**CS498 AMO Homework 2**

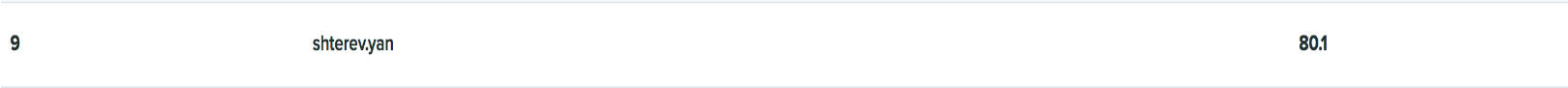
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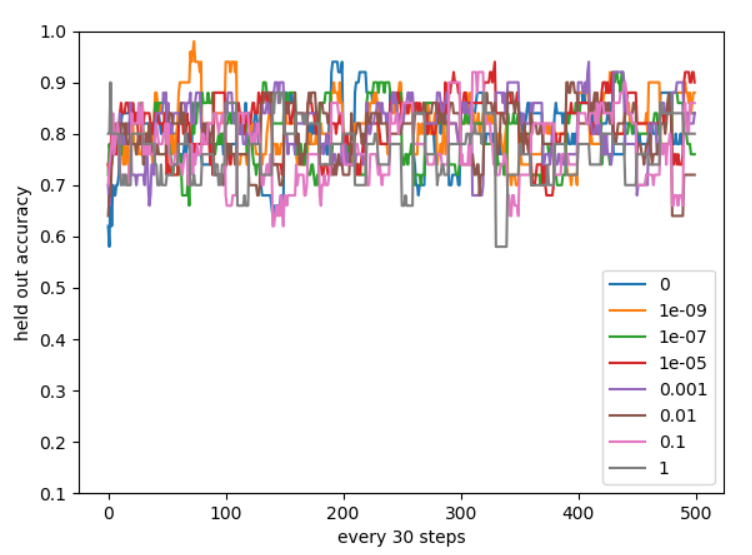
**Page 1 (15 points)**





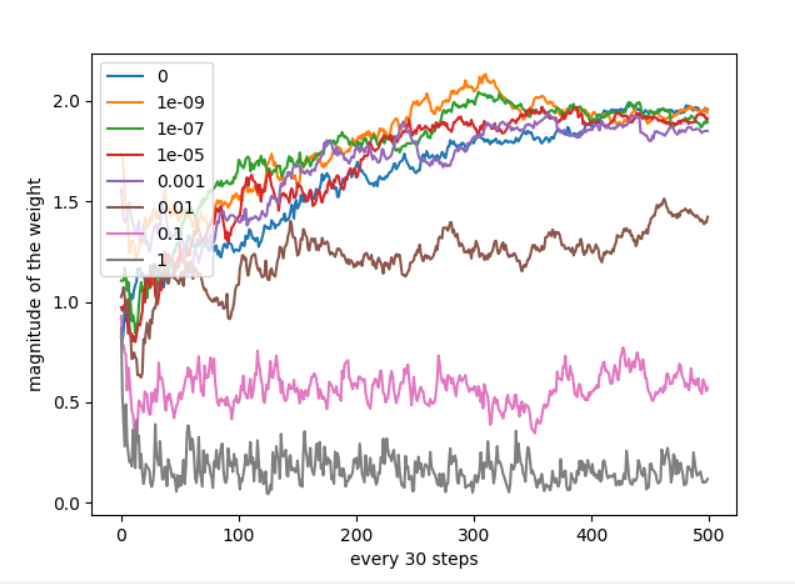
**Page 2 (20 points)**

A plot of the validation accuracy every 30 steps, for each value of the regularization constant.



**Page 3 (20 points)**

A plot of the magnitude of the coefficient vector every 30 steps, for each value of the regularization constant.



