E4 categorization

R. Cassano-Coleman

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This notebook analyzes categorization using Bayesian binomial generalized linear mixed effects models (GLMMs).

Set up

```
set.seed(15000)
```

```
data <- read_csv('../data/E1-E2-E4/categorization.csv')
```

```
## Rows: 864 Columns: 6
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (3): response, scramble, Musician
## dbl (3): exp_subject_id, Trial_Nr, yrs_mus_exp
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

Convert variables to factors.

```
data %<>%
  mutate(scramble = ifelse(scramble == 'intact', 'Intact', scramble)) %>%
  mutate(exp_subject_id = as.factor(exp_subject_id),
         response = ifelse(response == 'Correct', TRUE, FALSE),
         scramble = factor(scramble, levels = c('Intact', '8B', '2B', '1B')),
         Musician = factor(Musician, levels = c('Yes', 'No'))) %>%
  filter(!is.na(response))
```

Set the contrast for condition.

```
contrasts(data$scramble) <- contr.treatment(4)
print(contrasts(data$scramble))
```

```
##        2 3 4
## Intact 0 0 0
## 8B     1 0 0
## 2B     0 1 0
## 1B     0 0 1
```

Main analysis

Priors

Priors are expressed in log(odds) space.

Intercept: Given that chance is 25%, we assume that participants will perform somewhere between chance and ceiling. We expect the center of the distribution of accuracy to be somewhere around 60% or 65%. If we use a center of 65% and an SD of 1.5, 95% of the values fall between 8.46% and 97.4%.

```
prior_intercept <- set_prior('normal(log(0.65 / (1 - 0.65)), 1)', class = 'Intercept')
```

Group: We might expect musicians to do slightly better than non-musicians, on average.

In this range, a difference in 0.25 log odds gives us about a 5% decrease in accuracy.

```
prior_mus <- set_prior('normal(-0.25, 1)', coef = 'Musician1')
```

Scramble: We expect performance to improve as scramble level decreases. If we code 8B as reference level, then we expect 8B > 2B and 8B > 1B.

Since we're keeping the musician slope at SD = 1, we'll keep these (and the interactions) at SD = 1. This seems to be a pretty weak prior.

```
prior_scramble8B <- set_prior('normal(-0.1, 1)', coef = 'scramble2')
prior_scramble2B <- set_prior('normal(-0.2, 1)', coef = 'scramble3')
prior_scramble1B <- set_prior('normal(-0.3, 1)', coef = 'scramble4')
```

Interaction: We expect no interaction between group and scramble.

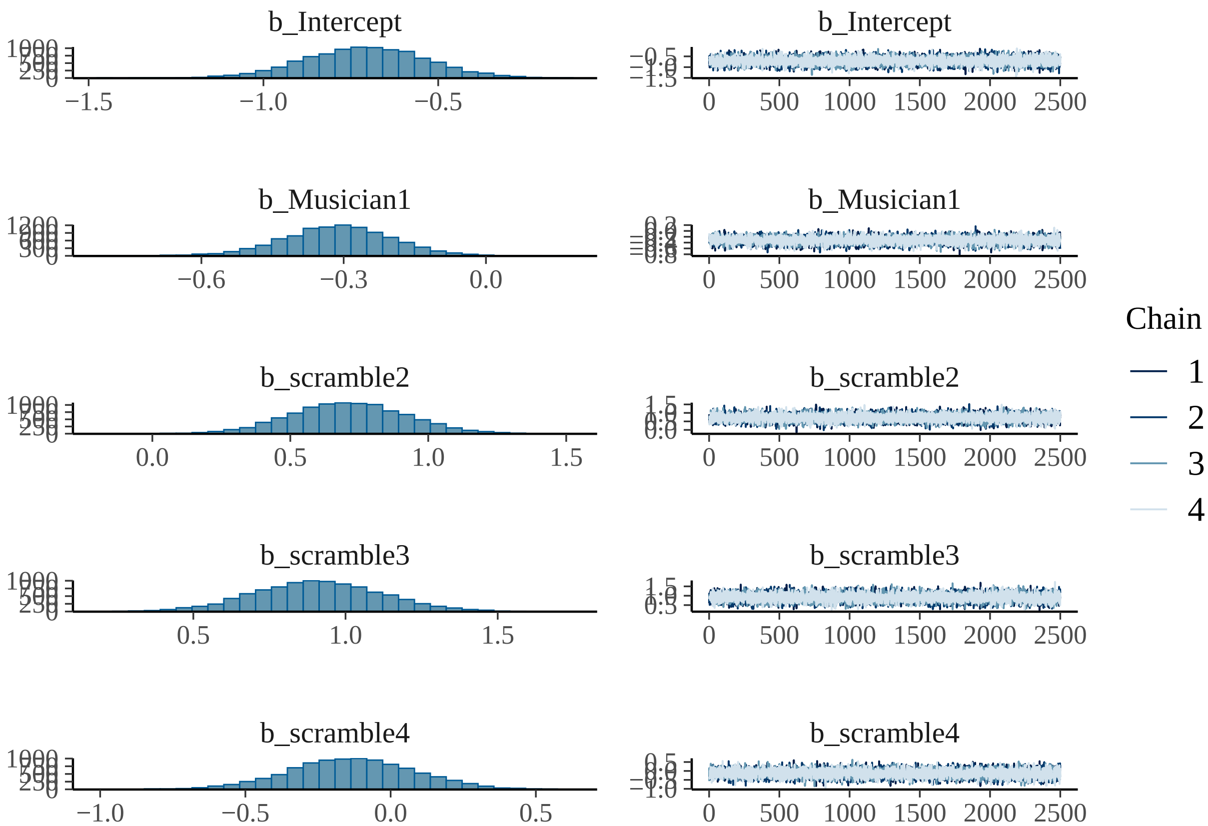
```
prior_int8B <- set_prior('normal(0, 1)', coef = 'Musician1:scramble2')
prior_int2B <- set_prior('normal(0, 1)', coef = 'Musician1:scramble3')
prior_int1B <- set_prior('normal(0, 1)', coef = 'Musician1:scramble4')
```

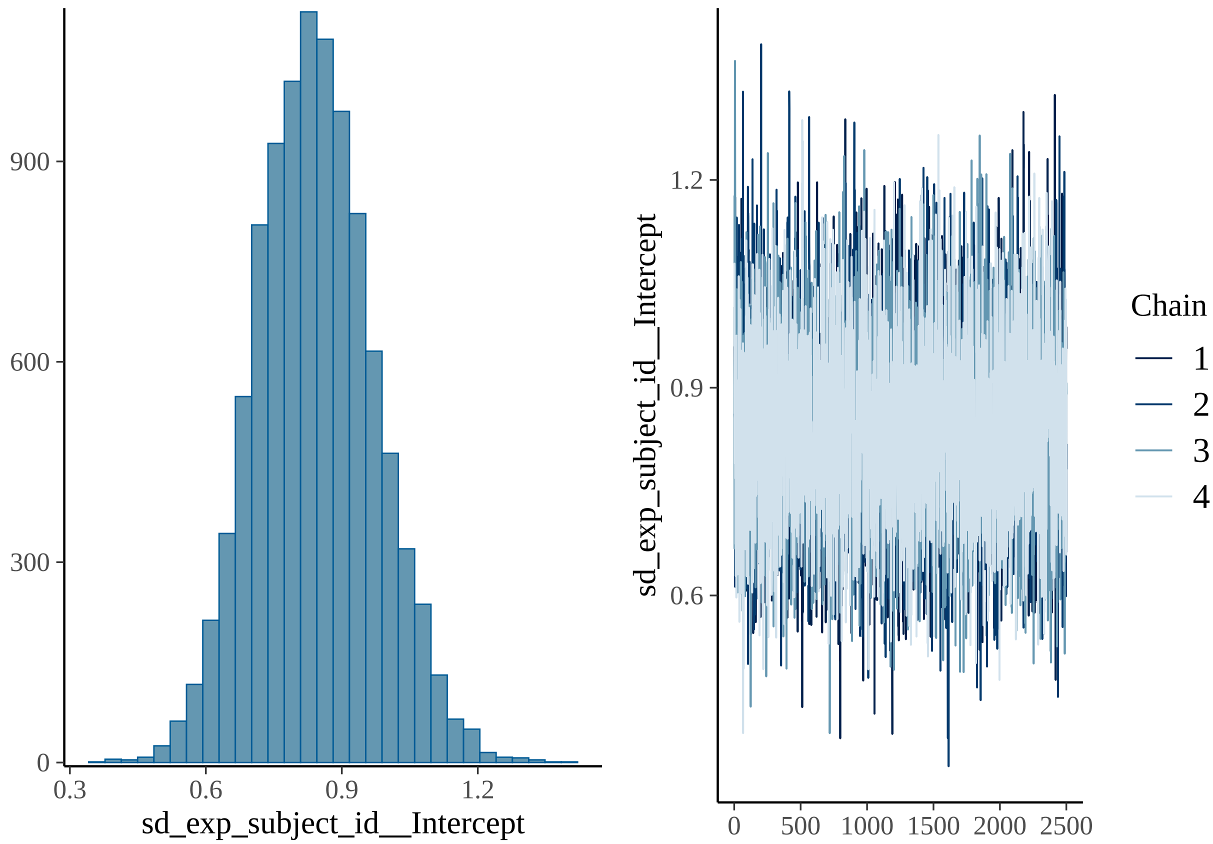
Random slope for subjects: *Leave this as default for now, may update.*

Main model with group and condition

