SGD_on_LinearRegression

September 1, 2018

1 Linear Regression using Stochastic Gradient Descent(SGD) on Boston House Prices

In [90]:
```
from sklearn.datasets import load_boston
import numpy as np
import random
import pandas as pd
import matplotlib.pyplot as plt
import sklearn
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.utils import shuffle
from sklearn.metrics import r2_score
from datetime import datetime
from sklearn.linear_model import SGDRegressor
from matplotlib.pyplot import scatter
```

In [3]:
```
boston_data = load_boston()
```

In [4]:
```
X = boston_data.data
```

In [5]:
```
X.shape
```

Out[5]:
```
(506, 13)
```

Observation: There are 506 Data points with 13 Features

In [6]:
```
y = boston_data.target
len(y)
```

Out[6]:
```
506
```

In [7]:
```
from sklearn.cross_validation import train_test_split
x_train,x_test,y_train,y_test = train_test_split(X,y,test_size=0.33)
```

```
C:\Users\Dell\Anaconda3\lib\site-packages\sklearn\cross_validation.py:44: DeprecationWarning: T
  "This module will be removed in 0.20.", DeprecationWarning)
```

1.0.1 Standardization

```
In [8]: std = StandardScaler()
        x_train = std.fit_transform(x_train)
        x_test = std.fit_transform(x_test)
```

1.1 Custom Linear Regression using Gradient Descent

```
In [9]: def linearRegressionGD(X,y,w = np.zeros(13),b = 0,iterations=5000,learning_rate=0.1,eps
            """
                Linear Regression Using Gradient Descent Optimization

                Parameters
                ----------
                X : numpy array or sparse matrix of shape [n_samples,n_features]
                    Training data

                y : numpy array of shape [n_samples, n_targets]
                    Target values

                w:  Weight Vector first initializad with 0's


                b:  y-intercept


                iterations: no.of iterations

                epsilon_val: Termination Criteria

                Returns
                -------
                w,b,cost or MSE
                """
            start = datetime.now()
            n = float(len(y))
            costs = [];
            decay_rate = 0.0001
            eta=learning_rate
            for i in range(iterations):

                #learning rate
                eta = eta * (1.0/(1+decay_rate*i))
                error = y -  predict(X,w,b) #y_act - y_actual

                #partial differentiation w.r.t w
                w_grad = (-2.0/n)*(X.T.dot(error))
```

```python
        #partial differentiation w.r.t b
        b_grad = (-2.0/n)*(np.sum(error))

        #MSE
        cost = (1.0/n)*np.sum(np.power(error,2))

        #updating weight vector
        w = w - (eta*w_grad)

        #updating y-intercept
        b = b - (eta*b_grad)

        costs.append(cost)

        #Stopping Criteria
        if i==0:
            w_prev = w;
        else:
            dist = (np.linalg.norm(w-w_prev))
            w_prev = w

            #Terminates the loop when difference between w and w_prev is very less
            if(round(dist,6)<epsilon_val):
                print("no.of iterations: ",i,"Cost: ",min(costs))
                break;

    print("Time: Taken: ",datetime.now() - start)
    return w,b,cost;



def predict(x,m,c):
    """
        It predicts the target value based on the input parameter values

        Parameters
        ----------
        x : numpy array or sparse matrix of shape [n_samples,n_features]
            Training data


    """
    y = np.dot(x,m) + c
    return y


def score(X,y,m,c):
```

```
        """
        It gives the Score or accuracy

        Parameters
            ----------
            X : numpy array or sparse matrix of shape [n_samples,n_features]
                Training data

            y : numpy array of shape [n_samples, n_targets]
                Target values

            m : slope

            c : y-intercept
        """

        from sklearn.metrics import r2_score
        return r2_score(y,predict(X,m,c).flatten())
```

```
In [20]: w1,b1,cost1 = linearRegressionGD(x_train,y_train)
```

```
no.of iterations:  131 Cost:  20.9300479465
Time: Taken:  0:00:00.011941
```

```
In [21]: score(x_test,y_test,w1,b1)
```

```
Out[21]: 0.7368587800798797
```

