# COMPM012 - Coursework 3

Esben A. Sørig

November 27, 2014

### 1 Practical

### 1.1 k-means implementation

```
function [clusterings, centers] = mykmeans(X, k)
        % Randomly initialize centers of clusters
         \begin{array}{l} c = \operatorname{datasample}(X,\ k,\ 'Replace',\ false); \\ r = \operatorname{repmat}(0\,,\ \operatorname{size}(X,\ 1)\,,\ k); \end{array} 
 3
 4
        oldr = 1; % something that is not equal to r initially
 5
 6
        dist = @(x, y) norm(x-y);
9
        % Loop as long as the clustering is changing
10
        while ~isequal(r, oldr)
             oldr = r;
11
             % Assign points to clusters
13
             for i = 1: size(X,1)
14
                   cluster = 1;
15
                   for j = 1:k
16
                        if dist(X(i, :), c(j, :)) < dist(X(i, :), c(j, :))
17
        cluster, :))
                             cluster = j;
18
                        \quad \text{end} \quad
19
                   end
20
21
                   r(i, :) = [repmat(0, 1, cluster - 1) \ 1 \ repmat(0, 1, k - 1)]
22
        cluster)];
             end
23
24
             \% Update center positions
25
             for i = 1:k
27
                   npoints = 0;
                   c(i, :) = 0;
28
                   for j = 1: size(r, 1)
29
```

```
c(i, :) = c(i, :) + r(j, i) *X(j, :);
30
                     npoints = npoints + r(j, i);
31
32
                end
                c(i, :) = c(i, :) / npoints;
33
           end
34
       end
35
36
       centers = c;
37
       % Output formatting (vector with cluster index for each row
       clustering = repmat(0, size(X,1), 1);
39
       for i = 1: size(X,1)
40
          for j = 1:k
41
               if r(i, j) == 1
42
                     clustering(i) = j;
43
44
                    break;
45
               end
          end
46
       end
47
48
       clusterings = clustering;
49
50 end
```

#### 1.2 k-means test on data generated from three gaussians

Firstly, we generate the data and run the k-means algorithm on it.

```
1 % Generate data
2 data = genData2;
4 % Put data for each cluster in a seperate list
5 \text{ cluster1} = [];
6 \text{ cluster2} = [];
7 \text{ cluster3} = [];
  [clusterings, centers] = mykmeans(data, 3);
  for i = 1: size(data, 1)
10
       if clusterings(i) == 1
11
            cluster1 = [cluster1; data(i, :)];
       end
13
       if clusterings(i) == 2
14
            cluster2 = [cluster2; data(i, :)];
15
16
       end
17
       if clusterings(i) == 3
            cluster3 = [cluster3; data(i, :)];
18
       end
19
20 end
```

We can now plot the clusters the algorithm has found

1 figure

```
hold on

scatter(centers(:, 1), centers(:, 2), 200, 'xblack');

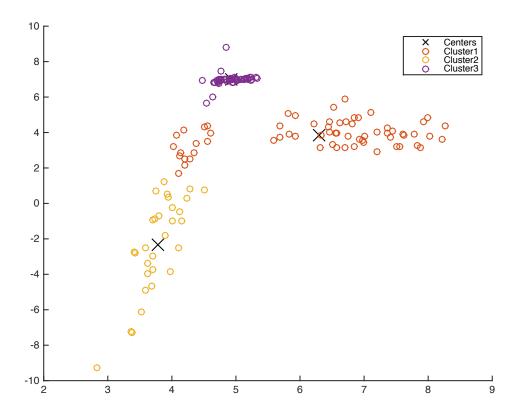
scatter(cluster1(:, 1), cluster1(:, 2));

scatter(cluster2(:, 1), cluster2(:, 2));

scatter(cluster3(:, 1), cluster3(:, 2));

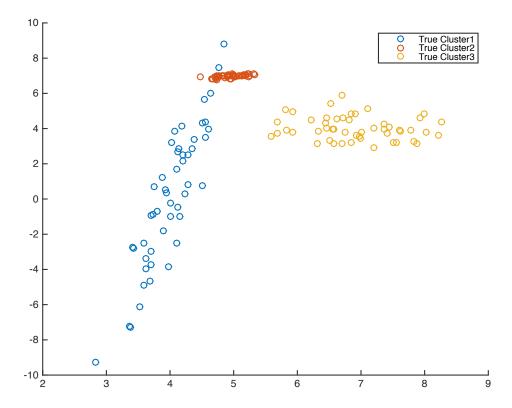
legend('Centers', 'Cluster1', 'Cluster2', 'Cluster3');

hold off
```



#### Comparing this to the true classifications

```
figure
hold on
scatter(data(1:50, 1), data(1:50, 2));
scatter(data(51:100, 1), data(51:100, 2));
scatter(data(101:150, 1), data(101:150, 2));
legend('True Cluster1', 'True Cluster2', 'True Cluster3');
hold off
```



We clearly get an intuition of how the k-means algorithm is performing on the data. Please see appendix 4.1 for the code that creates the animation of the convergence to a solution for this dataset.