**Page 4 (25 points)**

**The lambda consideration**

The best value of the regularization rate was while lambda is 0.01 (1e-2) based on the validation set accuracy we had:

Test data accuracy is for lambda 0 is: 80.0820250284414 %  
Test data accuracy is for lambda 1e-09 is: 79.95449374288964 %  
Test data accuracy is for lambda 1e-07 is: 80.09101251422071 %  
Test data accuracy is for lambda 1e-05 is: 80.13651877133105 %  
Test data accuracy is for lambda 0.001 is: 80.25028441410694 %  
Test data accuracy is for lambda 0.01 is: 80.25028441410694 %  
Test data accuracy is for lambda 0.1 is: 78.77133105802048 %  
Test data accuracy is for lambda 1 is: 76.35949943117178 %

Actually 1e-2, 1e-3 and 1e-5 all have very close performance; 1e-2 and 1e-3 have the same accuracy. We decided to choose 1e-2 over 1e-3 because we think larger regularization constant assists in preventing overfitting and reduce the variance for future data.

We also tested the extreme cases, for example lambda=0 (disabled regularization) and lambda=1 (lean more to regularization); we observed both cases are far from ideal.

By increasing lambda, the penalization factor increased on the weight magnitude, while features contribution to the learning was decreased. It could start causing model under-fitting if too large. On the other side, having low value of lambda caused the model over-fitting and resulted in lower accuracy on validation set.

**The learning rate (step length) consideration.**

The corresponding m and n parameters are part of the learning rate formula in our code: lr = step\_length\_m/(1\*i+step\_length\_n)

where we have step\_length\_m = 1 and step\_length\_n = 50, i is the current season. For the 1 in from of i (**1**\*i+….), 1 is chose as the multiplying factor to trim down the learning rate at later season (we also tried 0.1, 0.01).

From above it means we will have a starting learning rate of 0.02 (1/50) and slowly trimming down to 0.01(1/50+50) if total season is 50. We also tried other step\_length\_n, e.g. 10, 100, 150, 200, and they didn’t provide expected results.

If learning rate is too small, we will require more seasons to train the model until it is stable; if the learning rate is too large, it will become hard to converge at later stage since larger value caused the oscillating of the weights (e.g. making occasional large, bad, moves).

Especially in the case of batch size =1 (Stochastic Gradient Descent), smaller learning rate are recommended due to the fact that gradient is calculated on only one sample which means more variance. Initial weights also played a role on the final accuracy and learning rate, we used randomly initialized weight and choose small learning rate to avoid over shooting on the initial bad weights.

Having that said, we also noticed if we put a stop of the training once we reached a certain accuracy (e.g. record high) on the validation set, with batch size = 2, 3 or 5, it seems initial learning rate of 0.2 (step\_length\_n = 5) is quite a good choice; but this is out of scope of the discussion of this home work.

**Page 6+**

import numpy as np  
import csv  
import matplotlib.pyplot as plt  
import math  
  
  
class supportVectorMachine:  
 def \_\_init\_\_(self, weight, b=0.0, reg\_lambda=1e-1, step\_length=0.1):  
 self.reg\_lambda = reg\_lambda  
 self.weight = np.array(weight)  
 self.b = b  
 self.X = np.array([])  
 self.Y = np.array([])  
 self.cost = 0  
 self.training\_cost = np.array([])  
 self.step\_length = step\_length  
  
 def cost\_function(self, X, Y):  
 self.training\_cost = 1 - (np.dot(X, self.weight)+self.b)\*Y  
 self.training\_cost[self.training\_cost<0] = 0  
 self.cost = np.mean(self.training\_cost) + self.reg\_lambda\*np.dot(self.weight.T, self.weight)/2  
 print(**" training cost is "**, self.cost)  
  
