IDA Assignment 2

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Q1.

Suppose $Y_1, \cdots, Y_n$ are independent and identically distributed with cumulative distribution function given by

$$F(y;\theta) = 1 - e^{-y^2/(2\theta)}, \quad y \geq 0, \quad \theta > 0.$$

Further suppose that observations are (right) censored if $Y_i > C$, for some known $C > 0$, and let

$$X_i = \begin{cases} Y_i & \text{if} \quad Y_i \leq C, \\ C & \text{if} \quad Y_i > C, \end{cases} \qquad R_i = \begin{cases} 1 & \text{if} \quad Y_i \leq C \\ 0 & \text{if} \quad Y_i > C \end{cases}$$

a)

Show that the maximum likelihood estimator based on the observed data $\{(x_i, r_i)\}_{i=1}^n$ is given by

$$\hat{\theta} = \frac{\sum_{i=1}^n X_i^2}{2\sum_{i=1}^n R_i}.$$

Answer :

We first define the Survival function (from **Workshop 3**)as

$$S(C;\theta) = \mathbb{P}(Y_i > C;\theta) = 1 - F(y_i;\theta)$$

which also represents the censored observations. For the uncensored observations, we have

$$f(y_i;\theta) = \frac{d}{dy_i}F(y_i;\theta) = \frac{ye^{-y^2/2\theta}}{\theta}$$

Given that $Y_1, \ldots, Y_n$ are independent and identically distributed, we have the likelihood function as,

$$\begin{aligned} L(\theta|\boldsymbol{y}, \boldsymbol{r}) &= \prod_{i=1}^n \left([f(y_i;\theta)]^{r_i} [S(C;\theta)]^{1-r_i} \right) \\ &= \prod_{i=1}^n \left([\frac{ye^{-y^2/2\theta}}{\theta}]^{r_i} [e^{-C^2/\theta}]^{1-r_i} \right) \\ &= \left(\frac{y_i}{2\theta} \right)^{\sum_{i=1}^n r_i} \exp\left(\frac{\sum_{i=1}^n (r_i y_i^2 + (1-r_i)C^2)}{2\theta} \right) \end{aligned} \tag{1}$$

Now we can rewrite the term in the exponential as X_i can we expressed as

$$x_i = r_i y_i + C(1 - r_i)$$

Then by taking square on both sides we have,

$$x_i^2 = r_i^2 y_i^2 + (1-r_i)^2 C^2 + 2r_i y_i C(1-r_i)$$

Noting that R_i is binary, we can then conclude with the expression as

$$x_i^2 = r_i y_i^2 + (1-r_i)C^2 \tag{2}$$

Now we substitute (2) into (1) to have,

$$\begin{aligned} L(\theta|\boldsymbol{y},\boldsymbol{r}) &= \left(\frac{y_i}{2\theta}\right)^{\sum_{i=1}^n r_i} \exp\left(\frac{\sum_{i=1}^n x_i}{2\theta}\right) \\ \implies \log(L(\theta|\boldsymbol{y},\boldsymbol{r})) &= -\log\theta\sum_{i=1}^n r_i - \frac{\sum_{i=1}^n x_i^2}{2\theta} \qquad (3) \\ \implies \frac{d}{d\theta}\log L(\theta|\boldsymbol{y},\boldsymbol{r}) &= \frac{1}{\theta}\sum_{i=1}^n r_i + \frac{1}{2\theta^2}\sum_{i=1}^n x_i^2 \end{aligned}$$

By equating the derivative to 0, we can obtain the maximum likelihood estimate of θ as below.

$$\hat{\theta}_{MLE} = \frac{\sum_{i=1}^n x_i^2}{2\sum_{i=1}^n r_i} \quad \text{(shown)}$$

.

b)

Show that the expected Fisher Information for the observed data likelihood is

$$I(\theta) = \frac{n}{\theta^2}(1 - e^{-C^2/(2\theta)})$$

Note: $\int_0^C y^2 f(y;\theta)dy = -C^2 e^{-C^2/(2\theta)} + 2\theta(1 - e^{-C^2/(2\theta)})$, where $f(y;\theta)$ is the density function corresponding to the cumulative distribution function $F(y;\theta)$ defined above.

