CS145 Howework 4

Important Note: HW4 is due on 11:59 PM PT, Nov 20 (Friday, Week 7). Please submit through GradeScope.

Print Out Your Name and UID

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Before You Start

You need to first create HW4 conda environment by the given cs145hw4.ym1 file, which provides the name and necessary packages for this tasks. If you have conda properly installed, you may create, activate or deactivate by the following commands:

```
conda env create -f cs145hw4.yml
conda activate hw4
conda deactivate
```

OR

```
conda env create --name NAMEOFYOURCHOICE -f cs145hw4.yml
conda activate NAMEOFYOURCHOICE
conda deactivate
```

To view the list of your environments, use the following command:

```
conda env list
```

More useful information about managing environments can be found https://docs.conda.io/projects/conda/en/latest/user-guide/tasks/manage-environments.html).

You may also quickly review the usage of basic Python and Numpy package, if needed in coding for matrix operations.

In this notebook, you must not delete any code cells in this notebook. If you change any code outside the blocks (such as some important hyperparameters) that you are allowed to edit (between STRART/END YOUR CODE HERE), you need to highlight these changes. You may add some additional cells to help explain your results and observations.

```
In [25]: import numpy as np
    import pandas as pd
    import sys
    import random
    import math
    import matplotlib.pyplot as plt
    from scipy.stats import multivariate_normal
    %load_ext autoreload
    %autoreload 2
```

```
The autoreload extension is already loaded. To reload it, use: 
%reload_ext autoreload
```

If you can successfully run the code above, there will be no problem for environment setting.

1. Clustering Evaluation

This workbook will walk you through an example for calculating different clustering metrics.

Note: This is a "question-answer" style problem. You do not need to code anything and you are required to calculate by hand (with a scientific calculator).

Questions

Suppose we want to cluster the following 20 conferences into four areas, with ground truth label and algorithm output label shown in third and fourth column. Please evaluate the quality of the clustering algorithm according to four different metrics respectively.

ID	Conference Name	Ground Truth Label	Algorithm output Label
1	IJCAI	3	2
2	AAAI	3	2
3	ICDE	1	3
4	VLDB	1	3
5	SIGMOD	1	3
6	SIGIR	4	4
7	ICML	3	2
8	NIPS	3	2
9	CIKM	4	3
10	KDD	2	1
11	www	4	4
12	PAKDD	2	1
13	PODS	1	3
14	ICDM	2	1
15	ECML	3	2
16	PKDD	2	1
17	EDBT	1	2
18	SDM	2	1
19	ECIR	4	4
20	WSDM	4	4

Questions (please include intermediate steps)

- 1. Calculate purity.
- 2. Calculate precision.
- 3. Calculate recall.
- 4. Calculate F1-score.
- 5. Calculate normalized mutual information.

```
In [21]: ground_truth = [3,3,1,1,1,4,3,3,4,2,4,2,1,2,3,2,1,2,4,4]
         output = [2,2,3,3,3,4,2,2,3,1,4,1,3,1,2,1,2,1,4,4]
         def info(truth, ouptut):
             result = {'count':0, 'tp':0, 'fp':0, 'tn':0, 'fn':0}
             for i in range(len(truth)):
                 for j in range(len(output)):
                     # avoid repetitve pair
                     if i < j:
                          if truth[i] == truth[j]:
                              if output[i] == output[j]:
                                  result['tp'] += 1
                              else:
                                  result['fn'] += 1
                          else:
                              if output[i] == output[j]:
                                  result['fp'] += 1
                              else:
                                  result['tn'] += 1
                          result['count']+= 1
             return result
         def table(truth, output):
             result = dict()
             truth table = dict()
             output table = dict()
             for i in range(len(truth)):
                 if truth[i] not in truth table:
                     truth table[truth[i]] = list()
                 truth table[truth[i]].append(i)
             for j in range(len(output)):
                 if output[j] not in output table:
                     output_table[output[j]] = list()
                 output_table[output[j]].append(j)
             result['truth'] = truth_table
             result['output'] = output table
             return result
         def nmi(table, total):
             # I
             i = 0.
             for truth label in table['truth'].keys():
                 for output label in table['output'].keys():
                     truth_values = table['truth'][truth_label]
                     output_values = table['output'][output_label]
                      common = float(len(list(set(truth values).intersection(output values)
                      cur = common / total * np.log(total*common/len(truth values)/len(out)
                      i += cur
             # calculate entropy
             h truth = 0.
             for truth_label in table['truth'].keys():
                 truth length = float(len(table['truth'][truth label]))
                 h truth -= (truth length/total*np.log(truth length/total))
```

```
h output = 0.
    for output_label in table['output'].keys():
        output_length = float(len(table['output'][output_label]))
        h output -= (output length/total*np.log(output length/total))
    nmi = i/np.sqrt(h_truth*h_output)
    return nmi
table = table(ground truth, output)
info = info(ground truth,output)
print(info)
print(table)
print(nmi(table, len(output)))
{'count': 190, 'tp': 32, 'fp': 9, 'tn': 141, 'fn': 8}
{'truth': {3: [0, 1, 6, 7, 14], 1: [2, 3, 4, 12, 16], 4: [5, 8, 10, 18, 19], 2:
[9, 11, 13, 15, 17]}, 'output': {2: [0, 1, 6, 7, 14, 16], 3: [2, 3, 4, 8, 12],
4: [5, 10, 18, 19], 1: [9, 11, 13, 15, 17]}}
0.8152212305376372
```