```r
mus_scram <- brm(response ~ Musician + scramble + (1 | exp_subject_id), data = data,
                 family = bernoulli(),
                 prior = c(prior_intercept, prior_mus,
                           prior_scramble8B, prior_scramble2B, prior_scramble1B),
                 save_pars = save_pars(all = TRUE), iter = 5000,
                 file = 'models/E4_mus_scram')
```

```r
plot(mus_scram)
```






```r
print(summary(mus_scram), digits = 4)
```

```
##  Family: bernoulli
##   Links: mu = logit
## Formula: response ~ Musician + scramble + (1 | exp_subject_id)
##    Data: data (Number of observations: 825)
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
##
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 106)
##               Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sd(Intercept)   0.8422    0.1293   0.5979   1.1043 1.0001     4297     6368
##
## Regression Coefficients:
##           Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## Intercept  -0.7071    0.1728  -1.0471  -0.3661 1.0001    11873     7437
## Musician1  -0.3129    0.1146  -0.5409  -0.0930 0.9998     9751     7660
## scramble2   0.7118    0.2097   0.3023   1.1263 1.0000    12921     8289
## scramble3   0.9100    0.2101   0.4988   1.3293 0.9997    12182     7615
## scramble4  -0.1331    0.2153  -0.5599   0.2832 1.0001    13708     8650
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```r
emm_mus_scram_s <- emmeans(mus_scram, specs = "scramble")
summary(emm_mus_scram_s)
```

```
##  scramble   emmean lower.HPD upper.HPD
##  Intact   -0.70627    -1.048    -0.368
##  8B        0.00344    -0.348     0.331
##  2B        0.20343    -0.134     0.527
##  1B       -0.84006    -1.199    -0.492
##
## Results are averaged over the levels of: Musician
## Point estimate displayed: median
## Results are given on the logit (not the response) scale.
## HPD interval probability: 0.95
```

```r
contrast(emm_mus_scram_s, method = "pairwise")
```

```
##  contrast    estimate lower.HPD upper.HPD
##  Intact - 8B   -0.709    -1.099    -0.282
##  Intact - 2B   -0.908    -1.318    -0.489
##  Intact - 1B    0.134    -0.289     0.551
##  8B - 2B       -0.200    -0.600     0.244
##  8B - 1B        0.842     0.402     1.278
##  2B - 1B        1.042     0.610     1.471
##
## Results are averaged over the levels of: Musician
## Point estimate displayed: median
## Results are given on the log odds ratio (not the response) scale.
## HPD interval probability: 0.95
```

```r
emm_mus_scram_ms <- emmeans(mus_scram, specs = c("Musician", "scramble"))
summary(emm_mus_scram_ms)
```

```
##  Musician scramble emmean lower.HPD upper.HPD
##  Yes      Intact   -0.395   -0.7959   0.00399
##  No       Intact   -1.020   -1.4265  -0.60136
##  Yes      8B        0.317   -0.0873   0.72255
##  No       8B       -0.305   -0.7124   0.11702
##  Yes      2B        0.512    0.1266   0.91998
##  No       2B       -0.110   -0.4984   0.30549
##  Yes      1B       -0.527   -0.9215  -0.10908
##  No       1B       -1.149   -1.5819  -0.72118
##
## Point estimate displayed: median
## Results are given on the logit (not the response) scale.
## HPD interval probability: 0.95
```

```r
contrast(emm_mus_scram_ms, method = "pairwise")
```

```
##  contrast                estimate lower.HPD upper.HPD
##  Yes Intact - No Intact    0.6226     0.186    1.0821
##  Yes Intact - Yes 8B      -0.7089    -1.099   -0.2824
##  Yes Intact - No 8B       -0.0845    -0.695    0.5258
##  Yes Intact - Yes 2B      -0.9077    -1.318   -0.4889
##  Yes Intact - No 2B       -0.2868    -0.911    0.3061
##  Yes Intact - Yes 1B       0.1336    -0.289    0.5509
##  Yes Intact - No 1B        0.7542     0.133    1.3860
```

