

# Mixture of Gaussians and the EM Algorithm

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## Point 1

Implement the EM algorithm to estimate the parameters of a mixture of Gaussians when we have data of any dimension and any number of classes.

**Solution:**

```
source(file = "EM_function.R")
```

```
## Warning: package 'birdring' was built under R version 4.4.3
```

```
library(ggplot2)
library(mvtnorm)
```

```
## Warning: package 'mvtnorm' was built under R version 4.4.2
```

```
##
## Attaching package: 'mvtnorm'
```

```
## The following object is masked from 'package:birdring':
##
##      dmnorm
```

```
library(reshape)
```

```
## Warning: package 'reshape' was built under R version 4.4.3
```

```
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
## v dplyr      1.1.4      v readr      2.1.5
## v forcats    1.0.0      v stringr    1.5.1
## v lubridate  1.9.3      v tibble     3.2.1
## v purrr      1.0.2      v tidyr      1.3.1
```

```

## -- Conflicts ----- tidyverse_conflicts() --
## x tidyr::expand()      masks reshape::expand()
## x dplyr::filter()      masks stats::filter()
## x dplyr::lag()          masks stats::lag()
## x dplyr::rename()       masks reshape::rename()
## x lubridate::stamp()    masks reshape::stamp()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors

#Example usage:
library(MASS) # For generating multivariate normal data

##
## Attaching package: 'MASS'

## The following object is masked from 'package:dplyr':
##
##      select

# Generate some example data
set.seed(123)
n1 <- 200
n2 <- 150
X1 <- mvrnorm(n1, mu = c(0, 0), Sigma = matrix(c(1, 0, 0, 1), 2, 2))
X2 <- mvrnorm(n2, mu = c(5, 5), Sigma = matrix(c(1, 0.5, 0.5, 1), 2, 2))
X <- rbind(X1, X2)

# Set initial parameters
K <- 2
D <- 2

# Run EM algorithm with initial parameters
model <- em_gaussian_mixture(X, K, max_iter = 50)

## Iteration: 1
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1382.304 Improvement: Inf
## Iteration: 2
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1350.8 Improvement: 31.50387
## Iteration: 3
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1307.065 Improvement: 43.73533
## Iteration: 4
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1273.576 Improvement: 33.48868
## Iteration: 5
##   E-step: Computing responsibilities
##   M-step: Updating parameters

```

```

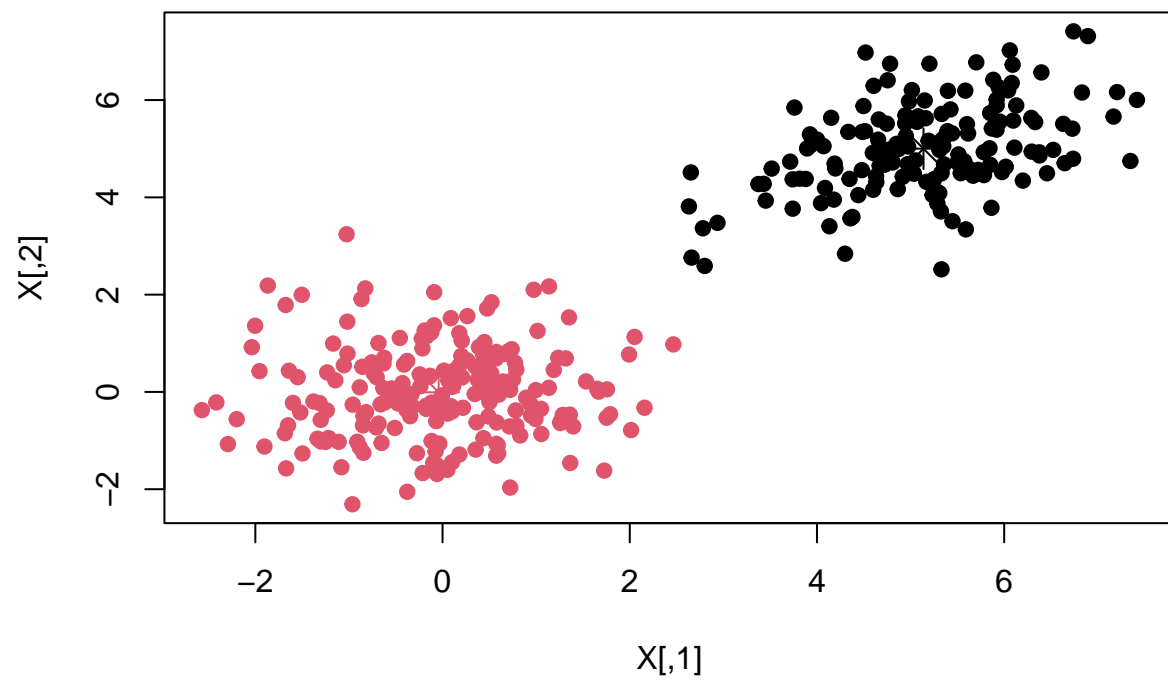
##   Log-likelihood: -1230.952 Improvement: 42.62426
## Iteration: 6
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1199.193 Improvement: 31.7585
## Iteration: 7
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1191.172 Improvement: 8.021464
## Iteration: 8
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1190.582 Improvement: 0.5896712
## Iteration: 9
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1190.577 Improvement: 0.005030017
## Iteration: 10
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1190.577 Improvement: 1.902908e-05
## Iteration: 11
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1190.577 Improvement: 6.8791e-08
## Converged after 11 iterations

```

```

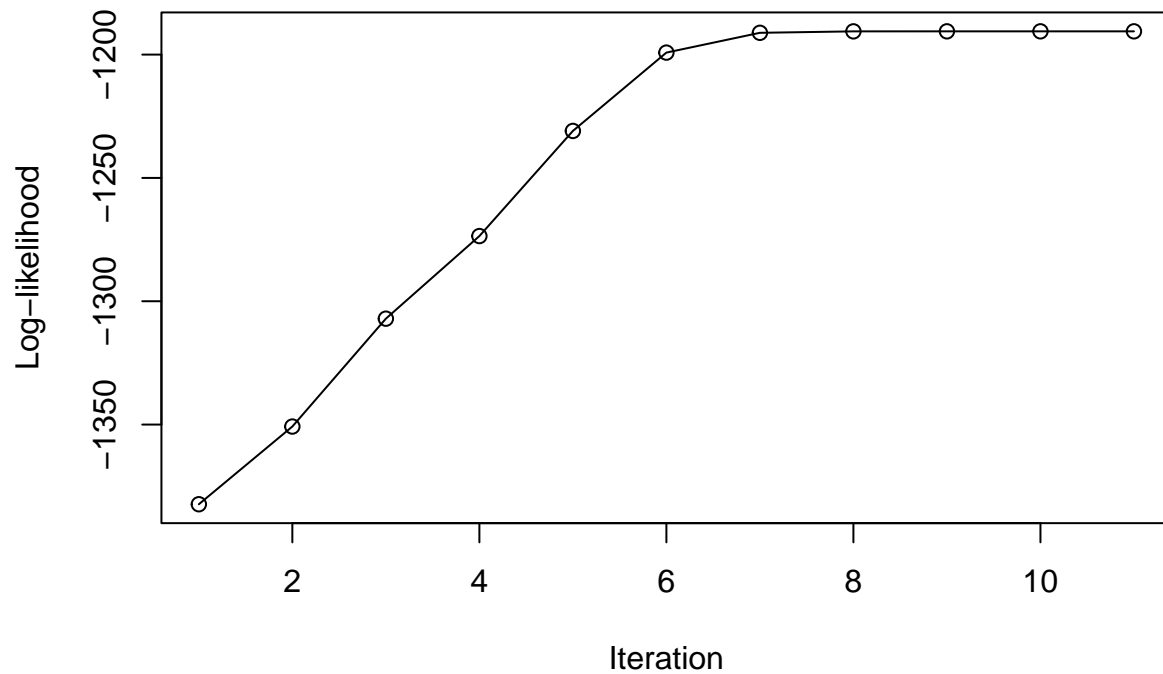
# Plot results
plot(X, col = predict_cluster(model, X), pch = 19)
points(model$mu, col = 1:model$K, pch = 8, cex = 2)

