CAB420 Machine Learning - Assignment 2 Report

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Support Vector Machines

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

% Load the datasets
svm_data = load('data_ps3_2.mat');
% Training Data
set1_train = svm_data.set1_train; % Set 1
set2_train = svm_data.set2_train; % Set 2
set3_train = svm_data.set3_train; % Set 3
set4_train = svm_data.set4_train; % Set 4

% Testing Data
set1_test = svm_data.set1_test; % Set 1
set2_test = svm_data.set2_test; % Set 2
set3_test = svm_data.set3_test; % Set 3
set4_test = svm_data.set4_test; % Set 4

%Set constant values
C = 1000;
polyOrder = 2;
SD1 = 1;
SD2 = 1.5;
```

Part 1:

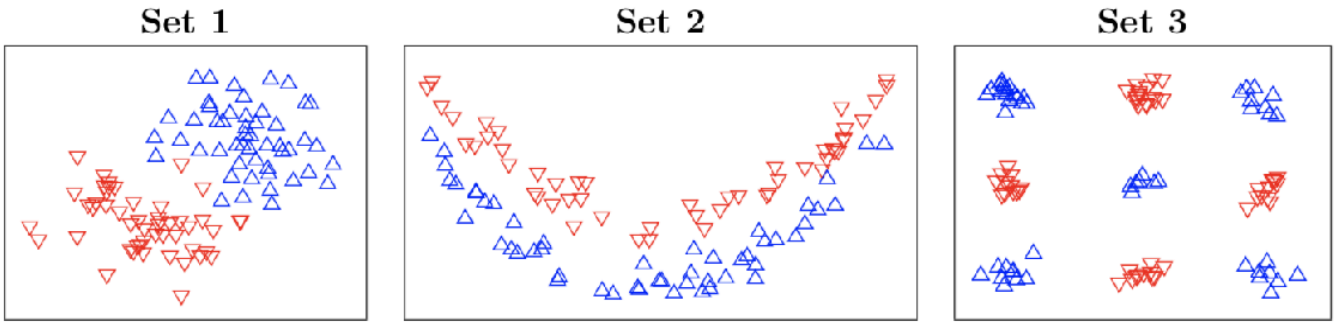
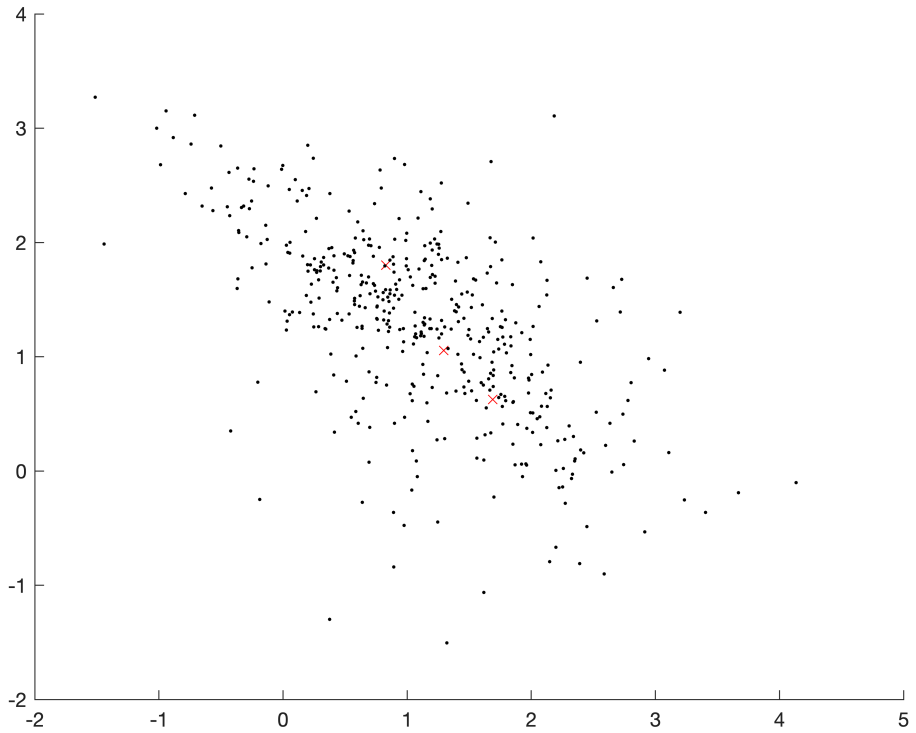


Figure 1: The 2-dimensional datasets of three sets

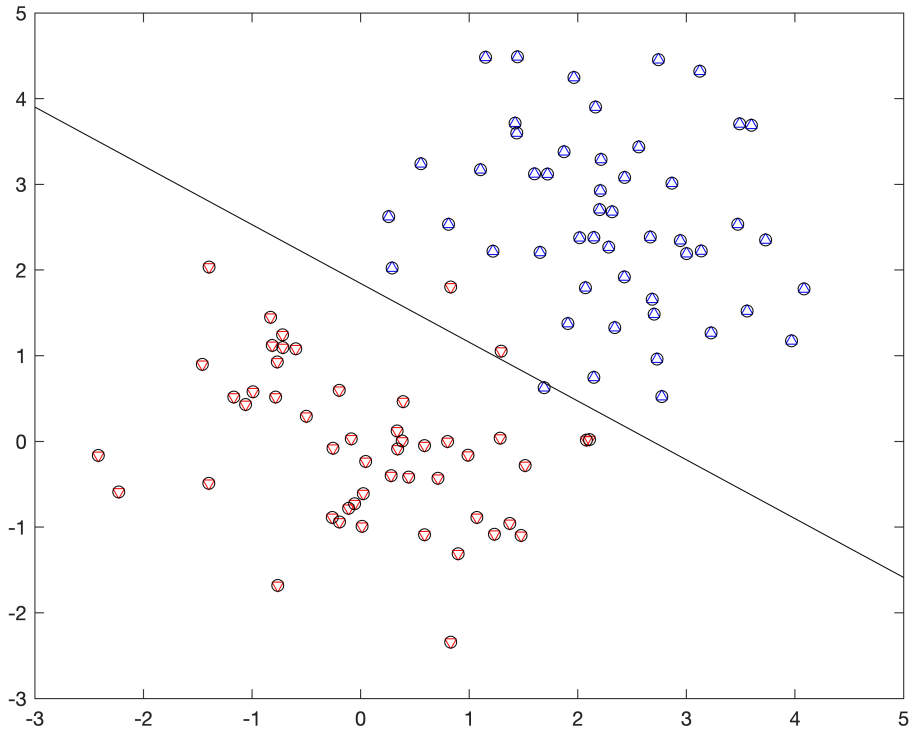
From the figure above, it is considered that the best kernels for training SVM classifiers on first, second and third datasets are linear, polynomial and Gaussian kernels respectively.

```
% For the first three datasets, consider the linear, second
% order polynomial, Gaussian of standard deviation 1 kernels
% Use C = 1000 for consistency

% Use linear kernels for dataset 1
svm_test(@Klinear,[],C,set1_train,set1_test);
```

```
The interior-point-convex algorithm does not accept an initial point.
Ignoring X0.

Minimum found that satisfies the constraints.

Optimization completed because the objective function is non-decreasing in
feasible directions, to within the default value of the optimality tolerance,
and constraints are satisfied to within the default value of the constraint tolerance.