```
##  No Intact - Yes 8B      -1.3386   -1.921   -0.6880
##  No Intact - No 8B       -0.7089   -1.099   -0.2824
##  No Intact - Yes 2B      -1.5359   -2.152   -0.9120
##  No Intact - No 2B       -0.9077   -1.318   -0.4889
##  No Intact - Yes 1B      -0.4936   -1.137    0.0773
##  No Intact - No 1B        0.1336   -0.289    0.5509
##  Yes 8B - No 8B           0.6226    0.186    1.0821
##  Yes 8B - Yes 2B         -0.2003   -0.600    0.2445
##  Yes 8B - No 2B           0.4252   -0.180    1.0495
##  Yes 8B - Yes 1B          0.8424    0.402    1.2779
##  Yes 8B - No 1B           1.4688    0.839    2.0973
##  No 8B - Yes 2B          -0.8212   -1.461   -0.2121
##  No 8B - No 2B           -0.2003   -0.600    0.2445
##  No 8B - Yes 1B           0.2171   -0.404    0.8420
##  No 8B - No 1B            0.8424    0.402    1.2779
##  Yes 2B - No 2B           0.6226    0.186    1.0821
##  Yes 2B - Yes 1B          1.0417    0.610    1.4707
##  Yes 2B - No 1B           1.6665    1.026    2.2945
##  No 2B - Yes 1B           0.4175   -0.192    1.0378
##  No 2B - No 1B            1.0417    0.610    1.4707
##  Yes 1B - No 1B           0.6226    0.186    1.0821
##
## Point estimate displayed: median
## Results are given on the log odds ratio (not the response) scale.
## HPD interval probability: 0.95
```

Main effects

```r
main_BF <- describe_posterior(mus_scram,
                              estimate = "median", dispersion = TRUE,
                              ci = .95, ci_method = "HDI",
                              test = c("bayes_factor"))
```

```
## Warning: Bayes factors might not be precise.
##   For precise Bayes factors, sampling at least 40,000 posterior samples is
##   recommended.
```

```r
print(main_BF, digits = 4)
```

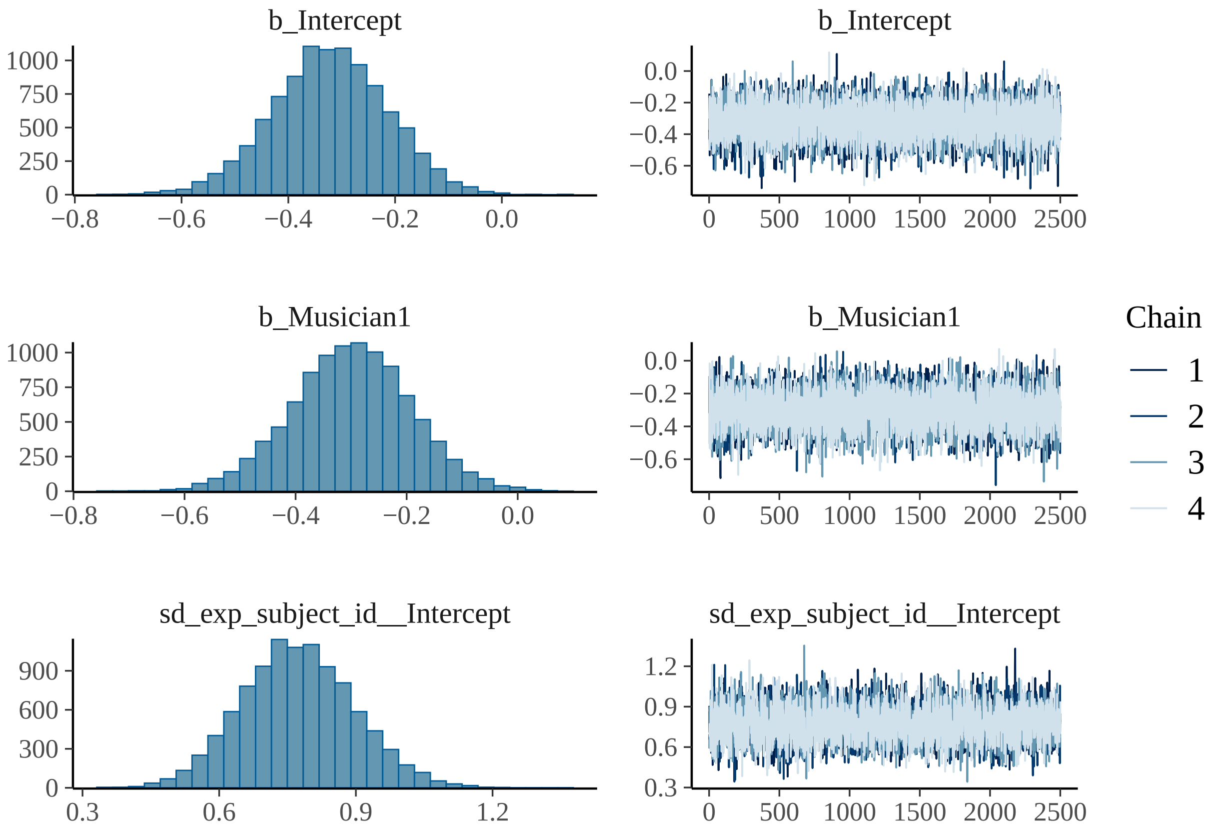
```
## Summary of Posterior Distribution
##
## Parameter   |  Median |    MAD |         95% CI |       BF |  Rhat |        ESS
## --------------------------------------------------------------------------------
## (Intercept) | -0.7063 | 0.1739 | [-1.05, -0.37] |   179.78 | 1.000 | 11777.0000
## Musician1   | -0.3113 | 0.1117 | [-0.54, -0.09] |     5.44 | 1.000 |  9652.0000
## scramble2   |  0.7089 | 0.2080 | [ 0.28,  1.10] |    57.71 | 1.000 | 12850.0000
## scramble3   |  0.9077 | 0.2106 | [ 0.49,  1.32] | 1.04e+03 | 1.000 | 12108.0000
## scramble4   | -0.1336 | 0.2154 | [-0.55,  0.29] |    0.252 | 1.000 | 13622.0000
```

Moderate evidence for a main effect of group.

To get the main effect of scramble level, fit the "null" model with group only to compare.

