

# The problem

Example of a multi-stage Gibbs sampler for reliability analysis. We want to set up a Bayesian analysis to eventually draw from the posterior distribution of the number of failures for a given time of observation of nuclear plant pumps based on some initial data.

Keywords: Reliability, Poisson process, Gibbs sampling, Poisson-Gamma model, Empirical Bayes

## Pump data

The data: numbers of failures and times of observation of 10 pumps in a nuclear plant (Source: Gaver and O'Muircheartaigh, 1987)

	Pump	Failures	Time
1	1	5.00	94.32
2	2	1.00	15.72
3	3	5.00	62.88
4	4	14.00	125.76
5	5	3.00	5.24
6	6	19.00	31.44
7	7	1.00	1.05
8	8	1.00	1.05
9	9	4.00	2.10
10	10	22.00	10.48

## Model and assumptions

The failure of the  $i$ th pump follow a Poisson process with parameter  $\lambda_i$ , for  $i = 1, 2, \dots, 10$ . For an observed time  $t_i$  the number of failures  $p_i$  is thus a Poisson  $\mathcal{P}(\lambda_i t_i)$  r.v.

Likelihood of failure

$$y_i \sim \mathcal{P}(\lambda_i t_i)$$

Prior on  $\lambda_i$  and prior on  $\beta$

$$\lambda_i \sim \mathcal{Ga}(\alpha, \beta)$$

$$\beta \sim \mathcal{Ga}(\gamma, \delta)$$

with  $\alpha = 1.8$ ,  $\gamma = 0.01$  and  $\delta = 1$  (see. Gaver and O'Muircheartaigh 1987 for a motivation of these numerical values)

# Joint and conditional distributions

Joint posterior distribution

$$\begin{aligned}\pi(\lambda_1, \dots, \lambda_{10}, \beta \mid t_1, \dots, t_{10}, p_1, \dots, p_{10}) \\ \propto \prod_{i=1}^{10} \left( (\lambda_i t_i)^{p_i} e^{-\lambda_i t_i} \lambda_i^{\alpha-1} e^{-\beta \lambda_i} \right) \beta^{10\alpha} \beta^{\gamma-1} e^{-\delta \beta} \\ \propto \prod_{i=1}^{10} \left( (\lambda_i)^{p_i + \alpha - 1} e^{-(t_i + \beta) \lambda_i} e^{-\beta \lambda_i} \right) \beta^{10\alpha + \gamma - 1} e^{-\delta \beta}\end{aligned}$$

and a natural decomposition of  $\pi$  in conditional distributions is

$$\lambda_i \mid \beta, t_i, p_i \sim \mathcal{Ga}(p_i + \alpha, t_i + \beta)$$

$$\beta \mid \lambda_1, \dots, \lambda_{10} \sim \mathcal{Ga}\left(\gamma + 10\alpha, \delta \sum_{i=1}^{10} \lambda_i\right)$$

# Multistage Gibbs sampler for Poisson-Gamma model

```
1 Gibbs_sampler_PG <- function(nsim, beta, alpha, gamma, delta, y, t, burnin) {
2
3   X = matrix(0, nrow = nsim, ncol = length(y)+1) # empty matrix to record the
      simulated values
4   X[1,1] = beta # beta prior parameter
5   X[1,c(2:(length(y)+1))] = rgamma(length(y), y + alpha, t + X[1,1]) # initial
      lambda
6
7   for(i in 2:nsim) {
8
9     X[i,c(2:(length(y)+1))] = rgamma(length(y), y + alpha, t + X[i-1,1]) #
      update lambda
10    X[i,1] = rgamma(1, length(y) * alpha + gamma, delta + sum(X[i-1,c(2:(length(
      y)+1))])) # update beta
11  }
12
13  b <- burnin + 1 # record the burn in period (observations to be discarded)
14  x <- X[b:nsim, ]
15
16  return(list('lambda' = as.numeric(x[,c(2:(length(y)+1))]), 'beta' = x[,1] ))
17 }
18
19 # posterior
20 set.seed(2023)
21 posterior <- Gibbs_sampler_PG(nsim = 10000, beta = 1, alpha = 1.8, gamma = 0.01,
22                               delta = 1, y = dataset[,2], t = dataset[,3],
      burnin = 1000)
```

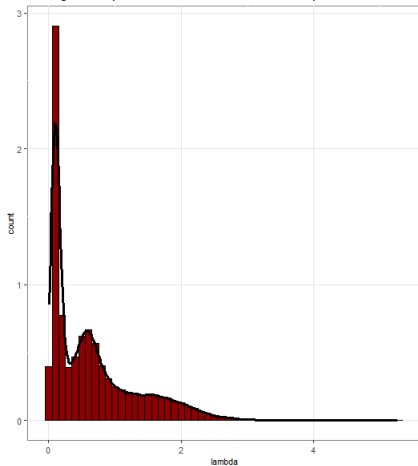
## Posterior quantities obtained from Gibbs sampling

	lambda	beta
post mean	0.6510	2.4598
post sd	0.6534	0.7101
2.5%	0.0431	1.3196
50%	0.4626	2.3690
97.5%	2.2652	4.0806

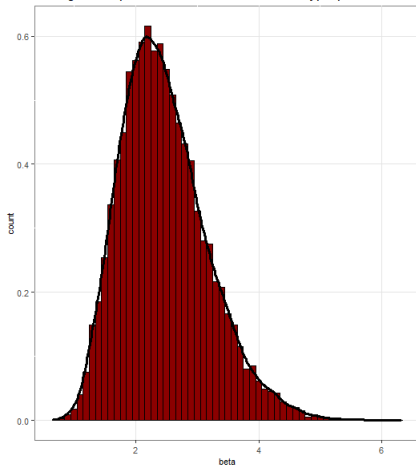
We see that the distribution of the number of failures given time is bimodal and right skewed. We can now draw our conclusions not only based on point estimates but we have the whole distribution.

# Posterior distributions

Histogram of posterior distribution of lambda parameter



Histogram of posterior distribution of beta hyperparameter



## References

Donald P. Gaver I. G. O'Muircheartaigh (1987) Robust Empirical Bayes Analyses of Event Rates, Technometrics, 29:1, 1-15, DOI: 10.1080/00401706.1987.10488178

Robert, C. P., Casella, G., Casella, G. (1999). Monte Carlo statistical methods (Vol. 2). New York: Springer.

The R Project for Statistical Computing:  
<https://www.r-project.org/>