Purity

```
output cluster 1: 10,12,14,16,18 ---> 5 matched with ground truth 2 output cluster 2: 1,2,7,8,15,17 ---> 5 matched with ground truth 3 output cluster 3: 3,4,5,9,13 ---> 4 matched with ground truth 1 output cluster 4: 6,11,19,20 ---> 4 mathced with ground truth 4  \text{Purity} = \frac{1}{N} \sum_k \max |c_k \cap \omega_j| = 18/20 = 0.9
```

Precision

```
Precision = TP/(TP+FP) = 32/(32+9) = 32/41 = 0.78049
```

Recall

```
Recall = TP/(TP+FN) = 32/(32+8) = 32/40 = 0.8
```

F1-score

F1-score = 2precisionrecall / (precision+recall) = 0.79012

NMI We used script above to calculate NMI = 0.81522

Your answer here:

Note: you can use several code cells to help you compute the results and answer the questions. Again you don't need to do any coding.

Please type your answer here!

```
answer 1: Purity is 0.9

answer 2: Precision is 0.7809

answer 3: Recall is 0.8

answer 4: F1-score is 0.79012

answer 5: NMI is 0.81522
```

2. K-means

In this section, we are going to apply K-means algorithm against two datasets (dataset1.txt, dataset2.txt) with different distributions, respectively.

For each dataset, it contains 3 columns, with the format: x1 \t x2 \t cluster_label. You need to use the first two columns for clustering, and the last column for evaluation.

```
In [32]: from hw4code.KMeans import KMeans
k = KMeans()
# As a sanity check, we print out a sample of each dataset
dataname1 = "data/dataset1.txt"
dataname2 = "data/dataset2.txt"
k.check_dataloader(dataname1)
k.check_dataloader(dataname2)
```

```
For dataset1: number of datapoints is 150

x y ground_truth_cluster
0 -0.163880 -0.219869 1
1 -0.886274 -0.356186 1
2 -0.978910 -0.893314 1
3 -0.658867 -0.371122 1
4 -0.072518 0.399157 1

For dataset2: number of datapoints is 200

x y ground_truth_cluster
```

```
x y ground_truth_cluster
0 1.068587 0.136921 1
1 0.705440 0.393068 1
2 0.840811 -0.054906 1
3 -0.923447 0.598501 1
4 0.784353 0.724743 1
```

2.1 Coding K-means

Complete the reassignClusters and getCentroid function in KMeans.py.

Print out each output cluster's size and centroid (x,y) for dataset1 and dataset2 respectively.

```
In [33]: k = KMeans()
#=========#
# STRART YOUR CODE HERE #
#=========#
k.main(dataname1)
k.main(dataname2)
#=========#
# END YOUR CODE HERE #
#=======#
```

```
For dataset1
Iteration :4
Cluster 0 size :50
Centroid [x=2.5737264423871213, y=-0.027462568841232982]
Cluster 1 size :50
Centroid [x=-0.4633368646347211, y=-0.466114096981958]
Cluster 2 size :50
Centroid [x=0.9888766205736857, y=2.0104789651972013]

For dataset2
Iteration :3
Cluster 0 size :102
Centroid [x=1.2708406269481842, y=-0.08583389704900131]
Cluster 1 size :98
Centroid [x=-0.2018593506236787, y=0.5726963240559536]
```

2.2 Purity and NMI Evaluation

Complete the compute_purity function in KMeans.py.

In order to compute NMI, you need to firstly compute NMI matrix and then do the calculation. That is to complete the getNMIMatrix and calcNMI functions in KMeans.py.

Print out the purity and NMI for each dataset respectively.

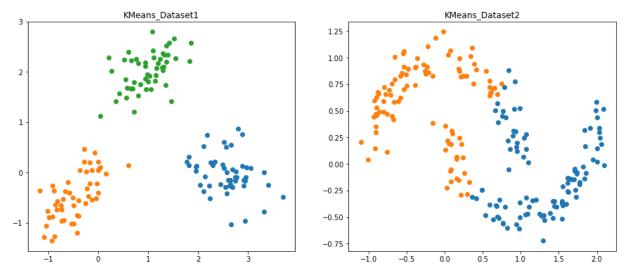
```
In [34]: k = KMeans()
#=========#
# STRART YOUR CODE HERE #
#==========#
k.main(dataname1, True)
k.main(dataname2, True)
#========#
# END YOUR CODE HERE #
#=======#
```

```
For dataset1
Iteration:4
Purity is 0.040000
NMI is 1.000000
Cluster 0 size :50
Centroid [x=2.5737264423871213, y=-0.027462568841232982]
Cluster 1 size :50
Centroid [x=-0.4633368646347211, y=-0.466114096981958]
Cluster 2 size :50
Centroid [x=0.9888766205736857, y=2.0104789651972013]
For dataset2
Iteration :3
Purity is 0.015000
NMI is 0.205096
Cluster 0 size :102
Centroid [x=1.2708406269481842, y=-0.08583389704900131]
Cluster 1 size :98
Centroid [x=-0.2018593506236787, y=0.5726963240559536]
```