```
mus_only <- brm(response ~ Musician + (1 | exp_subject_id), data = data,
                family = bernoulli(),
                prior = c(prior_intercept, prior_mus),
                save_pars = save_pars(all = TRUE), iter = 5000,
                file = 'models/E4_mus_only')
```

```
plot(mus_only)
```




```
print(summary(mus_only), digits = 4)
```

```
##  Family: bernoulli
##   Links: mu = logit
## Formula: response ~ Musician + (1 | exp_subject_id)
##    Data: data (Number of observations: 825)
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
##
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 106)
##               Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sd(Intercept)   0.7733    0.1236   0.5389   1.0241 1.0004     4099     5764
##
## Regression Coefficients:
##           Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## Intercept  -0.3219    0.1080  -0.5361  -0.1148 1.0001     9257     6906
## Musician1  -0.2994    0.1073  -0.5152  -0.0878 1.0002     8722     7401
##
```

```
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```r
BF_scramble <- bayes_factor(mus_scram, mus_only)
```

```
## Iteration: 1
## Iteration: 2
## Iteration: 3
## Iteration: 4
## Iteration: 5
## Iteration: 6
## Iteration: 1
## Iteration: 2
## Iteration: 3
## Iteration: 4
## Iteration: 5
```

```r
print(BF_scramble)
```

```
## Estimated Bayes factor in favor of mus_scram over mus_only: 202477.26749
```

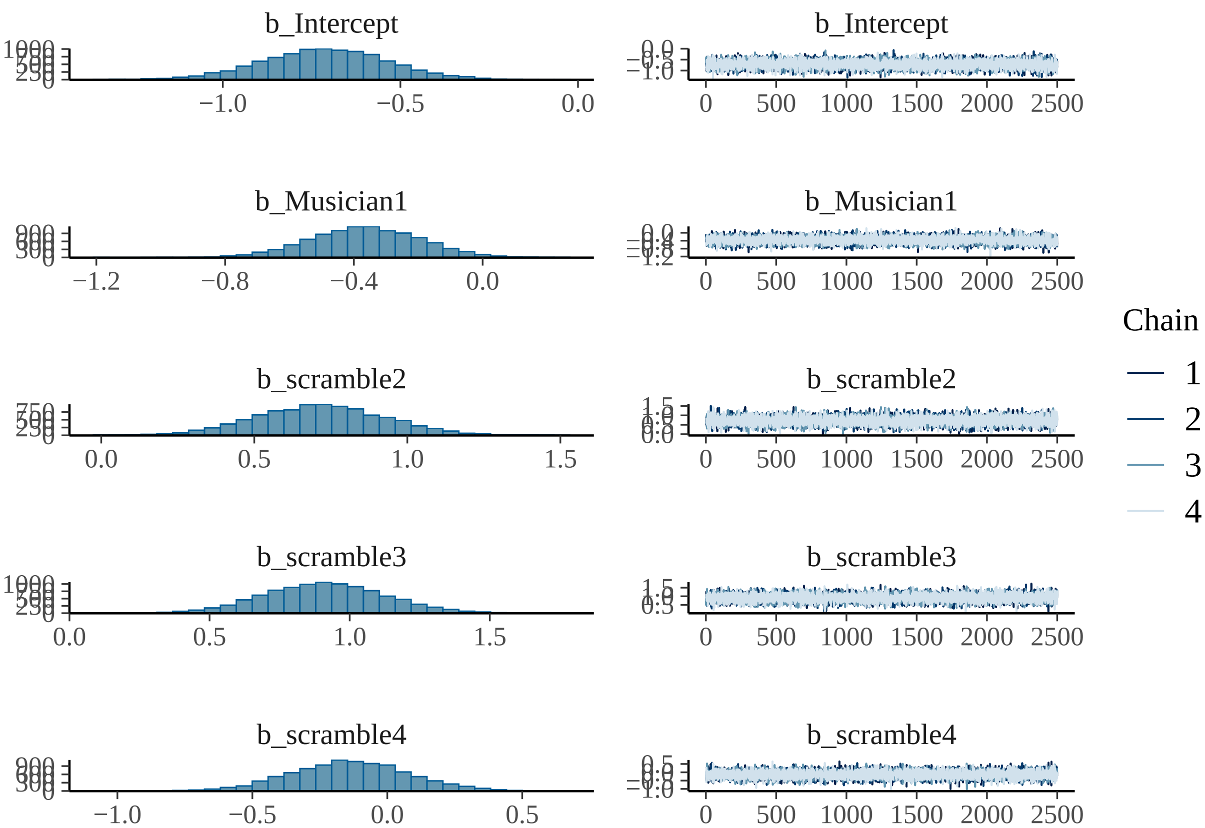
Very strong evidence for a main effect of scramble condition.

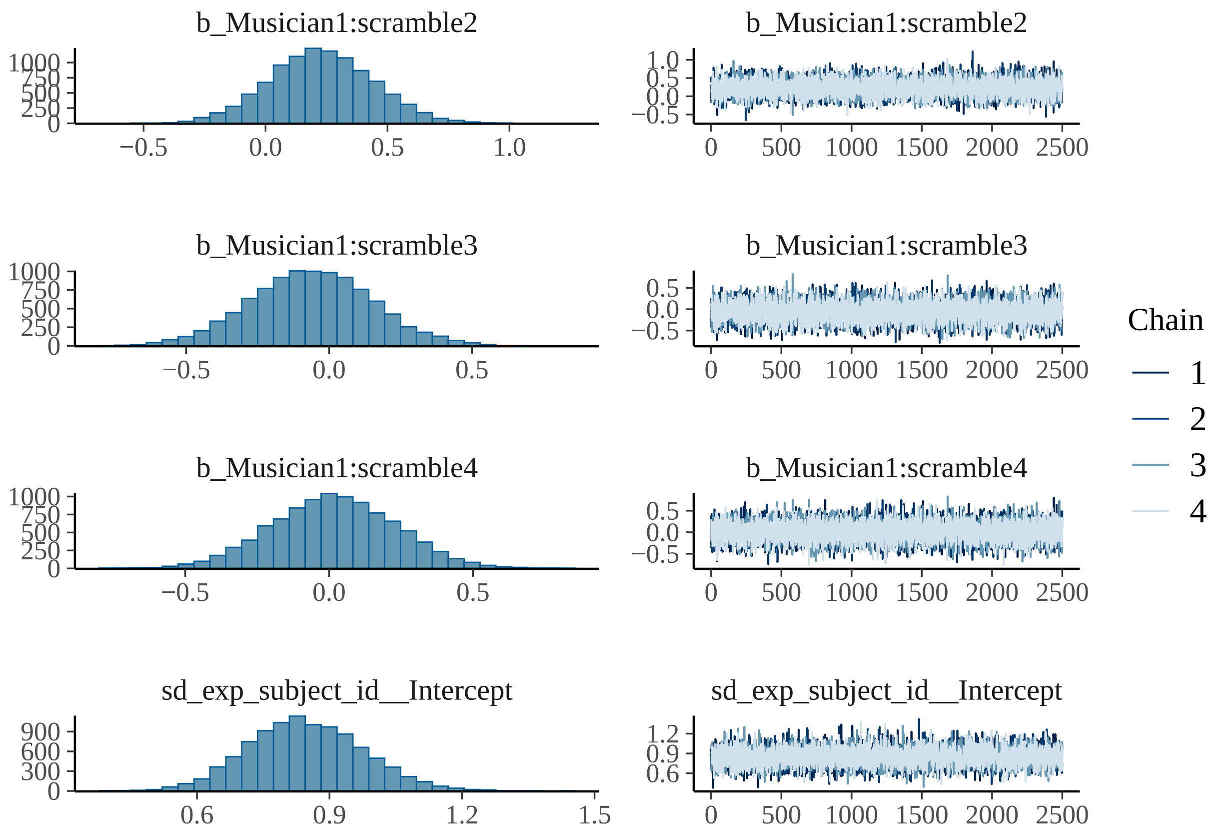
Interaction between group and condition?

Add an interaction between group and condition, and compare the model with the interaction to the one without.

