Linear Regression on Boston Housing Price

In [4]:

```
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 [5]:

```
bos=load_boston()
```

In [6]:

```
X = bos.data
Y = bos.target
```

In [13]:

```
scalar=preprocessing.StandardScaler()
```

In [7]:

```
bos_data=pd.DataFrame(X)
```

In [8]:

```
bos_data.columns=bos.feature_names
```

In [9]:

```
bos_data.head(2)
```

Out[9]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1.0	296.0	15.3	396.9	4.98
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2.0	242.0	17.8	396.9	9.14

In [10]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(bos_data,Y,test_size=0.33,random_state=6)
```

In [14]:

```
X_train=scalar.fit_transform(X_train)
```

In [17]:

```
X_test=scalar.transform(X_test)
```

In [18]:

```
import warnings
warnings.filterwarnings("ignore")
```

Sklearn SGD implementation

for alpha=0.0001 and n_iter=100 and eta=0.01
alpha:- Constant that multiplies the regularization term. Defaults to 0.0001
n_iter:- Number of iterations with no improvement to wait before early stopping.
eta :- learning_rate https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_split.html

In [19]:

```
clf = SGDRegressor(alpha=0.0001,n_iter=100,eta0=0.01)
clf.fit(X_train, y_train)
y_pred=clf.predict(X_test)
error_100=mean_squared_error(y_test, y_pred)
```

In [20]:

```
clf.coef_
```

Out[20]:

```
array([-0.6532897 ,  1.01312006, -0.401766  ,  0.66832809, -1.61719875,
        2.49550694, -0.11847322, -3.30790785,  2.46688552, -2.22281505,
       -2.06773426,  0.82506525, -3.65587934])
```

In [21]:

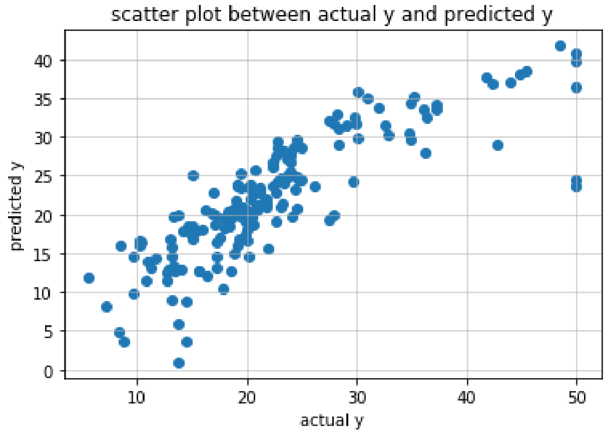
```
len(y_pred)
```

Out[21]:

```
167
```

In [22]:

```
plt.scatter(y_test,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('-----------------------------------------------------')
```



OBSERVATION
from above graph you can see that most of values are predicted correctly except some values

In [23]:

```
print(error_100)
```

26.590385569279555

aBOVE error is mean squared error

For alpha=0.0001 and n_iter=1000 and eta=0.01

In [24]:

```
clf = SGDRegressor(alpha=0.0001,n_iter=1000,eta0=0.01)
clf.fit(X_train, y_train)
y_pred=clf.predict(X_test)
error1=mean_squared_error(y_test, y_pred)
```

In [25]:

```
clf.coef_
```

Out[25]:

```
array([-0.68701814,  1.03372051, -0.33146296,  0.65491821, -1.64214491,
        2.47822998, -0.10825921, -3.31692227,  2.6859687 , -2.4635729 ,
       -2.08342196,  0.81429048, -3.66810295])
```

In [26]:

