Implement SGD

June 18, 2019

```
In []: ## reference link: https://spin.atomicobject.com/2014/06/24/gradient-descent-linear-r
In [23]: # Imported necessary libraries
        from sklearn.datasets import load_boston
        from sklearn.model_selection import train_test_split
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        from sklearn.metrics import mean_squared_error
        from sklearn import preprocessing
        from sklearn.linear_model import SGDRegressor
        # Data loaded
        bostan = load_boston()
         # Data shape
        bostan.data.shape
Out[23]: (506, 13)
In [24]: # Feature name
        bostan.feature_names
Out[24]: array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD',
                'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7')
In [25]: # This is y value i.e. target
        bostan.target.shape
Out[25]: (506,)
In [26]: # Convert it into pandas dataframe
        data = pd.DataFrame(bostan.data, columns = bostan.feature_names)
        data.head()
Out [26]:
                      ZN INDUS CHAS
                                                 RM
                                                      AGE
              CRIM
                                         NOX
                                                              DIS RAD
                                                                          TAX \
        0 0.00632 18.0
                                  0.0 0.538 6.575 65.2 4.0900 1.0 296.0
                           2.31
        1 0.02731
                     0.0
                           7.07
                                  0.0 0.469 6.421 78.9 4.9671 2.0 242.0
```

```
3.0
         3 0.03237
                       0.0
                              2.18
                                     0.0
                                          0.458
                                                  6.998
                                                         45.8
                                                                6.0622
                                                                              222.0
         4 0.06905
                       0.0
                              2.18
                                     0.0
                                          0.458
                                                         54.2
                                                                6.0622
                                                                        3.0
                                                                              222.0
                                                  7.147
            PTRATIO
                           В
                              LSTAT
         0
                15.3
                      396.90
                                4.98
         1
                17.8
                      396.90
                                9.14
         2
                17.8
                      392.83
                                4.03
         3
                18.7
                      394.63
                                2.94
         4
                18.7
                      396.90
                                5.33
In [27]: # Statistical summary
         data.describe()
Out [27]:
                       CRIM
                                      ZN
                                                INDUS
                                                              CHAS
                                                                            NOX
                                                                                          RM
         count
                 506.000000
                              506.000000
                                          506.000000
                                                       506.000000
                                                                    506.000000
                                                                                 506.000000
                   3.613524
                               11.363636
                                            11.136779
                                                          0.069170
                                                                      0.554695
                                                                                   6.284634
         mean
                   8.601545
                               23.322453
                                            6.860353
                                                          0.253994
                                                                                   0.702617
         std
                                                                      0.115878
         min
                   0.006320
                                0.000000
                                            0.460000
                                                         0.000000
                                                                      0.385000
                                                                                   3.561000
                                            5.190000
         25%
                   0.082045
                                0.00000
                                                         0.000000
                                                                      0.449000
                                                                                   5.885500
         50%
                   0.256510
                                0.000000
                                            9.690000
                                                          0.000000
                                                                      0.538000
                                                                                   6.208500
         75%
                   3.677083
                               12.500000
                                            18.100000
                                                          0.000000
                                                                      0.624000
                                                                                   6.623500
                  88.976200
                              100.000000
                                            27.740000
                                                          1.000000
                                                                      0.871000
                                                                                   8.780000
         max
                        AGE
                                     DIS
                                                  RAD
                                                               TAX
                                                                       PTRATIO
                                                                                           В
                 506.000000
                              506.000000
                                          506.000000
                                                       506.000000
                                                                                 506.000000
         count
                                                                    506.000000
                  68.574901
                                3.795043
                                             9.549407
                                                       408.237154
         mean
                                                                     18.455534
                                                                                 356.674032
                  28.148861
                                2.105710
                                             8.707259
                                                       168.537116
                                                                      2.164946
                                                                                  91.294864
         std
         min
                   2.900000
                                1.129600
                                            1.000000
                                                       187.000000
                                                                     12.600000
                                                                                   0.320000
         25%
                  45.025000
                                2.100175
                                            4.000000
                                                       279.000000
                                                                     17.400000
                                                                                 375.377500
         50%
                  77.500000
                                3.207450
                                             5.000000
                                                       330.000000
                                                                     19.050000
                                                                                 391.440000
                                            24.000000
                                                       666.000000
         75%
                  94.075000
                                5.188425
                                                                     20.200000
                                                                                 396.225000
                 100.000000
                               12.126500
                                            24.000000
                                                       711.000000
                                                                     22.000000
                                                                                 396.900000
         max
                      LSTAT
                 506.000000
         count
         mean
                  12.653063
         std
                   7.141062
         min
                   1.730000
         25%
                   6.950000
         50%
                  11.360000
         75%
                  16.955000
                  37.970000
         max
In [28]: #standardize for fast convergence to minima
         data = (data - data.mean())/data.std()
         data.head()
Out [28]:
                                     INDUS
                                                 CHAS
                                                             NOX
                                                                                       \
                 CRIM
                              ZN
                                                                        RM
                                                                                  AGE
                      0.284548 -1.286636 -0.272329 -0.144075 0.413263 -0.119895
         0 -0.419367
```

