Custom_SGD_Assignment_LR

March 13, 2022

1 Implement SGD Classifier with Logloss and L2 regularization Using SGD without using sklearn

There will be some functions that start with the word "grader" ex: grader_weights(), grader_sigmoid(), grader_logloss() etc, you should not change those function definition.Every Grader function has to return True.

Importing packages

[1]:
```
import numpy as np
import pandas as pd
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn import linear_model
```

Creating custom dataset

[2]:
```
# please don't change random_state
X, y = make_classification(n_samples=50000, n_features=15, n_informative=10,␣
 ↪n_redundant=5,
                           n_classes=2, weights=[0.7], class_sep=0.7,␣
 ↪random_state=15)
# make_classification is used to create custom dataset
# Please check this link (https://scikit-learn.org/stable/modules/generated/
 ↪sklearn.datasets.make_classification.html) for more details
```

[3]:
```
X.shape, y.shape
```

[3]:
```
((50000, 15), (50000,))
```

Splitting data into train and test

[4]:
```
#please don't change random state
# you need not standardize the data as it is already standardized
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,␣
 ↪random_state=15)
```

[5]:
```
X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

[5]:
```
((37500, 15), (37500,), (12500, 15), (12500,))
```

2 SGD classifier

[6]:
```
# alpha : float
# Constant that multiplies the regularization term.

# eta0 : double
# The initial learning rate for the ‘constant’, ‘invscaling’ or ‘adaptive’␣
↪schedules.

clf = linear_model.SGDClassifier(eta0=0.0001, alpha=0.0001, loss='log',␣
↪random_state=15, penalty='l2', tol=1e-3, verbose=2, learning_rate='constant')
clf
# Please check this documentation (https://scikit-learn.org/stable/modules/
↪generated/sklearn.linear_model.SGDClassifier.html)
```

[6]:
```
SGDClassifier(eta0=0.0001, learning_rate='constant', loss='log',
              random_state=15, verbose=2)
```

[7]:
```
clf.fit(X=X_train, y=y_train) # fitting our model
```

```
-- Epoch 1
Norm: 0.77, NNZs: 15, Bias: -0.316653, T: 37500, Avg. loss: 0.455552
Total training time: 0.01 seconds.
-- Epoch 2
Norm: 0.91, NNZs: 15, Bias: -0.472747, T: 75000, Avg. loss: 0.394686
Total training time: 0.01 seconds.
-- Epoch 3
Norm: 0.98, NNZs: 15, Bias: -0.580082, T: 112500, Avg. loss: 0.385711
Total training time: 0.02 seconds.
-- Epoch 4
Norm: 1.02, NNZs: 15, Bias: -0.658292, T: 150000, Avg. loss: 0.382083
Total training time: 0.02 seconds.
-- Epoch 5
Norm: 1.04, NNZs: 15, Bias: -0.719528, T: 187500, Avg. loss: 0.380486
Total training time: 0.03 seconds.
-- Epoch 6
Norm: 1.05, NNZs: 15, Bias: -0.763409, T: 225000, Avg. loss: 0.379578
Total training time: 0.03 seconds.
-- Epoch 7
Norm: 1.06, NNZs: 15, Bias: -0.795106, T: 262500, Avg. loss: 0.379150
Total training time: 0.04 seconds.
-- Epoch 8
```

