Page 1: Test Accuracy (from Autograder)

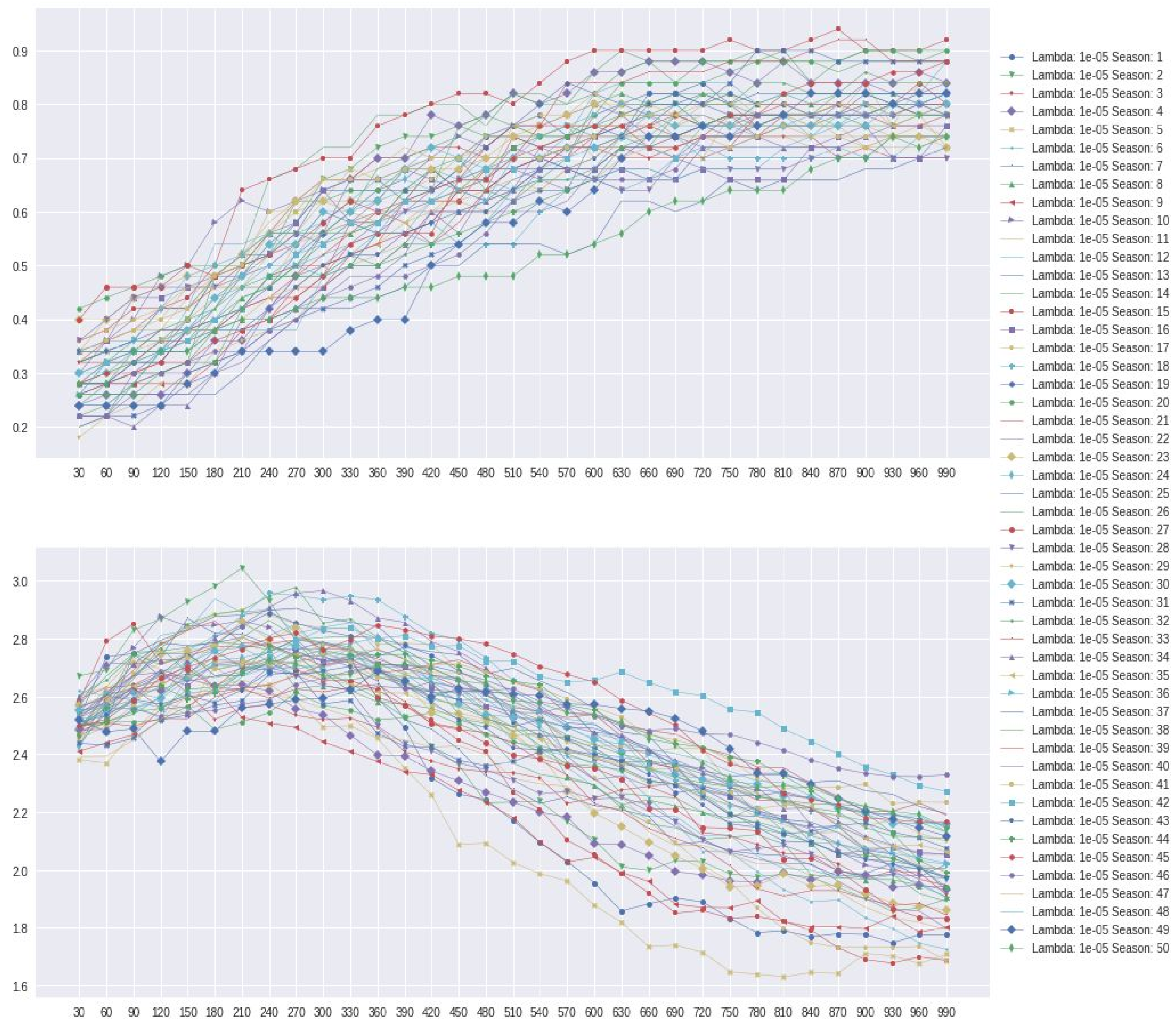
STUDENT

WORAWICH CHAIYAKUNAPRUK

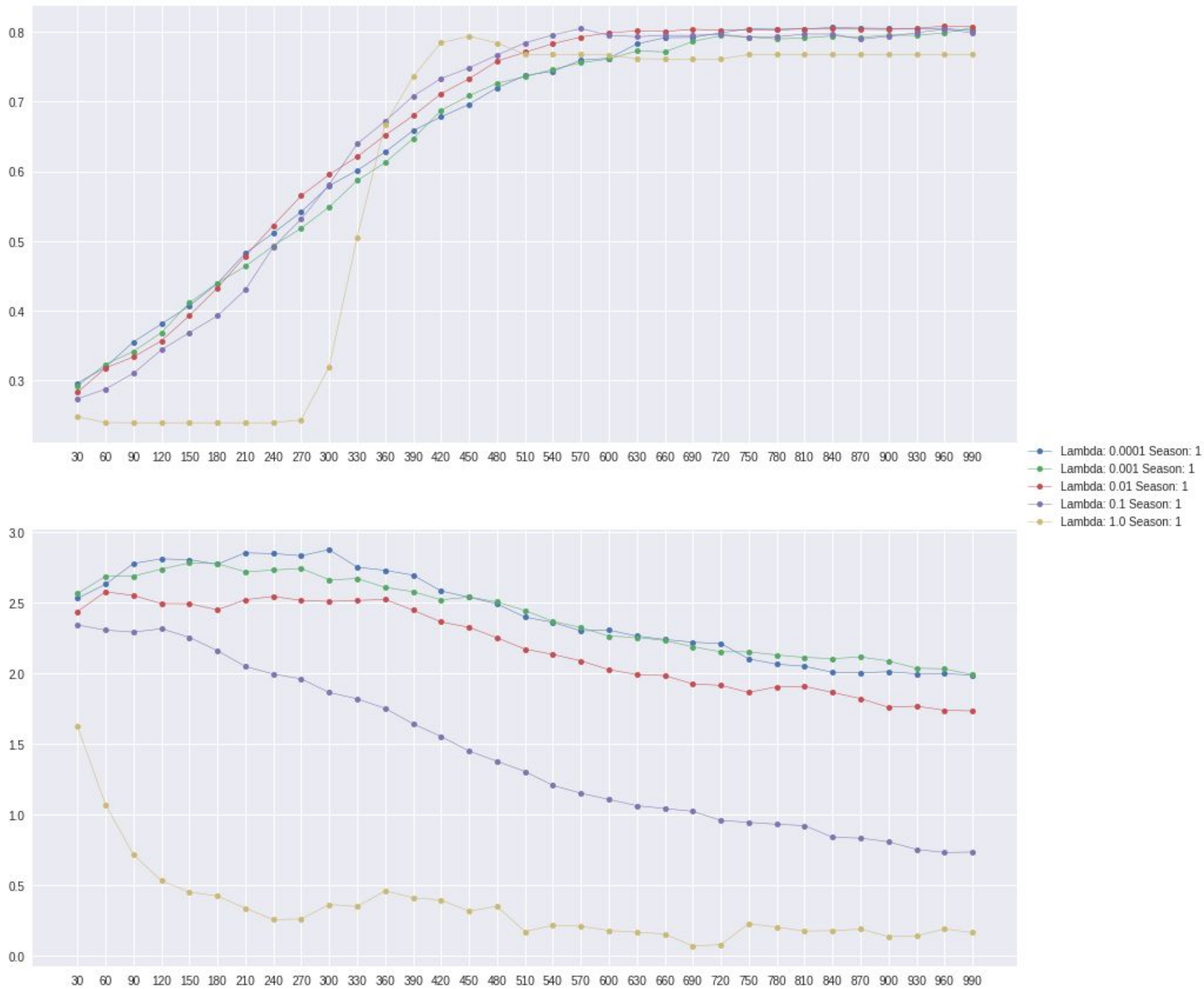
AUTOGRADER SCORE

81.66 / 100.0

Page 2: Learning Rate Validation



Page 3: Regularization Constant Validation



Page 4 Your estimate of the best value of the regularization constant, together with a brief description of why you believe that is a good value. What was your choice for the learning rate and why did you choose it?

```
Lambda = 0.01
Accuracy = 0.8080072793448589
a =  [ [0.37460604],
     [0.1551405 ],
     [0.55226118],
     [1.46628975],
     [0.498473  ],
     [0.37187249] ]
b =  [ -0.953125]
```