Answer :

From (3), we take another derivative of it and thus obtain as below

$$\frac{d^2}{d\theta^2}\log L(\theta) = \frac{1}{\theta^2}\sum_{i=1}^{n} r_i - \frac{x_i^2}{\theta^3}$$

Then, the Fisher Information for the observed data likelihood is,

$$\begin{aligned} I(\theta|\boldsymbol{x},\boldsymbol{r}) &= -\mathbb{E}\left(\frac{\sum_{i=1}^n r_i}{\theta^2} - \frac{x_i^2}{\theta^3}\right) \\ &= -\frac{n\mathbb{E}(R)}{\theta^2} + \frac{n\mathbb{E}(X^2)}{\theta^3} \\ I(\theta|\boldsymbol{y},\boldsymbol{r}) &= -\frac{n\mathbb{E}(R)}{\theta^2} + \frac{1}{\theta^3}\left(n\mathbb{E}(RY^2) + nC^2\mathbb{E}(1-R)\right) \end{aligned} \tag{4}$$

Again, noting that R_i is binary,

$$\begin{aligned} \mathbb{E}(R) &= 1 \cdot \mathbb{P}(R=1) + 0 \cdot \mathbb{P}(R=0) \\ &= \mathbb{P}(R=1) = \mathbb{P}(Y \le C) \\ &= F(C;\theta) = 1 - e^{-C^2/2\theta} \end{aligned} \tag{5}$$

With the given equation, $\mathbb{E}(RY^2) = \int_0^C y^2 f(y;\theta)dy = -C^2 e^{-C^2/(2\theta)} + 2\theta(1 - e^{-C^2/(2\theta)})$, we can combine all the above equations as express the expected Fisher Information again,

$$\begin{aligned} I(\theta|\boldsymbol{y},\boldsymbol{r}) &= \frac{n\mathbb{E}(R)}{\theta^2} + \frac{1}{\theta^3}\left(n\mathbb{E}(RY^2) + nC^2\mathbb{E}(1-R)\right) \\ &= \frac{-n}{\theta^2}(1 - e^{-C^2/2\theta}) - \frac{n}{\theta^3}(C^2 e^{-C^2/2\theta}) + \frac{n}{\theta^3}(2\theta(1 - e^{-C^2/2\theta})) + \frac{n}{\theta^3}(C^2 e^{-C^2/2\theta}) \\ &= \frac{n}{\theta^2}(1 - e^{-C^2/2\theta}) \quad \text{(shown)} \end{aligned} \tag{6}$$

c)

Appealing to the asymptotic normality of the maximum likelihood estimator, provide a 95% confidence interval for θ.

Answer :

By the Central Limit Theorem, asymptotic normality of the maximum likelihood estimator is given as,

$$\hat{\theta}_{MLE} \sim N_p(\theta, I(\theta)^{-1})$$

Thus, with 0 and $\frac{1}{I(\theta)}$ as the asymptotic mean and variance respectively, we can obtain the 95% confidence interval as below,

$$\hat{\theta}_{MLE} \pm \frac{1.96}{\sqrt{I(\theta)}} = \hat{\theta}_{MLE} \pm \frac{1.96 \cdot \theta_{MLE}}{\sqrt{n(1 - e^{-C^2/2\theta_{MLE}})}}$$

Q2.

Suppose that a dataset consists of 100 subjects and 10 variables. Each variable contains 10% of missing values. What is the largest possible subsample under a complete case analysis? What is the smallest? Justify.