<stopping criteria details>

WARNING: 3 training examples were misclassified!!!
```

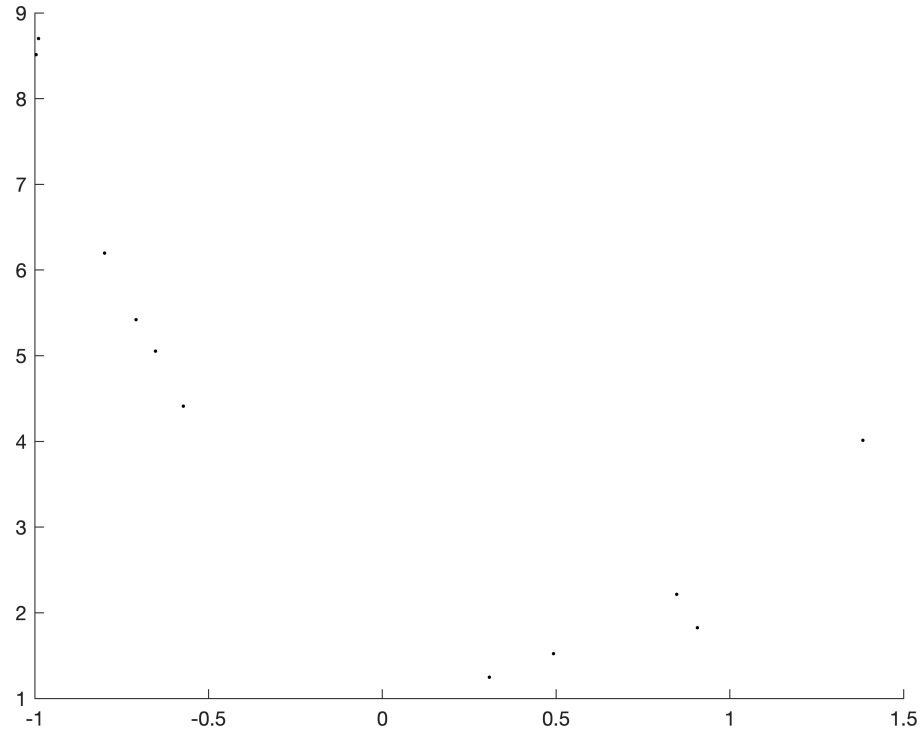


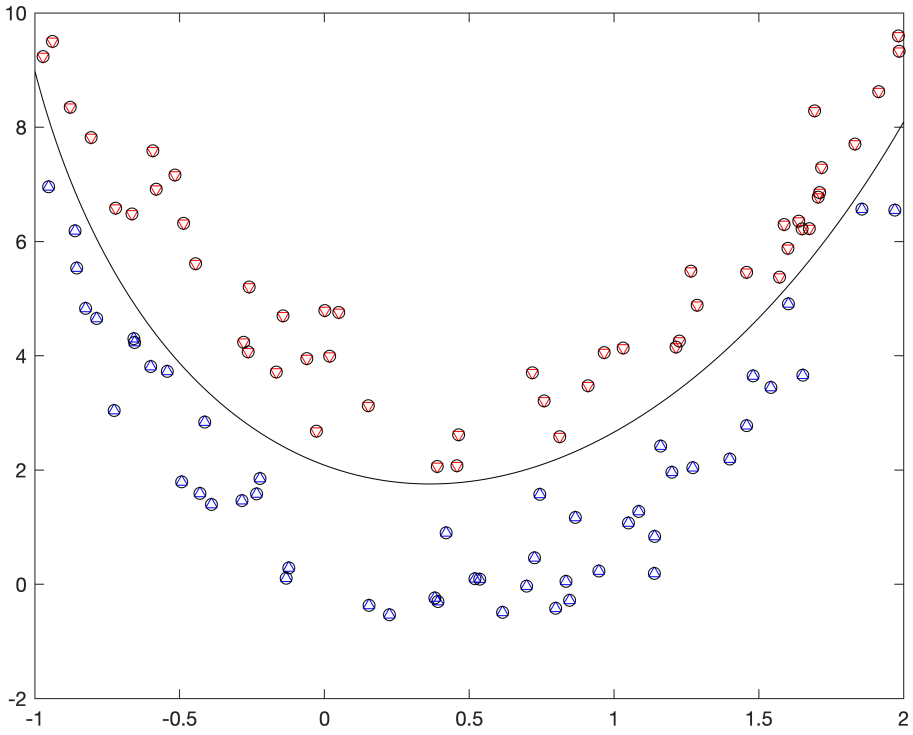

```
TEST RESULTS: 0.0446 of test examples were misclassified.
```




```
% Use second order kernels for dataset 2
svm_test(@Kpoly,polyOrder,C,set2_train,set2_test);
```

```
The interior-point-convex algorithm does not accept an initial point.
Ignoring X0.

Minimum found that satisfies the constraints.

Optimization completed because the objective function is non-decreasing in
feasible directions, to within the default value of the optimality tolerance,
and constraints are satisfied to within the default value of the constraint tolerance.

<stopping criteria details>

TEST RESULTS: 0.011 of test examples were misclassified.
```

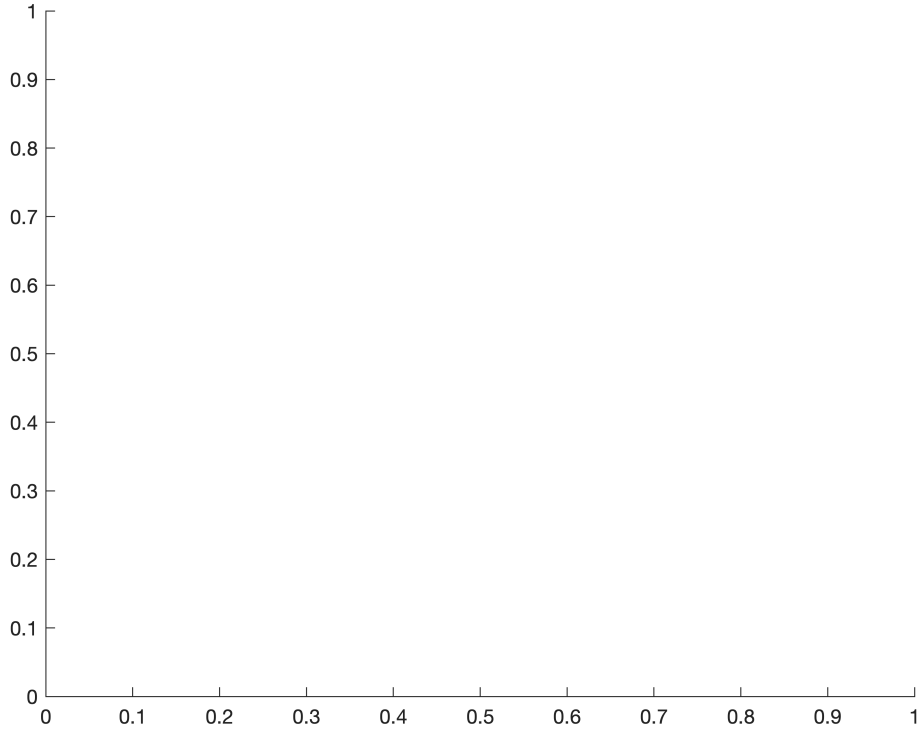


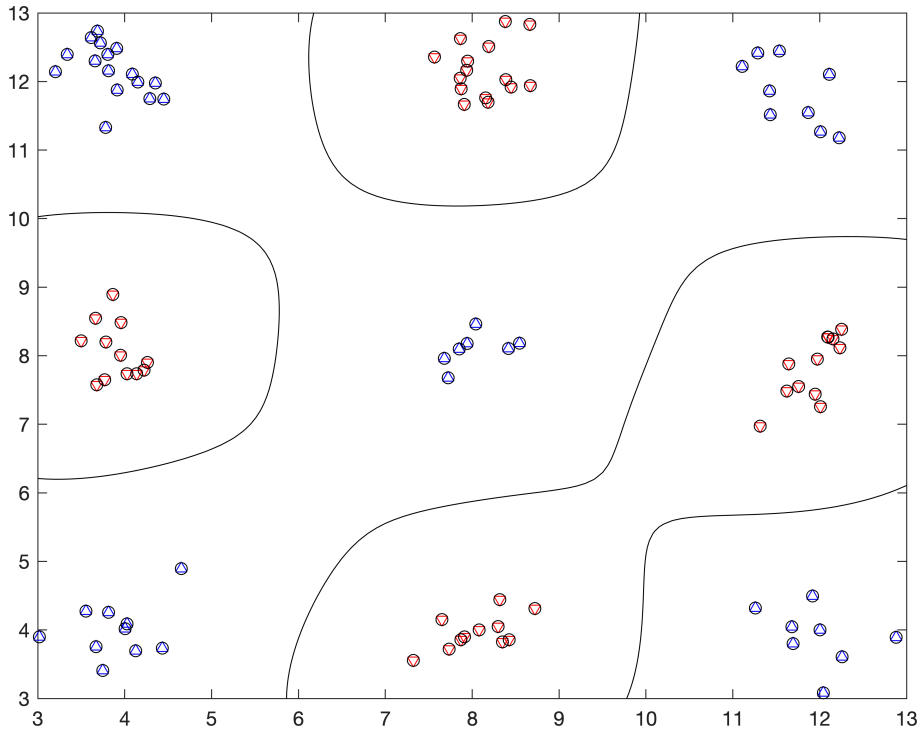