First of all, we found the *learning rate (eta)* value by iterating eta values based on a fixed *regularization constant (lambda)*. Our *eta* variable is defined as *m/(k+n)* where *m = 1, k = season iteration by index, and n = 50*. Then we iterated *eta* over 50 seasons, each season we calculated accuracy of *eta* validation set. Once we plotted accuracy of *eta* validation set versus number of steps, we had three matrices to determine the best learning rate: 1) sum of accuracy in each season, 2) sum of accuracy in the second half of each season, and 3) final accuracy of each season. From these three matrices, we picked season number 15 as shown in Page 9, which yielded learning rate of **1/64**.

Next, we used *regularization constants (lambda)* of [1e-4, 1e-3, 1e-2, 1e-1, 1] and plotted accuracy of *lambda* validation set versus *number of steps* for each *lambda* at a constant learning rate of 1/64. By applying the same matrices as the previous step, we found that *regularization constant* of 0.01 was the best. Then, we could obtain the correlating *a* and *b* from this best case to be used in the final prediction model.

Page 5+: A screenshot of your code.

```
from google.colab import drive
drive.mount('/content/drive/')
```

Mounted at /content/drive/

```
import numpy as np
import matplotlib.pyplot as plt

# Zero mean unit variance
def zmuv(a):
  a = (a-a.mean(axis=0))/a.std(axis=0)
  return a

# Import training data (f for features, l for labels)
train_f = np.genfromtxt('drive/My Drive/CS 498 AML/HW2/Data/train.txt', dtype=None, delimiter=",",
usecols=(0,2,4,10,11,12))
train_l = np.genfromtxt('drive/My Drive/CS 498 AML/HW2/Data/train.txt', dtype=np.string_, delimiter=",",
usecols=(14))

train_l[train_l==b' <=50K'] = -1
train_l[train_l==b' >50K'] = 1
train_l = np.asarray([train_l], dtype=int)
train_f = zmuv(train_f)

# Make a single array of standardized features and corresponding labels
train = np.concatenate([train_f,train_l.T],axis=1)

# Import test data (f for features, l for labels)
test_f = np.genfromtxt('drive/My Drive/CS 498 AML/HW2/Data/test.txt', dtype=None, delimiter=",",
usecols=(0,2,4,10,11,12))
test_f = zmuv(test_f)
```

Part 1: Finding an appropriate learning rate (eta)

```
# xi is a column vector of features
# yi is a label
# a is a column vector
# b is a scalar

# Predict and return sign
def predict(u, x):
  s = np.dot(u[0].T,x.T)+u[1]
  s = np.sign(s)
```