```
Norm: 1.06, NNZs: 15, Bias: -0.819925, T: 300000, Avg. loss: 0.378856
Total training time: 0.04 seconds.
-- Epoch 9
Norm: 1.07, NNZs: 15, Bias: -0.837805, T: 337500, Avg. loss: 0.378585
Total training time: 0.05 seconds.
-- Epoch 10
Norm: 1.08, NNZs: 15, Bias: -0.853138, T: 375000, Avg. loss: 0.378630
Total training time: 0.05 seconds.
Convergence after 10 epochs took 0.05 seconds
```

[7]:
```
SGDClassifier(eta0=0.0001, learning_rate='constant', loss='log',
              random_state=15, verbose=2)
```

[8]:
```
clf.coef_, clf.coef_.shape, clf.intercept_
#clf.coef_ will return the weights
#clf.coef_.shape will return the shape of weights
#clf.intercept_ will return the intercept term
```

[8]:
```
(array([[-0.42336692,  0.18547565, -0.14859036,  0.34144407, -0.2081867 ,
          0.56016579, -0.45242483, -0.09408813,  0.2092732 ,  0.18084126,
          0.19705191,  0.00421916, -0.0796037 ,  0.33852802,  0.02266721]]),
 (1, 15),
 array([-0.8531383]))
```

2.1 Implement Logistic Regression with L2 regularization Using SGD: without using sklearn

1. We will be giving you some functions, please write code in that functions only.
2. After every function, we will be giving you expected output, please make sure that you get that output.

- Initialize the weight_vector and intercept term to zeros (Write your code in def initialize_weights())
- Create a loss function (Write your code in def logloss())

$logloss = -1 * \frac{1}{n}\Sigma_{foreachYt,Y_{pred}}(Ytlog10(Y_{pred}) + (1 - Yt)log10(1 - Y_{pred}))$ - 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 (write your co

    $dw^{(t)} = x_n(y_n -  ((w^{(t)})^{T} x_n+b^{t}))- \frac{ }{N}w^{(t)})$ <br>

    - Calculate the gradient of the intercept (write your code in <font color='blue'> def gradi

       $ db^{(t)} = y_n-  ((w^{(t)})^{T} x_n+b^{t}))$

    - Update weights and intercept (check the equation number 32 in the above mentioned <a hre
```

```
    $w^{(t+1)}← w^{(t)}+ (dw^{(t)}) $<br>

    $b^{(t+1)}←b^{(t)}+ (db^{(t)}) $
- calculate the log loss for train and test with the updated weights (you can check the python
- And if you wish, you can compare the previous loss and the current loss, if it is not updatin
    you can stop the training
- append this loss in the list ( this will be used to see how loss is changing for each epoch a
```

Initialize weights

[9]:
```python
def initialize_weights(row_vector):
    ''' In this function, we will initialize our weights and bias'''
    w = np.zeros_like(X[0])
    b = 0
    return w,b
```

[10]:
```python
dim=X_train[0]
w,b = initialize_weights(dim)
print('w =',(w))
print('b =',str(b))
```

```
w = [0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
b = 0
```

Grader function - 1

[11]:
```python
dim=X_train[0]
w,b = initialize_weights(dim)
def grader_weights(w,b):
  assert((len(w)==len(dim)) and b==0 and np.sum(w)==0.0)
  return True
grader_weights(w,b)
```

[11]: True

Compute sigmoid

$sigmoid(z) = 1/(1 + exp(-z))$

[12]:
```python
def sigmoid(z):
    ''' In this function, we will return sigmoid of z'''
    return 1/(1 + np.exp(-z))
```

Grader function - 2

[13]:
```python
def grader_sigmoid(z):
  val=sigmoid(z)
  assert(val==0.8807970779778823)
  return True
grader_sigmoid(2)
```

[13]: True

Compute loss

$logloss = -1 * \frac{1}{n}\Sigma_{foreachYt,Y_{pred}}(Ytlog10(Y_{pred}) + (1-Yt)log10(1-Y_{pred}))$

[14]:
```
def logloss(y_true,y_pred):
    '''In this function, we will compute log loss '''

    sum = 0
    for i in range(len(y_true)):
        sum += (y_true[i] * np.log10(y_pred[i])) + ((1-y_true[i]) * np.
↪log10(1-y_pred[i]))
    loss = -1 * (1/len(y_true)) * sum

    return loss
```

Grader function - 3

[15]:
```
#round off the value to 8 values
def grader_logloss(true,pred):
  loss=logloss(true,pred)
  assert(np.round(loss,6)==0.076449)
  return True
true=np.array([1,1,0,1,0])
pred=np.array([0.9,0.8,0.1,0.8,0.2])
grader_logloss(true,pred)
```

[15]: True

Compute gradient w.r.to 'w'

$dw^{(t)} = x_n(y_n - ((w^{(t)})^T x_n + b^t)) - \frac{}{N} w^{(t)}$

[16]:
```
#make sure that the sigmoid function returns a scalar value, you can use dot␣
↪function operation
def gradient_dw(x,y,w,b,alpha,N):
    '''In this function, we will compute the gardient w.r.to w '''
    dw = x * (y - sigmoid(np.dot(w,x) + b) - (alpha/N) * w)

    return dw
```

Grader function - 4

[17]:
```
def grader_dw(x,y,w,b,alpha,N):
  grad_dw=gradient_dw(x,y,w,b,alpha,N)
  assert(np.round(np.sum(grad_dw),5)==4.75684)
  return True
```

```
grad_x=np.array([-2.07864835,  3.31604252, -0.79104357, -3.87045546, -1.
↪14783286,
       -2.81434437, -0.86771071, -0.04073287,  0.84827878,  1.99451725,
        3.67152472,  0.01451875,  2.01062888,  0.07373904, -5.54586092])
grad_y=0
grad_w=np.array([ 0.03364887,  0.03612727,  0.02786927,  0.08547455, -0.
↪12870234,
       -0.02555288,  0.11858013,  0.13305576,  0.07310204,  0.15149245,
       -0.05708987, -0.064768  ,  0.18012332, -0.16880843, -0.27079877])
grad_b=0.5
alpha=0.0001
N=len(X_train)
grader_dw(grad_x,grad_y,grad_w,grad_b,alpha,N)
```

