

## K-Means

Separate data points into K clusters with no other information.

Inputs:

X - D-by-N matrix of N points in D dimensions.

K - Integer number of clusters to detect.

Outputs:

mu - D-by-K matrix with the learned cluster centroids.

labels - Length N vector with integer (1, 2, ..., K) class assignments.

```
function [mu, labels] = km(X, K)
    [~, N] = size(X);

    %initialize clusters by random points
    idx = randperm(N,K);
    mu = X(:,idx);

    labels = zeros(N, 1);
    while true
        %Declare temp labels
        tlabels = labels;

        %E-step
        DIST = zeros(K,N);
        for i = 1:K
            DIST(i,:) = vecnorm(X - mu(:,i));
        end
        [~,labels] = min(DIST);

        if isequal(tlabels,labels)
            return
        end

        %M-step
        for i = 1:K
            mu(:,i) = mean(X(:,labels == i), 2);
        end
    end
end
```

## compute energy (cost) given X, mu, labels

calculate performance of k-mean clustering using sum of square cost (between data pts and its respective means)

```
function [E] = energy(X, mu, labels)
    [~,K] = size(mu);
    E = 0;

    for i = 1:K
        E = E + sum(vecnorm(X(:,labels == i) - mu(:,i)).^2);
    end
end
```

## Contents

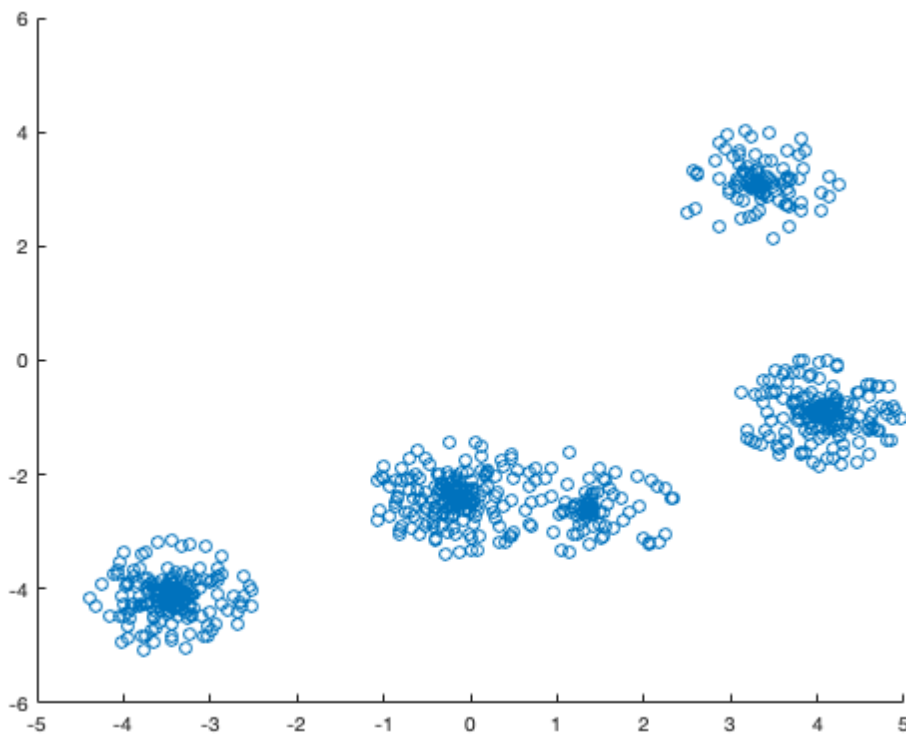
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### 3.2.1 Generate 5 pointclouds & examine data distribution

---

```
X = pointclouds();  
  
%visualize distribution of data in 5 point clouds  
scatter(X(1,:),X(2,:));
```



