In [1]: import numpy as np import pandas as pd import matplotlib.pyplot as plt import scipy.io as sio from collections import Counter import random from tabulate import tabulate In [2]: from sklearn import preprocessing from sklearn.model_selection import StratifiedKFold from sklearn.preprocessing import StandardScaler In [3]: data = sio.loadmat('mnist.mat') Converting data from uint8 to float In [4]: print("Type Before type-casting: "+str(type(data['trainX'][0][19]))) XTrain = data['trainX'].astype(float) yTrain = data['trainY'][0].astype(float) XTest = data['testX'].astype(float) yTest = data['testY'][0].astype(float) print("Type After type-casting: "+str(type(XTrain[0][19]))) Type Before type-casting: <class 'numpy.uint8'> Type After type-casting: <class 'numpy.float64'> In [5]: | scaler = StandardScaler() XTrain = scaler.fit_transform(XTrain) XTest = scaler.fit_transform(XTest) In [6]: print("Shape of XTrain: "+str(np.shape(XTrain))) print("Shape of yTrain: "+str(np.shape(yTrain))) print("Shape of XTest: "+str(np.shape(XTest))) print("Shape of yTest: "+str(np.shape(yTest))) Shape of XTrain: (60000, 784) Shape of yTrain: (60000,) Shape of XTest: (10000, 784) Shape of yTest: (10000,) In [7]: **def** sigmoid(x): **return** (1 / (1 + np.exp(-x))) def costFunction(h, theta, y): m = len(y)cost = (1 / m) * (np.sum(-y.T.dot(np.log(h)) - (1 - y).T.dot(np.log(1 - h))))def gradientDescent(X,h,theta,y,m,alpha=0.01): # This function calculates the theta value by gradient d gradient_value = np.dot(X.T, (h - y)) / m theta -= alpha * gradient_value return theta def predict(X, theta): X = np.insert(X, 0, 1, axis=1)X_predicted = [max((sigmoid(i.dot(thetaTemp)), c) for thetaTemp, c in theta)[1] for i in X] return X_predicted def getMisClassificationRate(y,yPred): total = 0for i in range(len(y)): if y[i] == yPred[i]: total+=1 return 1 - total/len(y) def plotCost(cost): df = pd.DataFrame(data=cost) for i in range(df.shape[1]): plt.plot(df[i],'r') plt.title("Cost Function Vs Iterations " + '(' + str(i) +" vs All)") plt.xlabel("Number of Iterations") plt.ylabel("Cost") plt.show() def plotMisClassificationRate(misClassificationRate, datasetType): plt.figure(figsize=(12,8)) plt.plot(misClassificationRate) plt.title("misClassificationRate Vs Iterations ("+str(datasetType) + ')', fontsize=18) plt.xlabel("Number of Iterations", fontsize=12) plt.ylabel("misClassificationRate", fontsize=12) plt.show() In [8]: def fitLogisticRegression(X, y, XTest, yTest, iterations): theta = [[]] * 10cost = np.zeros((iterations, 10)) # The bias component XT = X.copy()X = np.insert(X, 0, 1, axis=1)m = len(y)misClassificationRateTest = [] misClassificationRateTrain = [] # Building a one vs all model for iteration in range(iterations): for i in np.unique(y): # Unique values will be [0,1,2,3,4,5,6,7,8,9] $y_onevsall = np.where(y == i, 1, 0)$ # number of features (28 * 28 = 784) if iteration == 0: thetaTemp = np.zeros(X.shape[1]) else: thetaTemp = theta[int(i)][0] z = X.dot(thetaTemp)h = sigmoid(z)thetaTemp = gradientDescent(X,h,thetaTemp,y_onevsall,m) costTemp = costFunction(h, thetaTemp, y onevsall) theta[int(i)] = [thetaTemp,i] cost[iteration][int(i)] = costTemp predition1 = predict(XTest, theta) score1 = getMisClassificationRate(predition1,yTest) misClassificationRateTest.append(score1) predition2 = predict(XT, theta) score2 = getMisClassificationRate(predition2,y) misClassificationRateTrain.append(score2) $\textbf{return} \ \ \texttt{theta,cost,misClassificationRateTest, misClassificationRateTrain}$ In [9]: theta, cost, misClassificationRateTest, misClassificationRateTrain = fitLogisticRegression(XTrain, yTrain XTest, yTest, In [10]: plotCost(cost) Cost Function Vs Iterations (0 vs All) 0.6 0.5 0.4 0.3 0.2 0 100 200 300 400 500 Number of Iterations Cost Function Vs Iterations (1 vs All) 0.7 0.6 0.5 0.4 0.3 0.2 100 200 300 400 500 Number of Iterations Cost Function Vs Iterations (2 vs All) 0.7 0.6 0.5 0.4 0.3 0 100 200 300 400 500 Number of Iterations Cost Function Vs Iterations (3 vs All) 0.7 0.6 0.4 0.3 0 100 200 300 400 500 Number of Iterations Cost Function Vs Iterations (4 vs All) 0.7 0.6 0.4 0.3 0 100 200 300 400 500 Number of Iterations Cost Function Vs Iterations (5 vs All) 0.7 0.6 0.4 0.3 100 200 300 500 0 400 Number of Iterations Cost Function Vs Iterations (6 vs All) 0.7 0.6 0.5 0.4 0.3 0.2 0 100 200 300 400 500 Number of Iterations Cost Function Vs Iterations (7 vs All) 0.7 0.6 0.5 0.4 0.3 100 200 300 400 500 Number of Iterations Cost Function Vs Iterations (8 vs All) 0.6 0.5 8 0.3 100 200 300 400 500 Number of Iterations Cost Function Vs Iterations (9 vs All) 0.7 0.6 0.4 0.3 100 400 500 200 300 Number of Iterations In [11]: plotMisClassificationRate(misClassificationRateTest, "Test") misClassificationRate Vs Iterations (Test) 0.24 0.22 misClassificationRate 0.20 0.18 0.16 0.14 ó 100 200 300 400 500 Number of Iterations plotMisClassificationRate(misClassificationRateTrain, "Train") misClassificationRate Vs Iterations (Train) 0.26 0.24 misClassificationRate 0.22 0.20 0.18 0.16 0.14 100 400 200 300 500 Number of Iterations In [15]: finalTestMisClassificationRate = round(misClassificationRateTest[-1]*100,3) finalTrainMisClassificationRate = round(misClassificationRateTrain[-1]*100,3) The Final Train misclassification rate: 14.57% The Final Test misclassification rate: 13.86% **Resources:** 1) https://gluon.mxnet.io/chapter02_supervised-learning/softmax-regression-scratch.html 2) https://www.pugetsystems.com/labs/hpc/Machine-Learning-and-Data-Science-Multinomial-Multiclass-Logistic-Regression-1007/ 3) https://www.codeproject.com/Articles/821347/MultiClass-Logistic-Classifier-in-Python

HW6 Q1(d)