Custom SGD vs Sk-Learn SGD Using boston dataset

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
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from prettytable import PrettyTable
from sklearn.metrics import mean_squared_error
```

In [2]:

```
# loading boston datasets
from sklearn.datasets import load_boston
import pandas as pd
boston=load_boston()
print(boston.DESCR)
```

```
.. _boston_dataset:

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

**Data Set Characteristics:**

    :Number of Instances: 506

    :Number of Attributes: 13 numeric/categorical predictive. Median Va
lue (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 2
5,000 sq.ft.
        - INDUS    proportion of non-retail business acres per town
        - CHAS     Charles River dummy variable (= 1 if tract bounds ri
ver; 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 19
40
        - 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 blac
ks 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
Carnegie Mellon University.

The Boston house-price data of Harrison, D. and Rubinfeld, D.L. 'Hedoni
c
prices and the demand for clean air', J. Environ. Economics & Managemen
t,
vol.5, 81-102, 1978.   Used in Belsley, Kuh & Welsch, 'Regression diagn
ostics
...', 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 pape
rs that address regression
problems.

.. topic:: References

   - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influe
ntial Data and Sources of Collinearity', Wiley, 1980. 244-261.
   - Quinlan,R. (1993). Combining Instance-Based and Model-Based Learni
ng. In Proceedings on the Tenth International Conference of Machine Lea
rning, 236-243, University of Massachusetts, Amherst. Morgan Kaufmann.
```

In [3]:
```
boston_df = pd.DataFrame(boston.data, columns=boston.feature_names)
boston_df['PRICE'] = boston.target
```

In [4]:
```
# spliting the data into train and test
from sklearn.model_selection import train_test_split
X_train_data, X_test_data, y_train_data, y_test_data = train_test_split
(boston.data, boston.target, test_size = 0.20, random_state = 5)
```

In [5]:
```
#Function used to column standardize any given matrix
from sklearn.preprocessing import StandardScaler
scalar = StandardScaler()
X_train_data = scalar.fit_transform(X_train_data)
X_test_data = scalar.transform(X_test_data)
```

Custom SGD

In [6]:
```
#refered ::::https://github.com/saugatapaul1010/Implement-SGD-from-scra
tch./blob/master/Implement%20SGD%20for%20Linear%20Regression%20for%20Bo
ston%20Housing%20Dataset.ipynb
#computing manual sgd regressor
def manual_sgd_regressor(X_train_data, y_train_data, lr_rate, lr_rate_v
```

```
ariation, n_iterations, power_t):
    w_coeff=np.random.randn(13,1) #Randomly initalizing weights
    b_coeff=np.random.randn(1,1)  #Randomly picking up intercept value.

    for each_iterate in range(1,n_iterations+1):
        sum_errors = 0 #Sum of squared loss.
        N = X_train_data.shape[0] #The variable N in the SGD equation.

        for i in range(N):
            k = np.random.randint(0,N)  # random batch size for every i
teration i.e k batch_size
            X_i = X_train_data[k,:].reshape(1,X_train_data.shape[1])
            y_i = y_train_data[k].reshape(1,1)

            y_pred = np.dot(X_i,w_coeff) + b_coeff
            loss = y_pred - y_i
            sum_errors += loss**2

            w_grad = X_i.T.dot((y_pred - y_i))
            b_grad = (y_pred - y_i)

            w_coeff = w_coeff -(2/N)*lr_rate*(w_grad)
            b_coeff = b_coeff - (2/N)*lr_rate*(b_grad)


        if(lr_rate_variation=='invscaling'): #Implementing learning_rat
e 'invscaling' similar to that present in SGD Regressor.
            lr_rate = lr_rate / pow(each_iterate, power_t)
        else:
            pass

    return w_coeff, b_coeff
```

In [7]:

```
#This function is used to predict the class values given a test data.
def predict(X_test_data, w_coeff, b_coeff):
    X_test=np.array(X_test_data)
    y_pred =[]
    for i in range(0,len(X_test_data)):
        y=np.asscalar(np.dot(w_coeff,X_test_data[i]) + b_coeff) #Conver
```