```
mus_scram_int <- brm(response ~ Musician*scramble + (1 | exp_subject_id), data = data,
                     family = bernoulli(),
                     prior = c(prior_intercept, prior_mus,
                               prior_scramble8B, prior_scramble2B, prior_scramble1B,
                               prior_int8B, prior_int2B, prior_int1B),
                     save_pars = save_pars(all = TRUE), iter = 5000,
                     file = 'models/E4_mus_scram_int')
```

```
plot(mus_scram_int)
```






```r
print(summary(mus_scram_int), digits = 4)
```

```
##  Family: bernoulli
##   Links: mu = logit
## Formula: response ~ Musician * scramble + (1 | exp_subject_id)
##    Data: data (Number of observations: 825)
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
##
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 106)
##               Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sd(Intercept)   0.8464    0.1302   0.6004   1.1098 0.9999     4374     7001
##
## Regression Coefficients:
##                     Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS
## Intercept            -0.7124    0.1765  -1.0630  -0.3682 1.0004    10147
## Musician1            -0.3640    0.1704  -0.6959  -0.0331 1.0001     8745
## scramble2             0.7178    0.2136   0.3057   1.1355 1.0001    13819
## scramble3             0.9115    0.2156   0.4918   1.3367 1.0009    12623
## scramble4            -0.1380    0.2176  -0.5631   0.2900 1.0003    13328
## Musician1:scramble2   0.2294    0.2120  -0.1802   0.6476 0.9999    12137
## Musician1:scramble3  -0.0606    0.2149  -0.4842   0.3681 1.0000    12146
## Musician1:scramble4   0.0167    0.2162  -0.4026   0.4329 1.0001    12339
##                     Tail_ESS
## Intercept               7950
## Musician1               8647
## scramble2               7953
```

```
## scramble3              7768
## scramble4              8491
## Musician1:scramble2    8211
## Musician1:scramble3    8641
## Musician1:scramble4    8669
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```r
BF_int <- bayes_factor(mus_scram_int, mus_scram)
```

```
## Iteration: 1
## Iteration: 2
## Iteration: 3
## Iteration: 4
## Iteration: 5
## Iteration: 6
## Iteration: 1
## Iteration: 2
## Iteration: 3
## Iteration: 4
## Iteration: 5
## Iteration: 6
```

```r
print(BF_int)
```

```
## Estimated Bayes factor in favor of mus_scram_int over mus_scram: 0.02145
```

Strong evidence against an interaction between group and condition.

Figure 5

Create a helper function for the conversion from log odds to probability.

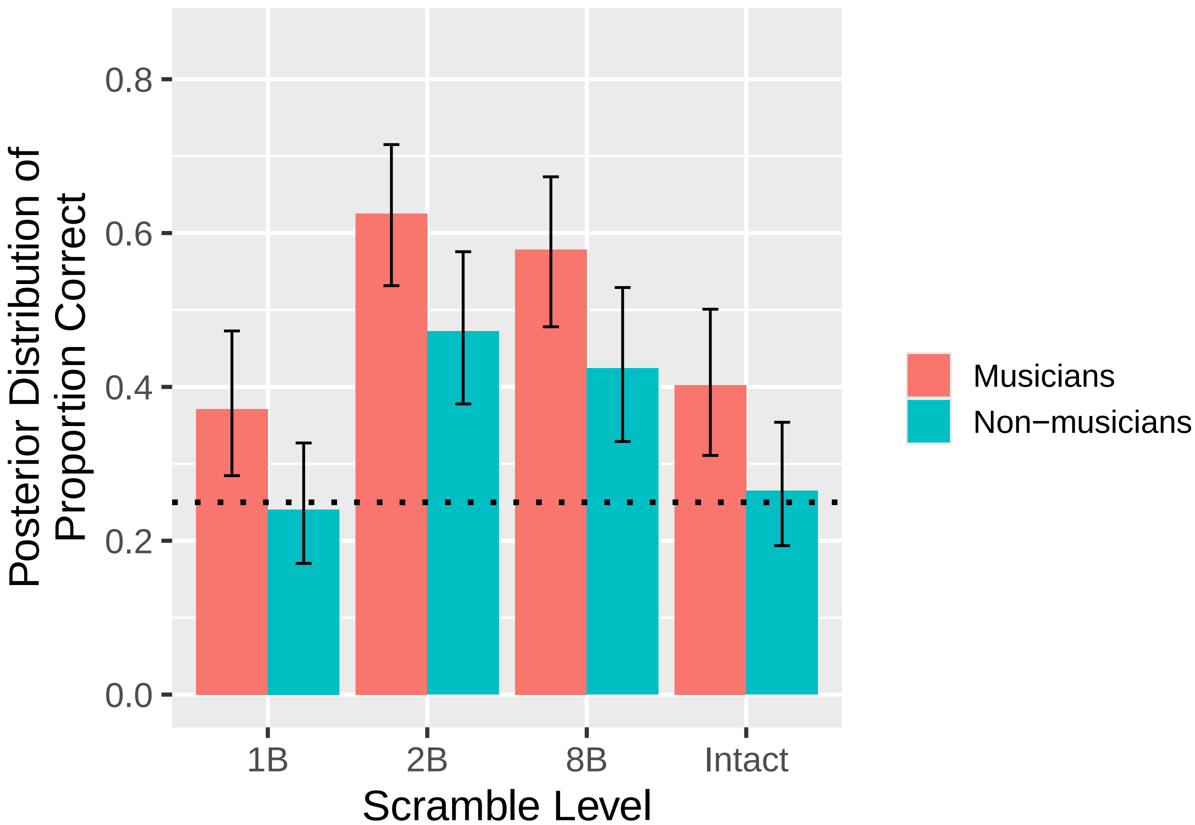
```
calculate_prob_from_logodds <- function(logodds) {
  return(exp(logodds) / (1 + exp(logodds)))
}
```

Visualize with posterior estimates and 95% CrI on the scale of accuracy.