Suppose that $Y_i \overset{\text{iid}}{\sim} N(\mu, \sigma^2)$ are iid for $i = 1, ..., n$. Further suppose that now observations are (left) censored if $Y_i < D$, for some known D and let

$$X_i = \begin{cases} Y_i & \text{if } Y_i \geq D, \\ D & \text{if } Y_i < D, \end{cases} \qquad R_i = \begin{cases} 1 & \text{if } Y_i \geq D \\ 0 & \text{if } Y_i < D \end{cases}$$

a)

Show that the log-likelihood of the observed data $\{(x_i, r_i)\}_{i=1}^n$ is given by

$$\log L(\mu, \sigma^2 | \boldsymbol{x}, \boldsymbol{r}) = \sum_{i=1}^n \left\{ r_i \log \phi(x_i; \mu, \sigma^2) + (1 - r_i) \log \Phi(x_i; \mu, \sigma^2) \right\}$$

where $\phi(\cdot; \mu, \sigma^2)$ and $\Phi(\cdot; \mu, \sigma^2)$ stands, respectively, for the density function and cumulative distribution function of the normal distribution with mean μ and variance σ^2.

Answer :

We first define the Survival function (from **Workshop 3**)as

$$S(D; \mu, \sigma^2) = \mathbb{P}(Y_i < D; \mu, \sigma^2) = \Phi(x_i; \mu, \sigma^2)$$

which also represents the censored observations. For the uncensored observation, we have

$$\phi(x_i; \mu, \sigma^2)$$

Given that $X_1, \ldots, X_n$ are independent and identically distributed, we have the likelihood function as,

$$\begin{aligned} L(\mu, \sigma^2 | \boldsymbol{x}, \boldsymbol{r}) &= \prod_{i=1}^n \left([\phi(x_i; \mu, \sigma^2)]^{r_i} [\Phi(x_i; \mu, \sigma^2)]^{1-r_i} \right) \\ \implies l(\mu, \sigma^2 | \boldsymbol{x}, \boldsymbol{r}) &= \log \prod_{i=1}^n \left(\phi(x_i; \mu, \sigma^2)]^{r_i} [\Phi(x_i; \mu, \sigma^2)]^{1-r_i} \right) \\ &= \log \left([\phi(x_i; \mu, \sigma^2)]^{\sum_{i=1}^n r_i} [\Phi(x_i; \mu, \sigma^2)]^{\sum_{i=1}^n (1-r_i)} \right) \\ &= \sum_{i=1}^n \left(r_i \log \phi(x_i; \mu, \sigma^2) + (1 - r_i) \log \Phi(x_i; \mu, \sigma^2) \right) \end{aligned} \tag{7}$$

b)

Determine the maximum likelihood estimate of μ based on the data available in the file `dataex2.Rdata`. Consider σ^2 known and equal to 1.5^2. **Note**: You can use a built in function such as `optim` or the `maxLik` package in your implementation.

Answer :

```r
#defining a function to simulate the log likelikhood
log.lik <- function(mu, data){
  x <- data[, 1]
  r <- data[, 2]
  sum((r*dnorm(x, mu, 1.5, log = TRUE) +
         (1-r)*pnorm(x, mu, 1.5, log = TRUE)))
}

#computing the maximum likelihood estimate of mu
mle <- maxLik(logLik = log.lik, data = dataex2, start = c(mu = 5))
summary(mle)
```

```
## --------------------------------------------
## Maximum Likelihood estimation
## Newton-Raphson maximisation, 3 iterations
## Return code 1: gradient close to zero (gradtol)
## Log-Likelihood: -336.3821
## 1  free parameters
## Estimates:
##    Estimate Std. error t value Pr(> t)
## mu   5.5328     0.1075   51.48  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## --------------------------------------------
```

We built a function `log.lik()` that produces the log likelihood and then used `maxLik()` to simulate μ based on the data. With Newton-Raphson method, we estimated $\hat{\mu} = 5.5328$ and standard error of 0.1075

Q3.

Consider a bivariate normal sample (Y_1, Y_2) with parameters $\theta = (\mu_1, \mu_2, \sigma_1^2, \sigma_{12}, \sigma_2^2)$. The variable Y_1 is fully observed, while some values of Y_2 are missing. Let R be the missingness indicator, taking the value 1 for observed values and 0 for missing values. For the following missing data mechanisms state, justifying, whether they are ignorable for likelihood-based estimation.

a)

$\text{logit}\{\mathbb{P}(R = 0|y_1, y_2, \theta, \psi)\} = \psi_0 + \psi_1 y_1, \quad \psi = (\psi_0, \psi_1)$ distinct from θ.