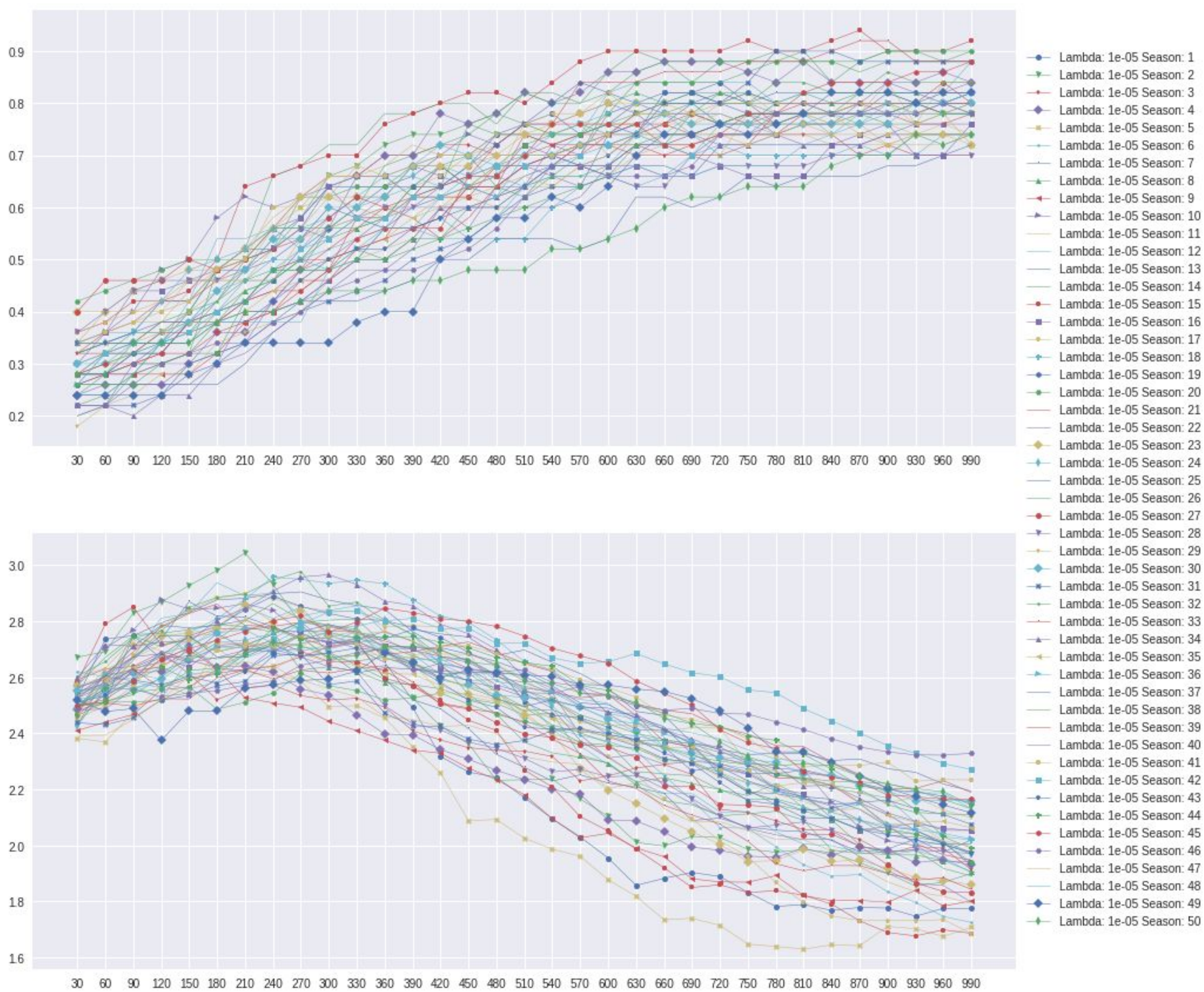
```
  return s.T

# Compare real and predicted labels and get accuracy
def accuracy(u, x, y):
  s = predict(u, x)
  acc = np.sum(y == s)/y.size
  return acc

# Calculate gradient of u. Return gradient w.r.t. to a and b
def gradient(yi, xi, u, lam=1e-3):
  crit = yi[0,0]*gamma(u, xi)
  if crit >= 1:
    grad_b = 0
    grad_a = lam * u[0]
  else:
    grad_b = -yi[0,0]
    grad_a = lam * u[0] - yi[0,0]*xi
  return [grad_a,grad_b]

# Taking a step with eta and gradient. Return new value of u
def step(u, grad, k):
  a_new = u[0] - eta(k)*grad[0]
  b_new = u[1] - eta(k)*grad[1]
  return [a_new, b_new]

# Calculate gamma
def gamma(u, xi):
  gam = np.dot(u[0].T,xi) + u[1]
  return gam

# Returns training cost
def training_cost(u, yi, xi, gam, lam=1e-3):
  cost = (1/len(yi))*np.amax([0,1-np.dot(yi,gamma(u, xi))])+(lam/2)*np.dot(u[0].T,u[0])
  return cost

# Calculate eta based on season#
def eta(k, m=1, n=50):
  return m/(k+n)
```

```
# Prepare data based on size of lambda validation set of 4396 (10%)
# Pick 10% of all training data for lambda validation set
# Pick 50 samples from training data for eta validation set
# Pick 1 sample from the remaining training data for learning
# ind is 10% of all training data
```

```
ind = 4396

shuffled = train.copy()
np.random.shuffle(shuffled)

lam_val = shuffled[0:ind,:]
lam_val_f = lam_val[:,0:6]
lam_val_l = np.array([lam_val[:,6]]).T

training_lesslam = shuffled[ind:,:]

# SVM Setup
num_step = 990
season = 50
lam = np.array([1e-5])

label = list()
step_acc_list = list()
acc_list = list()
new_ab_list = list()
markers=['o','v','*','D','X','.',',','^','<','>','1','2','3','4','8','s','p','P','h','H','+','x','D','d','|','_','o','v','*','D','X','.',',','^','<','>'
,'1','2','3','4','8','s','p','P','h','H','+','x','D','d','|','_']
plt.figure(figsize=(15,15))

# Loop through all regularization constants
for j in range(len(lam)):
#   Loop through all seasons
 for k in range(season):
#     Shuffle to get new validation sets and new training data
   foreta = training_lesslam.copy()
   np.random.shuffle(foreta)

   eta_val = foreta[0:50,:]
   eta_val_f = eta_val[:,0:6]
   eta_val_l = np.array([eta_val[:,6]]).T

#     Reinitialize a and b
   a = np.full((6,1),1)
   b = 4
   u = [a,b]
   new_ab = u.copy()
#     Reinitialize accuracy matrix
   acc = np.zeros((1,int(num_step/30)))
   step_acc = np.array([np.arange(0,num_step,30)])+30
```

```
    mag_a = np.zeros((1,int(num_step/30)))

