```
% Clear everything and turn off the warning
clc; clear all; close all;
warning('off','all');
```

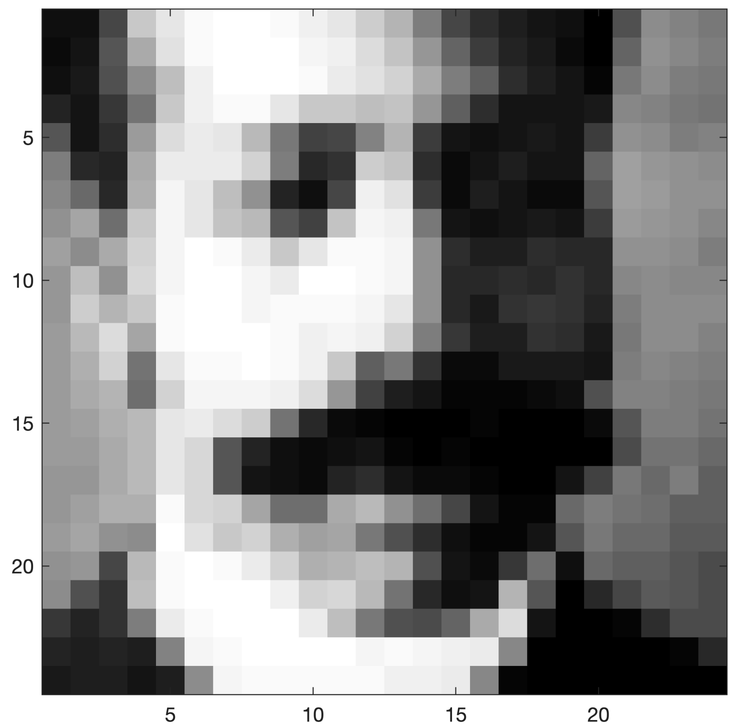
Bayes Classifiers

```
% Code is relavent to (A) and (B)
% Set the Training and Test data as well as other constants related to them
Xtr1 = [0,0,0,0,0,0,0,0,1,1,1,1,1,1,1,1];
Xtr2 = [0,0,0,0,1,1,1,1,0,0,0,1,1,1,1,1];
Ytr = [0,1,1,1,0,1,1,1,0,0,0,0,0,0,1,1];
Xtest = [0 1; 1 0; 1 1];
YtrLength = length(Ytr);
Ytr0Length = length(Ytr(Ytr==0));
Ytr1Length = length(Ytr(Ytr==1));

% Find the probabilities needed to create Joint Bayes classifier
% Find out the percentage occurrence of each possible class(Ytr) value
% to do this divide number of occurrences by the length of the total array
% considered. Repeat this process to calculate all probabilities needed for
% classification
P_0 = length(Ytr(Ytr==0)) / YtrLength;
P_1 = length(Ytr(Ytr==1)) / YtrLength;

%Find probabilities for Joint Bayes classifier, these are the percentage
%occurrence rates of an (X1,X2) combination for a specific y value
%P(x1,x2|y)
jbc_P_000 = length(Xtr1(Xtr1==0 & Xtr2==0 & Ytr == 0))/Ytr0Length;
jbc_P_010 = length(Xtr1(Xtr1==0 & Xtr2==1 & Ytr == 0))/Ytr0Length;
jbc_P_100 = length(Xtr1(Xtr1==1 & Xtr2==0 & Ytr == 0))/Ytr0Length;
jbc_P_110 = length(Xtr1(Xtr1==1 & Xtr2==1 & Ytr == 0))/Ytr0Length;
jbc_P_001 = length(Xtr1(Xtr1==0 & Xtr2==0 & Ytr == 1))/Ytr1Length;
jbc_P_011 = length(Xtr1(Xtr1==0 & Xtr2==1 & Ytr == 1))/Ytr1Length;
jbc_P_101 = length(Xtr1(Xtr1==1 & Xtr2==0 & Ytr == 1))/Ytr1Length;
jbc_P_111 = length(Xtr1(Xtr1==1 & Xtr2==1 & Ytr == 1))/Ytr1Length;

% Find probabilities for naÃ¯ve Bayes classifier, these are the percentage
% occurrence rates of P(x1|y) and P(x2|y)
nbc_x1_P_00 = length(Xtr1(Xtr1==0 & Ytr == 0))/Ytr0Length;
nbc_x1_P_10 = length(Xtr1(Xtr1==1 & Ytr == 0))/Ytr0Length;
nbc_x2_P_00 = length(Xtr1(Xtr2==0 & Ytr == 0))/Ytr0Length;
nbc_x2_P_10 = length(Xtr1(Xtr2==1 & Ytr == 0))/Ytr0Length;
nbc_x1_P_01 = length(Xtr1(Xtr1==0 & Ytr == 1))/Ytr1Length;
nbc_x1_P_11 = length(Xtr1(Xtr1==1 & Ytr == 1))/Ytr1Length;
nbc_x2_P_01 = length(Xtr1(Xtr2==0 & Ytr == 1))/Ytr1Length;
nbc_x2_P_11 = length(Xtr1(Xtr2==1 & Ytr == 1))/Ytr1Length;

% See hand working for classification and probabilities
% Remember to put handwritten scans into report
```

Section B: PCA & Clustering

EigenFaces (PCA)

```
X = load('data/faces.txt'); % load face dataset
img = reshape(X(2,:),[24 24]); % convert vectorized data to 24 x24 image patch
imagesc(img); axis square; colormap gray; % display an image patch
```



