

```

In [67]: 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 [68]: print(boston.data.shape)
(506, 13)

In [69]: print(boston.feature_names)
['CRIM' 'INDUS' 'CHAS' 'NOX' 'RM' 'AGE' 'DIS' 'RAD' 'TAX' 'PTRATIO'
 'B' 'LSTAT']

In [70]: print(boston.target)
[24. 21.6 34.7 33.4 36.2 28.7 22.9 27.1 16.5 18.9 15. 16.9 21.7 20.4
 18.2 19.9 23.1 17.5 20.2 18.2 13.6 14.6 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 33.6 23.3 19.6 18.7 16. 22.2 25. 35. 23.5 19.4 22. 17.4 20.9
 24.2 21.7 22.8 23.4 24.1 21.4 20.0 20.8 21.2 20.3 28. 23.9 24.8 22.9
 23.9 26. 22.5 22.2 23.6 26.7 22.6 22. 22.9 25. 20.6 28.4 21.4 38.7
 42.8 20.7 25.3 26.3 19.6 19.3 20.1 19.5 19.0 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. 3.9 19.2 19.6 23.5 18.4 15.6 18.1 17.4 17.1 13.3 17.8
 14.6 13.4 15. 15. 11.8 13.8 15.6 14.6 17.8 15.4 21.5 19.6 15.3 13.9
 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 19.4 23.1 23.5 22.6 22.6 49.4 23.2 24.6 29.9 37.2 39.8 36.2
 37.9 23.6 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. 42.2 5.4 24.2 40.
 21.7 19.3 22.4 28.1 23.7 25. 23.3 28.7 21.5 20.5 21.7 27.7 35.9 31.
 44.8 50. 37.6 61.3 44.6 7. 31.5 24.3 31.7 41.7 48.3 28. 24. 25.1 31.5
 23.7 23.3 22. 20.1 22.2 23.7 17.6 18.5 24.5 20.5 24.5 26.2 24.4 24.8
 25.6 42.8 22.9 20.9 44. 50. 36. 30.1 33.8 43.1 48.8 31. 36.2 22.8
 30.7 50. 43.5 20.7 21.1 25.2 24.4 35.2 32.4 35. 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 38.4 33.4 42.8
 22.8 20.3 16.1 22.1 19.4 21.6 25.8 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 37.7 16.5 23.9 31.2 17.5 17.2 23.1 24.8 26.6
 21.9 24.1 18.6 30.1 18.2 20.6 17.8 21.7 22.7 22.6 25. 19.9 20.8 14.8
 21.9 25.2 19.3 20.9 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 13.9 12.7 13.1 12.5 8.5 5. 6.3 5.6 7.2 12.1 8.3 8.5 9.
 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. 16.1 14.3
 11.7 11.4 9.6 8.7 8.4 12.8 10.8 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 23.4 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 61.3 23.1 23.7 25. 21.8 20.6 21.2 19.1 20.6 15.7 17.9
 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 [71]: print(boston.DESCR)
Boston House Prices dataset
=====

Notes
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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
- INDUS proportion of residential land zoned for lots over 25,000 sq.ft.
- CHAS Charles River dummy variable (= 1 if tract borders 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 a 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.B.

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, Ku & Welsh, "Regression diagnostics
vol.1", 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, Ku & Welsh, "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 [72]: import pandas as pd

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

   0      1      2      3      4      5      6      7      8      9     10  \
0  0.0662  18.0  2.31  0.0  0.538  6.575  65.9  4.0900  11.0  29.6  15.3
1  0.02731  0.0  7.07  0.0  0.469  6.421  76.9  4.9671  2.0  242.0  17.8
2  0.02729  0.0  7.07  0.0  0.469  6.183  61.1  4.9671  2.0  242.0  17.8
3  0.0237  0.0  2.18  0.0  0.458  6.398  45.8  6.0622  3.0  222.0  16.7
4  0.0695  0.0  2.18  0.0  0.458  7.147  54.2  6.0622  3.0  222.0  16.7

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 [73]: `bos['PRICE'] = bos.train_target
X = bos.drop('PRICE', axis = 1)
Y = bos['PRICE']`

In [74]: `print(bos.head())`