Answer :

Referring to the ignorability assumption (from **Lecture 6.1**), the missing in Y_2 is either **MAR** or **MCAR** and its model parameters, $\theta = (\mu_1, \mu_2, \sigma_1^2, \sigma_{12}, \sigma_2^2)$ and missing mechanism parameter, ψ.

First, the missing mechanism is **MAR**. This is because the missingness is only dependent on Y_1 which is a fully observed variable. The parameters, $\{\theta, \psi\}$ are also distinct. Therefore, the ignorability assumption holds here and (a) is ignorable for likelihood-based estimation.

b)

$\text{logit}\{\mathbb{P}(R = 0|y_1, y_2, \theta, \psi)\} = \psi_0 + \psi_1 y_2, \quad \psi = (\psi_0, \psi_1)$ distinct from θ.

Answer :

The missing mechanism is **MNAR** as the mechanism is only dependent on Y_2. Therefore, the missing value is depending on itself and possibly other factors. Therefore, by referring to the ignorability assumption (from **Lecture 6.1**), we conclude that (b) is not ignorable for likelihood-based estimation.

c)

$\text{logit}\{\mathbb{P}(R = 0|y_1, y_2, \theta, \psi)\} = 0.5(\mu_1 + \psi y_1)$, scalar ψ distinct from θ.

Answer :

The missing mechanism here is dependent on both μ_1 and Y_1. We can observe similarity to (a). Distinctness of the parameters means that the parameter space of (θ, ψ) is equal to the Cartesian product of their individual product spaces. However, the μ_1 also exists in the parameter space. This violates the ignorability assumption. Hence, (c) is not ignorable for likelihood-based estimation.

Q4.

$$Y_i \overset{\text{ind.}}{\sim} \text{Bernoulli}(p_i(\boldsymbol{\beta}))$$

$$p_i(\boldsymbol{\beta}) = \frac{exp(\beta_0 + x_i\beta_1)}{1 + exp(\beta_0 + x_i\beta_1)},$$

for $i = 1, \cdots, n$ and $\boldsymbol{\beta} = (\beta_0, \beta_1)'$. Although the covariate x is fully observed, the response variable Y has missing values. Assuming ignorability, derive and implement the EM algorithm to compute the MLE of $\boldsymbol{\beta}$ based on the data available in `dataex4.Rdata`. **Note**: 1) For simplicity, and without loss of generality because we have a univariate pattern of missingness, when writing down your expressions, you can assume that the first m values of Y are observed and the remaining $n - m$ are missing. 2) You can use a built in function such as `optim` or the `maxLik` package for the M-step.

Answer :

```
load("dataex4.Rdata")
head(dataex4)
```

```
##            X  Y
## 1 -0.4689827  1
## 2 -0.2557522  1
## 3  0.1457067  1
## 4  0.8164156 NA
## 5 -0.5966361  1
## 6  0.7967794 NA
```

```
cat("Number of missing values in Y:", sum(is.na(dataex4)))
```

```
## Number of missing values in Y: 95
```

Scrutinising on the dataset, we can observe that the missing value only occurs in Y and there are 95 missing values occurring in a univariate pattern

We first derive the likelihood function to implement the EM algorithm given that $y_{obs} = y_1, \ldots, y_m$ and $y_{mis} = y_{m+1}, \ldots, y_n$.