### 3.2.2, 3.3 k-means on pointclouds() (5 clusters)

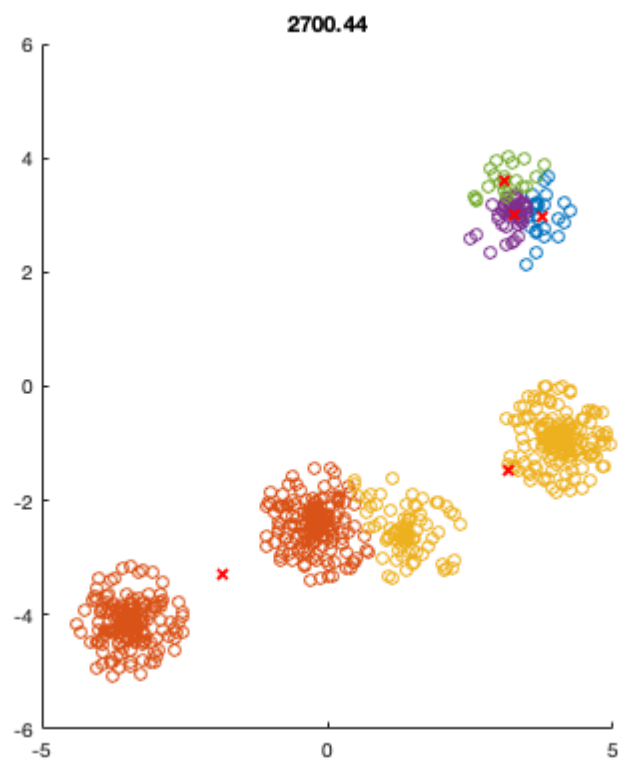
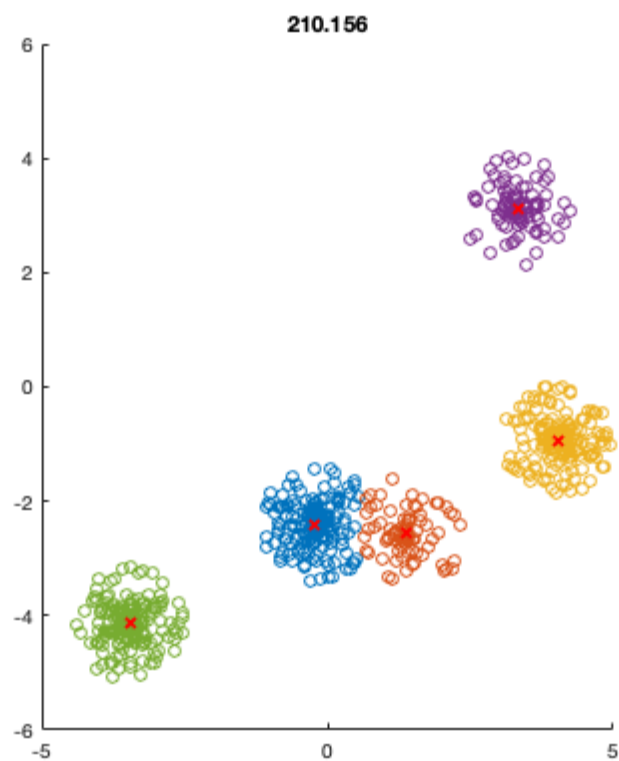
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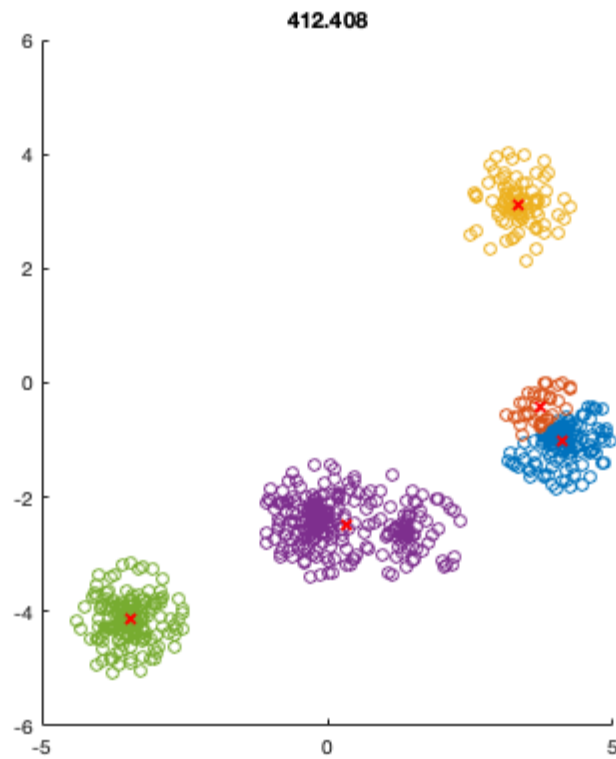
```
K = 5;  
  
%data points in different clusters are colour coded  
%red 'x' represents means of clusters  
for iter = 1:3  
    [mu, labels] = km(X,K);  
  
    figure;  
    for i = 1:K
```

```
        scatter(X(1,labels == i), X(2,labels == i)); hold on;
end
scatter(mu(1,:), mu(2,:), 'rx', 'linewidth', 2);

%energy helps quantify how well one iteration does w.r.t another (and
%with other types of point clouds)
%the smaller energy (cost) the better.
title(energy(X,mu,labels));
daspect([1 1 1]);
end
```

