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Homework 04

Problem 1

a)

```
clear;
close all

load data.mat
[d, N] = size(X);
T = 100;
K = 2;
fi_mul_x = zeros(d, 1);
fi = zeros(N, K);
nn = zeros(K, 1);
sumfi = zeros(K, 1);
pi_m = zeros(K, 1);
sigma_m = zeros(d, d, K);
ft = zeros(T, 1);

[labels, mu] = kmeans(X', K); % mu: K*d
mu_m = mu';
Y = X';

for j = 1:K
    sigma_m(:, :, j) = cov(Y(labels == j, :));
    pi_m(j) = sum(labels == j)/N;
end

for t = 1:T
    for j = 1:K
        for i = 1:N
            nor = mvnpdf(X(:, i), mu_m(:, j), sigma_m(:, :, j));
            fi(i, j) = pi_m(j) .* nor; % sum(pi_m .* nor); % num
        end
    end
    ft(t) = sum(log(sum(fi, 2)));

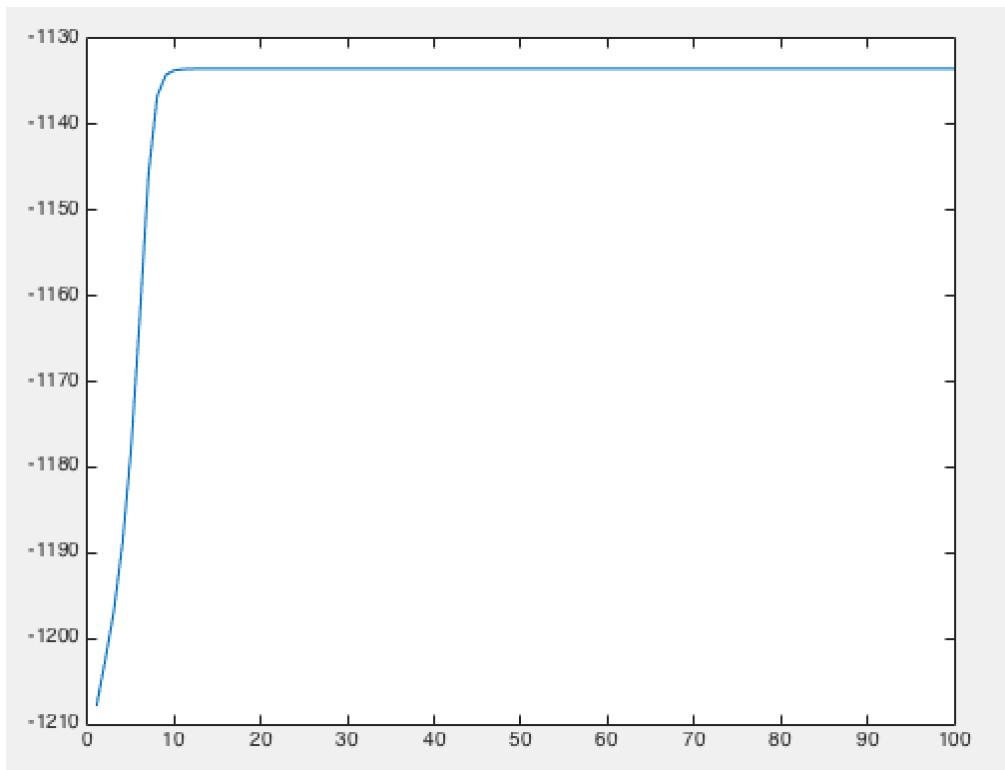
    fi = fi ./ repmat(sum(fi, 2), 1, K);

    for j = 1:K
        sumfi = sum(fi, 1);
        nn(j) = sumfi(j);
        summ = zeros(d, 1);
        for i = 1:N
            fi_mul_x = fi(i, j) .* X(:, i); % d*1
            summ = fi_mul_x + summ;
        end
        mu_m(:, j) = summ ./ nn(j); % d*1

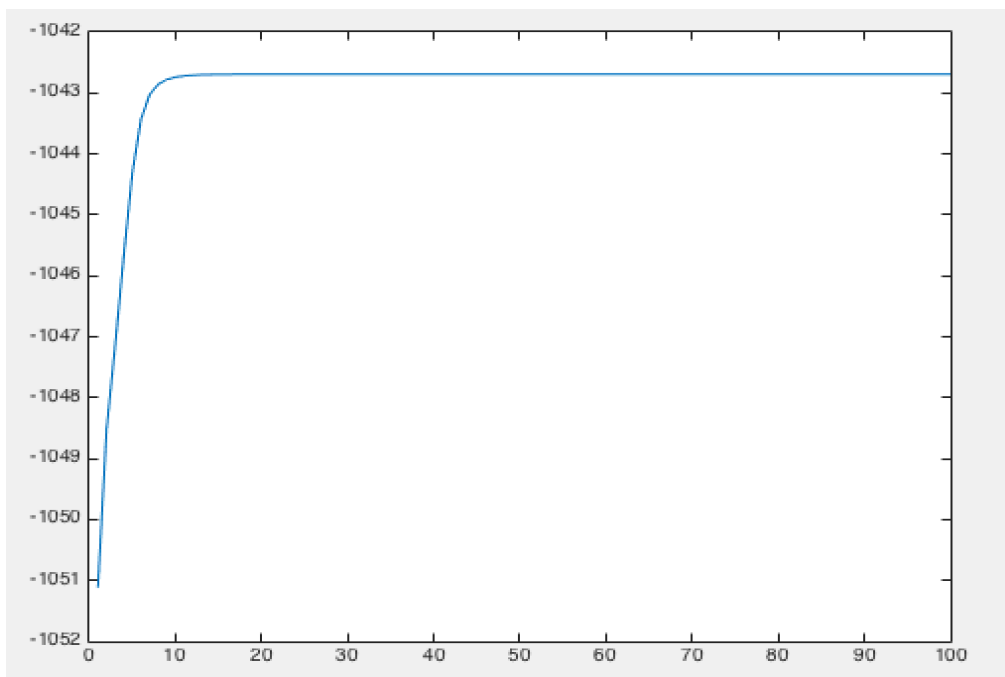
        sumfixx = zeros(d, d);
        for i = 1:N
            mul = fi(i, j) .* ((X(:, i) - mu_m(:, j)) * (X(:, i) - mu_m(:, j))');
            sumfixx = sumfixx + mul;
        end
        sigma_m(:, :, j) = sumfixx ./ nn(j); % d*d
        pi_m(j) = nn(j)/N;
    end
end
```

b)

