from sklearn import tree import scipy.io as sio import pandas as pd from numpy import count nonzero import matplotlib.pyplot as plt import scipy.sparse as ss from sklearn.metrics import accuracy_score from sklearn.metrics import f1_score from sklearn import tree from tabulate import tabulate In [2]: data = sio.loadmat('mnist.mat') Xtrain = data['trainX'][:10000, :].astype(int) Xtest = data['testX'].astype(int) ytrain = data['trainY'][0, :10000].astype(int) ytest = data['testY'][0, :].astype(int) idx = np.logical_or(np.equal(ytrain, 4), np.equal(ytrain, 9)) Xtrain = Xtrain[idx, :] ytrain = ytrain[idx] ytrain[np.equal(ytrain, 4)] = 1 ytrain[np.equal(ytrain, 9)] = -1idx = np.logical or(np.equal(ytest, 4), np.equal(ytest, 9)) Xtest = Xtest[idx, :] ytest = ytest[idx] ytest[np.equal(ytest, 4)] = 1ytest[np.equal(ytest, 9)] = -1sio.savemat('mnist_binary_small.mat', {'Xtrain': Xtrain, 'ytrain': ytrain, 'Xtest': Xtest, 'ytest': yte st}) data = sio.loadmat('mnist binary small.mat') print(Xtrain.shape, Xtest.shape, ytrain.shape, ytest.shape) (1958, 784) (1991, 784) (1958,) (1991,)**Helper Functions** In [3]: def get_misclass(y, yhat): incorrect = 0 totalSamples = len(y) for i in range(totalSamples): **if** y[i] != yhat[i]: incorrect += 1 return incorrect / totalSamples def getExponentialLoss(y, yhat): return np.sum(np.exp(-y * yhat)) / len(y) def plot(y, yLabel, title): x = list(range(len(y)))plt.figure(figsize=(14, 8)) plt.plot(x, y) plt.xlabel('Iterations', fontsize=12) plt.ylabel(yLabel, fontsize=12) plt.title(title , fontsize=18) plt.show() Without AdaBoost In [4]: clf = tree.DecisionTreeClassifier(criterion='entropy', splitter='best', $\max depth=1$, class_weight='balanced') w = [1/len(Xtrain)]*len(Xtrain) clf = clf.fit(Xtrain, ytrain, sample_weight = w) yPredTrain = clf.predict(Xtrain) yPredTest = clf.predict(Xtest) results = []results.append([1, get_misclass(ytrain, yPredTrain), get_misclass(ytest, yPredTest),]) columns = ['depth', 'misclassification rate (train)', 'misclassification rate (test)',] pd.set option("display.max colwidth",2) df = pd.DataFrame(results, columns=columns) print("Train andf test misclassification rates") print(tabulate(df.set_index('depth'), headers='keys', tablefmt='psql')) print("\n Train Exponential Loss Value: "+str(getExponentialLoss(ytrain, yPredTrain))) Train andf test misclassification rates depth | misclassification rate (train) | misclassification rate (test) | 0.109806 | 0.152687 | 1 | Train Exponential Loss Value: 0.6259675480492947 With AdaBoost In [5]: def predictAdaboost(X, stumps, stump_weights): # Stumps will be of size = (iterations,) -> For every iteration we get 1 stump # Stump weights will be of size = (iterations,) -> For every iteration we get 1 stump allStumpPredictions = [] for i in range(len(stumps)): allStumpPredictions.append((stumps[i].predict(X))) weightedStumpPredictions = allStumpPredictions * stump_weights[:, None] sumOfWeightedStumpPredictions = weightedStumpPredictions.sum(axis=0) finalStumpPrediction = np.sign(sumOfWeightedStumpPredictions) return finalStumpPrediction def getErrorAndAlpha(stumpWeight, stumpPrediction, y): error = np.sum(stumpWeight[(stumpPrediction != y)]) alpha = 1 / 2 * np.log((1 - error) / error)return error, alpha def fitAdaboost(XTrain, yTrain, XTest, yTest, iterations): # Total samples numberOfSamples = XTrain.shape[0] # initialization exponentialLossOnlyForTheCurrentStump = np.zeros(shape=iterations) exponentialLossConsideringAllStumps = np.zeros(shape=iterations) trainMisclassificationRate = np.zeros(shape=iterations) testMissclassificationRate = np.zeros(shape=iterations) trainMisclassificationRateContinuous = np.zeros(shape=iterations) testMissclassificationRateContinuous = np.zeros(shape=iterations) weights = np.zeros(shape=(iterations, numberOfSamples)) stumps = np.zeros(shape=iterations, dtype=object) stump_weights = np.zeros(shape=iterations) errors = np.zeros(shape=iterations) alphas = np.zeros(shape=iterations) # initialize weights uniformly # Initial weights will be 1/n # n -> number of samples weights[0] = np.ones(shape=numberOfSamples) / numberOfSamples for index in range(iterations): # We will create new stump for every iteration currentWeights = weights[index] stump = tree.DecisionTreeClassifier(criterion='entropy', splitter='best', max depth=1, max leaf nodes=2, class weight='balanced') stump = stump.fit(XTrain, yTrain, sample_weight=currentWeights) # Stump Predictions for Test Set and Train Set stumpTrainPrediction = stump.predict(XTrain) stumpTestPrediction = stump.predict(XTest) # Stump Train and Test Misclassification rates trainMisclassificationRate[index] = get misclass(yTrain, stumpTrainPrediction) testMissclassificationRate[index] = get misclass(yTest, stumpTestPrediction) exponentialLossOnlyForTheCurrentStump[index] = getExponentialLoss(stumpTrainPrediction, yTrain) error, alpha = getErrorAndAlpha(currentWeights, stumpTrainPrediction, yTrain) updatedSampleWeights = currentWeights * np.exp(-alpha * yTrain * stumpTrainPrediction) # Normalizing new