06_Implement_SGD

April 14, 2019

1 Import Required Packages

```
In [1]: import pandas as pd
        import numpy as np

        # preprocessing related packages
        from sklearn.preprocessing import StandardScaler

        # regression model related packages
        from sklearn.linear_model import SGDRegressor
        from sklearn.metrics import mean_squared_error

        # visualization related pacakges
        from prettytable import PrettyTable
        import matplotlib.pyplot as plt
        import seaborn as sns
        sns.set()

        # dataset loading from library
        from sklearn.datasets import load_boston
```

2 Load the dataset

```
In [2]: boston_data = load_boston()
        boston_data = boston_data

        X = boston_data.data
        y = boston_data.target
```

3 Scale the dataset

```
In [3]: scaler = StandardScaler()
        X = scaler.fit_transform(X)
        #y = scaler.fit_transform(y.reshape(-1, 1))
        y = y.flatten()
```

```
In [4]: print('Shape of featrues %d,%d, shape of labels : %d'%(X.shape + (y.shape[0],)))
```

```
Shape of featrues 506,13, shape of labels : 506
```

4 UTIL function

```
In [5]: def plot_the_prediction(actual_values, predicted_values, title_str):
            # plot two curves
            plt.plot(range(len(actual_values)), actual_values, label='Actual')
            plt.plot(range(len(predicted_values)), predicted_values, label='Predicted')
            plt.xlabel('Iteration Number')
            plt.ylabel('Label Value')
            plt.title(title_str)
            plt.legend()
            plt.show()
```

5 sklearn implementation

```
In [6]: sk_reg = SGDRegressor()
        sk_reg.fit(X, y)
        predicted_values = sk_reg.predict(X)
        mse_sklearn = mean_squared_error(y, predicted_values)
        print('MSE for skllearn version: ', mse_sklearn)
```

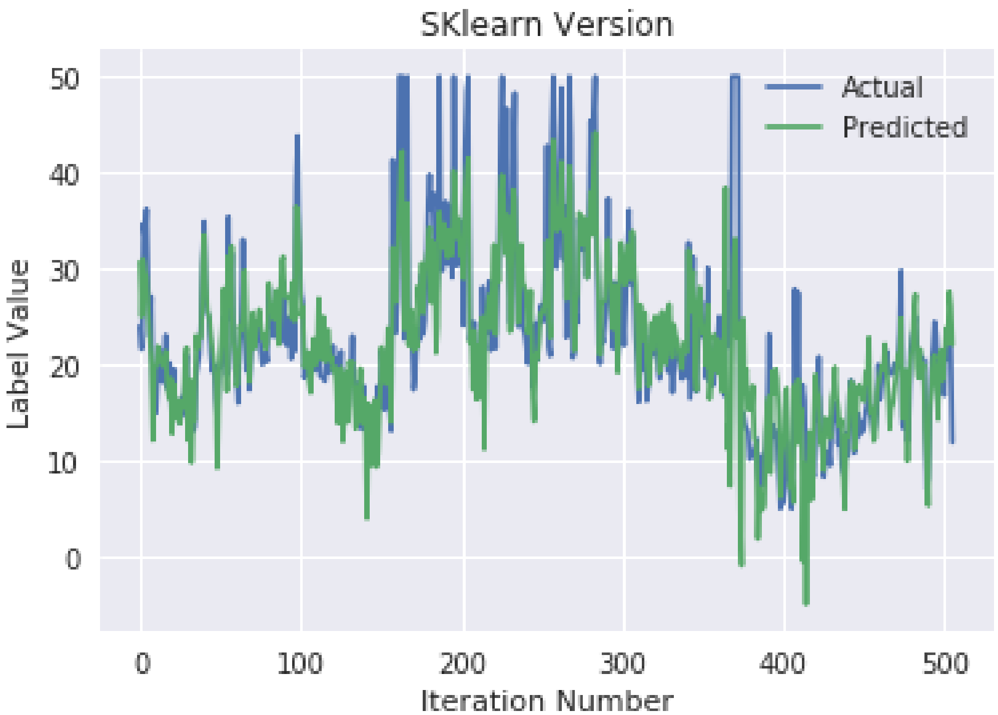
```
MSE for skllearn version:  22.931851381723657
```

```
/home/amd_3/anaconda3/lib/python3.6/site-packages/sklearn/linear_model/stochastic_gradient.py:12
  "and default tol will be 1e-3." % type(self), FutureWarning)
```

```
In [7]: sk_weights = sk_reg.coef_
        sk_bias = sk_reg.intercept_
```