```



```
plot_convergence(model)
```

## EM Algorithm Convergence



### Point 2

Check that it works for synthetic data generated according to a mixture of Gaussians in:

#### a) 1 dimensions

Solution:

```
Mu1 = 5
Mu2 = 7
S1 = 1
S2 = 2

pi = 1/3
n = 300

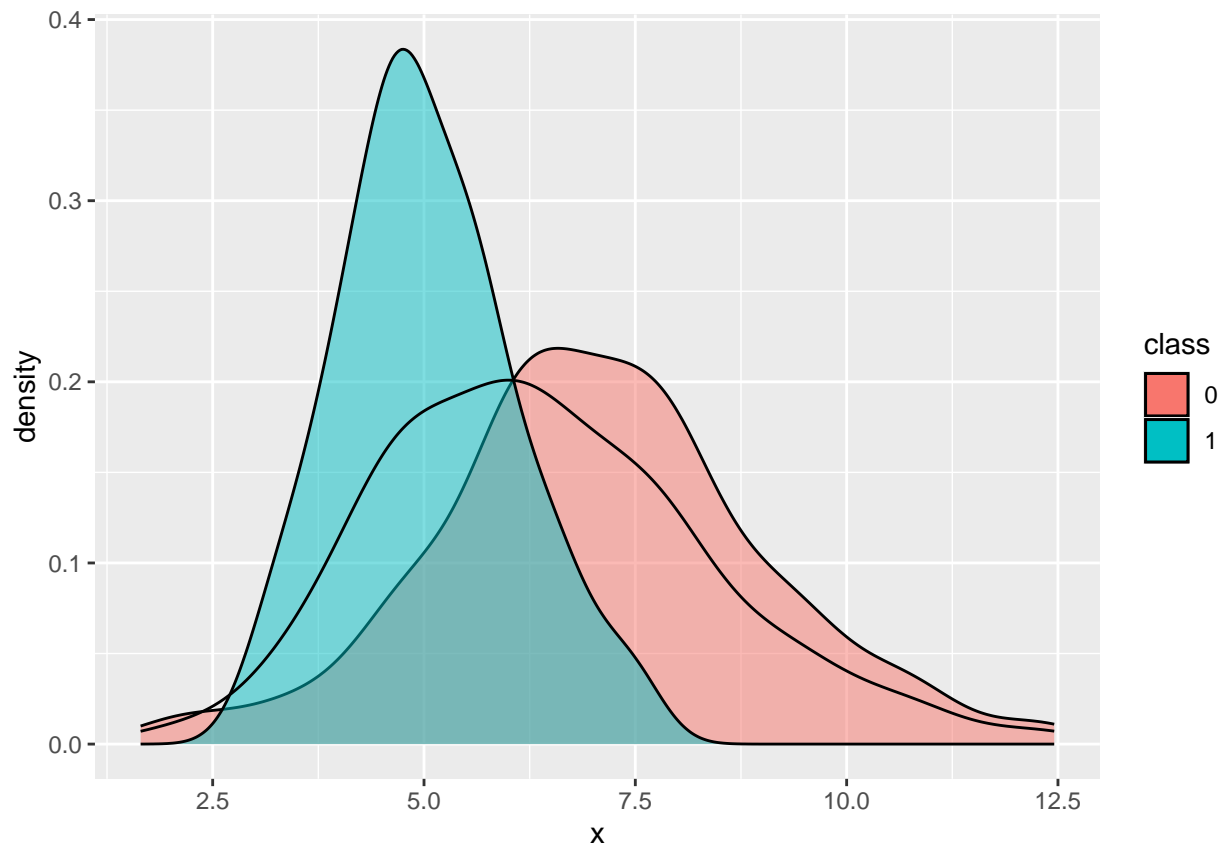
set.seed(100)
data = matrix(0, n, 1)
z = rep(0,n)
for (i in 1:n){
  z[i] = rbinom(1,1,pi)
  if (z[i] == 1){
    data[i,] = rnorm(1, Mu1,S1)
```

```

    }else{
      data[i,] = rnorm(1, Mu2,S2)
    }
  }

to.plot = data.frame(x = data[,1],
                     class = as.factor(z))
ggplot(to.plot) + geom_density(aes(x=x,fill=class), alpha=.5) + geom_density(aes(x=x))

```



The black line through the two distributions shows the mixed distribution curve.

```

X=data
K=2
# Run EM algorithm with initial parameters
model_1d <- em_gaussian_mixture(X, K, max_iter = 50)

## Iteration: 1
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -618.8413 Improvement: Inf
## Iteration: 2
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -618.4404 Improvement: 0.4009375
## Iteration: 3

```

```

## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3937 Improvement: 0.04666365
## Iteration: 4
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3862 Improvement: 0.007539204
## Iteration: 5
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3833 Improvement: 0.00289946
## Iteration: 6
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3812 Improvement: 0.002020967
## Iteration: 7
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3796 Improvement: 0.001608739
## Iteration: 8
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3783 Improvement: 0.001303829
## Iteration: 9
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3773 Improvement: 0.001058715
## Iteration: 10
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3764 Improvement: 0.0008598799
## Iteration: 11
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3757 Improvement: 0.0006987098
## Iteration: 12
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3751 Improvement: 0.0005683067
## Iteration: 13
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3747 Improvement: 0.0004629834
## Iteration: 14
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3743 Improvement: 0.0003780514
## Iteration: 15
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.374 Improvement: 0.0003096591
## Iteration: 16
## E-step: Computing responsibilities
## M-step: Updating parameters

```

```

## Log-likelihood: -618.3737 Improvement: 0.0002546534
## Iteration: 17
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3735 Improvement: 0.000210461
## Iteration: 18
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3733 Improvement: 0.0001749882
## Iteration: 19
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3732 Improvement: 0.0001465356
## Iteration: 20
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3731 Improvement: 0.000123727
## Iteration: 21
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.373 Improvement: 0.0001054505
## Iteration: 22
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3729 Improvement: 9.080918e-05
## Iteration: 23
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3728 Improvement: 7.908075e-05
## Iteration: 24
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3727 Improvement: 6.968443e-05
## Iteration: 25
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3727 Improvement: 6.215381e-05
## Iteration: 26
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3726 Improvement: 5.611478e-05
## Iteration: 27
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3726 Improvement: 5.126752e-05
## Iteration: 28
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3725 Improvement: 4.737204e-05
## Iteration: 29
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3725 Improvement: 4.423633e-05
## Iteration: 30

```



```

## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3724 Improvement: 4.170689e-05
## Iteration: 31
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3724 Improvement: 3.96611e-05
## Iteration: 32
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3724 Improvement: 3.800104e-05
## Iteration: 33
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3723 Improvement: 3.664857e-05
## Iteration: 34
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3723 Improvement: 3.554134e-05
## Iteration: 35
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3722 Improvement: 3.462964e-05
## Iteration: 36
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3722 Improvement: 3.387381e-05
## Iteration: 37
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3722 Improvement: 3.324227e-05
## Iteration: 38
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3721 Improvement: 3.270983e-05
## Iteration: 39
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3721 Improvement: 3.225644e-05
## Iteration: 40
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3721 Improvement: 3.186612e-05
## Iteration: 41
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3721 Improvement: 3.152614e-05
## Iteration: 42
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.372 Improvement: 3.122636e-05
## Iteration: 43
## E-step: Computing responsibilities
## M-step: Updating parameters