 def update\_weight(self):  
 #print("current weight: ", self.weight)  
 weight\_to\_update=self.X\*self.Y.reshape((self.Y.shape[0],1))  
 #print("X is:", self.X)  
 #print("Y is:", self.Y)  
 #print("weight\_to\_update of yx", weight\_to\_update)  
 zero\_cost\_matrix = 1 - (np.dot(self.X, self.weight)+self.b)\*self.Y  
 zero\_cost\_matrix[zero\_cost\_matrix<0]=0  
 #print("zero cost maxtrix as filter: ", zero\_cost\_matrix)  
 weight\_to\_update = weight\_to\_update\*((zero\_cost\_matrix!=0).reshape((zero\_cost\_matrix.shape[0],1)))  
 #print("masking 'cost = 0', weight\_to\_update", weight\_to\_update)  
 #print("regularization term is ", self.reg\_lambda\*self.weight)  
 weight\_to\_update = -(1/self.X.shape[0])\*np.sum(weight\_to\_update,axis=0)+self.reg\_lambda\*self.weight  
 #print("final weight\_to\_update: ",weight\_to\_update)  
 self.weight = self.weight - self.step\_length\*weight\_to\_update  
 #print("new weight: ", self.weight)  
 # to update b  
 #print("current b: ", self.b)  
 self.b = self.b - self.step\_length\*(-np.dot(self.Y, 1\*(zero\_cost\_matrix!=0))/self.X.shape[0])  
 #print("updated\_b: ", self.b)  
  
 def StochasticGradientDesc(self, X, Y):  
 self.X = X  
 self.Y = Y  
 self.update\_weight()  
  
 def predict(self, X):  
 #print("raw output is: ", np.dot(X, self.weight)+self.b)  
 return 2\*((np.dot(X, self.weight)+self.b)>0)-1  
  
 def set\_learningRate(self, lr):  
 self.step\_length = lr  
  
  
def save\_for\_submission(results):  
 fobj = open(**'./homework2/submission.txt'**, **'a+'**)  
 for i in results:  
 if i >= 1:  
 fobj.write(**'>50K**\n**'**)  
 else:  
 fobj.write(**'<=50K**\n**'**)  
 fobj.close()  
  
  
#################################################################  
# Import training data, shuffle, rescale & split #  
#################################################################  
data = []  
X = []  
Y = []  
# import the data from the csv.  
with open(**'./homework2/train.txt'**, newline=**''**) as f:  
 reader = csv.reader(f, delimiter=**','**)  
 for row in reader:  
 data.append(row)  
  
data = np.array(data)  
np.random.shuffle(data)  
# extract only continuous variable values to form X  
X = data[:, (0,2,4,10,11,12)].astype(float)  
# extract last col to form classes of 1 for >50K and -1 for <=50K  
Y = 2\*(data[:, 14] == **' >50K'**)-1  
# rescale the features to same variance and zero means.  
X = (X - np.mean(X, axis=0))/np.std(X,axis=0)  
rescaled\_data = np.column\_stack((X,Y))  
  
split\_idx = int(data.shape[0]\*0.1)  
hyperParmSearch\_data = rescaled\_data[:split\_idx, :]  
train\_data = rescaled\_data[split\_idx:, :]  
  
#################################################################  
# Hyper Parameters definition #  
#################################################################  
regularisation\_lambda = [0,1e-9, 1e-7, 1e-5, 1e-3, 1e-2, 1e-1, 1]  
step\_length\_m = 1  
step\_length\_n = 50  
total\_season = 50  
steps = 300  
batch\_size = 1  
  
#################################################################  
# Training using different lambda values #  
#################################################################  
# following history record the held out accuracy every 30 steps.  
accuracy\_history = np.zeros((len(regularisation\_lambda), int(steps\*total\_season/30)))  
weight\_magnitude\_history = np.zeros((len(regularisation\_lambda), int(steps\*total\_season/30)))  
# following accuracy report each lambda's performance against validation set.  
final\_validation\_accuracy\_history = np.zeros(len(regularisation\_lambda))  
svm = None  
max\_achieved\_accuracy = 0  
max\_achieved\_weight = []  
for idx\_lambda in range(len(regularisation\_lambda)):  
 weight = np.random.rand(X.shape[1])  
 svm = supportVectorMachine(weight=weight, reg\_lambda=regularisation\_lambda[idx\_lambda])  
 for i in range(total\_season):  
 print(**"\*\*\*\*\*\*season: "**, i,**" \*\*\*\*\*\*\*"**)  
 lr = step\_length\_m/(1\*i+step\_length\_n)  
 svm.set\_learningRate(lr)  
  