$$\begin{aligned}
L(\beta_0, \beta_1; \boldsymbol{x}, \boldsymbol{y_{obs}}, \boldsymbol{y_{mis}}) &= \prod_{i=1}^{n} \left([p_i(\beta_0, \beta_1)]^{y_i} [1 - p(\beta_0, \beta_1)]^{1-y_i} \right) \\
\implies L(\beta_0, \beta_1; \boldsymbol{x}, \boldsymbol{y_{obs}}, \boldsymbol{y_{mis}}) &= \prod_{i=1}^{n} \left(\frac{e^{\beta_0 + x_i\beta_1}}{1 + e^{\beta_0 + x_i\beta_1}} \right)^{y_i} \left(\frac{1}{1 + e^{\beta_0 + x_i\beta_1}} \right)^{1-y_i} \\
\implies \log L(\beta_0, \beta_1; \boldsymbol{x}, \boldsymbol{y_{obs}}, \boldsymbol{y_{mis}}) &= \sum_{i=1}^{n} \left(y_i \log \left(\frac{e^{\beta_0 + x_i\beta_1}}{1 + e^{\beta_0 + x_i\beta_1}} \right) + (1 - y_i) \log \left(\frac{1}{1 + e^{\beta_0 + x_i\beta_1}} \right) \right) \\
\implies \log L(\beta_0, \beta_1; \boldsymbol{x}, \boldsymbol{y_{obs}}, \boldsymbol{y_{mis}}) &= \sum_{i=1}^{n} \left(y_i \log(e^{\beta_0 + x_i\beta_1}) - \log(1 + e^{\beta_0 + x_i\beta_1}) - y_i \log(1 + e^{\beta + x_i\beta_1}) + y_i \log(1 + e^{\beta + x_i\beta_1}) \right) \\
\implies \log L(\beta_0, \beta_1; \boldsymbol{x}, \boldsymbol{y_{obs}}, \boldsymbol{y_{mis}}) &= \sum_{i=1}^{n} \left(y_i(\beta_0 + x_i\beta_1) - \log(1 + e^{\beta_0 + x_i\beta_1}) \right) \\
&= l(\boldsymbol{\beta}; \boldsymbol{x}, \boldsymbol{y_{obs}}, \boldsymbol{y_{mis}})
\end{aligned} \tag{8}$$

Then the score function is give by,

$$\begin{aligned} U(\beta_0) = \frac{d}{d\beta_0} l(\boldsymbol{\beta}; \boldsymbol{x}, \boldsymbol{y_{obs}}, \boldsymbol{y_{mis}}) = \sum_i^n \left(y_i - \frac{e^{\beta_0 + x_i\beta_1}}{1 + e^{\beta_0 + x_i\beta_1}} \right) \\ U(\beta_1) = \frac{d}{d\beta_1} l(\boldsymbol{\beta}; \boldsymbol{x}, \boldsymbol{y_{obs}}, \boldsymbol{y_{mis}}) = \end{aligned} \tag{9}$$

Now we proceed to implement the EM algorithm by calculating $Q(\boldsymbol{\beta}|\boldsymbol{\beta^{(t)}})$

$$\begin{aligned} Q(\boldsymbol{\beta}|\boldsymbol{\beta^{(t)}}) &= \mathbb{E}_{\boldsymbol{y_{mis}}}[l(\boldsymbol{\beta}; \boldsymbol{x}, \boldsymbol{y_{obs}}, \boldsymbol{y_{mis}})|\boldsymbol{y_{obs}}, \boldsymbol{x}, \boldsymbol{\beta^{(t)}}] \\ &= \sum_{i=1}^m \Big(y_i(\beta_0 + x_i\beta_i) \Big) - \sum_{i=1}^m \Big(\log(1 + e^{\beta_0 + x_i\beta_1}) \Big) + \sum_{i=m+1}^n \Big((\beta_0 + x_i\beta_1) \mathbb{E}_{\boldsymbol{y_{mis}}}[y_i|\boldsymbol{x}, \boldsymbol{y_{obs}}, \boldsymbol{\beta^{(t)}}] \Big) \\ &= \sum_{i=1}^m \Big(y_i(\beta_0 + x_i\beta_i) \Big) - \sum_{i=1}^m \Big(\log(1 + e^{\beta_0 + x_i\beta_1}) \Big) + \sum_{i=m+1}^n \Big((\beta_0 + x_i\beta_1) p_i(\beta) \Big) \\ & (\mathbb{E}(Y_i) = p_i(\boldsymbol{\beta}) \text{ as } Y_i \sim \text{Bernoulli}(p_i(\boldsymbol{\beta}))) \end{aligned} \tag{10}$$