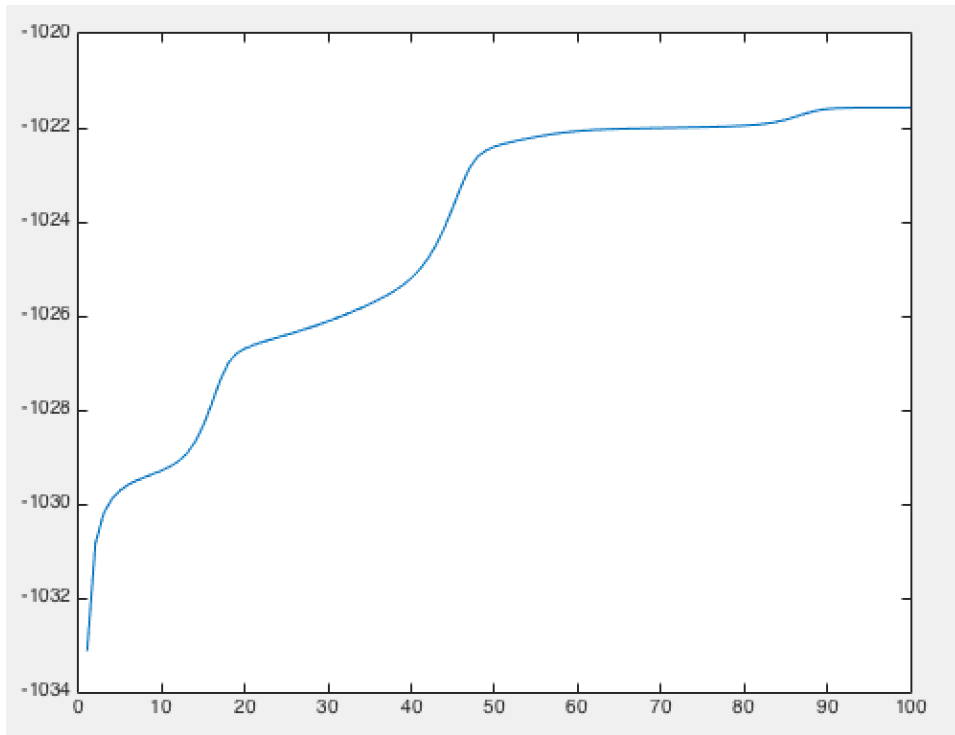
$K = 2$



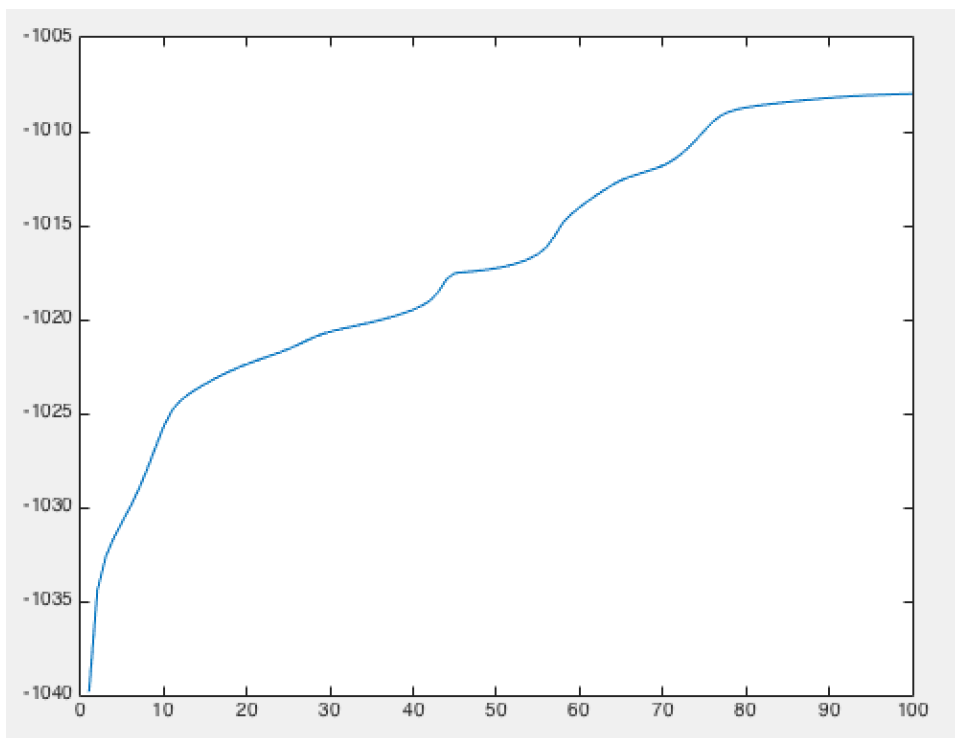
$K = 4$



$K = 8$



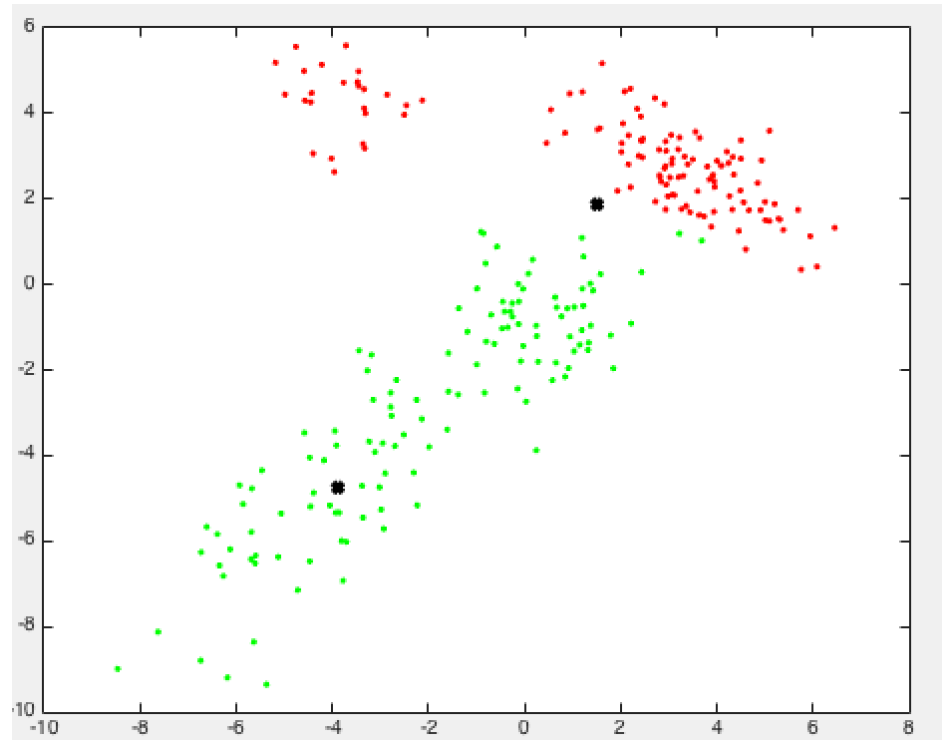
$K = 10$



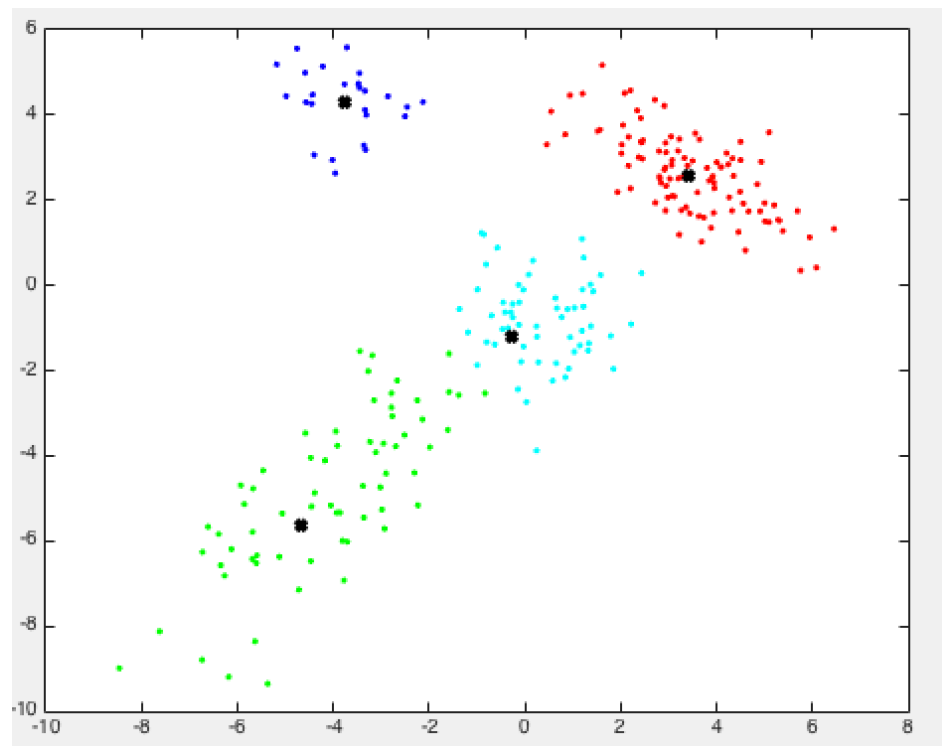
When K becomes larger (as we can see in $K = 8$ case and $K = 10$ case), the log likelihood does not converge as well as when K is small. So this might not be the best way to do model selection when K is large.

c)