2.3 Visualization

The clustering results for KMeans are saved as KMeans_dataset1.csv and KMeans_dataset2.csv respectively under your root folder. Plot the clustering results for the two datasets, with different colors representing different clusters.

```
In [36]: CSV FILE PATH1 = 'Kmeans dataset1.csv'
         CSV_FILE_PATH2 = 'Kmeans_dataset2.csv'
        df1 = pd.read csv(CSV FILE PATH1,header=None,names=['x','y','pred'])
         df2 = pd.read_csv(CSV_FILE_PATH2, header=None, names=['x', 'y', 'pred'])
         fig, [ax0,ax1] = plt.subplots(1, 2, figsize=(15, 6))
         ax0.title.set_text("KMeans_Dataset1")
         ax1.title.set text("KMeans Dataset2")
         #=======#
         # STRART YOUR CODE HERE
         #=======#
         groups1 = df1.groupby('pred')
         for name, group in groups1:
            ax0.plot(group["x"], group["y"], marker="o", linestyle="", label=name)
         groups2 = df2.groupby('pred')
         for name, group in groups2:
            ax1.plot(group["x"], group["y"], marker="o", linestyle="",label=name)
            END YOUR CODE HERE
         #=======#
         plt.show()
```



Question

Give the pros and cons of K-means algorithm. (At least one for pro and two for cons to get full marks)

Your answer here

Please type your answer here!

Pros:

1. Efficient: time complexity for K-means is O(tkn) which is close to O(n) as t,k <<< n usually.

2. Simple: it is easy to implement the algorithm.

Cons:

- 1. Sensitive to noise and outlier data.
- 2. Not suitable for cluster with non-convex shapes
- 3. Needs to specify the number of k before training

3 DBSCAN

In this section, we are going to use DBSCAN for clustering the same two datasets.

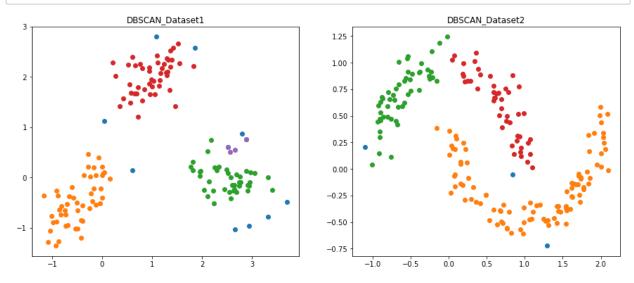
3.1 Coding DBSCAN

Complete the dbscan function in DBSCAN.py . Print out the purity, NMI and cluter size for each dataset respectively.

```
In [37]: from hw4code.DBSCAN import DBSCAN
        d = DBSCAN()
        #=======#
        # STRART YOUR CODE HERE #
        #=======#
        d.main(dataname1)
        d.main(dataname2)
        #=======#
           END YOUR CODE HERE
        #=======#
        For dataset1
        Esp: 0.3560832705047313
        Number of clusters formed :4
        Noise points :11
        Purity is 0.060000
        NMI is 0.959065
        Cluster 0 size :49
        Cluster 1 size :41
        Cluster 2 size :47
        Cluster 3 size :4
        For dataset2
        Esp :0.18652096476712493
        Number of clusters formed :3
        Noise points :3
        Purity is 0.020000
        NMI is 0.817349
        Cluster 0 size :99
```

The clustering results for DBSCAN are saved as DBSCAN_dataset1.csv and DBSCAN_dataset2.csv respectively under your root folder. Plot the clustering results for the two datasets, with different colors representing different clusters.

```
In [38]: CSV_FILE_PATH1 = 'DBSCAN_dataset1.csv'
        CSV_FILE_PATH2 = 'DBSCAN_dataset2.csv'
        df1 = pd.read_csv(CSV_FILE_PATH1,header=None,names=['x','y','pred'])
        df2 = pd.read_csv(CSV_FILE_PATH2, header=None, names=['x', 'y', 'pred'])
        fig, [ax0,ax1] = plt.subplots(1, 2, figsize=(15, 6))
        ax0.title.set_text("DBSCAN_Dataset1")
        ax1.title.set_text("DBSCAN_Dataset2")
        #=======#
        # STRART YOUR CODE HERE
        #=======#
        groups1 = df1.groupby('pred')
        for name, group in groups1:
            ax0.plot(group["x"], group["y"], marker="o", linestyle="", label=name)
        groups2 = df2.groupby('pred')
        for name, group in groups2:
            ax1.plot(group["x"], group["y"], marker="o", linestyle="",label=name)
        #======#
            END YOUR CODE HERE
        #=======#
        plt.show()
```



Question

Give the pros and cons of DBSCAN algorithm. (At least two for pro and one for cons to get full marks)

Your answer here

Please type your answer here!

Pros:

- 1. Does not need to specify number of k before.
- 2. Robust to outlier and noise.

Cons:

1. Has requirement of high density of dataset, also has problem with dataset with varying densities.

4 GMM

In this section, we are going to use GMM for clustering the same two datasets.

