SGD for linear regression

February 19, 2019

1 Assignment 6: Implement SGD for linear regression

The Boston Housing Dataset

A Dataset derived from information collected by the U.S. Census Service concerning housing in the area of Boston Mass.

This dataset contains information collected by the U.S Census Service concerning housing in the area of Boston Mass. It was obtained from the StatLib archive (http://lib.stat.cmu.edu/datasets/boston), and has been used extensively throughout the literature to benchmark algorithms. However, these comparisons were primarily done outside of Delve and are thus somewhat suspect. ***The dataset is small in size with only 506 cases***

Dataset Naming The name for this dataset is simply boston. It has two prototasks: nox, in which the nitrous oxide level is to be predicted; and price, in which the median value of a home is to be predicted

Dataset Information

- **Origin** The origin of the boston housing data is Natural.
- **Usage** This dataset may be used for Assessment.
- **Number of Cases** The dataset contains a total of 506 cases.
- **Order** The order of the cases is mysterious.
- **Variables** There are 14 attributes in each case of the dataset. They are: 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 10,000dollars PTRATIO - pupil-teacher ratio by town B - 1000(Bk - 0.63)^2 where Bk is the proportion of blacks by town LSTAT - percent lower status of the population MEDV - Median value of owner-occupied homes in $1000's

Importing the necessary libraries

In [50]:
```
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)

import pandas as pd
import numpy as np
```

```
from sklearn.datasets import load_boston
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import SGDRegressor
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.metrics import mean_squared_error
from tqdm import tqdm
import random
from sklearn.model_selection import train_test_split
```

Loading the dataset

```
In [51]: boston = load_boston()
         X = pd.DataFrame(boston.data)
         Y = np.array(boston.target)

         output_df = pd.DataFrame(columns=['Algorithm', 'Learning Rate', 'N-Iteration', 'M.S.E']
         n_iter_range = [10**i for i in range(0, 6)]
```

Splitting the dataset with 70-30 train-test ratio

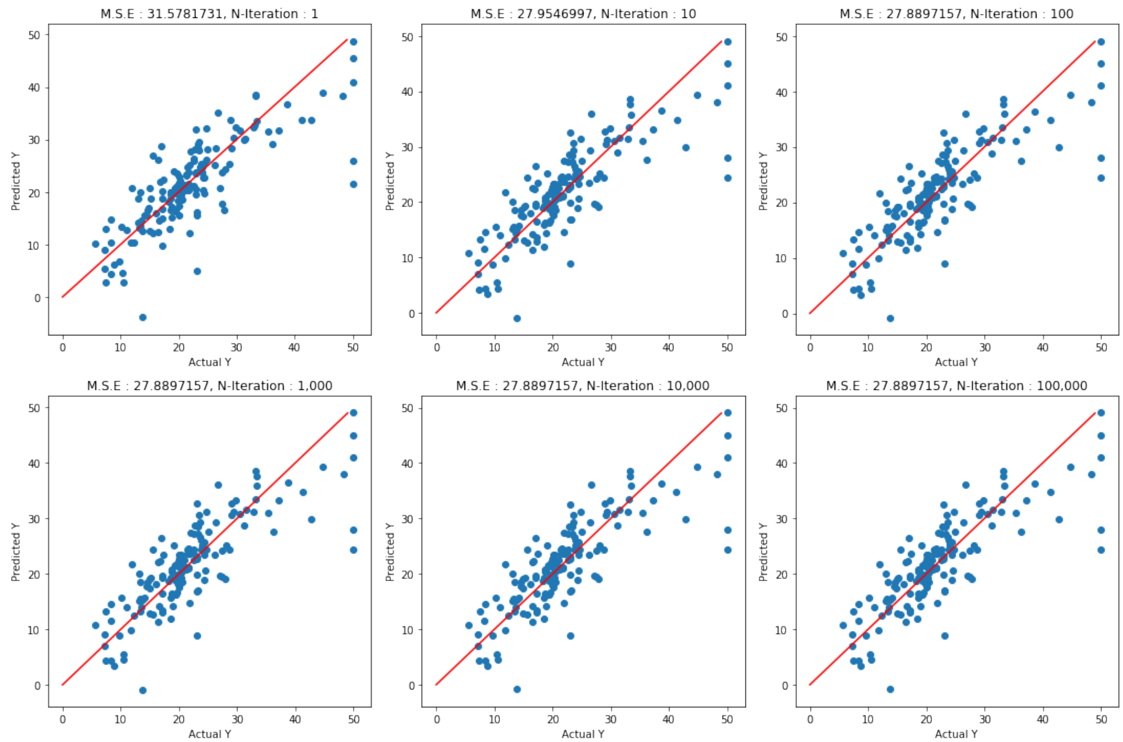
```
In [52]: XTrain, XTest, y_train, y_test = train_test_split(X, Y, test_size=0.30, random_state=0,
```

