

Bayesian Methods - Ex3a - Linear Mixed-Effects Model

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Full assignment in PDF

This assignment is supposed to be solved via JAGS and `library(runjags)`. List through the manual to find what you need.

Data and model description

We will work with the `aids` data from `library(JM)`, see `help(aids)` for more details. It is of both longitudinal and survival data nature. In this part of the exercise, we will focus on the **longitudinal** aspect:

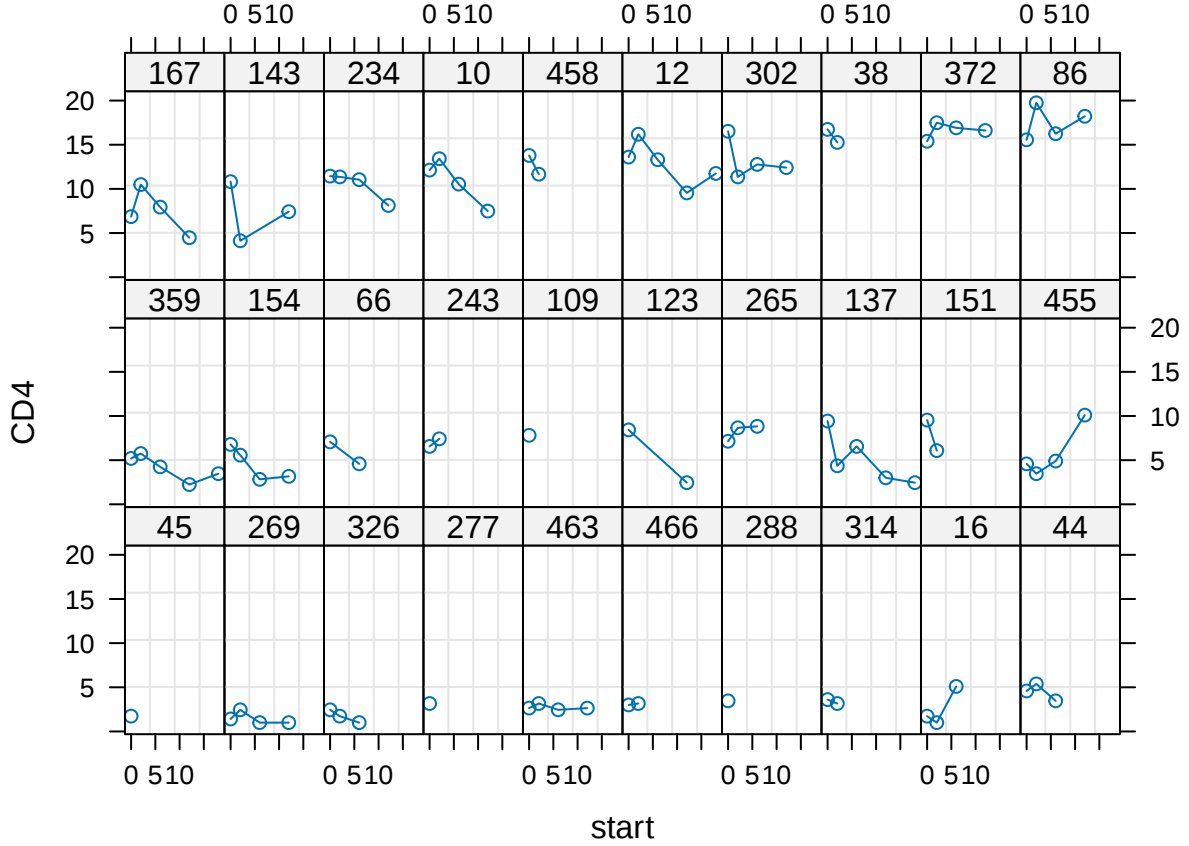
```
set.seed(123456789)
library(JM)
head(aids[,c("patient", "CD4", "obstime", "drug")], 15)
```

	patient	CD4	obstime	drug
## 1	1	10.677078	0	ddC
## 2	1	8.426150	6	ddC
## 3	1	9.433981	12	ddC
## 4	2	6.324555	0	ddI
## 5	2	8.124038	6	ddI
## 6	2	4.582576	12	ddI
## 7	2	5.000000	18	ddI
## 8	3	3.464102	0	ddI
## 9	3	3.605551	2	ddI
## 10	3	6.164414	6	ddI
## 11	4	3.872983	0	ddC
## 12	4	4.582576	2	ddC
## 13	4	2.645751	6	ddC
## 14	4	1.732051	12	ddC
## 15	5	7.280110	0	ddI

It consists of 467 HIV infected patients who were treated with two antiretroviral drugs (`drug`).

We will model the evolution of CD4 cell count for each individual `patient`.

The time at which the measurement of CD4 was taken is `obstime` in months. It is either 0, 2, 6, 12 or 18 (prescribed times of visits). Let us have a look on several random patients:



For some people the cell count decreases in time, for some increases. We will use this observation to construct linear mixed-effects (LME) model.

Task 1 - Frequentistic approach

Fit LME model (e.g. `lme` from `library(nlme)`) with random intercept and slope estimated with ML approach:

- $Y_{ij} = \beta_1 + B_{1i} + (\beta_2 + B_{2i})t_{ij} + \beta_3 D_i t_{ij} + \varepsilon_{ij}$, is the CD4 cell count of patient i at visit j ,
- $\varepsilon_{ij} \sim \mathcal{N}(0, \sigma^2)$ is the iid model error,
- t_{ij} is the time of the observation of patient i at visit j ,
- D_i is the indicator of **drug** level **ddI**,
- B_{1i} and B_{2i} are the random intercept and slope for patient i ,
- $\mathbf{B}_i = (B_{1i}, B_{2i})^\top \sim \mathcal{N}_2(\mathbf{0}, \Sigma)$, where Σ is general positive-definite matrix.

Notice that there is no $\beta_4 D_i$ within the formula. It would have the interpretation of difference between drug when $t = 0$ (study has not started yet). It is reasonable to assume $\beta_4 = 0$ and not include it within the model.

Print the summary of the model. Look at the magnitude of the coefficients including standard errors. Use this information to choose non-informative prior in the next Task.

Task 2 - Bayesian approach - JAGS implementation

Consider the same model from Task 1. Reparametrize the variance parameters through precisions instead: $\tau = \sigma^{-2}$, $\Omega = \Sigma^{-1}$. Move the parametrization of intercept and slope for patient i into the prior mean of respective random effects to reduce the autocorrelation:

$$\mathbb{E} B_{1i} = \beta_1 \quad \mathbb{E} B_{2i} = \beta_2 + \beta_3 D_i.$$

(You can implement other versions with $\mathbb{E} B_{1i} = 0$ or $\mathbb{E} B_{2i} = 0$ or $\mathbb{E} B_{2i} = \beta_2$ to see the difference for yourself.)

Assume the independent block structure of the prior for model parameters:

$$p(\beta, \tau, \Omega) = \prod_{j=1}^3 p(\beta_j) p(\tau) p(\Omega)$$

Choose weakly informative *normal* prior for β_j , *gamma* prior for τ and *Wishart* distribution (**dwish**) for Ω .

Write down (and print) the model implementation within JAGS.

Task 3 - Running JAGS

Sample two Markov chains using JAGS to approximate the posterior distribution $p(\beta, \tau, \Omega | \text{data})$. Choose appropriate **burnin** and **thin** by monitoring the trajectories and autocorrelation.

Task 4 - Monte Carlo estimates

Provide summaries including ET and HPD intervals for primary model parameters. Compare them to the outputs in Task 1.