5.0.1 Y vs Y_ plot for sklearn implementation

```
In [8]: title_str = 'SKlearn Version'
        plot_the_prediction(y, predicted_values, title_str)
```




```
In [9]: comparison_df = pd.DataFrame({'Actual':y, 'Predicted':predicted_values}, index=range(len
        comparison_df.head()
```

Out[9]:

	Actual	Predicted
0	24.0	30.692099
1	21.6	25.019310
2	34.7	31.014886
3	33.4	29.664846
4	36.2	29.131055

6 Custom Implementation

```
In [10]: class SGD_Linear_Regression:

             def __init__(self, with_momentum=False):

                 # initialize the required variables
                 self.num_iters = 60000
                 self.batch_size = 64

                 # variables for weight & intercept
                 self.weights = np.nan
```

```python
        # hyper params
        self.with_momentum = with_momentum
        self.tol = 1e-8 # quit the loop if weight chage is below this threshold
        self.momentum = 0.20
        self.learning_rate = 0.001

        # Parameters of linear regression
        self.coef_ = np.nan
        self.intercept_ = np.nan



    def adjust_param(self, val, min_bound, max_bound):
        """
        This function does a linear  change in momentum or learning rate as the number
        iterations increases.
        """
        mappd_value = min_bound + (max_bound - min_bound) * ((val - 1) / (self.num_iter

        return mappd_value


    def fit(self, X, y):
        """
        This function fit to the data using Stochastic Gradient Descent
        """
        # initialize the weight + bias
        self.weights = np.random.uniform(low=-1.0, high=1.0, size=X.shape[1] + 1)

        # to store previous gradients for momentum
        self.prev_grad = np.zeros(X.shape[1] + 1)

        print('inital weights assigned', self.weights)

        # create a data frame for training input
        train_df = pd.DataFrame(X)
        train_df['Target'] = y


        # run multiple iterations
        for index in range(1, self.num_iters + 1):

            # sample the dataset (current batch of size self.batch_size)
            sample_df = train_df.sample(n=self.batch_size)

            # split data set to features & labels
            labels_df = sample_df['Target']
            features_df = sample_df.drop(['Target'], axis=1)
```

```
            # add 1 to the last column to account bias as weight value
            features_df['bias'] = 1

            # compute the predicted values
            predicted_values =  (self.weights * features_df).sum(axis=1)

            # compute loss values
            loss_values = labels_df - predicted_values

            # compute the error
            mse_error = mean_squared_error(labels_df, predicted_values)

            # print the error
            if (index-1) % 10000 == 0:
                print('Iteration %d loss value: %f : lr:%f'%(index, mse_error, self.lea

            # get the current gradient
            gradient_weight = -2 * (features_df.mul(loss_values, axis=0)).mean(axis=0)

            # run the update step for momentum
            if self.with_momentum:

                # momentum term
                gradient_weight = self.momentum * self.prev_grad + self.learning_rate *
                self.prev_grad = gradient_weight
                self.momentum = self.adjust_param(index, 0.10, 0.90)

            else: # non-momentum version
                gradient_weight *= self.learning_rate

            # compute new weight vector
            new_weights = self.weights - gradient_weight

            # adjust learning rate
            self.learning_rate =  1e-3 - self.adjust_param(index, 1e-8, 1e-3)

            # terminate early if already converged
            if np.linalg.norm(new_weights - self.weights) < self.tol:
                break

            # update current weight as new weight
            self.weights = new_weights

        # Assign the final weights and biases
        self.coef_ = self.weights[:-1]
        self.intercept_ = np.array(self.weights[-1:])

    def predict(self, X):
```

```
            # convert X to data f
            return np.dot(X, self.coef_) + self.intercept_
```

In [11]:
```
sgd_reg_without_momentum = SGD_Linear_Regression(with_momentum=False)
sgd_reg_with_momentum = SGD_Linear_Regression(with_momentum=True)
```