```
% Use Gaussian of standard deviation 1 kernels for dataset 3
svm_test(@Kgaussian,SD1,C,set3_train,set3_test);
```

```
The interior-point-convex algorithm does not accept an initial point.
```

```
Ignoring X0.

Minimum found that satisfies the constraints.

Optimization completed because the objective function is non-decreasing in
feasible directions, to within the default value of the optimality tolerance,
and constraints are satisfied to within the default value of the constraint tolerance.

<stopping criteria details>

TEST RESULTS: 0 of test examples were misclassified.
```





Part 2:

```
TestError = zeros(3,1); % Initialize TestError variable
% Train and test 4th dataset with a linear kernel
svm_linear4 = svm_train(set4_train,@Klinear,[],C); % Training
```

```
The interior-point-convex algorithm does not accept an initial point.
Ignoring X0.

Minimum found that satisfies the constraints.

Optimization completed because the objective function is non-decreasing in
feasible directions, to within the default value of the optimality tolerance,
and constraints are satisfied to within the default value of the constraint tolerance.

<stopping criteria details>
```

```
y_linear4 = sign(svm_discrim_func(set4_test.X,svm_linear4)); % Prediction
errors_linear = find(y_linear4 ~= set4_test.y); % Testing Error
TestError(1) = length(errors_linear)/length(set4_test.y); % Output the result
fprintf('Linear SVM: %g of 4th test examples  were misclassified.\n',...
    length(errors_linear)/length(set4_test.y));
```

```
Linear SVM: 0.1375 of 4th test examples  were misclassified.
```

```
% Train and test 4th dataset with a polynomial of degree 2 kernel
svm_poly4 = svm_train(set4_train,@Klinear,polyOrder,C); % Training
```

```
The interior-point-convex algorithm does not accept an initial point.
Ignoring X0.

Minimum found that satisfies the constraints.

Optimization completed because the objective function is non-decreasing in
feasible directions, to within the default value of the optimality tolerance,
and constraints are satisfied to within the default value of the constraint tolerance.

<stopping criteria details>
```

```
y_poly4 = sign(svm_discrim_func(set4_test.X,svm_poly4)); % Prediction
errors_poly = find(y_poly4 ~= set4_test.y); % Testing Error
TestError(2) = length(errors_poly)/length(set4_test.y);% Output the result
fprintf('Polynomial SVM: %g of 4th test examples  were misclassified.\n',...
    length(errors_poly)/length(set4_test.y));
```

```
Polynomial SVM: 0.1375 of 4th test examples  were misclassified.
```

```
% Train and test 4th dataset with a Gaussian of standard deviation 1.5 kernels
svm_gaussian4 = svm_train(set4_train,@Kgaussian,SD2,polyOrder); % Training
```

```
The interior-point-convex algorithm does not accept an initial point.
Ignoring X0.

Minimum found that satisfies the constraints.

Optimization completed because the objective function is non-decreasing in
feasible directions, to within the default value of the optimality tolerance,
and constraints are satisfied to within the default value of the constraint tolerance.

<stopping criteria details>
```

```
y_gaussian4 = sign(svm_discrim_func(set4_test.X,svm_gaussian4)); % Prediction
errors_gaussian = find(y_gaussian4 ~= set4_test.y);  % Testing Error
TestError(3) =  length(errors_gaussian)/length(set4_test.y); % Output the result
fprintf('Gaussian SVM: %g of 4th test examples  were misclassified.\n',...
    length(errors_gaussian)/length(set4_test.y));
```

```
Gaussian SVM: 0.085 of 4th test examples  were misclassified.
```

```
Kernel = {'Linear';'Polynomial of degree 2';'Gaussian of std 1.5'};
% The test errors of 4th dataset trained on different kernels is as below:
t = table(TestError,Kernel);
display(t);
```

```
t = 3×2 table
```

	TestError	Kernel
1	0.1375	'Linear'
2	0.1375	'Polynomial...
3	0.0850	'Gaussian o...

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

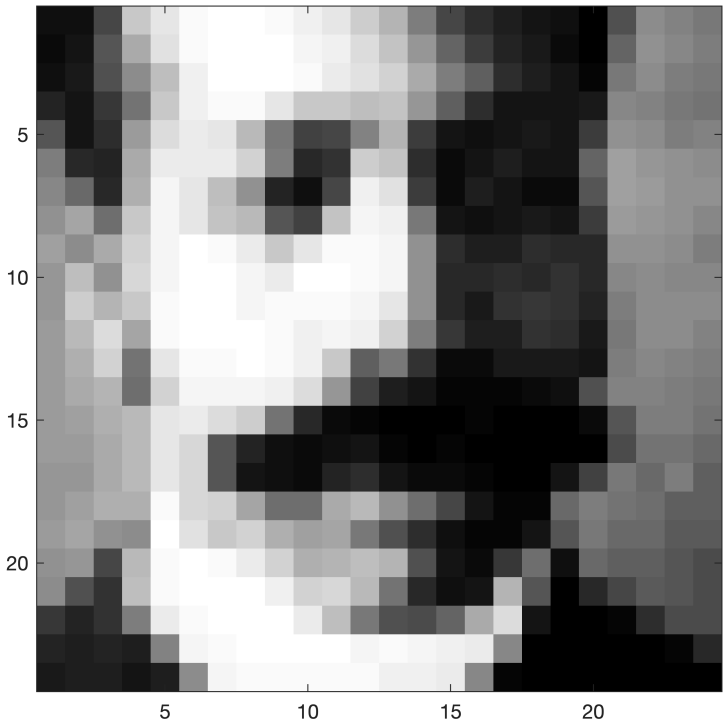
Bayes Classifiers

