Assignment-3

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1 Question A, B

Code for R

```
1 library (mixtools)
   rm(list=ls())
   expectation Maximization \leftarrow function(X, lm, mu1, mu2, sig1, sig2) {
       tol = 10^-5; lim = 100; i = 0
 6
       n = length(X)
       temp1 = dnorm(X, mean = mu1, sd = sig1)
       temp2 = dnorm(X, mean = mu2, sd = sig2)
      M1 = (lm*temp1) / (lm*temp1 + (1-lm)*temp2)
10
      M2 = 1 - M1
11
      \mathbf{Q} = -1
12
13
14
       repeat {
          lmt = lm; mu1t = mu1; mu2t = mu2; sig1t = sig1; sig2t = sig2;
15
          i = i + 1
16
          Q0 = \mathbf{Q}
17
18
          lm = sum(M1)/n
19
20
          mu1 = sum(M1 * X) / sum(M1)
21
          mu2 = sum(M2 * X) / sum(M2)
22
          sig1 = sqrt(sum(M1 * (X - mu1)^2) / sum(M1))
23
          sig2 = sqrt(sum(M2 * (X - mu2)^2) / sum(M2))
24
          temp1 = dnorm(X, mean = mu1, sd = sig1)
25
          temp2 = dnorm(X, mean = mu2, sd = sig2)
26
          M1 = (lm*temp1) / (lm*temp1 + (1-lm)*temp2)
27
          M2 = 1 - M1
28
29
30
          \mathbf{Q} = \mathbf{sum}(\mathbf{M1} * \mathbf{log}(\mathbf{lm} * \mathbf{temp1}) + \mathbf{M2} * \mathbf{log}((1 - \mathbf{lm}) * \mathbf{temp2}))
```

```
31
          if (abs(Q-Q0) < tol || i > lim) {
32
          # if ((abs(lm-lmt)+abs(mu1t-mu1)+abs(mu2t-mu2)+abs(sig1t-sig1)+abs(sig2t-sig2) < tol)) {
33
34
             # print(i)
             break
35
36
37
38
39
      return (list(lm = lm, mu1 = mu1, mu2 = mu2, sig1 = sig1, sig2 = sig2))
40
41
42
   n = 200
43
44 | lm = 0.4
45 | mu1 = mu2 = 0
46 | sig1 = 1
47 \mid sig 2 = 5
48
49 | temp_U = runif(n)
50 \mid \text{temp}_X 1 = \text{rnorm}(n, \text{mean} = \text{mul}, \text{sd} = \text{sig} 1)
51 temp_X2 = rnorm(n, mean = mu2, sd = sig2)
52
53 \mid X = \text{temp}_X1*(\text{temp}_U \le 0.4) + \text{temp}_X2*(\text{temp}_U > 0.4)
54
55
   print("From manual implementation of EM")
56 param = expectationMaximization(X, 0.5, 0, 0, 1, 10);
57
   print( sprintf("lambda = \%f, mu1 = \%f, mu2 = \%f, sig1 = \%f, sig2 = \%f",
58
      param$lm, param$mu1, param$mu2, param$sig1, param$sig2))
59
60 print ("From built in function normalmixEM")
   param = normalmixEM(X)
61
62 print ( "lambda = %f , mu1 = %f , mu2 = %f , sig1 = %f , sig2 = %f" ,
      param\$lambda[1], param\$mu[1], param\$mu[2], param\$sigma[1], param\$sigma[2]))
```

From manual implementation of EM

```
lambda = 0.399748, mu1 = -0.078376, mu2 = -0.745167, sig1 = 1.316884, sig2 = 5.610553
```

From built in function normalmixEM

```
lambda = 0.399763, mu1 = -0.078362, mu2 = -0.745193, sig1 = 1.316937, sig2 = 5.610606
```

We can see that the parameters found by EM algorithm are very close to the actual parameters. Both the EM implementations: manual and built-in give the same output.

