CS498 AML, AMO HW5 Report

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TOTAL POINTS

100 / 100

QUESTION 1

- 1 Experiment table 40 / 40
 - √ 0 pts Accuracy greater than 60%
 - 2 pts Maximum Accuracy between 55-60%
 - **5 pts** Maximum Accuracy between 50%-55%
 - 10 pts Maximum Accuracy between 40%-50%
 - 15 pts Maximum Accuracy between 30%-40%
 - 20 pts Maximum Accuracy between 20%-30%
 - 25 pts Maximum Accuracy less than 20%
 - 40 pts NA

QUESTION 2

- 2 Histograms 28 / 28
 - √ 0 pts 14 histograms (2pts per activity)

QUESTION 3

- 3 Confusion matrix 22 / 22
 - √ 0 pts Correct Diagonal Entries should be large |
 Possible confusion between "climb stairs-descend
 stairs", "eat meat-eat soup" (similar pairs)
 - 12 pts Seems incorrect/uninterpretable/confusing
 - 1 pts No explicit values in the confusion matrix.
 - 2 pts The values in the confusion matrix are larger than the number of data for some categories in one fold. In other words, should't sum the confusion matrix of the three folds. Instead, just present one matrix with the lowest error.

QUESTION 4

- 4 Code snippets 10 / 10
 - √ 0 pts Correct
 - **3 pts** Segmentation/Window length sample code not available
 - 2 pts k-means code not available
 - 3 pts conversion to histogram features code not

available

- 2 pts classifier training code not available
- **2 pts** Snippets are too vague to read. Please contact TAs with clear code snippets for regrading.

QUESTION 5

5 Late o/o

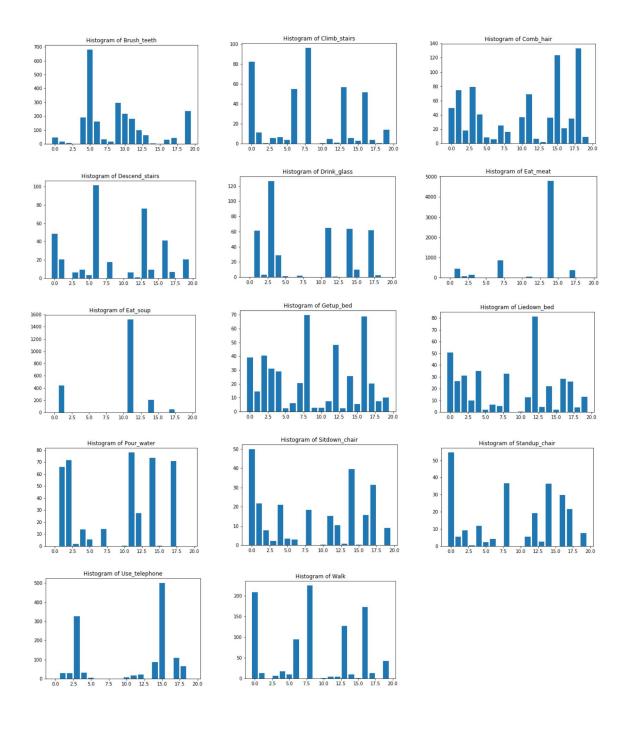
- √ 0 pts On time
 - **5 pts** 1 day
 - 10 pts 2 days
 - **15 pts** 3 days
 - 20 pts 4 days
 - 25 pts 5 days
 - 30 pts 6 days

Part 1 Experiment table:

For K-means please we have used Standard K-means. Following is the output generated using Random Forest Classifier:

```
Cluster: 4
Segment: 1
                             Accuracy: 71.73913043478261 %
Segment: 1
              Cluster: 8
                             Accuracy: 78.98550724637681 %
Segment: 1
              Cluster: 16
                              Accuracy: 86.59420289855072 %
                              Accuracy: 87.68115942028986 %
Segment: 1
              Cluster: 20
Segment: 1
              Cluster: 25
                              Accuracy: 83.69565217391305 %
              Cluster: 30
                              Accuracy: 83.69565217391305 %
Segment: 1
Segment: 1
              Cluster: 40
                              Accuracy: 84.05797101449275 %
Segment: 1
              Cluster: 50
                              Accuracy: 81.52173913043478 %
Segment: 4
              Cluster: 4
                             Accuracy: 70.28985507246377 %
Segment: 4
              Cluster: 8
                             Accuracy: 78.98550724637681 %
Segment: 4
              Cluster: 16
                              Accuracy: 85.5072463768116 %
                              Accuracy: 82.6086956521739 %
Segment: 4
              Cluster: 20
              Cluster: 25
                              Accuracy: 86.95652173913044 %
Segment: 4
                              Accuracy: 85.86956521739131 %
Segment: 4
              Cluster: 30
Segment: 4
              Cluster: 40
                              Accuracy: 82.6086956521739 %
                              Accuracy: 83.3333333333333 %
Segment: 4
              Cluster: 50
                             Accuracy: 68.47826086956522 %
Segment: 8
              Cluster: 4
Segment: 8
              Cluster: 8
                             Accuracy: 77.17391304347827 %
Segment: 8
              Cluster: 16
                              Accuracy: 78.62318840579711 %
                              Accuracy: 81.52173913043478 %
Segment: 8
              Cluster: 20
              Cluster: 25
                              Accuracy: 80.07246376811594 %
Segment: 8
                              Accuracy: 81.88405797101449 %
Segment: 8
              Cluster: 30
Segment: 8
              Cluster: 40
                              Accuracy: 82.97101449275362 %
                              Accuracy: 82.2463768115942 %
Segment: 8
              Cluster: 50
                              Accuracy: 66.30434782608695 %
              Cluster: 4
Segment: 32
Segment: 32
              Cluster: 8
                              Accuracy: 69.92753623188406 %
Segment: 32
              Cluster: 16
                              Accuracy: 75.36231884057972 %
Segment: 32
              Cluster: 20
                               Accuracy: 73.55072463768117 %
Segment: 32
              Cluster: 25
                              Accuracy: 77.17391304347827 %
Segment: 32
             Cluster: 30
                               Accuracy: 72.46376811594203 %
                               Accuracy: 73.55072463768117 %
Segment: 32
              Cluster: 40
              Cluster: 50
                               Accuracy: 74.27536231884058 %
Segment: 32
Segment: 64
              Cluster: 4
                              Accuracy: 61.23188405797102 %
Segment: 64
              Cluster: 8
                              Accuracy: 71.73913043478261 %
Segment: 64
              Cluster: 16
                               Accuracy: 72.46376811594203 %
              Cluster: 20
                               Accuracy: 73.18840579710145 %
Segment: 64
                               Accuracy: 73.91304347826086 %
Segment: 64
              Cluster: 25
                               Accuracy: 69.56521739130434 %
Segment: 64
              Cluster: 30
                               Accuracy: 71.01449275362319 %
              Cluster: 40
Segment: 64
Segment: 64
               Cluster: 50
                               Accuracy: 68.11594202898551 %
Best accuracy of 87.68115942028986% with 20.0 clusters and 1.0 segments
```

Part 2 Histograms: Used the Best accuracy clusters (20) and Segment (1) value for draw Histogram



Part 3 Confusion matrix:

o: Sitdown_chair, 1: Eat_meat, 2: Walk, 3: Use_telephone, 4: Drink_glass, 5: Descend_stairs, 6: Standup_chair, 7: Eat_soup, 8: Getup_bed, 9: Climb_stairs, 10: Brush_teeth, 11: Pour_water, 12: Liedown_bed, 13: Comb_hair

	Θ	1	2	3	4	5	6	7	8	9	10	11	12	13
Θ	3	0	1	0	Θ	Θ	Θ	Θ	Θ	0	0	0	0	Θ
1	Θ	33	0	1	Θ	Θ	Θ	Θ	Θ	0	0	0	0	Θ
2	Θ	0	8	0	Θ	Θ	Θ	1	Θ	Θ	0	0	1	Θ
3	Θ	2	0	12	Θ	Θ	Θ	Θ	Θ	Θ	0	0	0	Θ
4	Θ	0	0	0	33	Θ	0	Θ	Θ	Θ	0	0	0	Θ
5	Θ	0	0	0	Θ	1	0	Θ	Θ	0	0	0	0	Θ
6	Θ	0	0	0	Θ	Θ	Θ	Θ	Θ	1	0	0	0	Θ
7	Θ	0	0	0	Θ	Θ	Θ	28	Θ	0	0	5	0	Θ
8	Θ	0	0	0	Θ	Θ	0	3	2	Θ	2	2	0	Θ
9	Θ	0	0	0	Θ	Θ	Θ	Θ	Θ	33	0	0	0	Θ
10	Θ	0	0	0	Θ	Θ	0	1	1	0	24	7	0	Θ
11	Θ	0	0	0	Θ	Θ	0	1	Θ	Θ	9	24	0	Θ
12	Θ	0	0	0	1	Θ	Θ	Θ	Θ	Θ	0	0	3	Θ
13	Θ	7	0	0	Θ	0	Θ	1	Θ	0	0	0	0	25