$K = 2$

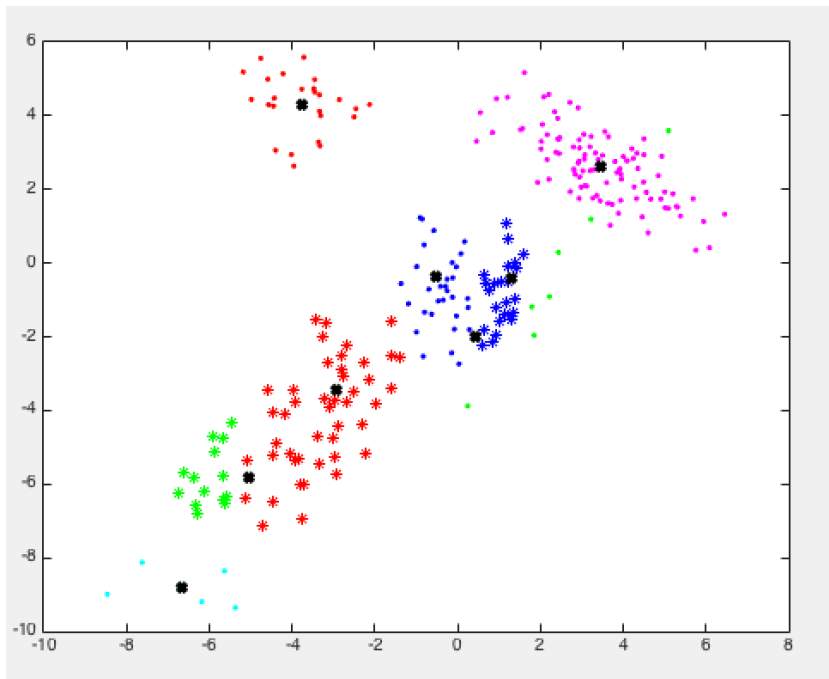


$K = 4$

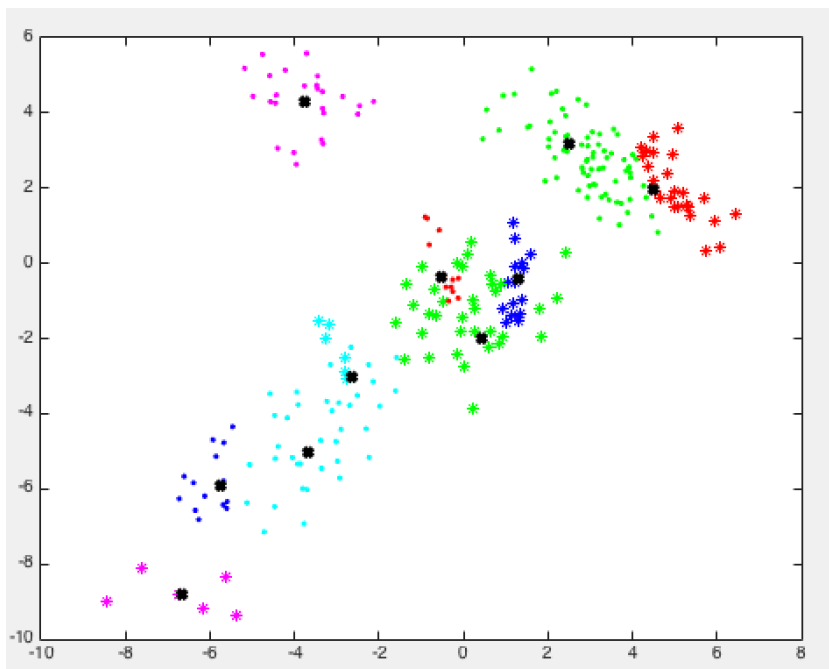


$K = 8$

("." in red and "*" in red represent different clusters, so do other colors)



$K = 10$

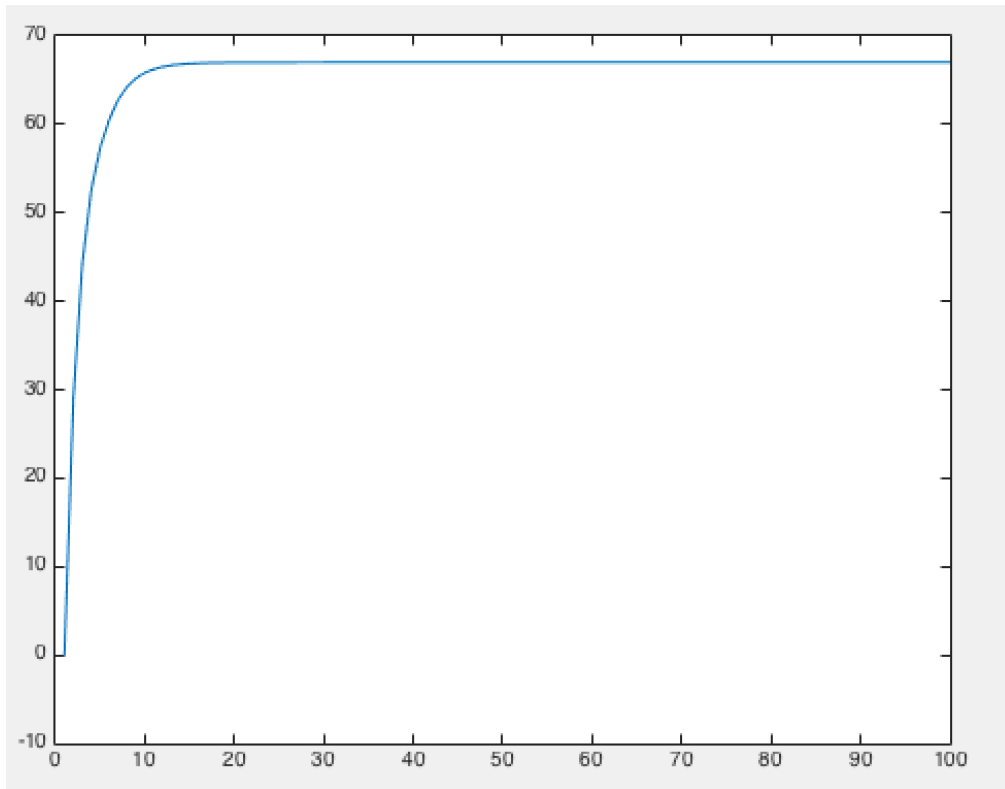


As K becomes larger, the boundary of each cluster is not as clear as when K is small. For example when $K = 8$, the green "." cluster is not classified well. This also indicates that this might not be the best way to do classification when K is large.

