E2 prediction

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

Set up

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

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

```
## Rows: 3210 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.

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

Set the contrast for condition.

```r
contrasts(data$scramble) <- contr.treatment(3)
print(contrasts(data$scramble))
```

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

```r
contrasts(data$Musician)
```

```
##     No
## Yes  0
## No   1
```

Main analysis

Priors

Priors are expressed in log(odds) space.

Intercept: Given that chance is 50%, we assume that participants will perform somewhere between chance and ceiling. We expect the center of the distribution of accuracy to be somewhere around 75% or 80%. If we use a center of 80% and an SD of 1, 95% of the values fall between 35.1% and 96.7%.

```
prior_intercept <- set_prior('normal(log(0.8 / (1 - 0.8)), 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_scramble2B <- set_prior('normal(-0.1, 1)', coef = 'scramble2')
prior_scramble1B <- set_prior('normal(-0.2, 1)', coef = 'scramble3')
```

Interaction: We expect no interaction between group and scramble.

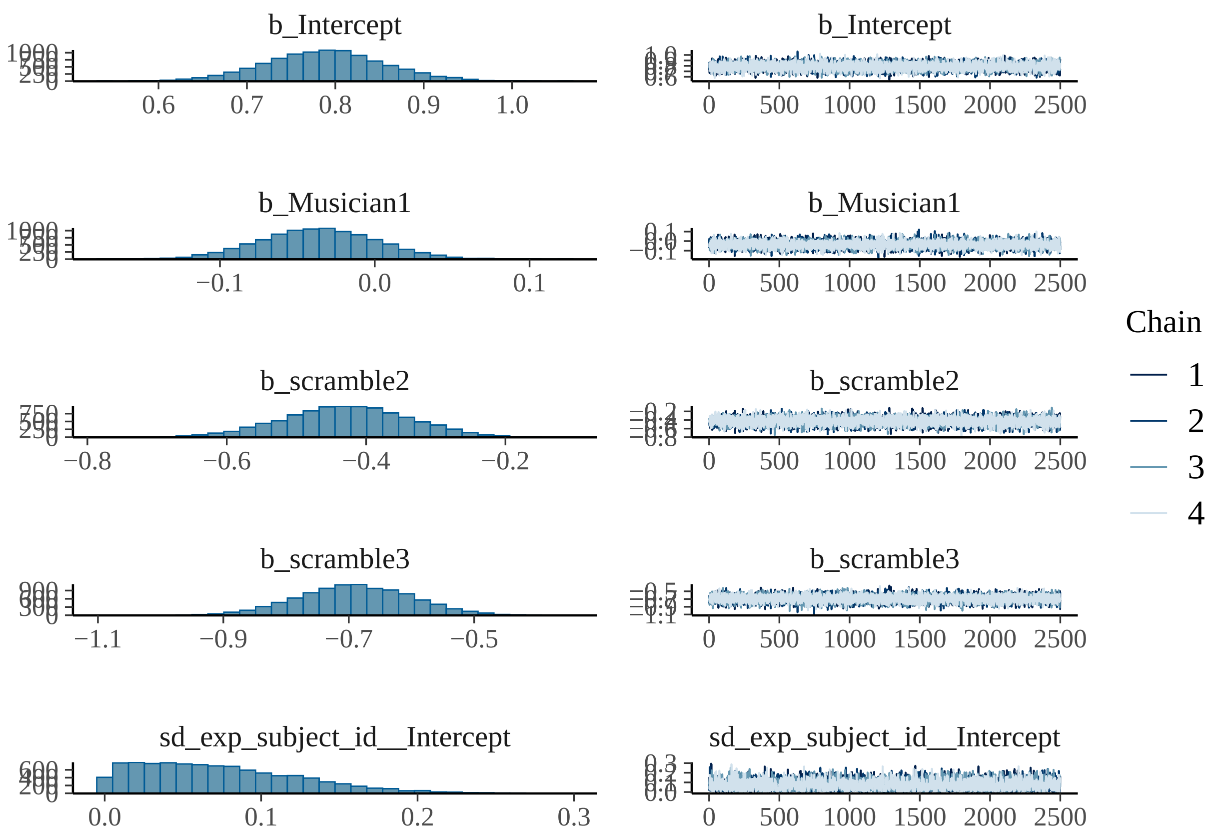
```
prior_int2B <- set_prior('normal(0, 1)', coef = 'Musician1:scramble2')
prior_int1B <- set_prior('normal(0, 1)', coef = 'Musician1:scramble3')
```

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_scramble2B, prior_scramble1B),
                 save_pars = save_pars(all = TRUE), iter = 5000,
                 file = 'models/E2_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: 3158)
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
##
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 105)
##               Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sd(Intercept)   0.0735    0.0506   0.0029   0.1867 1.0005     3759     4232
##
## Regression Coefficients:
##           Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## Intercept   0.7882    0.0666   0.6571   0.9209 1.0010     9660     7323
```

```
## Musician1  -0.0362    0.0377  -0.1093   0.0373 1.0001    12143     6990
## scramble2  -0.4278    0.0912  -0.6079  -0.2528 1.0004    10714     7748
## scramble3  -0.6901    0.0902  -0.8667  -0.5139 1.0004    10339     7786
##
## 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
##  8B       0.7884    0.6555     0.918
##  2B       0.3604    0.2401     0.489
##  1B       0.0969   -0.0217     0.223
##
## 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
##  8B - 2B     0.427     0.259     0.612
##  8B - 1B     0.691     0.512     0.864
##  2B - 1B     0.262     0.092     0.436
##
## 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      8B       0.8243    0.6688     0.973
##  No       8B       0.7519    0.6030     0.896
##  Yes      2B       0.3968    0.2488     0.541
##  No       2B       0.3245    0.1835     0.467
##  Yes      1B       0.1328   -0.0103     0.276
##  No       1B       0.0611   -0.0905     0.200
##
## 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 8B - No 8B    0.0725   -0.0739     0.219
##  Yes 8B - Yes 2B   0.4272    0.2588     0.612
##  Yes 8B - No 2B    0.5001    0.2819     0.743
##  Yes 8B - Yes 1B   0.6907    0.5121     0.864
##  Yes 8B - No 1B    0.7626    0.5281     0.999
##  No 8B - Yes 2B    0.3541    0.1297     0.595
```

```
##  No 8B - No 2B     0.4272    0.2588     0.612
##  No 8B - Yes 1B    0.6162    0.3880     0.842
##  No 8B - No 1B     0.6907    0.5121     0.864
##  Yes 2B - No 2B    0.0725   -0.0739     0.219
##  Yes 2B - Yes 1B   0.2616    0.0920     0.436
##  Yes 2B - No 1B    0.3351    0.0994     0.553
##  No 2B - Yes 1B    0.1905   -0.0276     0.417
##  No 2B - No 1B     0.2616    0.0920     0.436
##  Yes 1B - No 1B    0.0725   -0.0739     0.219
##
## Point estimate displayed: median
## Results are given on the log odds ratio (not the response) scale.
## HPD interval probability: 0.95
```

