

Signal Tandmobiel® Data: Multivariate Survival Data – an analysis using the package **bayesSurv**

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In this document we describe the analysis of the Signal Tandmobiel® data presented in Section 4.2 of Komárek and Lesaffre (2004).

The model we will consider is the following:

$$\begin{aligned}\log(T_{i,l} - 5) = & \beta_1 girl_{i,l} + \beta_2 dmf_{i,l} + \beta_3 girl_{i,l}dmf_{i,l} + \\ & + \beta_4 dmf_{i,l}lower4_{i,l} + \beta_5 dmf_{i,l}upper5_{i,l} + \beta_6 dmf_{i,l}lower5_{i,l} + \\ & + \beta_7 girl_{i,l}lower4_{i,l} + \beta_8 girl_{i,l}upper5_{i,l} + \beta_9 girl_{i,l}lower5_{i,l} + \\ & + b_{i,1} + b_{i,2}lower4_{i,l} + b_{i,3}upper5_{i,l} + b_{i,4}lower5_{i,l} + \varepsilon_{i,l},\end{aligned}$$

where $l = 1, \dots, 8$ indexes 8 permanent teeth (14, 24, 15, 25, 34, 44, 35, 45) in the mouth. Further, $girl_{i,l}$ is equal to 1 if the i th child is girl, $dmf_{i,l}$ is equal to 1 if the primary predecessor of the l th permanent tooth of the i th child has a positive dmf score. Variables $lower4_{i,l}$, $upper5_{i,l}$ and $lower5_{i,l}$, respectively are dummies for lower first premolars (teeth 34, 44), upper second premolars (teeth 15, 25) and lower second premolars (teeth 35, 45), respectively.

Time variable $T_{i,l}$ gives the emergence time of the l th permanent tooth of the i th child in years.

Finally, for the random effect vector \mathbf{b}_i it is assumed: $E(b_{i,1}) = 0$, $E(b_{i,m}) = \gamma_m$ ($m = 2, 3, 4$) and $\text{var}(\mathbf{b}_i) = \mathbb{D}$.

Dental therminology remark: upper jaw = maxilla, lower jaw = mandible. Teeth $10 + s$ are upper right teeth, teeth $20 + s$ are upper left, teeth $30 + s$ are lower left and teeth $40 + s$ are lower right with $s = 1, \dots, 8$. Dental index of a primary predecessor is obtained as *permanent* + 40 where *permanent* is the index of the permanent tooth (e.g. primary tooth 54 is predecessor of the permanent tooth 14).

1 Initial data manipulation

Specify the directory where data are stored and load the **bayesSurv** package:

```
> library(bayesSurv)
> wdir <- paste(getwd(), "/tandmob", sep = "")
```

Specify teeth we want to analyze (*dteeth* are corresponding deciduous teeth):

```
> pteeth <- c(14, 24, 34, 44, 15, 25, 35, 45)
> dteeth <- pteeth + 40
> nteeth <- length(pteeth)
```

Dummies for horizontally symmetric teeth (*upper4* = teeth 14 and 24, *lower4* = teeth 34 and 44, *upper5* = teeth 15 and 25, *lower5* = teeth 35 and 45) further used in the analysis:

```
> upper4 <- c(1, 1, 0, 0, 0, 0, 0, 0)
> lower4 <- c(0, 0, 1, 1, 0, 0, 0, 0)
> upper5 <- c(0, 0, 0, 0, 1, 1, 0, 0)
> lower5 <- c(0, 0, 0, 0, 0, 0, 1, 1)
```

Variables from the whole dataset that are needed or otherwise interesting (`timevars` are variables that determine the interval where the emergence was recorded, `dmfvars` give the caries status of corresponding deciduous teeth):

```
> childvars <- c("IDNR", "GENDER", "GENDERNum", "DOB", "PROVINCE",
+   "EDUC")
> timevars <- paste(c("EBEG.", "EEND."), rep(ptteeth, rep(2, nteeth)),
+   sep = ""))
> dmfvars <- paste("T", dteeth, ".DMF", sep = "")
> vars <- c(childvars, timevars, dmfvars)
> print(vars)

[1] "IDNR"      "GENDER"     "GENDERNum"   "DOB"        "PROVINCE"   "EDUC"
[7] "EBEG.14"    "EEND.14"    "EBEG.24"     "EEND.24"    "EBEG.34"    "EEND.34"
[13] "EBEG.44"    "EEND.44"    "EBEG.15"     "EEND.15"    "EBEG.25"    "EEND.25"
[19] "EBEG.35"    "EEND.35"    "EBEG.45"     "EEND.45"    "T54.DMF"   "T64.DMF"
[25] "T74.DMF"    "T84.DMF"    "T55.DMF"     "T65.DMF"    "T75.DMF"   "T85.DMF"
```

Read the data (full dataset), take only interesting variables and change some names. To see explanation of the variables take a look at the beginning of the file `./tandmob/tandmob2.dat`.

```
> data <- read.table(paste(wdir, "/tandmob2.dat", sep = ""), skip = 65,
+   header = TRUE, as.is = c(T, F, T, T, rep(F, 3), rep(T, 149)))
> data <- data[, vars]
```

Change the name of `GENDERNum` variable:

```
> names(data)[names(data) == "GENDERNum"] <- "GIRL"
> childvars[childvars == "GENDERNum"] <- "GIRL"
> vars[vars == "GENDERNum"] <- "GIRL"
```

Take only children for who deciduous dmf score is available for all studied teeth:

```
> is.dmf <- !is.na(data$T54.DMF) & !is.na(data$T64.DMF) & !is.na(data$T74.DMF) &
+   !is.na(data$T84.DMF) & !is.na(data$T55.DMF) & !is.na(data$T65.DMF) &
+   !is.na(data$T75.DMF) & !is.na(data$T85.DMF)
> data <- data[is.dmf, ]
```

Subtract 5.0 from all time variables (i.e. time 0 in the analyzes = 5 years of age):

```
> startage <- 5
> data[, timevars] <- data[, timevars] - startage
```

Now we take only subsample of 50 boys and 50 girls (their id's are given in the file `IDsampled50.dat`). In Komárek and Lesaffre (2004) an analysis of the subsample of 500 boys and 500 girls is presented (id's from `IDsampled500.dat`).

```
> nFromGender <- 50
> ids <- read.table(paste(wdir, "/IDsampled", nFromGender, ".dat",
+   sep = ""), header = TRUE)[, 1]
> wanna <- match(data$IDNR, ids, nomatch = 0)
> wanna <- as.logical(wanna)
> wanna[wanna > 1] <- TRUE
> data <- data[wanna, ]
```

Look at first few rows of the data:

```
> print(data[1:10, ])
```

IDNR	GENDER	GIRL	DOB	PROVINCE	EDUC	EBEG.14	EEND.14	EBEG.24	EEND.24
57	59	boy	0	04OCT89	4	0	2.4	5.7	2.4
126	130	boy	0	16OCT89	4	0	5.9	NA	5.9
178	183	girl	1	26APR89	1	0	5.7	NA	5.7
218	223	boy	0	31OCT89	0	0	5.0	5.9	5.9
265	270	girl	1	16SEP89	1	0	5.6	6.6	5.6
268	273	girl	1	04JAN89	2	0	4.8	5.7	4.8
283	288	boy	0	07AUG89	2	0	4.5	6.1	4.5
290	295	girl	1	20JUL89	1	0	5.4	6.3	5.4
330	335	boy	0	21MAY89	3	2	4.8	5.8	4.8
370	375	boy	0	27NOV89	2	1	4.0	NA	4.0
EBEG.34 EEND.34 EBEG.44 EEND.44 EBEG.15 EEND.15 EBEG.25 EEND.25 EBEG.35									
57	5.7	NA	2.4	5.7	2.4	5.7	5.7	NA	5.7
126	5.9	NA	5.9	NA	5.9	NA	5.9	NA	5.9
178	5.7	NA	5.7	NA	5.7	NA	5.7	NA	5.7
218	5.0	5.9	5.0	5.9	5.9	NA	5.9	NA	5.9
265	5.6	6.6	4.7	5.6	5.6	6.6	5.6	6.6	5.6
268	3.9	4.8	4.8	5.7	5.7	6.7	5.7	6.7	4.8
283	4.5	6.1	4.5	6.1	4.5	6.1	4.5	6.1	4.5
290	5.4	6.3	5.4	6.3	5.4	6.3	6.3	NA	6.3
330	4.0	4.8	4.8	5.8	4.8	5.8	4.8	5.8	4.0
370	3.2	4.0	3.2	4.0	4.0	NA	4.0	NA	4.0
EEND.35 EBEG.45 EEND.45 T54.DMF T64.DMF T74.DMF T84.DMF T55.DMF T65.DMF									
57	NA	5.7	NA	0	0	1	0	0	0
126	NA	5.9	NA	0	0	0	0	0	0
178	NA	5.7	NA	1	0	1	1	1	1
218	NA	5.9	NA	1	0	0	0	0	0
265	6.6	5.6	6.6	0	1	0	0	0	0
268	5.7	5.7	6.7	1	1	1	1	1	0
283	6.1	4.5	6.1	0	0	0	0	0	0
290	NA	6.3	NA	1	1	1	1	1	1
330	4.8	4.8	5.8	1	0	1	0	1	1
370	NA	4.0	NA	1	1	1	1	1	1
T75.DMF T85.DMF									
57	0	0							
126	0	0							
178	1	1							
218	0	0							
265	0	0							
268	1	0							
283	0	0							
290	1	1							
330	1	1							
370	1	1							

Now we have one row per child in the `data.frame` data. We reformat the data such that there is one row per tooth and create factors to determine the tooth:

```
> nchild <- dim(data)[1]
> longdata <- list()
> for (i in 1:length(childvars)) {
+   longdata[[i]] <- rep(data[[childvars[i]]], nteeth)
+ }
> names(longdata) <- childvars
> longdata <- as.data.frame(longdata)
> longdata$TOOTH <- as.factor(rep(pteeth, rep(nchild, nteeth)))
> longdata$UPPER4 <- rep(upper4, rep(nchild, nteeth))
> longdata$LOWER4 <- rep(lower4, rep(nchild, nteeth))
> longdata$UPPER5 <- rep(upper5, rep(nchild, nteeth))
```

```

> longdata$LOWER5 <- rep(lower5, rep(nchild, nteeth))
> dmf <- numeric()
> for (i in 1:nteeth) dmf <- c(dmf, data[[dmfvars[i]]])
> ebeg <- numeric()
> for (i in 1:nteeth) ebeg <- c(ebeg, data[[paste("EBEG.", pteeth[i],
+ sep = "")]]))
> eend <- numeric()
> for (i in 1:nteeth) eend <- c(eend, data[[paste("EEND.", pteeth[i],
+ sep = "")]]))
> longdata$DMF <- dmf
> longdata$EBEG <- ebeg
> longdata$EEND <- eend
> rm(list = c("dmf", "ebeg", "eend"))
> longdata <- longdata[order(longdata$IDNR), ]

```

Look at first few rows (2 children) of reformatted data:

```
> print(longdata[1:16, ])
```