Part 4 A screenshot of your code:

i) Segmentation of the vector

```
for j in range(train_num):
    train_activity = []
    cur_file = act_data[i][j]
    length = cur_file.shape[0]
    segment_num = math.floor(length/segment_size)

    for k in range(segment_num):
        train_activity.append(cur_file[k*segment_size:(k+1)*segment_size].T.flatten()[:segment_size*3+1])
        activities.append(cur_file[k*segment_size:(k+1)*segment_size].T.flatten()[:segment_size*3+1])
        train_activity = np.array(train_activity)

    train_activities.append(train_activity)

for j in range(train_num, train_num+test_num):
    test_activity = []
    cur_file = act_data[i][j]
    length = cur_file.shape[0]
    segment_num = math.floor(length/segment_size)

for k in range(segment_num):
        test_activity.append(cur_file[k*segment_size:(k+1)*segment_size].T.flatten()[:segment_size*3+1])

    test_activity = np.array(test_activity)
    test_activities.append(test_activity)
```

ii) K-means

```
def KMeans(activities, cluster_size, segment_size):
    kmeans = KMeans(n_clusters=cluster_size, random_state=0).fit(activities[:, :segment_size*3])
    train_centers = kmeans.cluster_centers_
    train_labels = kmeans.labels_
    return kmeans, train_labels, train_centers

def KMeansPredict(model, data):
    return model.predict(data)

model, train_labels, train_centers = KMeans(activities, cluster_size, segment_size)
```

iii) Generating the histogram

```
def draw(histograms, signals, cluster_size, act_name):
    for i in range(14):
        histogram_sum, count = np.zeros(cluster_size), 0.0
        for (histogram, signal) in zip(histograms, signals):
            if signal == i:
                histogram_sum += histogram
                count += 1.0
        histogram_sum /= count
    plt.bar(range(cluster_size), histogram_sum)
    plt.title('Histogram of ' + act_name[i])
    plt.savefig('%s.png'%i)
    plt.close()
```

iv) Classification

```
rf = RF(max_depth=32, random_state=0, n_estimators=200).fit(train_histogram, train_signal)
accurate = 0
cov_matrix = dict()
for i in range(test_samples):
    label = rf.predict(test_histogram[i].reshape(1, -1))[0]
    label_ori = act_test[i][0, segment_size*3]
    if label_ori not in cov_matrix:
        cov_matrix[label_ori] = [0]*14
    cov_matrix[label_ori][label] += 1
    if int(label) == label_ori:
        accurate = accurate + 1
```