```
posterior_est <- as.data.frame(emm_mus_scram_ms)
```

```
ggplot() +
  geom_col(aes(x = scramble, y = calculate_prob_from_logodds(emmean), fill = Musician),
           data = posterior_est,
           position = "dodge") +
  geom_errorbar(aes(x = scramble,
                    ymin = calculate_prob_from_logodds(lower.HPD),
                    ymax = calculate_prob_from_logodds(upper.HPD),
                    fill = Musician),
                data = posterior_est, position = position_dodge(width = 0.9), width = 0.2) +
  geom_hline(yintercept = 0.25, linetype = "dotted", color = "black", linewidth = 1) +
  theme_gray(base_size = 16) +
  scale_x_discrete(limits = rev) +
  ylim(0, 0.85) +
  xlab('Scramble Level') +
  ylab('Posterior Distribution of\nProportion Correct') +
  scale_fill_discrete(name="", labels=c('Musicians', 'Non-musicians')) +
  theme(legend.text = element_text(size = 12))
```

```
## Warning in geom_errorbar(aes(x = scramble, ymin =
## calculate_prob_from_logodds(lower.HPD), : Ignoring unknown aesthetics: fill
```




```
ggsave('../figures/Fig5_categorization.png', width = 7, height = 5)
```

Years of experience

Keep only the subjects for which we have years of experience data and average accuracy per condition.

```
yrs_exp <- data %>%
  filter(!is.na(yrs_mus_exp)) %>%
  group_by(exp_subject_id, scramble, yrs_mus_exp) %>%
  summarize(count = n(),
            n_correct = sum(response),
            accuracy = n_correct / count)
```

```
## `summarise()` has grouped output by 'exp_subject_id', 'scramble'. You can
## override using the `.groups` argument.
```

Priors

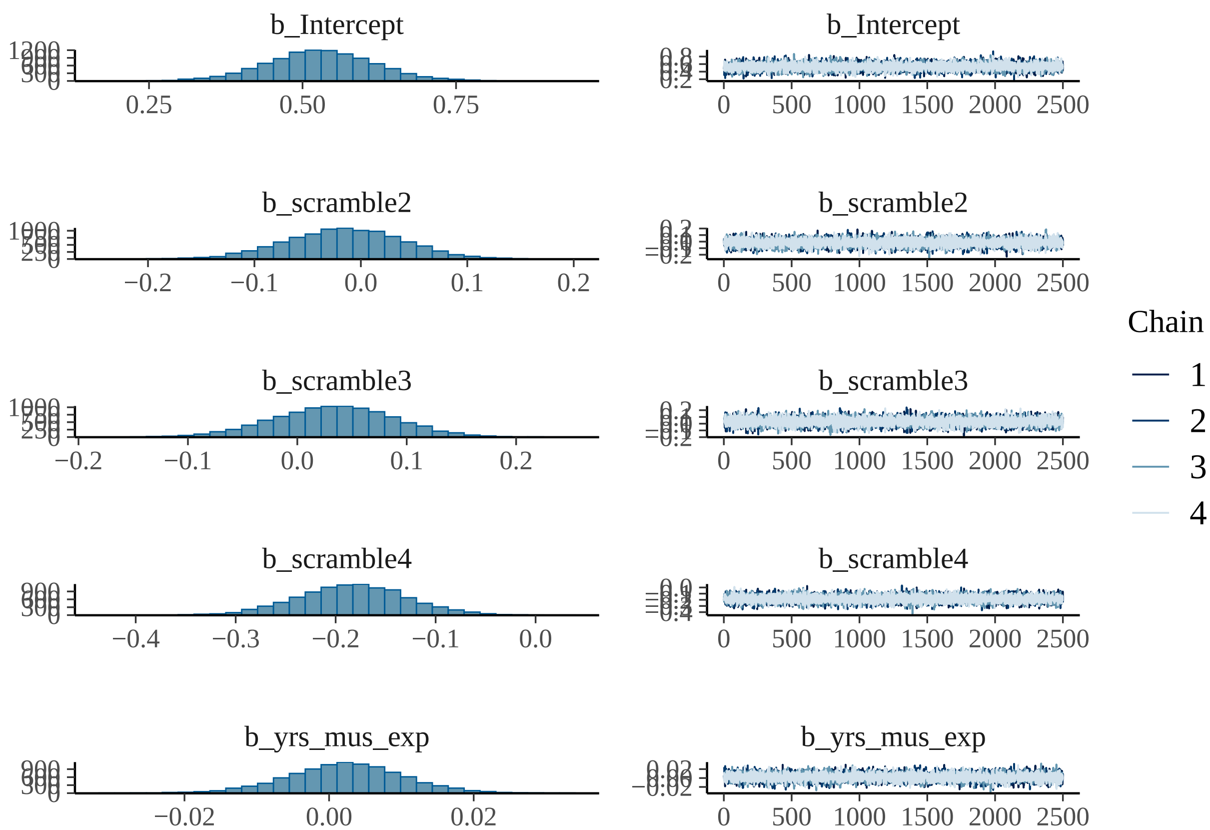
For this analysis, we're operating on the scale of accuracy. Because we don't see ceiling effects (i.e. participants aren't getting too close to perfect accuracy), a linear model is appropriate enough.

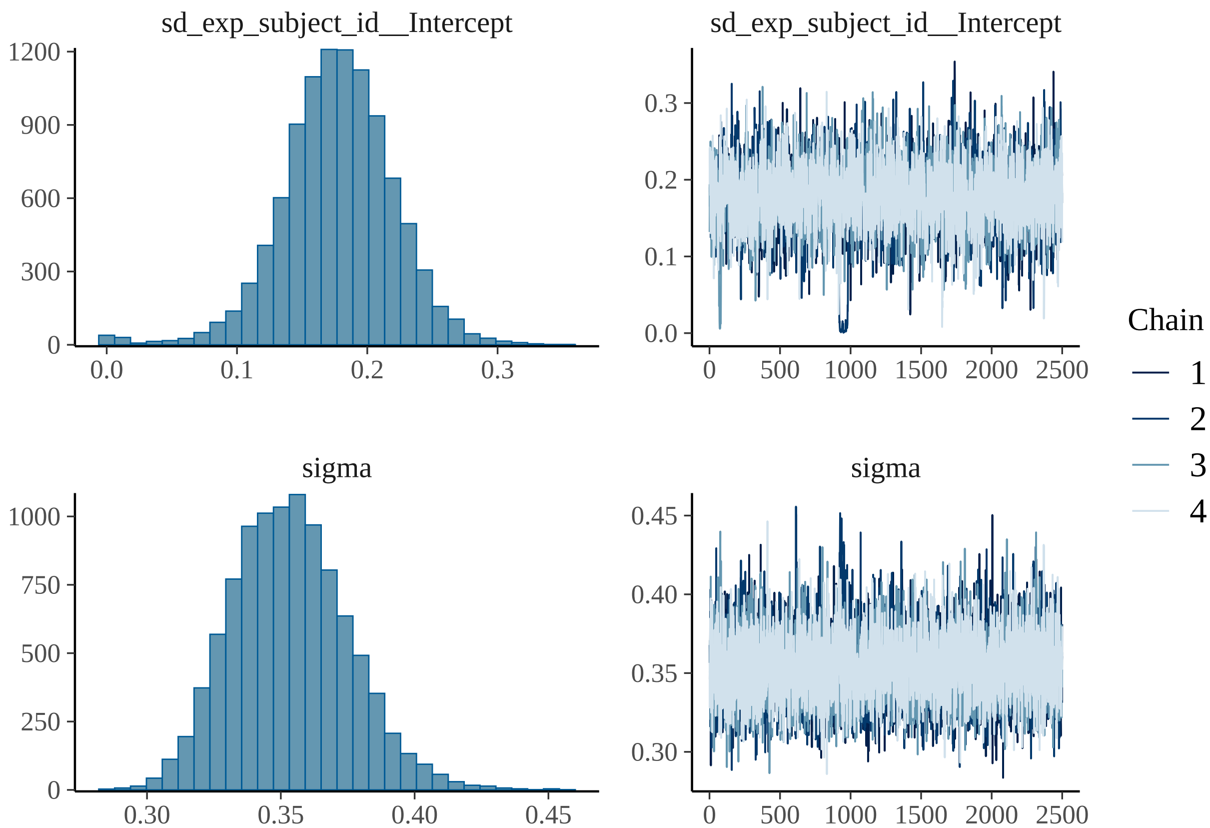
```
these_priors <- c(
  set_prior('normal(0.625, 0.1)', class = 'Intercept'),
  set_prior('normal(-0.1, 0.1)', coef = 'scramble2'),
  set_prior('normal(-0.2, 0.1)', coef = 'scramble3'),
  set_prior('normal(-0.3, 0.1)', coef = 'scramble4'),
  set_prior('normal(0, 0.1)', coef = 'yrs_mus_exp')
)
```

Main model