Standardizing the dataset

```
In [53]: # Standardizing the dataset with mean centering and variance scaling
         sc = StandardScaler()
         #Fitting and transforming the training dataset
         x_train = sc.fit_transform(XTrain)
         #Transforming the testing dataset
         x_test = sc.transform(XTest)
```

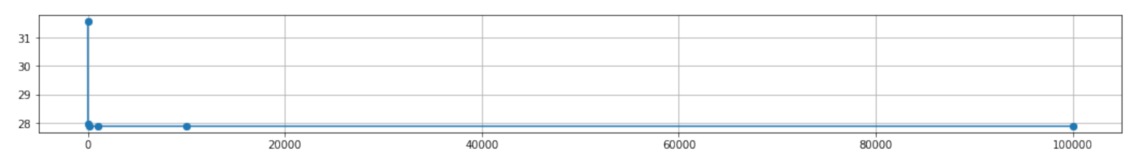
1.1 SGD Regressor with Learning Rate : 0.01

```
In [54]: f, axarr = plt.subplots(2, 3, figsize=(15,10))
         save_sgd_df = pd.DataFrame(columns=['Algorithm', 'Learning Rate','N-Iteration', 'M.S.E'
         for index, ite in enumerate(n_iter_range):
             clf = SGDRegressor(penalty='none', learning_rate='constant', eta0=0.01, shuffle=Fal
             clf.fit(x_train, y_train)
             y_pred = clf.predict(x_test)
             mse = mean_squared_error(y_test, y_pred)
             save_sgd_df = save_sgd_df.append({'Algorithm': 'SGDRegressor', 'Learning Rate': 0.0
             axarr[int(index/3), int(index%3)].plot(np.arange(50), np.arange(50), color='r')
             axarr[int(index/3), int(index%3)].scatter(y_test, y_pred)
             axarr[int(index/3), int(index%3)].set_xlabel ('Actual Y')
             axarr[int(index/3), int(index%3)].set_ylabel ('Predicted Y')
             axarr[int(index/3), int(index%3)].set_title('M.S.E : {0:.7f}'.format(mse) +  ', N-I
             plt.tight_layout()
             plt.grid()
         plt.show()
```



Plotting the N-Iterations vs M.S.E for SGDRegressor Algorithm

In [55]:
```
plt.figure(figsize=(18,2))
plt.scatter(save_sgd_df['N-Iteration'], save_sgd_df['M.S.E'])
plt.plot(save_sgd_df['N-Iteration'], save_sgd_df['M.S.E'], '-o')
plt.grid()
plt.show()
```



Printing the Weight Vector for SGD Regressor

In [56]:
```
sgd_op_w = pd.DataFrame(clf.coef_).T
sgd_op_w.index = ['SGDRegressor']
sgd_op_w
```