2

2 Part C

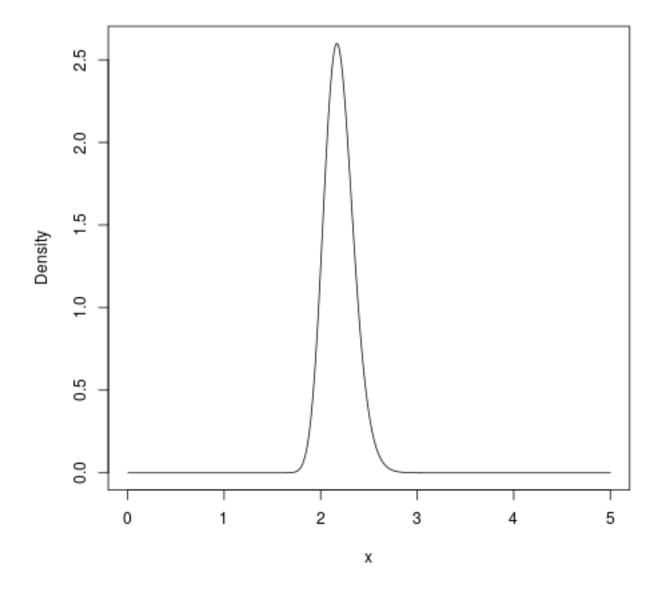
Code for R

```
1 | rm(list = ls())
 3 n = 100
 4 \mid X = \mathbf{rnorm}(n, \mathbf{mean} = 0, \mathbf{sd} = \mathbf{sqrt}(5))
 5 | \mathbf{sum}_{-} X2 = \mathbf{sum}(X^2)
 7 prior <- function (sig2) {
 8 return ((sig2^-3.5) * exp(-1/(2*sig2)))
 9
10
11 likelihood <- function (sig) {
12 return (exp(-sum_X2/(2*sig^2)) / (sqrt(2*pi)*sig)^n)
13 }
14
15 posterior Density <- function (sig) {
16 return (likelihood(sig)*prior(sig^2))
17 }
18
19 # Getting the Gamma distribution
20 k = 1/integrate (posterior Density, 0, Inf)$value
21 t = seq(0, 5, length = 1000)
22 dens = k*posteriorDensity(t)
23
24 png("posteriorDensity.png")
25 plot(t, dens, xlab="x", ylab="Density", type='l')
26 title ("Density of Posterior Inverse-Gamma distribution")
27 dev. off()
28
29 # Bayes Estimate
30 bayesEstimate <- function (t) {
31 return (t*k*posteriorDensity(t))
32 }
33
34 be = integrate(bayesEstimate, 0, Inf)$value
35 print (sprintf ("Bayes estimate = %f", be))
36
37 # MAP estimator
38 map = optimize (posterior Density, interval=c(0, 30), maximum=TRUE) $maximum
39 print(sprintf("MAP estimate = %f", map))
```

3

Posterior has Inverse Gamma distribution

Density of Posterior Inverse-Gamma distribution



Given, prior:

$$p(\sigma^2) \propto (\sigma^2)^{-\frac{5}{2}-1} \exp(-\frac{1}{2\sigma^2})$$

Likelihood:

$$f(X|\sigma) = \frac{1}{(\sqrt{2\pi}\sigma)^n} \exp(\frac{-\sum_{i=1}^n x_i^2}{2\sigma^2})$$

where n is the number of samples X. From the above statements we get posterior distribution:

$$p(\sigma^2|X) \propto f(X|\sigma) \ p(\sigma^2) \propto (\sigma^2)^{-\frac{n}{2} - \frac{5}{2} - 1} \exp(\frac{-1 - \sum_{i=1}^{n} x_i^2}{2\sigma^2})$$

The above equation resembles that on Inverse-Gamma distribution with parameters α and β , where

$$\alpha = \frac{5}{2} + \frac{n}{2}$$

$$\beta = \frac{-1 - \sum_{i=1}^{n} x_i^2}{2}$$

$$p(\sigma^2|X) \propto (\sigma^2)^{-\alpha-1} \exp(\frac{-\beta}{\sigma^2})$$

The graph also resembles the inverse gamma distribution with the above mentioned parameters.

Estimated parameters are:

Bayes estimate = 2.144515

MAP estimate = 2.167212