Main effects

```
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.
```

```
print(main_BF, digits = 5)
```

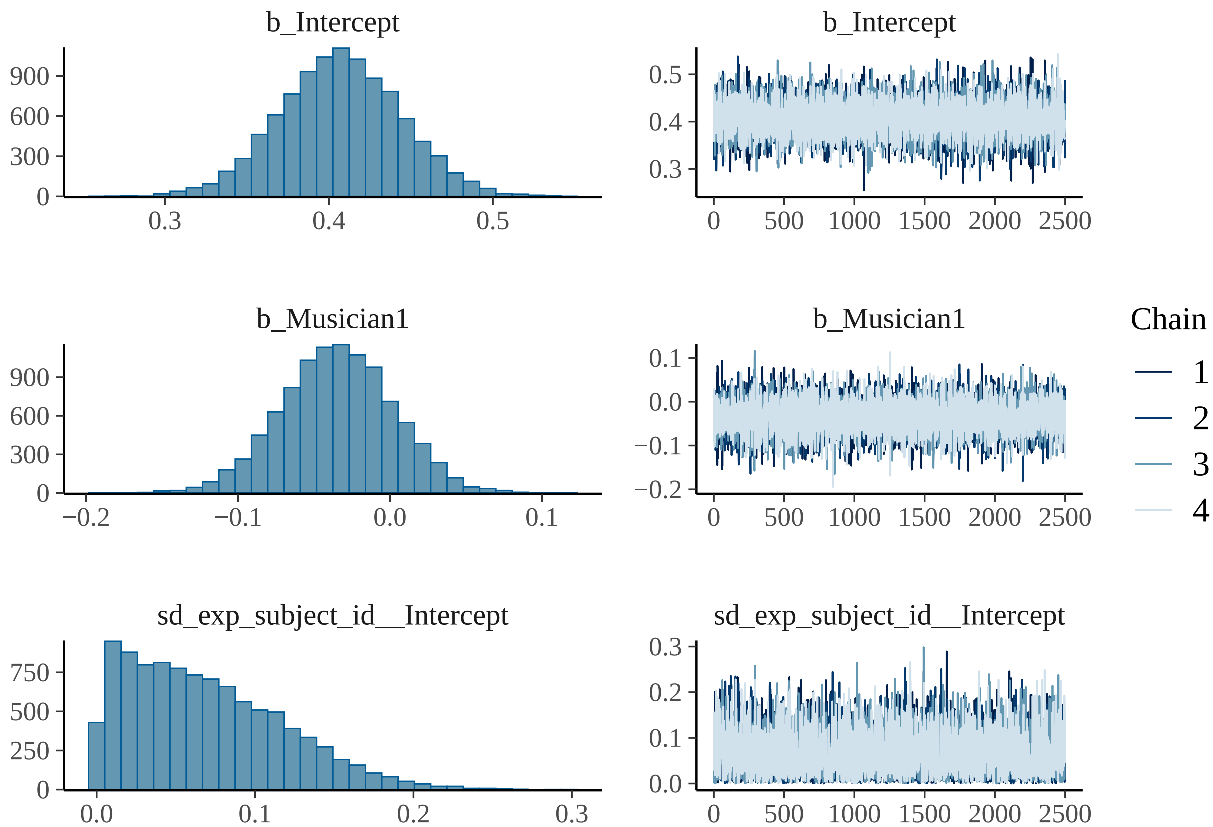
```
## Summary of Posterior Distribution
##
## Parameter   |   Median |     MAD |         95% CI |       BF |  Rhat |         ESS
## ---------------------------------------------------------------------------------
## (Intercept) |  0.78839 | 0.06576 | [ 0.66,  0.92] | 3.59e+14 | 1.000 |  9602.00000
## Musician1   | -0.03626 | 0.03757 | [-0.11,  0.04] |    0.058 | 1.000 | 12118.00000
## scramble2   | -0.42716 | 0.09121 | [-0.61, -0.26] |   973.08 | 1.000 | 10633.00000
## scramble3   | -0.69073 | 0.09091 | [-0.86, -0.51] | 1.29e+06 | 1.000 | 10298.00000
```

Strong evidence against a main effect of group.

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

```r
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/E2_mus_only')
```

```r
plot(mus_only)
```




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

```
##  Family: bernoulli 
##   Links: mu = logit 
## Formula: response ~ Musician + (1 | exp_subject_id) 
##    Data: data (Number of observations: 3158) 
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
## 
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 105) 
##               Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sd(Intercept)   0.0692    0.0488   0.0033   0.1787 1.0003     4349     5256
## 
## Regression Coefficients:
##           Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## Intercept   0.4070    0.0371   0.3344   0.4802 1.0003    17021     7080
## Musician1  -0.0346    0.0370  -0.1077   0.0366 1.0006    16707     6209
## 
```

```
## 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: 7
## Iteration: 1
## Iteration: 2
## Iteration: 3
## Iteration: 4
## Iteration: 5
## Iteration: 6
## Iteration: 7
## Iteration: 8
```

```r
print(BF_scramble)
```

```
## Estimated Bayes factor in favor of mus_scram over mus_only: 76447443676.54962
```