4.9671

2.0

242.0

7.07

0.0 0.469

7.185

61.1

0.0

2 0.02729

```
3 -0.416338 -0.487240 -1.305586 -0.272329 -0.834458 1.015298 -0.809088
         4 -0.412074 -0.487240 -1.305586 -0.272329 -0.834458 1.227362 -0.510674
                 DIS
                           RAD
                                     TAX
                                           PTRATIO
                                                           В
                                                                 LSTAT
        0 0.140075 -0.981871 -0.665949 -1.457558 0.440616 -1.074499
         1 \quad 0.556609 \quad -0.867024 \quad -0.986353 \quad -0.302794 \quad 0.440616 \quad -0.491953
         2 0.556609 -0.867024 -0.986353 -0.302794 0.396035 -1.207532
         3 1.076671 -0.752178 -1.105022 0.112920 0.415751 -1.360171
         4 1.076671 -0.752178 -1.105022 0.112920 0.440616 -1.025487
In [29]: # MEDV (median value is usually target), change it to price
        data["PRICE"] = bostan.target
        data.head()
Out [29]:
                CRIM
                           ZN
                                   INDUS
                                              CHAS
                                                         NOX
                                                                    RM
                                                                             AGE \
         1 - 0.416927 - 0.487240 - 0.592794 - 0.272329 - 0.739530 0.194082 0.366803
         2 -0.416929 -0.487240 -0.592794 -0.272329 -0.739530 1.281446 -0.265549
        3 -0.416338 -0.487240 -1.305586 -0.272329 -0.834458 1.015298 -0.809088
         4 -0.412074 -0.487240 -1.305586 -0.272329 -0.834458 1.227362 -0.510674
                DIS
                                          PTRATIO
                                                                LSTAT PRICE
                           RAD
                                     TAX
                                                           В
        0 0.140075 -0.981871 -0.665949 -1.457558 0.440616 -1.074499
                                                                         24.0
         1 \quad 0.556609 \quad -0.867024 \quad -0.986353 \quad -0.302794 \quad 0.440616 \quad -0.491953
                                                                         21.6
         2 0.556609 -0.867024 -0.986353 -0.302794 0.396035 -1.207532
                                                                         34.7
         3 1.076671 -0.752178 -1.105022 0.112920 0.415751 -1.360171
                                                                         33.4
         4 1.076671 -0.752178 -1.105022 0.112920 0.440616 -1.025487
                                                                         36.2
In [30]: # Target and features
        Y = data["PRICE"]
        X = data.drop("PRICE", axis = 1)
In [31]: from sklearn.model_selection import train_test_split
        x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size = 0.3)
        print(x_train.shape, x_test.shape, y_train.shape, y_test.shape)
        x_train["PRICE"] = y_train
(354, 13) (152, 13) (354,) (152,)
/home/pranay/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:5: SettingWithCopyWars
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

1 -0.416927 -0.487240 -0.592794 -0.272329 -0.739530 0.194082 0.366803 2 -0.416929 -0.487240 -0.592794 -0.272329 -0.739530 1.281446 -0.265549

11 11 11

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.htm

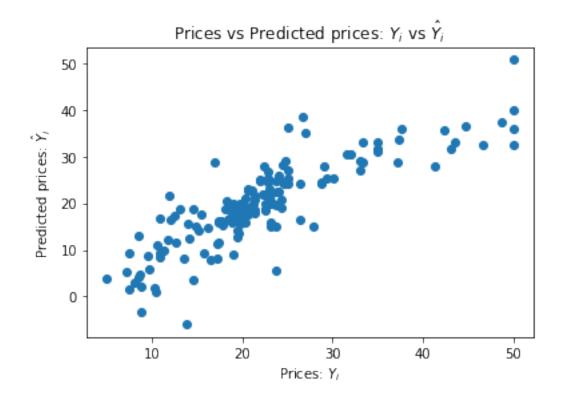
0.1 Custome SGD Implementation

iterations = 1000
gradient_m = 0
gradient_b = 0
cost train = []