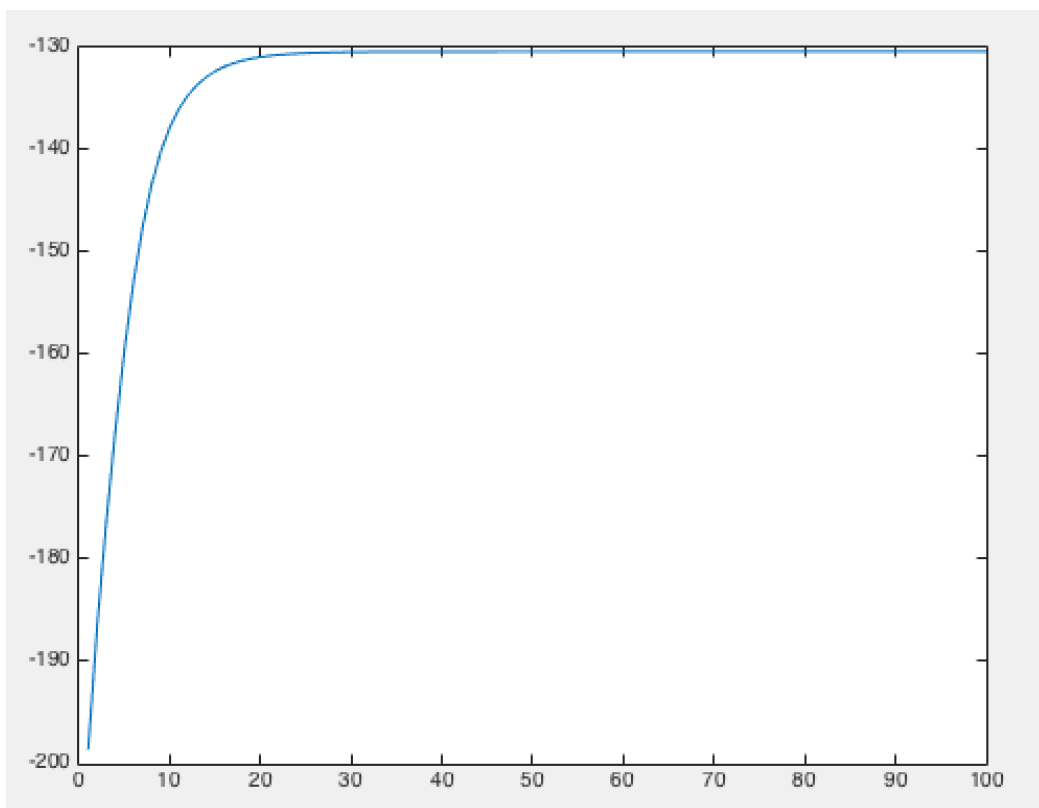
Problem 2

a)

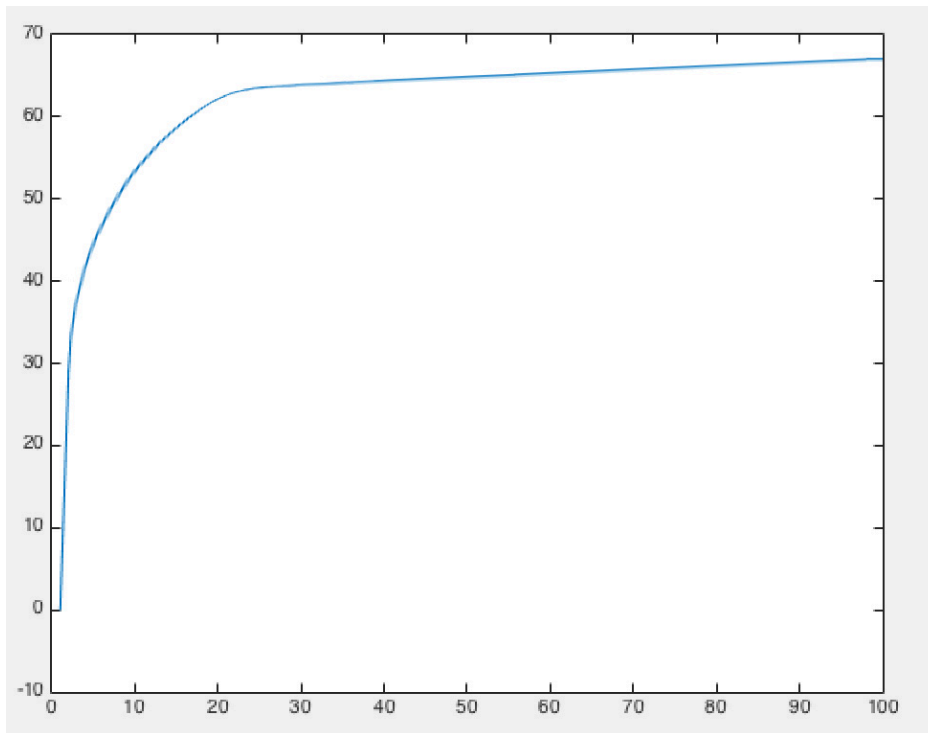
```
1 - clear;
2 - close all
3
4 - load data.mat
5 - [d, N] = size(X);
6 - K = 10;
7 - T = 100;
8 - t1 = zeros(K,1);
9 - t2 = zeros(K,1);
10 - t3 = zeros(K,1);
11 - t4 = zeros(K,1);
12 - alpha_0 = ones(K,1);
13 - alpha = ones(K,1);
14 - c = 10;
15 - a = d.*ones(K,1);
16 - a_0 = d.*ones(K,1);
17 - A = cov(X(1,:),X(2,:));%d*d
18 - B_0 = d/10.*A;%d*d
19 - B = zeros(d, d, K);%d*d*K
20 - sigma = zeros(d, d, K);
21 - n = zeros(K, 1);
22 - fi = zeros(N, K);
23 - fi_mul_x = zeros(d, 1);
24
25 - [labels, mu] = kmeans(X', K);% mu:K*d
26 - m = mu';%d*K
27 - %m = zeros(d, K);
28 - Y = X';
29
30 - for j = 1:K
31 -     B(:, :, j) = B_0;
32 -     sigma(:, :, j) = cov(Y(labels == j,:));
33 -     %sigma(:, :, j) = [0.9, 0.4;0.4, 0.3];
34 - end
35
36 - L = zeros(T,1);
37 - for t = 1:T
38 -     for j = 1:K
39 -         for i = 1:N
40 -             psia = 0;
41 -             for k = 1:d
42 -                 psia = psia + psi((1 - k + a(j))/2);
43 -             end
44 -             t1(j) = psia - log(det(B(:, :, j)));
45 -             t2(j) = (X(:, i) - m(:, j))'*(a(j).*pinv(B(:, :, j)))*(X(:, i) - m(:, j));
46 -             t3(j) = trace(a(j).*pinv(B(:, :, j))*sigma(:, :, j));
47 -             t4(j) = psi(alpha(j)) - psi(sum(alpha));
48 -             fi(i, j) = exp(0.5*t1(j) - 0.5*t2(j) - 0.5*t3(j) + t4(j));
49 -         end
50 -     end
51 -     fi = fi./repmat(sum(fi,2),1,K);
52 -     for j = 1:K
53 -         sumfi = sum(fi, 1);
54 -         n(j) = sumfi(j);
55 -         alpha(j) = alpha_0(j) + n(j);%.ones(K,1);
56 -         sigma(:, :, j) = pinv(1/c.*eye(d) + n(j).*a(j).*pinv(B(:, :, j)));
57 -         summ = zeros(d, 1);
58 -         for i = 1:N
59 -             fi_mul_x = fi(i, j).* X(:, i);%d*1
```

