CS 273a - Introduction to Machine Learning (Winter '15)* Prof. Alex Ihler

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Homework 5^{†‡}

Problem 1: Basics of Clustering

(a) The dataset is loaded in Matlab, as shown in Listing 1 and Figure 1

Listing 1: Loading Data

(b) The Listing 2 shows the code listing for problem of k-means for different values of k and initialization methods. The Figure 2 shows the plot of the created clusters.

Listing 2: K-Means on iris dataset for different values of k and initialization methods.

```
1 %% Problem b
2 k = 5;
3 [z,c,sumd] = kmeans(X,k);
4 [z1, c1, sumd1] = kmeans(X, k, 'k++');
  f = figure;
  plotClassify2D([],X,z);
   saveas(f,'kmeans_k_5_simple.png', 'png');
10 f = figure;
plotClassify2D([],X,z1);
12 saveas(f,'kmeans_k_5_kpp.png', 'png');
13
14 k = 20;
15 [z,c,sumd] = kmeans(X,k);
16 [z1, c1, sumd1] = kmeans(X, k, 'k++');
17
18 f = figure;
19 plotClassify2D([],X,z);
20 saveas(f,'kmeans_k_20_simple.png', 'png');
22 f = figure;
23 plotClassify2D([],X,z1);
24 saveas(f,'kmeans_k_20_kpp.png', 'png');
```

(c) The Listing 3 shows the code listing for problem of k-means for different values of k and initialization methods. The Figure 3 shows the plot of the created clusters.

^{*}Website: http://sli.ics.uci.edu/Classes/2015W-273a

[†]Questions available at http://sli.ics.uci.edu/Classes/2015W-273a?action=download&upname=HW5.pdf

[‡]All the figures and listing numbers are auto-referred.

Listing 3: Agglomerative clustering on iris dataset for different values of k and linkage methods.

```
1 %% Problem c
2 k = 5;
3 Z = linkage(X, 'single');
4 c = cluster(Z, 'maxclust', k);
5 f = figure;
6 plotClassify2D([],X,c);
7 saveas(f,'linkage_single_5.png', 'png');
8 f = figure;
9 dendrogram(Z)
10 saveas(f,'dendogram_5.png', 'png');
12 Z = linkage(X,'complete');
13 c = cluster(Z, 'maxclust', k);
14 f = figure;
15 plotClassify2D([],X,c);
saveas(f,'linkage_complete_5.png', 'png');
17
18 k = 20:
19 Z = linkage(X,'single');
20 c = cluster(Z, 'maxclust', k);
21 f = figure;
22 plotClassify2D([],X,c);
23 saveas(f,'linkage_single_20.png', 'png');
24 f = figure;
25 dendrogram(Z)
26 saveas(f,'dendogram_20.png', 'png');
28 Z = linkage(X,'complete');
29 c = cluster(Z, 'maxclust', k);
30 f = figure;
31 plotClassify2D([],X,c);
32 saveas(f,'linkage_complete_20.png', 'png');
```

(d) The EM Gaussian mixture model is run with 5 and 20 components, as shown in Listing 4. The generated clusters can be seen in Figure 4.

Listing 4: The EM Gaussian mixture model for 5 and 20 components.

```
1 %% Problem d
2 k = 5;
3 [zx,Tx,softx,llx] = emCluster(X,k);
4 f = figure;
5 plotClassify2D([],X,zx);
6 saveas(f,'emgm_5.png', 'png');
7
8 k = 20;
9 [zx,Tx,softx,llx] = emCluster(X,k);
10 f = figure;
11 plotClassify2D([],X,zx);
12 saveas(f,'emgm_20.png', 'png');
```

All the three clustering mechanisms bring different properties and have different usecases. The Agglomerative clustering has a simple architecture and works well for simple and small dataset. EM Gaussian mixture models are well suited for fuzzy nature of dataset where a data might not be strictly associated with any cluster. Traditional means as a low computational complexity compared to others, O(nkt), where n is the number of datapoints, k is the number of clusters and t is the number of iterations. And thus, it can be computed

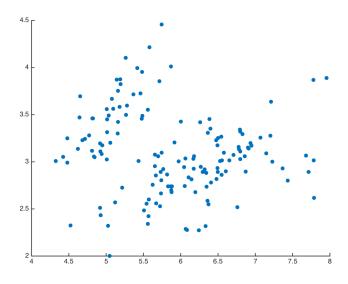


Figure 1: Data Loaded

repeatedly to search for a good configuration. With all the methods, 'k-means ++' gave good results.