```

      0      1      2      3      4      5      6      7      8      9     10 \
0  0.06632  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  0.06805  0.0  2.18  0.0  0.458  7.147  54.2  6.0622  3.0  222.0  18.7

```

11 12 PRICE

```

0 396.90 4.98 24.0
1 396.90 9.14 21.6
2 392.83 4.03 34.7
3 394.63 2.94 33.4
4 396.90 5.33 36.2

```

In [75]: `# 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))`

In [76]: `results=pd.DataFrame(columns=['emo', 'algo', 'alpha', 'init_lr_rate', 'n_iter', 'weight', 'intercept', 'error'])`

Applying manual SGD on Boston Dataset

In [77]: `def manual_sgd(alpha, lr_rate, n_iter):
 wj_plus1=np.zeros(shape=(1,13))
 bj_plus1=0
 n=1
 r=lr_rate
 n_iter=n_iter
 while n<=n_iter:`

```
while (n<=n_iter):
    wj=wj_plus1
```

```

b_j=bj_plus1
w_c=w_c+zeros(shape=(1,13))
h=0

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

    wj_plus1=wj+*(w_c - (-2/Y_data.shape[0]))
    bj_plus1=bj+*(b_c - (-2/Y_data.shape[0]))
    n=n+1

y_pred=[]
for i in range(len(X_data)):
    y=np.asarray(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()

manual_error=mean_squared_error(Y_data,y_pred)
print("error=",manual_error)

print("*****")
return wj_plus1, bj_plus1, manual_error

```

Applying sklearn SGD on boston dataset

```

In [78]: import seaborn as sns
import numpy as np
from sklearn.linear_model import SGDRegressor

def sklearn_sgd(alpha,lr_rate,n_iter):
    clf=SGDRegressor(alpha=alpha,eta0=-lr_rate,max_iter=n_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.xlabel('predicted y')
plt.grid(True, linewidth=0.5)
plt.show()

#kdeplot

sgd_error=mean_squared_error(Y_data,y_pred)
print('mean sq error:', sgd_error)
print('Maximum number of iterations', n_iter)

print('.....')
return clf.coef_, clf.intercept_, sgd_error

```

In [79]:

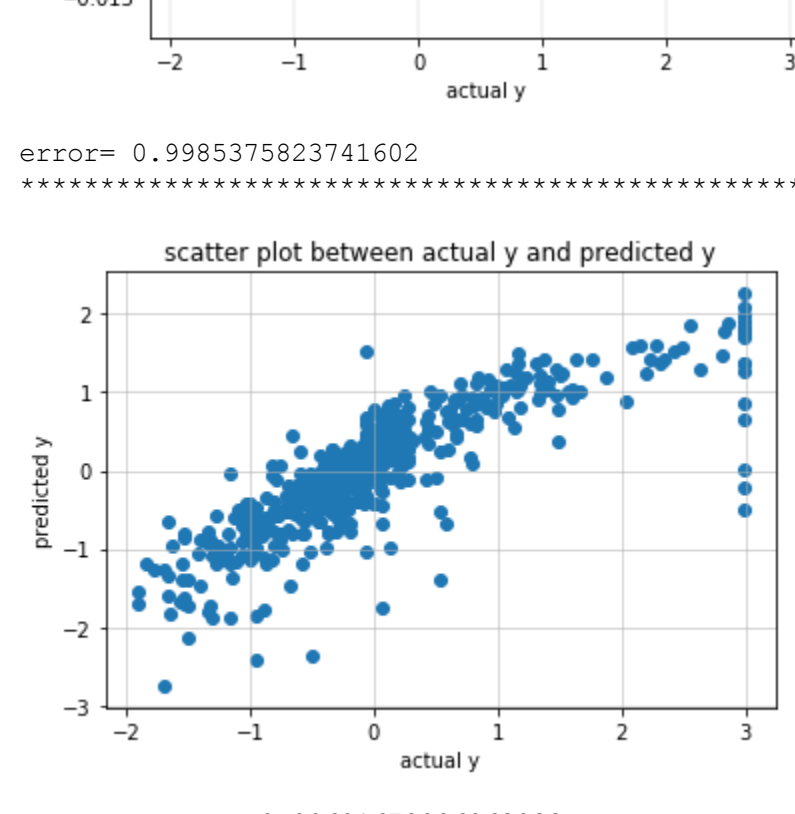
```

