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

```
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

```
# 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.
```

```
X.shape, y.shape
```

```
((50000, 15), (50000,))
```

Splitting data into train and test

```
#please don't change random state
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=15)
```

```
# Standardizing the data.
scaler = StandardScaler()
x_train = scaler.fit_transform(X_train)
x_test = scaler.transform(X_test)
```

```
X_train.shape, y_train.shape, X_test.shape, y_test.shape
```

```
((37500, 15), (37500,), (12500, 15), (12500,))
```

SGD classifier

```
# 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, pena
clf
# Please check this documentation (https://scikit-learn.org/stable/modules/generated/sklearn.
```

```
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='l2', power_t=0.5, random_state=15, shuffle=True,
              tol=0.001, validation_fraction=0.1, verbose=2, warm_start=False)
```

```
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: 0.02 seconds.
-- Epoch 3
Norm: 0.98, NNZs: 15, Bias: -0.580082, T: 112500, Avg. loss: 0.385711
Total training time: 0.03 seconds.
-- Epoch 4
Norm: 1.02, NNZs: 15, Bias: -0.658292, T: 150000, Avg. loss: 0.382083
Total training time: 0.05 seconds.
-- Epoch 5
Norm: 1.04, NNZs: 15, Bias: -0.719528, T: 187500, Avg. loss: 0.380486
Total training time: 0.06 seconds.
-- Epoch 6
Norm: 1.05, NNZs: 15, Bias: -0.763409, T: 225000, Avg. loss: 0.379578
Total training time: 0.07 seconds.
-- Epoch 7
Norm: 1.06, NNZs: 15, Bias: -0.795106, T: 262500, Avg. loss: 0.379150
Total training time: 0.08 seconds.
-- Epoch 8
Norm: 1.06, NNZs: 15, Bias: -0.819925, T: 300000, Avg. loss: 0.378856
Total training time: 0.09 seconds.
-- Epoch 9
Norm: 1.07, NNZs: 15, Bias: -0.837805, T: 337500, Avg. loss: 0.378585
```

```
Total training time: 0.10 seconds.
-- Epoch 10
Norm: 1.08, NNZs: 15, Bias: -0.853138, T: 375000, Avg. loss: 0.378630
Total training time: 0.11 seconds.
Convergence after 10 epochs took 0.11 seconds
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='l2', power_t=0.5, random_state=15, shuffle=True,
              tol=0.001, validation_fraction=0.1, verbose=2, warm_start=False)
```

```
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
```

```
(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]))
```

```
# This is formatted as code
```

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 code in def gradient_dw())

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

- Calculate the gradient of the intercept (write your code in def gradient_db()) check this

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

- Update weights and intercept (check the equation number 32 in the above mentioned pdf):

  $w^{(t+1)} \leftarrow w^{(t)} + \alpha(dw^{(t)})$

  $b^{(t+1)} \leftarrow b^{(t)} + \alpha(db^{(t)})$

- 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

Initialize weights

```
def initialize_weights(dim):
    ''' In this function, we will initialize our weights and bias'''
    #initialize the weights to zeros array of (1,dim) dimensions
    #you use zeros_like function to initialize zero, check this link https://docs.scipy.org/d
    #initialize bias to zero
    w=np.zeros_like(dim)
    b=0

    return w,b
```

```
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

```
dim=X_train[0]
w,b = initialize_weights(dim)
def grader_weights(w,b):
```

```
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)
```

    True

Compute sigmoid

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

```
import math


def sigmoid(z):
    ''' In this function, we will return sigmoid of z'''
    # compute sigmoid(z) and return

    return 1 / (1 + math.exp(-z))
```

Grader function - 2

```
def grader_sigmoid(z):
  val=sigmoid(z)
  assert(val==0.8807970779778823)
  return True
grader_sigmoid(2)
```

