COMPM012 - Coursework 3

Esben A. Sørig

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1 Practical

1.1 k-means implementation

```
function [clusterings, centers] = mykmeans(X, k)
    % Randomly initialize centers of clusters
    c = datasample(X, k, 'Replace', false);
    r = repmat(0, size(X, 1), k);
    oldr = 1; % something that is not equal to r initially

    dist = @(x, y) norm(x-y);

    % Loop as long as the clustering is changing
    while ~isequal(r, oldr)
        oldr = r;

        % Assign points to clusters
        for i = 1:size(X,1)
            cluster = 1;
            for j = 1:k
                if dist(X(i, :), c(j, :)) <  dist(X(i, :), c(cluster, :))
                    cluster = j;
                end
            end

            r(i, :) = [repmat(0, 1, cluster-1) 1 repmat(0, 1, k-cluster)];
        end

        % Update center positions
        for i = 1:k
            npoints = 0;
            c(i, :) = 0;
            for j = 1:size(r, 1)
```

```
                c(i, :) = c(i, :) + r(j, i)*X(j, :);
                npoints = npoints + r(j, i);
            end
            c(i, :) = c(i, :)/npoints;
        end
    end

    centers = c;
    % Output formatting (vector with cluster index for each row in X)
    clustering = repmat(0, size(X,1), 1);
    for i = 1:size(X,1)
        for j = 1:k
            if r(i, j) == 1
                clustering(i) = j;
                break;
            end
        end
    end

    clusterings = clustering;
end
```

1.2 k-means test on data generated from three gaussians

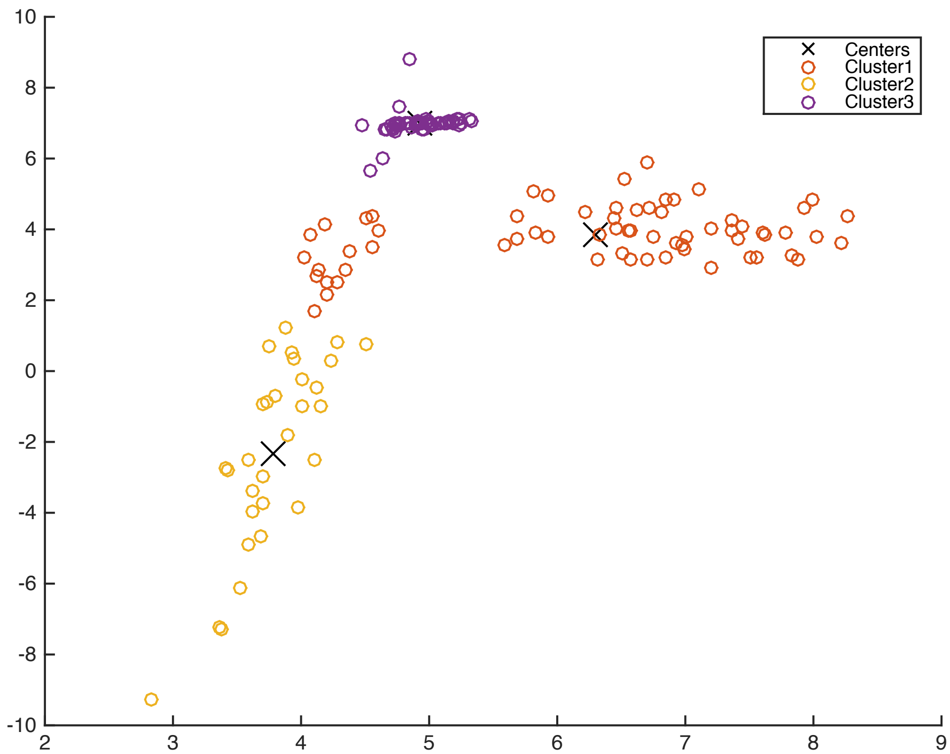
Firstly, we generate the data and run the k-means algorithm on it.

```
% Generate data
data = genData2;

% Put data for each cluster in a seperate list
cluster1 = [];
cluster2 = [];
cluster3 = [];
[clusterings, centers] = mykmeans(data, 3);

for i = 1:size(data, 1)
    if clusterings(i) == 1
        cluster1 = [cluster1; data(i, :)];
    end
    if clusterings(i) == 2
        cluster2 = [cluster2; data(i, :)];
    end
    if clusterings(i) == 3
        cluster3 = [cluster3; data(i, :)];
    end
end
```