4.1 Coding GMM

Complete the Estep and 'Mstep' function in GMM.py . Print out the purity, NMI, final mean, covariance and cluter size for each dataset respectively.

```
In [40]: from hw4code.GMM import GMM
       g = GMM()
       #======#
       # STRART YOUR CODE HERE #
       #=======#
       g.main(dataname1)
       g.main(dataname2)
       #=======#
           END YOUR CODE HERE
       #=======#
       For dataset1
       Number of Iterations = 22
       After Calculations
       Final mean =
        -0.46247285694404044
        -0.4638749980764899
       0.9898929396029765
       2.011802723814242
```

0.14918910487220216

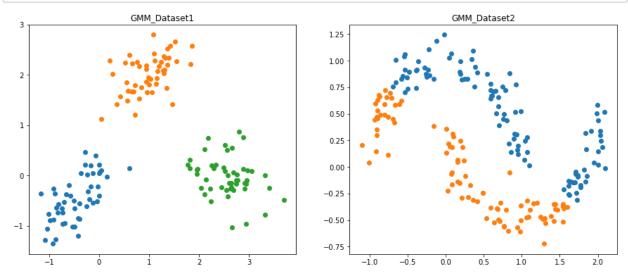
Final covariance =
For Cluster : 1

2.57342634413319 -0.027108746076609493

4.2 Visualization

The clustering results for GMM are saved as GMM_dataset1.csv and GMM_dataset2.csv respectively under your root folder. Plot the clustering results for the two datasets, with different colors representing different clusters.

```
In [41]: CSV FILE PATH1 = 'GMM dataset1.csv'
         CSV FILE PATH2 = 'GMM dataset2.csv'
        df1 = pd.read csv(CSV FILE PATH1,header=None,names=['x','y','pred'])
         df2 = pd.read_csv(CSV_FILE_PATH2, header=None, names=['x', 'y', 'pred'])
         fig, [ax0,ax1] = plt.subplots(1, 2, figsize=(15, 6))
         ax0.title.set_text("GMM_Dataset1")
         ax1.title.set text("GMM Dataset2")
         #=======#
         # STRART YOUR CODE HERE #
         #=======#
         groups1 = df1.groupby('pred')
         for name, group in groups1:
            ax0.plot(group["x"], group["y"], marker="o", linestyle="", label=name)
         groups2 = df2.groupby('pred')
         for name, group in groups2:
            ax1.plot(group["x"], group["y"], marker="o", linestyle="",label=name)
            END YOUR CODE HERE
         #=======#
         plt.show()
```



Questions

- 1. Give the pros and cons of GMM algorithm. (At least two for pro and two for cons to get full marks)
- 2. Compare the visualization results from three algorithms, analyze for each dataset why these algorithms would produce such result.

Your answer here:

Please type your answer here!

Pros of GMM:

- 1. Models are more general, so it can deal with different densities and sizes of cluster.
- 2. Clusters can be characterized by a small number of parameters.
- 3. The result may satisfy the statistical asssumptions of the generative models.

Cons of GMM:

- 1. It will converge to local optimal isntead of global.
- 2. Can only deal with spherical clusters.
- 3. Hard to estimate the number of clusters.

Reasoning over dataset1:

- 1. K-means: each of the three clusters are relatively far from each other while close inside the cluster, so the local optimum k-means reach is the global one this case.
- 2. DBSCAN: same reason that the three clusters are relatively far from each other. DBSCAN marks some outlier of each cluster and some points that are relatively between the cluster as noise as they are not density-reachable for given eps and minpts.
- 3. GMM: same reason that the clusters are far from each other making the final result the only possible local optimal for GMM.

Reasoning over dataset2:

- 1. K-means: the points are relatively uniformly distributed which makes k-means tend to create 2 cluster by just breaking the points in half by a linear separater.
- 2. DBSCAN: There is break in the upper half of the points which make DBSCAN cluster the upper swirl into two clusters while the bottom one is more densily-connected so clustered together. And there is certian space between the upper and bottom swirl so DBSCAN captures that and makes some points in between as noise.
- GMM: similar reason to K-means. K-means reach the local optimal by simply breaking the points in two halves by a relaitively linear separator.

5 Bonus Question

Prove that KMeans algorithm would guarantee covergence. (Hint: prove for each step the loss would descrease.)

$$J = \sum_{i=1}^k \sum_i w_{ij} ||x_i - c_j||^2$$
 as $w_{ij} = 1$ if x_i belongs to cluster j is the loss function.

Let J_i be the loss in i-th iteration, c_{ix} be the center assigned to x in i-th iteration.

Then
$$J_{i+1} - J_i = \sum ||x - c_{(i+1)x}||^2 - ||x - c_{ix}||^2$$

As $c_{(i+1)x}$ is created by $argmin_c(argmin_w(c_{ix}))$, then $\sum ||x - c_{(i+1)x}||^2 - ||x - c_{ix}||^2 \le 0$ and only =0 when $c_{(i+1)x} = c_{ix}$ for all x which is the stopping condition.

Because J always ≥ 0 . Then the algorithm can converge as loss function is monotonically decreasing until it reaches the stopping/optimal/minimal condition.

End of Homework 4:)

After you've finished the homework, please print out the entire ipynb notebook and four py files into one PDF file. Make sure you include the output of code cells and answers for questions. Prepare submit it to GradeScope. Also this time remember assign the pages to the questions on GradeScope