w,b,error=manual_sgd(alpha=0.0001,lr_rate=0.01,n_iter=1)
results.loc[0]=[0, 'Manual SGD', 0.0006, 0.03, 0, w, b, error]

w,b,error=sklearn_sgd(alpha=0.0001,lr_rate=0.01,n_iter=1)
results.loc[1]=[1, 'sklearn SGD', 0.0006, 0.03, 0, w, b, error]

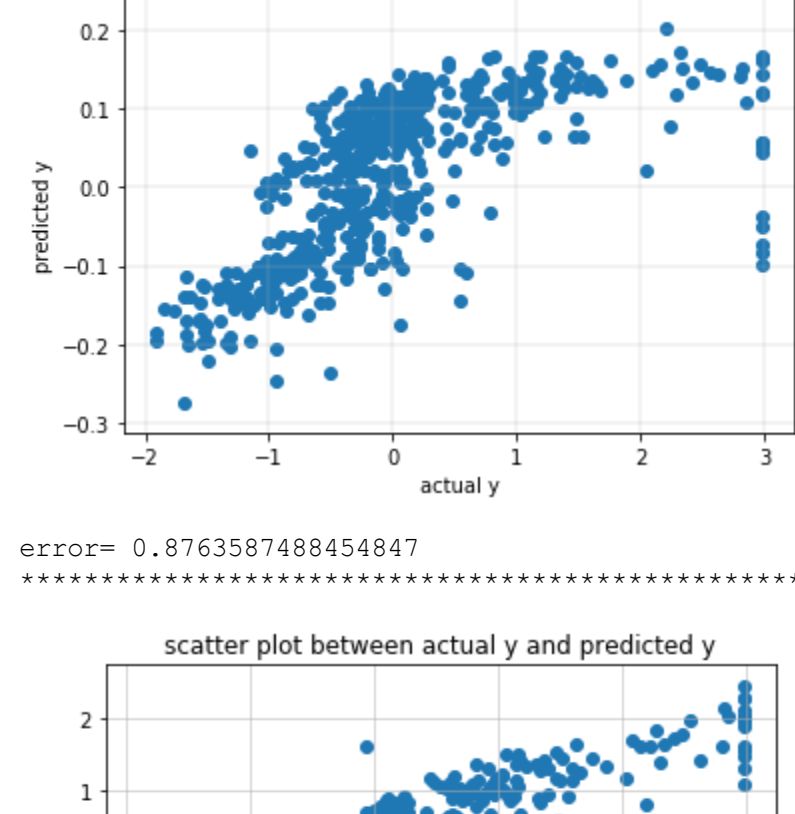
```

scatter plot between actual y and predicted y

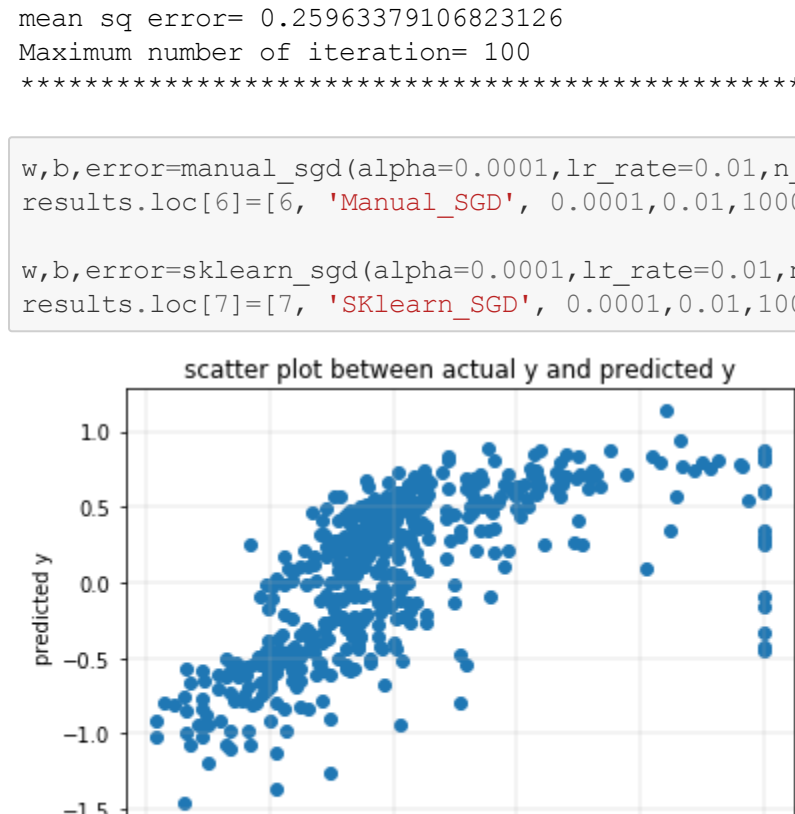


