
LDATS2130

Introduction to bayesian statistics

Project report of Group F

Authors :

Mathias Dah Fienon, noma: 04452100

&

Lavinia Myo Lemegne, noma: 16562200

Academic year: 2022-2023

We are working under the following assumptions:

- the evolution of the numbers $y(t)$ of cancer cells detected by the technician over time is a poisson distribution $y(t_j) \sim \text{Pois}(\mu(t_j))$ with

$$\mu(t_j) = \beta_0 \exp\left(\frac{\beta_1}{\beta_2}(1 - e^{-\beta_2 t_j})\right)$$

where $\beta_k > 0$ ($k = 0, 1, 2$) and the later is reparametrized as

$$\alpha_0 \exp(-\alpha_1 e^{-\alpha_2 t})$$

with $\alpha_k > 0$ ($k = 0, 1, 2$)

Question 1 :

(a) Examination of $\mu(t)$ and its relative change

Let's define $k(t) = (1 - e^{-\beta_2 t})$

$$k(t) = (1 - e^{-\beta_2 t}) \implies \mu(t) = \beta_0 \exp\left(\frac{\beta_1}{\beta_2} k(t)\right)$$

$$\frac{d\mu(t)}{dt} = \frac{\partial \mu(t)}{\partial k(t)} \frac{\partial k(t)}{\partial t} = \beta_0 \frac{\beta_1}{\beta_2} \exp\left(\frac{\beta_1}{\beta_2} k(t)\right) \beta_2 e^{-\beta_2 t}$$

$$\implies \frac{1}{\mu(t)} \frac{d\mu(t)}{dt} = \beta_1 e^{-\beta_2 t}$$

- **Parameters interpretation**

Table 1: values of μ and its relative change over time at $t = 0$ and $t \rightarrow \infty$

	$t = 0$	$t \rightarrow \infty$
$\mu(t)$	β_0	$\alpha_0 = \beta_0 \exp\left(\frac{\beta_1}{\beta_2}\right)$
$\frac{1}{\mu(t)} \frac{d\mu(t)}{dt}$	β_1	0

- β_0 is actually the expected value of the number of cancer cells in a given experiment at beginning of the latest.
- β_1 can be seen as the relative change of the expected mean of numbers of cancer cells in the experiment and $e^{-\beta_2}$ is the relative variation observed in this relative changes of the mean by time.

(b) Link between α_k and β_k

Given the available information,

$$\begin{aligned}\mu(t_j) &= \beta_0 \exp\left(\frac{\beta_1}{\beta_2}(1 - e^{-\beta_2 t_j})\right) \\ &= \beta_0 \exp\left(\frac{\beta_1}{\beta_2}\right) \exp\left(-\frac{\beta_1}{\beta_2} e^{-\beta_2 t}\right) = \alpha_0 \exp(-\alpha_1 e^{-\alpha_2 t}) \\ \implies \alpha_0 &= \beta_0 \exp\left(\frac{\beta_1}{\beta_2}\right), \alpha_1 = \frac{\beta_1}{\beta_2}, \alpha_2 = \beta_2\end{aligned}$$

Question 2

(a) Analytic form of likelihood function $\mathcal{L}(\alpha/\mathcal{D}_i)$

By defining : $\alpha = (\alpha_0, \alpha_1, \alpha_2)$, $y(t_j) = y_j$ the numbers of cancer cells detected by the technician at time t_j and $\mu(t_j) = \mu_j$ the parameter (the mean over time t_j) of the poisson distribution of y_j .

$$\begin{aligned}\mathcal{L}(\alpha/\mathcal{D}_i) &= \prod_{j=1}^J p(y_j) = \prod_{j=1}^J \frac{e^{-\mu_j} \mu_j^{y_j}}{y_j!} = \frac{\prod_{j=1}^J e^{-\mu_j} \mu_j^{y_j}}{\prod_{j=1}^J y_j!} \\ &= \frac{e^{-\sum_{i=1}^J \mu_j} \prod_{j=1}^J \mu_j^{y_j}}{\prod_{j=1}^J y_j!}\end{aligned}$$