1.2 Custom Linear Regression using SGD

```
In [56]: def linearRegressionSGD(X,y,w = np.zeros(13),b = 0,iterations=1000,case_size=100,lear
          """
              Linear Regression Using Gradient Descent Optimization

              Parameters
              ----------
              X : numpy array or sparse matrix of shape [n_samples,n_features]
                  Training data

              y : numpy array of shape [n_samples, n_targets]
                  Target values

              w:  Weight Vector first initializad with 0's


              b:  y-intercept
```

```
    iterations: no.of iterations


    case_size : bunch of points to be taken in each iteration


    epsilon_val: Termination Criteria


    Returns
    -------
    w,b,cost or MSE
    """
start = datetime.now()
n = float(len(y))
costs = [];
decay_rate = 0.0001
eta=learning_rate


for iters in range(iterations):
    eta = eta * (1.0/(1+decay_rate*iters))

    X,y =  shuffle(X,y,random_state=0,replace=True)


    for i in range(case_size):
        x_mini = X[i:i+case_size]
        y_mini = y[i:i+case_size]


        error = y_mini -  predict(x_mini,w,b) #y_act - y_predicted

        #partial differentiation w.r.t w
        w_grad = (-2.0/n)*(x_mini.T.dot(error))

        #partial differentiation w.r.t b
        b_grad = (-2.0/n)*(np.sum(error))

        #MSE
        cost = (1.0/n)*np.sum(np.power(error,2))

        #updating weight vector
        w = w - (eta*w_grad)

        #updating y-intercept
        b = b - (eta*b_grad)
```

```
                    costs.append(cost)


                #Stopping Criteria
                if iters==0:
                    w_prev = w;
                else:
                    dist = (np.linalg.norm(w-w_prev))
                    w_prev = w

                    #Terminates the loop when difference between w and w_prev is very less
                    if(round(dist,6)<epsilon_val):
                        print("no.of iterations: ",iters,"Cost: ",min(costs))
                        break;

            print("Time Taken: ",datetime.now() - start)
            return w,b,cost;
```

In [57]:
```
w,b,cost = linearRegressionSGD(x_train,y_train)
```

```
no.of iterations:  379 Cost:  2.3610421482
Time Taken:  0:00:00.901566
```

In [58]:
```
# final Weight Vector
w
```

Out[58]:
```
array([-0.44528049,  1.18336573, -0.00825891,  0.71232241, -2.15167063,
        2.69403028, -0.35533995, -3.51291847,  2.14806818, -1.61030112,
       -2.13751993,  0.96277588, -3.32768966])
```

In [59]:
```
# Final y-intercept
b
```

Out[59]:
```
22.598247491871987
```

In [60]:
```
cost
```

Out[60]:
```
6.0160838332641928
```

In [61]:
```
score(x_test,y_test,w,b)
```

Out[61]:
```
0.7428985195078156
```

1.3 Sklearn SGD Regressor

In [54]:
```
sgd_lr = SGDRegressor(eta0=0.1,shuffle=True)

sgd_lr.fit(x_train,y_train)
```

```
y_pred = sgd_lr.predict(x_test)

r2_score(y_test,y_pred)
```