    True

Compute loss

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

```
def logloss(y_true, y_pred):
    loss = 0
    for i in range(len(y_true)):
        loss += y_true[i] * math.log10(y_pred[i]) + \
                (1-y_true[i]) * math.log10(1-y_pred[i])
    loss = -1 * (1 / len(y_true)) * loss
    return loss
```

Grader function - 3

```
def grader_logloss(true,pred):
```

```
def grader_logloss(true,pred):
  loss=logloss(true,pred)
  assert(loss==0.07644900402910389)
  return True
true=[1,1,0,1,0]
pred=[0.9,0.8,0.1,0.8,0.2]
grader_logloss(true,pred)
```

```
True
```

Compute gradient w.r.to 'w'

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

```
def gradient_dw(x,y,w,b,alpha,N):

    dw =x*(y-sigmoid(np.dot(w,x)+b)) - ((alpha*w)/N)
    return dw
```

Grader function - 4

```
def grader_dw(x,y,w,b,alpha,N):
  grad_dw=gradient_dw(x,y,w,b,alpha,N)
  assert(np.sum(grad_dw)==2.613689585)
  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,grad_b=initialize_weights(grad_x)
alpha=0.0001
N=len(X_train)
grader_dw(grad_x,grad_y,grad_w,grad_b,alpha,N)
```

```
True
```

Compute gradient w.r.to 'b'

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

```
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

```
def grader_db(x,y,w,b):
  grad_db=gradient_db(x,y,w,b)
  assert(grad_db==-0.5)
  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,grad_b=initialize_weights(grad_x)
alpha=0.0001
N=len(X_train)
grader_db(grad_x,grad_y,grad_w,grad_b)
```

```
True
```

Implementing logistic regression

```
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
    #implement the code as follows
    # initalize the weights (call the initialize_weights(X_train[0]) function)
    w, b = initialize_weights(X_train[0])
    # for every epoch
    train_loss = []
    test_loss = []
    for epoch in range(epochs):
        # for every data point(X_train,y_train)
        for x, y in zip(X_train, y_train):
             #compute gradient w.r.to w (call the gradient_dw() function)
            dw = gradient_dw(x, y, w, b, alpha, len(X_train))
            #compute gradient w.r.to b (call the gradient_db() function)
            db = gradient_db(x, y, w, b)
            #update w, b
            w = w + eta0 * dw
            b = b + eta0 * db

        # predict the output of x_train[for all data points in X_train] using w,b
        y_pred = [sigmoid(np.dot(w, x) + b) for x in X_train]
        #compute the loss between predicted and actual values (call the loss function)
        train1 = round(logloss(y_train, y_pred),6)
        train_loss.append(train1)
        # store all the train loss values in a list
        # predict the output of x_test[for all data points in X_test] using w,b
        y_pred_test = [sigmoid(np.dot(w, x) + b) for x in X_test]
```

```
        print(f"EPOCH: {epoch} Train Loss: {round(logloss(y_train, y_pred),6)} Test Loss: {ro
        #compute the loss between predicted and actual values (call the loss function)
        tests = round(logloss(y_test, y_pred_test),6)
        # test_loss.append(logloss(y_test, y_pred_test))
        test_loss.append(tests)
        # you can also compare previous loss and current loss if the loss is not updating the

    return w,b, train_loss, test_loss
```

```
alpha=0.0001
eta0=0.0001
N=len(X_train)
epochs = 15
w,b, train_loss, test_loss = train(X_train,y_train,X_test,y_test,epochs,alpha,eta0)
```