```
t an array of size 1 to its scalar equivalent.
        y_pred.append(y)
    return np.array(y_pred)
```

In [8]:

```
#This function is used to plot the scatter plot between actual and pred
icted .
def plot_scatter(y_test_data,y_pred):
    plt.scatter(y_test_data,y_pred)
    plt.title('Scatter plot between Actual and Predicted Y.')
    plt.xlabel('Actual Y')
    plt.ylabel('Predicted Y')
    plt.grid(b=True, linewidth=0.5)
    plt.show()

    #Computing  the mean squared error between the actual and the predi
ctual values.
    mse=mean_squared_error(y_test_data,y_pred)
    print('MSE: ',mse)
    return mse
```

In [9]:

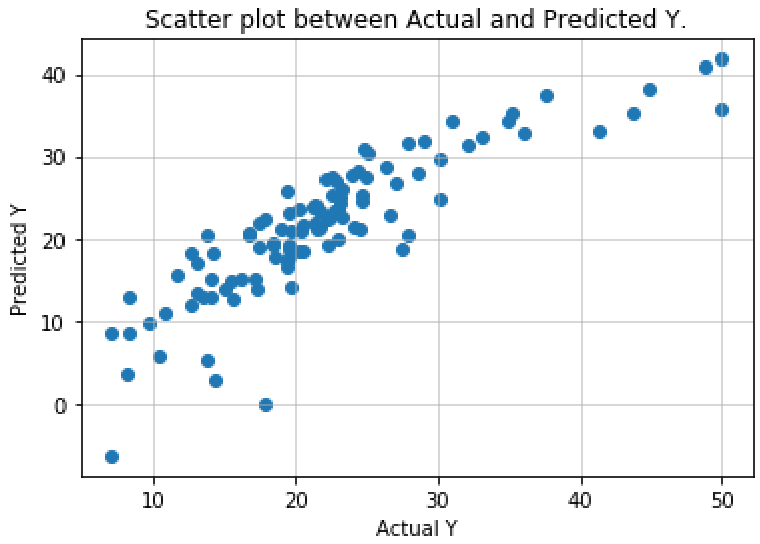
```
#above we declare function's below we calling functions with train data

#here we fitting our model with train data with 1000 iterations
w_coeff_optimal, b_coeff_optimal = manual_sgd_regressor(X_train_data, y
_train_data, lr_rate=0.01, lr_rate_variation='constant', n_iterations=1
000, power_t=None)
```

In [10]:

```
#Predict the class labels of the test set using the optimal values obta
ined from the previous step.
y_pred = predict(X_test_data, w_coeff_optimal.T, b_coeff_optimal)

#Draw the scatter plot
mse1=plot_scatter(y_test_data,y_pred)
```




```
MSE:  20.749334205773142
```

Observation

Almost all the values predicted good most of the values are matching with actual by predicted one's

So the optimal line will be like starts in between 0-10 and some points little far away from line

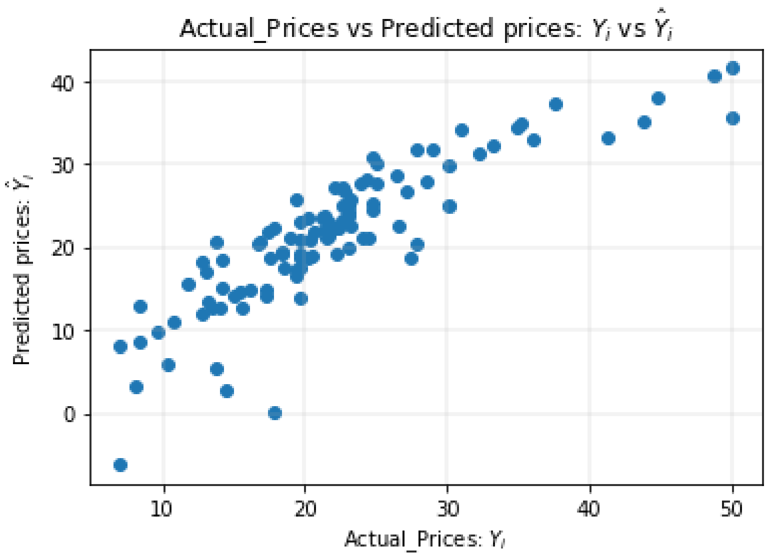
>=50 may act as outliers

In [11]:
```
wei=w_coeff_optimal
```

Implementing SK-Learn SGD

In [12]:
```
from sklearn.linear_model import SGDRegressor
#sklearn sgd for linear regression
lr_sgd = SGDRegressor(loss='squared_loss', alpha=0.0001, random_state=0
, learning_rate='invscaling', eta0=0.001, power_t=0.25, max_iter=1000)
```