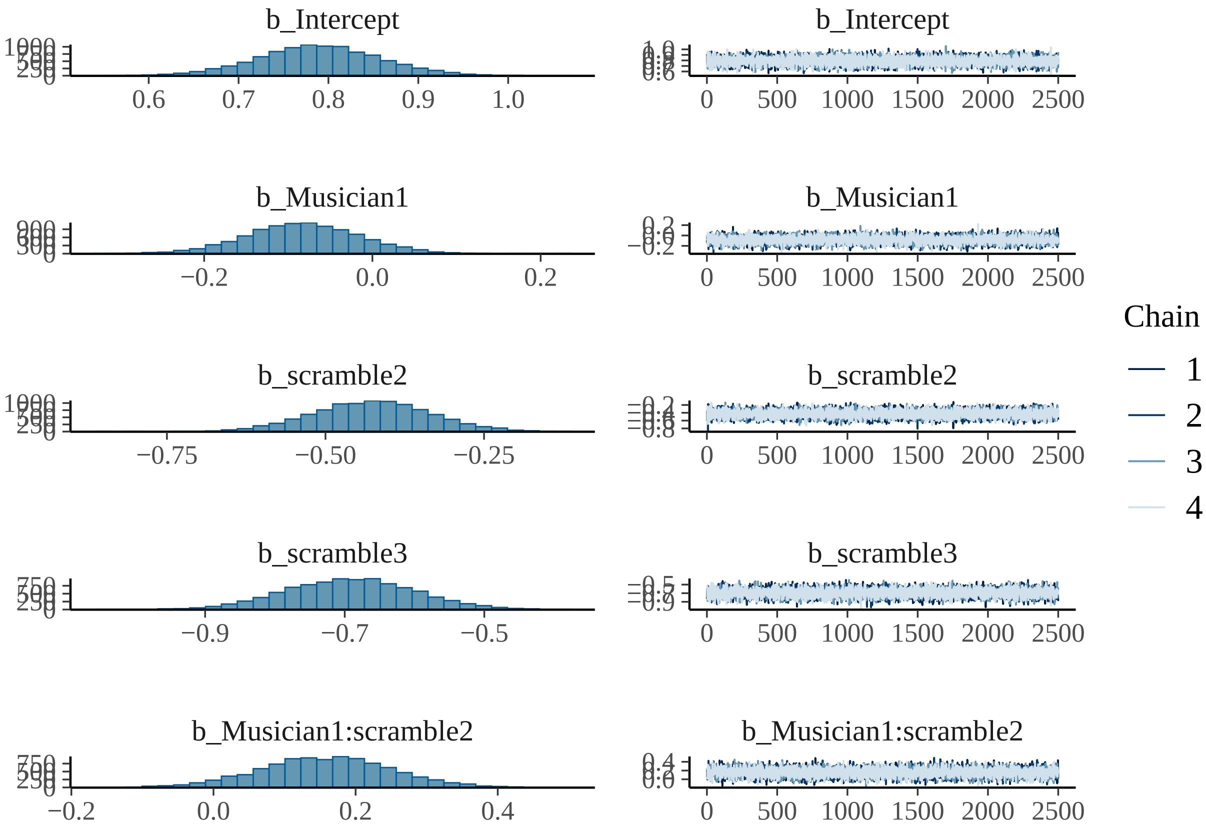
Very strong evidence for a main effect of scramble condition.

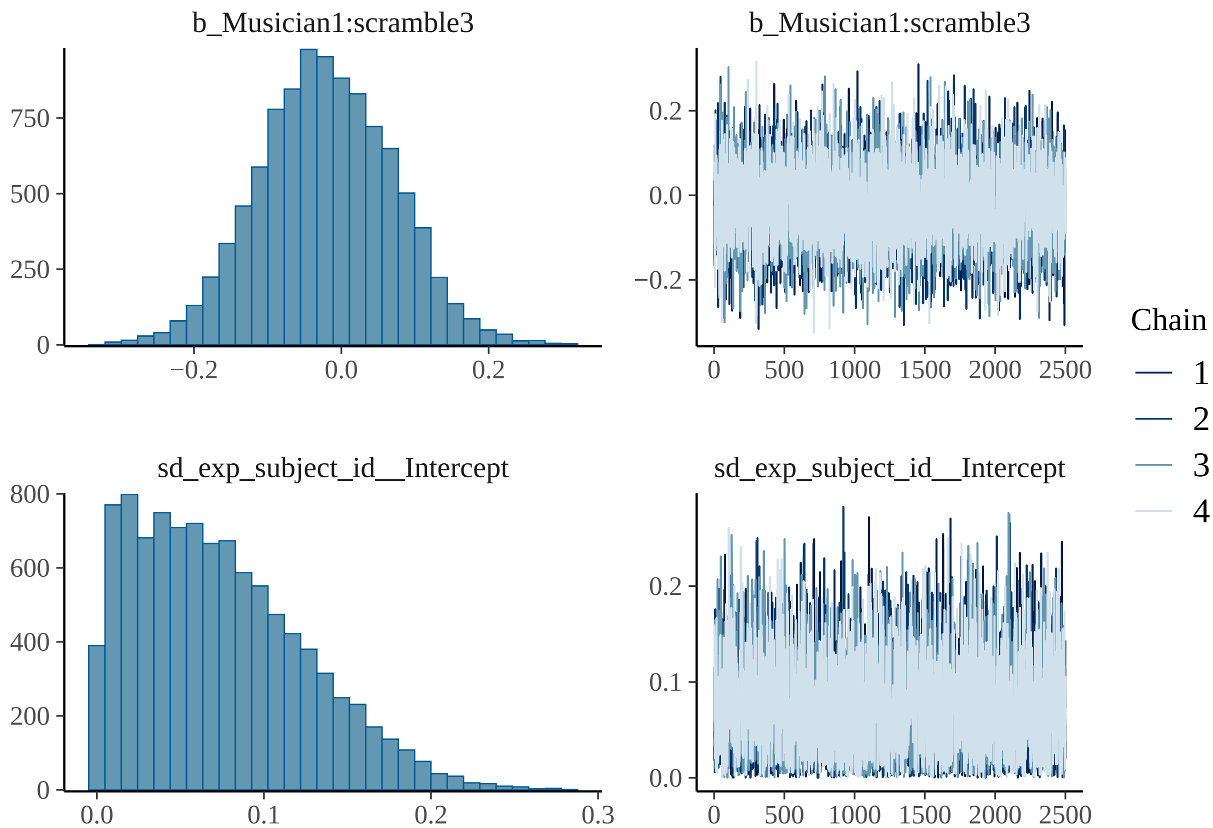
Interaction between group and condition?

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_scramble2B, prior_scramble1B,
                               prior_int2B, prior_int1B),
                     save_pars = save_pars(all = TRUE), iter = 5000,
                     file = 'models/E2_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: 3158)
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
##
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 105)
##               Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sd(Intercept)   0.0735    0.0508   0.0031   0.1871 1.0012     3226     3899
##
## Regression Coefficients:
##                     Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS
## Intercept             0.7898    0.0676   0.6572   0.9228 1.0003    10693
## Musician1            -0.0828    0.0669  -0.2154   0.0487 1.0013     6032
## scramble2            -0.4267    0.0921  -0.6069  -0.2457 1.0001    11551
## scramble3            -0.6922    0.0920  -0.8709  -0.5116 1.0000    11489
## Musician1:scramble2   0.1580    0.0919  -0.0231   0.3397 1.0015     7449
## Musician1:scramble3  -0.0202    0.0912  -0.1951   0.1569 1.0008     7739
##                     Tail_ESS
## Intercept               7100
## Musician1               6849
## scramble2               7427
## scramble3               7794
## Musician1:scramble2     7715
```