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	_	- 1	

11/17/2020 KMeans.py

```
1 from hw4code.DataPoints import DataPoints
2 from collections import Counter
3 import random
4 import sys
5 import math
6 import pandas as pd
7 import numpy as np
10 def sqrt(n):
     return math.sqrt(n)
11
12
13 | # ------
14 def getEuclideanDist(x1, y1, x2, y2):
15
     dist = sqrt(pow((x2 - x1), 2) + pow((y2 - y1), 2))
     return dist
16
17 | # -----
18 def compute_purity(clusters,total_points):
19
     # Calculate purity
20
21
     # Create list to store the maximum union number for each output cluster.
22
     maxLabelCluster = []
     num_clusters = len(clusters)
23
     # =======#
24
     # STRART YOUR CODE HERE #
25
     26
     for i in range(num_clusters):
27
28
        cluster = clusters[i]
29
        original_labels = [x.label for x in cluster]
30
        max union = max(original labels, key=original labels.count)
31
        maxLabelCluster.append(max union)
32
     # ========#
        END YOUR CODE HERE
33
     34
35
     purity = 0.0
     for j in range(num_clusters):
36
37
        purity += maxLabelCluster[j]
     purity /= total points
38
39
     print("Purity is %.6f" % purity)
40
42 def compute NMI(clusters, noOfLabels):
43
     # Get the NMI matrix first
44
     nmiMatrix = getNMIMatrix(clusters, noOfLabels)
45
     # Get the NMI matrix first
     nmi = calcNMI(nmiMatrix)
46
     print("NMI is %.6f" % nmi)
47
48
49
51 def getNMIMatrix(clusters, noOfLabels):
     # Matrix shape of [num_true_clusters + 1,num_output_clusters + 1] (example under
52
  week6's slide page 9)
     nmiMatrix = [[0 for x in range(len(clusters) + 1)] for y in range(noOfLabels +
53
  1)]
     clusterNo = 0
54
     for cluster in clusters:
55
56
        # Create dictionary {true class No: Number of shared elements}
        labelCounts = {}
57
58
        # ==================================
```

11/17/2020 KMeans.py 59 # STRART YOUR CODE HERE # 60 # ========# labels = [x.label for x in cluster] 61 labelCounts = Counter(labels) 62 # =======# 63 END YOUR CODE HERE # 64 # =======# 65 labelTotal = 0 66 67 labelCounts_sorted = sorted(labelCounts.items(), key=lambda item: item[1], reverse=True) for label, val in labelCounts_sorted: 68 nmiMatrix[label - 1][clusterNo] = labelCounts[label] 69 labelTotal += labelCounts.get(label) 70 71 # Populate last row (row of summation) 72 nmiMatrix[noOfLabels][clusterNo] = labelTotal 73 clusterNo += 1 74 labelCounts.clear() 75 # Populate last col (col of summation) 76 77 lastRowCol = 0 for i in range(noOfLabels): 78 79 totalRow = 0 for j in range(len(clusters)): 80 81 totalRow += nmiMatrix[i][j] 82 lastRowCol += totalRow nmiMatrix[i][len(clusters)] = totalRow 83 84 # Total number of datapoints 85 86 nmiMatrix[noOfLabels][len(clusters)] = lastRowCol 87 88 return nmiMatrix 89 91 def calcNMI(nmiMatrix): 92 # Num of true clusters + 1 93 row = len(nmiMatrix) # Num of output clusters + 1 94 95 col = len(nmiMatrix[0]) # Total number of datapoints 96 97 N = nmiMatrix[row - 1][col - 1]98 I = 0.0HOmega = 0.099 HC = 0.0100 101 for i in range(row - 1): 102 for j in range(col - 1): 103 # Compute the log part of each pair of clusters within I's formula. 104 105 logPart I = 1.0106 # ================================= # STRART YOUR CODE HERE 107 108 109 # stores total count in last row and column 110 111 logPart_I = N * float(nmiMatrix[i][j]) / (float(nmiMatrix[i][-1]) * nmiMatrix[-1][j]) 112 113 114 END YOUR CODE HERE 115 116

localhost:4649/?mode=python 2/6

11/17/2020 KMeans.py 117 if logPart_I == 0.0: 118 continue I += (nmiMatrix[i][j] / float(N)) * math.log(float(logPart_I)) 119 120 # Compute HOmega 121 # =======# # STRART YOUR CODE HERE # 122 123 124 p_wj = nmiMatrix[i][-1] / float(N) $HOmega += (p_wj * np.log(p_wj))$ 125 # =======# 126 127 END YOUR CODE HERE 128 # =======# 129 130 #Compute HC 131 132 # STRART YOUR CODE HERE # 133 134 for c in range(col-1): 135 p_cj = nmiMatrix[-1][c] / float(N) $HC += (p_cj * np.log(p_cj))$ 136 137 138 # END YOUR CODE HERE # # =======# 139 140 141 return I / math.sqrt(HC * HOmega) 142 143 144 145 146 148 class Centroid: 149 150 def __init__(self, x, y): 151 self.x = xself.y = y152 153 # -----154 def __eq__(self, other): 155 if not type(other) is type(self): 156 return False 157 if other is self: 158 return True 159 if other is None: 160 return False 161 if self.x != other.x: return False 162 163 if self.y != other.y: 164 return False 165 return True 166 def __ne__(self, other): 167 168 result = self.__eq__(other) if result is NotImplemented: 169 170 return result 171 return not result # -----172 173 def toString(self): return "Centroid [x=" + str(self.x) + ", y=" + str(self.y) + "]" 174 175 # -----def __str__(self): 176