Now we differentiate Q with respect to β_0 and β_1

$$\begin{aligned} \frac{d}{d\beta_0} Q(\boldsymbol{\beta}|\boldsymbol{\beta^{(t)}}) &= \sum_{i=1}^m \left(y_i - \frac{e^{\beta_0 + x_i\beta_1}}{1 + e^{\beta_0 + x_i\beta_1}} \right) + \sum_{i=m+1}^n \left(\frac{e^{\beta_0 + x_i\beta_1}}{1 + e^{\beta_0 + x_i\beta_1}} + x_i\beta_1 \frac{e^{\beta_0 + x_i\beta_1}}{(1 + e^{\beta_0 + x_i\beta_1})^2} + \beta_0 \frac{e^{\beta_0 + x_i\beta_1}}{(1 + e^{\beta_0 + x_i\beta_1})^2} \right) \\ \frac{d}{d\beta_1} Q(\boldsymbol{\beta}|\boldsymbol{\beta^{(t)}}) &= \sum_{i=1}^m \left(y_i x_i - x_i \frac{e^{\beta_0 + x_i\beta_1}}{1 + e^{\beta_0 + x_i\beta_1}} \right) + \sum_{i=m+1}^n \left(\beta_0 \frac{x_i e^{\beta_0 + x_i\beta_1}}{(1 + e^{\beta_0 + x_i\beta_1})^2} + x_i \frac{e^{\beta_0 + x_i\beta_1}}{1 + e^{\beta_0 + x_i\beta_1}} + x_i\beta_1 \frac{x_i e^{\beta_0 + x_i\beta_1}}{(1 + e^{\beta_0 + x_i\beta_1})^2} \right) \end{aligned} \tag{11}$$

The solutions of the derivatives have no closed form expression and thus we need to resort to numerical methods. Before we proceed to the code, we first need to preprocess `dataex4` by arranging it.

```
dataex4 <- dataex4[order(dataex4$Y),]
row.names(dataex4) <- NULL
head(dataex4,5)
```

```
##            X Y
## 1  0.3215956 0
## 2  0.2582281 0
## 3  0.4352370 0
## 4 -0.2277718 0
## 5 -0.3193020 0
```

```
tail(dataex4,5)
```

```
##             X  Y
## 496 0.6989142 NA
## 497 0.8936356 NA
## 498 0.7551561 NA
## 499 0.8782734 NA
## 500 0.6924915 NA
```

In the code, we have used for the stopping criterion as below

$$|\beta_0^{(t+1)} - \beta_0^{(t)}| + |\beta_1^{(t+1)} - \beta_1^{(t)}| < \varepsilon$$

```
log.lik.bernoulli <- function(param, data){
  beta0 <- param[1]; beta1 <- param[2]
  x <- data[, 1]; y <- data[, 2]
  express <- beta0+x[1:405]*beta1
  express.na <- beta0+x[406:500]*beta1
  # sum(y[1:405]-(express/(1+express)))+sum((express/(1+express))+x[406:500]*(express/(1+express)^2)+be
  sum(y[1:405]*express-log(1+express)+express.na*express.na/(1+express.na))
}

mle <- maxLik(logLik = log.lik.bernoulli, data=dataex4, start=c(0, 0))$estimate
# mle <- optim(c(0, 0), log.lik.bernoulli, data = dataex4, control = list(fnscale = -1), hessian = TRUE
beta <- c(0,0)
i <- TRUE
diff <- 1
while(diff > 0.00001){
#     mle <- optim(beta, log.lik.bernoulli, data = dataex4,
# control = list(fnscale = -1), hessian = TRUE)$par
    mle <- maxLik(logLik = log.lik.bernoulli, data=dataex4, start = beta)
    diff <- sum(abs(mle$estimate-beta))
    print(diff)
    beta <- mle$estimate
  # if(diff >0.00001){
  #
  # }
  # else{
  #   i==FALSE
  # }
}
```

```
## [1] 1.003097
## [1] 9.224039e-06
```

```
beta
```

```
## [1] -0.6067501 -0.3963565
```