```
## Musician1:scramble3     7468
##
## 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: 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: 0.07156
```

Strong evidence against an interaction between group and condition.

Figure 2B

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

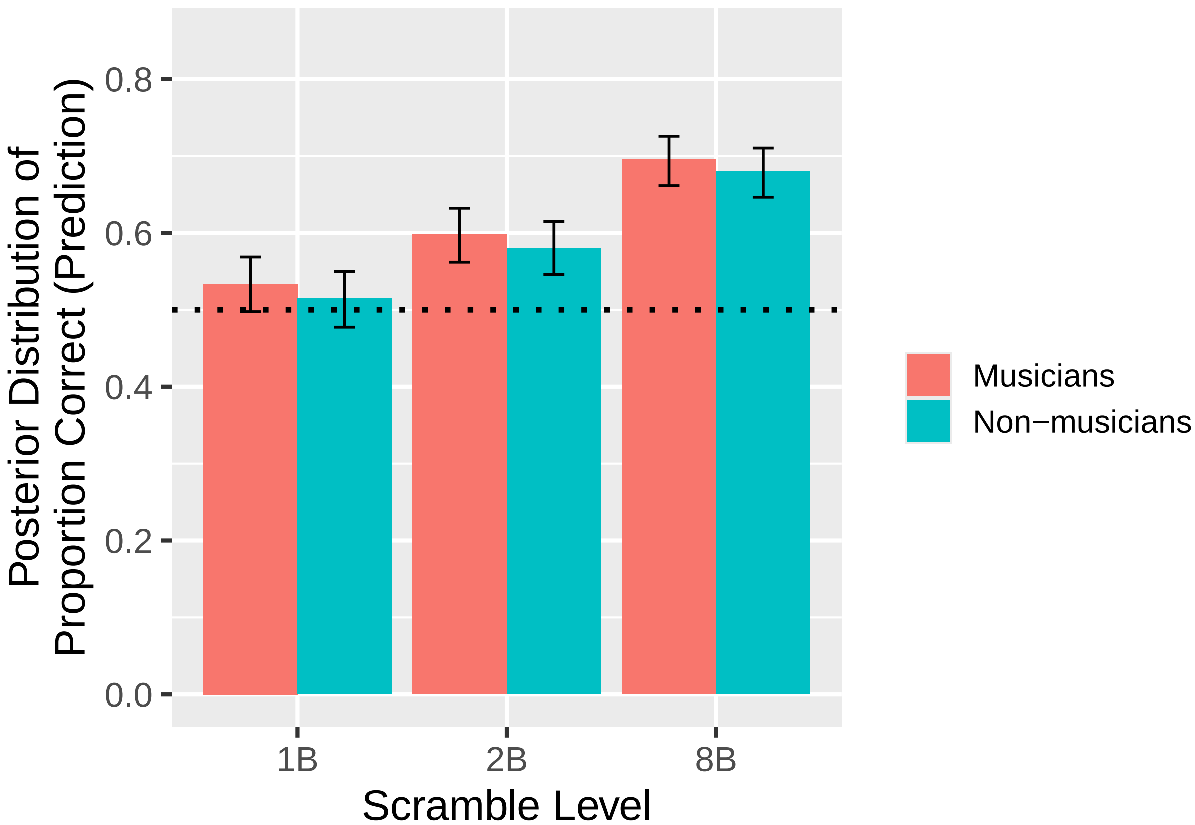
```
calculate_prob_from_logodds <- function(logodds) {
  return(exp(logodds) / (1 + exp(logodds)))
}
```

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 = 0.5, 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 (Prediction)') +
  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/Fig2B_prediction.png', width = 7, height = 5)
```

1B condition at chance?

There is technically no “right” answer, so performance in the 1B condition should be at chance.

```
data1B <- filter(data, scramble == '1B')
```

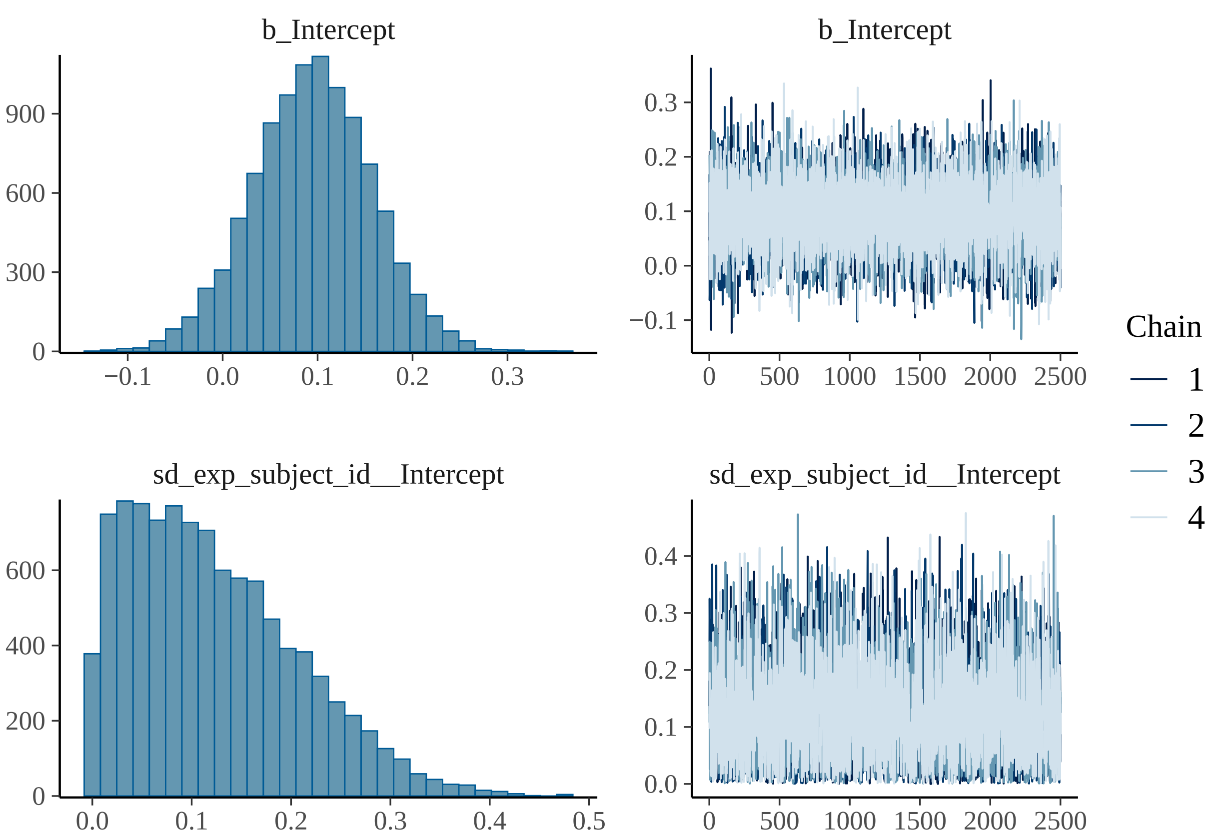
```
get_prior(response ~ 1 + (1 | exp_subject_id), data = data1B)
```

```
##                   prior     class      coef          group resp dpar nlpar lb ub
##  student_t(3, 0, 2.5) Intercept
##  student_t(3, 0, 2.5)        sd                                              0
##  student_t(3, 0, 2.5)        sd           exp_subject_id                     0
##  student_t(3, 0, 2.5)        sd Intercept exp_subject_id                     0
##  student_t(3, 0, 2.5)     sigma                                              0
##        source
##       default
##       default
##  (vectorized)
##  (vectorized)
##       default
```