```

```

## Log-likelihood: -618.372 Improvement: 3.09587e-05
## Iteration: 44
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.372 Improvement: 3.071675e-05
## Iteration: 45
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3719 Improvement: 3.049537e-05
## Iteration: 46
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3719 Improvement: 3.029049e-05
## Iteration: 47
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3719 Improvement: 3.009887e-05
## Iteration: 48
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3718 Improvement: 2.991792e-05
## Iteration: 49
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3718 Improvement: 2.974558e-05
## Iteration: 50
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -618.3718 Improvement: 2.95802e-05

```

```

# Plot results

```

```

to.plot = data.frame(x = data[,1],
                     class = as.factor(predict_cluster(model_1d, X)))

```

```

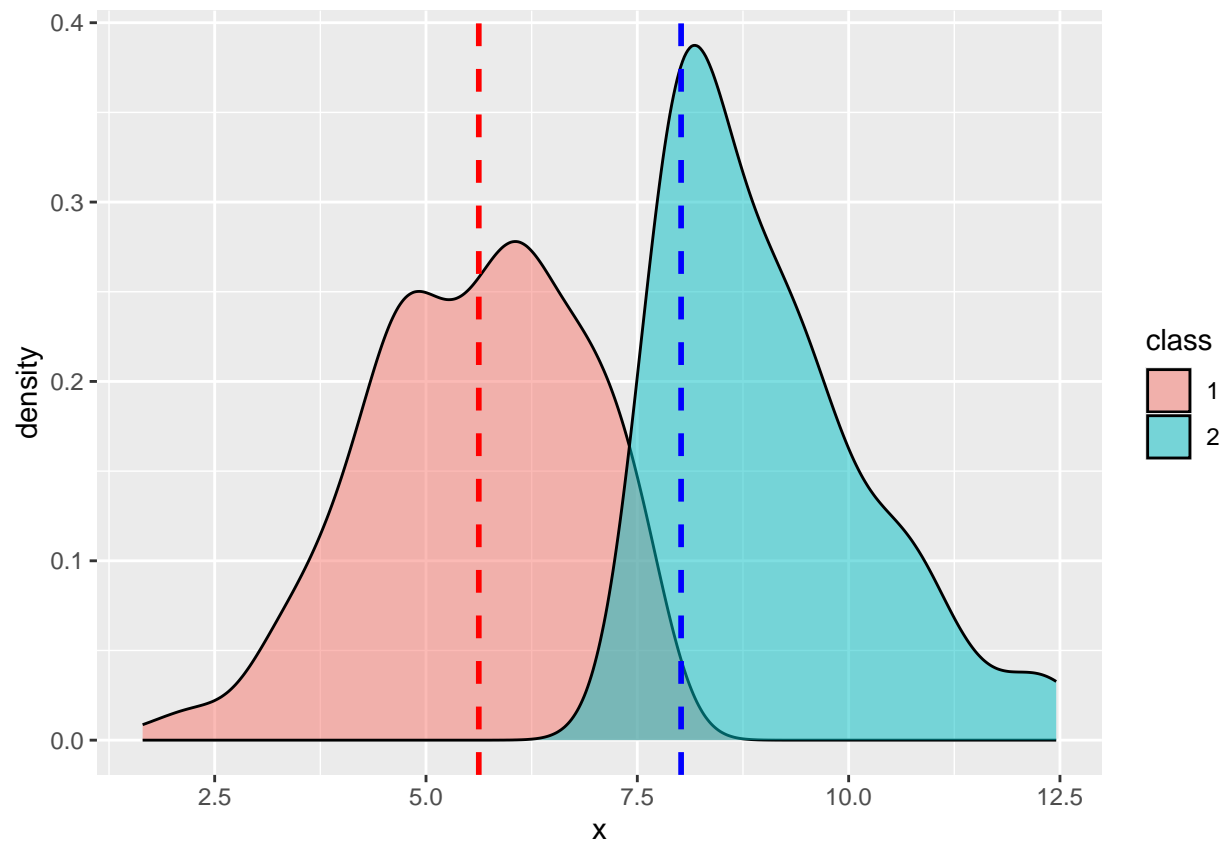
# hist(X, col = predict_cluster(model_1d, X), pch = 19)

```

```

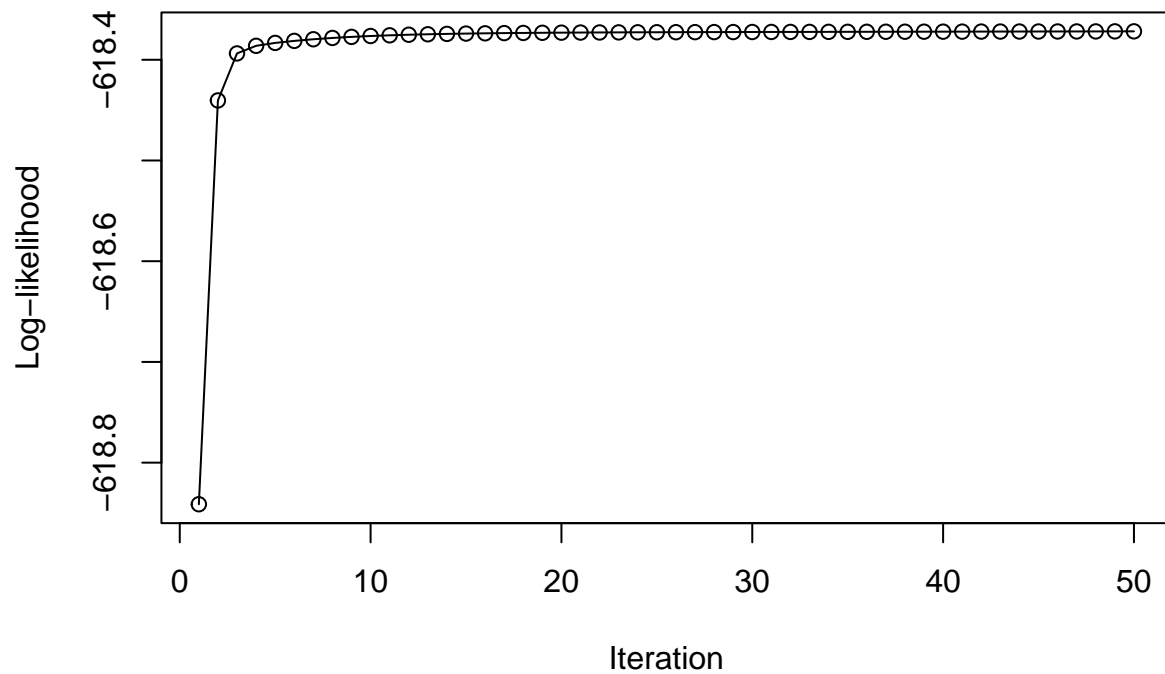
ggplot(to.plot) + geom_density(aes(x=x,fill=class), alpha=.5)+
  geom_vline(aes(xintercept = model_1d$mu[1]), color = "red", linetype = "dashed", size = 1)+
  geom_vline(aes(xintercept = model_1d$mu[2]), color = "blue", linetype = "dashed", size = 1)