```
mean sq error= 0.29601678286863233
Maximum number of iteration= 1
*****
In [80]: w,b,error=manual_sgd(alpha=0.0001,lr_rate=0.01,n_iter=100)
         results.loc[4]=[4, "Manual SGD", 0.0001,0.01,100, w, b, error]
w,b,error=sklearn_sgd(alpha=0.0001,lr_rate=0.01,n_iter=100)
         results.loc[5]=[5, "SKlearn SGD", 0.0001,0.01,100, w,b,error]
```

scatter plot between actual y and predicted y



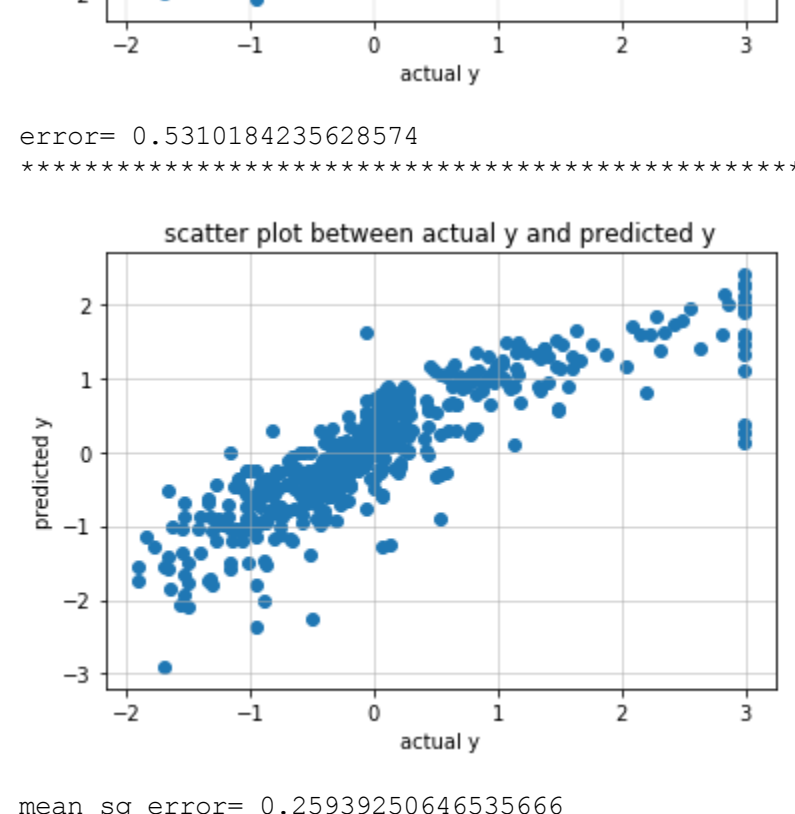
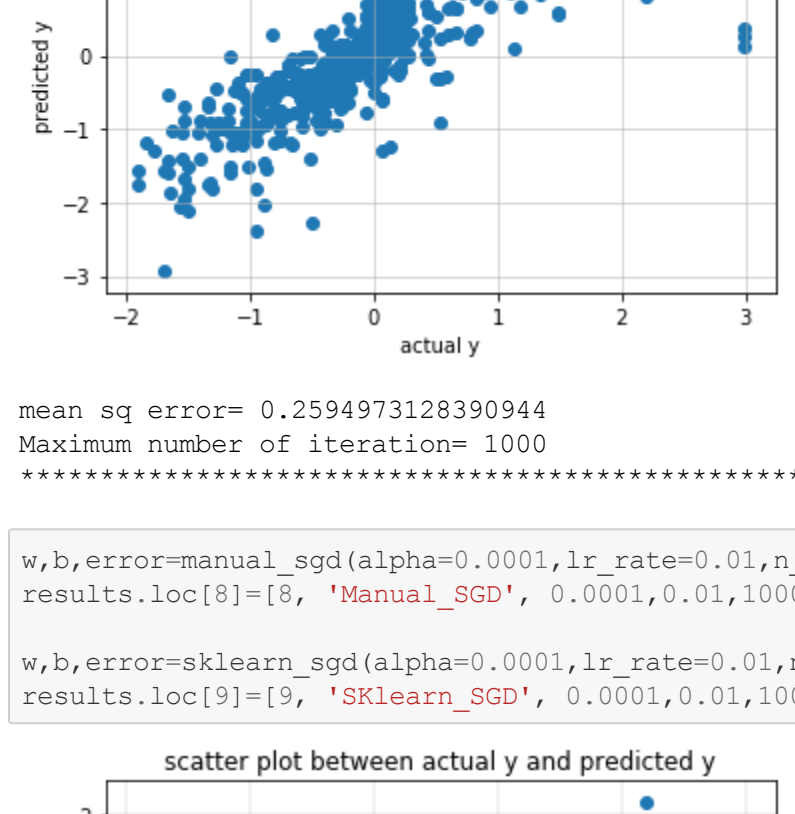
A scatter plot showing the relationship between predicted and actual values. The x-axis is labeled 'actual y' and ranges from -2 to 3. The y-axis is labeled 'predicted y' and ranges from -3 to 1. The data points are blue dots, showing a strong positive correlation, with most points clustered between -1 and 1 on both axes.