We can now plot the clusters the algorithm has found

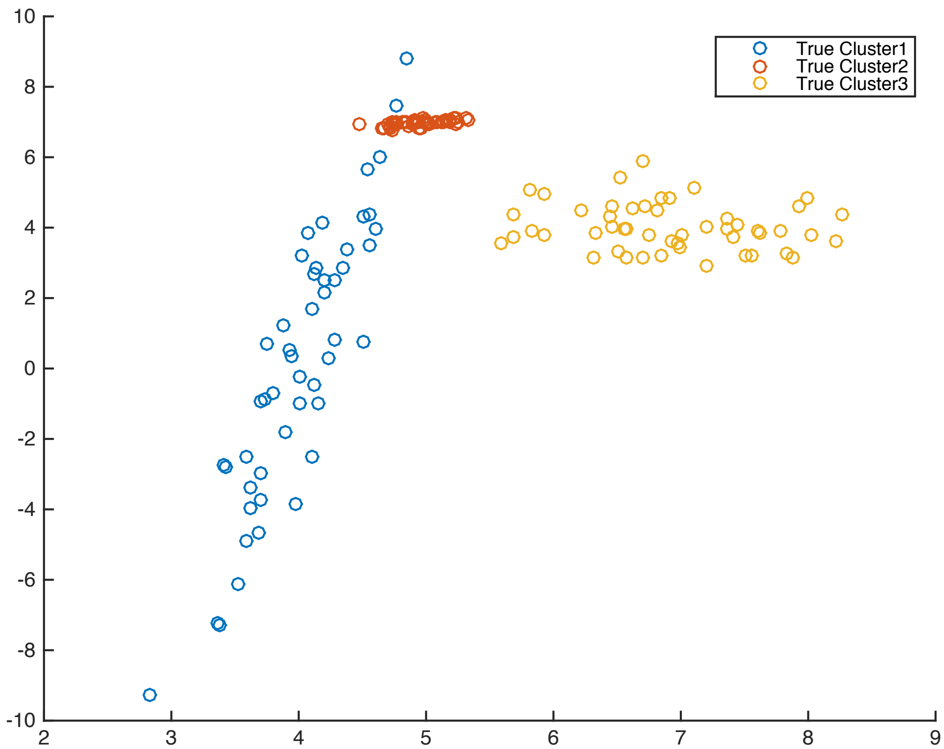
```
figure
```

```
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.

```
%% Error measurements
errors = [];
for j = 1:100
    [clusterings, centers] = mykmeans(data, 3);

    % keep track of the classifications of each true cluster
    firstcluster = [0,0,0];
    secondcluster = [0,0,0];
    thirdcluster = [0,0,0];
    for i = 1:50
        firstcluster(clusterings(i)) = 1 + firstcluster(
    clusterings(i));
    end
    for i = 51:100
```

```
        secondcluster(clusterings(i)) = 1 + secondcluster(clusterings(i));
    end
    for i = 101:150
        thirdcluster(clusterings(i)) = 1 + thirdcluster(clusterings(i));
    end
    % We assume that the mode of the classifications of a true 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);
    secondcluster = sort(secondcluster);
    thirdcluster = sort(thirdcluster);
    misclassifications = firstcluster(1) + firstcluster(2) + secondcluster(1) + secondcluster(2) + thirdcluster(1) + thirdcluster(2);
    errors = [errors misclassifications/150];
end

meanerror = mean(errors)
stddeviationerror = std(errors)
```

Which returns:

```
meanerror =
    0.1438
stddeviationerror =
    0.0155
```

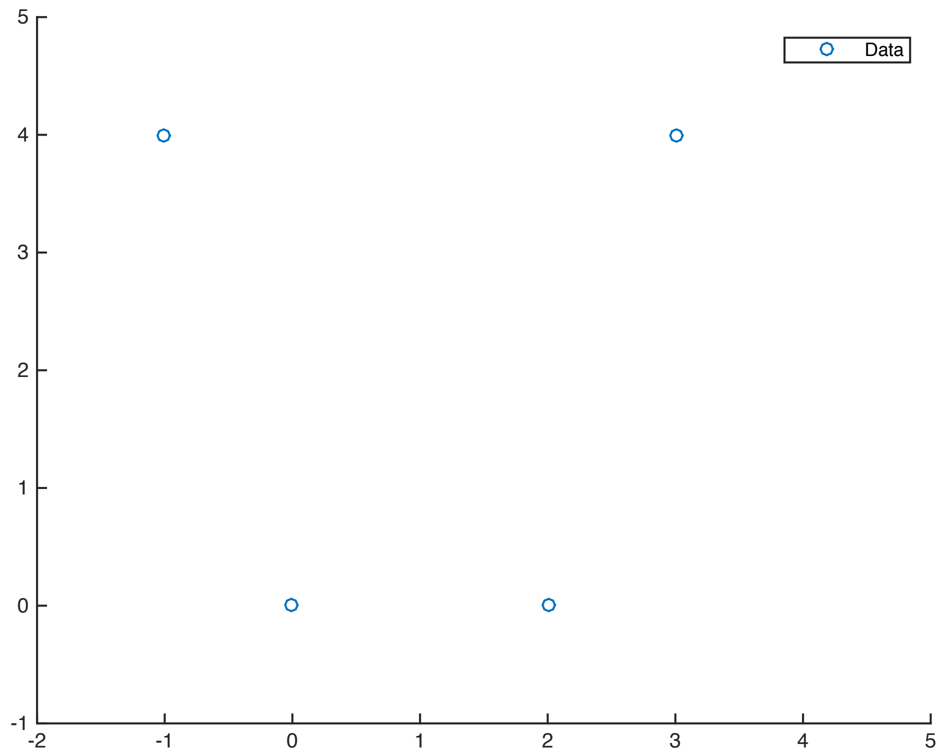
2 Questions

2.1 Dataset with local minima

We can easily construct a dataset on which our k-means algorithm has local minima. An example of such a dataset is the set $\{(0,0),(2,0),(-1,4),(3,4)\}$. This is clear if we plot the data.

```
X = [0, 0; 2,0; -1 4; 3 4];

hold on
axis([-2 5 -1 5]);
scatter(X(:, 1), X(:, 2));
```

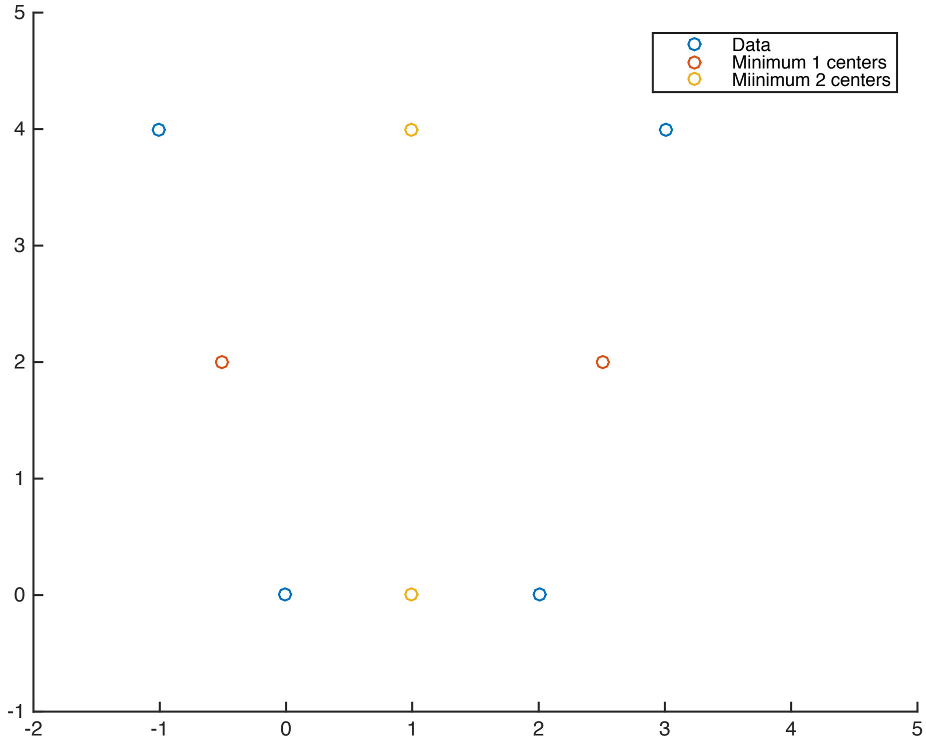
Which gives the plot:



Running k-means on this dataset will converge in one of two local minima. We run the algorithm twice and plot the centers of the clusters: (in order to get two different results, this code may have to be run several times)