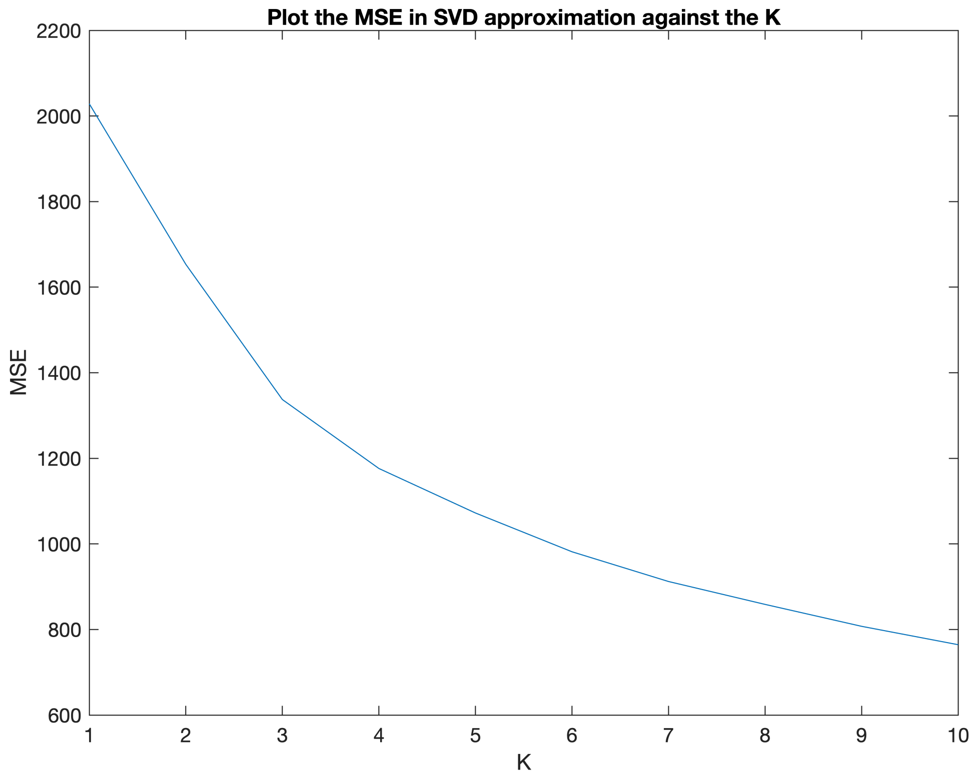
Part A: Subtract the mean of the face images to make the data zero-mean

```
mean_X = mean(X); % Mean of data
X0 = X - mean_X; % Subtract the mean to make data zero-mean
[U S V] = svd(X0); % Take the SVD of the data
W = U * S;
```

Part B: Compute the mean square error in SVD's approximation

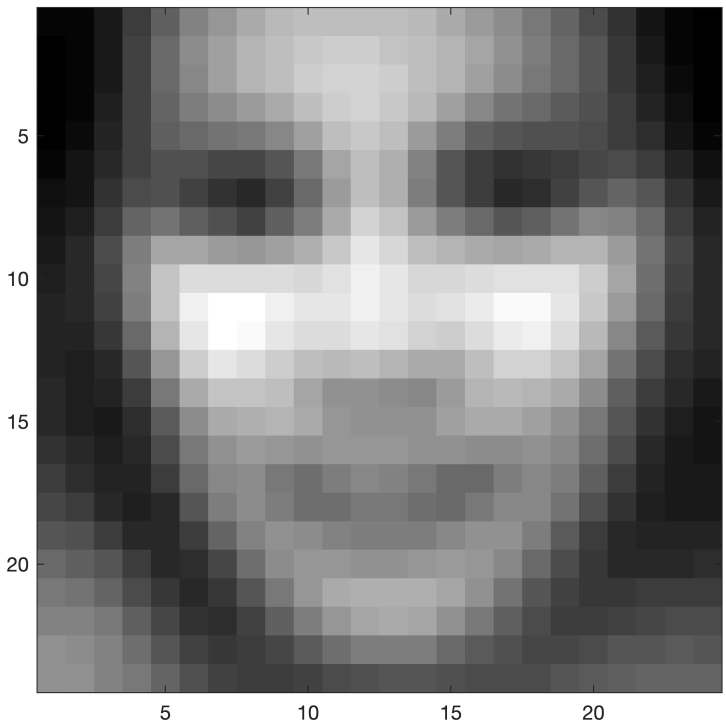
```
errors = zeros(1,10); % Initialize errors variable
K = 1:10; % Intialize K values
for i = 1:length(K)
    [U_k S_k V_k] = svds(X0,K(i)); % Take the SVD of data with different K
    X0_svd = U_k * S_k * V_k';  % Recover the data
    mse_svd = mean(mean((X0 - X0_svd).^2)); % Compute MSE in the SVD's approximation
```

```
    errors(i) = mse_svd;
end
figure(1);
plot(K,errors);
title('Plot the MSE in SVD approximation against the K');
xlabel('K'); ylabel('MSE');
```

