SGD_Assignment

March 22, 2020

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[1]: import numpy as np
     import pandas as pd
     from tqdm.notebook import tqdm
     from sklearn.datasets import make_classification
[2]: X, y = make_classification(n_samples=50000, n_features=15, n_informative=10,__
      \rightarrown_redundant=5,
                                n_classes=2, weights=[0.7], class_sep=0.7,_
      →random_state=15)
[3]: X.shape, y.shape
[3]: ((50000, 15), (50000,))
[4]: from sklearn.model_selection import train_test_split
[5]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,__
      →random_state=15)
[6]: X_train.shape, y_train.shape, X_test.shape, y_test.shape
[6]: ((37500, 15), (37500,), (12500, 15), (12500,))
[7]: from sklearn import linear_model
[8]: # alpha : float
     # Constant that multiplies the regularization term.
     # eta0 : double
     # The initial learning rate for the 'constant', 'invscaling' or 'adaptive'
     \rightarrow schedules.
     clf = linear_model.SGDClassifier(eta0=0.0001, alpha=0.0001, loss='log', __
     →random_state=15, penalty='12', tol=1e-3, verbose=2, learning_rate='constant')
     clf
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[8]: SGDClassifier(alpha=0.0001, average=False, class_weight=None,
                   early_stopping=False, epsilon=0.1, eta0=0.0001,
                   fit_intercept=True, l1_ratio=0.15, learning_rate='constant',
                   loss='log', max_iter=1000, n_iter_no_change=5, n_jobs=None,
                   penalty='12', power_t=0.5, random_state=15, shuffle=True,
                   tol=0.001, validation_fraction=0.1, verbose=2, warm_start=False)
[9]: clf.fit(X=X_train, y=y_train)
    -- Epoch 1
    Norm: 0.77, NNZs: 15, Bias: -0.316653, T: 37500, Avg. loss: 0.455552
    Total training time: 0.02 seconds.
    -- Epoch 2
    Norm: 0.91, NNZs: 15, Bias: -0.472747, T: 75000, Avg. loss: 0.394686
    Total training time: 0.04 seconds.
    -- Epoch 3
    Norm: 0.98, NNZs: 15, Bias: -0.580082, T: 112500, Avg. loss: 0.385711
    Total training time: 0.06 seconds.
    -- Epoch 4
    Norm: 1.02, NNZs: 15, Bias: -0.658292, T: 150000, Avg. loss: 0.382083
    Total training time: 0.08 seconds.
    -- Epoch 5
    Norm: 1.04, NNZs: 15, Bias: -0.719528, T: 187500, Avg. loss: 0.380486
    Total training time: 0.10 seconds.
    -- Epoch 6
    Norm: 1.05, NNZs: 15, Bias: -0.763409, T: 225000, Avg. loss: 0.379578
    Total training time: 0.12 seconds.
    -- Epoch 7
    Norm: 1.06, NNZs: 15, Bias: -0.795106, T: 262500, Avg. loss: 0.379150
    Total training time: 0.14 seconds.
    -- Epoch 8
    Norm: 1.06, NNZs: 15, Bias: -0.819925, T: 300000, Avg. loss: 0.378856
    Total training time: 0.17 seconds.
    -- Epoch 9
    Norm: 1.07, NNZs: 15, Bias: -0.837805, T: 337500, Avg. loss: 0.378585
    Total training time: 0.19 seconds.
    -- Epoch 10
    Norm: 1.08, NNZs: 15, Bias: -0.853138, T: 375000, Avg. loss: 0.378630
    Total training time: 0.21 seconds.
    Convergence after 10 epochs took 0.22 seconds
[9]: SGDClassifier(alpha=0.0001, average=False, class_weight=None,
                   early_stopping=False, epsilon=0.1, eta0=0.0001,
                   fit_intercept=True, l1_ratio=0.15, learning_rate='constant',
                   loss='log', max_iter=1000, n_iter_no_change=5, n_jobs=None,
```

penalty='12', power_t=0.5, random_state=15, shuffle=True,

tol=0.001, validation_fraction=0.1, verbose=2, warm_start=False)

0.1 Implement Logistc Regression with L2 regularization Using SGD: without using sklearn

0.1.1 Instructions

- Load the datasets(train and test) into the respective arrays
- Initialize the weight_vector and intercept term randomly
- Calculate the initial log loss for the train and test data with the current weight and intercept and store it in a list
- for each epoch:
 - for each batch of data points in train: (keep batch size=1)
 - * calculate the gradient of loss function w.r.t each weight in weight vector
 - * Calculate the gradient of the intercept check this
 - * Update weights and intercept (check the equation number 32 in the above mentioned pdf): $w^{(t+1)} \leftarrow (1-\overline{N})w^{(t)} + x_n(y_n ((w^{(t)})^Tx_n + b^t)) b^{(t+1)} \leftarrow (b^t + (y_n ((w^{(t)})^Tx_n + b^t))$
 - * calculate the log loss for train and test with the updated weights (you can check the python assignment 10th question)
 - * And if you wish, you can compare the previous loss and the current loss, if it is not updating, then you can stop the training
 - * append this loss in the list (this will be used to see how loss is changing for each epoch after the training is over)
- Plot the train and test loss i.e on x-axis the epoch number, and on y-axis the loss
- GOAL: compare your implementation and SGDClassifier's the weights and intercept, make sure they are as close as possible i.e difference should be in terms of 10^-3

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[12]: #We already have data loaded to X_train, X_test, y_train, y_test #Vales of Weight vector and intercept term are initially set to 0
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[13]: #Sigmoid function
def sigmoid(w,x,b):
    val=1/(1+np.exp(-(np.dot(x,w.T)+b)))
```