We measure the mean error and standard deviation of the error of the clustering over a 100 runs of the algorithm.

```
1 % Error measurements
  errors = [];
  for j = 1:100
      [clusterings, centers] = mykmeans(data, 3);
      % keep track of the classifications of each true cluster
6
      firstcluster = [0,0,0];
      secondcluster = [0,0,0];
8
      thirdcluster = [0,0,0];
9
      for i = 1:50
10
           firstcluster(clusterings(i)) = 1 + firstcluster(
11
      clusterings(i));
      end
12
      for i = 51:100
13
```

```
secondcluster(clusterings(i)) = 1 + secondcluster(
14
      clusterings(i));
      end
15
      for i = 101:150
16
          thirdcluster(clusterings(i)) = 1 + thirdcluster(
17
      clusterings(i));
18
      \% We assume that the mode of the classifications of a true
19
      cluster is the class of the true cluster. Therefore, the
      error of a cluster is the frequency of other classifications
      appearing for that cluster.
      firstcluster = sort(firstcluster);
20
21
      secondcluster = sort(secondcluster);
      thirdcluster = sort(thirdcluster);
22
      misclassifications = firstcluster(1) + firstcluster(2) +
23
      secondcluster(1) + secondcluster(2) + thirdcluster(1) +
      thirdcluster (2);
      errors = [errors misclassifications/150];
25 end
26
meanerror = mean(errors)
28 stddeviationerror = std(errors)
```

#### Which returns:

```
meanerror =

0.1438

stddeviationerror =

0.0155
```

## 2 Questions

- 2.1 Dataset with local minima
- 2.2 Argument that the centroid is the minimizer of the sum of squared distances
- 2.3 Proof of convergence in finite amount of steps
- 3 Extension
- 3.1 k-means segmentation
- 3.2 (p, k)-means
- 4 Appendix
- 4.1 Movie generation code

```
1 ‰ Movie
 _{2} X = data;
 3 k = 3;
 4 % Randomly initialize centers of clusters
\begin{array}{lll} \text{5 c} &= & \text{datasample}\left(X, \ k, \ \text{'Replace', false'}\right); \\ \text{6 r} &= & \text{repmat}\left(0\,, \ \text{size}\left(X, \ 1\right), \ k\right); \end{array}
 7 \text{ oldr} = 1; \% \text{ something that is not equal to r initially}
 8 \text{ movie} = [];
10 dist = @(x, y) \text{ norm}(x-y);
12 % Loop as long as the clustering is changing
while ~isequal(r, oldr)
          oldr = r;
14
15
         % Assign points to clusters
16
          for i = 1: size(X,1)
17
                cluster = 1;
18
                for j = 1:k
19
                      if \;\; dist \, (X(\,i\,\,,\,\,:)\,\,,\,\, c\,(\,j\,\,,\,\,:)\,\,) \;<\;\; dist \, (X(\,i\,\,,\,\,:)\,\,,\,\, c\,(\,cluster
20
         , :))
                             cluster = j;
                      end
22
                end
23
24
                r(i, :) = [repmat(0, 1, cluster - 1) \ 1 \ repmat(0, 1, k -
25
         cluster)];
         end
```

```
27
      %MOVIE GENERATION
28
      % Split the data into the three clusters
29
       cluster1 = [];
       cluster2 = [];
31
       cluster3 = [];
32
33
       for i = 1: size(X, 1)
34
           if r(i,1) == 1
35
                cluster1 = [cluster1; X(i, :)];
           end
37
           if r(i,2) == 1
38
                cluster2 = [cluster2; X(i, :)];
39
           end
40
           if r(i,3) == 1
41
                cluster3 = [cluster3; X(i, :)];
42
43
           end
       end
44
45
      \% Plot the centers and the three clusters
46
       hold on
47
       scatter(c(:, 1), c(:, 2), 200, 'xblack');
48
       if size (cluster1, 1) \tilde{}=0
49
           scatter(cluster1(:, 1), cluster1(:, 2));
50
51
       end
       if size (cluster 2, 1) = 0
52
53
           scatter(cluster2(:, 1), cluster2(:, 2));
       end
54
       if size(cluster3, 1) = 0
55
           scatter(cluster3(:, 1), cluster3(:, 2));
56
57
       legend('Centers', 'Cluster1', 'Cluster2', 'Cluster3');
58
       hold off
59
       movie = [movie getframe];
60
       clf;
61
      \% MOVIE GENERATION OVER
62
63
      % Update center positions
64
       for i = 1:k
65
           npoints = 0;
66
           c(i, :) = 0;
67
           for j = 1: size(r, 1)
68
               c(i, :) = c(i, :) + r(j, i) *X(j, :);
69
                npoints = npoints + r(j, i);
70
71
           c(i, :) = c(i, :) / npoints;
72
       end
73
74 end
75 movie2avi(movie, 'k-means.avi', 'fps', 1);
```