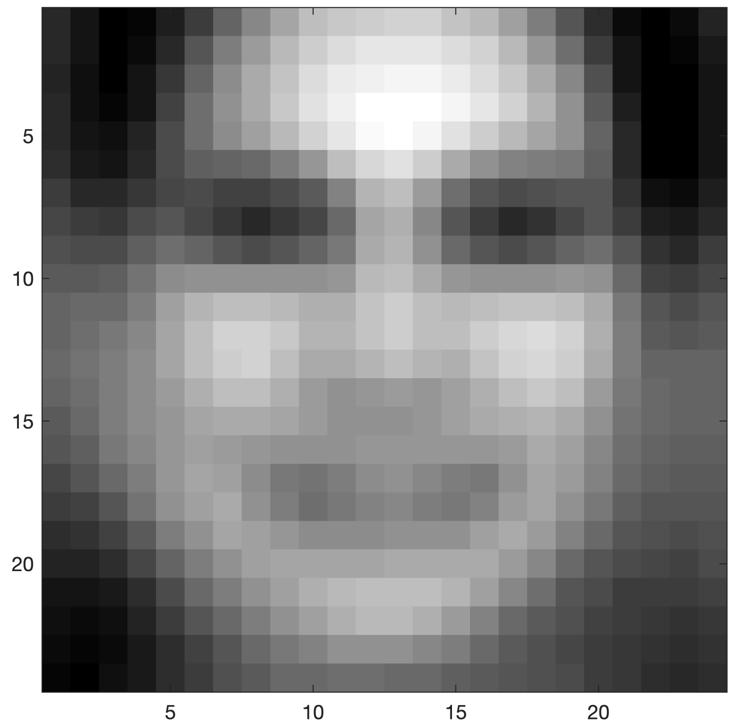


Part C: Display a first few principal directions of the data

```
alpha = 2 * median(abs(W(:,10))); % Scale factor
direction1 = reshape(mean_X + alpha * V(:,10)',[24,24]); % 1st principal direction
direction2 = reshape(mean_X - alpha * V(:,10)',[24,24]); % 2nd principal direction
figure(2);
imagesc(direction1); axis square; colormap gray; % Reshape and view as face image
```

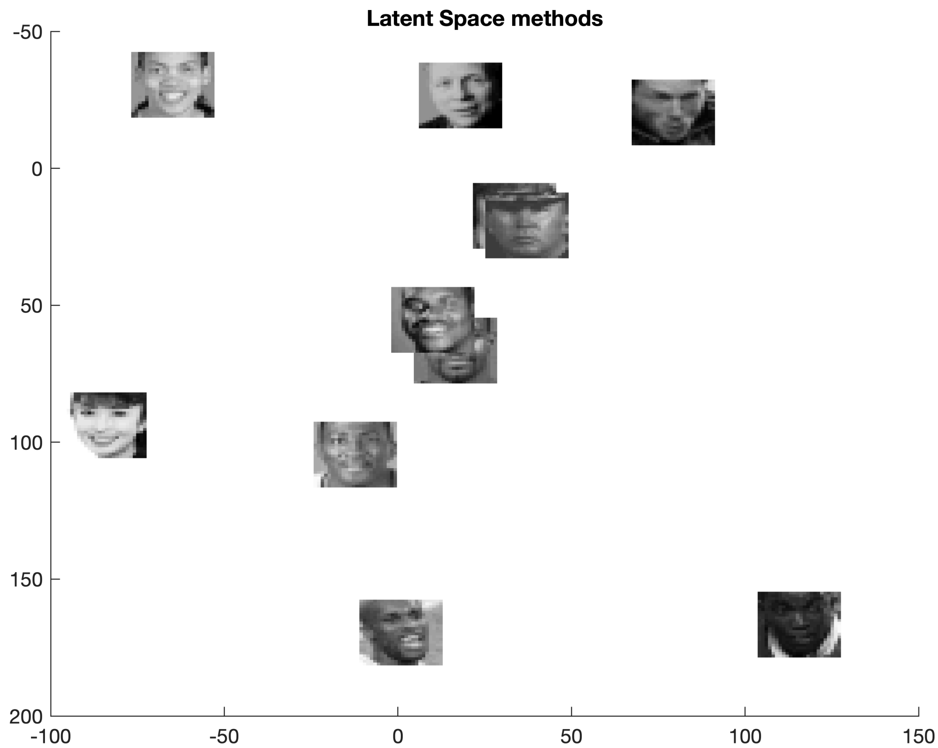



```
figure(3);
imagesc(direction2); axis square; colormap gray; % Reshape and view as face image
```



Part D: Latent Space methods

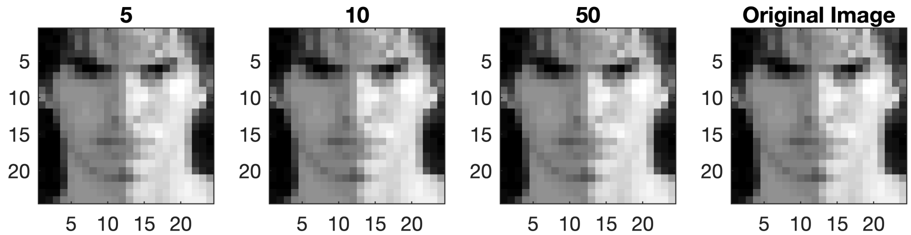
```
idx = 15:25; % random indices of data
figure(4); title('Latent Space methods');  hold on; axis ij; colormap(gray);
range = max(W(idx,1:2)) - min(W(idx,1:2)); % find range of coordinates to be plotted
scale = [200 200]./range;                  % want 24x24 to be visible
for i=1:length(idx)
    imagesc(W(idx(i),1) * scale(1), W(idx(i),2) * scale(2), reshape(X(idx(i),:),24,24)); % Scal
end
```