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[14]: #Log Loss function
               # Loq loss= -((1/N)*[(y*log(p))+((1-y)*log(1-p))])
              def log_loss(w,x,b,y):
                        sigmoid_val=sigmoid(w,x,b)
                        first_term=y*np.log(sigmoid_val)
                        second_term=(1-y)*np.log(1-sigmoid_val)
                        val=-((first_term+second_term)/(len(x)))
                        return np.sum(val)
[15]: # write your code to implement SGD as per the above instructions
               # please choose the number of iternations on your own
[31]: def SGD(w,b,epoch,x_train,y_train,x_test,y_test):
                        log_loss_train=[]
                        log_loss_test=[]
                        N=len(x_train)
                        #Caluculate initial log loss and storing the values
                        log_loss_train.append(log_loss(w,x_train,b,y_train))
                        log_loss_test.append(log_loss(w,x_test,b,y_test))
                        for epo in tqdm(range(epoch)):
                                  for i in range(N):
                                            w= ((1-(alpha*eta0)/
                 →N)*w)+((alpha*x_train[i])*(y_train[i]-sigmoid(w,x_train[i],b)))
                                            b= (b+(alpha*(y_train[i]-sigmoid(w,x_train[i],b))))
                                  log_val_train=log_loss(w,x_train,b,y_train)
                                  log_val_test=log_loss(w,x_test,b,y_test)
                                  log_loss_train.append(log_val_train)
                                  log_loss_test.append(log_val_test)
                                  if abs((np.sum(log_loss_train[epo+1]-log_loss_train[epo])))<=0.0001:</pre>
                                            print('Updation is completed in {} epochs'.format(epo+1))
                                            break
                        return w,b,log_loss_train,log_loss_test,epo+1
[32]: epochs=20
              updated_w,updated_b,train_log_loss,test_log_loss,convergence_epoch=SGD(w,b,epochs,X_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_train,y_tr
                 →X_test, y_test)
             HBox(children=(IntProgress(value=0, max=20), HTML(value='')))
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return val

Updation is completed in 10 epochs

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[34]: print(updated_w)
      print(updated_b)
      \begin{bmatrix} -0.42315311 & 0.19095979 & -0.14588118 & 0.33814991 & -0.21196623 & 0.56525978 \end{bmatrix} 
      -0.44538357 -0.09171679 0.21795314 0.16977398 0.19522044 0.00229554
      -0.07781461 0.33882618 0.02214234]
     -0.8500967712837224
[35]: # these are the results we got after we implemented sgd and found the optimal
       \rightarrow weights and intercept
      updated_w-clf.coef_, updated_b-clf.intercept_
[35]: (array([[ 0.0002138 , 0.00548413, 0.00270918, -0.00329416, -0.00377953,
                0.00509399, 0.00704126, 0.00237134, 0.00867994, -0.01106728,
               -0.00183147, -0.00192361, 0.00178909, 0.00029817, -0.00052487]
       array([0.00304153]))
[36]: def pred(w,b, X):
          N = len(X)
          predict = []
          for i in range(N):
              if sigmoid(w, X[i], b) >= 0.5: # sigmoid(w, x, b) returns 1/
       \hookrightarrow (1+exp(-(dot(x,w)+b)))
                  predict.append(1)
              else:
                  predict.append(0)
          return np.array(predict)
      print(1-np.sum(y_train - pred(updated_w,updated_b,X_train))/len(X_train))
      print(1-np.sum(y_test - pred(updated_w,updated_b,X_test))/len(X_test))
     0.95536
     0.95296
[43]: import matplotlib.pyplot as plt
      #Plotting without initial log loss as it is very high and makes the two curve
      → in the plot to be not clear
      plt.plot(range(1,convergence_epoch+1),train_log_loss[1:], label='Training Data_u
       →log loss', color='blue')
      plt.plot(range(1,convergence_epoch+1),test_log_loss[1:], label='Test Data log_u
      →loss', color='green')
      plt.ylabel('Log Loss')
      plt.xlabel('epochs')
      plt.title('Log loss')
      plt.legend()
      plt.show()
```

