Kidney: Weibull regression with random efects

McGilchrist and Aisbett (1991) analyse time to first and second recurrence of infection in kidney patients on dialysis using a Cox model with a multiplicative frailty parameter for each individual. The risk variables considered are age, sex and underlying disease (coded other, GN, AN and PKD). A portion of the data are shown below.

Patient Number	Recurrence time t	Event (2 = cens)	Age at time t	Sex (1 = female)	Disease (0 = other; 1 = GN 2 = AN; 3 = PKD)
1	8,16	1,1	28,28	0	0
2	23,13	1,2	48,48	1	1
3	22,28	1,1	32,32	0	0
4	447,318	1,1	31,32	1	0
.....					
35	119,8	1,1	22,22	1	1
36	54,16	2,2	42,42	1	1
37	6,78	2,1	52,52	1	3
38	63,8	1,2	60,60	0	3

We have analysed the same data assuming a parametric Weibull distribution for the survivor function, and including an additive random effect b_i for each patient in the exponent of the hazard model as follows

$$t_{ij} \sim \text{Weibull}(r, \mu_{ij}) \quad i = 1,...,38; \; j = 1,2$$

$$\log\mu_{ij} = \alpha + \beta_{age}AGE_{ij} + \beta_{sex}SEX_i + \beta_{disease1}DISEASE_{i1} + \beta_{disease2}DISEASE_{i2} + \beta_{disease3}DISEASE_{i3} + b_i$$

$$b_i \sim \text{Normal}(0, \tau)$$

where AGE_{ij} is a continuous covariate, SEX_i is a 2-level factor and $DISEASE_{ik}$ (k = 1,2,3) are dummy variables representing the 4-level factor for underlying disease. Note that the the survival distribution is a truncated Weibull for censored observations as discussed in the mice example. The regression coefficients and the precision of the random effects τ are given independent ``non-informative'' priors, namely

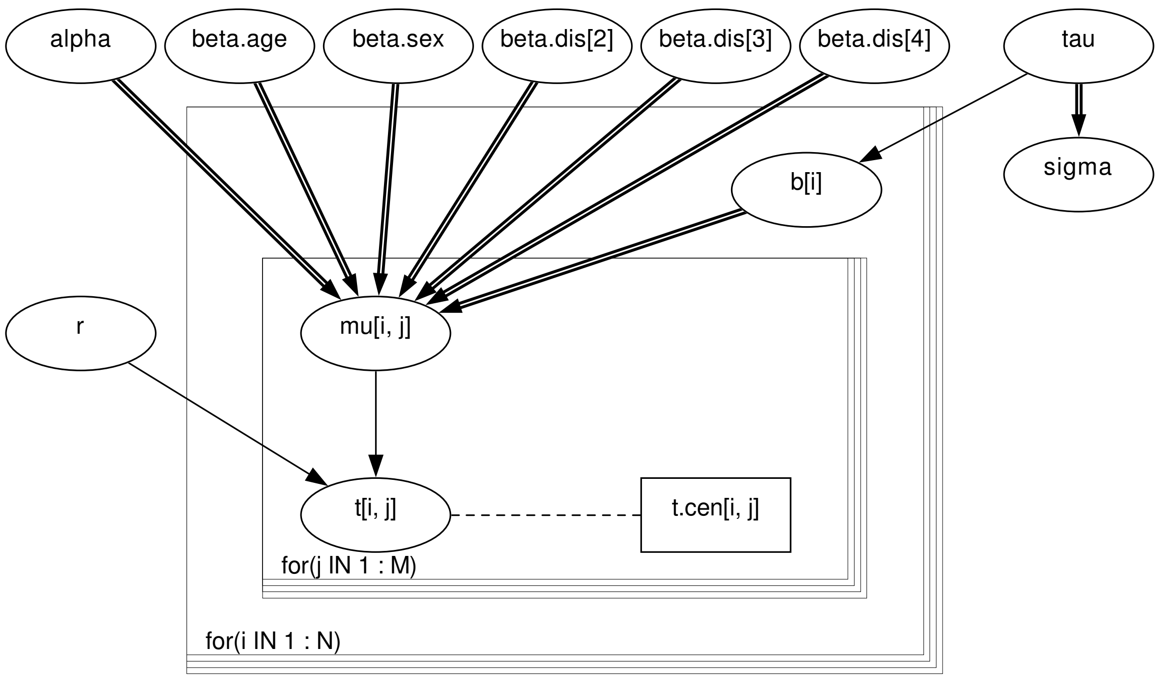
$$b_k \sim \text{Normal}(0, 0.0001)$$

$$\tau \sim \text{Gamma}(0.0001, 0.0001)$$

The shape parameter of the survival distribution r is given a Gamma(1, 0.0001) prior which is slowly decreasing on the positive real line.

The graphical model and *BUGS* language are given below.

Graphical model for kidney example:



BUGS *language for kidney example*

```
model
{
   for (i in 1 : N) {
      for (j in 1 : M) {
# Survival times bounded below by censoring times:
         t[i,j] ~ dweib(r, mu[i,j]) I(t.cen[i, j], );
         log(mu[i,j ]) <- alpha + beta.age * age[i, j]
               + beta.sex  *sex[i]
               + beta.dis[disease[i]] + b[i];
      }
# Random effects:
      b[i] ~ dnorm(0.0, tau)
   }
# Priors:
   alpha ~ dnorm(0.0, 0.0001);
```

```
    beta.age ~ dnorm(0.0, 0.0001);
    beta.sex ~ dnorm(0.0, 0.0001);
#   beta.dis[1] <- 0;  # corner-point constraint
    for(k in 2 : 4) {
       beta.dis[k] ~ dnorm(0.0, 0.0001);
    }
    tau ~ dgamma(1.0E-3, 1.0E-3);
    r ~ dgamma(1.0, 1.0E-3);
    sigma <- 1 / sqrt(tau); # s.d. of random effects
}
```

Data (click to open)

Inits (click to open)

Results

A 1000 update burn in followed by a further 10000 updates gave the parameter estimates

	mean	sd	MC_error	val2.5pc	median	val97.5pc	start	sample
alpha	-4.529	0.9036	0.06244	-6.348	-4.473	-2.932	1001	10000
beta.dis[2]	0.1265	0.5679	0.01859	-0.9922	0.1201	1.3	1001	10000
beta.dis[3]	0.5995	0.5781	0.02205	-0.5284	0.5863	1.815	1001	10000
beta.dis[4]	-1.198	0.8483	0.03147	-2.805	-1.206	0.5525	1001	10000
beta.sex	-1.945	0.5019	0.028	-3.054	-1.906	-1.042	1001	10000
r	1.205	0.1711	0.01523	0.9005	1.2	1.541	1001	10000
sigma	0.6367	0.3802	0.03159	0.04092	0.6494	1.366	1001	10000