Part 5 Screenshots of all your source code:

```
import math
import random
import numpy as np
import pandas as pd
from collections import defaultdict
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.model_selection import KFold
from sklearn.ensemble import RandomForestClassifier as RF
act_num = 14
def readData(path):
       readuata(patn):
# activities: data of all activities
# activity: data of each activity
# cur_file: data of each file
# cur_act: data of each line
folders = os.listdir(path)
       folders = [x for x in folders if 'MODEL' not in x and 'DS_Store' not in x]
       #print(folders)
       activities = []
       for i in range(act_num):
               range(act_num):
activity = []
path1 = "" + path + "/" + folders[i]
files = os.listdir(path1)
random_select = random.sample(range(len(files)), len(files))
               for j in random_select:
    file = files[j]
    cur_file = []
                      cur_act.append(int(num[0]))
cur_act.append(int(num[1]))
cur_act.append(int(num[2]))
                                             cur_act.append(i)
cur_act = np.array(cur_act)
                                     cur_file.append(cur_act)
cur_file = np.array(cur_file)
activity.append(cur_file)
               activity = np.array(activity)
activities.append(activity)
       activities = np.array(activities)
#print(activities)
return folders, activities
def splitData(act_data, percent, segment_size):
       activities = []
train_activities = []
      test activities = []
```

```
def splitData(act_data, percent, segment_size):
    activities = []
    train_activities = []
    for i in range(sct_num):
        file_num = act_data[i].ahape[0]
        test_num = ath_foor(file_num*(1-percent))
        if(sest_num = ath_foor(file_num*(1-percent))
        if(sest_num = i):
        train_num = file_num-test_num

    for j in range(train_num):
        train_activity = []
        cur_file = act_data[i][j]
        length = cur_file.ahape[0]
        segment_num = math.floor(length/segment_size)

    for k in range(segment_num):
        train_activity.appand(cur_file[k*segment_size)(k+1)*segment_size].T.flatten()[:segment_size*3+1])
        activities.appand(cur_file[k*segment_size)(k+1)*segment_size].T.flatten()[:segment_size*3+1])
        train_activity = np.arrsy(train_activity)

    for j in range(train_num, train_num-test_num):
        test_activity = []
        cur_file = act_data[i][j]
        length = cur_file.ahape[0]
        segment_num = math.floor(length/segment_size)

        for k in range(segment_num):
              test_activity = np.arrsy(test_activity)
              test_activities = np.arrsy(test_activity)
        activities = np.arrsy(test_activity)
        activities = np.arrsy(test_activity)
        activities = np.arrsy(test_activities)
        return activities, train_activities, test_activities

        def TrainHistogrand(data, cluster_size, labels, segment_size):
        length = data.ahape[0]
        index = 0
        label = []
        histograms = []
        signal = data[i][0, segment_size*3]
        signal = count[label] + 1
```

```
index += 1
       histograms.append(count)
   histograms = np.array(histograms)
   signals = np.array(signals)
   for i in range(length):
       total = np.sum(histograms[i])
       for j in range(cluster_size):
           histograms[i][j] = float(histograms[i][j]) # normalization
    return histograms, signals
def TestHistogram(data, cluster_size, labels):
   count = np.zeros(cluster_size)
   length = data.shape[0]
    for i in range(length):
       label = labels[i]
       count[label] = count[label] + 1
   total = np.sum(count)
   for i in range(cluster_size):
       count[i] = float(count[i])
    return count
def KMeans(activities, cluster_size, segment_size):
    kmeans = KMeans(n_clusters=cluster_size, random_state=0).fit(activities[:, :segment_size*3])
   train_centers = kmeans.cluster_centers_
    train_labels = kmeans.labels_
   return kmeans, train_labels, train_centers
def KMeansPredict(model, data):
    return model.predict(data)
def getCenter(data ,labels, cluster_size, segment_size):
   centers = np.array([np.zeros(segment_size*3)]*cluster_size)
    label_count = defaultdict(float)
   for i in range(data.shape[0]):
       label, point = labels[i], data[i]
       centers[label] += point
       label_count[label] += 1
    for i in range(cluster_size):
       centers[i] = centers[i] / label_count[i]
    return centers
def getLable(data, centers):
   dist, label = float('inf'), 0
    for i in range(centers.shape[0]):
       cur_dist = np.linalg.norm(data-centers[i])
       if cur_dist < dist:</pre>
           dist, label = cur_dist ,i
    return np.array([label])
def draw(histograms, signals, cluster_size, act_name):
     for i in range(14):
         histogram_sum, count = np.zeros(cluster_size), 0.0
         for (histogram, signal) in zip(histograms, signals):
              if signal == i:
                  histogram_sum += histogram
                  count += 1.0
         histogram_sum /= count
         plt.bar(range(cluster_size), histogram_sum)
         plt.title('Histogram of ' + act_name[i])
         plt.savefig('%s.png'%i)
         plt.close()
```

```
def createFolds(data):
      folds = []
      kf = KFold(n_splits=3, shuffle=True)
for train_indexes, test_indexes in kf.split(data):
    fold = np.array([train_indexes, test_indexes])
    folds.append(fold)
      folds = np.array(folds)
      return folds
def crossValidateAndTrain(allData, activities, cluster_size, segment_size,act_name):
     dataFoldsIdx = createFolds(allData)
accuracies = []
      for fold in dataFoldsIdx:
            # Get Data
           act_train = allData.take(fold[0], axis=0)
act_train = np.array(act_train)
activities = np.array(activities)
act_test = allData.take(fold[1], axis=0)
act_test = np.array(act_test)
            model, train_labels, train_centers = KMeans(activities, cluster_size, segment_size)
            train_histogram, train_signal = TrainHistogram(act_train, cluster_size, train_labels, segment_size)
            draw(train_histogram, train_signal, cluster_size, act_name)
            oraw(train_istogram, train_sign
test_labels = []
test_samples = act_test.shape[0]
for i in range(test_samples):
    test_label = []
                  for j in range(act_test[i].shape[0]):  # each segment
    test_label.append(KMeansPredict(model, act_test[i][j, :segment_size*3].reshape(1, -1)))
                  test_label = np.array(test_label)
test_labels.append(test_label)
            test_labels = np.array(test_labels)
            test_histogram = []
for i in range(test_samples):
                  {\tt test\_histogram.append}({\tt TestHistogram}({\tt act\_test[i]},\ {\tt cluster\_size},\ {\tt test\_labels[i]}))
            rf = RF(max_depth=32, random_state=0, n_estimators=200).fit(train_histogram, train_signal)
            accurate = 0
             cov_matrix = dict()
            for i in range(test_samples):
    label = rf.predict(test_histogram[i].reshape(1, -1))[0]
                  label_ori = act_test[i][0, segment_size*3]
if label_ori not in cov_matrix:
    cov_matrix[label_ori] = [0]*14
                  cov_matrix[label_ori][label] += 1
if int(label) == label_ori:
    accurate = accurate + 1
            accurate = accurate + 1

cov_df = pd.DataFrame.from_dict(cov_matrix, orient='index', columns=[str(x) for x in range(14)])
accuracy = (accurate/ len(act_test))*100
            print(accuracy)
            accuracies.append(accuracy)
            cms.append(cov_df)
      return accuracies, cms
```