Q5

Consider a random sample $Y_1, ..., Y_n$ from the mixture distribution with density

$$f(y) = pf_{\text{LogNormal}}(y; \mu, \sigma^2) + (1-p)f_{\text{Exp}}(y; \lambda),$$

with

$$\begin{aligned} f_{\text{LogNormal}}(y; \mu, \sigma^2) &= \frac{1}{y\sqrt{2\pi\sigma^2}} \exp\left\{\frac{1}{2\sigma^2}(\log y - \mu)^2\right\}, \quad y > 0, \quad \mu \in \mathbb{R},\ \sigma > 0 \\ f_{\text{Exp}}(y; \lambda) &= \lambda e^{-\lambda y}, \quad y \geq 0, \quad \lambda > 0 \end{aligned}$$

and $\boldsymbol{\theta} = (p, \mu, \sigma^2, \lambda)$

a)

Derive the EM algorithm to find the updating equations for $\boldsymbol{\theta}^{(t+1)} = (p^{(t+1)}, \mu^{(t+1)}, (\sigma^{(t+1)})^2, \lambda^{(t+1)})$.

Answer :

Let us consider a mixture model of Log-Normal and Exponential distributions.

$$\mathbb{P}(Y \leq y) = p \cdot \frac{1}{y\sqrt{2\pi\sigma^2}} \exp\left\{\frac{1}{2\sigma^2}(\log y - \mu)^2\right\} + (1-p) \cdot \lambda e^{-\lambda y}$$

Let z_i be the binary latent variables indicating component membership, i.e.

$$z_i = \begin{cases} 1 & \text{if } y_i \text{ belong to } f_{\text{LogNormal}}(y; \mu, \sigma^2) \\ 0 & \text{if } y_i \text{ belong to } f_{\text{Exp}}(y; \lambda) \end{cases}$$

The observed data in this context is $\boldsymbol{y} = (y_1 \ldots y_n)$ and the missing data is $\boldsymbol{z} = (z_1 \ldots z_n)$. The likelihood of the complete data $(\boldsymbol{y}, \boldsymbol{z})$ is

$$\begin{aligned} L(\theta; \boldsymbol{y}, \boldsymbol{z}) &= \prod_{i=1}^{n} \left(p \cdot \frac{1}{y_i\sqrt{2\pi\sigma^2}} \exp\left\{\frac{1}{2\sigma^2}(\log y_i - \mu)^2\right\}\right)^{z_i} \left((1-p) \cdot \lambda e^{-\lambda y_i}\right)^{1-z_i} \\ \implies \log L(\theta; \boldsymbol{y}, \boldsymbol{z}) &= \sum_{i=1}^{n} z_i \log\left(p \cdot \frac{1}{y_i\sqrt{2\pi\sigma^2}} \exp\left\{\frac{1}{2\sigma^2}(\log y_i - \mu)^2\right\}\right) + \sum_{i=1}^{n}(1-z_i)\log\left((1-p) \cdot \lambda e^{-\lambda y_i}\right) \end{aligned} \tag{12}$$

with the corresponding log likelihood, we proceed to E-Step,

$$\begin{aligned} Q(\boldsymbol{\theta}|\boldsymbol{\theta}^{(t)}) &= \mathbb{E}_Z(\log L(\theta; \boldsymbol{y}, \boldsymbol{z})|\boldsymbol{y}, \boldsymbol{\theta}^{(t)}) \\ &= \sum_{i=1}^{n} \mathbb{E}(Z_i|y_i, \theta^{(t)}) \log\left(p \cdot \frac{1}{y_i\sqrt{2\pi\sigma^2}} \exp\left\{\frac{1}{2\sigma^2}(\log y_i - \mu)^2\right\}\right) \\ &+ \sum_{i=1}^{n}(1 - \mathbb{E}(Z_i|y_i, \theta^{(t)})) \log\left((1-p) \cdot \lambda e^{-\lambda y_i}\right) \end{aligned} \tag{13}$$

