COEN 240 MACHINE LEARNING HOMEWROK TWO

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PROBLEM ONE

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This is the choser center upolate step.

Our good is to derive
$$\overline{m}_k$$
 such that

$$\overline{m}_k = \underset{n=1}{\operatorname{arg}} \underset{n=1}{\operatorname{min}} \sum_{k=1}^{K} || \operatorname{rkn} || || \overline{m}_k^* - \overline{\chi}_n ||_2^2$$

What we want is: $\frac{\partial e J_1}{\partial m_k}$

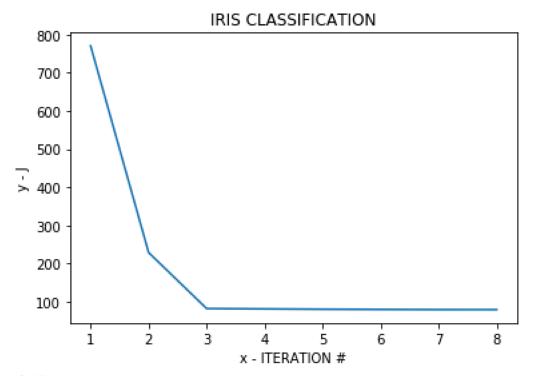
$$= \frac{\partial^{M_k} \int_{n=1}^{K} || \operatorname{rkn} || \overline{m}_k - \overline{\chi}_n ||_2^2}{\partial \overline{m}_k}$$

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$$= \frac{\partial^{M_k} \int_{n=1}^{K} || \operatorname{rkn} || \overline{m}_k - \overline{\chi}_n ||_2^2}{\partial \overline{m}_k} \cdot || \operatorname{rkn} || \overline{\chi}_n - \overline{\chi}_n \cdot || \overline{m}_k + \overline{\chi}_n \cdot || \overline{\chi}_n - \overline{\chi}_n \cdot || \overline{m}_k + \overline{\chi}_n \cdot || \overline{\chi}_n - \overline{\chi}_n \cdot || \overline{\chi}_n - \overline{\chi}_n \cdot || \overline{m}_k + \overline{\chi}_n \cdot || \overline{\chi}_n - \overline{\chi}_n \cdot || \overline{\chi}_n -$$

PROBLEM TWO:

ITERATION	#1	770.3261
ITERATION	#2	228.4977
ITERATION	#3	81.6952
ITERATION	#4	80.8064
ITERATION	#5	79.8736
ITERATION	#6	79.3444
ITERATION	#7	78.9213
ITERATION	#8	78.8557



DONE

This is a typical result of our algorithm. After several repeats, it is found that the best our algorithm can do is to minimize the error function to some figure around 78.85. We can see our model converges really fast, normally taking 6 to 14 iterations, which means the model can quickly approximate the real cluster centers We can also find that for a majority of iteration, the algorithms is just adjusting the cluster center around its final position for better accuracy.

There is one more thing we should be aware of. The random initialization of cluster center can possibly lead to different convergence results. Sometimes we might not get result as good as the graph show above. For example, the following graphs are examples of convergence to a not so good local optimum.

ITERATION #1 556.7213 ITERATION #2 173.8028 ITERATION #3 146.1369 ITERATION #4 142.7846 ITERATION #5 142.7541

10 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0 x - ITERATION

DONE

PROBLEM THREE

a. We use y to denote the logistic regression output. $y = S(a) = \frac{1}{1 + exp(a)}$, where $a = \overline{w}^T \cdot \overline{X}n$, and we have to know a bias term is already included in $\overline{w}^T \cdot \overline{X}n$.

The criterion: if y > 0.5, classify it as C_1

b. Only ONE weight, w, needs to be calculated in this method.

PROBLEM FOUR

Q. We also us y to denote the output $y = \max_{Ck} \frac{P(Ck) \cdot P(\vec{x}|Ck)}{P(Ck)} = \frac{P(Ck) \cdot P(\vec{x}|Ck)}{\sum_{j=1}^{k} P(C_j) \cdot P(\vec{x}|C_j)}$ The criterion is to classe the class with the highest probability.

b. K weights, the same number as total classes, need to be calculated in this method.