```
years_mus_scram <- brm(accuracy ~ scramble + yrs_mus_exp + (1|exp_subject_id), data = yrs_exp,
                       prior = these_priors,
                       save_pars = save_pars(all = TRUE), iter = 5000,
                       file = 'models/E4_years')
```

```
plot(years_mus_scram)
```






```
print(summary(years_mus_scram), digits = 4)
```

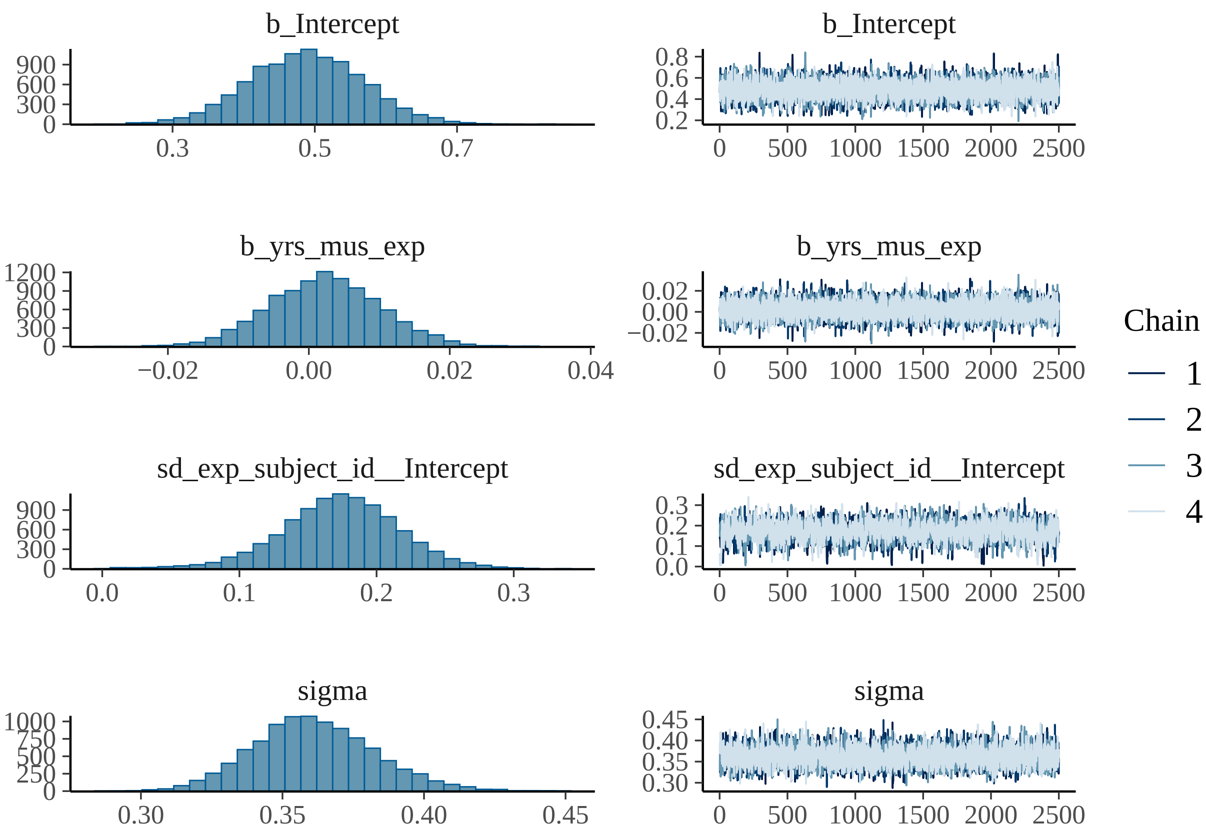
```
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: accuracy ~ scramble + yrs_mus_exp + (1 | exp_subject_id)
##    Data: yrs_exp (Number of observations: 203)
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
##
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 51)
##               Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sd(Intercept)   0.1771    0.0431   0.0894   0.2587 1.0023     1778     1018
##
## Regression Coefficients:
##             Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## Intercept     0.5298    0.0876   0.3554   0.7064 1.0003    10476     7922
## scramble2    -0.0150    0.0548  -0.1214   0.0909 0.9998    14722     8491
## scramble3     0.0333    0.0552  -0.0760   0.1399 1.0002    14290     8461
## scramble4    -0.1831    0.0544  -0.2901  -0.0761 0.9999    14396     7439
## yrs_mus_exp   0.0023    0.0080  -0.0138   0.0180 1.0009     9663     7553
##
## Further Distributional Parameters:
##       Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sigma   0.3535    0.0219   0.3143   0.3999 1.0011     3858     3243
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
```