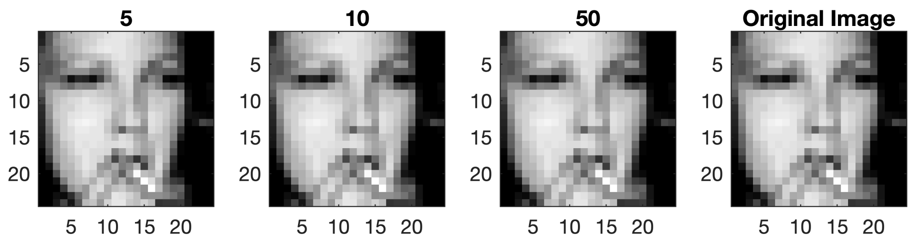


Part E: Choose two faces and reconstruct using only K principal directions

```
K_recover = [5,10,50]; % K principal directions
indices = randperm(size(X0,1));
index1 = indices(1); index2 = indices(2); % Random two indices
% Choose random two images
img1 = X(index1,:); % Image 1
img2 = X(index2,:); % Image 2
figure(5);
title('Construct image using K principal directions');
for i = 1:length(K_recover)
    [U1 S1 V1] = svds(img1,K_recover(i)); % Take SVD of 1st image with different K
    recovered_img1 = U1 * S1 * V1'; % Recover the data
    subplot(2,4,i);
    imagesc(reshape(recovered_img1,24,24)); axis square; colormap gray; % Display the recovere
    title([num2str(K_recover(i))]);
    [U2 S2 V2] = svds(img2,K_recover(i)); % Take SVD of 2nd image with different K
    recovered_img2 = U2 * S2 * V2'; % Recover the data
    subplot(2,4,i+4);
    imagesc(reshape(recovered_img2,24,24)); axis square; colormap gray; % Display the recovere
    title([num2str(K_recover(i))]);
end
subplot(2,4,4); imagesc(reshape(img1,24,24)); axis square; colormap gray; % Display image 1
title('Original Image');
subplot(2,4,8); imagesc(reshape(img2,24,24)); axis square; colormap gray; % Display image 2
```

```
title('Original Image');
```

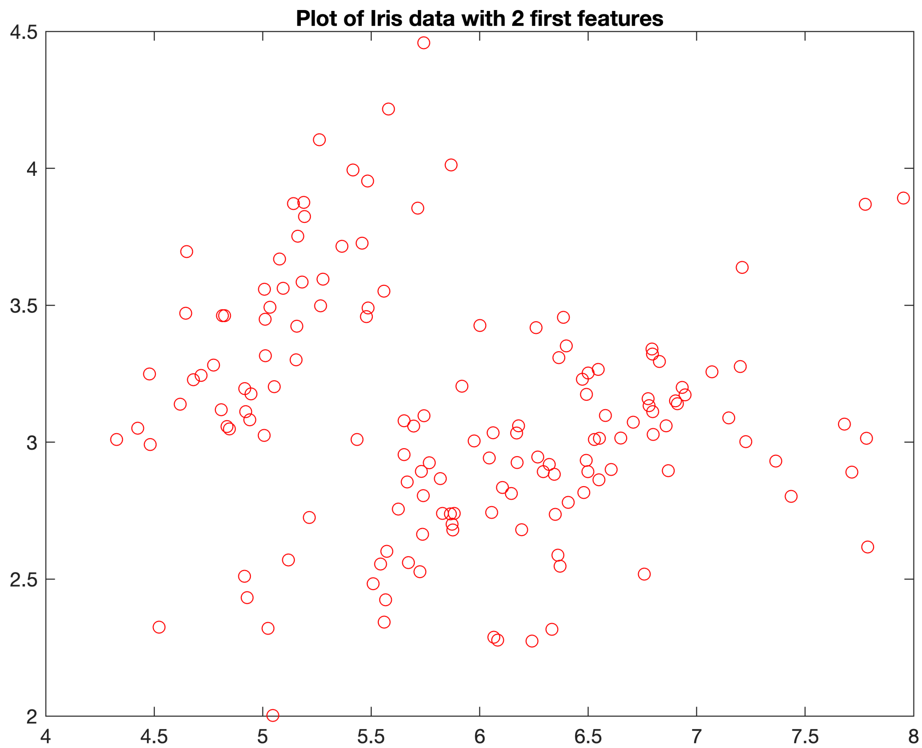




Clustering

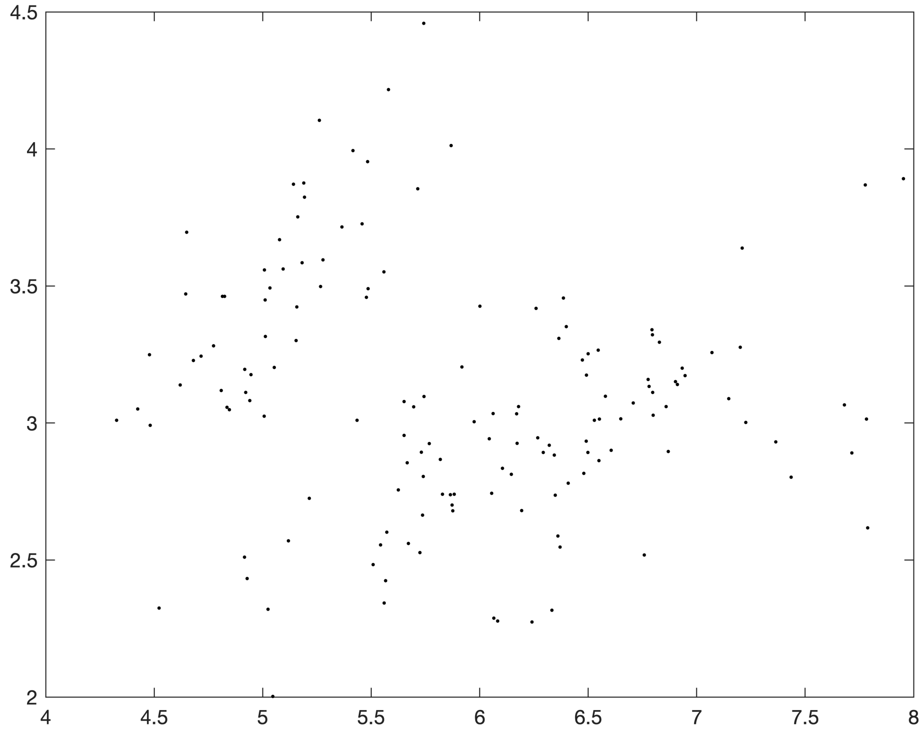
Part A: Load the usual Iris data with 2 features and plot

```
iris = load('data/iris.txt'); % Load Iris data
X_iris = iris(:,1:2);         % Use only two first features
figure(6);
plot(X_iris(:,1),X_iris(:,2),'ro');
title('Plot of Iris data with 2 first features');
```