```



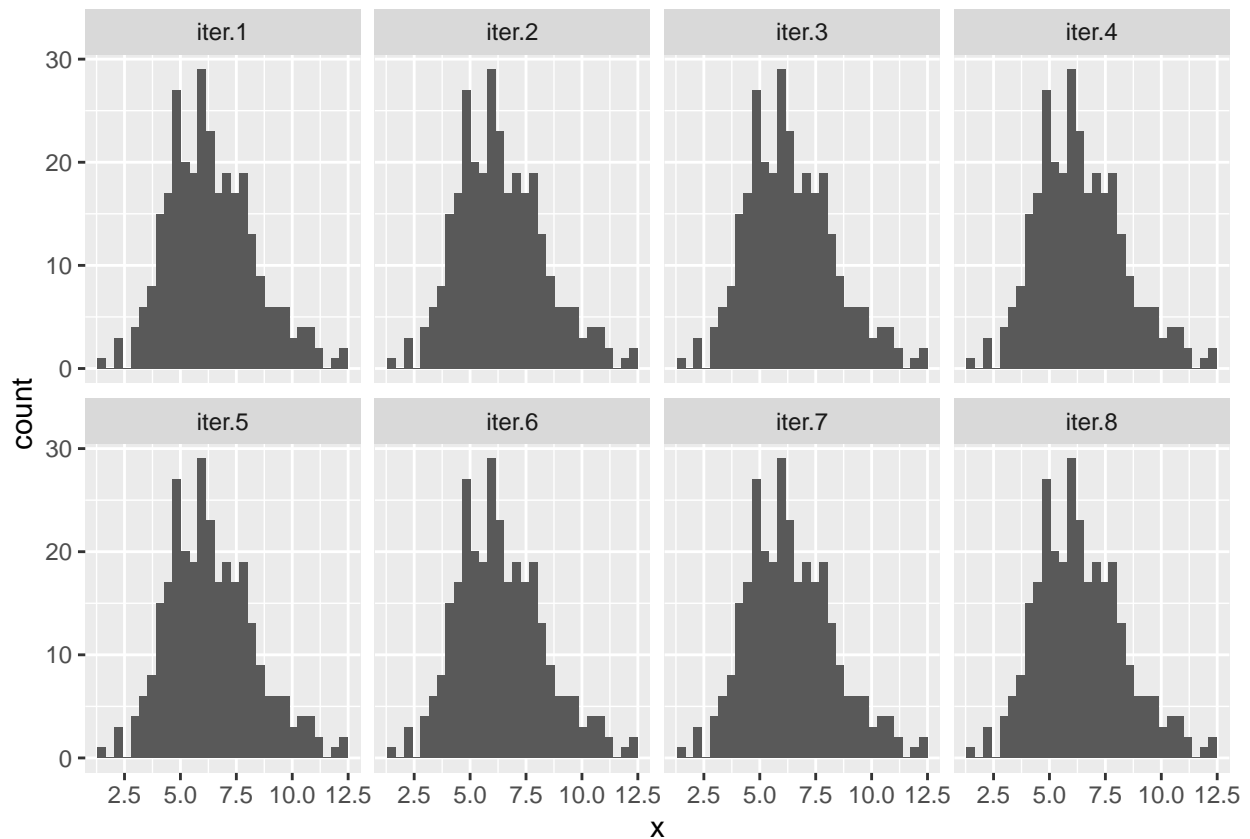
```
plot_convergence(model_1d)
```

## EM Algorithm Convergence



```
to.plot = data.frame(x = data[,1],  
                     iter = model_1d$Alpha[,1:8])  
to.plot <- pivot_longer(to.plot, cols = -c("x"))  
  
ggplot(to.plot)+aes(x, color = value)+  
  geom_histogram()+facet_wrap(~name, nrow = 2)
```

```
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
```



## b) 2 dimensions

Solution:

```
library(ggplot2)
library(mvtnorm)
Mu1 = c(1,1)
Mu2 = c(7,7)
Mu3 = c(3,3)
Sigma1 = matrix(c(2, 1, 1, 1), 2,2)
Sigma2 = matrix(c(2, 2, 2, 5), 2,2)
Sigma3 = matrix(c(3, 2, 2, 3), 2,2)

pi = 1/3
n = 300

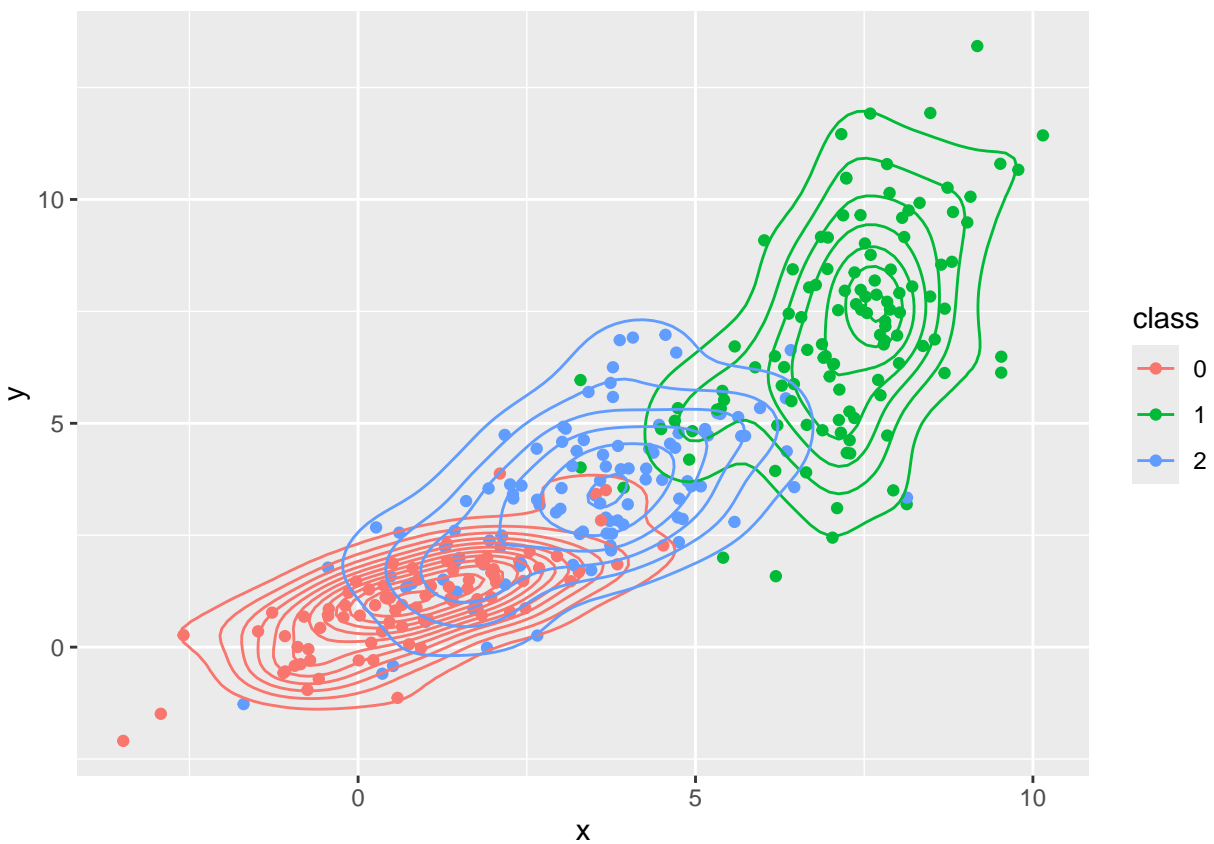
set.seed(100)
data = matrix(0, n, 2)
z = rep(0,n)
for (i in 1:n){
  z[i] = runif(1) #generate a random val to determine from what dist it comes
  if (z[i] <= 0.33){
    data[i,] = rmvnorm(1, Mu1,Sigma1)
    z[i] = 0
  }else if (z[i] >= 0.67){
```

```

    data[i,] = rmvnorm(1, Mu2,Sigma2)
    z[i] = 1
  }else {
    data[i,] = rmvnorm(1, Mu3,Sigma3)
    z[i] = 2
  }
}

to.plot = data.frame(x = data[,1],
                     y = data[,2],
                     class = as.factor(z))
ggplot(to.plot)+ aes(x, y, color = class)+
  geom_point()+geom_density_2d()