```
lr_sgd.fit(X_train_data, y_train_data)
Y_pred_sgd = lr_sgd.predict(X_test_data)
#plotting
plt.scatter(y_test_data, Y_pred_sgd)
plt.grid(b=True, linewidth=0.3)
plt.xlabel("Actual_Prices: $Y_i$")
plt.ylabel("Predicted prices: $\hat{Y}_i$")
plt.title("Actual_Prices vs Predicted prices: $Y_i$ vs $\hat{Y}_i$")
plt.show()
```



Observation

Here also optimal line starts in between 0-10 and points >=50 may act as outliers

In [13]:
```
#Computing MSE for SGD Linear regression
sk_mse =mean_squared_error(y_test_data,Y_pred_sgd)
sk_mse
```

Out[13]: 20.666060631866618

In [14]:
```
#sk-learn sgd weights
weight_sgd=lr_sgd.coef_
```

In [15]:
```
#applying hstack to both weight's for  better view of results
sgd_wei=np.asarray(weight_sgd)
wei = np.asarray(wei)
```

Comparing Custom SGD weights and Sk-learn SGD weights

In [16]:
```
a=np.hstack(sgd_wei)
b=np.hstack(wei)
df=pd.DataFrame()
df['sklearn_sgd_weights']=a
df['manual_sgd_weights']=b
df
```

Out[16]:

	sklearn_sgd_weights	manual_sgd_weights
0	-1.087573	-1.091179
1	1.057798	1.033346
2	-0.246502	-0.352066
3	0.724791	0.768723
4	-1.735503	-1.704433
5	2.416593	2.437497
6	-0.008287	-0.042099
7	-3.035109	-3.050201
8	2.466201	2.227559
9	-1.442188	-1.203465

	sklearn_sgd_weights	manual_sgd_weights
10	-2.050813	-2.033712
11	1.039966	1.055046
12	-4.149943	-4.130119

Comparing Custom SGD MSE and Sk-Learn SGD MSE

In [17]:
```
print("MSE of  Custom SGD\t:",mse1)
print("MSE of SK Learn SGD\t:",sk_mse)
```

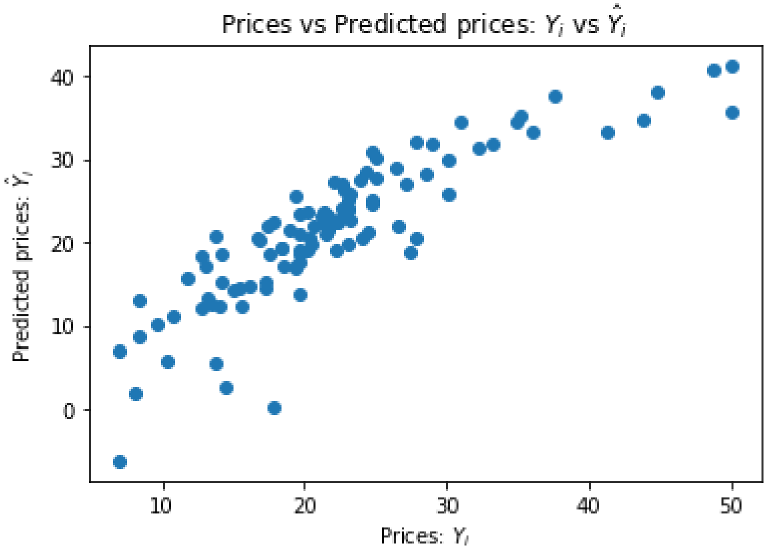
```
MSE of  Custom SGD      : 20.749334205773142
MSE of SK Learn SGD     : 20.666060631866618
```

LInear regression

In [18]:
```
#applying sk-learn linear regression
from sklearn.linear_model import LinearRegression