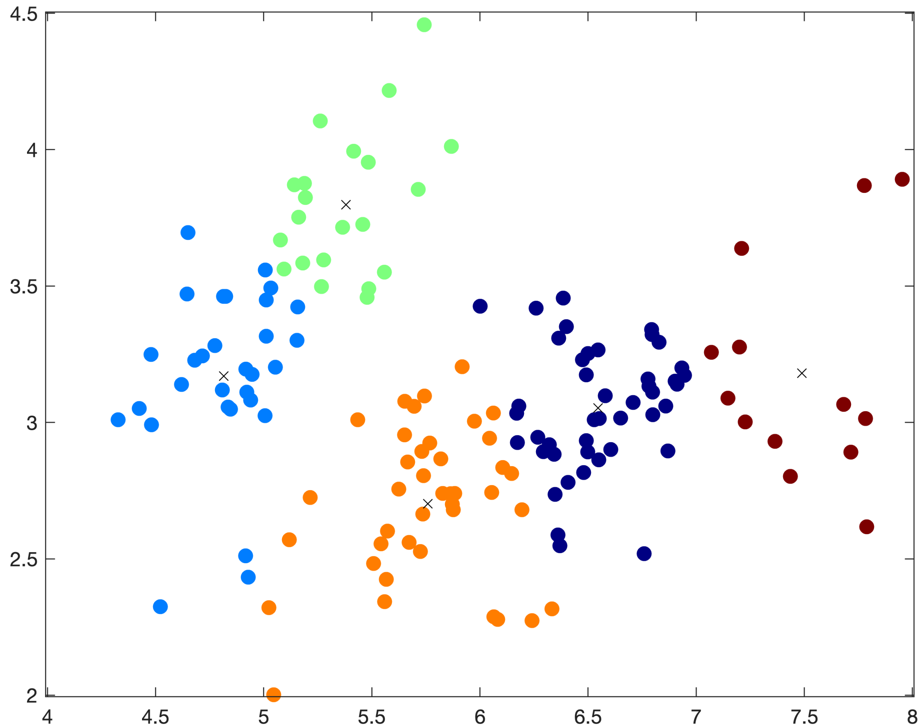


Part B: K-Means on the data

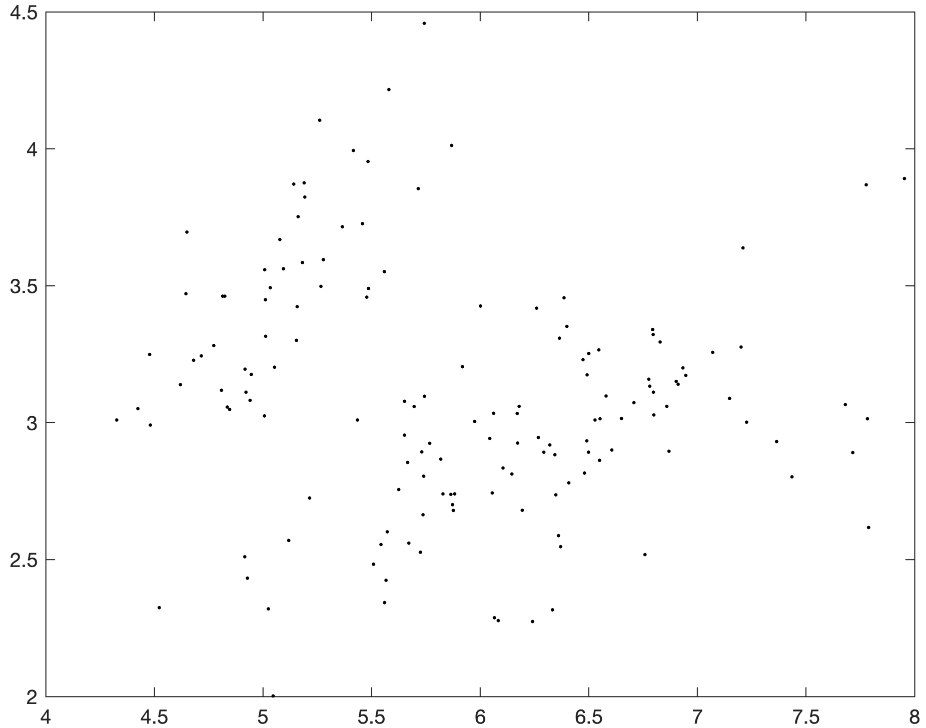
```
% Choose the initialization with the best score
% Run k-means with k = 5 with farthest initialization
figure(7);
title('k-means on the data with k = 5');
[z5 c5 sumd5] = kmeans(X_iris,5,'farthest',100);
plotClassify2D([],X_iris,z5);
```