By: Shrashti Singhal & Ankush Singhal

APPLIED MACHINE LEARNING Assignment 5

```
def main():
    act_name, act_data = readData('./HMP_Dataset')
    print("Experiments...")
trainSize = 2/3
    clustersToTry = [4, 8, 16, 20, 25, 30, 40, 50]
segmentSizesToTry = [1, 4, 8, 32, 64]
inertiasBySegment = {}
    accPerClusterNumAndSegmentSize = []
    for segment_size in segmentSizesToTry:
         inertias = []
         for cluster_size in clustersToTry:
             activities, act_train, act_test = splitData(act_data, trainSize, segment_size)
             model, train_labels, train_centers = KMeans(activities, cluster_size, segment_size)
             inertias.append(model.inertia_)
             train_histogram, train_signal = TrainHistogram(act_train, cluster_size, train_labels, segment_size)
             #draw(train_histogram, train_signal, cluster_size, act_name)
             test_labels = []
              test_samples =
             for i in range(test_samples):
    test_label = []
                                                                        # each file
                  for j in range(act_test[i].shape[0]):
                      \label.append(kmsPredict(model, act_test[i][j, :segment_size*3].reshape(1, -1))) \\ \# \ test_label.append(getLable((act_test[i][j, :segment_size*3]), \ train_centers))
                 test_label = np.array(test_label)
test_labels.append(test_label)
             test_labels = np.array(test_labels)
             test_histogram = []
             for i in range(test_samples):
                 test_histogram.append(TestHistogram(act_test[i], cluster_size, test_labels[i]))
             \verb|rf = RF(max_depth=32, random_state=0, n_estimators=200).fit(train_histogram, train_signal)|\\
             accurate = 0
             cov_matrix = dict()
             for i in range(test_samples):
                  label = rf.predict(test_histogram[i].reshape(1, -1))[0]
                  label_ori = act_test[i][0, segment_size*3]
                 if label_ori not in cov_matrix:
    cov_matrix[label_ori] = [0]*14
                  cov_matrix[label_ori][label] +
             if int(label) == label_ori:
    accurate = accurate + 1
#cov_df = pd.DataFrame.from_dict(cov_matrix, orient='index', columns=[str(x) for x in range(14)])
#cov_df.to_csv('cov.csv', index=False)
             acc = (accurate/ len(act_test))*100
print(" ")
             print('Segment: ',segment_size,' Cluster: ', cluster_size,' Accuracy: ', acc,'%')
             accPerClusterNumAndSegmentSize.append([cluster_size, segment_size, acc])
         inertiasBySegment[segment size] = inertias
    {\tt accPerClusterNumAndSegmentSize = np.array(accPerClusterNumAndSegmentSize)}
    best Accuracy = acc Per Cluster Num And Segment Size [acc Per Cluster Num And Segment Size [:,2]. argsort ()] [-1] \\
    print("
    print(f'Best accuracy of {bestAccuracy[2]}% with {bestAccuracy[0]} clusters and {bestAccuracy[1]} segments')
    print(" ")
    segment_size= int(bestAccuracy[1])
    cluster_size= int(bestAccuracy[0])
    matrix_output=True
    activities, act_train, act_test = splitData(act_data, trainSize, segment_size)
    allDataSegmented = np.concatenate((act_train, act_test), axis=0)
    allDataSegmented = np.array(allDataSegmented)
    #print(allDataSegmented)
    results = crossValidateAndTrain(allDataSegmented, activities, cluster_size, segment_size,act_name )
    best_accuracy, best_matrix = results[0][np.argmax(results[0])], results[1][np.argmax(results[0])]
    print(f'Best Accuracy of {best_accuracy}%')
    print(best_matrix)
```