```
cost_test = []
             for j in range(1, iterations):
                 # Random Train
                 train_sample = points.sample(160)
                 y = np.asmatrix(train_sample["PRICE"])
                 x = np.asmatrix(train_sample.drop("PRICE", axis = 1))
                 for i in range(len(x)):
                     dot_prod = np.dot(x[i], w0) + b0
                     substract_term =y[:,i] - dot_prod
                     gradient_m += np.dot(-2*x[i].T , substract_term)
                     gradient_b += -2*(substract_term)
         #
                       print(substract_term.shape)
                 w1 = w0 - learning_rate * gradient_m
                 b1 = b0 - learning_rate * gradient_b
                 if (w0==w1).all():
                     break
                 else:
                     w0 = w1
                     b0 = b1
                     learning_rate = learning_rate/2
             return w0, b0
         def mse_metric(b, m, features, target):
             totalError = 0
             for i in range(0, len(features)):
                 x = features
                 y = target
                 totalError += (y[:,i] - (np.dot(x[i], m) + b)) ** 2
             return totalError / len(x)
In [33]: learning_rate = 0.001
         w0_random = np.random.rand(13)
         w0 = np.asmatrix(w0_random).T
         b0 = np.random.rand()
         optimal_w, optimal_b = gradient_decent(w0, b0, x_train, x_test, y_test, learning_rate
         print("Coefficient: {} \n y_intercept: {}".format(optimal_w, optimal_b))
                                         4
```

In [32]: def gradient_decent(w0, b0, points, x_test, y_test, learning_rate):

```
Coefficient: [[-0.68292829]
 [ 1.13355708]
 [-0.13956617]
 [ 3.11930798]
 [-0.24116852]
 [ 4.15839783]
 [ 0.28884544]
 [-0.66286099]
 [ 0.16888711]
 [-0.34984621]
[ 0.06535574]
 [ 1.62262885]
 [-3.5635532]]
y_intercept: [[20.65043429]]
In [34]: # Implemented SGD
         # The mean squared error
         mse_error = mse_metric(optimal_b, optimal_w, np.asmatrix(x_test), np.asmatrix(y_test)
         print("Custom SGD Mean squared error: %.2f" % mse_error)
Custom SGD Mean squared error: 34.08
In [35]: y_pred= [(np.dot(np.asmatrix(x_test), optimal_w) + optimal_b)]
         # manual_error=plot_(y_pred)
         plt.scatter(y_test, y_pred)
         plt.xlabel("Prices: $Y_i$")
        plt.ylabel("Predicted prices: $\hat{Y}_i$")
         plt.title("Prices vs Predicted prices: $Y_i$ vs $\hat{Y}_i$")
         plt.show()
```



0.2 SKLearn SGD Implementation

```
In [36]: X = load_boston().data
         Y = load_boston().target
         df=pd.DataFrame(X)
         df.head()
         # standardise data
         scaler = preprocessing.StandardScaler()
         X = scaler.fit_transform(X)
         df=pd.DataFrame(X)
         df['price']=Y
         df.head()
Out [36]:
                   0
                                                                      5
                             1
                                       2
                                                  3
                                                                                6
         0 -0.419782  0.284830 -1.287909 -0.272599 -0.144217
                                                               0.413672 -0.120013
         1 -0.417339 -0.487722 -0.593381 -0.272599 -0.740262
                                                               0.194274 0.367166
         2 -0.417342 -0.487722 -0.593381 -0.272599 -0.740262
                                                              1.282714 -0.265812
         3 -0.416750 -0.487722 -1.306878 -0.272599 -0.835284 1.016303 -0.809889
         4 -0.412482 -0.487722 -1.306878 -0.272599 -0.835284 1.228577 -0.511180
```