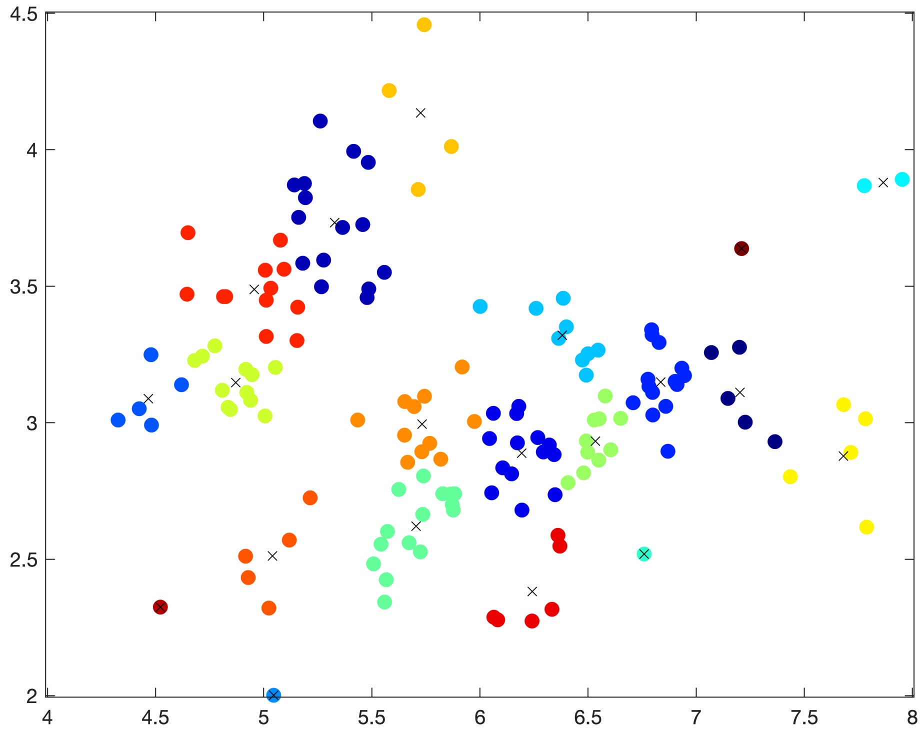

```
hold on
plot(c5(:,1),c5(:,2),'kx');
```




```
% Run k-means with k = 20 with k++ initialization
figure(8);
title('k-means on the data with k = 20');
[z20 c20 sumd20] = kmeans(X_iris,20,'k++',100);
plotClassify2D([],X_iris,z20);
```

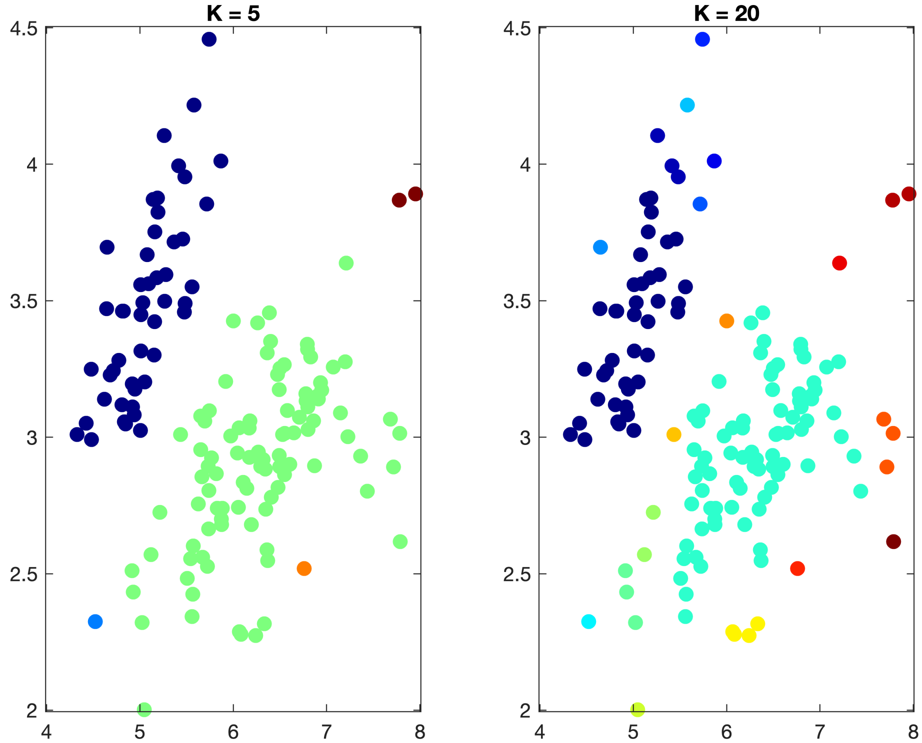



```
hold on
plot(c20(:,1),c20(:,2),'kx');
```