	IDNR	GENDER	GIRL	DOB	PROVINCE	EDUC	TOOTH	UPPER4	LOWER4	UPPER5	LOWER5
1	59	boy	0	04OCT89		4	0	14	1	0	0
101	59	boy	0	04OCT89		4	0	24	1	0	0
201	59	boy	0	04OCT89		4	0	34	0	1	0
301	59	boy	0	04OCT89		4	0	44	0	1	0
401	59	boy	0	04OCT89		4	0	15	0	0	1
501	59	boy	0	04OCT89		4	0	25	0	0	1
601	59	boy	0	04OCT89		4	0	35	0	0	0
701	59	boy	0	04OCT89		4	0	45	0	0	1
2	130	boy	0	16OCT89		4	0	14	1	0	0
102	130	boy	0	16OCT89		4	0	24	1	0	0
202	130	boy	0	16OCT89		4	0	34	0	1	0
302	130	boy	0	16OCT89		4	0	44	0	1	0
402	130	boy	0	16OCT89		4	0	15	0	0	1
502	130	boy	0	16OCT89		4	0	25	0	0	1
602	130	boy	0	16OCT89		4	0	35	0	0	1
702	130	boy	0	16OCT89		4	0	45	0	0	1
						DMF	EBEG	EEND			
1						0	2.4	5.7			
101						0	2.4	5.7			
201						1	5.7	NA			
301						0	2.4	5.7			
401						0	2.4	5.7			
501						0	5.7	NA			
601						0	5.7	NA			
701						0	5.7	NA			
2						0	5.9	NA			
102						0	5.9	NA			
202						0	5.9	NA			
302						0	5.9	NA			
402						0	5.9	NA			
502						0	5.9	NA			
602						0	5.9	NA			
702						0	5.9	NA			

2 Finding reasonable values for hyperparameters and initial values

We fit the log-normal AFT model without any random effects to get initial values for model parameters and reasonable values for hyperparameters:

```
> ifit <- survreg(Surv(EBEG, EEND, type = "interval2") ~ GIRL *
+     DMF + (DMF + GIRL) * (LOWER4 + UPPER5 + LOWER5), dist = "lognormal",
+     data = longdata)
> summary(ifit)

Call:
survreg(formula = Surv(EBEG, EEND, type = "interval2") ~ GIRL *
    DMF + (DMF + GIRL) * (LOWER4 + UPPER5 + LOWER5), data = longdata,
    dist = "lognormal")

            Value Std. Error      z      p
(Intercept) 1.7410    0.0395 44.046 0.00e+00
GIRL        -0.0816    0.0464 -1.757 7.89e-02
DMF         -0.1154    0.0479 -2.410 1.59e-02
LOWER4       0.0388    0.0542  0.717 4.74e-01
UPPER5       0.1734    0.0556  3.116 1.83e-03
LOWER5       0.2214    0.0565  3.918 8.92e-05
GIRL:DMF     0.1113    0.0432  2.578 9.94e-03
DMF:LOWER4   -0.0417   0.0586 -0.711 4.77e-01
DMF:UPPER5   -0.0623   0.0605 -1.030 3.03e-01
DMF:LOWER5   -0.0632   0.0609 -1.037 3.00e-01
GIRL:LOWER4  -0.0614   0.0589 -1.043 2.97e-01
GIRL:UPPER5   0.0264   0.0609  0.434 6.64e-01
GIRL:LOWER5  -0.0459   0.0615 -0.747 4.55e-01
Log(scale)   -1.3850   0.0378 -36.624 1.21e-293

Scale= 0.250

Log Normal distribution
Loglik(model)= -910.1 Loglik(intercept only)= -955.7
Chisq= 91.2 on 12 degrees of freedom, p= 2.9e-14
Number of Newton-Raphson Iterations: 5
n= 800
```

3 Specification of priors

To specify correctly the prior hyperparameters for β and γ parameters we have to know how the covariates are sorted in the design matrix. Normally, the same order should be used as in the `formula` specification. However, one never knows...

The following command returns the design matrix and we look at first few rows to see how are the covariates sorted in the columns. We also define the variable `nregres` (number of covariates). The same model `formula` is used as in the future function call.

```
> X <- bayessurvreg1(Surv(EBEG, EEND, type = "interval2") ~ GIRL *
+     DMF + (DMF + GIRL) * (LOWER4 + UPPER5 + LOWER5) + cluster(IDNR),
+     random = ~LOWER4 + UPPER5 + LOWER5, data = longdata[1:80,
+     ], onlyX = TRUE)
```

Print first few lines of `X` to see how `betas` are sorted. Remember that both β and γ parameters from Komárek and Lesaffre (2004) are put into one long vector `beta` in the R functions.

```

> print(X[1:5, ])

```

	GIRL	DMF	LOWER4	UPPER5	LOWER5	GIRL:DMF	DMF:LOWER4	DMF:UPPER5	DMF:LOWER5
1	0	0	0	0	0	0	0	0	0
101	0	0	0	0	0	0	0	0	0
201	0	1	1	0	0	0	1	0	0
301	0	0	1	0	0	0	0	0	0
401	0	0	0	1	0	0	0	0	0

	GIRL:LOWER4	GIRL:UPPER5	GIRL:LOWER5
1	0	0	0
101	0	0	0
201	0	0	0
301	0	0	0
401	0	0	0

```

> nregres <- dim(X)[2]
> nobs <- dim(longdata)[1]

```

So we see that $\beta_{1:12} = (\beta(girl), \beta(dmf), \gamma(lower4), \gamma(upper5), \gamma(lower5), \beta(girl : dmf), \beta(dmf : lower4), \beta(dmf : upper5), \beta(dmf : lower5), \beta(girl : lower4), \beta(girl : upper5), \beta(girl : lower5))'$.

Notice that the random effect vector is now 4-dimensional, i.e. $\mathbf{b}_i = (b_{i,1}, b_{i,2}, b_{i,3}, b_{i,4})'$ and $E(b_{i,1}) = 0$, $E(b_{i,2}) = \gamma(lower4)$, $E(b_{i,3}) = \gamma(upper5)$, $E(b_{i,4}) = \gamma(lower5)$.

3.1 Priors for the mixture

```
> prior <- list()
```

Prior for the number of mixture components k will be truncated Poisson(λ, k_{max}) with $k_{max} = 30$ and $\lambda = 5$. Alternative prior distribution would be uniform specified by

```
prior$k.prior = ``uniform"
```

```
> prior$kmax <- 30
> prior$k.prior <- "poisson"
> prior$poisson.k <- 5
```

Prior for mixture weights w_1, \dots, w_k will be Dirichlet(δ, \dots, δ) with $\delta = 1$.

```
> prior$dirichlet.w <- 1
```

Prior for mixture means μ_1, \dots, μ_k will be $N(\xi, \kappa)$ with $\xi = 1.8$ (taken from `survreg(dist = "lognormal")` fit (approx intercept)) and $\kappa = 0.75^2 \approx (3 \times 0.25)^2$ (0.25 was approximately estimated scale parameter by `survreg`).

```
> prior$mean.mu <- 1.8
> prior$var.mu <- 0.75^2
```

Prior for mixture inverse-variances $\sigma_1^{-2}, \dots, \sigma_k^{-2}$ will be Gamma(ζ, η) and prior for η will be Gamma(g, h), with $\zeta = 2.0$, $g = 0.2$ and $h = 0.1$.

```
> prior$shape.invsig2 <- 2
> prior$shape.hyper.invsig2 <- 0.2
> prior$rate.hyper.invsig2 <- 0.1
```

Probabilities of the split move (given current value of k) will be always 0.5 except when $k = 1$ or $k = k_{max}$.

```
> prior$pi.split <- c(1, rep(0.5, prior$kmax - 2), 0)
```

Probabilities of the birth move (given current value of k) will be always 0.5 except when $k = 1$ or $k = k_{max}$.

```
> prior$pi.birth <- c(1, rep(0.5, prior$kmax - 2), 0)
```

The last component of the list `prior` should be always set to `FALSE`. Its value equal to `TRUE` served only for some exploratory purposes of the author.

```
> prior$Eb0.depend.mix <- FALSE
```

Look how it looks like:

```
> print(prior)
```

```
$kmax  
[1] 30
```

```
$k.prior  
[1] "poisson"
```

```
$poisson.k  
[1] 5
```

```
$dirichlet.w  
[1] 1
```

```
$mean.mu  
[1] 1.8
```

```
$var.mu  
[1] 0.5625
```

```
$shape.invsig2  
[1] 2
```

```
$shape.hyper.invsig2  
[1] 0.2
```

```
$rate.hyper.invsig2  
[1] 0.1
```

```
$pi.split  
[1] 1.0 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5  
[20] 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5
```

```
$pi.birth  
[1] 1.0 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5  
[20] 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.0
```

```
$Eb0.depend.mix  
[1] FALSE
```

3.2 Priors for regression parameters β and means of random effects γ

In this section we specify the prior hyperparameters for `beta[1:12] = (β(girl), β(dmf), γ(lower4), γ(upper5), γ(lower5), β(girl : dmf), β(dmf : lower4), β(dmf : upper5), β(dmf : lower5), β(girl : dmf))`

$lower4$), $\beta(girl : upper5)$, $\beta(girl : lower5))'$ and the way these parameters will be updated. In other words, we define a list with all the information needed.

```
> prior.beta <- list()
```

Here we specify prior means (all will be zero) and prior variances (all will be 100) for the beta parameters.

```
> prior.beta$mean.prior <- rep(0, nregres)
> prior.beta$var.prior <- rep(100, nregres)
```

Further, we do not have to do anything, i.e. default way to update the **beta** parameters will be used. That is by the Gibbs move in two blocks (all fixed effects β in one block and means γ of all random effects in the second block).

Look how the list looks like:

```
> print(prior.beta)

$mean.prior
[1] 0 0 0 0 0 0 0 0 0 0 0 0

$var.prior
[1] 100 100 100 100 100 100 100 100 100 100 100 100
```

3.3 Prior specification for the random effects b_i related parameters

Now, we have to specify the prior for the variance matrix \mathbb{D} of the random effect vector \mathbf{b}_i . Again, we define a list with all the information:

```
> prior.b <- list()
```

We use an inverse-Wishart prior for \mathbb{D} with $\tau = 4$ degrees of freedom and a scale matrix \mathbb{S} equal to

$$\mathbb{S} = 0.002 \times \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}.$$

Observe that only the lower triangle of \mathbb{S} is given to `prior$scale.D`.

```

> prior.b$df.D <- 4
> prior.b$scale.D <- 0.002 * c(1, 0, 0, 0, 1, 0, 0, 1, 0, 1)
> prior.b$prior.D <- "inv.wishart"

```

Finally, we specify how the individual random effects will be updated (using the Gibbs move):

```
> prior.b$type.upd <- "gibbs"
```

Look how the list looks like:

```
> print(prior.b)
```

```
$df.D  
[1] 4  
  
$scale.D  
[1] 0.002 0.000 0.000 0.000 0.002 0.000 0.000 0.002 0.000 0.002
```

```
$prior.D
[1] "inv.wishart"

$type.upd
[1] "gibbs"
```

3.4 Parameters to perform reversible jumps

```
> prop.revjump <- list()
```

Type of the algorithm:

```
> prop.revjump$algorithm <- "correlated.av"
```

Parameters of a moody ring (ϵ , δ , see paper Brooks et al. (2003) for details). Remember, ϵ = time dependence, δ = component dependence.

```
> prop.revjump$moody.ring <- c(0.1, 0.05)
```

Transformation of a canonical seed for split-combine move:

```
> prop.revjump$transform.split.combine <- "brooks"
> prop.revjump$transform.split.combine.parms <- c(2, 2, 2, 2, 1,
+      1)
```

Transformation of a canonical seed for birth-death move:

```
> prop.revjump$transform.birth.death <- "richardson.green"
```

Look how it looks like:

```
> print(prop.revjump)

$algorithm
[1] "correlated.av"

$moody.ring
[1] 0.10 0.05

$transform.split.combine
[1] "brooks"

$transform.split.combine.parms
[1] 2 2 2 2 1 1

$transform.birth.death
[1] "richardson.green"
```

4 Specification of initial values for the MCMC

We give two sets of initial values to run two chains. Undefined initials are sampled automatically by the program.