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```
11/17/2020
                                               KMeans.py
177
            return self.toString()
178
179
        def __repr__(self):
            return self.toString()
180
181
182
183
184
185
186
187
189 class KMeans:
190
191
        def __init__(self):
192
            self.K = 0
193
        def main(self, dataname, isevaluate=False):
194
195
            seed = 71
            self.dataname = dataname[5:-4]
196
197
            print("\nFor " + self.dataname)
198
            self.dataSet = self.readDataSet(dataname)
            self.K = DataPoints.getNoOFLabels(self.dataSet)
199
            random.Random(seed).shuffle(self.dataSet)
200
201
            self.kmeans(isevaluate)
202
203
204
        def check dataloader(self,dataname):
205
            df = pd.read_table(dataname,sep = "\t", header=None, names=
206
    ['x','y','ground_truth_cluster'])
207
            print("\nFor " + dataname[5:-4] + ": number of datapoints is %d" %
    df.shape[0])
208
            print(df.head(5))
209
210
211
212
        def kmeans(self,isevaluate=False):
213
            clusters = []
214
            k = 0
            while k < self.K:
215
216
                cluster = set()
                clusters.append(cluster)
217
218
                k += 1
219
220
            # Initially randomly assign points to clusters
221
            i = 0
            for point in self.dataSet:
222
223
                clusters[i % k].add(point)
224
                i += 1
225
226
            # calculate centroid for clusters
            centroids = []
227
228
            for j in range(self.K):
229
                centroids.append(self.getCentroid(clusters[j]))
230
            self.reassignClusters(self.dataSet, centroids, clusters)
231
232
233
            # continue till converge
234
            iteration = 0
```

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11/17/2020 KMeans.py 235 while True: 236 iteration += 1 # calculate centroid for clusters 237 238 centroidsNew = [] 239 for j in range(self.K): 240 centroidsNew.append(self.getCentroid(clusters[j])) 241 isConverge = False 242 243 for j in range(self.K): if centroidsNew[j] != centroids[j]: 244 245 isConverge = False 246 else: 247 isConverge = True 248 if isConverge: 249 break 250 251 for j in range(self.K): 252 clusters[j] = set() 253 self.reassignClusters(self.dataSet, centroidsNew, clusters) 254 255 for j in range(self.K): centroids[j] = centroidsNew[j] 256 print("Iteration :" + str(iteration)) 257 258 259 if isevaluate: # Calculate purity and NMI 260 261 compute_purity(clusters, len(self.dataSet)) compute NMI(clusters, self.K) 262 263 264 # write clusters to file for plotting f = open("Kmeans_"+ self.dataname + ".csv", "w") 265 for w in range(self.K): 266 print("Cluster " + str(w) + " size :" + str(len(clusters[w]))) 267 268 print(centroids[w].toString()) 269 for point in clusters[w]: $f.write(str(point.x) + "," + str(point.y) + "," + str(w) + "\n")$ 270 f.close() 271 272 273 def reassignClusters(self, dataSet, c, clusters): 274 # reassign points based on cluster and continue till stable clusters found 275 dist = [0.0 for x in range(self.K)] 276 for point in dataSet: 277 278 for i in range(self.K): 279 dist[i] = getEuclideanDist(point.x, point.y, c[i].x, c[i].y) 280 281 minIndex = self.getMin(dist) 282 # assign point to the closest cluster 283 # =======# # STRART YOUR CODE HERE # 284 285 # =================================== 286 clusters[minIndex].add(point) 287 # =======# 288 END YOUR CODE HERE 289 # =======# # ------290 291 def getMin(self, dist): 292 min = sys.maxsize 293 minIndex = -1294 for i in range(len(dist)):

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11/17/2020 KMeans.py if dist[i] < min:</pre> 295 min = dist[i] 296 297 minIndex = i298 return minIndex 299 # -----300 301 def getCentroid(self, cluster): 302 # mean of x and mean of ycx = 0303 304 cy = 0305 # ================================== 306 # STRART YOUR CODE HERE # # ========# 307 308 cx = np.average([c.x for c in cluster]) cy = np.average([c.y for c in cluster]) 309 310 # =======# END YOUR CODE HERE 311 312 # =======# 313 return Centroid(cx, cy) # -----314 315 @staticmethod 316 def readDataSet(filePath): 317 dataSet = [] with open(filePath) as f: 318 319 lines = f.readlines() 320 lines = [x.strip() for x in lines] for line in lines: 321 points = line.split('\t') 322 x = float(points[0]) 323 y = float(points[1]) 324 325 label = int(points[2]) 326 point = DataPoints(x, y, label) dataSet.append(point) 327 328 return dataSet 329

11/17/2020 DBSCAN.py

```
1 from hw4code.KMeans import KMeans,compute_purity,compute_NMI,getEuclideanDist
2 from hw4code.DataPoints import DataPoints
3 import random
4
5
6 class DBSCAN:
7
      # -----
      def __init__(self):
8
         self.e = 0.0
9
         self.minPts = 3
10
         self.noOfLabels = 0
11
12
      # ------
      def main(self, dataname):
13
14
         seed = 71
15
         self.dataname = dataname[5:-4]
16
         print("\nFor " + self.dataname)
17
         self.dataSet = KMeans.readDataSet(dataname)
18
19
         random.Random(seed).shuffle(self.dataSet)
         self.noOfLabels = DataPoints.getNoOFLabels(self.dataSet)
20
         self.e = self.getEpsilon(self.dataSet)
21
22
         print("Esp :" + str(self.e))
23
         self.dbscan(self.dataSet)
24
25
      26
27
      def getEpsilon(self, dataSet):
28
         distances = []
         sumOfDist = 0.0
29
30
         for i in range(len(dataSet)):
31
             point = dataSet[i]
             for j in range(len(dataSet)):
32
                if i == j:
33
34
                    continue
35
                pt = dataSet[j]
                dist = getEuclideanDist(point.x, point.y, pt.x, pt.y)
36
37
                distances.append(dist)
38
39
             distances.sort()
             sumOfDist += distances[7]
40
             distances = []
41
42
         return sumOfDist/len(dataSet)
43
      # ------
44
      def dbscan(self, dataSet):
45
         clusters = []
         visited = set()
46
47
         noise = set()
48
         # Iterate over data points
49
50
         for i in range(len(dataSet)):
             point = dataSet[i]
51
             if point in visited:
52
53
                continue
54
             visited.add(point)
55
             N = []
56
             minPtsNeighbours = 0
57
             # check which point satisfies minPts condition
58
59
             for j in range(len(dataSet)):
                if i==j:
```