We know that $\mathbb{E}(Z_i|\boldsymbol{y}, \boldsymbol{\theta}^{(t)}) = \mathbb{P}(Z_i = 1|y_i, \theta^{(t)})$, and applying Bayes Theorem and the Law of Total Probability, we obtain,

$$
\begin{aligned}
\mathbb{E}(Z_i|\boldsymbol{y},\boldsymbol{\theta^{(t)}}) &= \mathbb{P}(Z_i=1|y_i,\theta^{(t)}) \\
&= \frac{\left(p^{(t)}\cdot\frac{1}{y_i\sqrt{2\pi(\sigma^2)^{(t)}}}\exp\left\{\frac{1}{2(\sigma^2)^{(t)}}(\log y_i-\mu^{(t)})^2\right\}\right)}{\left(p\cdot\frac{1}{y_i\sqrt{2\pi(\sigma^2)^{(t)}}}\exp\left\{\frac{1}{2(\sigma^2)^{(t)}}(\log y_i-\mu^{(t)})^2\right\}\right)\left((1-p^{(t)})\cdot\lambda^{(t)}e^{-\lambda^{(t)}y_i}\right)} \\
&= \tilde{p}_i^{(t)}, \quad i=1,\dots,n
\end{aligned} \tag{14}
$$

Therefore, we substitute 14 into 13

$$
\begin{aligned}
Q(\boldsymbol{\theta}|\boldsymbol{\theta^{(t)}}) = \sum_{i=1}^{n}\tilde{p}_i^{(t)}\log\left(p\cdot\frac{1}{y_i\sqrt{2\pi\sigma^2}}\exp\left\{\frac{1}{2\sigma^2}(\log y_i-\mu)^2\right\}\right) \\
+\sum_{i=1}^{n}(1-\tilde{p}_i^{(t)})\log\left((1-p)\cdot\lambda e^{-\lambda y_i}\right)
\end{aligned} \tag{15}
$$

For the M-step, we only need to compute the partial derivatives

$$
\begin{aligned}
\frac{\partial}{\partial p}Q(\boldsymbol{\theta}|\boldsymbol{\theta^{(t)}}) = 0 &\implies p^{(t+1)} = \frac{\sum_{i=1}^{n}\tilde{p}_i^{(t)}}{n} \\
\frac{\partial}{\partial \mu}Q(\boldsymbol{\theta}|\boldsymbol{\theta^{(t)}}) = 0 &\implies \mu^{(t+1)} = \frac{\sum_{i=1}^{n}\tilde{p}_i^{(t)}y_i}{\sum_{i=1}^{n}\tilde{p}_i^{(t)}} \\
\frac{\partial}{\partial \sigma^2}Q(\boldsymbol{\theta}|\boldsymbol{\theta^{(t)}}) = 0 &\implies (\sigma^2)^{(t+1)} = \frac{\sum_{i=1}^{n}\tilde{p}_i^{(t)}y_i(y_i-\mu^{(t)})^2}{\sum_{i=1}^{n}\tilde{p}_i^{(t)}y_i} \\
\frac{\partial}{\partial \lambda}Q(\boldsymbol{\theta}|\boldsymbol{\theta^{(t)}}) = 0 &\implies \lambda^{(t+1)} = \frac{\sum_{i=1}^{n}(1-\tilde{p}_i^{(t)})}{\sum_{i=1}^{n}y_i(1-\tilde{p}_i^{(t)})}
\end{aligned} \tag{16}
$$

b)

Using the dataset `datasetex5.Rdata` implement the EM algorithm and find the MLEs for each component of θ. As starting values, you might want to consider $\theta^{(0)} = (p^{(0)}, \mu^{0)}, (\sigma^{(0)})^2, \lambda^{(0)}) = (0.1, 1, 0.5^2, 2)$. Draw the histogram of the data with the estimated density superimposed.

Answer :

```
load("dataex5.Rdata")
```

In the code, we have used for the stopping criterion

$$|p^{(t+1)} - p^{(t)}| + |\mu^{(t+1) - \mu(t)}| + |(\sigma^2)^{(t+1)} - (\sigma^2)^{(t)}| + |\lambda^{(t+1)} - \lambda^{(t)}| < \varepsilon$$

with $\varepsilon = 0.00001$. For the starting values we use $\theta^{(0)} = (p^{(0)}, \mu^{0)}, (\sigma^{(0)})^2, \lambda^{(0)}) = (0.1, 1, 0.5^2, 2)$ as given.