#     Loop through all steps
    for i in range(num_step):
      rand = int(np.random.randint(foreta.shape[0]-50))
      training_sample = foreta[rand+50,:]
      training_sample_f = np.array([training_sample[0:6]])
      training_sample_l = np.array([[training_sample[6]]])

      xi = training_sample_f.T
      yi = training_sample_l
      grad = gradient(yi, xi, new_ab)
      new_ab = step(new_ab, grad, k)
#       Calculate accuracy every 30 steps
      if (1+i)%30 == 0:
        m = int((1+i)/30)
        acc[0,m-1] = accuracy(new_ab, eta_val_f, eta_val_l)
        mag_a[0,m-1] = np.linalg.norm(new_ab[0])

    acc_list.append((acc[0]))
    step_acc_list.append('Lambda: %s Season: %s' %(lam[j], k+1))
    new_ab_list.append(new_ab[:])

    plt.subplot(211)
    label.append(plt.plot(step_acc[0],acc[0],linewidth=0.5, label = 'Lambda: %s Season: %s' %(lam[j], k+1),
marker = markers[j+k+j+j+j],  markersize=5))
    plt.xticks(np.arange(min(step_acc[0]), max(step_acc[0])+1, 30))

    plt.subplot(212)
    label.append(plt.plot(step_acc[0],mag_a[0],linewidth=0.5, label = 'Lambda: %s Season: %s' %(lam[j], k+1),
marker = markers[j+k+j+j+j],  markersize=5))
    plt.xticks(np.arange(min(step_acc[0]), max(step_acc[0])+1, 30))

plt.legend(label)
plt.legend(loc='center left', bbox_to_anchor=(1, 1.1))
plt.show()

acc_list = np.array(acc_list)
step_acc_list = np.array(step_acc_list)
new_ab_list = np.array(new_ab_list)

print("max sum in >>>>", step_acc_list[sum(acc_list.T).argmax()] , "\na, b = ",
new_ab_list[sum(acc_list.T[:]).argmax()])
print("max half sum in >>>>", step_acc_list[sum(acc_list.T[7:]).argmax()], "\na, b = ",
new_ab_list[sum(acc_list.T[7:]).argmax()])
```

```
print("max single last step in >>>> ", step_acc_list[(acc_list.T[-1]).argmax()], "at: ",max(acc_list.T[-1]), "\na, b = ", new_ab_list[np.unravel_index((acc_list).argmax(),acc_list.shape)[0]])
```




```
max sum in >>>> Lambda: 1e-05 Season: 15
a, b =  [array([[0.31804914],
       [0.14026951],
       [0.53318245],
       [1.52159757],
       [0.22748698],
       [0.26621688]])
 -0.90625]
max half sum in >>>> Lambda: 1e-05 Season: 15
a, b =  [array([[0.31804914],
       [0.14026951],
       [0.53318245],
       [1.52159757],
       [0.22748698],
       [0.26621688]])
```

```
 -0.90625]
max single last step in >>>>  Lambda: 1e-05 Season: 15 at:  0.92
a, b =  [array([[0.31804914],
       [0.14026951],
       [0.53318245],
       [1.52159757],
       [0.22748698],
       [0.26621688]])
 -0.90625]
```