(Leave the default prior for this intercept.)

```
only1B <- brm(response ~ 1 + (1 | exp_subject_id), data = data1B,
              family = bernoulli(),
              save_pars = save_pars(all = TRUE), iter = 5000,
              file = 'models/E2_only1B')
```

```
plot(only1B)
```



```r
print(summary(only1B), digits = 4)
```

```
## Warning: There were 1 divergent transitions after warmup. Increasing
## adapt_delta above 0.8 may help. See
## http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup

##  Family: bernoulli
##   Links: mu = logit
## Formula: response ~ 1 + (1 | exp_subject_id)
##    Data: data1B (Number of observations: 1054)
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
##
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 105)
##               Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sd(Intercept)   0.1220    0.0844   0.0053   0.3105 1.0011     3537     4513
##
## Regression Coefficients:
##           Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## Intercept   0.0948    0.0627  -0.0301   0.2176 1.0004    14871     6900
##
## 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).
```

Is intercept different from 0?

```r
bf_pointnull(only1B, null = 0)
```

```
## Sampling priors, please wait...

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

## Bayes Factor (Savage-Dickey density ratio)
##
## Parameter   |    BF
## -------------------
## (Intercept) | 0.074
##
## * Evidence Against The Null: 0
```

There is strong evidence that performance in the 1B condition is at chance.

What if we just look at 8B and 2B?

The main thing here is to see if the interaction we see between group and condition (that we see visually) shows up when we take out 1B.

```
data_no1B <- filter(data, scramble != '1B')
```

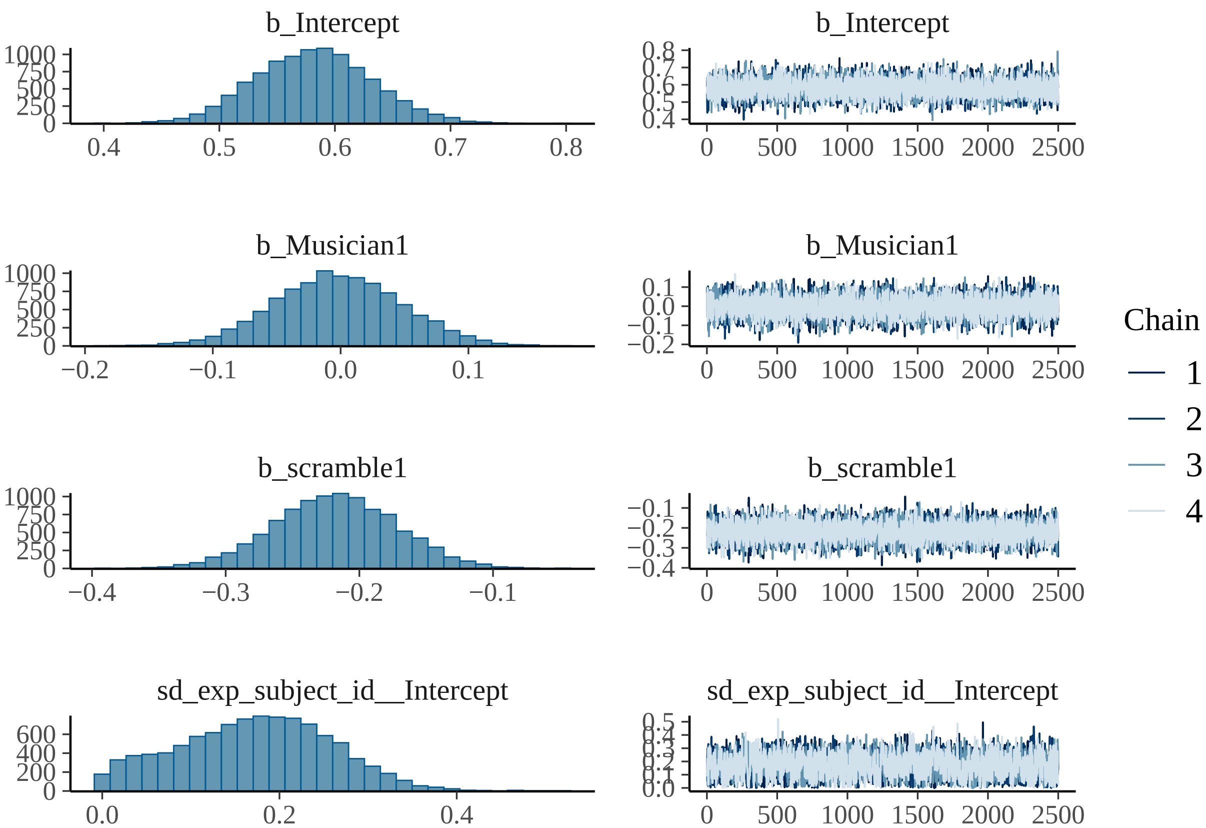
```
get_prior(response ~ Musician + scramble + (1 | exp_subject_id), data = data_no1B)
```

```
## Warning: contrasts dropped from factor scramble due to missing levels
```

```
##                 prior     class       coef          group resp dpar nlpar lb ub
##                (flat)         b
##                (flat)         b MusicianNo
##                (flat)         b scramble2B
##  student_t(3, 0, 2.5) Intercept
##  student_t(3, 0, 2.5)        sd                                           0
##  student_t(3, 0, 2.5)        sd            exp_subject_id                 0
##  student_t(3, 0, 2.5)        sd  Intercept exp_subject_id                 0
##  student_t(3, 0, 2.5)     sigma                                           0
##        source
##       default
##  (vectorized)
##  (vectorized)
##       default
##       default
##  (vectorized)
##  (vectorized)
##       default
```

```
no1B <- brm(response ~ Musician + scramble + (1 | exp_subject_id), data = data_no1B,
            family = bernoulli(),
            prior = c(
              prior_intercept, prior_mus, set_prior('normal(-0.1, 1)', coef = 'scramble1')
              ),
            save_pars = save_pars(all = TRUE), iter = 5000,
            file = 'models/E2_no1B')
```

```
plot(no1B)
```




```r
print(summary(no1B), digits = 4)
```

```
##  Family: bernoulli
##   Links: mu = logit
## Formula: response ~ Musician + scramble + (1 | exp_subject_id)
##    Data: data_no1B (Number of observations: 2104)
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
##
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 105)
##               Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sd(Intercept)   0.1717    0.0854   0.0127   0.3321 1.0010     2032     2408
##
## Regression Coefficients:
##           Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## Intercept   0.5818    0.0502   0.4864   0.6820 1.0003     9046     6511
## Musician1  -0.0017    0.0496  -0.0979   0.0957 1.0001     8824     6942
## scramble1  -0.2178    0.0457  -0.3088  -0.1284 1.0003    12179     7537
##
## 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
get_prior(response ~ Musician*scramble + (1 | exp_subject_id), data = data_no1B)
```