```



```

X=data
K=3
# Run EM algorithm with initial parameters
model_2d <- em_gaussian_mixture(X, K, max_iter = 50)

```

```

## Iteration: 1
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1244.113 Improvement: Inf
## Iteration: 2
##   E-step: Computing responsibilities

```

```

## M-step: Updating parameters
## Log-likelihood: -1237.93 Improvement: 6.183235
## Iteration: 3
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1236.04 Improvement: 1.889729
## Iteration: 4
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1235.109 Improvement: 0.9305814
## Iteration: 5
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1234.501 Improvement: 0.608576
## Iteration: 6
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1234.043 Improvement: 0.4578222
## Iteration: 7
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1233.676 Improvement: 0.3671716
## Iteration: 8
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1233.372 Improvement: 0.3035804
## Iteration: 9
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1233.117 Improvement: 0.2553471
## Iteration: 10
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1232.899 Improvement: 0.2174851
## Iteration: 11
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1232.712 Improvement: 0.1873507
## Iteration: 12
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1232.549 Improvement: 0.1632364
## Iteration: 13
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1232.405 Improvement: 0.1438995
## Iteration: 14
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1232.277 Improvement: 0.128392
## Iteration: 15
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1232.161 Improvement: 0.115986

```

```

## Iteration: 16
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1232.054 Improvement: 0.1061303
## Iteration: 17
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1231.956 Improvement: 0.09841874
## Iteration: 18
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1231.863 Improvement: 0.09256498
## Iteration: 19
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1231.775 Improvement: 0.08838473
## Iteration: 20
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1231.689 Improvement: 0.08578386
## Iteration: 21
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1231.605 Improvement: 0.08475349
## Iteration: 22
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1231.519 Improvement: 0.08537231
## Iteration: 23
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1231.431 Improvement: 0.08781676
## Iteration: 24
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1231.339 Improvement: 0.09237989
## Iteration: 25
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1231.239 Improvement: 0.09949855
## Iteration: 26
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1231.13 Improvement: 0.109785
## Iteration: 27
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1231.006 Improvement: 0.1240483
## Iteration: 28
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1230.862 Improvement: 0.1432658
## Iteration: 29
##   E-step: Computing responsibilities

```



```

## M-step: Updating parameters
## Log-likelihood: -1230.694 Improvement: 0.1684187
## Iteration: 30
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1230.494 Improvement: 0.2000353
## Iteration: 31
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1230.257 Improvement: 0.2372651
## Iteration: 32
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1229.98 Improvement: 0.2765356
## Iteration: 33
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1229.669 Improvement: 0.3106394
## Iteration: 34
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1229.339 Improvement: 0.3301096
## Iteration: 35
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1229.011 Improvement: 0.3279218
## Iteration: 36
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1228.707 Improvement: 0.3043793
## Iteration: 37
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1228.44 Improvement: 0.2667686
## Iteration: 38
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1228.216 Improvement: 0.2240954
## Iteration: 39
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1228.033 Improvement: 0.1827812
## Iteration: 40
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1227.887 Improvement: 0.1460091
## Iteration: 41
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1227.773 Improvement: 0.1148538
## Iteration: 42
## E-step: Computing responsibilities
## M-step: Updating parameters
## Log-likelihood: -1227.683 Improvement: 0.089327

```

```

## Iteration: 43
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1227.614 Improvement: 0.06894645
## Iteration: 44
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1227.561 Improvement: 0.05301273
## Iteration: 45
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1227.52 Improvement: 0.04076181
## Iteration: 46
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1227.489 Improvement: 0.03145837
## Iteration: 47
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1227.465 Improvement: 0.02444955
## Iteration: 48
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1227.445 Improvement: 0.01918868
## Iteration: 49
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1227.43 Improvement: 0.01523782
## Iteration: 50
##   E-step: Computing responsibilities
##   M-step: Updating parameters
##   Log-likelihood: -1227.418 Improvement: 0.01225776