Part 2: Finding an appropriate regularization constant (lambda)

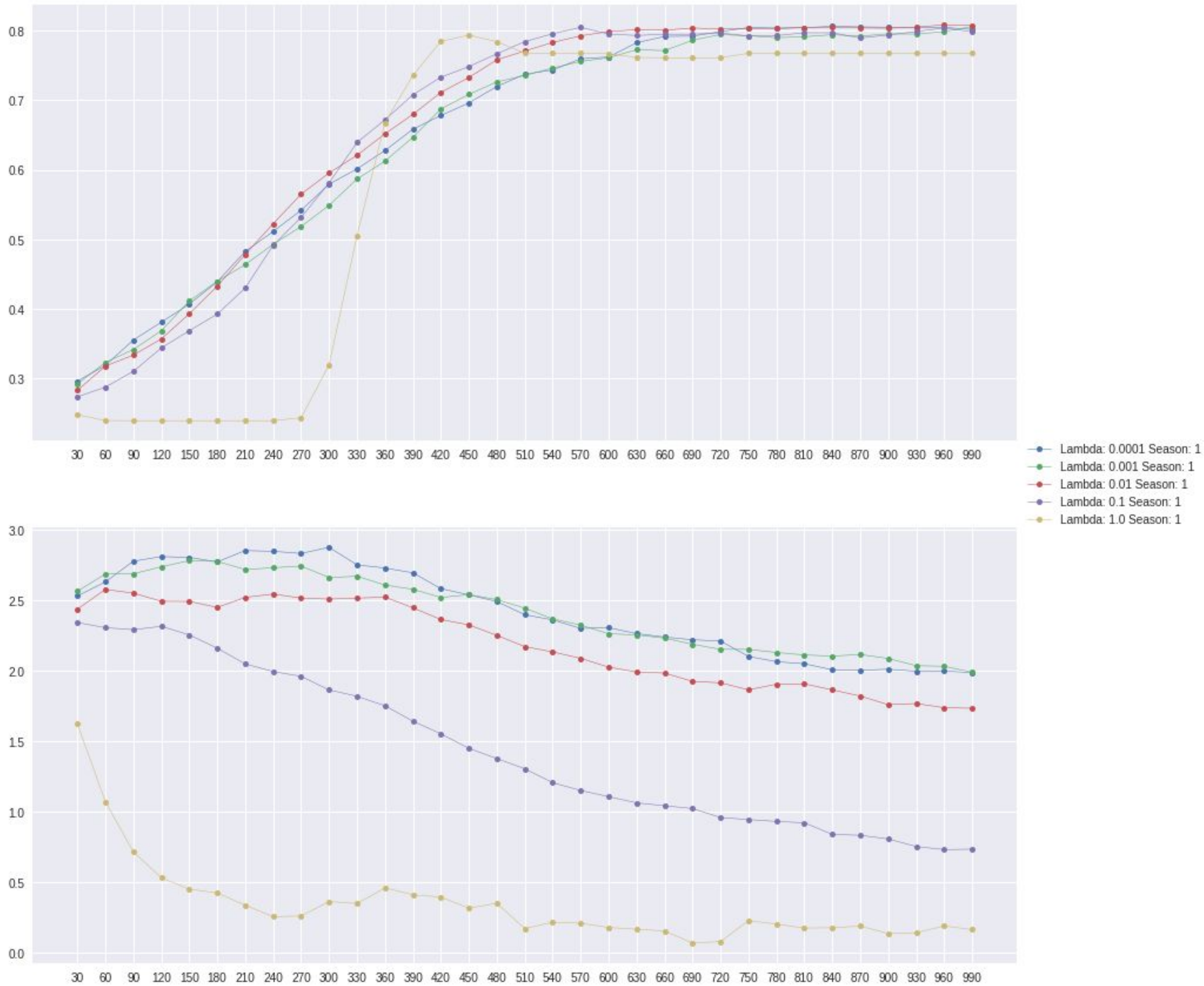
```
# xi is a column vector of features
# yi is a label
# a is a column vector
# b is a scalar

# Predict and return sign
def predict(u, x):
  s = np.dot(u[0].T,x.T)+u[1]
  s = np.sign(s)
  return s.T

# Compare real and predicted labels and get accuracy
def accuracy(u, x, y):
  s = predict(u, x)
  acc = np.sum(y == s)/y.size
  return acc

# Calculate gradient of u. Return gradient w.r.t. to a and b
def gradient(yi, xi, u, lam=1e-3):
  crit = yi[0,0]*gamma(u, xi)
  if crit >= 1:
    grad_b = 0
    grad_a = lam * u[0]
  else:
    grad_b = -yi[0,0]
    grad_a = lam * u[0] - yi[0,0]*xi
  return [grad_a,grad_b]

# Taking a step with eta and gradient. Return new value of u
def step(u, grad, k):
  a_new = u[0] - eta(k)*grad[0]
  b_new = u[1] - eta(k)*grad[1]
  return [a_new, b_new]
```

```
# Calculate gamma
def gamma(u, xi):
  gam = np.dot(u[0].T,xi) + u[1]
  return gam

# Returns training cost
def training_cost(u, yi, xi, gam, lam=1e-3):
  cost = (1/len(yi))*np.amax([0,1-np.dot(yi,gamma(u, xi))])+(lam/2)*np.dot(u[0].T,u[0])
  return cost

# Use fixed eta
def eta(k, m=1, n=50):
  return 1/64 #m/(2*k+n)
```

```
# Prepare data based on size of lambda validation set of 4396 (10%)
# Pick 10% of all training data for lambda validation set
# Pick 50 samples from training data for eta validation set
# Pick 1 sample from the remaining training data for learning
# ind is 10% of all training data

ind = 4396

shuffled = train.copy()
np.random.shuffle(shuffled)

lam_val = shuffled[0:ind,:]
lam_val_f = lam_val[:,0:6]
lam_val_l = np.array([lam_val[:,6]]).T

training_lesslam = shuffled[ind:,:]

# SVM Setup
num_step = 990
season = 1
lam = np.array([1e-4, 1e-3, 1e-2, 1e-1, 1])

label = list()
label2 = list()

step_acc_list = list()
acc_list = list()
new_ab_list = list()