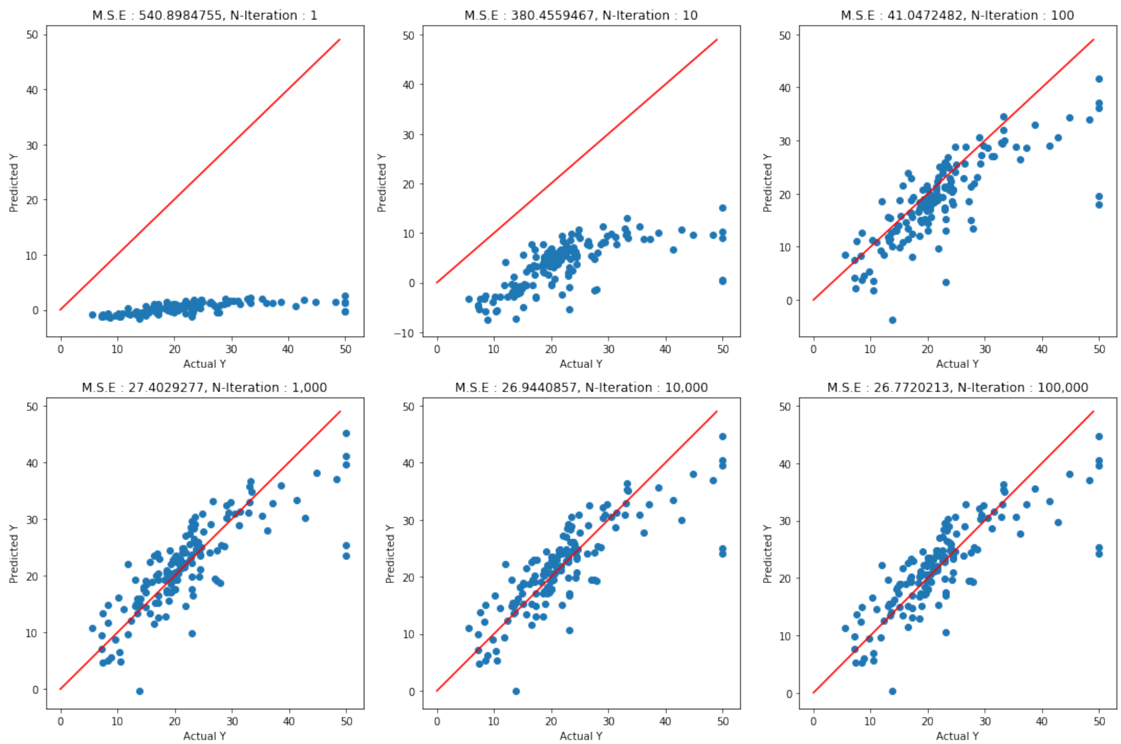
Out[56]:
```
                     0         1         2         3         4         5  \
SGDRegressor -1.191457  1.241887  0.269344  1.286084 -1.871315  3.039862
```

```
                     6         7         8         9        10        11  \
SGDRegressor -0.139336 -3.418594  2.470299 -1.982521 -2.657993  0.787101

                    12
SGDRegressor -3.644444
```

1.2 Implementing SDG Regressor with learning rate : 0.01 from scratch

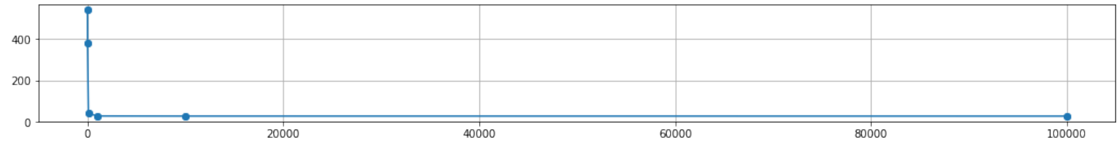
In [57]:
```
plt.close()
f, axarr = plt.subplots(2, 3, figsize=(15,10))

learning_rate = 0.01
N = x_train.shape[0]
features = x_train.shape[1]

save_mnlsgd_df = pd.DataFrame(columns=['Algorithm', 'Learning Rate','N-Iteration', 'M.S
#Selecting the batch size for SGD to be constant as 50% of training dataset
k = int(0.5 * N)

for index,ite in enumerate(n_iter_range):
    #Randomly selecting the gradient_w vector from the data itself
    w_optimal = np.zeros(shape=(features,))
    #Selecting Intercept term as 0
    b_optimal = 0

    for it in np.arange(ite):
        res_w = np.zeros((features,))
        res_b = 0
        batch_li = np.array([random.randint(1, N-1) for _ in range(k)])
        for i in batch_li:
            y_pred = np.dot(w_optimal, x_train[i]) + b_optimal
            err = y_train[i] - y_pred
            res_w =  np.array(res_w + (err * x_train[i]), dtype=np.float64)
            res_b =  res_b + err
        grad_w = (-2 / k) * res_w
        grad_b = (-2 / k) * res_b
        w_optimal = w_optimal - (learning_rate * grad_w)
        b_optimal = b_optimal - (learning_rate * grad_b)

    y_pred_ = []
    for i in range(len(x_test)):
        y=np.asscalar(np.dot(w_optimal,x_test[i]) + b_optimal)
        y_pred_.append(y)
    mse = mean_squared_error(y_test, y_pred_)
    save_mnlsgd_df = save_mnlsgd_df.append({'Algorithm': 'Manual SGD', 'Learning Rate':
    axarr[int(index/3), int(index%3)].plot(np.arange(50), np.arange(50), color='r')
    axarr[int(index/3), int(index%3)].scatter(y_test, y_pred_)
    axarr[int(index/3), int(index%3)].set_xlabel ('Actual Y')
```

```
        axarr[int(index/3), int(index%3)].set_ylabel ('Predicted Y')
        axarr[int(index/3), int(index%3)].set_title('M.S.E : {0:.7f}'.format(mse) +  ', N-I
        plt.tight_layout()
        plt.grid()
    plt.show()
```