```
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

Null model (for plotting purposes)

```
years_mus <- brm(accuracy ~ yrs_mus_exp + (1|exp_subject_id), data = yrs_exp,
                 prior = c(
                   set_prior('normal(0.625, 0.1)', class = 'Intercept'),
                   set_prior('normal(0, 0.1)', coef = 'yrs_mus_exp')),
                 save_pars = save_pars(all = TRUE), iter = 5000,
                 file = 'models/E4_years_null')
```

```
plot(years_mus)
```




```
print(summary(years_mus), digits = 4)
```

```
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: accuracy ~ yrs_mus_exp + (1 | exp_subject_id)
##    Data: yrs_exp (Number of observations: 203)
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
##
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 51)
##               Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sd(Intercept)   0.1731    0.0435   0.0822   0.2559 1.0003     2325     2914
##
## Regression Coefficients:
```

```
##             Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## Intercept     0.4880    0.0811   0.3296   0.6485 1.0003     9029     7534
## yrs_mus_exp   0.0023    0.0079  -0.0130   0.0180 1.0002     9390     7531
##
## Further Distributional Parameters:
##       Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sigma   0.3613    0.0214   0.3218   0.4060 1.0000     6420     5982
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```r
yrs_BF <- describe_posterior(years_mus_scram,
                             estimate = "median", dispersion = TRUE,
                             ci = .95, ci_method = "HDI",
                             test = c("bayes_factor"))
```

```
## Warning: Bayes factors might not be precise.
##   For precise Bayes factors, sampling at least 40,000 posterior samples is
##   recommended.
```

```r
print(yrs_BF, digits = 4)
```

```
## Summary of Posterior Distribution
##
## Parameter   |  Median |    MAD |          95% CI |       BF |  Rhat |        ESS
## ---------------------------------------------------------------------------------
## (Intercept) |  0.5294 | 0.0859 | [ 0.34,  0.69] | 1.82e+04 | 1.000 | 10394.0000
## scramble2   | -0.0144 | 0.0550 | [-0.12,  0.09] |    0.348 | 1.000 | 14888.0000
## scramble3   |  0.0342 | 0.0551 | [-0.07,  0.14] |    0.093 | 1.000 | 14482.0000
## scramble4   | -0.1828 | 0.0543 | [-0.30, -0.08] |     1.11 | 1.000 | 14173.0000
## yrs_mus_exp |  0.0024 | 0.0077 | [-0.01,  0.02] |    0.080 | 1.000 |  9558.0000
```

```r
yrs_null_BF <- describe_posterior(years_mus,
                                  estimate = "median", dispersion = TRUE,
                                  ci = .95, ci_method = "HDI",
                                  test = c("bayes_factor"))
```

```
## Warning: Bayes factors might not be precise.
##   For precise Bayes factors, sampling at least 40,000 posterior samples is
##   recommended.
```

```r
print(yrs_null_BF, digits = 4)
```

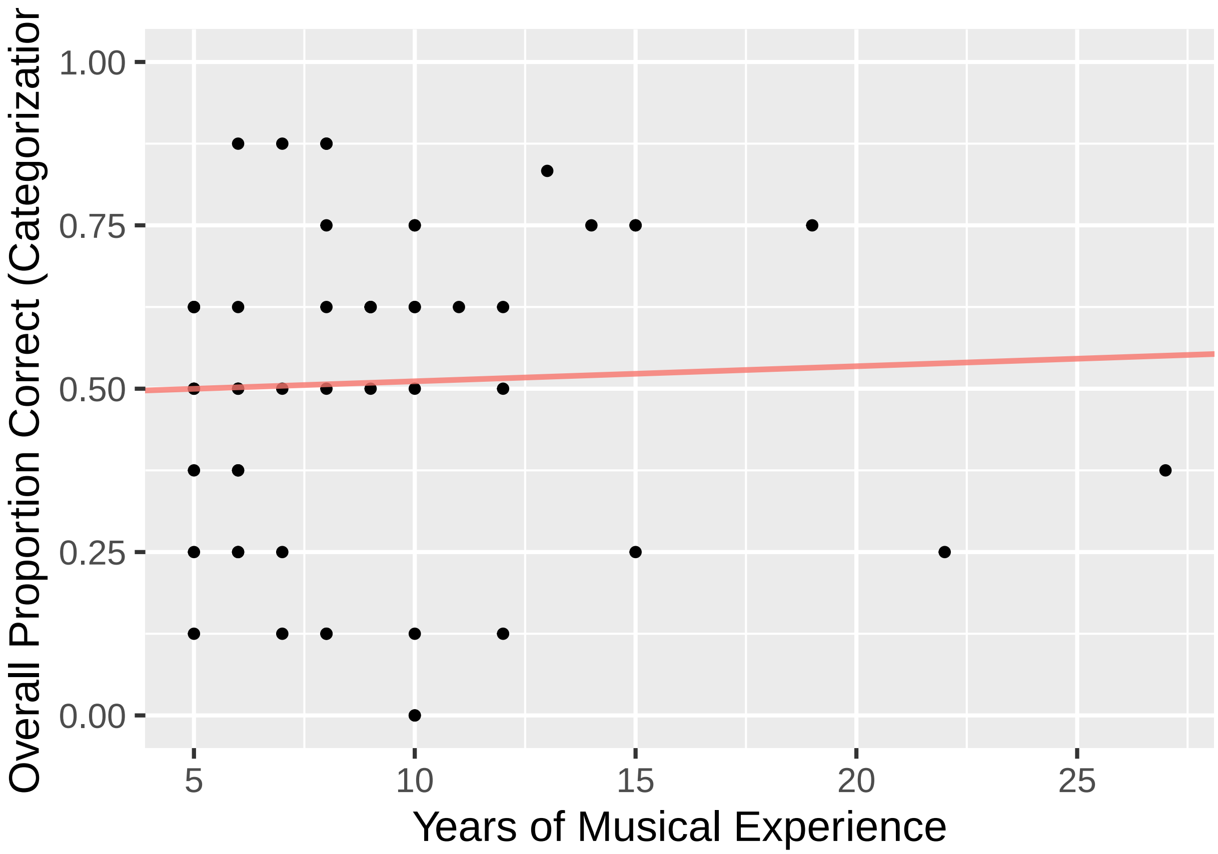
```
## Summary of Posterior Distribution
##
## Parameter   | Median |    MAD |         95% CI |       BF |  Rhat |       ESS
## ------------------------------------------------------------------------------
## (Intercept) | 0.4883 | 0.0814 | [ 0.33, 0.65] | 1.51e+04 | 1.000 | 8987.0000
## yrs_mus_exp | 0.0023 | 0.0079 | [-0.01, 0.02] |    0.083 | 1.000 | 9381.0000
```

Strong evidence against an effect of years of musical experience.

Figure S1C

```
yrs_exp %>%
  group_by(exp_subject_id, yrs_mus_exp) %>%
  summarize(mean_acc = mean(accuracy)) %>%
  ggplot(aes(yrs_mus_exp, mean_acc)) +
  geom_point() +
  geom_abline(intercept = yrs_null_BF$Median[1], slope = yrs_null_BF$Median[2],
              color = '#F8766D', linewidth = 1, alpha = 0.8) +
  xlab('Years of Musical Experience') +
  ylab('Overall Proportion Correct (Categorization)') +
  scale_x_continuous(breaks = seq(5,30,5)) +
  scale_y_continuous(breaks = seq(0, 1, 0.1)) +
  ylim(0,1) +
  theme_gray(base_size = 16)
```

```
## `summarise()` has grouped output by 'exp_subject_id'. You can override using
## the `.groups` argument.
## Scale for y is already present. Adding another scale for y, which will replace
## the existing scale.
```




```
ggsave('../figures/FigS1C_categorization.png', width = 5, height = 5)
```