4.1 Initials for chain 1

```
> init1 <- list()
```

Iteration number of the nulth iteration:

```
> init1$iter <- 0
```

Initial mixture (from `survreg(dist = "lognormal")`). It will have one component with $w_1 = 1$, $\mu_1 = 1.8$ and $\sigma_1^2 = 0.25^2$.

```
> init1$mixture <- c(1, 1, rep(0, prior$kmax - 1), 1.8, rep(0,
+      prior$kmax - 1), 0.25^2, rep(0, prior$kmax - 1))
```

Initial regression parameters β and means of random effects γ (from `survreg(dist = "lognormal")`):

```
> init1$beta <- c(-0.09, -0.11, -0.01, 0.16, 0.17, 0.05, 0.02,
+      0.01, 0.03, -0.02, 0.01, 0)
```

Initial covariance matrix \mathbb{D} of the random effects will be identity matrix (only its lower triangle)

```
> init1$D <- c(1, 0, 0, 0, 1, 0, 0, 1, 0, 1)
```

Initial values of individual random effects for each child:

```
> b0 <- rep(0, nchild)
> b1 <- rnorm(nchild, 0, 0.3)
> b2 <- rnorm(nchild, 0.16, 0.3)
> b3 <- rnorm(nchild, 0.16, 0.3)
> init1$b <- as.numeric(rbind(b0, b1, b2, b3))
```

Initial (augmented) log(event) times – let the program sample them:

```
> init1$y <- NULL
```

Initial component pertinence of the observations to the mixture (all observations belong to the first component):

```
> init1$r <- rep(1, nobs)
```

Initial value of a hyperparameter η (sample it from a prior distribution):

```
> init1$otherp <- rgamma(1, shape = prior$shape.hyper.invsig2,
+      rate = prior$rate.hyper.invsig2)
```

Initial values of canonical variables for reversible move (sample it from a uniform distribution):

```
> init1$u <- c(runif(1), 0, 0, runif(3 * (prior$kmax - 1)))
```

4.2 Initials for chain 2

```
> init2 <- list()
```

Iteration number of the nulth iteration:

```
> init2$iter <- 0
```

Initial mixture. It will have one component with $w_1 = 1$, $\mu_1 = 1.7$ and $\sigma_1^2 = 0.2^2$.

```
> init2$mixuture <- c(1, 1, rep(0, prior$kmax - 1), 1.7, rep(0,
+      prior$kmax - 1), 0.2^2, rep(0, prior$kmax - 1))
```

Initial regression parameters β and means of random effects γ (all zeros):

```
> init2$beta <- rep(0, nregres)
```

Initial covariance matrix \mathbb{D} of the random effects. Now we take such matrix \mathbb{D} that $\text{var}(b_{i,m}) = 0.01$ ($m = 1, 2, 3, 4$) and $\text{corr}(b_{i,m}, b_{i,s}) = 0.2$ ($m \neq s = 1, 2, 3, 4$).

```
> varb <- c(0.01, 0.01, 0.01, 0.01)
> corb <- c(0.2, 0.2, 0.2, 0.2, 0.2, 0.2)
> Corb <- diag(4)
> Corb[lower.tri(Corb, diag = FALSE)] <- corb
> Corb[upper.tri(Corb, diag = FALSE)] <- t(Corb)[upper.tri(t(Corb),
+      diag = FALSE)]
> Covb <- diag(sqrt(varb)) %*% Corb %*% diag(sqrt(varb))
> init2$D <- Covb[lower.tri(Covb, diag = TRUE)]
```

Initial values of individual random effects for each child:

```
> b0 <- rnorm(nchild, 0, sqrt(init2$D[1]))
> b1 <- rnorm(nchild, 0, sqrt(init2$D[5]))
> b2 <- rnorm(nchild, 0.16, sqrt(init2$D[8]))
> b3 <- rnorm(nchild, 0.16, sqrt(init2$D[10]))
> init2$b <- as.numeric(rbind(b0, b1, b2, b3))
```

Initial (augmented) log(event) times – let the program sample them:

```
> init2$y <- NULL
```

Initial component pertinence of the observations to the mixture (all observations belong to the first component):

```
> init2$r <- rep(1, nobs)
```

Initial value of a hyperparameter η (sample it from a prior distribution):

```
> init2$otherp <- rgamma(1, shape = prior$shape.hyper.invsig2,
+      rate = prior$rate.hyper.invsig2)
```

Initial values of canonical variables for reversible move (sample it from a uniform distribution):

```
> init2$u <- c(runif(1), 0, 0, runif(3 * (prior$kmax - 1)))
```

5 Running the MCMC simulation

Now we are ready to run the MCMC to sample from the posterior distribution.

Here we define which quantities that are not necessarily needed for the inference will be stored.

```
> store <- list(y = FALSE, r = FALSE, u = FALSE, b = FALSE, MHb = FALSE,
+      regresres = FALSE)
```

How long simulation we want to run? For illustration purposes, only limited simulation is specified here.

```
> nsimul <- list(niter = 100, nthin = 3, nburn = 50, nwrite = 50)
```

For the analysis presented in Komárek and Lesaffre (2004) we used

```
> nsimul <- list(niter = 15000, nthin = 3, nburn = 1500, nnoadapt = 0, nwrite = 1000)
```

which performed 3×1500 iterations of burn-in and additionally 3×13500 iterations from which each 3rd value was stored. Further, after cumulating 1000 sampled values, these were stored on a disk.

Define directories where first and second chain will be stored (create them first):

```
> dir.create("tandchain1")
> dir.create("tandchain2")
> dirsim <- character()
> dirsim[1] <- paste(getwd(), "/tandchain1", sep = "")
> dirsim[2] <- paste(getwd(), "/tandchain2", sep = "")
```

Run the simulation for the first and the second chain:

```
> sim1 <- bayessurvreg1(Surv(EBEG, EEND, type = "interval2") ~
+     GIRL * DMF + (DMF + GIRL) * (LOWER4 + UPPER5 + LOWER5) +
+     cluster(IDNR), random = ~LOWER4 + UPPER5 + LOWER5, data = longdata,
+     dir = dirsim[1], nsimul = nsimul, prior = prior, init = init1,
+     prop.revjump = prop.revjump, prior.beta = prior.beta, prior.b = prior.b,
+     store = store)

Simulation started on           Fri Sep 10 11:41:54 2004
Iteration 50
Simulation without adaptation finished on   Fri Sep 10 11:41:55 2004 (iteration 50)
Iteration 100
Simulation finished on          Fri Sep 10 11:41:57 2004 (iteration 100)

> sim2 <- bayessurvreg1(Surv(EBEG, EEND, type = "interval2") ~
+     GIRL * DMF + (DMF + GIRL) * (LOWER4 + UPPER5 + LOWER5) +
+     cluster(IDNR), random = ~LOWER4 + UPPER5 + LOWER5, data = longdata,
+     dir = dirsim[2], nsimul = nsimul, prior = prior, init = init2,
+     prop.revjump = prop.revjump, prior.beta = prior.beta, prior.b = prior.b,
+     store = store)

Simulation started on           Fri Sep 10 11:41:57 2004
Iteration 50
Simulation without adaptation finished on   Fri Sep 10 11:42:00 2004 (iteration 50)
Iteration 100
Simulation finished on          Fri Sep 10 11:42:02 2004 (iteration 100)
```

6 Running additional MCMC simulation to compute predictive quantities

First we have to define covariate values for which we want to do a prediction. These will be all combinations of boy/girl \times dmf>0/dmf=0 \times upper4/lower4/upper5/lower5:

```
> newIDNR = c(1, 1, 1, 1, 2, 2, 2, 3, 3, 3, 3, 4, 4, 4, 4)
> newGIRL = c(0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1)
> newUPPER4 = c(1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0)
> newLOWER4 = c(0, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0)
> newUPPER5 = c(0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 0)
```

```

> newLOWER5 = c(0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1)
> newDMF = c(0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1)
> newEBEG = rep(1, 16)
> newEEND = rep(NA, 16)
> preddata <- data.frame(IDNR = newIDNR, GIRL = newGIRL, UPPER4 = newUPPER4,
+   LOWER4 = newLOWER4, UPPER5 = newUPPER5, LOWER5 = newLOWER5,
+   DMF = newDMF, EBEG = newEBEG, EEND = newEEND)
> print(preddata)

```

	IDNR	GIRL	UPPER4	LOWER4	UPPER5	LOWER5	DMF	EBEG	EEND
1	1	0	1	0	0	0	0	1	NA
2	1	0	0	1	0	0	0	1	NA
3	1	0	0	0	1	0	0	1	NA
4	1	0	0	0	0	1	0	1	NA
5	2	0	1	0	0	0	1	1	NA
6	2	0	0	1	0	0	1	1	NA
7	2	0	0	0	1	0	1	1	NA
8	2	0	0	0	0	1	1	1	NA
9	3	1	1	0	0	0	0	1	NA
10	3	1	0	1	0	0	0	1	NA
11	3	1	0	0	1	0	0	1	NA
12	3	1	0	0	0	1	0	1	NA
13	4	1	1	0	0	0	1	1	NA
14	4	1	0	1	0	0	1	1	NA
15	4	1	0	0	1	0	1	1	NA
16	4	1	0	0	0	1	1	1	NA

Observe that variables EBEG and EEND may contain whatever (under the condition that the values are acceptable for Surv).

Further, we specify what we want to predict (with this, survivor function and hazard function). Also, specify whether sampled quantities should be stored, otherwise, only quantiles and predictive means are computed (which usually suffice).

```

> predict <- list(Et = TRUE, t = FALSE, Surv = TRUE, hazard = TRUE,
+   cum.hazard = FALSE)
> store <- list(Et = FALSE, t = FALSE, Surv = FALSE, hazard = FALSE,
+   cum.hazard = FALSE)

```

Grid of values in which predictive survivor and hazard curves should be computed. Observe that this grid takes into account the fact we shifted the response by 5 years in the model. Here we return back to the original time scale, i.e. we wish to see predictive curves between 6.5 and 13 years of age.

```
> grid <- seq(6.5, 13, by = 0.1)
```

How many MCMC iterations we want to perform (niter should be \leq length of already sampled chain) and how often should sampled quantities be written to disk

```

> nsimul.pred <- list(niter = nsimul$niter - nsimul$nburn, nthin = 1,
+   nwrite = nsimul$niter - nsimul$nburn)

```

Run MCMC simulation to sample from the predictive distribution (only chain 1 will be used here). Observe how we used parameter time0 in the function call to specify that the response was shifted in the model by startage = 5.

```

> simulp1 <- predictive(Surv(EBEG, EEND, type = "interval2") ~
+   GIRL * DMF + (DMF + GIRL) * (LOWER4 + UPPER5 + LOWER5) +
+   cluster(IDNR), random = ~LOWER4 + UPPER5 + LOWER5, time0 = startage,
+   data = preddata, dir = dirs[1], nsimul = nsimul.pred, predict = predict,
+   store = store, grid = grid, type = "mixture")

```

```

Simulation started on           Fri Sep 10 11:42:02 2004
Iteration 50
Computing quantiles.
Storing quantiles.
Simulation finished on        Fri Sep 10 11:42:03 2004

```

In a directory `./tandchain1` few new files should appear:

```

^ quantS1.sim - quantS8.sim;
^ quanhazard1.sim - quanhazard8.sim;
^ quantET.sim.

```

Files `quantS*.sim` and `quanhazard*.sim` contain pointwise (evaluated at the grid specified above) posterior predictive quantiles and means of the survivor and hazard function for each combination of covariates specified in `predata`. File `quantET.sim` contains posterior predictive quantiles and mean for expected survivor time of each combination of covariates. Note that

1. There is one file per survivor/hazard function and per covariate combination. Indeces of these files (1, ..., 8) correspond to rows of `predata`. Structure of these files is following

1st row	=	grid values
2nd row	=	post. predictive 0% quantile (minimum)
3rd row	=	post. predictive 2.5% quantile
4th row	=	post. predictive 50% quantile (median)
5th row	=	post. predictive 97.5% quantile
6th row	=	post. predictive 100% quantile (maximum)
last row	=	post. predictive mean

2. There is only one file for posterior predictive expected survivor times and all combinations of covariates (`quantET.sim`). Structure of this file is following:

1st row	=	character labels ET1 - ET8 indicating that each column corresponds to one covariate combination
remaining rows	=	same as for <code>quantS*.sim</code> or <code>quanhazard*.sim</code>

You might specify also other quantiles (parameter `quantile` in function `predictive`) to be computed. Posterior predictive mean is always computed and stored on the last row.