```
11/17/2020
                                              DBSCAN.py
                        continue
 61
 62
                    pt = dataSet[j]
                    dist = getEuclideanDist(point.x, point.y, pt.x, pt.y)
 63
 64
                    if dist <= self.e:</pre>
 65
                        minPtsNeighbours += 1
 66
                        N.append(pt)
 67
                if minPtsNeighbours >= self.minPts:
 68
 69
                    cluster = set()
 70
                    cluster.add(point)
                    point.isAssignedToCluster = True
 71
 72
 73
                    j = 0
 74
                    while j < len(N):
 75
                        point1 = N[j]
 76
                        minPtsNeighbours1 = 0
 77
                        N1 = []
 78
                        if not point1 in visited:
 79
                           visited.add(point1)
 80
                            for 1 in range(len(dataSet)):
 81
                               pt = dataSet[1]
                               dist = getEuclideanDist(point1.x, point1.y, pt.x, pt.y)
 82
                               if dist <= self.e:</pre>
 83
 84
                                   minPtsNeighbours1 += 1
 85
                                   N1.append(pt)
 86
                           if minPtsNeighbours1 >= self.minPts:
 87
                               self.removeDuplicates(N, N1)
 88
 89
                        # Add point1 is not yet member of any other cluster then add it
    to cluster
 90
                        # Hint: use self.isAssignedToCluster function to check if a point
    is assigned to any clusters
                        # ========#
 91
 92
                        # STRART YOUR CODE HERE #
 93
                        # ========#
 94
                        if not point1.isAssignedToCluster:
 95
                           cluster.add(point1)
 96
                           point1.isAssignedToCluster = True
 97
                        # =======#
 98
                          END YOUR CODE HERE
 99
                        100
                        j += 1
101
102
                    # add cluster to the list of clusters
                    clusters.append(cluster)
103
104
105
                else:
106
                    noise.add(point)
107
108
            # List clusters
109
110
            print("Number of clusters formed :" + str(len(clusters)))
            print("Noise points :" + str(len(noise)))
111
112
            # Calculate purity
113
            compute_purity(clusters,len(self.dataSet))
114
115
            compute_NMI(clusters, self.noOfLabels)
            DataPoints.writeToFile(noise, clusters, "DBSCAN_"+ self.dataname + ".csv")
116
        # -----
117
118
        def removeDuplicates(self, n, n1):
```

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11/17/2020 DBSCAN.py for point in n1: 119 isDup = False 120 121 for point1 in n: if point1 == point: 122 123 isDup = True break 124 if not isDup: 125 126 n.append(point) 127

128

11/17/2020 GMM.py