markers=['o','v','*','D','X','.',',','^','<','>','1','2','3','4','8','s','p','P','h','H','+','x','D','d','|','_']
plt.figure(figsize=(15,15))
```

```
# Loop through all lambdas
for j in range(len(lam)):
#   Loop through all seasons
 for k in range(season):
#     Shuffle to get new validation sets and new training data
   foreta = training_lesslam.copy()
   np.random.shuffle(foreta)

   eta_val = foreta[0:50,:]
   eta_val_f = eta_val[:,0:6]
   eta_val_l = np.array([eta_val[:,6]]).T

#     Reinitialize a and b
   a = np.full((6,1),1)
   b = 4
   u = [a,b]
   new_ab = u.copy()
#     Reinitialize accuracy matrix
   acc = np.zeros((1,int(num_step/30)))
   mag_a = np.zeros((1,int(num_step/30)))
   step_acc = np.array([np.arange(0,num_step,30)])+30
#     Loop through all steps
   for i in range(num_step):
     rand = int(np.random.randint(foreta.shape[0]-50))
     training_sample = foreta[rand+50,:]
     training_sample_f = np.array([training_sample[0:6]])
     training_sample_l = np.array([[training_sample[6]]])

     xi = training_sample_f.T
     yi = training_sample_l
     grad = gradient(yi, xi, new_ab,lam[j])
     new_ab = step(new_ab, grad, k)
#       Calculate accuracy every 30 steps
     if (1+i)%30 == 0:
       m = int((1+i)/30)
       acc[0,m-1] = accuracy(new_ab, lam_val_f, lam_val_l)
       mag_a[0,m-1] = np.linalg.norm(new_ab[0])

   acc_list.append((acc[0]))
   step_acc_list.append('Lambda: %s Season: %s' %(lam[j], k+1))
   new_ab_list.append(new_ab[:])

   plt.subplot(211)
   label.append(plt.plot(step_acc[0],acc[0],linewidth=0.5, label = 'Lambda: %s Season: %s' %(lam[j], k+1),
```

```
marker = markers[k],  markersize=5))
    plt.xticks(np.arange(min(step_acc[0]), max(step_acc[0])+1, 30))

    plt.subplot(212)
    label.append(plt.plot(step_acc[0],mag_a[0],linewidth=0.5, label = 'Lambda: %s Season: %s' %(lam[j], k+1),
marker = markers[k],  markersize=5))