7 Drawing of posterior predictive emergence curves

Here we draw predictive emergence curves (cumulative distribution functions), separately for each pair of horizontally symmetric teeth (14+24, 34+44, 15+25, 35+45), for boys and girls and finally depending on the *dmf* score of the primary predecessor. We use simulated predictive curves based on the first chain. See Figure 1 for the result.

```

> ch <- 1
> line <- numeric(13)
> line[1] <- 1
> line[5] <- 2
> line[9] <- 1
> line[13] <- 2
> col <- character(13)
> col[1] <- "blue"
> col[5] <- "blue"

```

```

> col[9] <- "red"
> col[13] <- "red"
> title <- c("Maxilla 4", "Mandible 4", "Maxilla 5", "Mandible 5")
> lwd <- 2
> xlim <- c(7, 12)
> par(mfrow = c(2, 2))
> for (i in 1:4) {
+   for (j in c(1, 5, 9, 13)) {
+     gridS <- scan(paste(dirsim[ch], "/quantS", (i - 1) +
+       j, ".sim", sep = ""), nlines = 1)
+     Sfun <- read.table(paste(dirsim[ch], "/quantS", (i -
+       1) + j, ".sim", sep = ""), header = TRUE)
+     rownames(Sfun) <- c("0%", "2.5%", "50%", "97.5%", "100%",
+       "mean")
+     if (j == 1)
+       plot(gridS, 1 - Sfun["mean", ], type = "l", lty = line[1],
+         ylim = c(0, 1), xlab = "Age", ylab = "Emergence",
+         bty = "n", lwd = lwd, col = col[1], xlim = xlim)
+     else lines(gridS, 1 - Sfun["mean", ], lty = line[j],
+       lwd = lwd, col = col[j])
+     legend(7, 1, legend = c("Girl, dmf>0", "Girl, sound",
+       "Boy, dmf>0", "Boy, sound"), lty = line[c(13, 9,
+       5, 1)], col = col[c(13, 9, 5, 1)], lwd = lwd, bty = "n")
+   }
+   title(main = title[i])
+ }

```

8 Summary statistics

Check how many chains we have

```

> ncchains <- length(dirsim)
> print(ncchains)

```

```
[1] 2
```

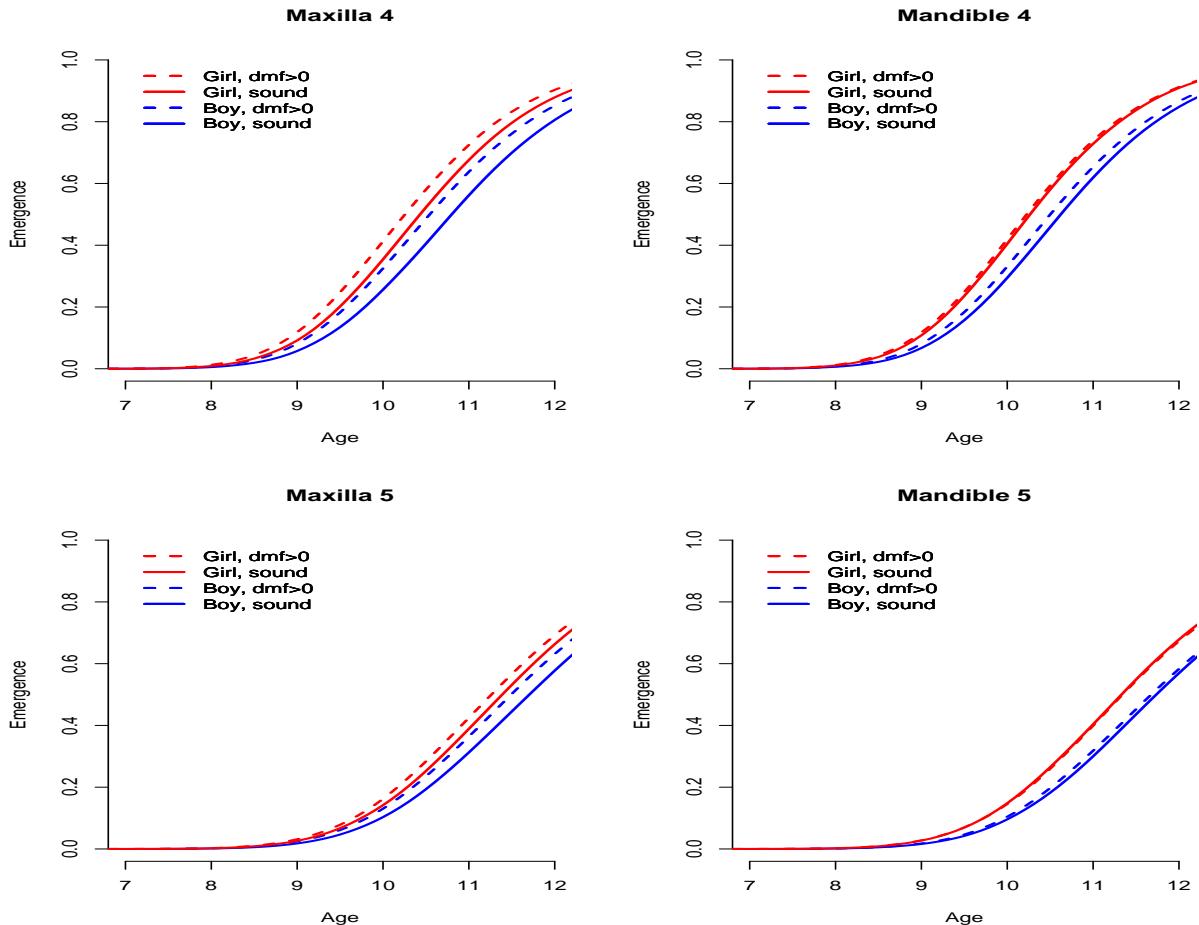
Read sampled \mathbb{D} matrix and perform some transformation on it. Data frames in `covb` will store chains for standard deviations of $b_{i,1}, b_{i,2}, b_{i,3}, b_{i,4}$ and correlations among b 's. Further, to see an inter-teeth relationship we define $d_{i,1} = b_{i,1}$, $d_{i,2} = b_{i,1} + b_{i,2}$, $d_{i,3} = b_{i,1} + b_{i,3}$ and $d_{i,4} = b_{i,1} + b_{i,4}$, i.e. each d is actually the child-tooth-specific (apart the horizontal symmetry) shift of log-emergence time ($d_{i,1}$ for teeth 14, 24, $d_{i,2}$ for teeth 34, 44, $d_{i,3}$ for teeth 15, 25 and $d_{i,4}$ for teeth 35, 45). Data frames in `covt` then store chains for standard deviations of $d_{i,1}, d_{i,2}, d_{i,3}, d_{i,4}$ and correlations among d 's.

```

> covb <- list()
> covt <- list()
> for (ch in 1:ncchains) {
+   dd <- read.table(paste(dirsim[ch], "/D.sim", sep = ""), header = TRUE)
+   varb <- cbind(dd$D.1.1, dd$D.2.2, dd$D.3.3, dd$D.4.4)
+   sdb <- sqrt(varb)
+   corb12 <- dd$D.2.1/sqrt(dd$D.1.1 * dd$D.2.2)
+   corb13 <- dd$D.3.1/sqrt(dd$D.1.1 * dd$D.3.3)
+   corb14 <- dd$D.4.1/sqrt(dd$D.1.1 * dd$D.4.4)
+   corb23 <- dd$D.3.2/sqrt(dd$D.2.2 * dd$D.3.3)
+   corb24 <- dd$D.4.2/sqrt(dd$D.2.2 * dd$D.4.4)
+   corb34 <- dd$D.4.3/sqrt(dd$D.3.3 * dd$D.4.4)
+   covb[[ch]] <- data.frame(sdb, corb12, corb13, corb14, corb23,

```

Figure 1: Predictive emergence curves.



```

+      corb24, corb34)
+ colnames(covb[[ch]]) <- c(paste("sd", 1:4, sep = ""), paste("cor",
+           c(12, 13, 14, 23, 24, 34), sep = ""))
+ sdt1 <- sqrt(dd$D.1.1)
+ sdt2 <- sqrt(dd$D.1.1 + dd$D.2.2 + 2 * dd$D.2.1)
+ sdt3 <- sqrt(dd$D.1.1 + dd$D.3.3 + 2 * dd$D.3.1)
+ sdt4 <- sqrt(dd$D.1.1 + dd$D.4.4 + 2 * dd$D.4.1)
+ cort12 <- (dd$D.1.1 + dd$D.2.1)/(sdt1 * sdt2)
+ cort13 <- (dd$D.1.1 + dd$D.3.1)/(sdt1 * sdt3)
+ cort14 <- (dd$D.1.1 + dd$D.4.1)/(sdt1 * sdt4)
+ cort23 <- (dd$D.1.1 + dd$D.2.1 + dd$D.3.1 + dd$D.3.2)/(sdt2 *
+           sdt3)
+ cort24 <- (dd$D.1.1 + dd$D.2.1 + dd$D.4.1 + dd$D.4.2)/(sdt2 *
+           sdt4)
+ cort34 <- (dd$D.1.1 + dd$D.3.1 + dd$D.4.1 + dd$D.4.3)/(sdt3 *
+           sdt4)
+ covt[[ch]] <- data.frame(sdt1, sdt2, sdt3, sdt4, cort12,
+           cort13, cort14, cort23, cort24, cort34)
+
}

```

Read sampled β and γ parameters:

```

> beta <- list()
> for (ch in 1:nchains) {
+   beta[[ch]] <- read.table(paste(dirsim[ch], "/beta.sim", sep = ""),
+                           header = TRUE)

```

```
+ }
```

Read sampled numbers of mixture components k and mixture overall mean (intercept) and mixture overall standard deviation (scale):

```
> mixture <- list()
> for (ch in 1:nchains) {
+   mixture[[ch]] <- read.table(paste(dirsim[ch], "/mixmoment.sim",
+     sep = ""), header = TRUE)
+ }
```

Create CODA mcmc objects from sampled chains:

```
> library(coda)
> mcovb <- list()
> mcovt <- list()
> mbeta <- list()
> mmixture <- list()
> for (ch in 1:nchains) {
+   mcovb[[ch]] <- files2coda(data.frames = "covb", thin = 1,
+     chain = ch)
+   mcovt[[ch]] <- files2coda(data.frames = "covt", thin = 1,
+     chain = ch)
+   mbeta[[ch]] <- files2coda(data.frames = "beta", thin = 1,
+     chain = ch)
+   mmixture[[ch]] <- files2coda(data.frames = "mixture", thin = 1,
+     chain = ch)
+ }
> mcovb <- mcmc.list(mcovb[[1]], mcovb[[2]])
> mcovt <- mcmc.list(mcovt[[1]], mcovt[[2]])
> mbeta <- mcmc.list(mbta[[1]], mbta[[2]])
> mmixture <- mcmc.list(mmixture[[1]], mmixture[[2]])
```