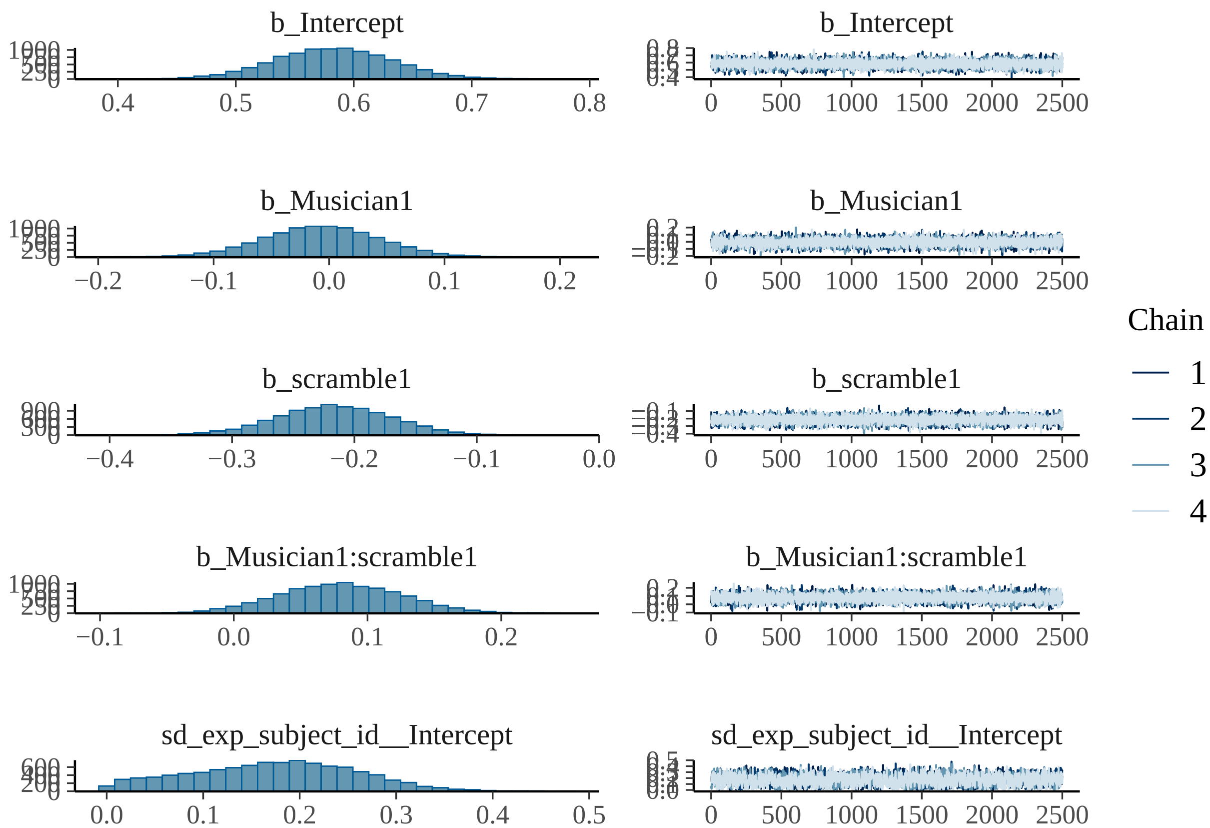
```
## Warning: contrasts dropped from factor scramble due to missing levels
```

```
##                 prior     class                    coef          group resp dpar
```

```
##                 (flat)         b
##                 (flat)         b            MusicianNo
##                 (flat)         b MusicianNo:scramble2B
##                 (flat)         b            scramble2B
##  student_t(3, 0, 2.5) Intercept
##  student_t(3, 0, 2.5)        sd
##  student_t(3, 0, 2.5)        sd                        exp_subject_id
##  student_t(3, 0, 2.5)        sd             Intercept exp_subject_id
##  student_t(3, 0, 2.5)     sigma
##  nlpar lb ub       source
##                   default
##              (vectorized)
##              (vectorized)
##              (vectorized)
##                   default
##         0         default
##         0    (vectorized)
##         0    (vectorized)
##         0         default
```

```
no1B_int <- brm(response ~ Musician*scramble + (1 | exp_subject_id), data = data_no1B,
                family = bernoulli(),
                prior = c(
                  prior_intercept, prior_mus,
                  set_prior('normal(-0.1, 1)', coef = 'scramble1'),
                  set_prior('normal(0, 1)', coef = 'Musician1:scramble1')
                  ),
                save_pars = save_pars(all = TRUE), iter = 5000,
                file = 'models/E2_no1B_int')
```

```
plot(no1B_int)
```




```
print(summary(no1B_int), digits = 4)
```

```
##  Family: bernoulli
##   Links: mu = logit
## Formula: response ~ Musician * scramble + (1 | exp_subject_id)
##    Data: data_no1B (Number of observations: 2104)
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
##
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 105)
##               Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sd(Intercept)   0.1720    0.0844   0.0150   0.3317 1.0016     2138     3201
##
## Regression Coefficients:
##                     Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS
## Intercept             0.5825    0.0497   0.4861   0.6799 1.0002     9966
## Musician1            -0.0068    0.0503  -0.1069   0.0901 1.0005    10016
## scramble1            -0.2164    0.0466  -0.3085  -0.1254 1.0002    12902
## Musician1:scramble1   0.0798    0.0460  -0.0093   0.1693 1.0000    13173
##                     Tail_ESS
## Intercept               7076
## Musician1               7388
## scramble1               7357
## Musician1:scramble1     6636
##
## 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_no1B_int <- bayes_factor(no1B_int, no1B)
```

```
## Iteration: 1
## Iteration: 2
## Iteration: 3
## Iteration: 4
## Iteration: 5
## Iteration: 6
## Iteration: 1
## Iteration: 2
## Iteration: 3
## Iteration: 4
## Iteration: 5
## Iteration: 6
## Iteration: 7
```

```r
print(BF_no1B_int)
```

```
## Estimated Bayes factor in favor of no1B_int over no1B: 0.20473
```

Still moderate evidence against an interaction between group and condition.