---





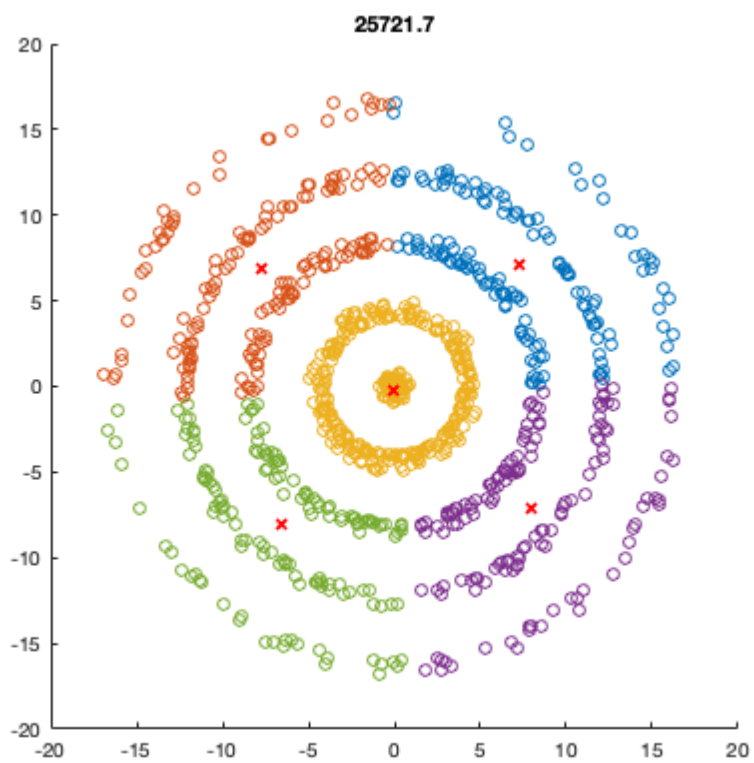
### 3.4 k-means on pointrings() (5 clusters)

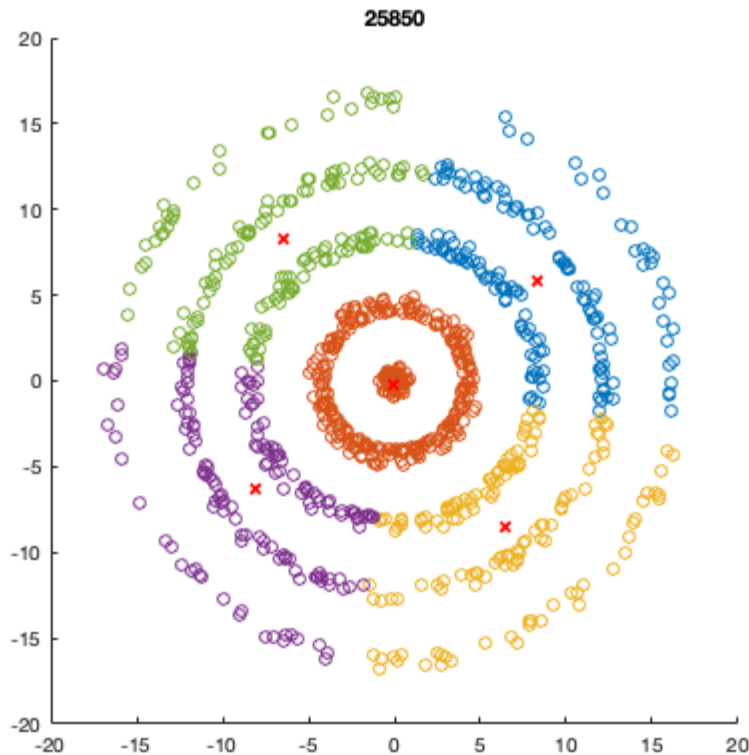
```
X = pointrings();
K = 5;

for iter = 1:3
    [mu, labels] = km(X,K);

    figure;
    for i = 1:K
        scatter(X(1,labels == i), X(2,labels == i)); hold on;
    end

    scatter(mu(1,:), mu(2,:), 'rx', 'linewidth', 2);
    title(energy(X,mu,labels));
    daspect([1 1 1]);
end
```





### 3.5 Why k-means performed better in pointclouds() than pointrings())

%basic idea is: the way k-means works is grouping by proximity to a common mean  $\mu$  for each cluster so the distance between points within a cluster to its cluster center is minimized whereas distances between points across different clusters is maximized. So it is perfect for pointclouds() where points are sampled randomly from 5 distant balls of some given radius.

%The problem with data cloud sampled from rings is that each ring does not have a well defined center that all points are "bunched up" on in euclidean space. So its quite hard for k-means to identify the rings as distinct groups. %In short, rings are not linearly separable in euclidean space.

### 3.6 k-means on plane image

```
%Vectorizing image data into X, each pixel being a vector in  $R^3$ 
[X,I,dims] = im2rgb('plane_small.png');

[mu, labels] = km(X,10);
```

### 3.7 k-means on plane (result)

%Observation: notice how there is now only a few colours (10) in image instead of a large variety. However, the modified image is still a good representation as k-means bring only similar colours to a common one, so larger differences in colours are still recognized and distinguished whereas small nuances may not be separated (but smaller nuances is less obvious to our eyes).

```
figure;
imshow(rgb2im(mu(:,labels), dims));
```



```
title(energy(X,mu,labels));
```

```
figure;  
imshow(I);
```



551.287



## extra for mountain

```
[X,I,dims] = im2rgb('mountains_small.png');
```

```
[mu, labels] = km(X,10);
```

```
%Observation: I feel like k-means actually works pretty well on Mountains  
%since original image has clear distinct shades of colours: dark green, light  
%green, white, light blue, dark blue, brown, etc. Though it usually fails to  
%recognize the brown mud as its own colour
```

```
figure;  
imshow(rgb2im(mu(:,labels), dims));  
title(energy(X,mu,labels));
```

```
figure;  
imshow(I);
```

581.469

