A few Bayesian lectures for the Uninitiated

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Part 5: a mixed-effect model example

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Mixed effect model

- Mixed effect model $\in$ hierarchical models
- hierarchy: some parameters describe the response y, others internal, higher-level *unobservables*
- PISA school study: all measurements are at the level of the individual pupil, but there are parameters for schools, states and nations in the model
- mixed effect: subjects are random draws from the population of interest $\longrightarrow$ *subject-level* effects, and *population-level* effects

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Example: 10 subject were measured 20 times. $j \in \{1, \ldots, 10\}$, while $i \in \{1, \ldots, 200\}$.

Z is in this case a dummy matrix with 10 columns, and each column has one estimate for its subject u_j.

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Let's write this as equations:

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Final touch: Bayesian here only means that you have to have a prior for the βs, the σs, the zs and indeed for c.

In JAGS

```
for (i in 1:N){
    Reaction[i] ~ dnorm(muHat[i], tau)
    # random intercept model:
    muHat[i] <- beta0[subjectNr[i]] + beta1 * Days[i]
}
# priors
for (j in 1:k){
    beta0[j] ~ dnorm(beta00, tau.random) # random intercept
}
beta00 ~ dnorm(300, 0.001)          # grand mean
tau ~ dgamma(0.001, 0.001)
tau.random ~ dgamma(0.001, 0.001)
```

Easy!

Will this never end?

Next time:
State-space models

Useful links:
https://www.r-bloggers.com/2022/04/bayesian-analyses-made-easy-glmms-in-r-package-brms/