## Bayesian Linear Mixed Modelling vs. Generalized Linear Mixed Modelling

The R package brms provides an lme4-like interface for the fitting of Bayesian Mixed Models. It allows users who have experience with the fitting of Mixed Models with lme4 to access these methods with little additional programming training necessary. I stress, however, that this ease in access should *not* tempt researchers who have mainly experience with data analysis in a frequentist framework to jump right into model fitting without the necessary foundations in Bayesian analysis. The brms documentation provides an excellent starting point (<https://paul-buerkner.github.io/brms/articles/brms_distreg.html>), especially if you already have some general knowledge about Bayesian analysis, but it focusses on apply the package correctly and is therefore by no means complete. For a more exhaustive reading, we recommend the following articles and books:

[ADD BOOKS]

brms allows Bayesian analysis based on the same principles as the GLMM approach described above. We can fit a model with ConditionOfInterest, Difference and their interaction as main effects, and random intercepts and slopes for Difference per participant ID and StandardValues as random effects. Please note that brms requires “bernoulli()” as family, while the command for lme4 is “binomial(link = “probit”)” or “binomial(link = “logit”)”. This is roughly equivalent. [EXPAND]

BayesianGLMM = brm(bf(Yes ~ ConditionOfInterest\*Difference + (ConditionOfInterest + Difference | ID) + (ConditionOfInterest + Difference | StandardValues)),

data = Psychometric,

family = bernoulli())

We simulated one dataset with 20 participants, 15 participants, two standard values (5 and 8), a PSE difference of 10%, a JND difference of 30% and 100 repetitions per condition and fitted the above model to this dataset.

> BayesianGLMM

[…]

Population-Level Effects:

Estimate Est.Error l-95% CI u-95% CI Rhat Bulk\_ESS Tail\_ESS

Intercept -0.21 1.41 -3.51 3.01 1.01 506 293

ConditionOfInterest 1.05 1.41 -2.52 4.34 1.00 835 681

Difference 1.75 2.63 -4.54 7.55 1.00 811 722

ConditionOfInterest:Difference -0.34 0.10 -0.53 -0.14 1.00 2430 2688

[…]

Without ConditionOfInterest for random slopes: ADD MORE

BayesianGLMM\_2 = brm(bf(Yes ~ ConditionOfInterest\*Difference + (Difference | ID) + (Difference | StandardValues)),

data = Psychometric,

family = bernoulli())

ADD MORE

Population-Level Effects:

Estimate Est.Error l-95% CI u-95% CI Rhat Bulk\_ESS Tail\_ESS

Intercept -0.26 1.23 -3.38 2.31 1.06 62 495

ConditionOfInterest 1.15 0.07 1.00 1.28 1.17 220 2113

Difference 0.42 3.67 -5.44 7.41 1.24 12 35

ConditionOfInterest:Difference -0.27 0.10 -0.44 -0.11 1.12 22 128

For comparison, we fitted a Generalized Linear Mixed Model to the same dataset with the following syntax:

GLMM = glmer(cbind(Yes, Total - Yes) ~ ConditionOfInterest\*Difference + (Difference| ID) + (Difference| StandardValues),

family = binomial(link = "probit"),

data = Psychometric,

nAGQ = 0,

control = glmerControl(optimizer = "nloptwrap"))

The fixed effects table reads as follows:

> summary(GLMM)

[…]

Fixed effects:

Estimate Std. Error z value Pr(>|z|)

(Intercept) 0.35910 0.11366 3.159 0.00158 \*\*

ConditionOfInterest -0.60188 0.04244 -14.181 < 2e-16 \*\*\*

Difference 0.75271 0.06129 12.282 < 2e-16 \*\*\*

ConditionOfInterest:Difference -0.15210 0.03281 -4.636 3.56e-06 \*\*\*

[…]

The most important difference in terms of fixed effects is that the computed Std. Error in the GLMM is one magnitude smaller than the coefficient for Difference. The error computed in the Bayesian model