(b) R function of log-likelihood

- **log-likelihood function $\log(\mathcal{L}(\alpha/\mathcal{D}_i))$**

$$\begin{aligned}\log(\mathcal{L}(\alpha/\mathcal{D}_i)) &= \log\left(\prod_{j=1}^J p(y_j)\right) \\ &= \log\left(e^{-\sum_{i=1}^J \mu_j} \prod_{j=1}^J \mu_j^{y_j}\right) - \log\left(\prod_{j=1}^J y_j!\right) \\ &= \log\left(e^{-\sum_{i=1}^J \mu_j}\right) + \log\left(\prod_{j=1}^J \mu_j^{y_j}\right) - \log\left(\prod_{j=1}^J y_j!\right) \\ &= -\sum_{i=1}^J \mu_j + \sum_{i=1}^J y_j \log(\mu_j) - \sum_{i=1}^J \log(y_j!)\end{aligned}$$

- R function defining the log-likelihood

```
loglikelihood <- function(theta0, theta1, theta2, data = dt[[2]], day = dt[[1]]){

  sum_mu_j <- sum(exp(theta0)*exp(exp(-(exp(theta1)*exp(-day*exp(theta2))))))
  sum_yj_log_muj <- sum(data*
                        log(exp(theta0)*exp(exp(-(exp(theta1)
                                                         *exp(-day*exp(theta2)))))))

  sum_log_yj <- sum(factorial(log(data)))

  return(-sum_mu_j + sum_yj_log_muj - sum_log_yj)
}

loglikelihood(.5, .2, .3)
```

```
## [1] -364958
```

(c) R function of log-posterior $p(\theta/\mathcal{D}_i)$

- log-posterior function

Let's define the prior distribution of parameters $\theta = (\theta_0, \theta_1, \theta_2)$

Under independence assumptions between θ s and the large variances,

$$p(\theta) = p(\theta_0, \theta_1, \theta_2,) \propto 1$$

Considering $\theta_k = \log(\alpha_k)$ we have

$$\mu(t_j) = e^{\theta_0} \exp(-e^{\theta_1} e^{-t_j e^{\theta_2}})$$

This boils down the posterior distribution of θ to the following :

$$\begin{aligned} p(\theta|\mathcal{D}_j) &= \mathcal{L}(\mathcal{D}_j|\theta) \times p(\theta) \\ &= \mathcal{L}(\mathcal{D}_j|\theta) \times 1 \\ &= \frac{e^{-\sum_{j=1}^J \mu_j} \prod_{j=1}^J \mu_j^{y_j}}{\prod_{j=1}^J y_j!} \\ &\propto e^{-\sum_{j=1}^J \mu_j} \prod_{j=1}^J \mu_j^{y_j} \\ &\propto \exp\left(-e^{\theta_0} \sum_{j=1}^J \exp(-e^{\theta_1} e^{-t_j e^{\theta_2}})\right) \prod_{j=1}^J \left(e^{\theta_0} \exp(-e^{\theta_1} e^{-t_j e^{\theta_2}})\right)^{y_j} \end{aligned}$$

From the above, the log-posterior is :

$$\begin{aligned}
\log(p(\boldsymbol{\theta}|\mathcal{D}_y)) &= \log(\mathcal{L}(\mathcal{D}_y|\boldsymbol{\theta})) + \log(p(\boldsymbol{\theta})) \\
&\propto \left(-e^{\theta_0} \sum_{j=1}^J \exp(-e^{\theta_1} e^{-t_j} e^{\theta_2}) \right) + \sum_{j=1}^J y_j \log \left(e^{\theta_0} \exp(-e^{\theta_1} e^{-t_j} e^{\theta_2}) \right) \\
&\propto \left(-e^{\theta_0} \sum_{j=1}^J \exp(-e^{\theta_1} e^{-t_j} e^{\theta_2}) \right) + \sum_{j=1}^J y_j \left(\theta_0 - e^{\theta_1} e^{-t_j} e^{\theta_2} \right) \\
&\propto \left(-e^{\theta_0} \sum_{j=1}^J \exp(-e^{\theta_1} e^{-t_j} e^{\theta_2}) \right) + \theta_0 \sum_{j=1}^J y_j - e^{\theta_1} \sum_{j=1}^J y_j e^{-t_j} e^{\theta_2}
\end{aligned}$$

- R function of log-posterior

```

logposterior <- function(theta0,theta1, theta2, data=dt[[2]], day=dt[[1]],variance=1){
  firstsum <- -exp(theta0) * sum(exp(-exp(theta1)*exp(-day*exp(theta2))))
  secondsum <- theta0*sum(data)
  thirdsum <- exp(theta1)*sum(data*exp(-day*exp(theta2)))
  return(firstsum+secondsum-thirdsum)
}

logposterior(.5, .2, .3)

```

```
## [1] 50634.28
```