

# ADVANCED BAYESIAN MODELING

# JAGS Analysis: First Attempt

$y_{ijk}$  = number of damage incidents to ships in category  $(i, j, k)$

$t_{ijk}$  = total months of service represented by category  $(i, j, k)$

$i$  : type of ship       $j$  : era of construction       $k$  : period of operation

# Loglinear Rate Model

$$y_{ijk} \mid \beta, t_{ijk} \sim \text{indep. Poisson}(\lambda_{ijk}) \qquad \lambda_{ijk} = t_{ijk} r_{ijk}$$

$$\log \lambda_{ijk} = \log(t_{ijk} r_{ijk}) = \log t_{ijk} + \beta^0 + \beta_i^t + \beta_j^e + \beta_k^p$$

$$\beta_i^t \mid \sigma_t^2 \sim \text{iid N}(0, \sigma_t^2) \qquad \beta_j^e \mid \sigma_e^2 \sim \text{iid N}(0, \sigma_e^2) \qquad \beta_k^p \mid \sigma_p^2 \sim \text{iid N}(0, \sigma_p^2)$$

$$\beta^0 \sim \text{N}(0, 100^2) \qquad \sigma_t, \sigma_e, \sigma_p \sim \text{iid U}(0, 100)$$

In file `ships1.bug`:

```
model {  
  for (i in 1:length(incidents)) {  
    incidents[i] ~ dpois(lambda[i])  
    log(lambda[i]) <- logservice[i] + beta0 + beta.t[type[i]] + beta.e[era[i]] +  
                      beta.p[period[i]]  
  
    incidentsrep[i] ~ dpois(lambda[i])  
  }  
}
```

(continued ...)

Anticipating posterior predictive checking, we define replicated data `incidentsrep`.

```

beta0 ~ dnorm(0, 0.0001)
for (i in 1:max(type)) {
  beta.t[i] ~ dnorm(0, 1/sigma.t^2)
}
for (j in 1:max(era)) {
  beta.e[j] ~ dnorm(0, 1/sigma.e^2)
}
for (k in 1:max(period)) {
  beta.p[k] ~ dnorm(0, 1/sigma.p^2)
}

sigma.t ~ dunif(0, 100)
sigma.e ~ dunif(0, 100)
sigma.p ~ dunif(0, 100)
}

```

Set up data and initializations for four chains:

```
> d1 <- list(incidents = shipssub$incidents,  
+           logservice = log(shipssub$service),  
+           type = unclass(shipssub$type),  
+           era = unclass(factor(shipssub$year)),  
+           period = unclass(factor(shipssub$period)))  
  
> inits1 <- list(list(beta0=100, sigma.t=90, sigma.e=90, sigma.p=90),  
+               list(beta0=-100, sigma.t=0.01, sigma.e=90, sigma.p=90),  
+               list(beta0=100, sigma.t=90, sigma.e=0.01, sigma.p=0.01),  
+               list(beta0=-100, sigma.t=0.01, sigma.e=0.01, sigma.p=0.01))
```

Recall unclass produces the integer codes of a factor.

```

> library(rjags)
...

> m1 <- jags.model("ships1.bug", d1, inits1, n.chains=4, n.adapt=1000)
...

> update(m1, 1000) # burn-in
|*****| 100%

> x1 <- coda.samples(m1, c("beta0","sigma.t","sigma.e","sigma.p"), n.iter=2000)
|*****| 100%

```

Note: For checking convergence, we monitor only the top-level nodes.



```
> gelman.diag(x1, autoburnin=FALSE)
```

Potential scale reduction factors:

	Point est.	Upper C.I.
beta0	90.57	196.05
sigma.e	1.35	1.89
sigma.p	1.02	1.06
sigma.t	1.17	1.46

Multivariate psrf

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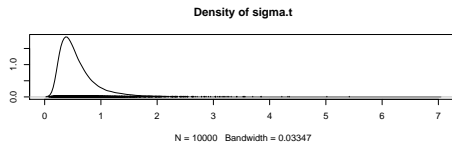
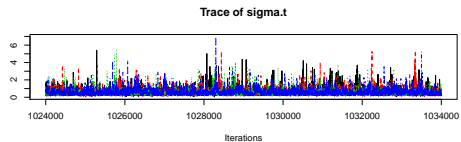
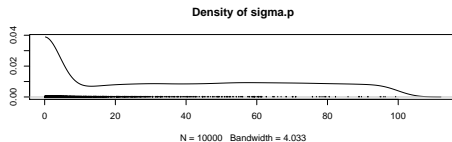
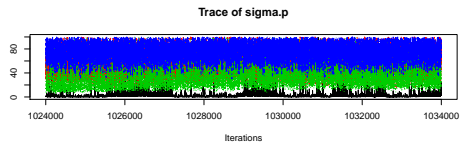
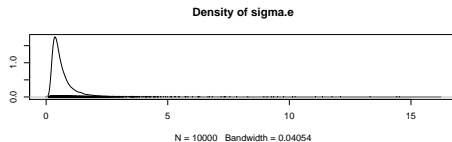
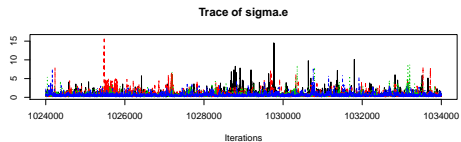
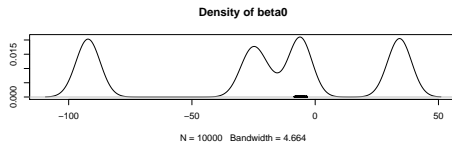
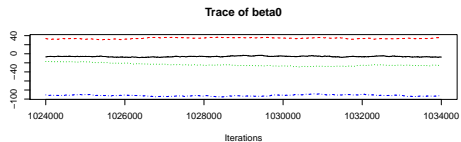
I tried repeatedly running the chains and checking for convergence, doubling the number of iterations each time.

Even after over a million iterations, there was still no convergence.

Trace plots suggest why:

```
> x1 <- coda.samples(m1, c("beta0", "sigma.t", "sigma.e", "sigma.p"), n.iter=10000)
  |*****| 100%

> plot(x1, smooth=FALSE)
```



The chain shows dramatically slow mixing for  $\beta^0$  and  $\sigma_p$ , and some chains have  $\sigma_p$  values near the arbitrary upper bound of 100.

Since the data has only two periods of operation ( $k = 1, 2$ ), it is possible that  $\sigma_p^2$  is poorly defined – it is the variance of only two random effects.

An improved model might treat  $\beta_1^p$  and  $\beta_2^p$  as fixed effects instead.