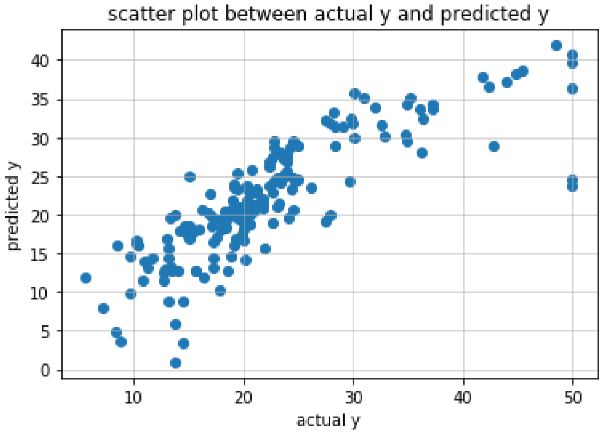
```
len(y_pred)
```

Out[26]:

167

In [27]:

```
plt.scatter(y_test,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('-----------------------------------------------------')
```



```
--------------------------------------------------------
```

In [28]:

```
print(error1)
```

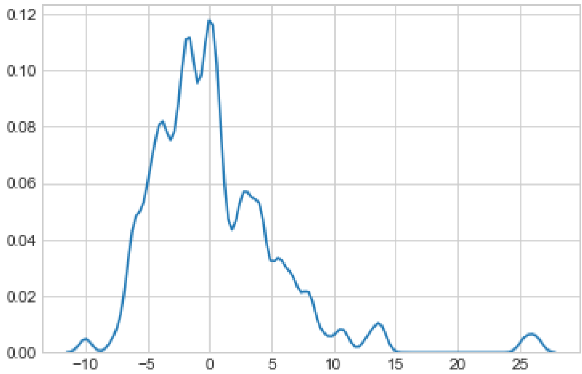
```
26.621146535672167
```

When we compare both of our model one with n_itr=100 and another with n_iter=1000 we can see that mean squared error is nearly same for both

In [29]:

```
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()
```



KDE PLot generally tells about the PDF
from above graph it is seen that highest peak is at 0 which is good
Graph performs bad for -ve point but it performs good for +ve points

In [30]:

```
weight_actual=clf.coef_
```

In [31]:

```
weight_actual=list(weight_actual)
```

In [32]:

```
weight_actual[0:5]
```

Out[32]:

```
[-0.6870181445906263,
 1.0337205124906286,
 -0.33146296159248617,
 0.6549182136858445,
 -1.642144913594435]
```

MANNUAL SGD

In [33]:

```
manual_train=pd.DataFrame(data=X_train)
manual_train['price']=y_train
```

In [34]:

```
def manual_fit(X, lr_rate_variation, alpha=0.0001, lr_rate=0.01, n_iter=1000):
    w_new=np.zeros(shape=(1,13))
    b_new=0
    t=1
    r=lr_rate

    while(t<=n_iter):
        w_old=w_new
        b_old=b_new
        w_=np.zeros(shape=(1,13))
        b_=0
        x_data=X.sample(10)
        x=np.array(x_data.drop('price',axis=1))
        y=np.array(x_data['price'])


        for i in range(10):  # for getting the derivatives using sgd with k=10
            y_curr=np.dot(w_old,x[i])+b_old
            w_+=x[i] * (y[i] - y_curr)
            b_+=(y[i]-y_curr)


        w_*=(-2/x.shape[0])
        b_*=(-2/x.shape[0])

        #updating the parameters
        w_new=(w_old-r*w_)
        b_new=(b_old-r*b_)



        t+=1

    return w_new, b_new
```

In [35]:

```
w,b=manual_fit(X=manual_train, lr_rate_variation='constant' , n_iter=1000)
```

In [36]:

```
b
```

Out[36]:

```
array([22.77173996])
```

In [37]:

```
def pred(x,w, b):
    y_pred=[]
    for i in range(len(x)):
        y=np.asscalar(np.dot(w,x[i])+b)
        y_pred.append(y)
    return np.array(y_pred)
```

In [38]:

```
y_pred_manual=pred(np.array(X_test),w,b)
```

In [39]:

```
y_pred_manual=list(y_pred_manual)
```

In [40]:

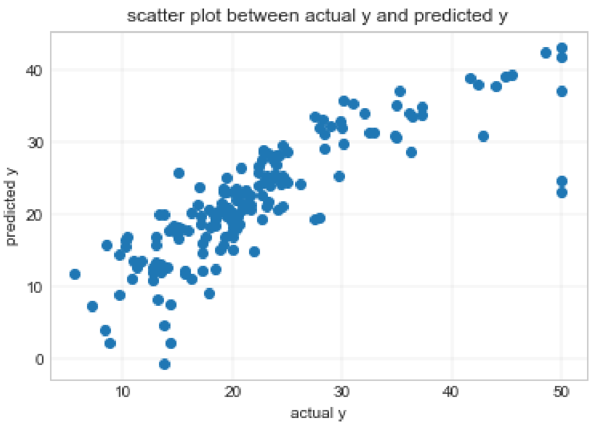
```
y_pred_manual[0:5]
```

Out[40]:

```
[25.843656622856763,
 25.397201637357764,
 29.960802743136068,
 24.039562865596835,
 19.822291609170843]
```

In [41]:

```
 plt.scatter(y_test,y_pred_manual)
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('**************************************************************')
```




```
**************************************************************
```

In [42]:

```
mean_error=[]
for i in range(len(y_test)):
    mean_error.append((y_test[i]-y_pred_manual[i]))
```

In [43]:

```
sum1=0
for i in range(len(mean_error)):
    sum1=sum1+((mean_error[i])**2)
final_error=(sum1)/len(mean_error)
```

In [44]:

```
final_error
```

Out[44]:

```
26.571115185626212
```

In [45]:

```
data = pd.DataFrame({'y_manual_diff':mean_error, 'y_sklearn_diff':delta_y} )
data.head(2)
```

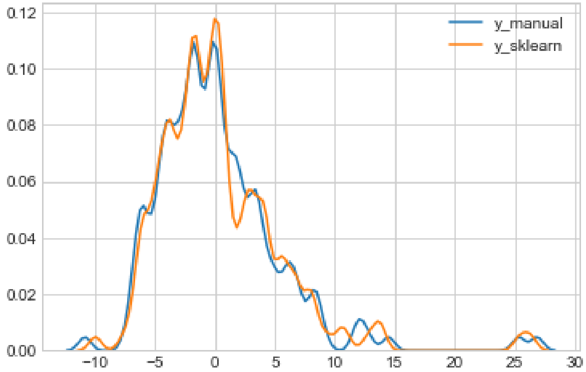
Out[45]:

	y_manual_diff	y_sklearn_diff
0	-10.843657	-9.969437
1	-2.297202	-1.613594

In [46]:

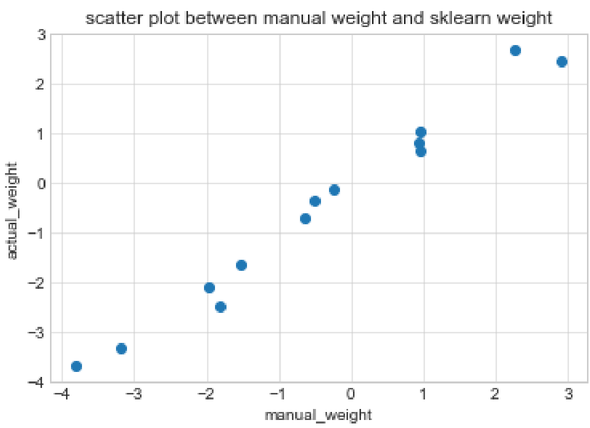
```
import seaborn as sns;
import numpy as np;
sns.set_style('whitegrid')
sns.kdeplot(np.array(data['y_manual_diff']), bw=0.5,label='y_manual')
sns.kdeplot(np.array(data['y_sklearn_diff']),bw=0.5,label='y_sklearn')

plt.show()
```



