e-01  -5.37864974e-03  -3.09437989e-01   1.60089299e-02
  -4.38150247e-01]
```

In [19]:

```
#prediction of y on test data
pred = []
w = np.asarray(w)
b = b
for test_row in X_test:
    tmp = predict_y(test_row,w,b)
    pred.append(tmp)
```

In [20]:

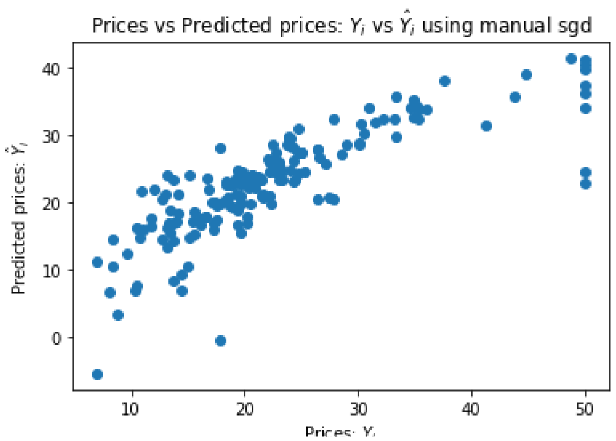
```
pred_t = np.asarray(pred)
pred_t.shape
```

Out[20]:

```
(167,)
```

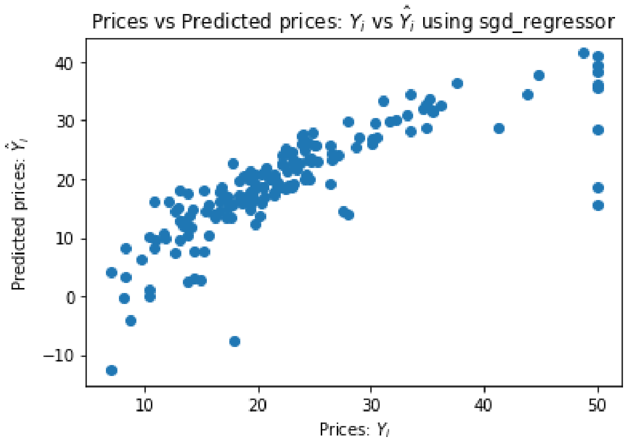
In [21]:

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



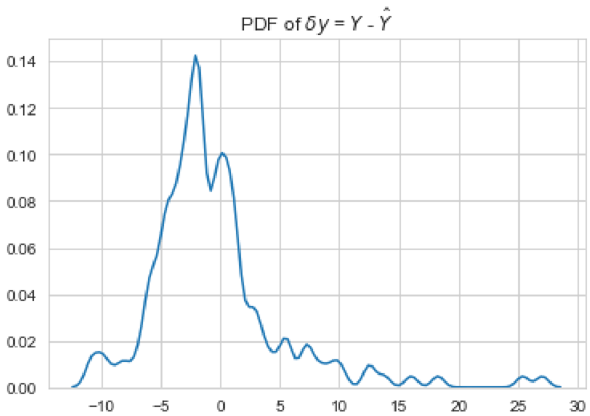
In [22]:

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



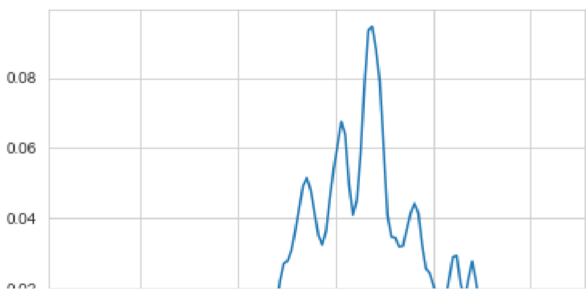
In [23]:

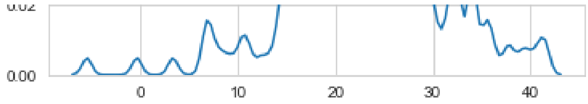
```
delta_y = Y_test - pred;

import seaborn as sns;
import numpy as np;
sns.set_style('whitegrid')
sns.kdeplot(np.array(delta_y), bw=0.5)
plt.title('PDF of $\delta{y}$ = ${Y}$ - $\hat{Y}$')
plt.show()
```



In [24]:

```
sns.set_style('whitegrid')
sns.kdeplot(np.array(pred), bw=0.5)
plt.show()
```





In [27]:

```
import sklearn
```

In [28]:

```
print("MEAN SQUARED ERROR:",sklearn.metrics.mean_squared_error(Y_test, pred))
```

```
MEAN SQUARED ERROR: 31.5771946339
```

In [29]:

```
print("MEDIAN ABSOLUTE ERROR:",sklearn.metrics.median_absolute_error(Y_test, pred))
```

```
MEDIAN ABSOLUTE ERROR: 2.70747473875
```

In [30]:

```
print("MEAN SQUARED ERROR:",sklearn.metrics.mean_squared_error(Y_test, pred_))
```

```
MEAN SQUARED ERROR: 42.9779721366
```

In [31]:

```
print("MEDIAN ABSOLUTE ERROR:",sklearn.metrics.median_absolute_error(Y_test, pred_))
```

```
MEDIAN ABSOLUTE ERROR: 2.33763654496
```

Observation:

1.From the above PDF we can observe that our model is good. 2.The MAE is approximately similar for both the models.