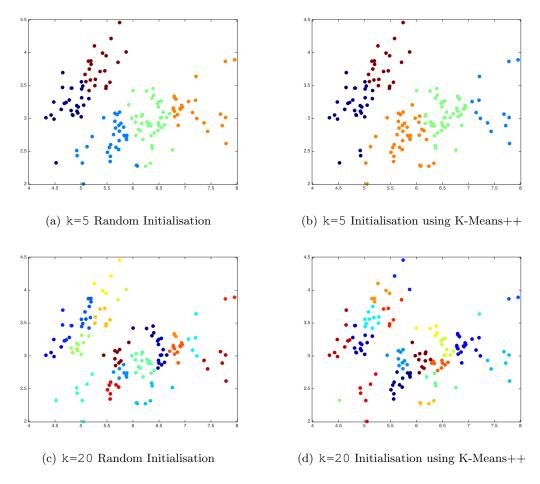


Figure 2: Various runs of K-Means different values of k and initialization methods

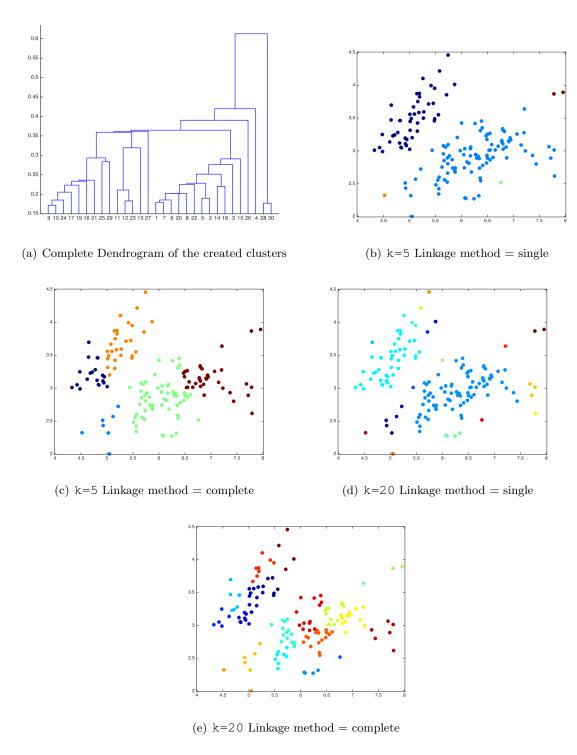


Figure 3: Various runs of Agglomerative clustering with different values of k and linkage methods

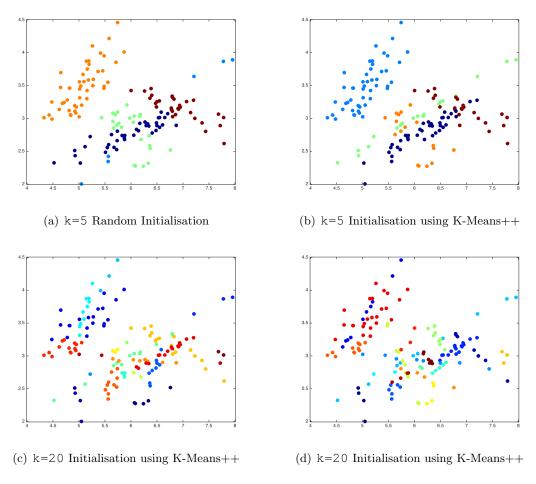


Figure 4: EM Gaussian mixture model with different values of k and initialization methods

Problem 2: K Means Clustering on Text

(a) The clusters are computed using kmeans() method provided by Matlab and the code that produces can be seen in Listing 5.

Listing 5: K-means on textual data with k=20 and for part (b), the number of runs = 20

```
1 %% Problem (a, b)
2 k = 20;
3 [z,c,sumd] = kmeans(Xn,k);
4 disp(sumd)
5 disp('--
6 for i=1:20;
       [z1,c1,sumd1] = kmeans(Xn,k);
       disp(sumd1)
       if sumd1 < sumd
10
           z = z1;
11
            c = c1;
            sumd = sumd1;
12
       end;
13
14 end;
15 display('Minimum-sumd')
16 disp(sumd)
17
18
       2.4211
19
       2.0789
20
       2.1009
21
       2.0453
22
       2.0625
23
       2.0861
24
       2.4494
25
       2.0615
26
       2.0709
27
       2.0646
28
       2.1144
       2.0098
       2.0530
32
       2.4806
       2.0479
33
       2.0587
34
       2.0811
35
       2.4695
36
       1.9865
37
       2.4891
38
       2.0573
39
40
   Minimum-sumd
41
       1.9865
42
43 %}
```

- (b) Listing 5 shows 20 runs of K-Means on the textual data and I got the best value of the cost function to be sumd = 1.9865.
- (c) For counting the document accusation with clusters, I use a function called <code>count_unique()</code>, and it gives the output as given in Listing 6 as well as the bar graph of the distribution can be seen at Figure 5. For the second part of the question, I used a slight modification of the original code given in the homework to populate the document terms. The code and the output can be seen in Listing 7.