Plotting the N-Iterations vs M.S.E for ManualSGD Algorithm

```
In [58]: plt.figure(figsize=(18,2))
         plt.scatter(save_mnlsgd_df['N-Iteration'], save_mnlsgd_df['M.S.E'])
         plt.plot(save_mnlsgd_df['N-Iteration'], save_mnlsgd_df['M.S.E'], '-o')
         plt.grid()
         plt.show()
```



Printing the Weight Vector for Manual/Scratch SGD Regressor

```
In [59]: man_sgd_op_w = pd.DataFrame(w_optimal).T
         man_sgd_op_w.index = ['Manual-SGD']
         man_sgd_op_w
```

```
Out[59]:                    0         1         2         3         4         5   \
         Manual-SGD -0.955591  1.010319  0.080567  0.642676 -1.800255  2.662878

                            6         7         8         9        10        11   \
         Manual-SGD -0.224925 -3.115612  2.213754 -1.886661 -2.261027  0.612757

                           12
         Manual-SGD -3.651006
```

```
In [60]: out_resp = pd.DataFrame(columns=['Algorithm', 'Learning Rate','N-Iteration', 'M.S.E'])
         for i in range(6):
             out_resp = out_resp.append(save_sgd_df.iloc[i])
             out_resp = out_resp.append(save_mnlsgd_df.iloc[i])

         #Reporting the weight vector result
         w_out_resp = pd.concat([sgd_op_w, man_sgd_op_w])
```

1.3 Results

Checking the Weight Vector for both algorithm implementation

```
In [61]: w_out_resp
```

```
Out[61]:                    0         1         2         3         4         5   \
         SGDRegressor -1.191457  1.241887  0.269344  1.286084 -1.871315  3.039862
         Manual-SGD   -0.955591  1.010319  0.080567  0.642676 -1.800255  2.662878

                              6         7         8         9        10        11   \
         SGDRegressor -0.139336 -3.418594  2.470299 -1.982521 -2.657993  0.787101
         Manual-SGD   -0.224925 -3.115612  2.213754 -1.886661 -2.261027  0.612757

                             12
         SGDRegressor -3.644444
         Manual-SGD   -3.651006
```

Checking the MeanSquaredError (M.S.E) for both algorithm implementations for all N-Iterations

```
In [62]: out_resp
```

```
Out[62]:       Algorithm  Learning Rate N-Iteration       M.S.E
         0  SGDRegressor           0.01           1   31.578173
         0    Manual SGD           0.01           1  540.898476
         1  SGDRegressor           0.01          10   27.954700
         1    Manual SGD           0.01          10  380.455947
         2  SGDRegressor           0.01         100   27.889716
         2    Manual SGD           0.01         100   41.047248
         3  SGDRegressor           0.01        1000   27.889716
         3    Manual SGD           0.01        1000   27.402928
```

4	SGDRegressor	0.01	10000	27.889716
4	Manual SGD	0.01	10000	26.944086
5	SGDRegressor	0.01	100000	27.889716
5	Manual SGD	0.01	100000	26.772021

1.4 Conclusion

- As the number of iterations for the manual/scratch SGD regressor algorithm is increasing, the Mean Squared Error (M.S.E) decreases.
- At nearly 1k iterations, our manual/scratch SGD Regressor algorithm MSE value becomes significantly equal to the SGDRegressor algorithm.
- We can see that our manual/scratch SGD Regressor algorithm performs well and is implemented correctly.