```
% 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
```



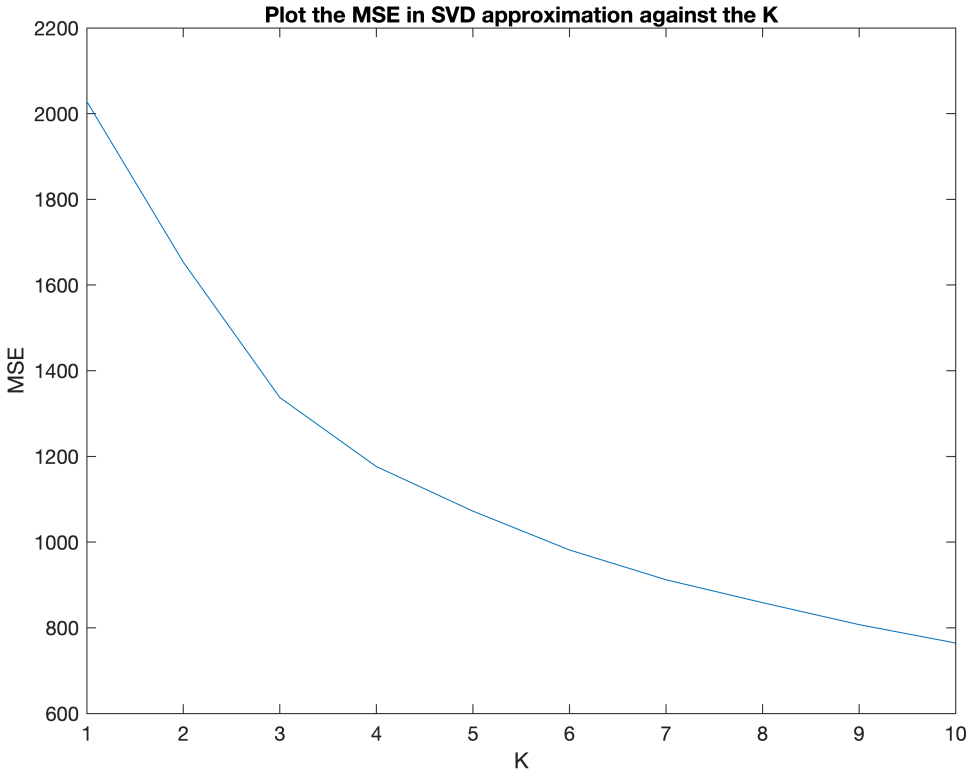
Part A: Subtract the mean of the face images to make the data zero-mean

```
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 approxination

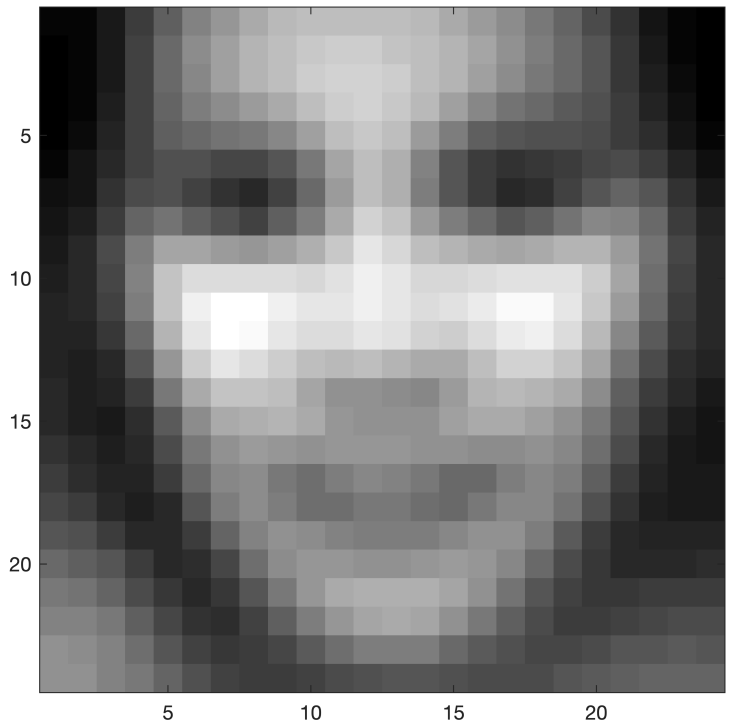
```
errors = zeros(1,10); % Initialize errors variable
K = 1:10; % Intialize K values
for i = 1:length(K)
    [U_k S_k V_k] = svds(X0,K(i)); % Take the SVD of data with different K
    X0_svd = U_k * S_k * V_k';  % Recover the data
    mse_svd = mean(mean((X0 - X0_svd).^2)); % Compute MSE in the SVD's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

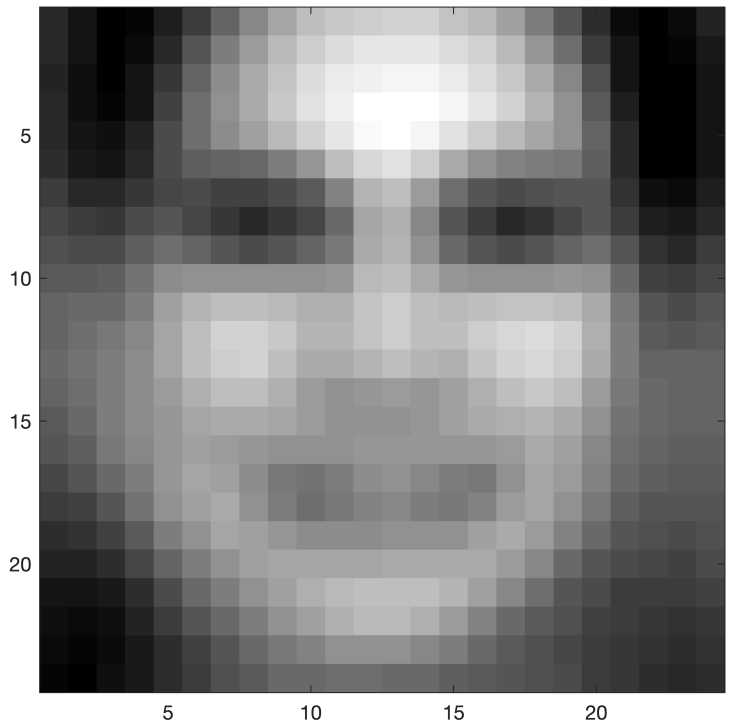


Part C: Display a first few principal directions of the data