[17]: True

Compute gradient w.r.to 'b'

$ db^{(t)} = y_n- ((w$^{(t)})$$\{T\}$ x_n+b^{t})$

[18]:
```
#sb should be a scalar value
def gradient_db(x,y,w,b):

    '''In this function, we will compute gradient w.r.to b '''
    db = y - sigmoid(np.dot(w,x) + b)

    return db
```

Grader function - 5

[19]:
```
def grader_db(x,y,w,b):
  grad_db=gradient_db(x,y,w,b)
  assert(np.round(grad_db,4)==-0.3714)
  return True
grad_x=np.array([-2.07864835,  3.31604252, -0.79104357, -3.87045546, -1.
↪14783286,
       -2.81434437, -0.86771071, -0.04073287,  0.84827878,  1.99451725,
        3.67152472,  0.01451875,  2.01062888,  0.07373904, -5.54586092])
grad_y=0.5
grad_b=0.1
grad_w=np.array([ 0.03364887,  0.03612727,  0.02786927,  0.08547455, -0.
↪12870234,
       -0.02555288,  0.11858013,  0.13305576,  0.07310204,  0.15149245,
       -0.05708987, -0.064768  ,  0.18012332, -0.16880843, -0.27079877])
alpha=0.0001
N=len(X_train)
grader_db(grad_x,grad_y,grad_w,grad_b)
```

[19]: True

[20]:
```
# prediction function used to compute predicted_y given the dataset X
def pred(w,b, X):
    N = len(X)
    predict = []
    for i in range(N):
        z=np.dot(w,X[i])+b
        if sigmoid(z) >= 0.5: # sigmoid(w,x,b) returns 1/(1+exp(-(dot(x,w)+b)))
            predict.append(1)
        else:
            predict.append(0)
    return np.array(predict)
```

Implementing logistic regression

[21]:
```
def train(X_train,y_train,X_test,y_test,epochs,alpha,eta0):
    ''' In this function, we will implement logistic regression'''
    #Here eta0 is learning rate

    train_loss = []
    test_loss = []
    w,b = initialize_weights(X_train[0]) # Initialize the weights

    for i in range(epochs):
        train_pred = []
        test_pred = []

        for j in range(N):
            dw = gradient_dw(X_train[j], y_train[j], w, b, alpha, N)
            db = gradient_db(X_train[j],y_train[j],w,b)
            w = w + (eta0 * dw)
            b = b + (eta0 * db)

        for val in range(N):
            train_pred.append(sigmoid(np.dot(w, X_train[val]) + b))

        loss1 = logloss(y_train, train_pred)
        train_loss.append(loss1)

        for val in range(len(X_test)):
            test_pred.append(sigmoid(np.dot(w, X_test[val]) + b))

        loss2 = logloss(y_test, test_pred)
        test_loss.append(loss2)

    return w,b,train_loss,test_loss
```

[23]:
```
alpha=0.0001
eta0=0.0001
N=len(X_train)
epochs=50
w,b,train_loss,test_loss=train(X_train,y_train,X_test,y_test,epochs,alpha,eta0)
```

[24]:
```
#print thr value of weights w and bias b
print(w)
print(b)
```

```
[-0.42979244  0.1930352  -0.14846992  0.33809366 -0.22128236  0.56994894
 -0.44518164 -0.08990399  0.22182949  0.17382965  0.19874847 -0.00058427
 -0.08133409  0.33909012  0.02298795]
-0.892252167976083
```

2.2 Goal of assignment

Compare your implementation and SGDClassifier's the weights and intercept, make sure they are as close as possible i.e difference should be in order of 10^-2