```
error= 0.5771405881414906
```

.....

scatter plot between actual y and predicted y

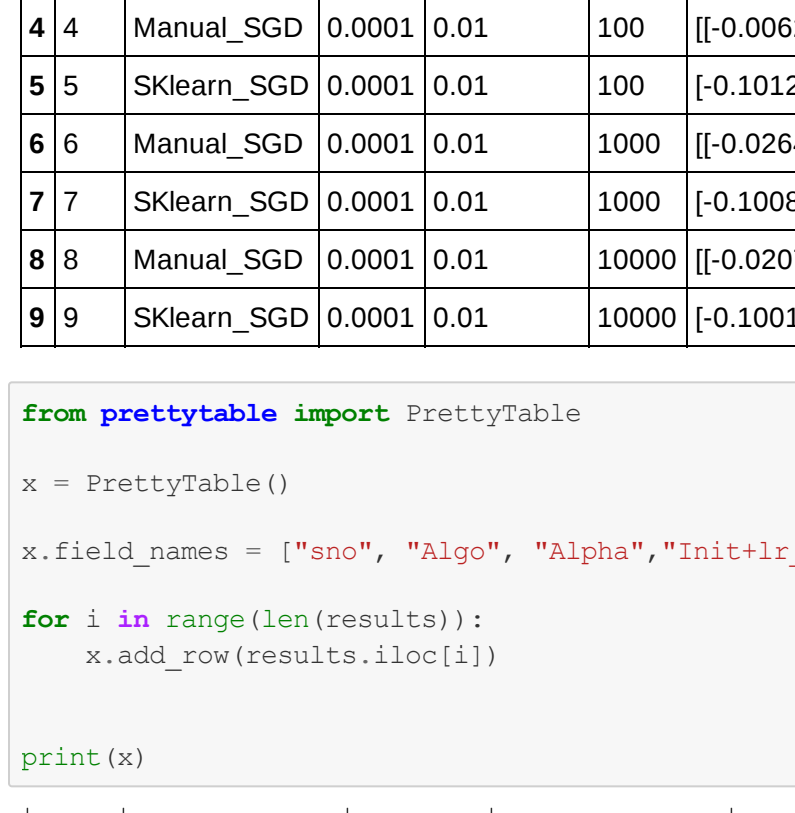