Compute some summary statistics:

```
> quant <- c(0, 0.025, 0.5, 0.75, 0.975, 1)
> qnames <- paste(quant * 100, "\\", sep = "")
> meancovb <- apply(rbind(covb[[1]], covb[[2]]), 2, mean)
> meancovt <- apply(rbind(covt[[1]], covt[[2]]), 2, mean)
> meanbeta <- apply(rbind(beta[[1]], beta[[2]]), 2, mean)
> meanmixture <- apply(rbind(mixture[[1]], mixture[[2]]), 2, mean)
> quantcovb <- apply(rbind(covb[[1]], covb[[2]]), 2, quantile,
+   probs = quant)
> quantcovt <- apply(rbind(covt[[1]], covt[[2]]), 2, quantile,
+   probs = quant)
> quantbeta <- apply(rbind(beta[[1]], beta[[2]]), 2, quantile,
+   probs = quant)
> quantmixture <- apply(rbind(mixture[[1]], mixture[[2]]), 2, quantile,
+   probs = quant)
> sumcovb <- rbind(meancovb, quantcovb[c("50%", "2.5%", "97.5%"),
+   ])
> rownames(sumcovb)[1] <- "Mean"
> sumcovt <- rbind(meancovt, quantcovt[c("50%", "2.5%", "97.5%"),
+   ])
> rownames(sumcovt)[1] <- "Mean"
> sumbeta <- rbind(meanbeta, quantbeta[c("50%", "2.5%", "97.5%"),
+   ])
> rownames(sumbeta)[1] <- "Mean"
> summixture <- rbind(meanmixture, quantmixture[c("50%", "2.5%",
```

```

+      "97.5%"), ])
> rownames(summixture)[1] <- "Mean"
> sumwant <- cbind(sumcovt, sumbeta, summixture)
> print(sumwant)

    sdt1      sdt2      sdt3      sdt4      cort12      cort13      cort14
Mean  0.2042222 0.1983714 0.2048045 0.2023484 0.8864512 0.9139874 0.8410793
50%   0.2040386 0.1982670 0.2046224 0.2021866 0.8870772 0.9144700 0.8418553
2.5%   0.1916935 0.1862445 0.1898085 0.1874332 0.8556079 0.8867081 0.8038447
97.5%  0.2175396 0.2111030 0.2209952 0.2179746 0.9138670 0.9379874 0.8742514
          cort23      cort24      cort34      GIRL      DMF      LOWER4
Mean   0.7922175 0.8947478 0.8467664 -0.06836461 -0.04570800 -0.03254852
50%   0.7929055 0.8952042 0.8474862 -0.06803672 -0.04574820 -0.03258596
2.5%   0.7487231 0.8644521 0.8103506 -0.10033914 -0.06311243 -0.04947324
97.5%  0.8316609 0.9227729 0.8797049 -0.03675370 -0.02842491 -0.01590043
          UPPER5      LOWER5      GIRL.DMF  DMF.LOWER4  DMF.UPPER5  DMF.LOWER5
Mean   0.1432326 0.1490098 0.010493725 0.025446662 0.013957467 0.03665927
50%   0.1429807 0.1488353 0.010514335 0.025279185 0.013890850 0.03659677
2.5%   0.1245450 0.1281856 -0.007339762 0.007152071 -0.005376605 0.01586346
97.5%  0.1632935 0.1709299 0.027908040 0.044379541 0.033329682 0.05797958
          GIRL.LOWER4  GIRL.UPPER5  GIRL.LOWER5      k Intercept      Scale
Mean   0.001477880 0.018245946 0.003253059 8.881216 1.756950 0.1049977
50%   0.001631572 0.018354980 0.003202558 8.000000 1.756604 0.1045545
2.5%  -0.018682192 -0.002988832 -0.020633988 3.000000 1.733759 0.0991566
97.5%  0.021706223 0.039228161 0.026901881 18.000000 1.782165 0.1139403

```

In the previous table, $sdt1 = \sqrt{\text{var}(d_{i,1})}$, $sdt2 = \sqrt{\text{var}(d_{i,2})}$, $sdt3 = \sqrt{\text{var}(d_{i,3})}$, $sdt4 = \sqrt{\text{var}(d_{i,4})}$, $cort12 = \text{corr}(d_{i,1}, d_{i,2})$, ..., $cort34 = \text{corr}(d_{i,3}, d_{i,4})$.

Bayesian *p*-values for regression parameters:

```

> regres <- list()
> pval <- numeric(9)
> for (i in 1:12) {
+   regres[[i]] <- c(beta[[1]][, i], beta[[2]][, i])
+   M <- length(regres[[i]])
+   p1 <- sum(regres[[i]] < 0)/M
+   p2 <- sum(regres[[i]] > 0)/M
+   pval[[i]] <- 2 * min(p1, p2)
+   names(pval)[i] <- colnames(beta[[1]])[i]
+ }
> pval <- round(pval, 3)
> rm(list = "regres")
> print(pval)

```

GIRL	DMF	LOWER4	UPPER5	LOWER5	GIRL.DMF
0.000	0.000	0.000	0.000	0.000	0.237
DMF.LOWER4	DMF.UPPER5	DMF.LOWER5	GIRL.LOWER4	GIRL.UPPER5	GIRL.LOWER5
0.006	0.157	0.000	0.875	0.095	0.791

Bayesian *p*-values for effect of dmf for different teeth (maxillary 4, mandibular 4, maxillary 5, mandibular 5) and different genders (*p*-values for proper combinations of β and γ parameters):

```

> betaall <- rbind(beta[[1]], beta[[2]])
> dmfeff <- data.frame(girl.max4 = betaall$DMF + betaall$GIRL.DMF,
+   boy.max4 = betaall$DMF, girl.max5 = betaall$DMF + betaall$GIRL.DMF +
+   betaall$DMF.UPPER5, boy.max5 = betaall$DMF + betaall$DMF.UPPER5,
+   girl.man4 = betaall$DMF + betaall$GIRL.DMF + betaall$DMF.LOWER4,

```

```

+     boy.man4 = betaall$DMF + betaall$DMF.LOWER4, girl.man5 = betaall$DMF +
+         betaall$GIRL.DMF + betaall$DMF.LOWER5, boy.man5 = betaall$DMF +
+         betaall$DMF.LOWER5)
> meandmfeff <- apply(dmfeff, 2, mean)
> quantdmfeff <- apply(dmfeff, 2, quantile, probs = quant)
> sumdmfeff <- rbind(meandmfeff, quantdmfeff[c("50%", "2.5%", "97.5%"),
+   ])
> rownames(sumdmfeff)[1] <- "Mean"
> dmfpval <- numeric()
> for (i in 1:8) {
+   M <- length(dmfeff[[i]])
+   p1 <- sum(dmfeff[[i]] < 0)/M
+   p2 <- sum(dmfeff[[i]] > 0)/M
+   dmfpval[[i]] <- 2 * min(p1, p2)
+   names(dmfpval)[i] <- colnames(dmfeff)[i]
+ }
> print(sumdmfeff)

      girl.max4    boy.max4    girl.max5    boy.max5    girl.man4
Mean -0.03521428 -0.04570800 -0.021256809 -0.03175053 -0.009767615
50% -0.03515911 -0.04574820 -0.021231418 -0.03170497 -0.009751722
2.5% -0.05221067 -0.06311243 -0.038973509 -0.05004472 -0.026684948
97.5% -0.01851130 -0.02842491 -0.003534773 -0.01346895  0.006972091

      boy.man4    girl.man5    boy.man5
Mean -0.020261340  0.001444998 -0.009048727
50% -0.020126970  0.001486195 -0.009006635
2.5% -0.037790925 -0.016229219 -0.028287810
97.5% -0.003177792  0.019252297  0.009795347

> print(dmfpval)

      girl.max4    boy.max4    girl.max5    boy.max5    girl.man4    boy.man4
0.0000000000 0.0000000000 0.0189189189 0.0008648649 0.2551351351 0.0208648649
      girl.man5    boy.man5
0.8704864865 0.3529729730

```

9 Selected convergence diagnostics and further summary using the coda package

We show some basic convergence diagnostics and some additional summary based on the first chain.

Posterior densities for regression parameters β , means of random effects γ , standard deviations and correlations of transformed random effects d_i and overall mixture mean (intercept), mixture standard deviation (scale) and number of mixture components. See Figures 2, 3, 4 for the results.

```

> ch <- 1
> par(mfrow = c(3, 4))
> for (i in 1:12) {
+   densplot2(mcmc(beta[[ch]][, i]), main = colnames(beta[[ch]])[i])
+ }

> par(mfrow = c(3, 4))
> for (i in 1:10) {
+   densplot2(mcmc(covt[[ch]][, i]), main = colnames(covt[[ch]])[i])
+ }

```

```

> par(mfrow = c(2, 2))
> for (i in 1:3) {
+   densplot2(mcmc(mixture[[ch]][, i]), main = colnames(mixture[[ch]])[i])
+ }

```

Autocorrelation plots for regression parameters β , means of random effects γ , standard deviations and correlations of transformed random effects d_i and overall mixture mean (intercept), mixture standard deviation (scale) and number of mixture components. See Figures 5, 6, 7 for the results.

```

> par(mfrow = c(3, 4))
> autocorr.plot(mcmc(beta[[ch]]), auto.layout = FALSE, ask = FALSE,
+     bty = "n")

> par(mfrow = c(3, 4))
> autocorr.plot(mcmc(covt[[ch]]), auto.layout = FALSE, ask = FALSE,
+     bty = "n")

> par(mfrow = c(2, 2))
> autocorr.plot(mcmc(mixture[[ch]]), auto.layout = FALSE, ask = FALSE,
+     bty = "n")

```

Trace-plots for regression parameters β , means of random effects γ , standard deviations and correlations of transformed random effects d_i and overall mixture mean (intercept), mixture standard deviation (scale) and number of mixture components. See Figures 8, 9, 10 for the results.

```

> par(mfrow = c(3, 4))
> traceplot2(mcmc(beta[[ch]]))

> par(mfrow = c(3, 4))
> traceplot2(mcmc(covt[[ch]]))

> par(mfrow = c(2, 2))
> traceplot2(mcmc(mixture[[ch]]))

```

Gelman-Rubin convergence diagnostics:

```

> gelm.beta <- gelman.diag(mbeta)
> gelm.covt <- gelman.diag(mcovt)
> gelm.mixture <- gelman.diag(mmixture)
> rownames(gelm.beta$psrf) <- dimnames(mbeta[[1]])[[2]]
> rownames(gelm.covt$psrf) <- dimnames(mcovt[[1]])[[2]]
> rownames(gelm.mixture$psrf) <- dimnames(mmixture[[1]])[[2]]

> print(gelm.beta)

```

Potential scale reduction factors:

	Point est.	97.5% quantile
GIRL	1.14	1.50
DMF	1.02	1.07
LOWER4	1.05	1.20
UPPER5	1.07	1.26
LOWER5	1.04	1.16
GIRL.DMF	1.00	1.00
DMF.LOWER4	1.03	1.12
DMF.UPPER5	1.02	1.10

DMF.LOWER5	1.01	1.06
GIRL.LOWER4	1.01	1.03
GIRL.UPPER5	1.03	1.13
GIRL.LOWER5	1.01	1.04

Multivariate psrf

1.15+0i

> *print(gelm.covt)*

Potential scale reduction factors:

	Point est.	97.5% quantile
sdt1	1.01	1.03
sdt2	1.00	1.00
sdt3	1.00	1.01
sdt4	1.00	1.00
cort12	1.00	1.00
cort13	1.00	1.00
cort14	1.00	1.00
cort23	1.00	1.00
cort24	1.01	1.03
cort34	1.00	1.00

Multivariate psrf

1.02+0i

> *print(gelm.mixture)*

Potential scale reduction factors:

	Point est.	97.5% quantile
k	1.07	1.25
Intercept	1.27	1.87
Scale	1.14	1.38

Multivariate psrf

1.20

Figure 2: Posterior distribution of β and γ parameters.