 np.random.shuffle(train\_data)  
 held\_out = train\_data[:50, :]  
 train = train\_data[50:, :]  
 for j in range(1, steps+1):  
 selected = np.random.randint(train.shape[0], size=batch\_size)  
 svm.StochasticGradientDesc(train[selected, :-1], train[selected, -1])  
 if j % 30 == 0:  
 print(**"--->Step: "**, j, **" <----"**)  
 validation\_result = svm.predict(held\_out[:, :-1])  
 validation\_accuracy = sum(validation\_result == held\_out[:, -1]) / held\_out.shape[0]  
 print(**" Validation accuracy is "**, validation\_accuracy\*100, **"%"**)  
 #svm.cost\_function(held\_out[:, :-1], held\_out[:, -1])  
 accuracy\_history[idx\_lambda, int((i\*steps+j)/30)-1] = validation\_accuracy  
 weight\_magnitude\_history[idx\_lambda, int((i\*steps+j)/30)-1] = math.sqrt(np.sum(svm.weight \*\* 2))  
  
 test\_result = svm.predict(hyperParmSearch\_data[:, :-1])  
 test\_accuracy = sum(test\_result == hyperParmSearch\_data[:, -1]) / hyperParmSearch\_data.shape[0]  
 final\_validation\_accuracy\_history[idx\_lambda] = test\_accuracy  
 if test\_accuracy >= max\_achieved\_accuracy:  
 max\_achieved\_accuracy = test\_accuracy  
 max\_achieved\_weight = (svm.weight, svm.b, idx\_lambda)  
  
#################################################################  
# Plot the graph for different lambdas #  
#################################################################  
x\_axis = range(int(steps\*total\_season/30))  
plt.subplot(1, 2, 1)  
for idx\_lambda in range(len(regularisation\_lambda)):  
 print(**" Test data accuracy is for lambda "**,regularisation\_lambda[idx\_lambda],**" is: "**, final\_validation\_accuracy\_history[idx\_lambda]\*100, **"%"**)  
 plt.plot(x\_axis, accuracy\_history[idx\_lambda])  
plt.ylim((0.1,1))  
plt.legend(regularisation\_lambda, loc=**'lower right'**)  
plt.xlabel(**'every 30 steps'**)  
plt.ylabel(**'held out accuracy'**)  
plt.subplot(1, 2, 2)  
for idx\_lambda in range(len(regularisation\_lambda)):  
 plt.plot(x\_axis, weight\_magnitude\_history[idx\_lambda])  
plt.xlabel(**'every 30 steps'**)  
plt.ylabel(**'magnitude of the weight'**)  
plt.legend(regularisation\_lambda, loc=**'upper left'**)  
plt.show()  
  
  
#################################################################  
# Predict on the test set for submission #  
#################################################################  
svm.weight = max\_achieved\_weight[0]  
svm.b = max\_achieved\_weight[1]  
grader\_data = []  
with open(**'./homework2/test.txt'**, newline=**''**) as f:  
 reader = csv.reader(f, delimiter=**','**)  
 for row in reader:  
 grader\_data.append(row)  
  
grader\_data = np.array(grader\_data)  
grader\_X = grader\_data[:, (0,2,4,10,11,12)].astype(float)  
# rescale the features to same variance and zero means.  
grader\_X = (grader\_X - np.mean(grader\_X, axis=0))/np.std(grader\_X,axis=0)  
grader\_result = svm.predict(grader\_X)  
save\_for\_submission(grader\_result)