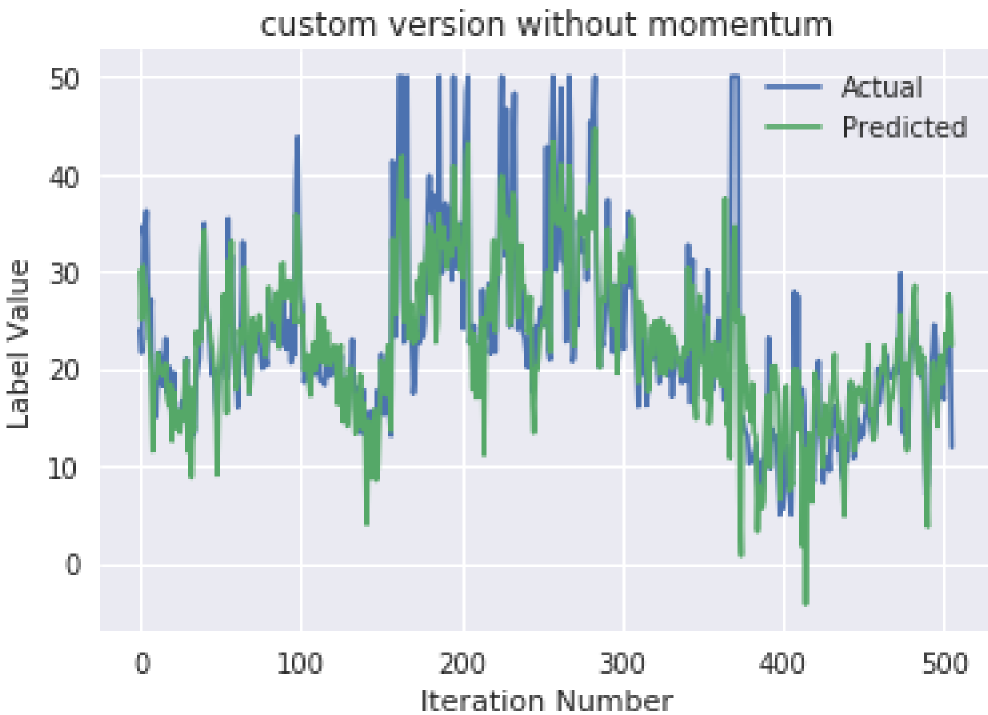
6.1 a) Without momentum version

In [12]:
```
sgd_reg_without_momentum.fit(X, y)
predicted_values = sgd_reg_without_momentum.predict(X)
mse_without_momentum = mean_squared_error(y, predicted_values)
print('The final MSE value without momentum', mse_without_momentum)
# get bias and weights
without_weights = sgd_reg_without_momentum.coef_
withouts_bias = sgd_reg_without_momentum.intercept_
```

```
inital weights assigned [-0.10699758  0.1326927  -0.59571568 -0.74806401 -0.61674516 -0.83652181
  0.22077201  0.53785738  0.24364007 -0.50370687 -0.63793894  0.30277594
 -0.29353685 -0.52790142]
Iteration 1 loss value: 624.118738 : lr:0.001000
Iteration 10001 loss value: 20.217794 : lr:0.000833
Iteration 20001 loss value: 14.649243 : lr:0.000667
Iteration 30001 loss value: 23.965127 : lr:0.000500
Iteration 40001 loss value: 19.374366 : lr:0.000333
Iteration 50001 loss value: 12.894435 : lr:0.000167
The final MSE value without momentum 21.89824079416991
```

6.1.1 Y vs Y_ plot for custom version without momentum

In [13]:
```
title_str = 'custom version without momentum'
plot_the_prediction(y, predicted_values, title_str)
```




```
In [14]: comparison_df = pd.DataFrame({'Actual':y, 'Predicted':predicted_values}, index=range(le
         comparison_df.head()
```

Out[14]:

	Actual	Predicted
0	24.0	30.031080
1	21.6	25.031326
2	34.7	30.571907
3	33.4	28.612655
4	36.2	27.951806