Out[54]: 0.7236731566748813

In [55]:
```
sgd_lr.coef_
```

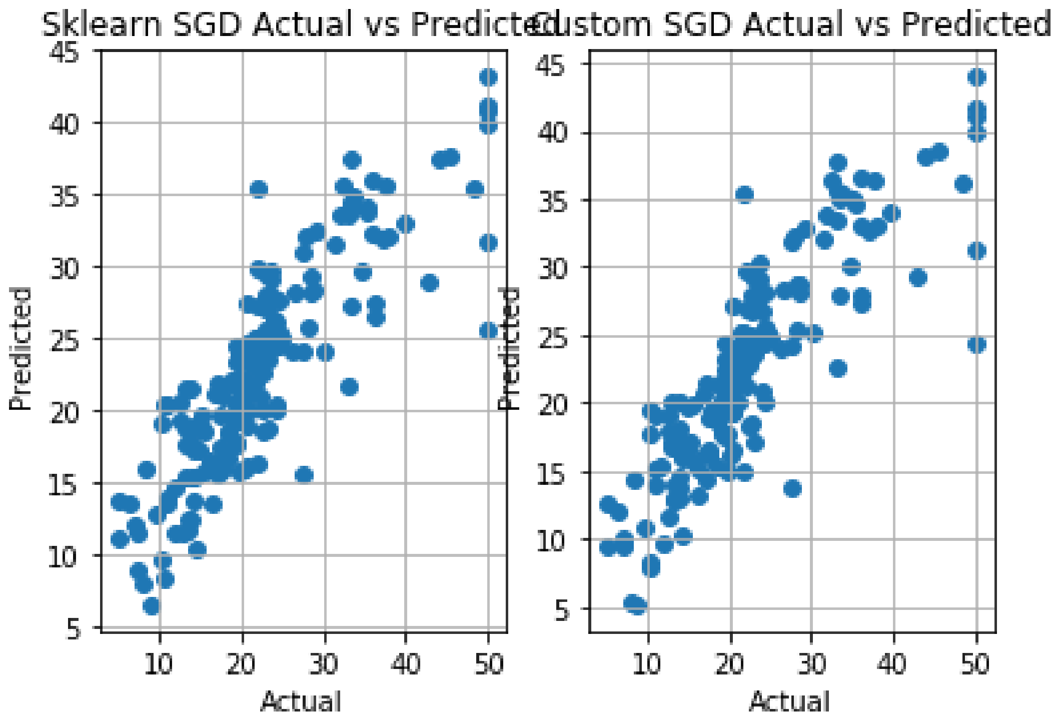
Out[55]:
```
array([-0.51154757,  1.16277626,  0.45075066,  0.54998761, -2.0917407 ,
        2.51920819, -0.59341105, -3.59284535,  1.99623011, -1.07285643,
       -2.19643933,  1.53888722, -3.21550559])
```

1.4 Scatter Plots of Actual Vs Predictions of Sklearn and Custom Impls

In [91]:
```
plt.subplot(121)
plt.scatter(x=y_test, y=y_pred);
plt.title('Sklearn SGD Actual vs Predicted')
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.grid()

plt.subplot(122)
plt.scatter(x=y_test, y=predict(x_test,w,b).flatten());
plt.title('Custom SGD Actual vs Predicted')
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.grid()

plt.show()
```



1.5 Weight Vectors Comparision

```
In [64]: print("Custom GD Linear Regression Weight Vector:  ",w1)
         print("Custom SGD Linear Regression Weight Vector:  ",w)
         print("SkLearn SGD Linear Regression Weight Vector:  ",sgd_lr.coef_)
```

```
Custom GD Linear Regression Weight Vector:   [-0.31488545  1.01598113 -0.04944872  0.77237078
 -0.49479217 -3.30437067  1.55003278 -1.20937898 -2.08453311  0.99504223
 -3.0701105 ]
Custom SGD Linear Regression Weight Vector:   [-0.44528049  1.18336573 -0.00825891  0.71232241
 -0.35533995 -3.51291847  2.14806818 -1.61030112 -2.13751993  0.96277588
 -3.32768966]
SkLearn SGD Linear Regression Weight Vector:   [-0.51154757  1.16277626  0.45075066  0.5499876
 -0.59341105 -3.59284535  1.99623011 -1.07285643 -2.19643933  1.53888722
 -3.21550559]
```

1.6 Scores Custom vs Sklearn Implementation

```
In [63]: print("Custom GD Linear Regression Score: ",score(x_test,y_test,w1,b1))
         print("Custom SGD Linear Regression Score: ",score(x_test,y_test,w,b))
         print("SkLearn SGD Linear Regression Score: ",r2_score(y_test,y_pred))
```

```
Custom GD Linear Regression Score:  0.73685878008
Custom SGD Linear Regression Score:  0.742898519508
```

```
SkLearn SGD Linear Regression Score:  0.723673156675
```

Accuracy is almost similar, Custome Sgd Implementation got highest score here, but Scores may change slightly based on the shuffle.