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

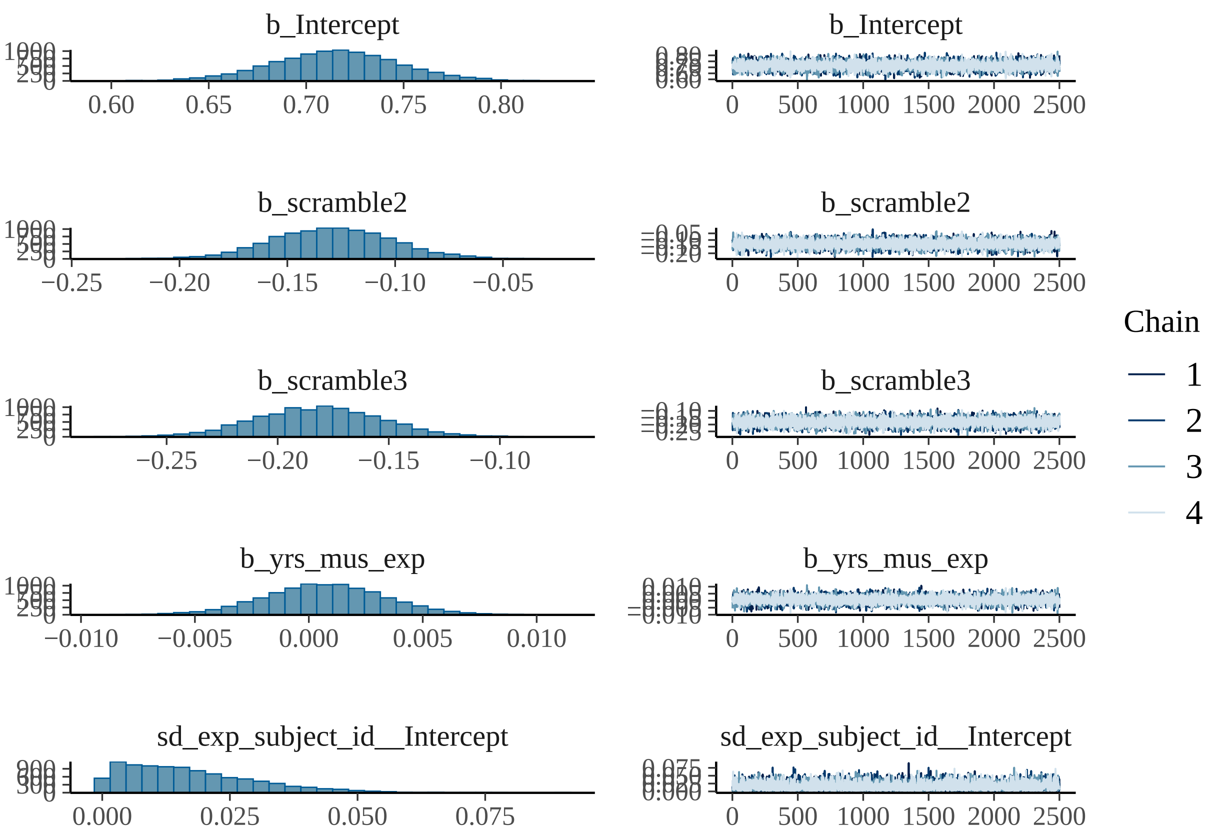
For this analysis, we're operating on the scale of accuracy. Because we don't see ceiling effects (i.e. participants aren't getting too close to perfect accuracy), a linear model is appropriate enough.

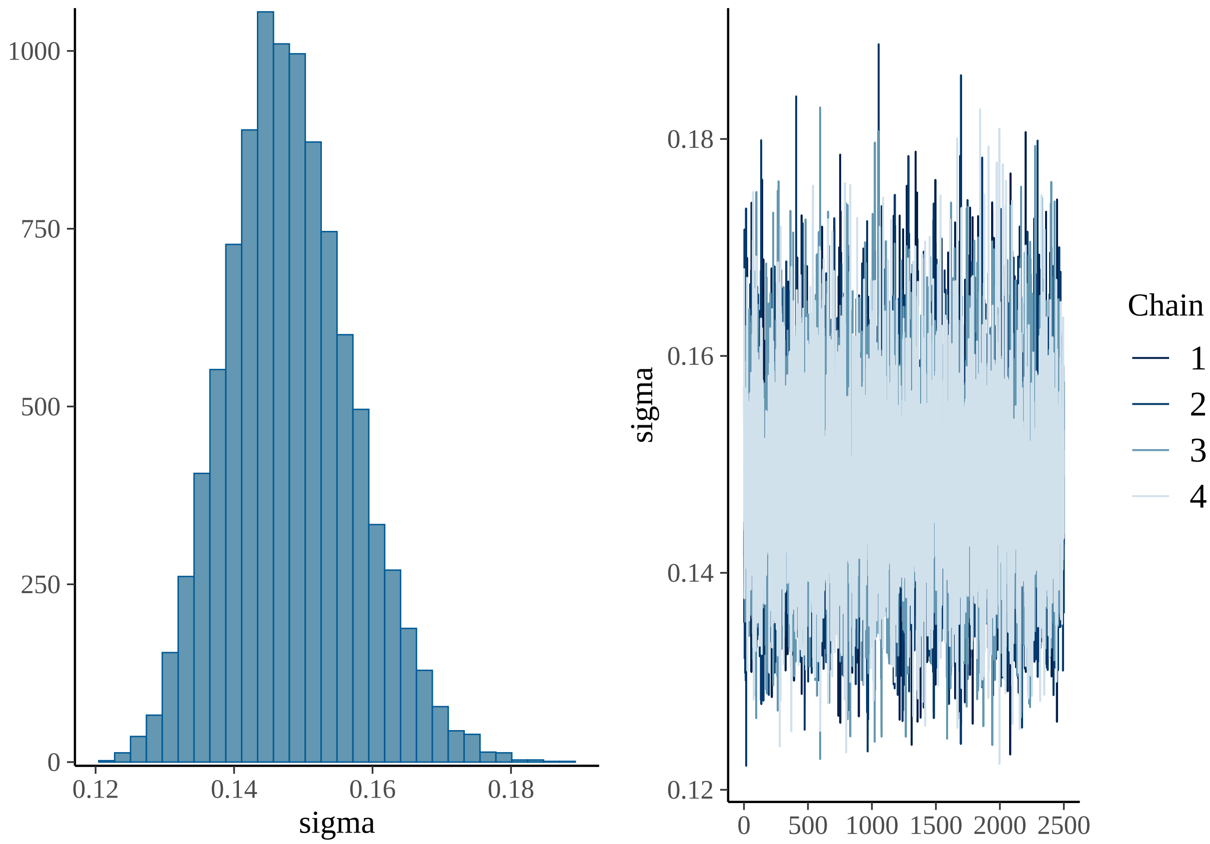
```
these_priors <- c(
  set_prior('normal(0.75, 0.1)', class = 'Intercept'),
  set_prior('normal(-0.1, 0.1)', coef = 'scramble2'),
  set_prior('normal(-0.2, 0.1)', coef = 'scramble3'),
  set_prior('normal(0, 0.1)', coef = 'yrs_mus_exp')
)
```