sample weights updatedSampleWeights /= updatedSampleWeights.sum() # If not final iteration, update sample weights for t+1 if index != iterations - 1: weights[index + 1] = updatedSampleWeights stumps[index] = stump stump weights[index] = alpha # All the required results for plotting cummilative stump train prediction = predictAdaboost(XTrain, stumps[:index + 1], stump weights [:index + 1])cummilative stump test prediction = predictAdaboost(XTest, stumps[:index + 1], stump weights[:i ndex + 1])errors[index] = error alphas[index] = alphaexponentialLossConsideringAllStumps[index] = getExponentialLoss(cummilative stump train predict trainMisclassificationRateContinuous[index] = get misclass(yTrain, cummilative stump train pred iction) testMissclassificationRateContinuous[index] = get misclass(yTest, cummilative stump test predic tion) output = [stumps, stump weights, exponentialLossOnlyForTheCurrentStump, trainMisclassificationRate, testMissclassificationRate, exponentialLossConsideringAllStumps, trainMisclassificationRateContinuous, testMissclassificationRateContinuous, errors, alphas] return output In [6]: | iterations = 100 modelParameters = fitAdaboost(Xtrain, ytrain, Xtest, ytest, iterations) stumps = modelParameters[0] stump weights = modelParameters[1] exponentialLossOnlyForTheCurrentStump = modelParameters[2] trainMisclassificationRate = modelParameters[3] testMissclassificationRate = modelParameters[4] exponentialLossConsideringAllStumps = modelParameters[5] trainMisclassificationRateContinuous = modelParameters[6] testMissclassificationRateContinuous = modelParameters[7] errors = modelParameters[8] alphas = modelParameters[9] yPredTrain = predictAdaboost(Xtrain, stumps, stump_weights) yPredTest = predictAdaboost(Xtest, stumps, stump weights) results = [[get_misclass(ytrain, yPredTrain), get_misclass(ytest, yPredTest),]] columns = ['misclassification rate (train)', 'misclassification rate (test)',] pd.set_option("display.max_colwidth", 2) df = pd.DataFrame(results, columns=columns) print("Train andf test misclassification rates after " + str(iterations) + " iterations") print(tabulate(df, headers='keys', tablefmt='psql')) print("\n Train Exponential Loss Value after " + str(iterations) + " iterations: " + str(getExponentialLoss(ytrain, yPredTrain))) Train andf test misclassification rates after 100 iterations misclassification rate (train) | misclassification rate (test) | | 0 | 0.014811 | 0.048217 | Train Exponential Loss Value after 100 iterations: 0.4026913253549667 In [7]: plot(trainMisclassificationRate, 'Train Misclassification Rate', 'Train Misclassification Rate Vs Iterat ions (After every stump)') plot(testMissclassificationRate, 'Test Misclassification Rate', 'Test Misclassification Rate Vs Iterati ons (After every stump)') plot(exponentialLossOnlyForTheCurrentStump, 'Exponential Loss', 'Exponential Loss Vs Iterations (After every stump)') Train Misclassification Rate Vs Iterations (After every stump) 0.6 0.5 Train Misclassification Rate 0.2 0.1 20 40 60 100 Iterations Test Misclassification Rate Vs Iterations (After every stump) 0.6 0.5 **Test Misclassification Rate** 0.2 20 40 60 80 100 Iterations Exponential Loss Vs Iterations (After every stump) 1.6 1.4 Exponential Loss 1.0 0.6 20 40 60 80 100 **Iterations** Comments 1) Misclassification rate and exponential loss after every stump by itself does not have a great value by themselves and is quiet evident from the graph as each stump is a weak learner. plot(trainMisclassificationRateContinuous, 'Train Misclassification Rate', 'Train Misclassification Ra In [8]: te Vs Iterations (Considering All Stumps)') plot(testMissclassificationRateContinuous, 'Test Misclassification Rate' 'Test Misclassification Rat e Vs Iterations (Considering All Stumps)') plot(exponentialLossConsideringAllStumps , 'Exponential Loss' 'Exponential Loss Vs Iterat ions (Considering All Stumps)') Train Misclassification Rate Vs Iterations (Considering All Stumps) 0.10 Train Misclassification Rate 0.08 0.06 0.04 0.02 20 100 Iterations Test Misclassification Rate Vs Iterations (Considering All Stumps) 0.14 0.12 **Test Misclassification Rate** 0.10 0.08 0.06 20 40 60 80 100 Iterations Exponential Loss Vs Iterations (Considering All Stumps) 0.60 0.55 Exponential Loss 0.50 0.45 0.40 20 60 100 Iterations **Comments** 1) Misclassification rate and exponential loss are reducing after every iteration and that can be confirmed with the graph as as well. The difference between the first set of graphs and the latter are: In the first set, we were computing values only for that stump. For the second set, we are computing values for all the stumps calculated until then. $\epsilon^{(t)}$, $\alpha^{(t)}$ as a function of t plot(errors , 'Error' , 'Error Vs Iterations') In [9]: plot(alphas , 'Alpha' , 'Alpha Vs Iterations') Error Vs Iterations 0.45 0.40 0.35 0.30 0.30 0.25 0.20 0.15 0.10 20 Ó 40 60 80 100 Iterations Alpha Vs Iterations 1.0 0.8 20 60 80 100 40 Iterations

In [1]: import numpy as np

import matplotlib.pyplot as plt