lm = LinearRegression()
lm.fit(X_train_data, y_train_data)

Y_pred_lm = lm.predict(X_test_data)
#plotting
plt.scatter(y_test_data , Y_pred_lm)
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 [19]:
```
#mse of linear regression
lr_mse =mean_squared_error(y_test_data ,Y_pred_lm)
print("MSE of  Linear regression\t:",lr_mse)
```

```
MSE of  Linear regression       : 20.869292183770813
```

In [20]:
```
#sk-learn linear regression  weights
weight_lm=lm.coef_
e=np.hstack(weight_lm)
e
```

Out[20]:
```
array([-1.13502719,  1.15814527,  0.00737057,  0.68709635, -1.82837001,
        2.36271879,  0.03166538, -3.06632775,  3.16621482, -2.21457852,
       -2.08600876,  1.0449511 , -4.17627077])
```

In [21]:
```
df['sk_learn_linear_reg']=e
print("comparing weights for sk-learn sgd, manual sgd, and sk-learn lin
ear regression ")
df
```

```
comparing weights for sk-learn sgd, manual sgd, and sk-learn linear reg
```

```
ression
```

Out[21]:

	sklearn_sgd_weights	manual_sgd_weights	sk_learn_linear_reg
0	-1.087573	-1.091179	-1.135027
1	1.057798	1.033346	1.158145
2	-0.246502	-0.352066	0.007371
3	0.724791	0.768723	0.687096
4	-1.735503	-1.704433	-1.828370
5	2.416593	2.437497	2.362719
6	-0.008287	-0.042099	0.031665
7	-3.035109	-3.050201	-3.066328
8	2.466201	2.227559	3.166215
9	-1.442188	-1.203465	-2.214579
10	-2.050813	-2.033712	-2.086009
11	1.039966	1.055046	1.044951
12	-4.149943	-4.130119	-4.176271

comparing mse's for manual ,sklearn sgd's and sklearn linear regression

In [22]:

```
#comparing mse's for manual ,sklearn sgd's and sklearn linear regressio
n
print("MSE of  Custom SGD\t\t:",mse1)
print("MSE of SK Learn SGD\t\t:",sk_mse)
print("MSE of  Linear regression\t:",lr_mse)
```

```
MSE of  Custom SGD              : 20.749334205773142
```

```
MSE of SK Learn SGD              : 20.666060631866618
MSE of  Linear regression        : 20.869292183770813
```

Obervations

1.Above implemented Custom SGD for linear regression with learning rate 0.01 and 1000 iteratons
2.If iterations increases MSE will decreases or constant is observed
3.By comparing weights and MSE of both Custom and Sklearn SGD gives almost same results when high iteration
4.Weights are changing for every run time cells because of we took random k points from the training data ,So MSE will vary at multiple executions
5.Sk-learn SGD with good code complex and all these caluclations done internally in sk-learn SGD how ever results are almost same compare to custom SGD
6.How ever we caluclated sk-learn linear regression and compare with both custom sgd and sk-learn sgd
7.Linear regression from sk-learn also gives almost similar weights and similar for Linear Regreesion sk-learn MSE(20) and sk-learn sgd MSE(20) and custom sgd MSE(20)
8.We get 20 as mse values for manual sgd and sk-learn's sgd and linear regression MSE at 20 is good
9.So final statement is there no much difference in weights and MSE in manual SGD and sk-learn SGD and sk-learn linear regression are giving similar results