```

```

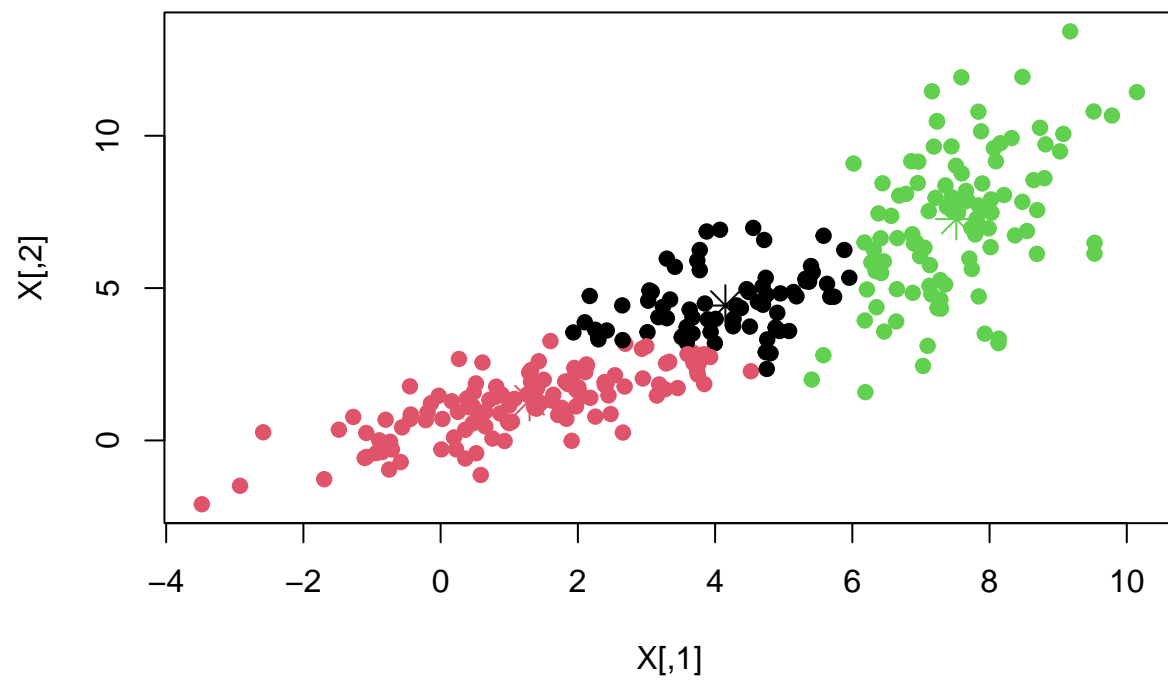
# Plot results

```

```

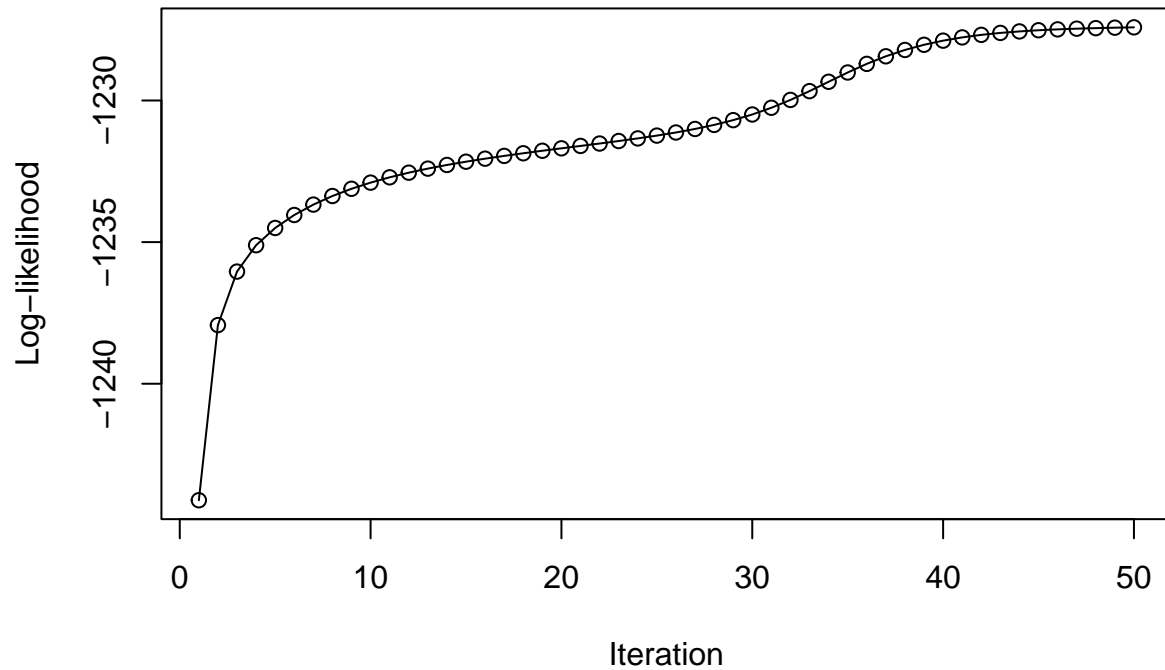
plot(X, col = predict_cluster(model_2d, X), pch = 19)
points(model_2d$mu, col = 1:model_2d$K, pch = 8, cex = 2)

```

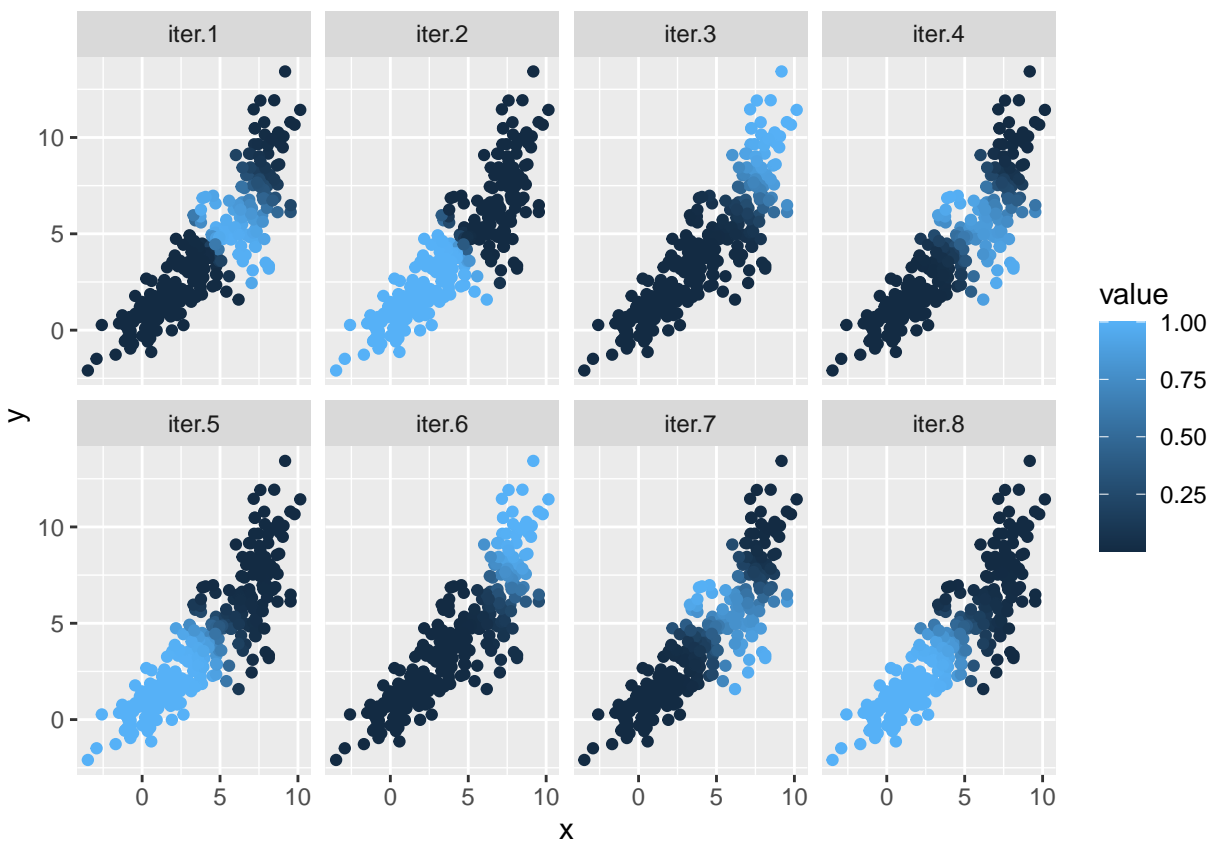


```
plot_convergence(model_2d)
```

## EM Algorithm Convergence



```
to.plot = data.frame(x = data[,1],  
                     y = data[,2],  
                     iter = model_2d$Alpha[,1:8])  
  
to.plot = melt(to.plot, id.vars = c("x", "y"))  
  
# model_2d$Alpha  
ggplot(to.plot)+aes(x,y, color = value)+  
  geom_point()+facet_wrap(~variable, nrow = 2)
```



### c) 3 dimensions

Solution:

```
library(rgl)
```

```
## Warning: package 'rgl' was built under R version 4.4.2
```

```
Mu1 = c(1,1,1)
Mu2 = c(5,5,5)
Sigma1 = matrix(c(2, 1, 1, 1, 2, 1,1,1,2), 3,3)
Sigma2 = matrix(c(2, 2, 1, 2, 2, 2,1,2,2), 3,3)
Sigma2
```

```
##      [,1] [,2] [,3]
## [1,]    2    2    1
## [2,]    2    2    2
## [3,]    1    2    2
```

```
pi = 1/3
n = 300
set.seed(100)
```

[illegible]

[illegible]

[illegible]



[illegible]

[illegible]

[illegible]

[illegible]



##	[28,]	4.12125169	0.84307314	2.08908878
##	[29,]	6.25291144	7.35012456	7.70972914
##	[30,]	0.16943085	1.48145382	-0.81941553
##	[31,]	5.42181720	5.29696612	5.07890944
##	[32,]	0.99915318	1.27918049	1.36118826
##	[33,]	4.20379721	3.49689068	3.26174904
##	[34,]	5.94091859	5.33281694	4.62025758
##	[35,]	2.36885424	2.19198570	2.16312357
##	[36,]	0.86537718	-1.09492015	-0.06840800
##	[37,]	5.23974845	4.81733048	4.45224504
##	[38,]	0.38916256	-0.04342378	1.49600319
##	[39,]	4.87757557	6.05487058	6.90108460
##	[40,]	5.58754216	5.69724699	5.58811435
##	[41,]	3.88011560	4.42677175	5.15334093
##	[42,]	-0.82610968	-0.95791897	-0.28162294
##	[43,]	3.85556611	4.57085416	5.42083365
##	[44,]	6.93282378	6.29760290	5.25511723
##	[45,]	7.85345971	7.41755461	6.22287742
##	[46,]	5.38017540	5.15063659	4.87381908
##	[47,]	10.03643539	9.54628482	7.62924030
##	[48,]	-0.15402437	0.22327614	-0.21465624
##	[49,]	4.30279031	4.56210720	4.95886084
##	[50,]	5.11624835	5.15946618	5.15263406
##	[51,]	2.93145041	2.58151945	2.99065120
##	[52,]	6.66561356	6.03935616	5.08688713
##	[53,]	5.65439934	6.55007940	6.95925256
##	[54,]	4.45598430	3.76602923	3.46336742
##	[55,]	4.97129126	4.14444870	3.58612890
##	[56,]	6.13794141	6.25248417	5.97392309
##	[57,]	0.37054945	0.70197927	-0.03387040
##	[58,]	4.89915574	5.36934409	5.72361035
##	[59,]	2.39709725	1.09546349	1.72682141
##	[60,]	-1.24622945	-3.25448767	0.09867690
##	[61,]	1.51777238	2.93903224	1.48130065
##	[62,]	-1.08606691	1.93428575	0.36836416
##	[63,]	8.80771593	8.99883706	7.93488583
##	[64,]	5.02283891	5.13832907	5.21040336
##	[65,]	4.33955197	5.09407384	5.81906976
##	[66,]	6.18591585	5.87032699	5.28157788
##	[67,]	3.00212776	2.65298008	0.93662312
##	[68,]	4.15132841	4.83956197	5.57815051
##	[69,]	1.38031666	1.32606326	1.00346318
##	[70,]	1.84436261	2.42351864	3.81132740
##	[71,]	0.43857481	0.36094389	1.00187332
##	[72,]	7.29449202	5.90905134	4.23829642
##	[73,]	4.21099330	4.28039862	4.57565756
##	[74,]	4.01784463	4.23720679	4.69597872
##	[75,]	7.85434919	7.60931704	6.54532637
##	[76,]	6.16949039	6.48360318	6.33207326
##	[77,]	1.98398894	-0.32898701	1.23650957
##	[78,]	2.17893692	2.05894055	2.72756679
##	[79,]	6.04595071	6.86793909	7.10365734
##	[80,]	0.50886234	0.92273260	-2.30587262
##	[81,]	0.44999182	2.25939149	0.80768975