Listing 6: The number of documents for each cluster

```
1 >> [uniques, numUnique] = count_unique(z)
2 >> [uniques, numUnique]
3 ans =
        1
              21
4
        2
              4.5
5
               4
        3
6
               2
        4
7
        5
              7
8
         6
              8
9
        7
              69
10
        8
11
              3
        9
              10
12
       10
              2
       11
              2
       12
              1
15
       13
               1
16
              3
       14
17
       15
               1
18
       16
               1
19
       17
             15
20
       18
               2
21
22
       19
               3
23
       20
               2
```

Listing 7: The "Most-Likely" terms in the 20 clusters

```
1 %% Problem (c) - 2
2 for i =1:size(c, 1);
       [sorted, order] = sort( c(i,:), 2, 'descend');
3
      fprintf('Doc %d: ',i);
4
      fprintf('%s', vocab{order(1:10)});
5
      fprintf(' \ n');
6
7 end;
8 %{
9 Doc 1: times square millennium city 2000 night 000 eve york midnight
10 Doc 2: team game season coach games players league play going win
11 Doc 3: archbishop york bishop cardinal sports church began column ...
      american close
12 Doc 4: america boat team zealand cup nippon gilmour challengers round true
13 Doc 5: book century marks amp war week finds lives school boy
14 Doc 6: yeltsin putin russia russian president power political kremlin ...
      chechnya russians
15 Doc 7: city american national president 000 home millennium end political \dots
      going
16 Doc 8: fireworks island city midnight celebration lot millennium hour ...
     calls celebrations
17 Doc 9: y2k koskinen system problems saturday 2000 reported computers ...
      friday officials
18 Doc 10: tutsi hutu rwanda burundi ethnic country experts africa van 1994
19 Doc 11: texas arkansas yards line offensive game season sacks games defensive
20 Doc 12: test end houston 000 0101 0102 100 1900 1900s 1968
21 Doc 13: cats beijing owners police association called carry chinese eat ...
      eating
22 Doc 14: hijackers hostages pakistan burger told government indian india ...
      passengers killed
23 Doc 15: sports angeles began brooklyn column los seen young eye game
24 Doc 16: economy government putin system america businesses country ...
      economic president russia
25 Doc 17: 2000 computer internet government systems york problem problems ...
      news city
_{26} Doc 18: lakers jackson game star phil players record conference practice \dots
  monday
```

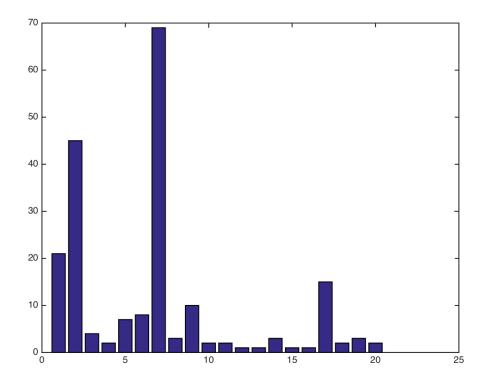


Figure 5: Distribution of the documents spread across k=20 clusters.

```
27 Doc 19: news atlanta constitution journal service moved cox y2k cnn ...
millennium
28 Doc 20: buses authority diesel natural gas plan mta city york hybrid
29 %}
```

(d) A

Problem 3: Eigen Faces

(a) Loading Eigen Faces Data, as can be seen in Listing 9. Also see Figure 6

Listing 8: Loading Face Dataset

```
1 clc;close all;clear all;
2 rand('seed',0);
3 X = load('data/faces.txt'); % load face dataset
```

(b) Normalisng the dataset.

Listing 9: Normalizing

```
1 %% Faces A
2 mu = mean(X);
3 X0 = bsxfun(minus, X, mu); size(mu); ans =1 576
```

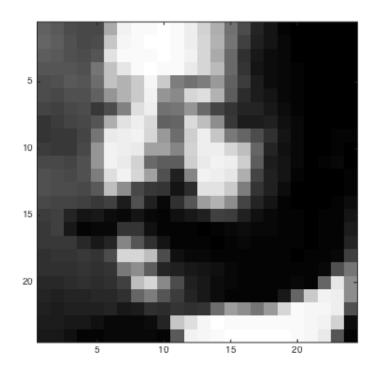


Figure 6: Face sample.