```
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
```

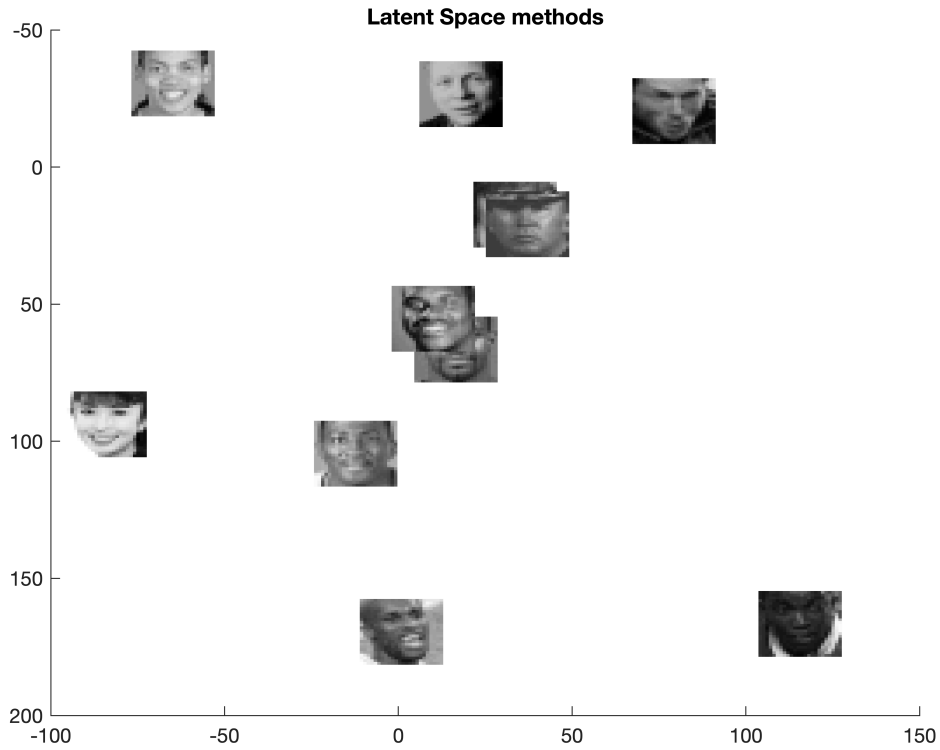



```
figure(3);
imagesc(direction2); axis square; colormap gray; % Reshape and view as face image
```



Part D: Latent Space methods

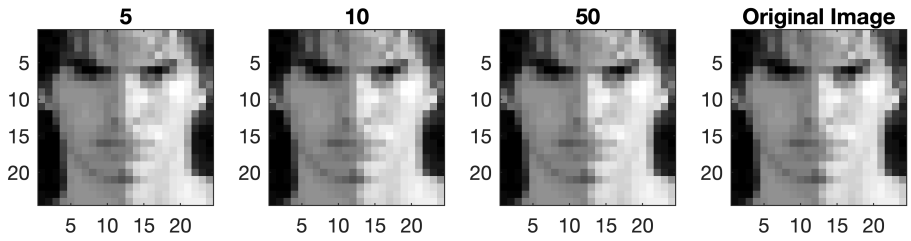
```
idx = 15:25; % random indices of data
figure(4); title('Latent Space methods');  hold on; axis ij; colormap(gray);
range = max(W(idx,1:2)) - min(W(idx,1:2)); % find range of coordinates to be plotted
scale = [200 200]./range;                  % want 24x24 to be visible
for i=1:length(idx)
    imagesc(W(idx(i),1)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

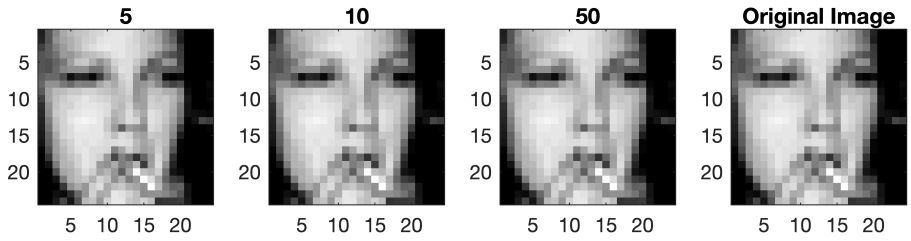


Part E: Choose two faces and reconstruct using only K principal directions

```
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 recovered
    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 recovered
    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');
```

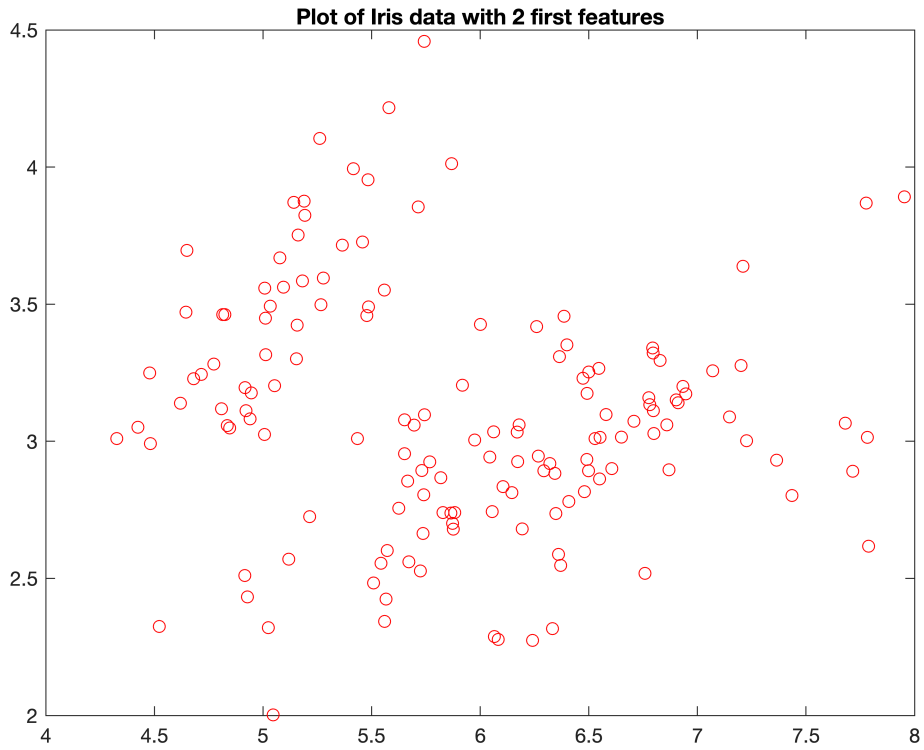




Clustering

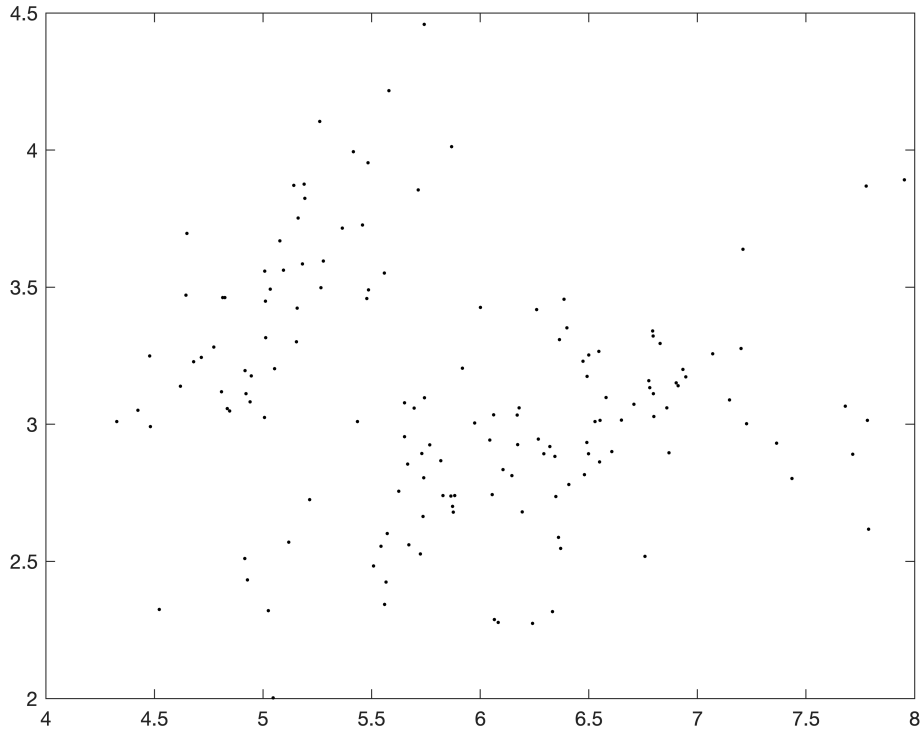
Part A: Load the usual Iris data with 2 features and plot

```
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');
```