##	[82,]	6.02330825	6.21764941	6.02981993
##	[83,]	3.88693622	3.60138312	3.75479900
##	[84,]	3.95868512	4.40621191	5.04010463
##	[85,]	6.80638630	6.39966019	5.55363765
##	[86,]	1.02688635	-1.10717021	-1.64259104
##	[87,]	4.76177688	5.46214211	6.01745973
##	[88,]	6.39176598	6.26254235	5.73705801
##	[89,]	4.27831341	4.80814602	5.39819379
##	[90,]	4.16548271	4.02691945	4.19376661
##	[91,]	4.60692849	3.57247997	2.98607194
##	[92,]	1.93070996	-0.07237935	2.04109897
##	[93,]	3.46460182	3.94329180	4.75363952
##	[94,]	6.74757601	7.18961430	6.94442170
##	[95,]	4.18235069	5.05386736	5.90847725
##	[96,]	5.85323432	5.61395864	5.18198630
##	[97,]	4.01317823	4.11032351	4.48670207
##	[98,]	5.24003566	4.47483335	3.87445950
##	[99,]	3.20966927	2.72875805	4.71148988
##	[100,]	6.10235156	6.02273040	5.62211576
##	[101,]	4.03512799	3.41706077	3.29581380
##	[102,]	6.25415149	6.63843520	6.50848073
##	[103,]	2.20111525	3.19133455	4.74922040
##	[104,]	9.80071670	9.42329570	7.65758204
##	[105,]	5.16462145	5.16164700	5.10793813
##	[106,]	5.44933296	5.58905080	5.54388955
##	[107,]	1.32190793	1.08099061	-0.47117610
##	[108,]	-1.23048135	1.11379401	1.12417557
##	[109,]	5.15472291	6.29303104	7.02550931
##	[110,]	3.72324739	3.18705255	3.21986819
##	[111,]	1.07872701	2.23457141	2.45699670
##	[112,]	4.75140862	5.56318622	6.19820257
##	[113,]	0.97418868	-0.84060181	2.04431080
##	[114,]	1.92911013	1.64605626	2.41566895
##	[115,]	5.23699270	4.88928011	4.57631799
##	[116,]	3.14361213	4.06416799	5.27844346
##	[117,]	7.19419691	5.66287960	3.92351134
##	[118,]	6.69231690	7.26361213	7.12445156
##	[119,]	5.62478700	6.09216734	6.21676076
##	[120,]	-2.04455422	-0.18130455	-0.96380123
##	[121,]	5.50530970	6.71712491	7.39000443
##	[122,]	6.00164926	5.73493267	5.23755060
##	[123,]	5.18587415	4.56356893	4.07824167
##	[124,]	5.65558175	5.41629872	5.04635645
##	[125,]	3.73845521	4.45255221	5.33847081
##	[126,]	1.43777979	-2.07232790	-0.36806760
##	[127,]	4.44499511	4.47058449	4.66233586
##	[128,]	2.33595243	0.04180287	0.80264957
##	[129,]	2.39319596	2.72880977	3.77725785
##	[130,]	6.09531835	5.58713951	4.89468145
##	[131,]	4.98716842	5.10451447	5.18905767
##	[132,]	3.94688992	3.82266196	4.06795253
##	[133,]	6.10636896	6.79198812	6.91517507
##	[134,]	0.43076862	1.42702033	0.24325096
##	[135,]	7.72555497	7.22343377	6.02346713