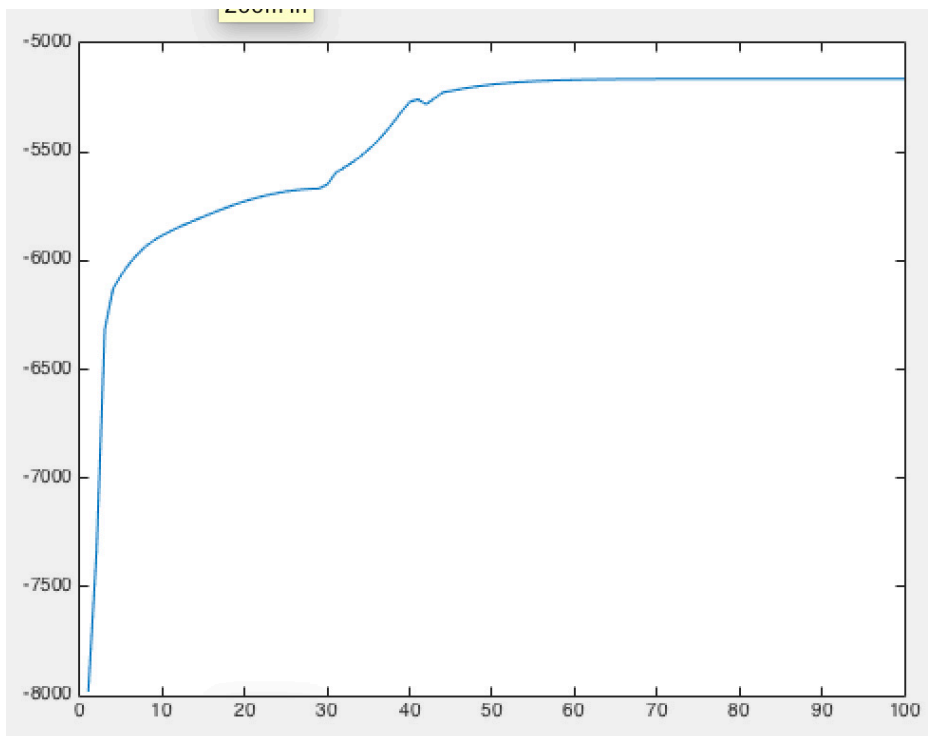
$K = 4$



$k = 10$

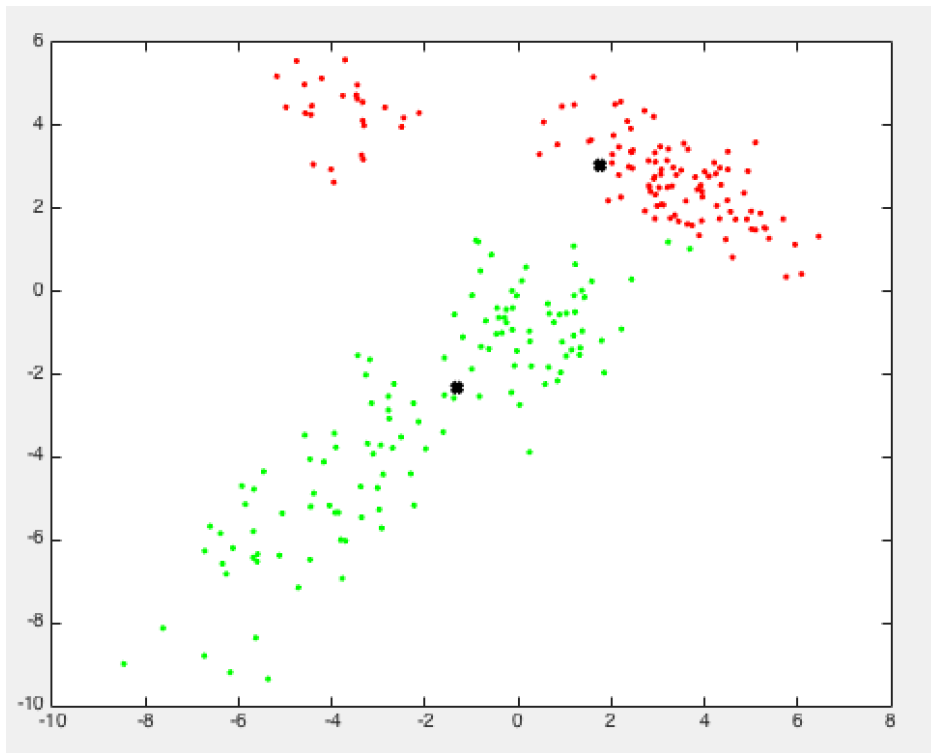


$K = 25$

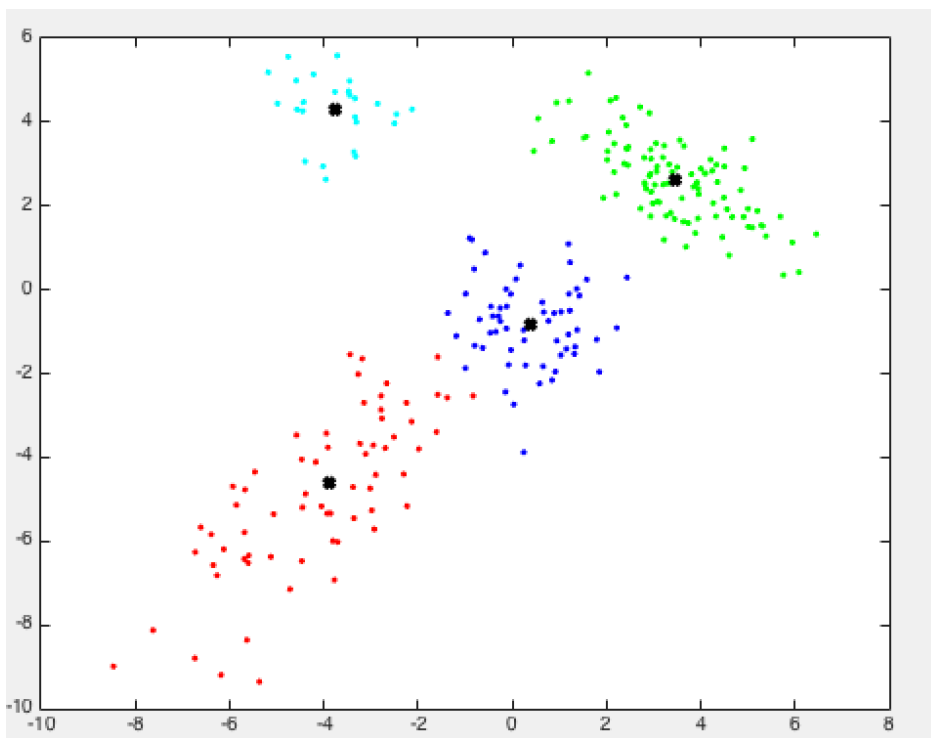


We notice that when K becomes larger, the objective function is not convergent as well as when K is small. When K is 25, the objective function becomes kind of out of shape. But this performs better than EM.