```
8
                                                10
                                                          11
                                                                    12 price
        0 0.140214 -0.982843 -0.666608 -1.459000 0.441052 -1.075562
                                                                         24.0
         1 0.557160 -0.867883 -0.987329 -0.303094 0.441052 -0.492439
                                                                         21.6
        2 0.557160 -0.867883 -0.987329 -0.303094 0.396427 -1.208727
                                                                         34.7
         3 1.077737 -0.752922 -1.106115 0.113032 0.416163 -1.361517
                                                                         33.4
         4 1.077737 -0.752922 -1.106115 0.113032 0.441052 -1.026501
                                                                         36.2
In [37]: # standardise data
        scaler = preprocessing.StandardScaler()
        X = scaler.fit_transform(X)
        df=pd.DataFrame(X)
        df['price']=Y
         df.head()
Out [37]:
                                                                     5
                             1
                                       2
                                                 3
        0 -0.419782 0.284830 -1.287909 -0.272599 -0.144217 0.413672 -0.120013
         1 - 0.417339 - 0.487722 - 0.593381 - 0.272599 - 0.740262 0.194274 0.367166
         2 -0.417342 -0.487722 -0.593381 -0.272599 -0.740262 1.282714 -0.265812
         3 -0.416750 -0.487722 -1.306878 -0.272599 -0.835284 1.016303 -0.809889
         4 -0.412482 -0.487722 -1.306878 -0.272599 -0.835284 1.228577 -0.511180
                   7
                                                10
                                                          11
                                                                    12 price
        0 0.140214 -0.982843 -0.666608 -1.459000 0.441052 -1.075562
                                                                         24.0
         1 0.557160 -0.867883 -0.987329 -0.303094 0.441052 -0.492439
                                                                         21.6
         2 0.557160 -0.867883 -0.987329 -0.303094 0.396427 -1.208727
                                                                         34.7
         3 1.077737 -0.752922 -1.106115 0.113032 0.416163 -1.361517
                                                                         33.4
         4 1.077737 -0.752922 -1.106115 0.113032 0.441052 -1.026501
                                                                         36.2
In [38]: # Split data into train and test
        X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.33, random_state
        print(X_train.shape)
        print(X_test.shape)
        print(Y_train.shape)
        print(Y_test.shape)
(339, 13)
(167, 13)
(339,)
(167,)
In [39]: from sklearn.linear_model import SGDRegressor
         from sklearn.metrics import mean_squared_error, r2_score
         clf = SGDRegressor()
         clf.fit(X_train, Y_train)
         Y_pred = clf.predict(X_test)
        print("Coefficients: \n", clf.coef_)
        print("Y_intercept", clf.intercept_)
```

```
Coefficients:

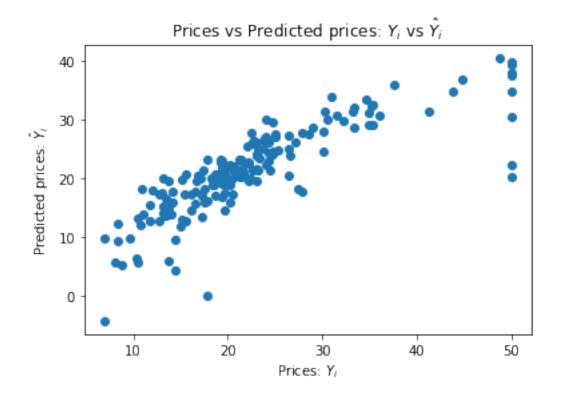
[-0.9266483  0.19881195 -0.6338864  0.27567329 -0.45419415  3.06297705

-0.40894034 -1.82317767  1.04266262 -0.41628519 -1.98692311  0.97787009

-3.06916569]

Y_intercept [21.75067408]
```

/home/pranay/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/stochastic_gradient.py FutureWarning)



```
In [45]: import pandas as pd
        from prettytable import PrettyTable
        x = PrettyTable()
        x.field names = ['Metric', 'Sklearn', 'Custokm SGD']
        x.add_row(["MSE vales ", 30.59,34.08])
        print('\n')
        print(x)
  Metric | Sklearn | Custokm SGD |
+----+
| MSE vales | 30.59 | 34.08
+----+
0.2.1 final weight from Custom SGD
In [43]: print("Coefficient: {} \n y_intercept: {}".format(optimal_w, optimal_b))
Coefficient: [[-0.68292829]
 [ 1.13355708]
[-0.13956617]
 [ 3.11930798]
 [-0.24116852]
 [ 4.15839783]
 [ 0.28884544]
 [-0.66286099]
 [ 0.16888711]
 [-0.34984621]
 [ 0.06535574]
 [ 1.62262885]
 [-3.5635532]]
 y_intercept: [[20.65043429]]
0.2.2 final weight from SGD Sklearn
In [44]: print("Coefficients: \n", clf.coef_)
        print("Y_intercept", clf.intercept_)
Coefficients:
             0.19881195 -0.6338864
 [-0.9266483]
                                     0.27567329 -0.45419415 3.06297705
-0.40894034 \ -1.82317767 \ 1.04266262 \ -0.41628519 \ -1.98692311 \ 0.97787009
-3.06916569]
```

Y_intercept [21.75067408]