    plt.xticks(np.arange(min(step_acc[0]), max(step_acc[0])+1, 30))

plt.legend(label)
plt.legend(loc='center left', bbox_to_anchor=(1, 1.1))
plt.show()

acc_list = np.array(acc_list)
step_acc_list = np.array(step_acc_list)
new_ab_list = np.array(new_ab_list)

print("max sum in >>>>", step_acc_list[sum(acc_list.T).argmax()] , "\na, b = ",
new_ab_list[sum(acc_list.T[:]).argmax()])
print("max half sum in >>>>", step_acc_list[sum(acc_list.T[7:]).argmax()], "\na, b = ",
new_ab_list[sum(acc_list.T[7:]).argmax()])
print("max single last step in >>>> ", step_acc_list[(acc_list.T[-1]).argmax()], "at: ",max(acc_list.T[-1]), "\na, b
= ", new_ab_list[np.unravel_index((acc_list).argmax(),acc_list.shape)[0]])
```




```
max sum in >>>> Lambda: 0.01 Season: 1
a, b =  [array([[0.37460604],
       [0.1551405 ],
       [0.55226118],
       [1.46628975],
       [0.498473  ],
       [0.37187249]])
 -0.953125]
max half sum in >>>> Lambda: 0.01 Season: 1
a, b =  [array([[0.37460604],
       [0.1551405 ],
       [0.55226118],
       [1.46628975],
       [0.498473  ],
       [0.37187249]])
 -0.953125]
max single last step in >>>>  Lambda: 0.01 Season: 1 at:  0.8080072793448589
a, b =  [array([[0.37460604],
       [0.1551405 ],
       [0.55226118],
```

```
    [1.46628975],
    [0.498473  ],
    [0.37187249]])
-0.953125]
```

Part 3: Generating test set prediction file for autograder based on trained SVM model

```
#   Generate test set prediction file for autograder
a1 = np.array([0.37460604,\
      0.1551405 ,\
      0.55226118,\
      1.46628975,\
      0.498473  ,\
      0.37187249])
b1 = -0.953125

u1 = np.array((a1,b1))
pre = predict(u1, test_f)
pretxt = ""
for i in range(pre.size):
  if pre[i]==-1:
    pretxt=pretxt+'<=50K\n'
  else:
    pretxt=pretxt+'>50K\n'
f = open('drive/My Drive/CS 498 AML/HW2/submission6.txt', 'w')
f.write(pretxt)
f.close()
```