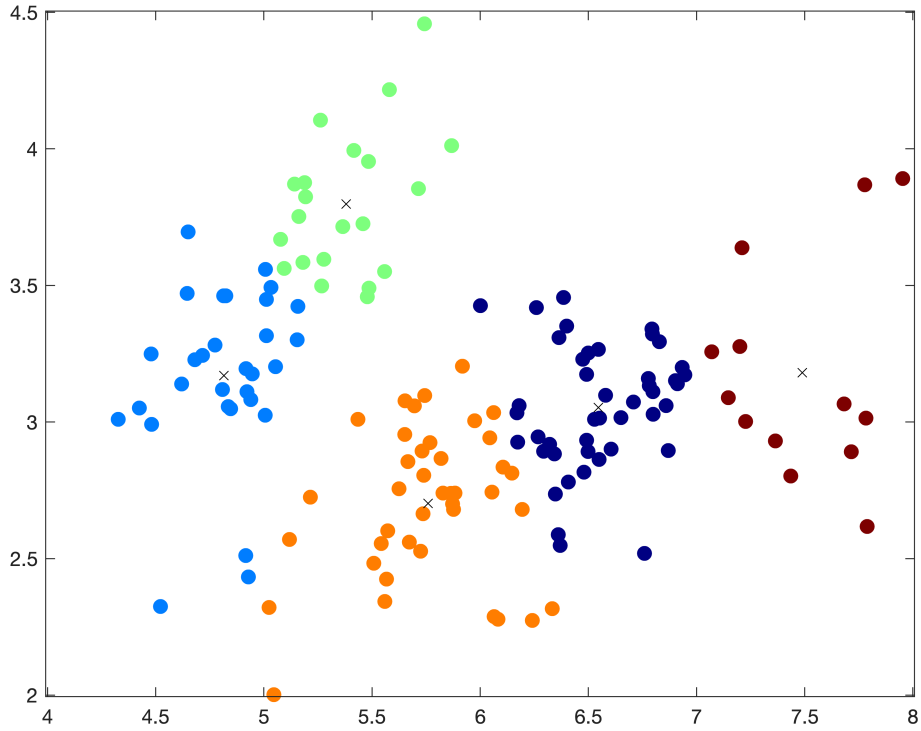


Part B: K-Means on the data

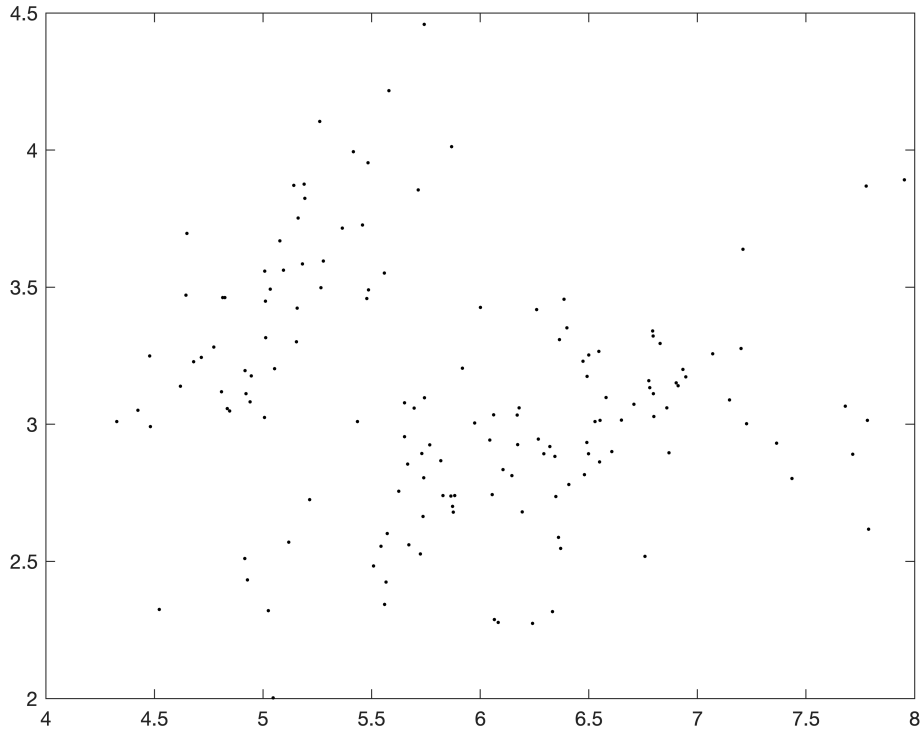
```
% Choose the initialization with the best score
% Run k-means with k = 5 with farthest initialization
figure(7);
title('k-means on the data with k = 5');
[z5 c5 sumd5] = kmeans(X_iris,5,'farthest',100);
plotClassify2D([],X_iris,z5);
```



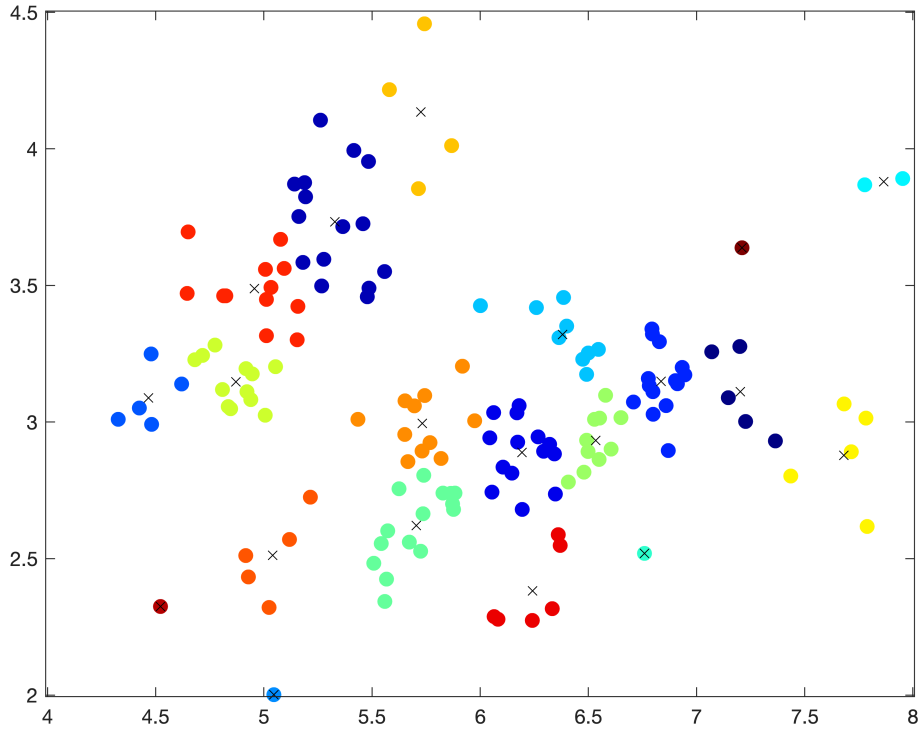

```
hold on
plot(c5(:,1),c5(:,2),'kx');
```




```
% 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);
```

