Statistical Computing Homework 5, EM algorithm

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Finite Mixture Regression:

Derive the update formula

 $\Psi = (\pi_1, \beta_1, \pi_2, \beta_2, ..., \pi_m, \beta_m, \sigma)^T$, by the E-step in EM algorithm, we have:

$$\begin{split} Q(\boldsymbol{\Psi}|\boldsymbol{\Psi}^k) &= \sum_{\mathbf{z}} p(\mathbf{z}|\mathbf{x}, \mathbf{y}, \boldsymbol{\Psi}^k) \log(p(\mathbf{x}, \mathbf{y}, \mathbf{z}|\boldsymbol{\Psi})) \\ &= \sum_{i=1}^n \sum_{j=1}^m p(z_{ij} = 1|\mathbf{x}, \mathbf{y}, \boldsymbol{\Psi}^k) \log(p(z_{ij} = 1, \mathbf{x}, \mathbf{y}|\boldsymbol{\Psi})) \end{split}$$

In order to get the update formula for p_{ij} , which is $p(z_{ij} = 1 | \mathbf{x}_i, \mathbf{y}_i, \Psi^k)$, by Bayes rule, it's equal to

$$\begin{aligned} & \frac{p(z_{ij} = 1, \mathbf{x}_i, \mathbf{y}_i | \Psi^k)}{p(\mathbf{x}_i, \mathbf{y}_i | \Psi^k)} \\ = & \frac{p(z_{ij} = 1 | \Psi^k) p(\mathbf{x}_i, \mathbf{y}_i | z_{ij} = 1, \Psi^k)}{p(\mathbf{x}_i, \mathbf{y}_i | \Psi^k)} \end{aligned}$$

So if we only look at the numerator, it's $\pi_j^k \phi(y_i - x_i^T \beta_j^k; 0, \sigma^{2(k)})$. So we have the update form for p_{ij}^{k+1} as in the question if sum over j in the numerator to get the denominator. Since we also know in E-step, we have:

$$Q(\Psi|\Psi^k) = \sum_{i=1}^n \sum_{j=1}^m p_{ij}^{k+1} \{ \log \pi_j + \log \phi(y_i - x_i^T \beta_j; 0, \sigma^2) \}$$

So in M-step, if we minimize the $Q(\Psi|\Psi^k)$ with respect to π_j , β_j^{k+1} and $\sigma^{2(k+1)}$, then we will get the update formula these three sets of parameters as in the questoion.

Implementation of EM algorithm

- y: Response vector
- xmat: Design matrix
- **pi.init**: Initial values of π_j 's(m × 1)
- **beta.init**: Initial values of β_j 's (p×m, where p is ncol(xmat))

- sigma.init: Initial values of σ
- control: list for controlling max iteration number and convergence tolerance

```
regmix_em <- function(y, xmat, pi.init, beta.init, sigma.init, control = list(maxit = 1000, tol = 1e-5)
  p.iter <- matrix(0, nrow = dim(xmat)[1], ncol = length(pi.init) )</pre>
  pi.iter <- pi.init; beta.iter <- beta.init; sigma.iter <- sigma.init</pre>
  \#temp_pi.iter \leftarrow c(0.9, 0.05, 0.05)
  xmat <- as.matrix(xmat)</pre>
  iter <- 1; maxit <- control$maxit; tol <- control$tol</pre>
  while ( (iter <= maxit) ) {</pre>
    for (j in 1:dim(p.iter)[2]) {
      for (i in 1:dim(p.iter)[1]) {
        temp.sum <- sum(pi.iter * dnorm(y[i] - xmat[i,]%*%beta.iter, mean=0, sd=sigma.iter^0.5))
        p.iter[i, j] <- pi.iter[j] * dnorm(y[i] - xmat[i,]%*%beta.iter[ , j], mean=0, sd=sigma.iter^0.5
      }
    }
    #temp_pi.iter <- pi.iter</pre>
    for (j in 1:dim(p.iter)[2]) {
      pi.iter[j] <- mean(p.iter[,j])</pre>
      beta.iter[ ,j]<- solve( t(xmat) %*% ( xmat * matrix(rep(p.iter[,j],2), ncol = 2) ) ) %*% t(xmat)
    }
    #temp_pi.iter <- pi.iter</pre>
    sigma.iter <- sum( p.iter * (matrix(rep(y, length(pi.iter)), ncol = length(pi.iter)) - xmat %*% bet
    iter <- iter + 1
 }
  return(list(pi.iter, beta.iter, sigma.iter))
}
```

Simulation Study

```
set.seed(1205)
dat <- regmix_sim(n, pi, bet, sig)</pre>
result <- regmix_em(y = dat[,1], xmat = dat[,-1],
           \#pi.init = pi / pi / length(pi),
           pi.init = c(0.8, 0.1, 0.1),
           beta.init = bet * 0 + rnorm(6),
           sigma.init = sig / sig,
           control = list(maxit = 1000, tol = 1e-5))
result
## [[1]]
## [1] 0.3453959 0.2687802 0.3858238
##
## [[2]]
##
              [,1]
                          [,2]
                                    [,3]
## [1,] -0.9136895 0.9911949 0.8796621
## [2,] -1.1990373 -1.2424624 0.9341928
##
## [[3]]
## [1] 1.047753
```

We need to choose initial values of π and β matrix wisely, in order to get relatively godd convergence.