ATTACHMENTS

PROBLEM TWO CODE

```
import numpy as np
import pandas as pd
import random
import sys
import matplotlib.pyplot as plt
def initializeCenter(X, centers):
  attr max = np.zeros((NUM COLUMN, 1))
  attr min = np.zeros((NUM COLUMN, 1))
  for i in range(NUM COLUMN):
    attr val = X[:, i]
    attr max[i] = np.amax(attr val)
    attr min[i] = np.amin(attr val)
  for center in centers:
    for i in range(X.shape[1]):
      center[i][0] = random.uniform(attr min[i], attr max[i])
# X is a list of lists, where each component list represents a cluster
def assignCenter(X, centers):
  new_X = []
  for i in range(NUM CENTER):
    new X.append([])
  M = 0
  for cluster in X:
    for point in cluster:
      point = point.reshape(NUM_COLUMN,1)
      index, min distance = findCorresCenter(point, centers)
      new X[index].append(point)
      M = M + min distance
  return new X, M
def findCorresCenter(point, centers):
  index = 0
  min distance = np.linalg.norm(point-centers[0])**2
  for i in range(len(centers)):
    temp = np.linalg.norm(point-centers[i])**2
    if (temp < min distance):
      min distance = temp
      index = i
  return index, min_distance
```

```
def calculateCenter(X, centers):
  new centers = []
  for i in range(NUM CENTER):
    cluster = X[i]
    cluster center = np.zeros((NUM COLUMN, 1))
    if (len(cluster) == 0):
      new centers.append(centers[i])
      continue
    for i in range(NUM_COLUMN):
      cluster = np.array(cluster)
      cluster = cluster.reshape(cluster.shape[0], NUM COLUMN)
      attr val = cluster[:, i]
      cluster center[i][0] = np.mean(attr val)
    new_centers.append(cluster_center)
  return new centers
# READ FROM ORIGINAL XLS FILE INTO NUMPY ARRAY
file path xls = "/Users/bosen/Library/Mobile Documents/com~apple~CloudDocs/Portal/COEN
240/Assignment/HW02/Iris.xls"
file path csv = "/Users/bosen/Library/Mobile Documents/com~apple~CloudDocs/Portal/COEN
240/Assignment/HW02/Iris.csv"
iris xls = pd.read excel(file path xls)
iris xls.to csv(file path csv, index = None, header=False)
iris raw = np.genfromtxt(file path csv, delimiter=',')[:, 1:]
del(iris xls)
NUM ROW = iris raw.shape[0]
NUM COLUMN = iris raw.shape[1]-1
X = iris raw[:,:NUM COLUMN]
t = iris raw[:, NUM COLUMN].reshape(NUM ROW,1)
# DEFINE HYPERPARAMETERS AND INITIALIZE CENTERS
M = sys.float info.max
Ms = []
EPSILON = 10**(-5)
NUM CENTER = 3
NUM ITERATION = 0
centers = []
for i in range(NUM_CENTER):
  center = np.zeros((NUM COLUMN, 1))
  centers.append(center)
initializeCenter(X, centers)
X = np.array([X])
```

```
# ALTERNATES BETWEEN ASSIGNMENT AND CLUSTER-CENTER UPDATE
while(True):
  NUM_ITERATION = NUM_ITERATION+1
 X, new_M = assignCenter(X, centers) # THE FORM OF X
  if (M - new_M < EPSILON):
    break
  M = new_M
  Ms.append(M)
  print("ITERATION #%d\t%.4f" % (NUM_ITERATION, M))
 centers = calculateCenter(X, centers)
# PLOTTING
plt.plot(range(1, len(Ms)+1, 1), Ms)
plt.xlabel('x - ITERATION #')
plt.ylabel('y - J')
plt.title('IRIS CLASSIFICATION')
plt.show()
print("DONE")
```