

Examen part 2

Monday, June 08, 2015

7'5 / 12

Answer the following questions.

1. What is the contribution to the likelihood function of the i -th experiment result when the observation y_i is equal to 0? And what is this contribution when $|y_i| > 1$?

The contribution when $y_i = 0$ will be the probability of y_i equal to 0. However, this probability will be, in fact, the probability of x_i between 1 and -1. In other words, the contribution will be:

$$P(Y_i = 0) = P(-1 \leq X_i \leq 1) = \Phi\left(\frac{1-\mu}{\sigma}\right) - \Phi\left(\frac{-1-\mu}{\sigma}\right)$$

The contribution when $|y_i| > 1$ will be:

$$P(Y_i = y_i) = P(X_i = y_i) = \frac{1}{\sigma} \phi\left(\frac{y_i - \mu}{\sigma}\right)$$

2. Write down the log-likelihood function for the complete data, and the log-likelihood for the observed data.

Using what has been previously said, we can write the log-likelihood for both the observed and the complete data.

Complete data: $(X_1, \dots, X_n) = (x_1, \dots, x_n)$

$$L^c(\mu, \sigma; x) = \prod_{i=1}^n \frac{1}{\sigma} \phi\left(\frac{x_i - \mu}{\sigma}\right)$$

Hence,

$$l^c(\mu, \sigma; x) = \log L^c(\mu, \sigma; x) = -n \log \sigma + \sum_{i=1}^n \log \left(\phi\left(\frac{x_i - \mu}{\sigma}\right) \right)$$

Observed data: $(Y_1, \dots, Y_n) = (y_1, \dots, y_n)$. Let δ_i be 1 if $y_i = 0$ and 0 otherwise; and $n_0 = \sum \delta_i$.

$$L^o(\mu, \sigma; x) = \prod_{i=1}^n \left(\Phi\left(\frac{1-\mu}{\sigma}\right) - \Phi\left(\frac{-1-\mu}{\sigma}\right) \right)^{\delta_i} \left(\frac{1}{\sigma} \phi\left(\frac{y_i - \mu}{\sigma}\right) \right)^{1-\delta_i}$$

Therefore,

$$l^o(\mu, \sigma; x) = \log L^o(\mu, \sigma; x) = n_0 \log \left(\Phi \left(\frac{1-\mu}{\sigma} \right) - \Phi \left(\frac{-1-\mu}{\sigma} \right) \right) - (n-n_0) \log \sigma + \sum_{i=1}^n (1-\delta_i) \log \left(\phi \left(\frac{y_i - \mu}{\sigma} \right) \right)$$

3. E step in the EM algorithm.
4. M step in the EM algorithm.
5. Write an R code implementing this EM algorithm.

No extra needed

```

Estep <- function(sample, mu, sigma) {
  ## Calculates the Expectation using current mu and sigma. Formula from 3. I
  ## use 4. results

  expr <- mu + sigma * (dnorm((-1 - mu)/sigma) - dnorm((1 - mu)/sigma)) / (pnorm((1 -
    mu)/sigma) - pnorm((-1 - mu)/sigma))
  sample2 <- ifelse(abs(sample) > 1, sample, expr)
  return(sample2)
}

Mstep <- function(sample2, mu, sigma) {
  ## update mu and sigma (those maximizing Estep. maximize Estep, or
  ## equivalently use 4. results.

  mu <- mean(sample2)
  sigma <- sqrt(1/length(sample2) * sum((sample2 - mu)^2))
  return(c(mu, sigma))
}

EMalgorithm <- function(mu0, sigma0, sample, its) {
  mu <- NULL
  mu[1] <- mu0
  sigma <- NULL
  sigma[1] <- sigma0
  i <- 2

  while (i <= its) {
    sample2 <- Estep(sample, mu[i - 1], sigma[i - 1])
    aux <- Mstep(sample2, mu[i - 1], sigma[i - 1])
    mu[i] <- aux[1]
    sigma[i] <- aux[2]
    i <- i + 1
  }
  return(list(mu = mu, sigma = sigma))
}

```

6. Use your EM algorithm for estimating (μ, σ) by maximum likelihood.

```

y <- read.table("results.txt", col.names=FALSE)[,1]
EMalgorithm(mu=mean(y), sigma=sd(y), y, its=100)

```

```
## $mu
```

```

## [1] 0.2585526 0.2666553 0.2669991 0.2670104 0.2670107 0.2670108 0.2670108
## [8] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [15] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [22] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [29] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [36] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [43] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [50] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [57] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [64] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [71] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [78] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [85] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [92] 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108 0.2670108
## [99] 0.2670108 0.2670108
##
## $sigma
## [1] 1.975969 1.965025 1.964983 1.964981 1.964981 1.964981 1.964981 1.964981
## [8] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [15] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [22] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [29] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [36] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [43] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [50] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [57] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [64] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [71] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [78] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [85] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [92] 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981 1.964981
## [99] 1.964981 1.964981

```

Fixem-nos que ambdós paràmetres convergeixen, obtenint $\mu = 0.267$ i $\sigma = 1.965$ aproximadament.