```
[clustering1, centers1] = mykmeans(X, 2);
[clustering2, centers2] = mykmeans(X, 2);
legend('Data');

scatter(centers1(:, 1), centers1(:, 2));
scatter(centers2(:, 1), centers2(:, 2));

legend('Data', 'Minimum 1 centers', 'Miinimum 2 centers');
hold off
```

Which produces:



Here we clearly see the two local minima of the convergence on the four data points.

2.2 Argument that the centroid is the minimizer of the sum of squared distances

We can minimize the summed squared error

$$SSE = \sum_{i=1}^{k} \sum_{\mathbf{x} \in C_i} ||\mathbf{x} - \mathbf{c}_i||^2 = \sum_{i=1}^{k} \sum_{\mathbf{x} \in C_i} (\mathbf{x} - \mathbf{c}_i)^2 \tag{1}$$

for the k^{th} centroid by setting the derivative with respect to the k^{th} centroid equal to zero.

$$\begin{aligned}
\frac{\delta}{\delta \mathbf{c}_k} \sum_{i=1}^{k} \sum_{\mathbf{x} \in C_i} (\mathbf{x} - \mathbf{c}_i)^2 &= \sum_{i=1}^{k} \sum_{\mathbf{x} \in C_i} \frac{\delta}{\delta \mathbf{c}_k} (\mathbf{x} - \mathbf{c}_i)^2 \\
&= \sum_{\mathbf{x} \in C_k} 2(\mathbf{x}_k - \mathbf{c}_k) = 0 \\
\implies \sum_{\mathbf{x} \in C_k} \mathbf{c}_k &= \sum_{\mathbf{x} \in C_k} \mathbf{x}_k \\
\implies \mathbf{c}_k &= \frac{1}{\sum_{\mathbf{x} \in C_k} 1} \sum_{\mathbf{x} \in C_k} \mathbf{x}_k
\end{aligned} \tag{2}$$

We see that the minimizer of $\mathbf{c}_k$ is equivalent to the centroid of the cluster.

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

```
%% Movie
X = data;
k = 3;
% Randomly initialize centers of clusters
c = datasample(X, k, 'Replace', false);
r = repmat(0, size(X, 1), k);
oldr = 1; % something that is not equal to r initially
movie = [];

dist = @(x, y) norm(x-y);

% Loop as long as the clustering is changing
while ~isequal(r, oldr)
    oldr = r;

    % Assign points to clusters
    for i = 1:size(X,1)
```

```
        cluster = 1;
        for j = 1:k
            if dist(X(i, :), c(j, :)) <  dist(X(i, :), c(cluster
    , :))
                cluster = j;
            end
        end

        r(i, :) = [repmat(0, 1, cluster-1) 1 repmat(0, 1, k-
    cluster)];
    end

    %MOVIE GENERATION
    % Split the data into the three clusters
    cluster1 = [];
    cluster2 = [];
    cluster3 = [];

    for i = 1:size(X, 1)
        if r(i,1) == 1
            cluster1 = [cluster1; X(i, :)];
        end
        if r(i,2) == 1
            cluster2 = [cluster2; X(i, :)];
        end
        if r(i,3) == 1
            cluster3 = [cluster3; X(i, :)];
        end
    end

    % Plot the centers and the three clusters
    hold on
    scatter(c(:, 1), c(:, 2), 200, 'xblack');
    if size(cluster1, 1) ~= 0
        scatter(cluster1(:, 1), cluster1(:, 2));
    end
    if size(cluster2, 1) ~= 0
        scatter(cluster2(:, 1), cluster2(:, 2));
    end
    if size(cluster3, 1) ~= 0
        scatter(cluster3(:, 1), cluster3(:, 2));
    end
    legend('Centers', 'Cluster1', 'Cluster2', 'Cluster3');
    hold off
    movie = [movie getframe];
    clf;
    % MOVIE GENERATION OVER

    % Update center positions
```

```
    for i = 1:k
        npoints = 0;
        c(i, :) = 0;
        for j = 1:size(r, 1)
            c(i, :) = c(i, :) + r(j, i)*X(j, :);
            npoints = npoints + r(j, i);
        end
        c(i, :) = c(i, :)/npoints;
    end
end
movie2avi(movie, 'k-means.avi', 'fps', 1);
```