In [47]:

```
plt.scatter(w,weight_actual)
plt.title('scatter plot between manual weight and sklearn weight')
plt.xlabel('manual_weight')
plt.ylabel('actual_weight')
plt.grid(b=True, linewidth=0.5)
plt.show()
print('------------------------------------------------------')
```




```
------------------------------------------------------
```

from below example we will understand that for higher n_iter our both manual and sklearn SGDReggressor error is almost same but for lower iteration there is diff

In [48]:

```
w_100,b_100=manual_fit(X=manual_train, lr_rate_variation='constant' , n_iter=100)
b_100
```

Out[48]:

```
array([19.84386906])
```

In [49]:

```
def pred(x,w_100, b_100):
    y_pred_100=[]
    for i in range(len(x)):
```

```
        y=np.asscalar(np.dot(w_100,x[i])+b_100)
        y_pred_100.append(y)
    return np.array(y_pred_100)
```

In [50]:

```
y_pred_manual_100=pred(np.array(X_test),w_100,b_100)
```

In [51]:

```
y_pred_manual_100=list(y_pred_manual_100)
```

In [52]:

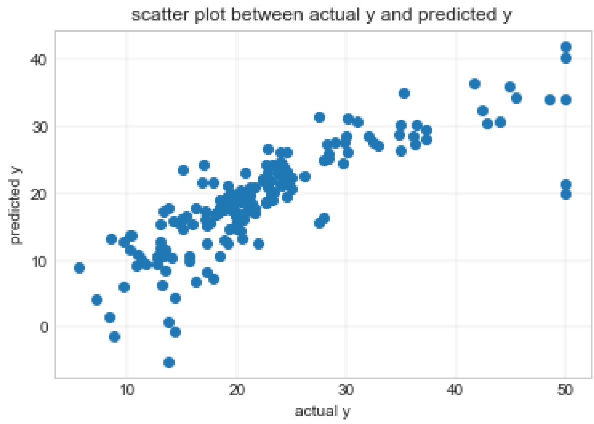
```
y_pred_manual_100[0:5]
```

Out[52]:

```
[23.443133262756056,
 21.81362149619836,
 26.215457332205965,
 21.761073939044262,
 15.761996601199247]
```

In [53]:

```
 plt.scatter(y_test,y_pred_manual_100)
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('***********************************************************************')
```




```
***********************************************************************
```

In [54]:

```
mean_error=[]
for i in range(len(y_test)):
    mean_error.append((y_test[i]-y_pred_manual_100[i]))
```

In [55]:

```
sum1=0
for i in range(len(mean_error)):
    sum1=sum1+((mean_error[i])**2)
final_error_100=(sum1)/len(mean_error)
```

In [56]:

```
final_error_100
```

Out[56]:

38.719936950843426

In [57]:

```
data = pd.DataFrame({'y_manual_diff':mean_error, 'y_sklearn_diff':delta_y} )
data.head(2)
```

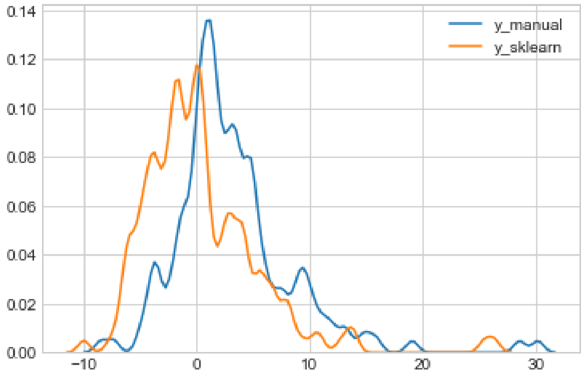
Out[57]:

	y_manual_diff	y_sklearn_diff
0	-8.443133	-9.969437
1	1.286379	-1.613594

In [58]:

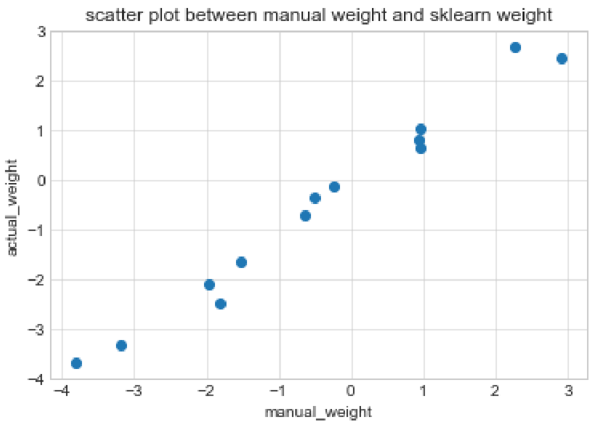
```
import seaborn as sns;
import numpy as np;
sns.set_style('whitegrid')
sns.kdeplot(np.array(data['y_manual_diff']), bw=0.5,label='y_manual')
sns.kdeplot(np.array(data['y_sklearn_diff']),bw=0.5,label='y_sklearn')

plt.show()
```



In [59]:

```
plt.scatter(w,weight_actual)
plt.title('scatter plot between manual weight and sklearn weight')
plt.xlabel('manual_weight')
plt.ylabel('actual_weight')
plt.grid(b=True, linewidth=0.5)
plt.show()
print('------------------------------------------------------------')
```



CONCLUSION

In [60]:

```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names=['Weight vector manual','Weight vector SGD sklearn']
for i in range(13):
    x.add_row([w[0][i],weight_actual[i]])
print(x)
```

```
+----------------------+--------------------------+
| Weight vector manual | Weight vector SGD sklearn |
+----------------------+--------------------------+
| -0.6387900674902751  |    -0.6870181445906263    |
|  0.9647979489790537  |     1.0337205124906286    |
| -0.5137126758953119  |    -0.33146296159248617   |
|  0.9686434184642032  |     0.6549182136858445    |
| -1.5229675364910689  |     -1.642144913594435    |
|  2.9199837791875844  |     2.478229981371889     |
| -0.23951506080900944 |    -0.10825920649889233   |
| -3.1959027116298064  |    -3.3169222722807468    |
|  2.2629081920149594  |     2.685968699318519     |
| -1.8231163490954958  |    -2.4635728999674247    |
| -1.9745147858978296  |    -2.0834219560594565    |
|  0.93891282112653 1  |     0.8142904764203849    |
| -3.8123696169183563  |     -3.66810294945099     |
+----------------------+--------------------------+
```

In [62]:

```
x = PrettyTable()
x.field_names=['MSE_mannual','MSE_SGD sklearn','learning_Rate','n_iter']
x.add_row([final_error_100,error_100,'0.01','100'])
x.add_row([final_error,error1,'0.01','1000'])

print(x)
```

```
+--------------------+--------------------+---------------+--------+
|    MSE_mannual     |  MSE_SGD sklearn   | learning_Rate | n_iter |
+--------------------+--------------------+---------------+--------+
| 38.719936950843426 | 26.590385569279555 |      0.01     |  100   |
| 26.571115185626212 | 26.621146535672167 |      0.01     |  1000  |
+--------------------+--------------------+---------------+--------+
```

OBSERVATION

1. WE IMPLEMENT SGD REGRESSOR MANNUALY AND WITH SKLEARN
2. WE COMPARE OUR MODEL WITH PRETTY TABLE
3. WE FOUND THAT BOTH MANUAL AND SKLEARN SGD REGRESSOR PERFOMS NEARLY SAME FOR HIGHER ITERATION
4. FOR LOWER ITERATION THERE IS DIFF IN MSE.
5. SGDReggressor performs well on Boston Housing price we see using PDF.

END