```
EPOCH: 0 Train Loss: 0.175457 Test Loss: 0.175955
EPOCH: 1 Train Loss: 0.168672 Test Loss: 0.169399
EPOCH: 2 Train Loss: 0.166392 Test Loss: 0.167206
EPOCH: 3 Train Loss: 0.165368 Test Loss: 0.166217
EPOCH: 4 Train Loss: 0.164857 Test Loss: 0.16572
EPOCH: 5 Train Loss: 0.164588 Test Loss: 0.165456
EPOCH: 6 Train Loss: 0.164443 Test Loss: 0.165311
EPOCH: 7 Train Loss: 0.164363 Test Loss: 0.165231
EPOCH: 8 Train Loss: 0.164318 Test Loss: 0.165186
EPOCH: 9 Train Loss: 0.164293 Test Loss: 0.16516
EPOCH: 10 Train Loss: 0.164279 Test Loss: 0.165146
EPOCH: 11 Train Loss: 0.164271 Test Loss: 0.165137
EPOCH: 12 Train Loss: 0.164266 Test Loss: 0.165133
EPOCH: 13 Train Loss: 0.164264 Test Loss: 0.16513
EPOCH: 14 Train Loss: 0.164262 Test Loss: 0.165128
```

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 terms of 10^-3

```
print(w)
print("------------------------------------------------------------------------------------------
print(b)
```

```
[-4.28180804e-01  1.92534041e-01 -1.47858302e-01  3.38107274e-01
 -2.19042252e-01  5.68820894e-01 -4.45207209e-01 -9.03368967e-02
  2.20891208e-01  1.72850106e-01  1.97896252e-01  1.12215163e-04
 -8.04841355e-02  3.39015970e-01  2.27804817e-02]
------------------------------------------------------------------------------------------
-0.88207772553045
```

```
w-clf.coef_, b-clf.intercept_
```

```
(array([[-0.00481389,  0.00705839,  0.00073206, -0.0033368 , -0.01085555,
          0.00865511,  0.00721762,  0.00375123,  0.01161801, -0.00799116,
          0.00084435, -0.00410694, -0.00088044,  0.00048795,  0.00011327]]),
 array([-0.02893943]))
```

Plot epoch number vs train , test loss

- epoch number on X-axis
- loss on Y-axis

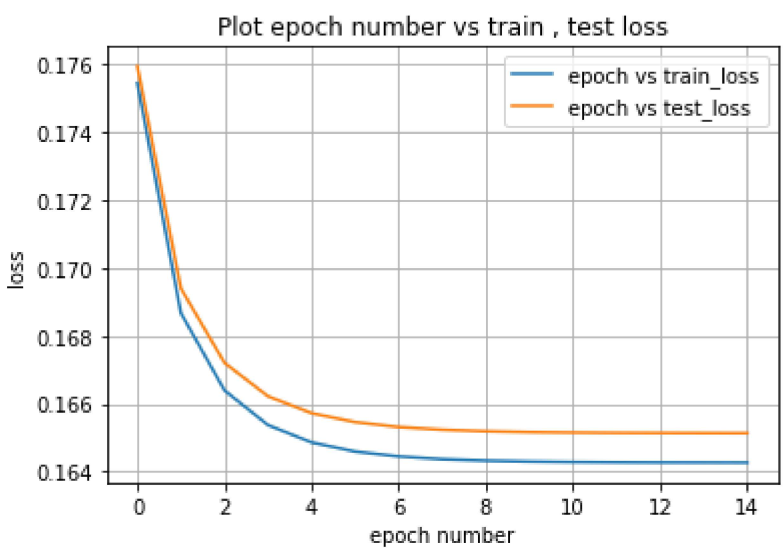
```
import matplotlib.pyplot as plt

epoch = []
for i in range(0,15):
  epoch.append(i)

plt.plot(epoch, train_loss, label='epoch vs train_loss')
plt.plot(epoch, test_loss, label='epoch vs test_loss')



plt.legend()
plt.xlabel("epoch number")
plt.ylabel("loss")
plt.title("Plot epoch number vs train , test loss")
plt.grid()
plt.show()
```




```
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)
print(1-np.sum(y_train - pred(w,b,X_train))/len(X_train))
print(1-np.sum(y_test  - pred(w,b,X_test))/len(X_test))
```

```
0.9530133333333334
0.95064
```

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