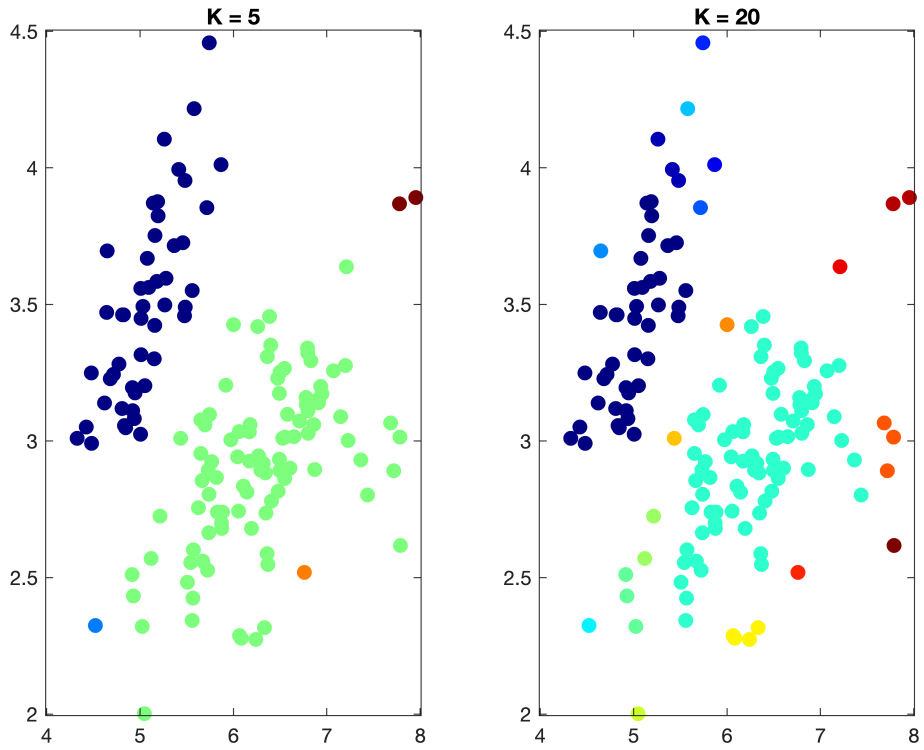



```
hold on
plot(c20(:,1),c20(:,2),'kx');
```

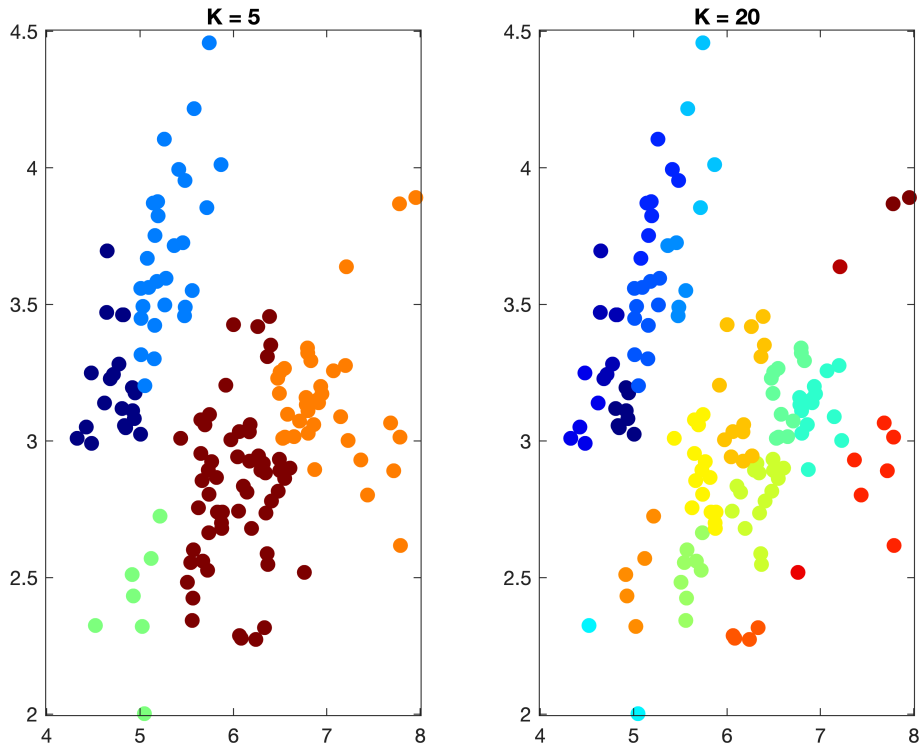


Part C: Run agglomerative clustering on the data

```
% 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');
```