```
Maximum number of iteration= 10000
*****

In [83]: results

Out[83]:
```

sno	algo	alpha	init_lr_rate	n_iter	weight	intercept	error
0	Manual_SGD	0.0001	0.01	1	[1.6931550483673108e-05, -8.718166531702745e-...	[0.00010636189911452092]	0.998538
1	SKlearn_SGD	0.0001	0.01	1	[-0.07742519238874486, 0.0480428807342034, -0...	[-0.007162827025503435]	0.296017

[illegible]

							-2.74510817e-04]]				
		1	SKlearn_SGD 0.0001	0.01		1	[-0.07742519	0.04804329 -0.06534176	0.09012836 -0.05484795	0.33	
	496082	[-0.00716283]	0.29601678286263233								
							-0.03285229	-0.11374552	0.01548553	-0.05875127 -0.17276461	0.08

[illegible][illegible][illegible]

```
| 9 | SKlearn_GCD | 0.0001 | 0.01 | 10000 | [-0.10014996 | 0.11751494 | 0.01536462 | 0.07419924 -0.22420865 | 0.29  
074026 | [0.00017026] | 0.25939325064653566 |  
| | | | | 0.00245992 -0.33800395 | 0.26898308 -0.2257533 -0.22465394 | 0.09  
2393506 |  
| | | | | ~-0.40816289!  
-----+-----
```

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 [ ]: # code source:https://medium.com/@haydar_ai/learning-data-science-day-9-linear-regression-on-boston-housing-dataset-cd62a8077
#sklearn
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:  $\hat{Y}_{15}$ ")
plt.ylabel("Predicted prices:  $\hat{Y}$ hat( $W_{15}$ )")
plt.title("Prices vs Predicted prices:  $\hat{Y}_{15}$  vs  $\hat{Y}$ hat( $W_{15}$ )")
plt.show()
```

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

```
In [ ]: # 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 [ ]: # Estimate linear regression coefficients using stochastic gradient descent
def coefficients_ogd(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 = row[-1] - yhat
            for i in range(len(row)-1):
                coef[i + 1] += l_rate * error * row[i]
            coef[0] += l_rate * error
```

```

        # Compute the error
        for row in train:
            yhat = predict(row, coef)
            error = yhat - row[-1]
            coef[i] = coef[i] - 1_rate * error
        for i in range(len(row)-1):
            coef[i + 1] = coef[i + 1] - 1_rate * error * row[i]
        # print(i_rate, n_epoch, error)

    return coef

```

```
def linear_regression_sqd(train, test, l_rate, n_epoch):
    predictions = list()
    coef = coefficients_sqd(train, l_rate, n_epoch)
    for row in test:
        yhat = predict(row, coef)
        predictions.append(yhat)
    return(predictions)
```