```
1 from hw4code.DataPoints import DataPoints
2 from hw4code.KMeans import KMeans, compute purity, compute NMI
3 import math
4 from scipy.stats import multivariate_normal
7 class GMM:
      # -----
8
      def __init__(self):
9
10
          self.dataSet = []
          self.K = 0
11
12
          self.mean = [[0.0 for x in range(2)] for y in range(3)]
          self.stdDev = [[0.0 for x in range(2)] for y in range(3)]
13
          self.coVariance = [[[0.0 for x in range(2)] for y in range(2)] for z in
14
  range(3)]
15
          self.W = None
16
          self.w = None
      # -----
17
18
      def main(self, dataname):
19
          self.dataname = dataname[5:-4]
20
          print("\nFor " + self.dataname)
21
22
          self.dataSet = KMeans.readDataSet(dataname)
23
          self.K = DataPoints.getNoOFLabels(self.dataSet)
24
          # weight for pair of data and cluster
25
          self.W = [[0.0 for y in range(self.K)] for x in range(len(self.dataSet))]
          # weight for pair of data and cluster
26
          self.w = [0.0 for x in range(self.K)]
27
28
          self.GMM()
29
30
      def GMM(self):
31
          clusters = []
32
          # [num_clusters,2]
33
34
          self.mean = [[0.0 for y in range(2)] for x in range(self.K)]
35
          # [num clusters,2]
          self.stdDev = [[0.0 for y in range(2)] for x in range(self.K)]
36
37
          # [num clusters,2]
          self.coVariance = [[[0.0 for z in range(2)] for y in range(2)] for x in
38
  range(self.K)]
39
          k = 0
40
          while k < self.K:
41
              cluster = set()
42
              clusters.append(cluster)
43
              k += 1
44
          # Initially randomly assign points to clusters
45
46
          for point in self.dataSet:
47
48
              clusters[i % self.K].add(point)
49
50
51
          # Initially assign equal prior weight for each cluster
52
          for m in range(self.K):
              self.w[m] = 1.0 / self.K
53
54
55
          # Get Initial mean, std, covariance matrix
56
          DataPoints.getMean(clusters, self.mean)
57
          DataPoints.getStdDeviation(clusters, self.mean, self.stdDev)
          DataPoints.getCovariance(clusters, self.mean, self.stdDev, self.coVariance)
58
```

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11/17/2020 GMM.py 59 60 length = 0 while True: 61 mle old = self.Likelihood() 62 63 self.Estep() 64 self.Mstep() length += 1 65 mle_new = self.Likelihood() 66 67 68 # convergence condition 69 if abs(mle_new - mle_old) / abs(mle_old) < 0.000001:</pre> 70 71 72 print("Number of Iterations = " + str(length)) 73 print("\nAfter Calculations") print("Final mean = ") 74 75 self.printArray(self.mean) 76 print("\nFinal covariance = ") 77 self.print3D(self.coVariance) 78 79 # Assign points to cluster depending on max prob. 80 for j in range(self.K): clusters[j] = set() 81 82 83 i = 0for point in self.dataSet: 84 85 index = -1prob = 0.086 87 for j in range(self.K): 88 if self.W[i][j] > prob: 89 index = jprob = self.W[i][j] 90 temp = clusters[index] 91 92 temp.add(point) 93 i += 194 95 # Calculate purity and NMI 96 compute purity(clusters,len(self.dataSet)) 97 compute_NMI(clusters, self.K) 98 99 # write clusters to file for plotting f = open("GMM_" + self.dataname + ".csv", "w") 100 101 for w in range(self.K): print("Cluster " + str(w) + " size :" + str(len(clusters[w]))) 102 for point in clusters[w]: 103 f.write(str(point.x) + "," + str(point.y) + "," + str(w) + "\n") 104 105 f.close() # -----106 def Estep(self): 107 108 # Update self.W 109 for i in range(len(self.dataSet)): 110 denominator = 0.0 111 for j in range(self.K): gaussian = multivariate_normal(self.mean[j], self.coVariance[j]) 112 113 # Compute numerator for self.W[i][j] below numerator = 0.0114 115 # ========# 116 # STRART YOUR CODE HERE # 117 # ================================= 118

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11/17/2020 GMM.py 119 $\# w_{ij} = w_{j}*f(xi)$ 120 numerator = self.w[j]*gaussian.pdf([self.dataSet[i].x, self.dataSet[i].y]) 121 # ========# 122 END YOUR CODE HERE 123 124 self.W[i][j] = numerator 125 denominator += numerator 126 # normalize W[i][j] into probabilities 127 128 129 # STRART YOUR CODE HERE # # ========# 130 131 self.W[i] = self.W[i] / denominator 132 # ========# 133 END YOUR CODE HERE 134 135 136 def Mstep(self): 137 for j in range(self.K): 138 denominator = 0.0 $numerator_x = 0.0$ 139 numerator_y = 0.0 140 141 $cov_xy = 0.0$ 142 updatedMean x = 0.0updatedMean_y = 0.0 143 144 # update self.w[j] and self.mean 145 146 for i in range(len(self.dataSet)): 147 denominator += self.W[i][j] updatedMean_x += self.W[i][j] * self.dataSet[i].x 148 updatedMean_y += self.W[i][j] * self.dataSet[i].y 149 150 151 self.w[j] = denominator / len(self.dataSet) 152 153 #update self.mean 154 # STRART YOUR CODE HERE # 155 156 157 self.mean[j][0] = updatedMean_x / denominator self.mean[j][1] = updatedMean y / denominator 158 159 END YOUR CODE HERE 160 161 162 # update covariance matrix 163 164 for i in range(len(self.dataSet)): numerator_x += self.W[i][j] * pow((self.dataSet[i].x - self.mean[j] 165 [0]), 2) numerator_y += self.W[i][j] * pow((self.dataSet[i].y - self.mean[j] 166 [1]), 2)167 # Compute conv_xy +=? 168 169 # STRART YOUR CODE HERE # 170 # ========# 171 covar = (self.dataSet[i].x - self.mean[j][0]) * (self.dataSet[i].y -172 self.mean[j][1]) 173 cov xy += self.W[i][j] * covar 174

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```
11/17/2020
                                              GMM.py
175
                       END YOUR CODE HERE
176
                   177
                self.stdDev[j][0] = numerator_x / denominator
178
                self.stdDev[j][1] = numerator_y / denominator
179
180
181
                self.coVariance[j][0][0] = self.stdDev[j][0]
182
                self.coVariance[j][1][1] = self.stdDev[j][1]
183
                self.coVariance[j][0][1] = self.coVariance[j][1][0] = cov_xy /
184
    denominator
185
        # -----
186
        def Likelihood(self):
187
            likelihood = 0.0
188
            for i in range(len(self.dataSet)):
189
                numerator = 0.0
190
                for j in range(self.K):
191
                   gaussian = multivariate_normal(self.mean[j], self.coVariance[j])
192
                   numerator += self.w[j] * gaussian.pdf([self.dataSet[i].x,
    self.dataSet[i].v])
193
                likelihood += math.log(numerator)
            return likelihood
194
        # ------
195
        def printArray(self, mat):
196
197
            for i in range(len(mat)):
                for j in range(len(mat[i])):
198
                   print(str(mat[i][j]) + " "),
199
               print("")
200
201
        def print3D(self, mat):
202
            for i in range(len(mat)):
203
                print("For Cluster : " + str((i + 1)))
204
                for j in range(len(mat[i])):
205
206
                   for k in range(len(mat[i][j])):
                       print(str(mat[i][j][k]) + " "),
207
                   print("")
208
209
                print("")
210
212 if __name__ == "__main__":
        g = GMM()
213
        dataname = "dataset1.txt"
214
        g.main(dataname)
215
```

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