6.2 b) With momentum version

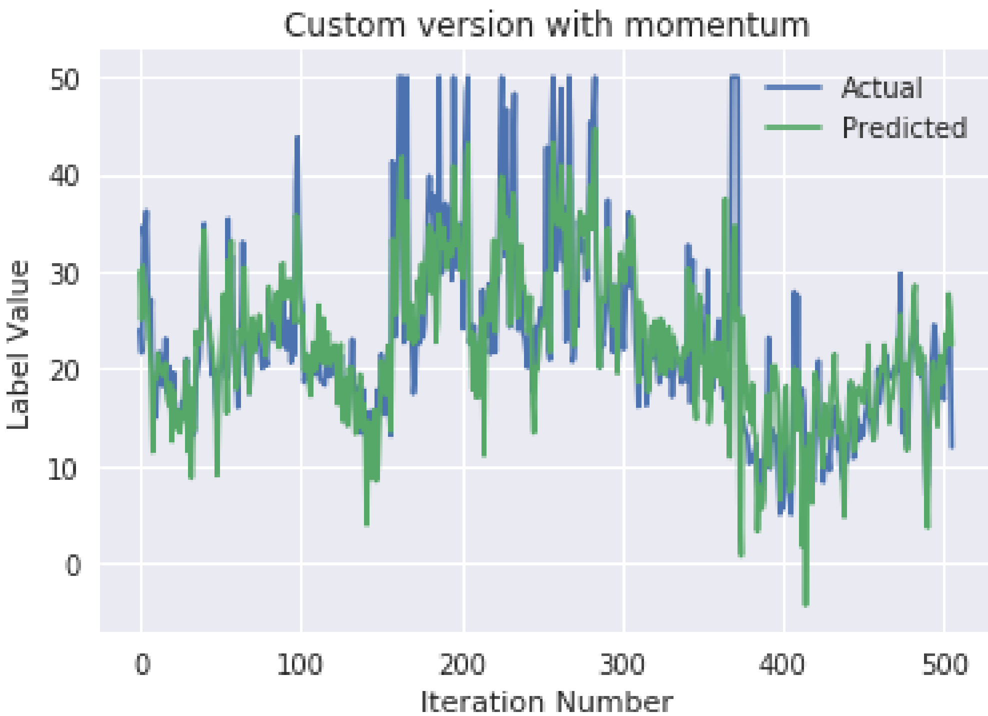
```
In [15]: sgd_reg_with_momentum.fit(X, y)
         predicted_values = sgd_reg_with_momentum.predict(X)
         mse_withmomentum = mean_squared_error(y, predicted_values)
         print('The final MSE value with momentum', mse_withmomentum)
         # get bias and weights
         with_weights = sgd_reg_with_momentum.coef_
         with_bias = sgd_reg_with_momentum.intercept_
```

```
inital weights assigned [ 0.34436705  0.05880664 -0.58824649  0.7545802   0.66926351  0.46999522
 -0.26835904 -0.85713751 -0.57609302 -0.00371549  0.85743946  0.03037301
 -0.27145042 -0.21153613]
Iteration 1 loss value: 527.617726 : lr:0.001000
```

```
Iteration 10001 loss value: 26.383148 : lr:0.000833
Iteration 20001 loss value: 19.388833 : lr:0.000667
Iteration 30001 loss value: 16.247267 : lr:0.000500
Iteration 40001 loss value: 18.176866 : lr:0.000333
Iteration 50001 loss value: 20.411124 : lr:0.000167
The final MSE value with momentum 21.898794101026567
```

6.2.1 Y vs Y_ plot for Custom version with momentum

In [16]:
```
title_str = 'Custom version with momentum'
plot_the_prediction(y, predicted_values, title_str)
```



In [17]:
```
comparison_df = pd.DataFrame({'Actual':y, 'Predicted':predicted_values}, index=range(le
comparison_df.head()
```

Out[17]:

	Actual	Predicted
0	24.0	30.016968
1	21.6	25.032358
2	34.7	30.575248
3	33.4	28.623558
4	36.2	27.942372

6.3 Comparsion of Weights from all three models

In [18]:
```
weights_table = pd.DataFrame({'SK_Learn':sk_weights, 'Without_momentum':without_weights
                               'With_momentum' : with_weights}, index=range(len(sk_weigh
bias_table = pd.DataFrame({'SK_Learn':sk_bias, 'Without_momentum': withouts_bias,
                               'With_momentum' : with_bias})
```

6.4 a) Weights table

In [19]:
```
weights_table = weights_table[['SK_Learn', 'Without_momentum', 'With_momentum']]
weights_table
```

Out[19]:

	SK_Learn	Without_momentum	With_momentum
0	-0.752903	-0.906675	-0.922864
1	0.597092	1.074215	1.091047
2	-0.508069	0.124804	0.143693
3	0.775476	0.685810	0.690379
4	-1.044620	-2.051741	-2.067917
5	3.147765	2.676833	2.650176
6	-0.261840	0.022977	0.021907
7	-2.043230	-3.096169	-3.118597
8	0.844388	2.610523	2.664484
9	-0.524075	-2.034974	-2.079862
10	-1.803282	-2.060391	-2.048109
11	0.915453	0.850923	0.861836
12	-3.412783	-3.740848	-3.784314