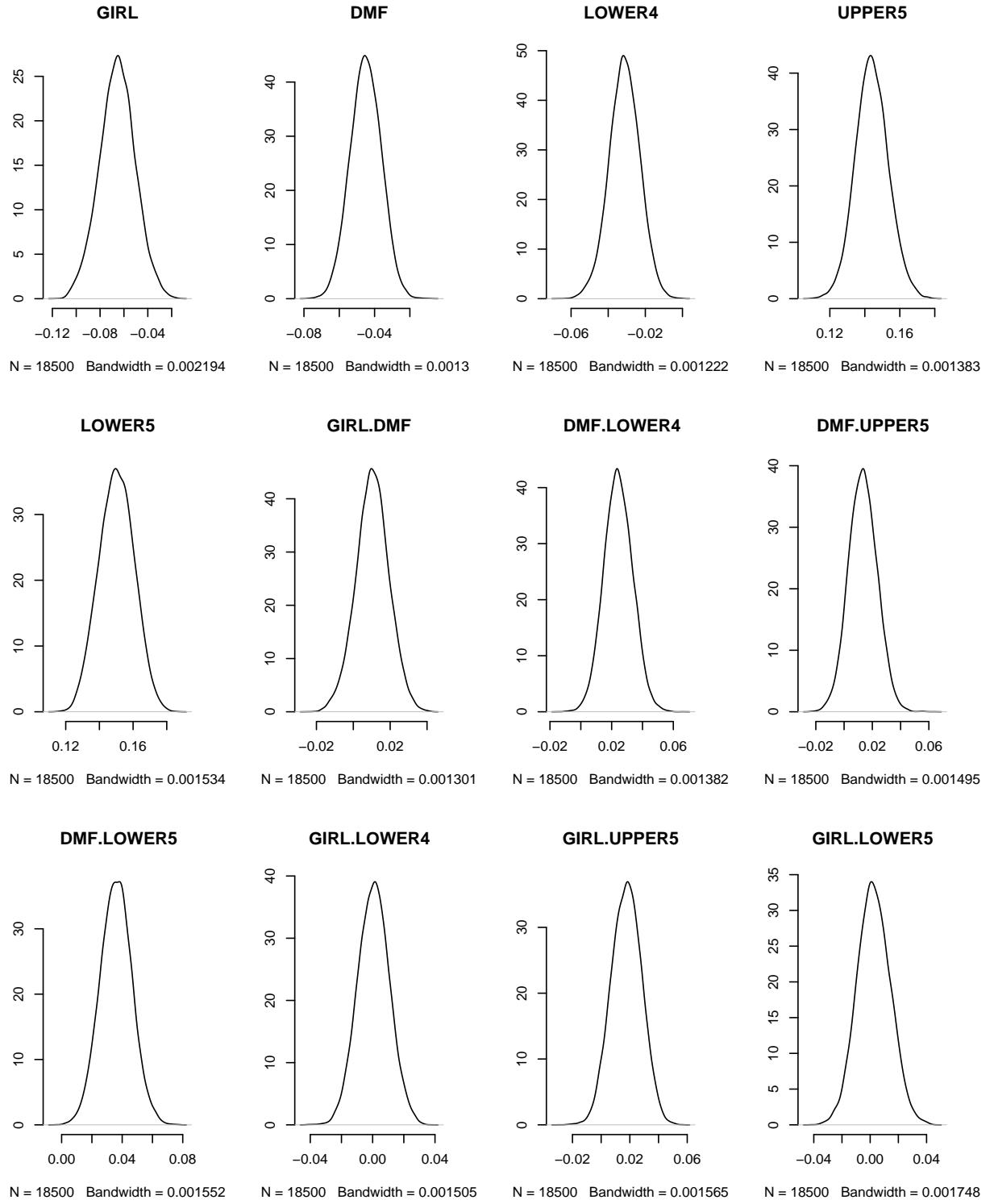


Figure 3: Posterior distribution of standard deviations and correlations of transformed random effects d_i .

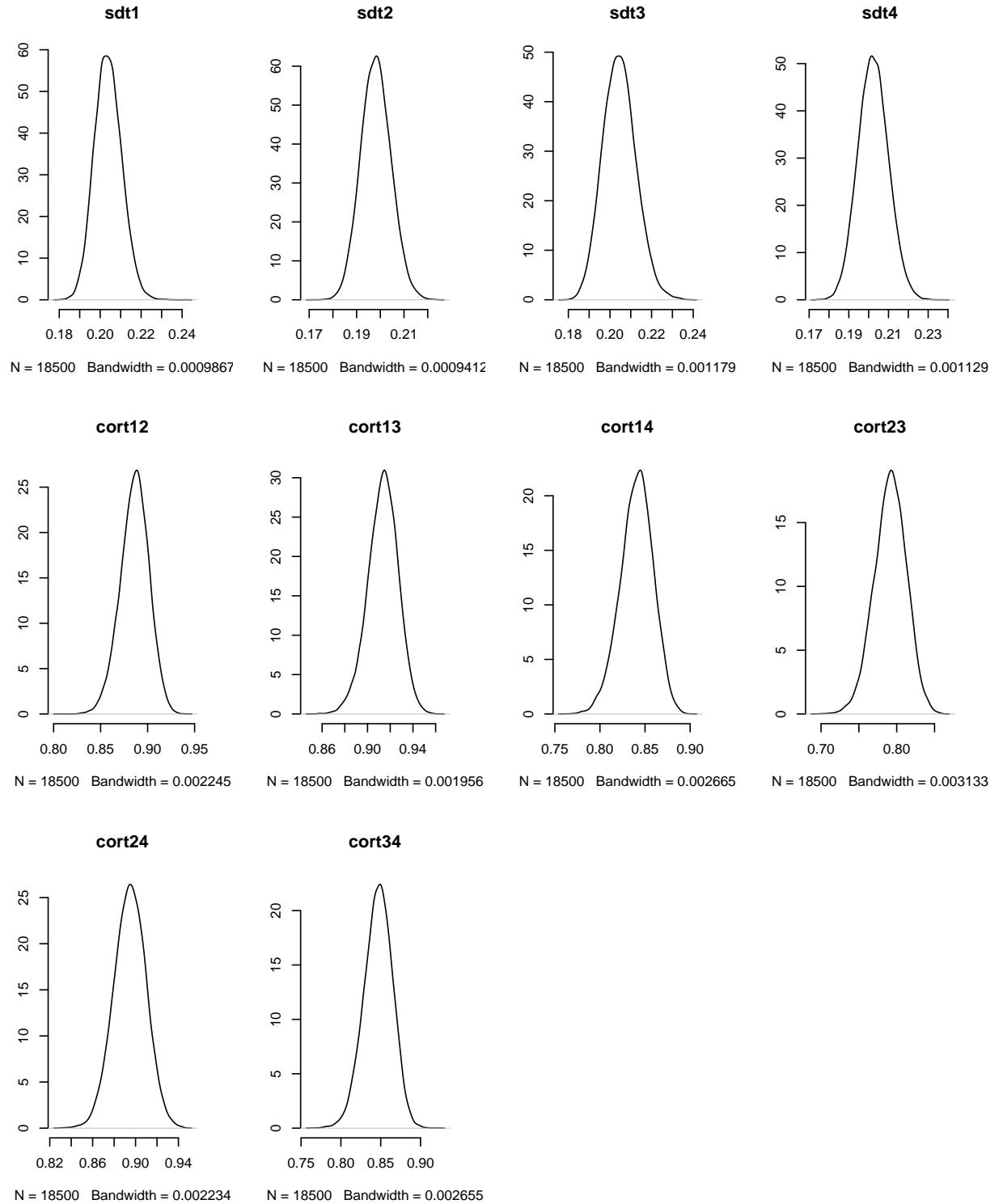


Figure 4: Posterior distribution for mixture related parameters.

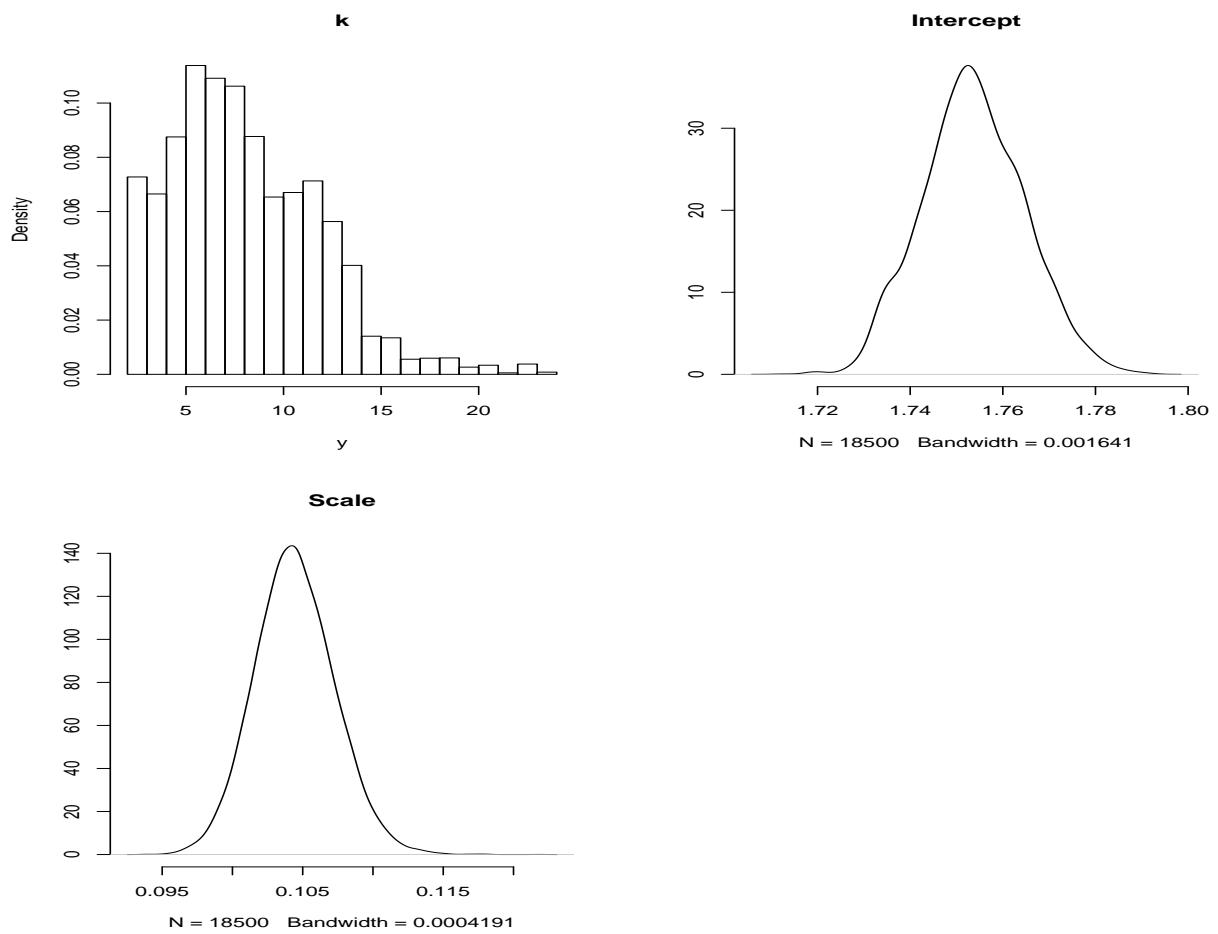


Figure 5: Autocorrelation for β and γ parameters.