Grader function - 6

[25]:
```
print("Weights and Bias of SGDClassifier :-\n")
print("Weights -", clf.coef_)
print("Bias - ", clf.intercept_)

print("\n\nWeights and Bias of Custom implementation :-\n")
print("Weights -", w)
print("Bias - ", b)

# these are the results we got after we implemented sgd and found the optimal
 ↪weights and intercept

print("\nThe difference between the weights:-",w-clf.coef_)
print("\nThe difference between the Bias:-", b-clf.intercept_)
```

```
Weights and Bias of SGDClassifier :-

Weights - [[-0.42336692  0.18547565 -0.14859036  0.34144407 -0.2081867
0.56016579
  -0.45242483 -0.09408813  0.2092732   0.18084126  0.19705191  0.00421916
  -0.0796037   0.33852802  0.02266721]]
Bias -  [-0.8531383]


Weights and Bias of Custom implementation :-

Weights - [-0.42979244  0.1930352  -0.14846992  0.33809366 -0.22128236
0.56994894
```

```
 -0.44518164 -0.08990399  0.22182949  0.17382965  0.19874847 -0.00058427
 -0.08133409  0.33909012  0.02298795]
Bias -  -0.892252167976083

The difference between the weights:- [[-0.00642552  0.00755954  0.00012044
-0.00335041 -0.01309566  0.00978315
   0.00724319  0.00418414  0.01255629 -0.00701161  0.00169656 -0.00480343
  -0.00173039  0.0005621   0.00032074]]

The difference between the Bias:- [-0.03911387]
```

[26]:
```
#this grader function should return True
#the difference between custom weights and clf.coef_ should be less than or␣
 ↪equal to 0.05
def differece_check_grader(w,b,coef,intercept):
    val_array=np.abs(np.array(w-coef))
    assert(np.all(val_array<=0.05))
    print('The custom weights are correct')
    return True
differece_check_grader(w,b,clf.coef_,clf.intercept_)
```

```
The custom weights are correct
```

[26]:
```
True
```

Plot your train and test loss vs epochs

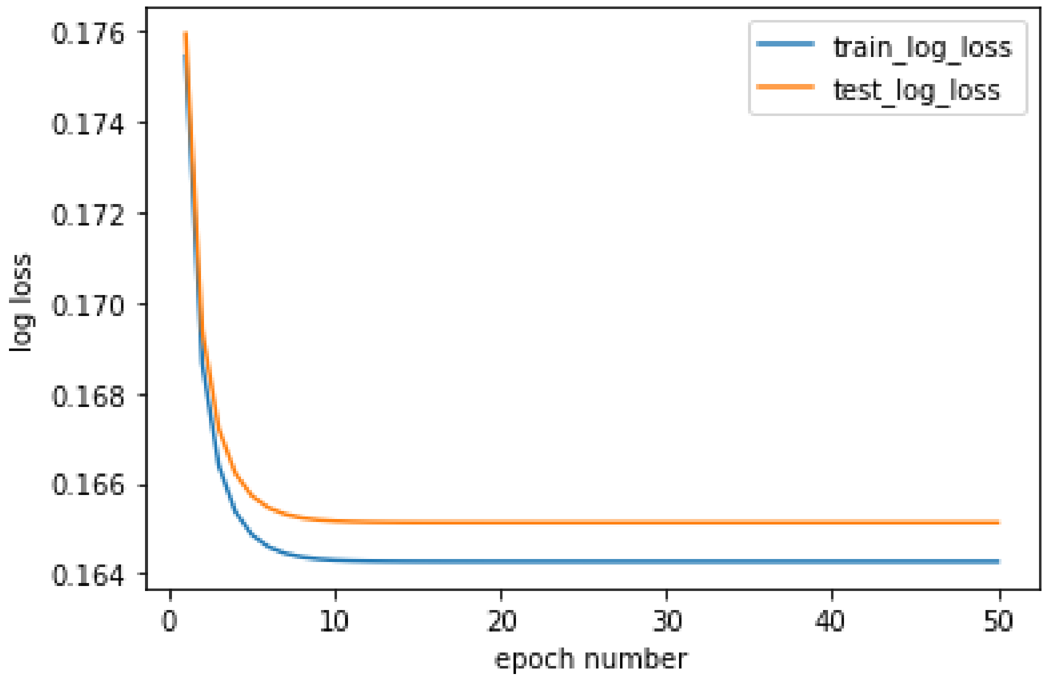
plot epoch number on X-axis and loss on Y-axis and make sure that the curve is converging

[27]:
```
from matplotlib import pyplot as plt

epoch = [i for i in range(1,51,1)]

plt.plot(epoch,train_loss , label='train_log_loss')
plt.plot(epoch,test_loss, label='test_log_loss')
plt.xlabel("epoch number")
plt.ylabel("log loss")
plt.legend()
plt.show
```

[27]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```


train_log_loss
test_log_loss
log loss
0.176
0.174
0.172
0.170
0.168
0.166
0.164
0
10
20
30
40
50
epoch number