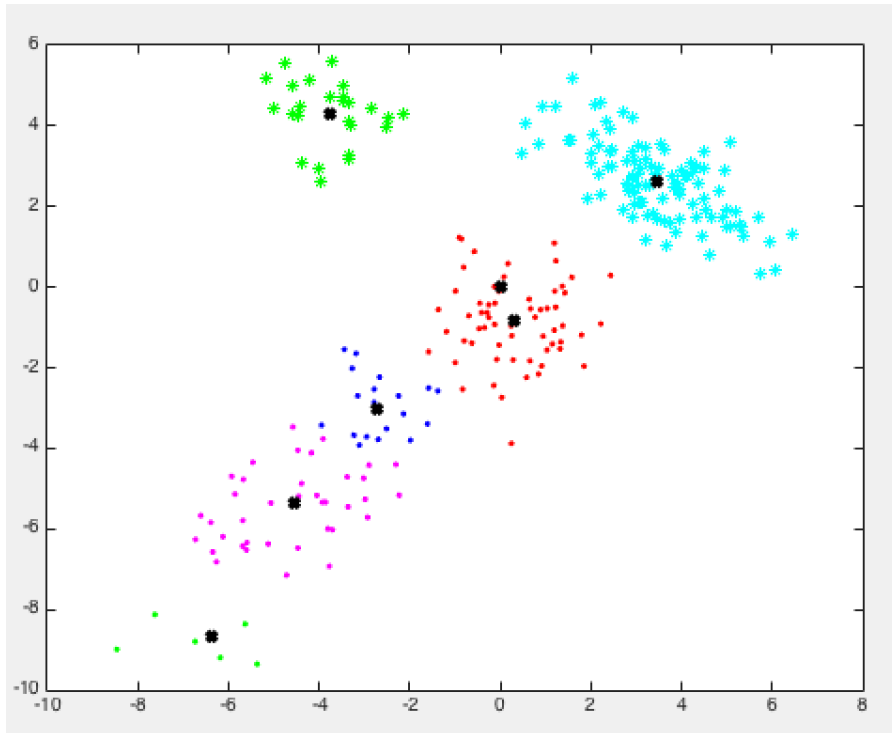
c)
 $K = 2$



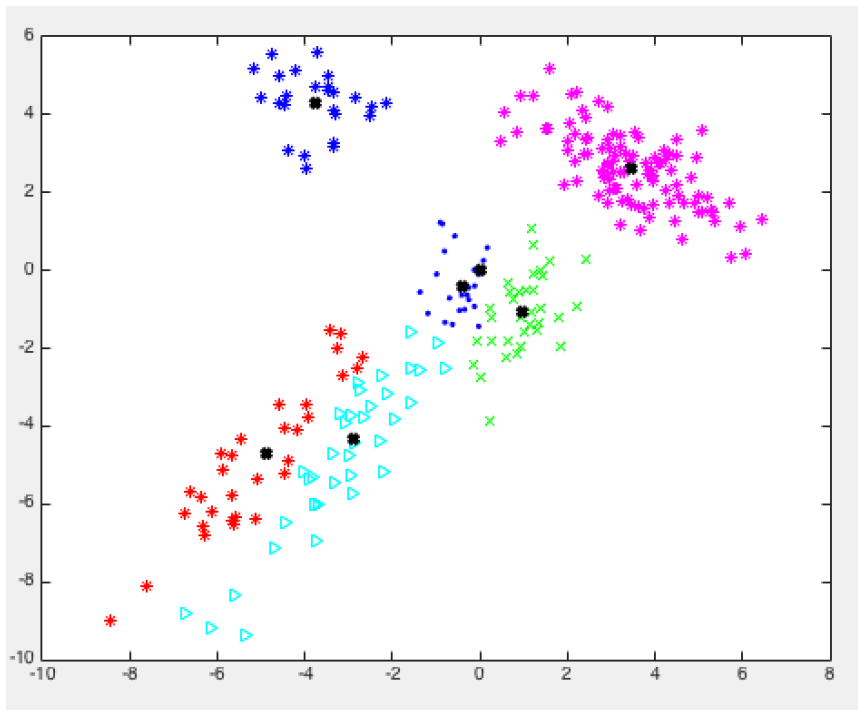
$K = 4$



$K = 10$



$K = 25$



As K becomes larger, VI can only have about 6 clusters. Although the result may be a little different for each cluster, the boundary is pretty clear. VI performs better than EM and the number of the clusters is convergent as K becomes larger.