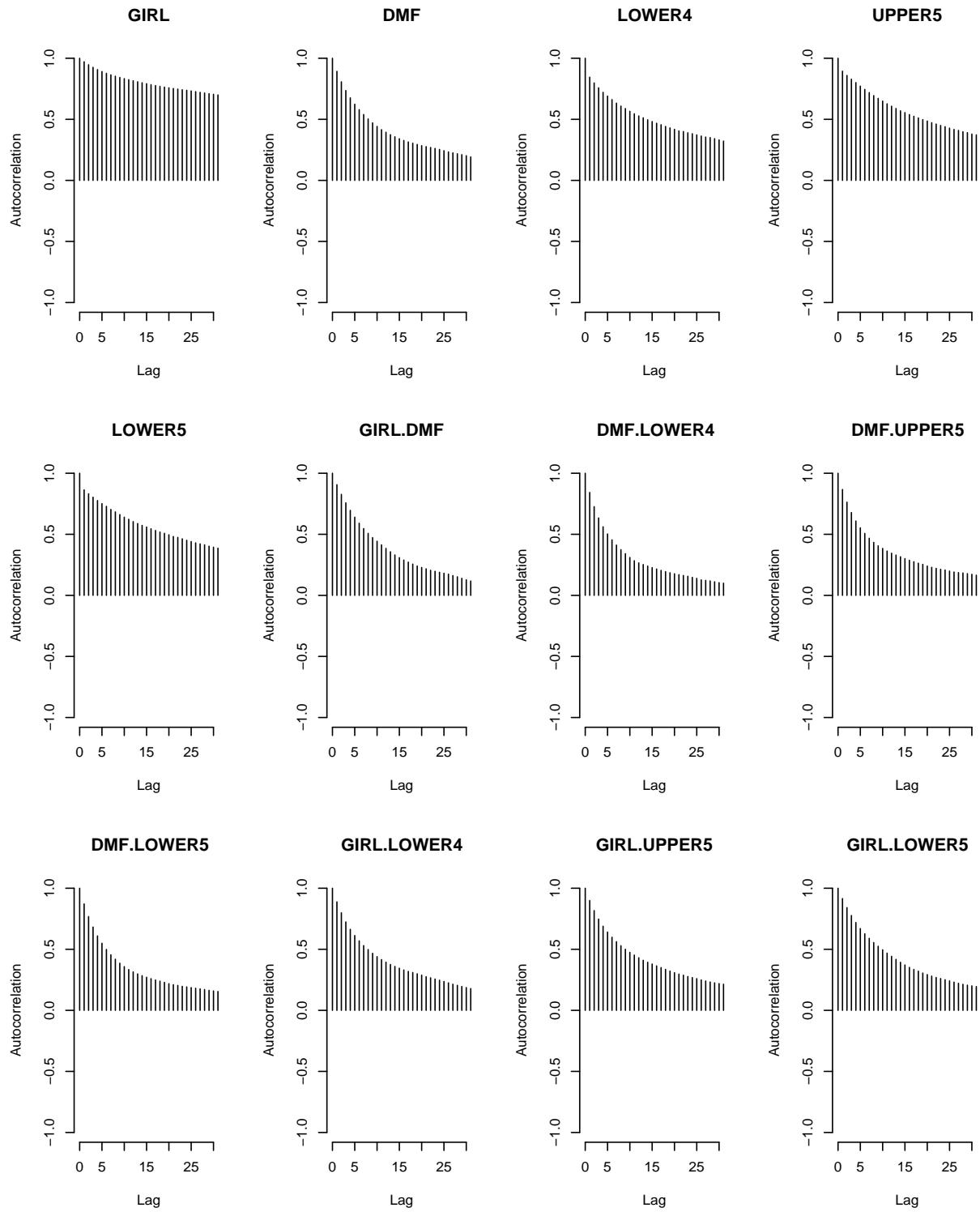


Figure 6: Autocorrelation for standard deviations and correlations of transformed random effects d_i .

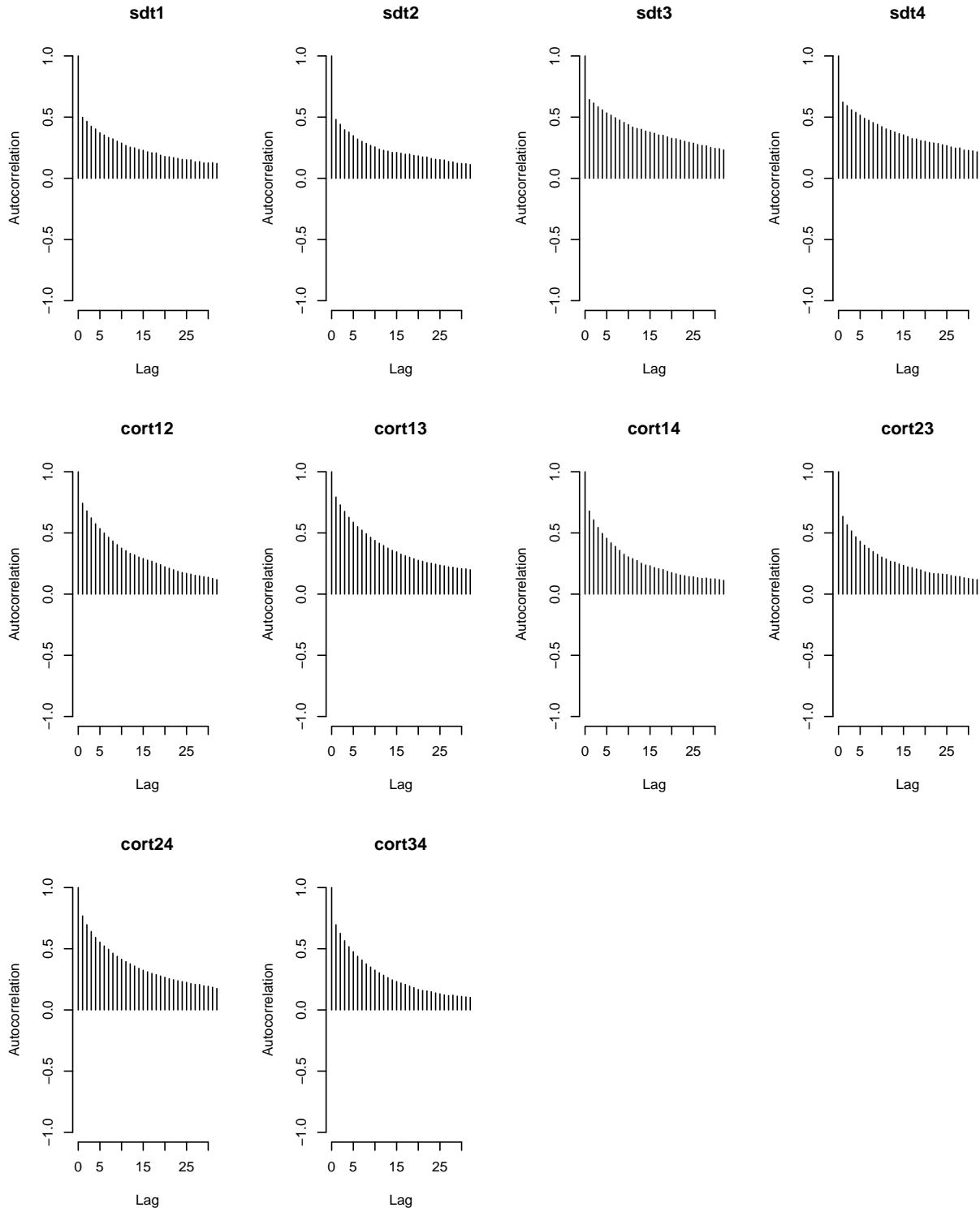


Figure 7: Autocorrelation for mixture related parameters.

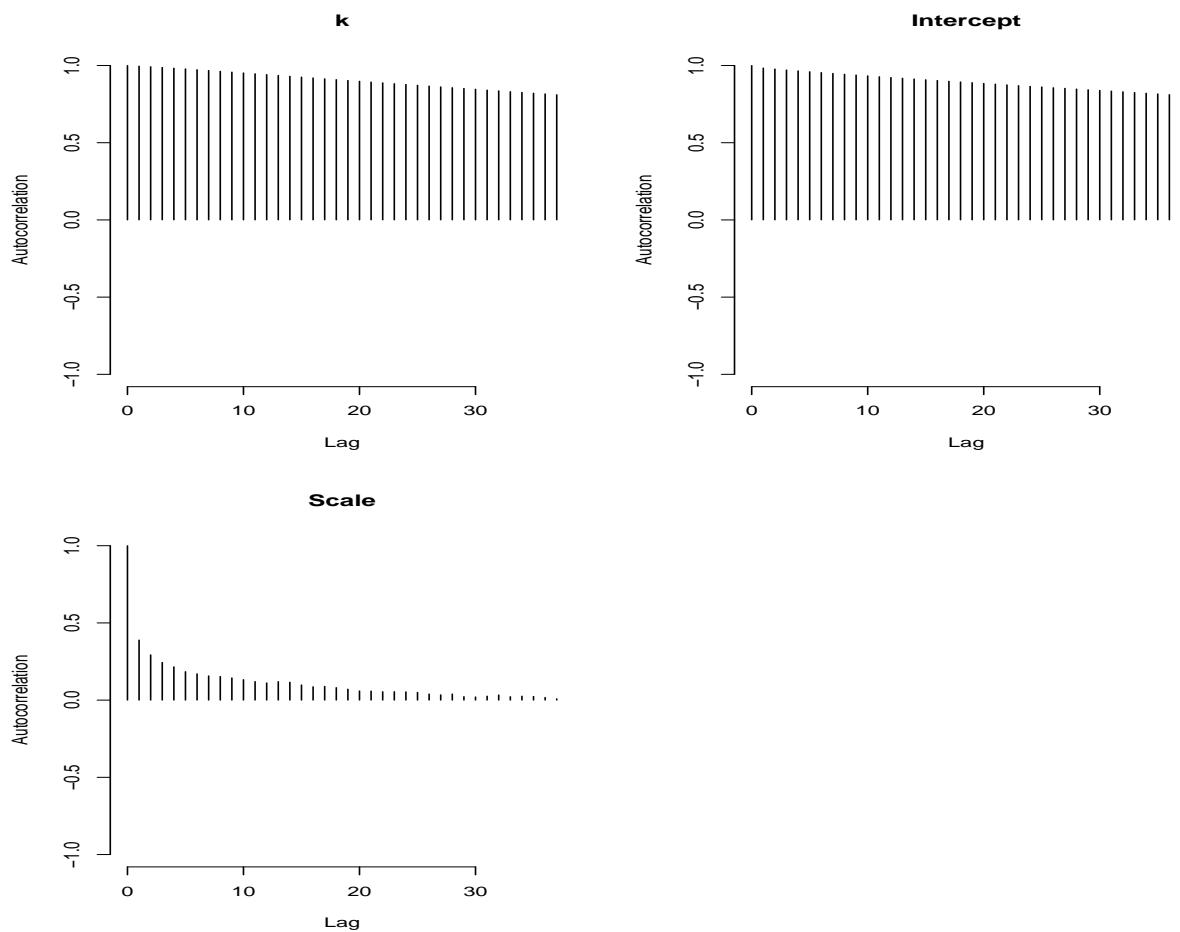


Figure 8: Trace-plots for β and γ parameters.

