

# MAS4303 Modern Bayesian Inference

## Part 2

TEST: SOLUTION

Semester 1, 2008-9

Davies and Goldsmith (1972) give the following data on piston ring failures in steam-driven compressors. There were four identical compressors in the same compressor house, each oriented the same way, and each had three legs. The data give the number of failures in each leg of each compressor over a period of some years.

Compressor Number	North Leg	Centre Leg	South Leg
1	17	17	12
2	11	9	13
3	11	8	19
4	14	7	28

Let the number of failures in leg  $j$  (North:  $j = 1$ , Centre:  $j = 2$ , South:  $j = 3$ ) of compressor  $i$  be  $Y_{i,j}$ . Suppose that we believe that, given parameters  $\lambda_{i,j} > 0$ , each  $Y_{i,j}$  has a  $\text{Poisson}(\lambda_{i,j})$  distribution, independently of the others. That is, given  $\lambda_{i,j}$ ,

$$Y_{i,j} \sim \text{Poisson}(\lambda_{i,j}).$$

We also believe that

$$\log(\lambda_{i,j}) = \alpha_i + \beta_j + \gamma_{i,j}.$$

- The compressor effects  $\alpha_i$  are regarded as random. Given the value of  $\tau_\alpha$ , we have  $\alpha_1, \dots, \alpha_4$  independent with

$$\alpha_i \sim N(0, \tau_\alpha^{-1}).$$

The prior distribution for  $\tau_\alpha$  is

$$\tau_\alpha \sim \text{gamma}(1, 1).$$

- The interaction effects  $\gamma_{i,j}$  are regarded as random. Given the value of  $\tau_\gamma$ , we have  $\gamma_{1,1}, \dots, \gamma_{4,3}$  independent with

$$\gamma_{i,j} \sim N(0, \tau_\gamma^{-1}).$$

The prior distribution for  $\tau_\gamma$  is

$$\tau_\gamma \sim \text{gamma}(1, 1).$$

- In the prior distribution  $\tau_\alpha$  is independent of  $\tau_\gamma$  and of  $\beta_1, \beta_2, \beta_3$  and  $\tau_\gamma$  is independent of  $\beta_1, \beta_2, \beta_3$ .
- The leg means  $\beta_1, \beta_2, \beta_3$  are regarded as fixed but unknown. The prior distribution for  $\beta_1, \beta_2, \beta_3$  is multivariate normal with

$$\begin{aligned} \text{E}(\beta_1) = \text{E}(\beta_2) = \text{E}(\beta_3) &= 12.0, \\ \text{var}(\beta_1) = \text{var}(\beta_2) = \text{var}(\beta_3) &= 25.0, \\ \text{covar}(\beta_1, \beta_2) = \text{covar}(\beta_1, \beta_3) = \text{covar}(\beta_2, \beta_3) &= 16.0. \end{aligned}$$

1. A hierarchical prior structure is proposed for  $\beta_1, \beta_2, \beta_3$  with

$$\beta_j \mid \mu \sim N(\mu, v_\beta)$$

and

$$\mu \sim N(m, v_\mu).$$

Find the values of  $m$ ,  $v_\mu$  and  $v_\beta$ .

We obtain

$$\begin{aligned} m &= \underline{12.0}, \\ v_\mu &= \underline{16.0}, \\ v_\beta = 25.0 - 16.0 &= \underline{9.0}. \end{aligned}$$

2. Use BRugs to evaluate the posterior distribution.
- (a) Write down your BRugs model specification.

A suitable BRugs model specification is as follows.

```
model compressor

{for (i in 1:12)
  {y[i]~dpois(lambda[i])
   log(lambda[i])<-alpha[comp[i]]+beta[leg[i]]+gamma[i]
   gamma[i]~dnorm(0,tau.gamma)
  }

  for (k in 1:4)
    {alpha[k]~dnorm(0,tau.alpha)
    }

  for (j in 1:3)
    {beta[j]~dnorm(mu,tau.beta)
    }

  mu~dnorm(m,tau.mu)

  m<-12.0
  tau.mu<-1/16.0
  tau.beta<-1/9.0

  tau.alpha~dgamma(1,1)
  tau.gamma~dgamma(1,1)
}
```

- (b) Write down the commands which you use.

```

> modelCheck("test09bug.txt")
> modelData("test09data.txt")
> modelCompile(2)
> modelGenInits()
> samplesSet(c("tau.alpha", "tau.gamma", "alpha", "beta", "gamma", "lambda"))
> modelUpdate(1000)
> samplesHistory("tau.alpha")
> modelUpdate(10000)
> samplesHistory("tau.alpha")
> samplesHistory("tau.gamma")
> samplesHistory("alpha")
> samplesHistory("beta")
> samplesHistory("gamma")
> samplesHistory("lambda")

```

(convergence checked)

```

> modelCheck("test09bug.txt")
> modelData("test09data.txt")
> modelCompile()
> modelGenInits()
> modelUpdate(10000)
> samplesSet(c("beta", "lambda", "tau.alpha"))
> modelUpdate(30000)
> samplesStats(c("beta", "lambda", "tau.alpha"))

```

	mean	sd	MC_error	val2.5pc	median	val97.5pc	start	sample
beta[1]	2.725	0.7717	0.04562	1.5530	2.645	4.696	10001	30000
beta[2]	2.445	0.7945	0.04662	1.1920	2.368	4.477	10001	30000
beta[3]	3.005	0.7821	0.04640	1.7670	2.935	4.979	10001	30000
lambda[1]	16.700	3.9200	0.02205	9.9250	16.400	25.270	10001	30000
lambda[2]	16.030	3.8450	0.02107	9.5000	15.700	24.390	10001	30000
lambda[3]	13.200	3.4810	0.02277	7.2720	12.890	20.870	10001	30000
lambda[4]	11.110	3.1300	0.01843	5.9080	10.810	18.060	10001	30000
lambda[5]	8.948	2.7910	0.01676	4.3930	8.654	15.270	10001	30000
lambda[6]	13.370	3.4840	0.01982	7.4570	13.070	20.970	10001	30000
lambda[7]	11.250	3.1710	0.01981	5.9590	10.940	18.310	10001	30000
lambda[8]	8.330	2.6690	0.01682	3.9630	8.041	14.310	10001	30000
lambda[9]	18.600	4.1500	0.02238	11.4100	18.280	27.550	10001	30000
lambda[10]	14.100	3.5540	0.01809	8.0230	13.810	21.840	10001	30000
lambda[11]	7.924	2.6080	0.01931	3.6890	7.627	13.790	10001	30000
lambda[12]	26.970	5.0850	0.02630	17.9500	26.610	37.840	10001	30000
tau.alpha	2.021	1.3800	0.03177	0.1766	1.738	5.451	10001	30000

- (c) Find the posterior mean of  $\tau_\alpha$ .

The posterior mean of  $\tau_\alpha$  is 2.021.

- (d) Find a symmetric 95% posterior interval for  $\beta_1$ .

The interval is  $1.5530 < \beta_1 < 4.696$ .

- (e) Find a symmetric 95% posterior interval for  $\lambda_{1,1}$ .

The interval is  $9.9250 < \lambda_{1,1} < 25.270$ .

- (f) Comment on the behaviour of the MCMC sampler (e.g. convergence, mixing).

Convergence appears to take up to about 8000 iterations for some quantities and mixing is poor so a large burn-in and a large number of samples are required for a good approximation to the posterior distribution.