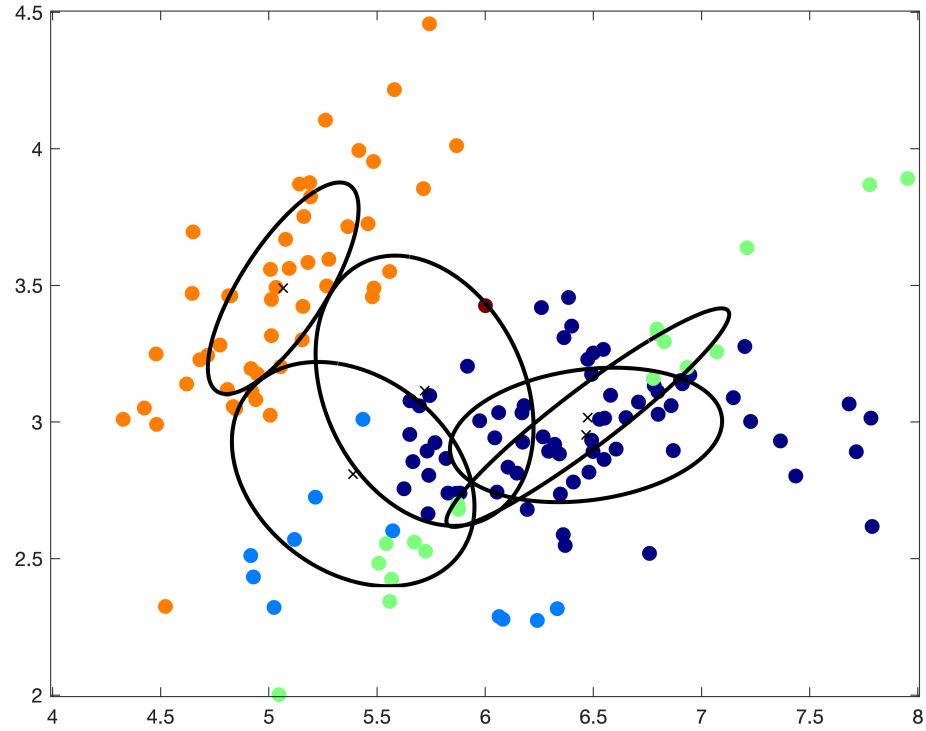


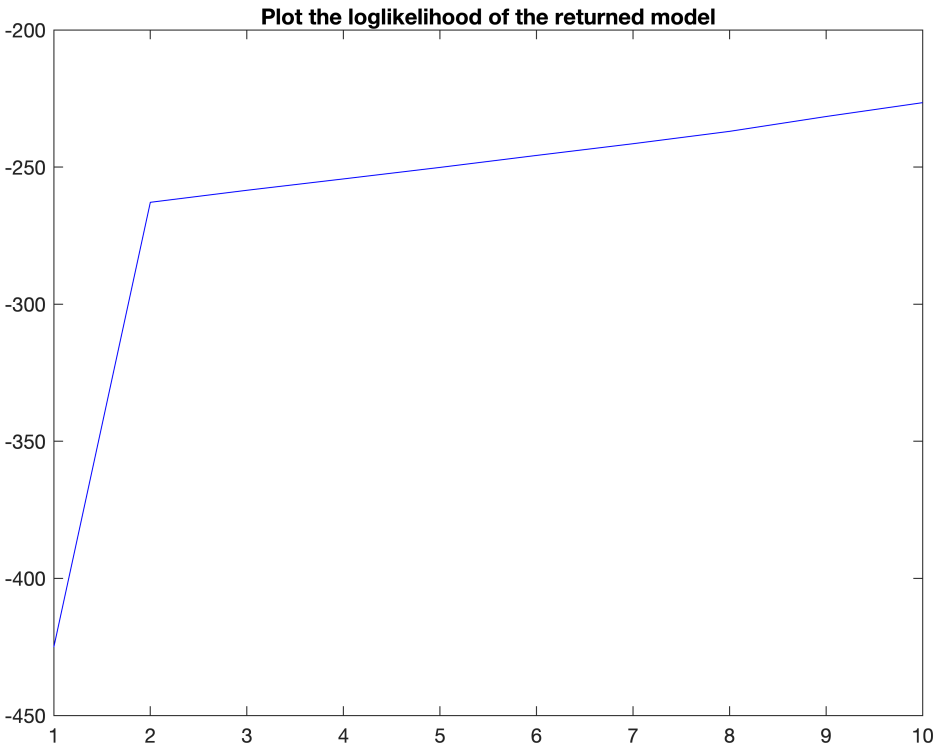

```
% Using complete linkage on Iris data
[z5_max_agg join] = agglomCluster(X_iris,5,'max'); % k = 5
[z20_max_agg join] = agglomCluster(X_iris,20,'max'); % k = 20
figure(10);
subplot(1,2,1);
plotClassify2D([],X_iris,z5_max_agg);
title('K = 5');
subplot(1,2,2);
plotClassify2D([],X_iris,z20_max_agg);
title('K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

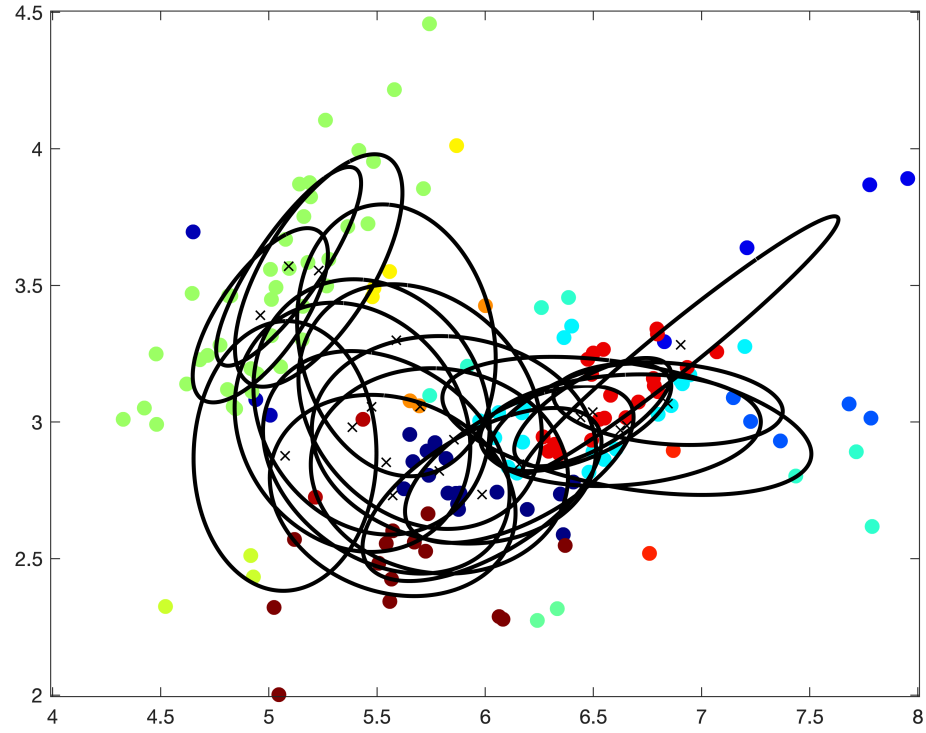


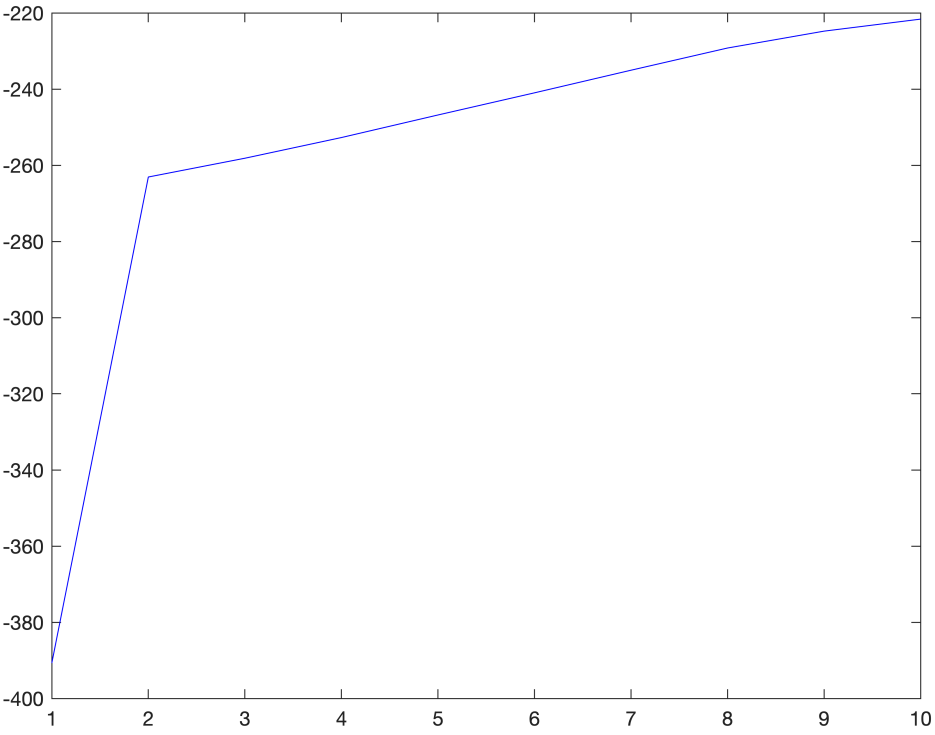
Part D: Run the EM Gaussian Mixture Model

```
% 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