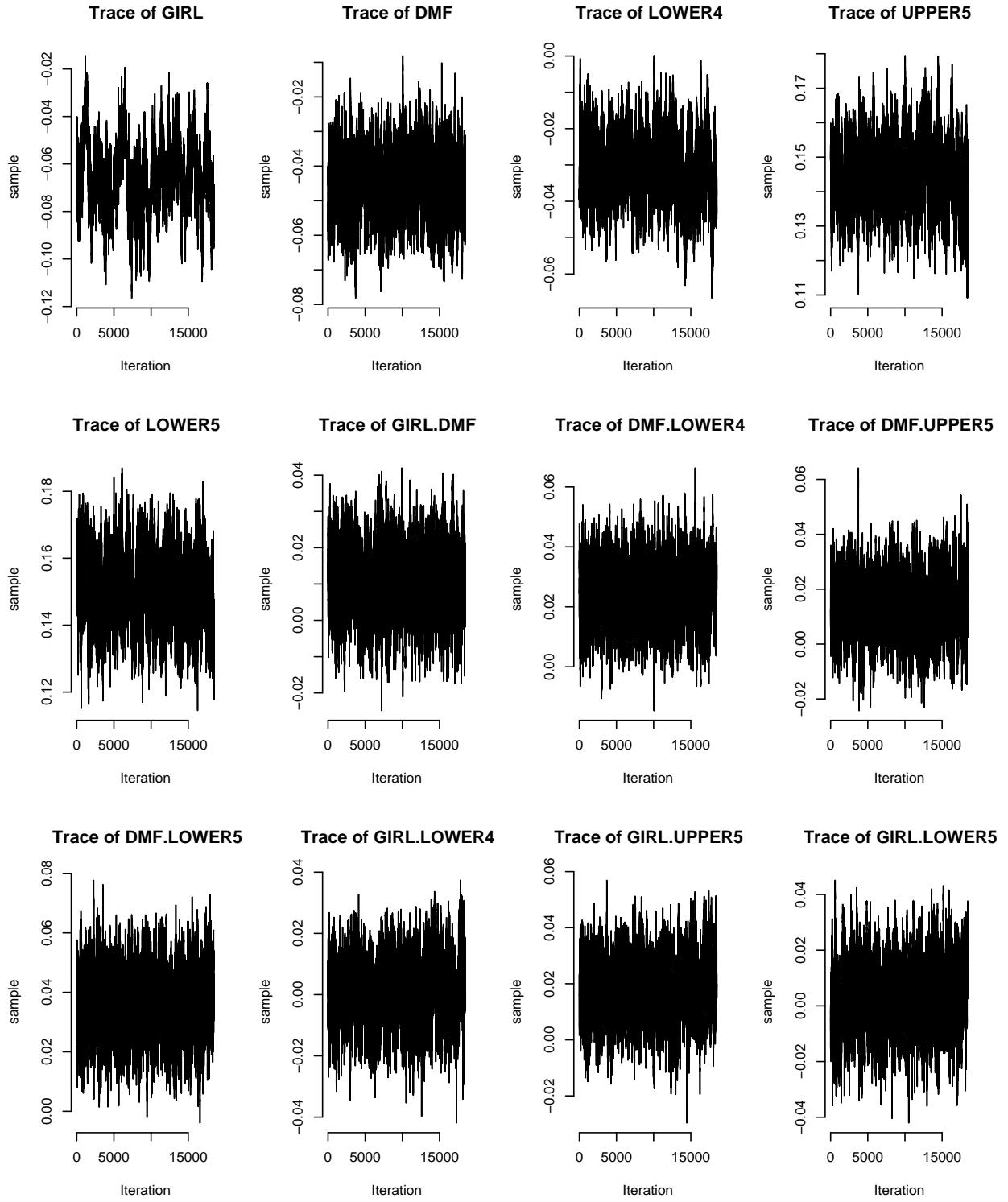


Figure 9: Trace-plots for standard deviations and correlations of transformed random effects d_i .

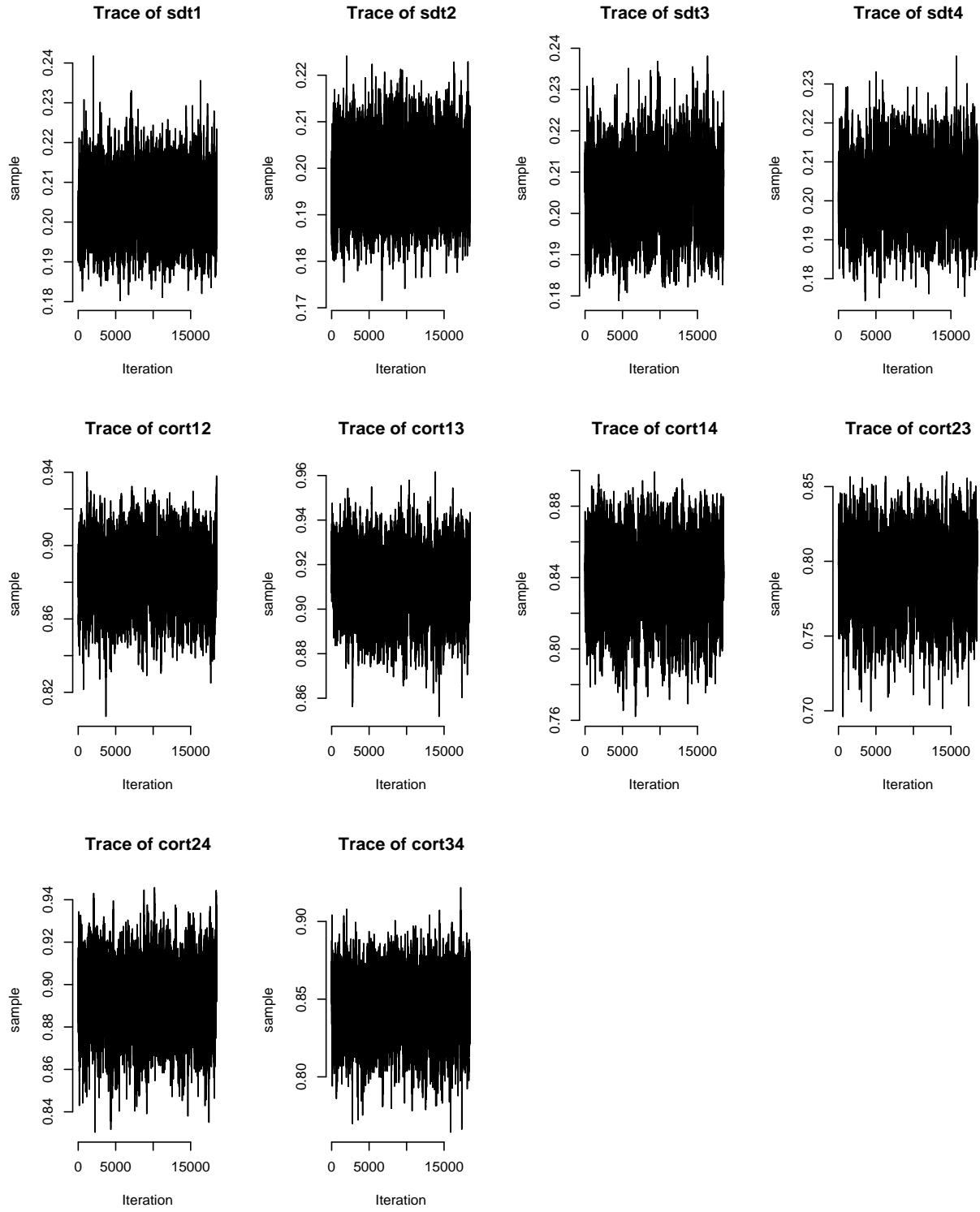
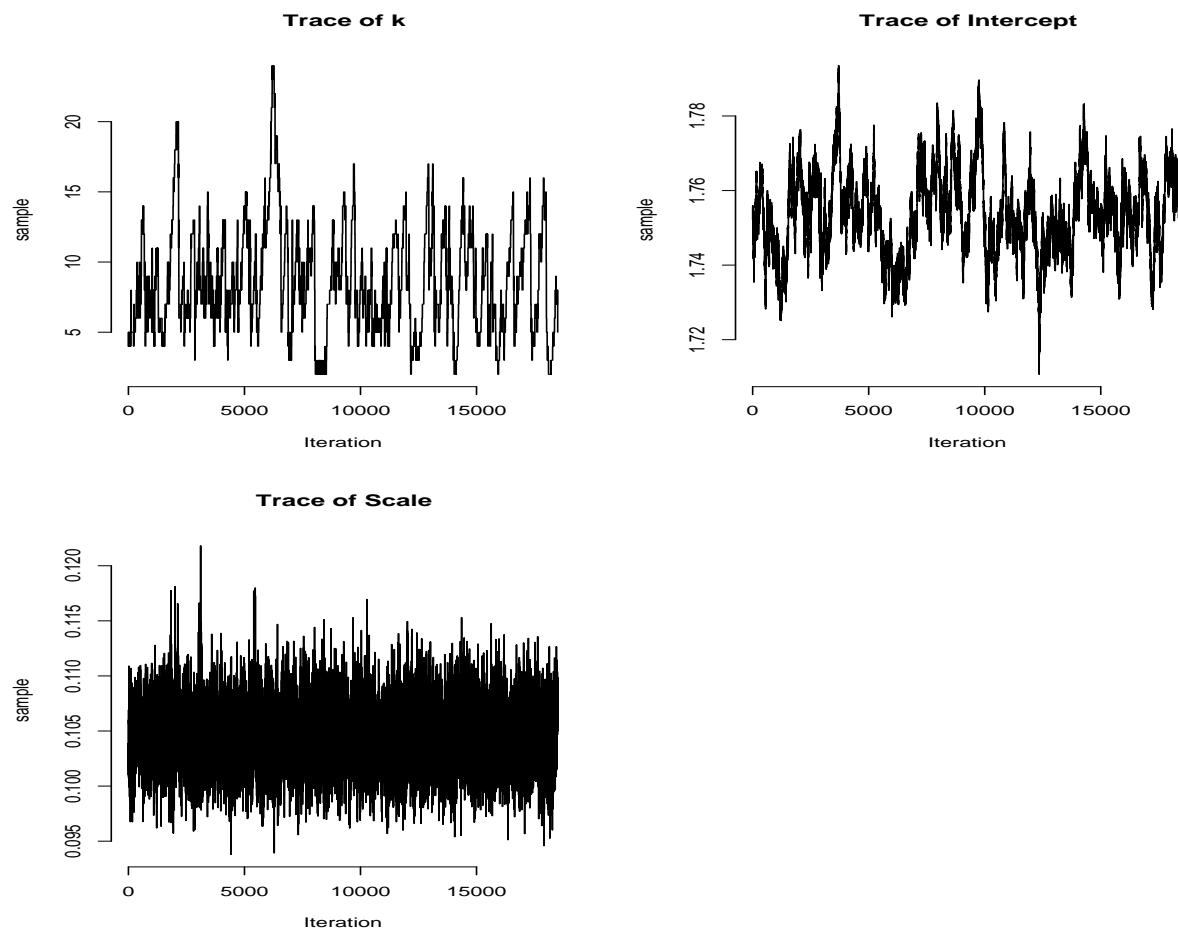


Figure 10: Trace-plots for mixture related parameters.



10 Posterior predictive error distribution

Based separately on both chains (see Figure 11 for the result):

```
> dens <- list()
> dens[[1]] <- bayesDensity(dirsim[[1]], grid = seq(1.4, 2, by = 0.005),
+   stgrid = seq(-3, 2, by = 0.05))
```

Computing predictive densities.

```
> dens[[2]] <- bayesDensity(dirsim[[2]], grid = seq(1.4, 2, by = 0.005),
+   stgrid = seq(-3, 2, by = 0.05))
```

Computing predictive densities.

Now, we can draw them (see Figure 11 for the result). Observe that conditional on k we draw only densities for $k = 1, \dots, 10$.

```
> par(mfrow = c(2, 2), bty = "n")
> plot(dens[[1]], standard = TRUE, dim.plot = FALSE, main = "Standardized, chain 1",
+   k.cond = 0:10)
> plot(dens[[1]], standard = FALSE, dim.plot = FALSE, main = "Unstandardized, chain 1",
+   k.cond = 0:10)
> plot(dens[[2]], standard = TRUE, dim.plot = FALSE, main = "Standardized, chain 2",
+   k.cond = 0:10)
> plot(dens[[2]], standard = FALSE, dim.plot = FALSE, main = "Unstandardized, chain 2",
+   k.cond = 0:10)
```

Finally, we perform cleaning of generated files:

```
> files1 <- dir("./tandchain1")
> files2 <- dir("./tandchain2")
> file.remove(paste("./tandchain1/", files1, sep = ""))
> file.remove(paste("./tandchain2/", files2, sep = ""))
> file.remove("tandchain1")
> file.remove("tandchain2")
```

Figure 11: Posterior predictive error densities.