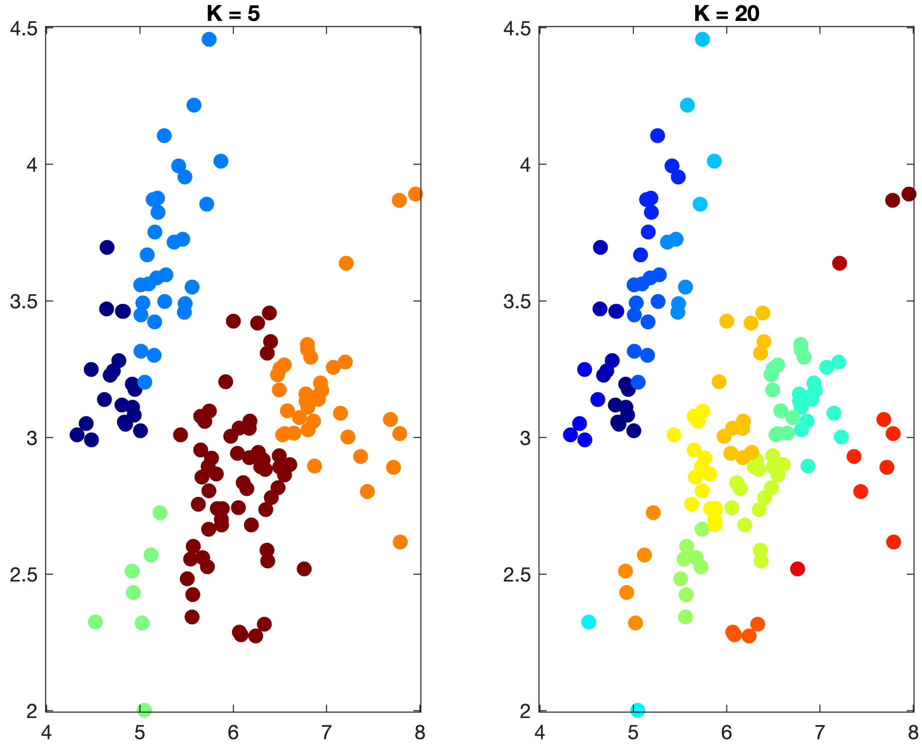


Part C: Run agglomerative clustering on the data

```
% Using single linkage on Iris data
[z5_min_agg join] = agglomCluster(X_iris,5,'min'); % k = 5
[z20_min_agg join] = agglomCluster(X_iris,20,'min'); % k = 20
figure(9);
subplot(1,2,1);
plotClassify2D([],X_iris,z5_min_agg);
title('K = 5');
subplot(1,2,2);
plotClassify2D([],X_iris,z20_min_agg);
title('K = 20');
```

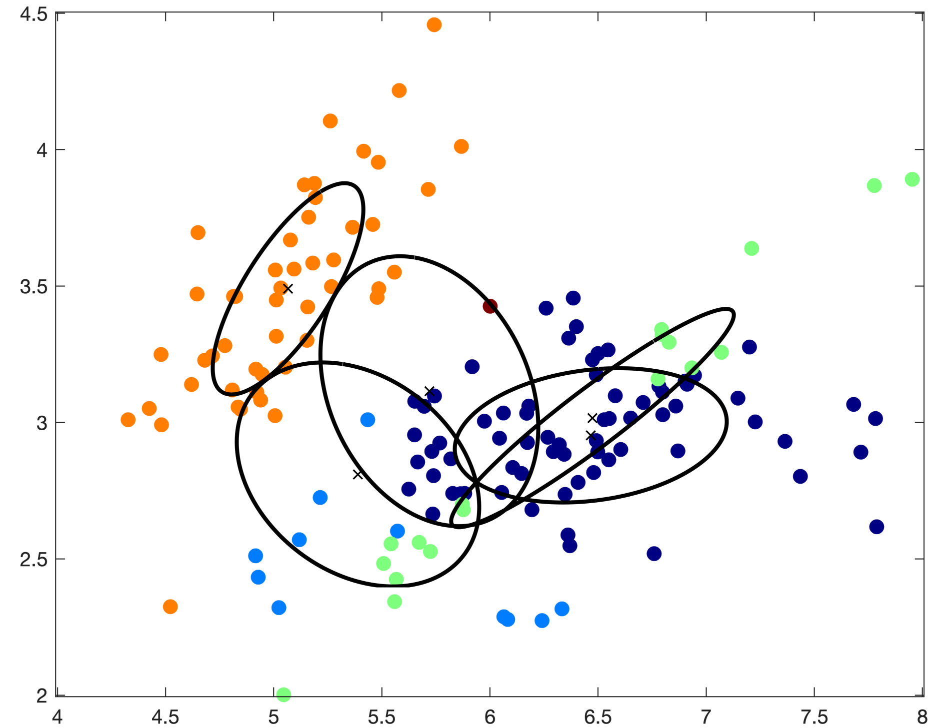



```
% Using complete linkage on Iris data
[z5_max_agg join] = agglomCluster(X_iris,5,'max'); % k = 5
[z20_max_agg join] = agglomCluster(X_iris,20,'max'); % k = 20
figure(10);
subplot(1,2,1);
plotClassify2D([],X_iris,z5_max_agg);
title('K = 5');
subplot(1,2,2);
plotClassify2D([],X_iris,z20_max_agg);
title('K = 20');
```