6.5 b) Bias Table

In [20]:
```
bias_table = bias_table[['SK_Learn', 'Without_momentum', 'With_momentum']]
bias_table
```

Out[20]:

	SK_Learn	Without_momentum	With_momentum
0	22.341985	22.531998	22.533082

6.6 Observation

Bias holds larger values when compared with weights

7 Predict House Price given a Raw Data Point

7.1 Proceudre for predicting the house price

As the first step, we need to scale the given data point (x) to scaled domain using the parameters of standard scaler (the scaler we used at the time of training)

We need to use two parameters mean (μ) and standard deviation (σ) of the scaler and scale it using $\frac{x-\mu}{\sigma}$

Once the scaling is done, we can feed the point to model and get the predicted value as output from it

```
In [21]: def predict_the_price(model, scaler, x):
             """
             This function helps to predict the price of a data point
             given the model and its scaler.
             """

             # get parameters
             mu = scaler.mean_
             sigma = np.sqrt(scaler.var_)

             # scale the input data
             x_new = (x - mu) / sigma

             # predict the price
             predicted_price = model.predict(x_new)

             return predicted_price
```

7.2 Raw input data

```
In [22]: raw_data_points = boston_data.data[0:5]
         raw_data_points_labels = boston_data.target[0:5]
```

7.3 Predict the price

7.3.1 a) using the sklearn version

```
In [23]: predicted_values_ver1 = predict_the_price(sk_reg, scaler, raw_data_points)
```

7.3.2 b) using the custom without momentum version

```
In [24]: predicted_values_ver2 = predict_the_price(sgd_reg_without_momentum, scaler, raw_data_po
```

7.3.3 c) using the custom with momentum version

```
In [25]: predicted_values_ver3 = predict_the_price(sgd_reg_with_momentum, scaler, raw_data_point
```

7.4 Prediction Results

```
In [26]: predicted_df = pd.DataFrame({'SK_learn' : predicted_values_ver1,
                          'Custom_without_momentum' :predicted_values_ver2,
                         'Custom_with_momentum' :predicted_values_ver3,
                         'Actual' : raw_data_points_labels}, index=range(len(predicted_values_ver1)
         predicted_df = predicted_df[['SK_learn', 'Custom_without_momentum', 'Custom_with_moment
         predicted_df
```

Out[26]:

	SK_learn	Custom_without_momentum	Custom_with_momentum	Actual
0	30.692099	30.031080	30.016968	24.0
1	25.019310	25.031326	25.032358	21.6

```
2   31.014886                30.571907               30.575248   34.7
3   29.664846                28.612655               28.623558   33.4
4   29.131055                27.951806               27.942372   36.2
```

8 Procedure Summary

Scale the featues of dataset using standard scaler
Train all the three models using the scaled dataset
Evaluate the models using MSE metric
Compare the weights, biases obtained for all models
Compare the actual and predicted values of all models
Predict the house price given a non-scaled raw input data set

9 Results Summary

In [27]:
```
from prettytable import PrettyTable
```

In [28]:
```
ptable = PrettyTable()
ptable.title = 'SGD Regression Method Comparison'
ptable.field_names = ['Method', 'MSE Value']
```

In [29]:
```
ptable.add_row(['Sk-learn Version', mse_sklearn])
ptable.add_row(['Custom Version without momentum', mse_without_momentum])
ptable.add_row(['Custom Version with momentum', mse_withmomentum])
```

In [30]:
```
print(ptable)
```

```
+-------------------------------------------------------+
|           SGD Regression Method Comparison            |
+---------------------------------+---------------------+
|              Method             |      MSE Value      |
+---------------------------------+---------------------+
|         Sk-learn Version        |  22.931851381723657 |
| Custom Version without momentum |  21.89824079416991  |
|   Custom Version with momentum  |  21.898794101026567 |
+---------------------------------+---------------------+
```

10 Conclusion

The weights obtained from both momentum and non momentum version are very similar
Many of the weights obtained from sklearn implementation are close to the custom implementation weights
The final MSE error from all three methods are roughly same
The performace of momentum version is better compared to non-momentum version (from the mse values obtained at different iterations 10K, 20K, 30K etc.)