problem 3

























```
1 - clear;
2 - close all
3
4 - load data.mat
5 - [d, N] = size(X);
6 - Y = X';
7 - labels = ones(N,1);
8
9 - m_0 = mean(Y)'; %2*1
10 - c_0 = 0.1;
11 - a_0 = d;
12 - A_0 = cov(X(1,:),X(2,:));
13 - B_0 = c_0*d.*A_0;
14 - alpha = 1;
15
16 - K = 1;
17
18 - T = 1;
19 - for t = 1:T
20 -     s = zeros(N,1); %size of cluster j
21 -     sumx = zeros(d,1);
22 -     m = zeros(d,1);
23 -     c = zeros(N,1);
24 -     a = zeros(N,1);
25 -     B = zeros(d, d, N);
26 -     sigma = zeros(d, d, N);
27 -     fi = zeros(N,1);
28 -     fi_new = zeros(N,1);
29 -     mu = zeros(d,1);
30 -     for j = 1:K
31 -         n = zeros(N,1);
32 -         for ii = 1:N %calculate n(i) & s(j)
```

```

33 -         if(labels(ii) == j)
34 -             s(j) = s(j) + 1;%how many numbers in cluster j
35 -         end
36 -         n(j) = s(j) - 1;
37 -         if (labels(ii) == j)
38 -             sumx = sumx + X(:,ii);
39 -         end
40 -     end%calculate n(i)
41 -
42 -     x_b = sumx./s(j);%d*1
43 -     m(:,j) = c_0/(c_0 + s(j)).*m_0 + 1/(c_0 + s(j)).*sumx;
44 -     c(j) = s(j) + c_0;
45 -     a(j) = s(j) + a_0;
46 -     sumxsxb = zeros(d, d, N);
47 -
48 -     for ii = 1:N
49 -         if (labels(ii) == j)
50 -             sumxsxb(:, :, j) = sumxsxb(:, :, j) + (X(:,ii)-x_b)*(X(:,ii)-x_b)';
51 -         end
52 -     end
53 -     B(:, :, j) = B_0 + sumxsxb(:, :, j) + s(j)/(a(j)*s(j)+1).*(x_b - m(:,j))*(x_b - m(:,j))';
54 -
55 -     sigma(:, :, j) = wishrnd(B(:, :, j), a(j));
56 -     mu(:, j) = mvnrnd(m(:, j), pinv(c(j).*sigma(:, :, j)));
57 - end
58 -
59 -
60 - for i = 1:3
61 -     for j = 1:K
62 -         %calculate phi for current cluster
63 -         fi(j) = mvnpdf(X(:,i), mu(:,j), pinv(sigma(:, :, j))) .* (n(j)/(alpha + N -1));
64 -
65 -         %calculate phi for a new cluster
66 -         part1 = c_0/(pi*(1+c_0))^(d/2);
67 -         part2 = det(B_0 + (c_0/(1+c_0)).*(X(:,i)-m_0)*(X(:,i)-m_0)')^(-0.5*(a_0+1));
68 -         part3 = det(B_0)^(-0.5*a_0);
69 -         part4 = exp(gamaln((a_0+1)/2) + gamaln(a_0/2) - gamaln(a_0/2) - gamaln((a_0-1)/2));
70 -         fi_new(j) = alpha/(alpha + N - 1)*(part1 * part2/part3 * part4);
71 -
72 -         fi_oldd = fi(j)/(fi(j) + fi_new(j));
73 -         fi_neww = fi_new(j)/(fi(j) + fi_new(j));
74 -     end
75 -     class = discretisample([fi_oldd, fi_neww], 1);
76 -     if (class == 2)
77 -         K = K + 1;
78 -         %[labels, mu] = kmeans(X', K);%random sample
79 -         labels(i) = K;%put i in the new cluster
80 -
81 -         x_b = X(:,i);%d*1
82 -         sumx = X(:,i);%d*1
83 -         m(:,K) = c_0/(c_0 + 1).*m_0 + 1/(c_0 + 1).*sumx;
84 -         c(K) = 1 + c_0;
85 -         a(K) = 1 + a_0;
86 -         sumxsxb(:, :, K) = (X(:,i)-x_b)*(X(:,i)-x_b)';
87 -
88 -         B(:, :, K) = B_0 + sumxsxb(:, :, K) + 1/(a(K)+1).*(x_b - m(:,K))*(x_b - m(:,K))';
89 -
90 -         sigma(:, :, K) = wishrnd(B(:, :, K), a(K));
91 -         mu(:, K) = mvnrnd(m(:, K), pinv(c(K).*sigma(:, :, K)));
92 -     end
93 - %end
94 - end
95 - end

```

The workspace is like follows:

Workspace	
Name ▲	Value
 a	250x1 double
 a_0	2
 A_0	[12.3038,7.5328;...
 alpha	1
 B	2x2x250 double
 B_0	[2.4608,1.5066;1...
 c	250x1 double
 c_0	0.1000
 class	2
 d	2
 fi	250x1 double
 fi_new	250x1 double
 fi_neww	1
 fi_oldd	0
 i	3
 ii	250
 j	3
 K	4
 labels	250x1 double
 m	[1.1946e-16,3.7...
 m_0	[1.1946e-16;-3....
 mu	[-6.9640e-05,5....
 n	250x1 double
 N	250

part1	0.0289
part2	0.0449
part3	0.2501
part4	0.5000
s	<i>250x1 double</i>
sigma	<i>2x2x250 double</i>
sumx	[4.9085;1.7415]
sumxsxb	<i>2x2x250 double</i>
t	1
T	1
X	<i>2x250 double</i>
x_b	[4.9085;1.7415]
Y	<i>250x2 double</i>

We can guess that K is convergent with iterations.