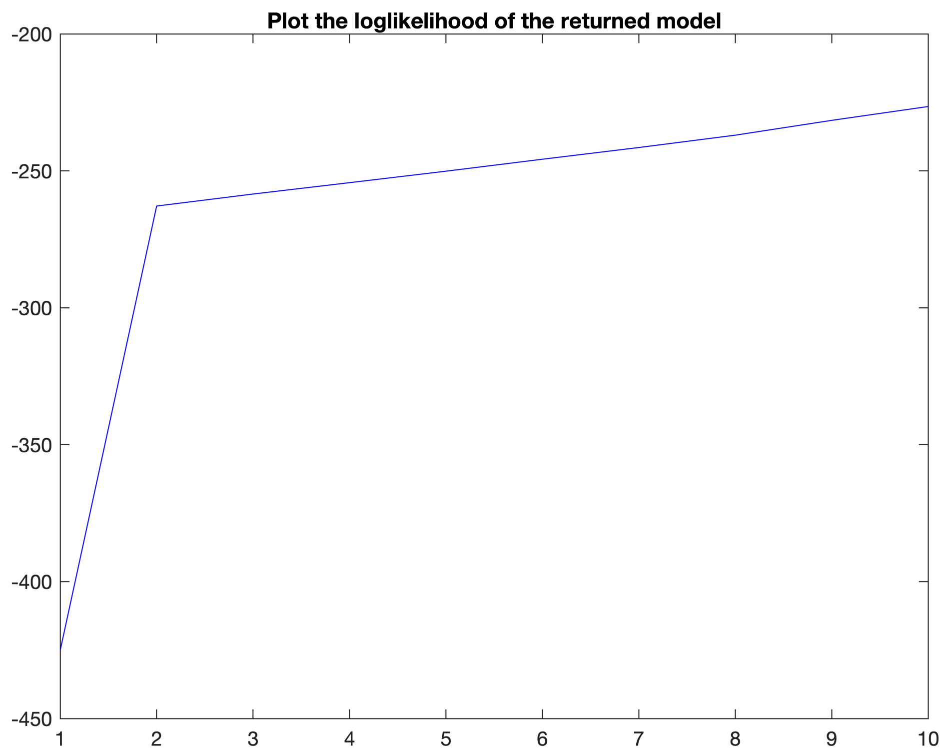


Part D: Run the EM Gaussian Mixture Model

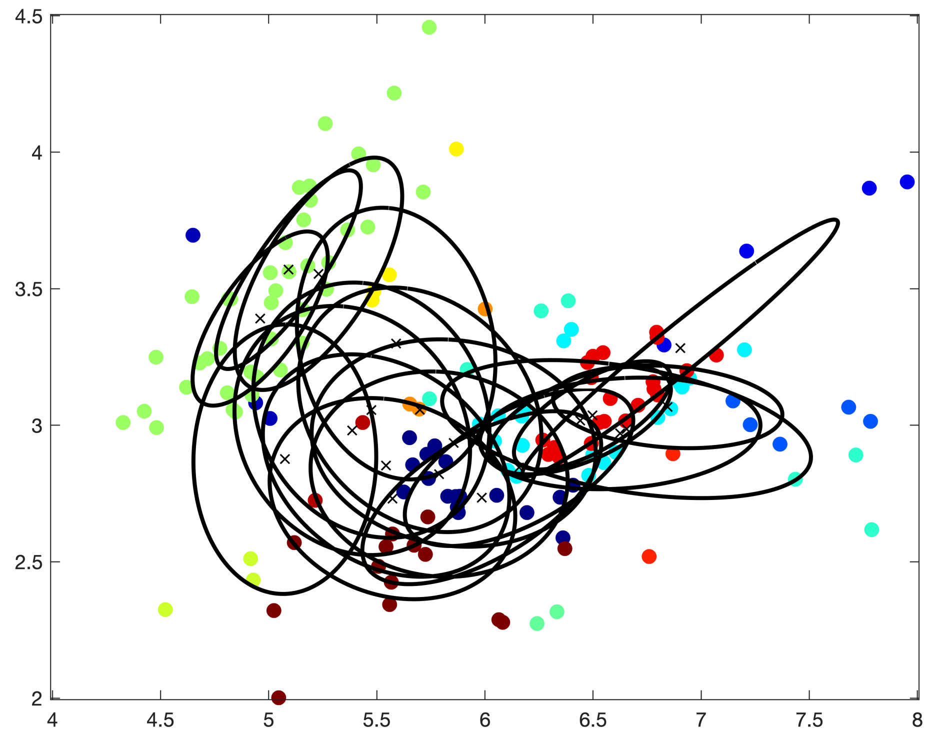
```
% Use doPlot = true in emCluster to observe the evolution of mixture components's locations and
% EM Gaussian mixture model with k = 5
[z5_em,T,soft,ll] = emCluster(X_iris,5,'farthest',10);
% EM Gaussian mixture model with k = 20
[z20_em,T,soft,ll] = emCluster(X_iris,20,'farthest',10);
```



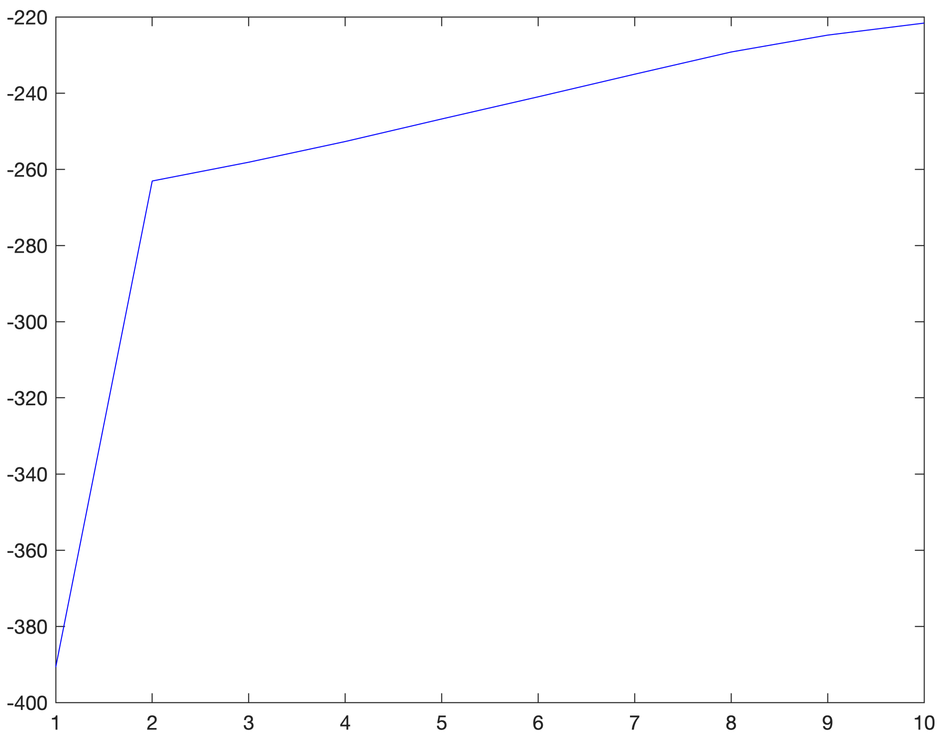
4.5
4
3.5
3
2.5
2
4
4.5
5
5.5
6
6.5
7
7.5
8



Plot the loglikelihood of the returned model
-200
-250
-300
-350
-400
-450
1
2
3
4
5
6
7
8
9
10



4.5
4
3.5
3
2.5
2
4
4.5
5
5.5
6
6.5
7
7.5
8



-220
-240
-260
-280
-300
-320
-340
-360
-380
-400
1
2
3
4
5
6
7
8
9
10