##	[136,]	-0.76586516	0.41606464	3.00655698
##	[137,]	7.70012779	7.19852240	6.00689022
##	[138,]	1.50835446	2.58675148	1.70601663
##	[139,]	6.99326244	6.30474642	5.20672355
##	[140,]	0.06926732	0.77604639	0.47314127
##	[141,]	2.95133055	1.31359323	4.13558527
##	[142,]	3.04311756	2.99570895	3.57736581
##	[143,]	4.61791088	4.58052358	4.67479287
##	[144,]	4.74795799	3.36828982	2.50074913
##	[145,]	5.93785712	3.99032616	2.35969077
##	[146,]	4.63986853	4.88772181	5.17081466
##	[147,]	0.25523507	0.22431411	0.05006581
##	[148,]	5.52021611	4.04559565	2.87052390
##	[149,]	4.93522998	4.72388139	4.59919520
##	[150,]	0.85939767	3.52039042	3.38193553
##	[151,]	3.98701998	3.93239548	4.21284863
##	[152,]	6.36447529	7.53034168	7.90203670
##	[153,]	5.23557317	4.67709710	4.21996712
##	[154,]	5.04370121	5.29883001	5.46016822
##	[155,]	4.65240511	4.45891829	4.43525502
##	[156,]	5.48912146	5.67618418	5.65102018
##	[157,]	-0.40130794	1.51743886	0.51535209
##	[158,]	-0.19950532	1.38384294	0.92960832
##	[159,]	8.28426016	6.79209673	4.73746701
##	[160,]	2.39943781	3.65152420	3.33398345
##	[161,]	1.72315971	-0.10856454	1.18183989
##	[162,]	4.81487089	3.79245049	3.14903078
##	[163,]	6.31689028	6.47133282	6.16398381
##	[164,]	6.08456844	6.06073391	5.70397813
##	[165,]	2.23669870	2.41182408	3.39927265
##	[166,]	7.55822195	7.44353443	6.56192081
##	[167,]	1.72490219	2.51590723	4.08656797
##	[168,]	5.04648312	4.81618297	4.64357551
##	[169,]	1.61446062	0.38020077	0.58405289
##	[170,]	4.77050208	4.10039151	3.71263147
##	[171,]	5.29065028	5.64344154	5.79428266
##	[172,]	9.55254846	8.88814184	7.00340559
##	[173,]	5.00624693	5.74224632	6.24528477
##	[174,]	4.87355447	4.04353716	3.51371463
##	[175,]	4.38828750	5.90718825	7.14135949
##	[176,]	2.66432271	4.01852442	5.68077139
##	[177,]	5.62667450	5.25734950	4.80725295
##	[178,]	6.72833905	5.86263974	4.72619289
##	[179,]	-1.99032114	-0.52817794	0.01276754
##	[180,]	5.56804603	5.94201656	6.02032640
##	[181,]	0.21201277	-0.46875927	-0.21244616
##	[182,]	6.23795905	5.99285494	5.43613404
##	[183,]	0.48872638	-1.17948827	0.20969475
##	[184,]	3.03336379	3.56214774	4.54221505
##	[185,]	5.29901853	6.14481744	6.63130471
##	[186,]	0.36750251	1.70910648	4.08358811
##	[187,]	6.05292840	6.27829623	6.10245884
##	[188,]	6.75351610	7.86917062	8.08430915
##	[189,]	6.75933045	8.09239172	8.45487697



```

## [190,] 6.00393232 5.88269843 5.48442140
## [191,] 6.36691141 6.98751850 6.98432435
## [192,] 5.51098249 3.63850658 2.19334810
## [193,] -2.11584253 1.23494043 0.23695933
## [194,] 5.28811207 6.08555444 6.54228541
## [195,] 1.90130911 1.55675191 2.23595964
## [196,] 5.31887693 4.81031369 4.36128527
## [197,] 0.58338043 2.05481192 2.95556022
## [198,] 4.47352946 3.46083722 2.93122559
## [199,] -0.41089944 1.79487965 2.68479223
## [200,] 0.31742499 -0.60384229 0.76741978
## [201,] 0.72241780 2.44640675 3.16672607
## [202,] 5.04077797 6.46134325 7.42325230
## [203,] 1.28157586 -0.15898745 -1.45810759
## [204,] -0.99399730 1.50485057 0.88982025
## [205,] 5.88703936 5.79813029 5.45872057
## [206,] 2.59839538 3.38706817 4.66213593
## [207,] 1.02787280 2.16866213 -0.56037001
## [208,] 0.96275909 -0.33533385 -0.53205166
## [209,] 5.23636809 5.19822148 5.09786121
## [210,] 4.65851616 4.11622430 3.85131370
## [211,] 2.77019355 1.98410308 1.62873186
## [212,] 2.17750638 0.51537898 0.88448998
## [213,] 3.28041734 4.31634111 5.56683761
## [214,] 0.28265699 0.31204469 0.20418643
## [215,] 1.79785570 2.19490571 3.47236075
## [216,] 3.02947894 2.10488297 2.08894652
## [217,] 2.49912791 2.12210901 2.64834307
## [218,] 4.62530155 3.09759406 4.55715568
## [219,] 6.07802885 6.07843647 5.74036673
## [220,] 3.77694848 4.91856679 6.08574367
## [221,] 3.76199386 3.75745042 4.14289277
## [222,] 3.63076707 4.74852219 4.46862626
## [223,] 2.92746926 2.82379057 3.40313553
## [224,] 2.20581218 2.16925598 1.09920384
## [225,] 5.86700146 6.13020707 6.03868663
## [226,] 1.74741629 2.40246870 2.23473127
## [227,] 5.58577882 6.67653416 7.24109360
## [228,] -0.39344837 1.78980752 -1.14837580
## [229,] -0.90466711 -0.58809104 -0.58717735
## [230,] 4.98206339 5.35923839 5.62366307
## [231,] 4.22735232 3.58877275 3.39312004
## [232,] 0.48642743 0.64416994 2.45513938
## [233,] 6.52095939 5.51619937 4.34942537
## [234,] 0.41339136 1.89954164 1.63287096
## [235,] 5.76734813 5.12955256 4.45109571
## [236,] 4.42168912 4.35715510 4.49438395
## [237,] 1.51049096 1.26696757 2.50857709
## [238,] 2.87124318 2.58384914 2.94566326
## [239,] 5.15624813 4.89567764 4.66784970
## [240,] 5.43579295 5.56257340 5.51278494
## [241,] 0.55648987 -0.04000271 -0.02785067
## [242,] 3.01813777 3.41618778 3.06470608
## [243,] 0.05013209 1.62692413 -0.15642026

```

```

## [244,] 3.54951867 2.34289330 0.95564811
## [245,] 1.67834913 1.80174763 2.92894750
## [246,] 6.27578846 6.34790855 5.99697496
## [247,] -0.05217252 -0.20127869 0.19063295
## [248,] 3.33795191 3.51442056 1.92045787
## [249,] 7.60296355 8.19812772 7.78952964
## [250,] 1.18749077 0.47522157 0.99227095
## [251,] 0.72881439 2.70895898 2.75190873
## [252,] 2.45403071 2.12393492 2.69651900
## [253,] 4.70512306 5.31366974 5.82376825
## [254,] 1.90906637 2.49622296 -0.14806946
## [255,] 4.94263636 4.12732690 3.58591403
## [256,] 4.38262585 2.85234502 2.00483304
## [257,] 3.90267660 4.35736915 5.01375740
## [258,] 4.82195980 4.74584053 4.74949159
## [259,] 4.57504987 3.83843969 3.46639606
## [260,] 6.99958928 5.51004654 3.86042092
## [261,] 3.77283937 3.40948755 3.54533291
## [262,] 3.05666750 0.27099533 2.76980703
## [263,] 3.34228082 3.08656004 3.43139026
## [264,] 3.41495517 4.39470488 5.56443211
## [265,] -0.12339278 0.36307248 0.09891415
## [266,] 5.14377417 5.37049353 5.48093004
## [267,] 5.99500626 4.78686238 3.64561373
## [268,] 4.57504035 4.52053001 4.61650580
## [269,] 3.31132793 4.06796548 5.11713076
## [270,] 3.23649743 3.77579839 4.69932646
## [271,] 5.60518480 5.16911585 4.67996831
## [272,] 3.85860693 3.70942633 3.96530433
## [273,] 5.07775485 5.33294103 5.48363055
## [274,] -0.24831942 -1.08300643 -0.62491904
## [275,] 1.81933578 3.03145913 2.29088519
## [276,] -0.55566848 1.25945341 -1.14224521
## [277,] -0.39122659 -2.12151813 0.68684364
## [278,] 5.26913750 4.68918323 4.20678171
## [279,] 0.33845545 -0.01992513 0.65077041
## [280,] 5.73787011 6.05731129 6.04490545
## [281,] 1.27624930 0.24518497 1.45848546
## [282,] 0.57875634 -1.33951194 -0.62904342
## [283,] 1.93474139 3.61730153 2.57184503
## [284,] 4.37160195 4.97791080 5.59115256
## [285,] 5.46286486 5.77508252 5.84403329
## [286,] 2.08719401 2.89073837 4.35629418
## [287,] -0.08724756 1.17450487 -0.05766964
## [288,] 6.20843813 6.61495245 6.51459887
## [289,] 2.76252190 2.84972995 3.61182034
## [290,] 5.35816739 4.47727371 3.76044256
## [291,] 6.06568284 5.80242783 5.28732336
## [292,] 0.68404762 0.98556471 1.00902484
## [293,] 0.38627195 1.01734112 -0.09959872
## [294,] 3.97535081 4.59482637 5.34146945
## [295,] 5.11143146 5.90715346 6.41815688
## [296,] -0.79238075 -1.30796368 -0.43519518
## [297,] 0.41297860 -0.09753303 0.49828114

```

```
## [298,] 6.75337042 7.03115070 6.67143536
## [299,] 6.14041078 6.63896456 6.62311401
## [300,] 5.36099776 5.70563767 5.82880661
```

```
to.plot = data.frame(x = data[,1],
                     y = data[,2],
                     z = data[,2],
                     class = as.factor(z))

mycolors <- c('royalblue1', 'darkorange')
color <- mycolors[ as.numeric(to.plot$class) ]
plot3d(to.plot, col = color)
```

## Point 3

Once you know the algorithm works, apply it to segment three images where you think there are different classes and show the result.