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/E2_years')
```

```
plot(years_mus_scram)
```






```r
print(summary(years_mus_scram), digits = 5)
```

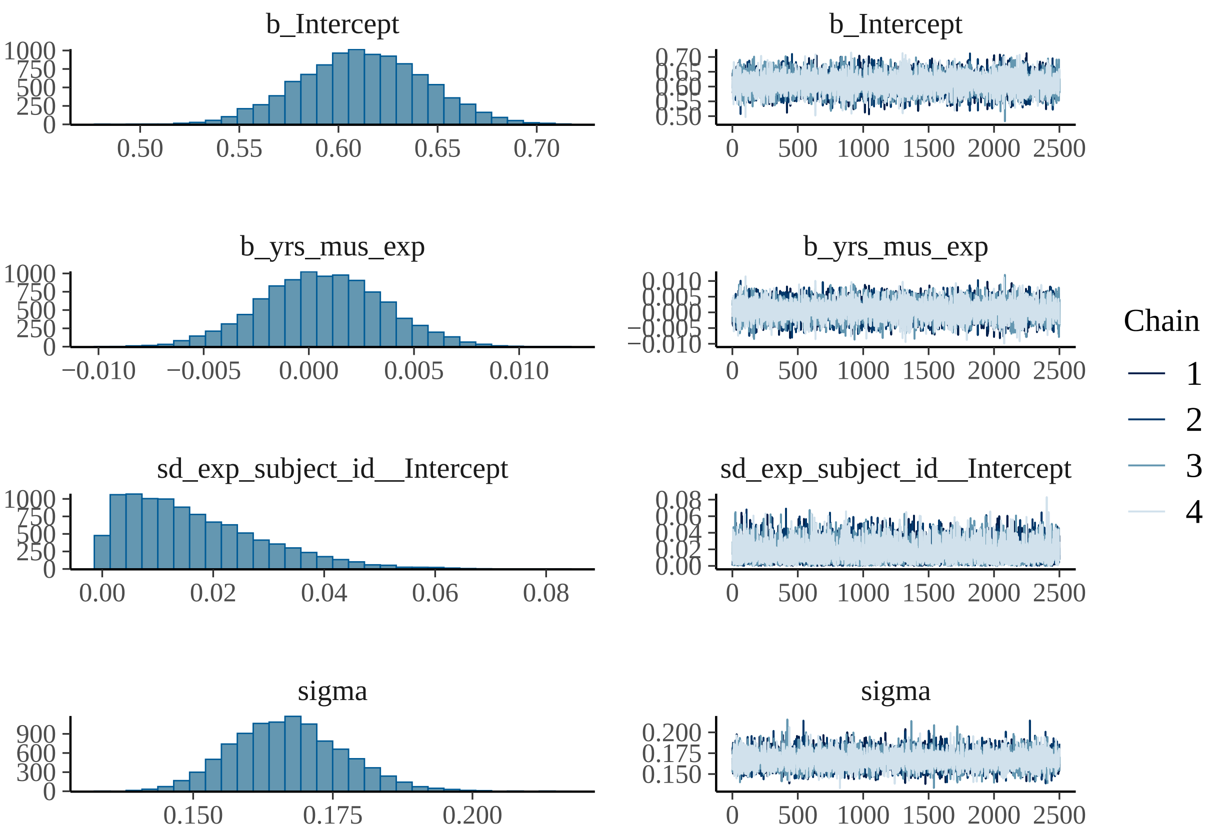
```
## Warning: There were 1 divergent transitions after warmup. Increasing
## adapt_delta above 0.8 may help. See
## http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup

##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: accuracy ~ scramble + yrs_mus_exp + (1 | exp_subject_id)
##    Data: yrs_exp (Number of observations: 147)
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
##
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 49)
##               Estimate Est.Error l-95% CI u-95% CI    Rhat Bulk_ESS Tail_ESS
## sd(Intercept)  0.01719   0.01267  0.00077  0.04706 1.00055     6212     5659
##
## Regression Coefficients:
##             Estimate Est.Error l-95% CI u-95% CI    Rhat Bulk_ESS Tail_ESS
## Intercept    0.71512   0.03258  0.64939  0.77971 1.00083    15991     7104
## scramble2   -0.12905   0.02794 -0.18375 -0.07313 1.00017    15253     8207
## scramble3   -0.18167   0.02816 -0.23750 -0.12666 0.99982    14505     7673
## yrs_mus_exp  0.00071   0.00265 -0.00453  0.00592 1.00042    15685     6425
##
## Further Distributional Parameters:
##       Estimate Est.Error l-95% CI u-95% CI    Rhat Bulk_ESS Tail_ESS
## sigma  0.14815   0.00912  0.13174  0.16754 1.00029    16196     7120
```

```
##
## 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)

```r
years_mus <- brm(accuracy ~ yrs_mus_exp + (1|exp_subject_id), data = yrs_exp,
                 prior = c(
                   set_prior('normal(0.75, 0.1)', class = 'Intercept'),
                   set_prior('normal(0, 0.1)', coef = 'yrs_mus_exp')),
                 save_pars = save_pars(all = TRUE), iter = 5000,
                 file = 'models/E2_years_null')
```

```r
plot(years_mus)
```




```r
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: 147)
##   Draws: 4 chains, each with iter = 5000; warmup = 2500; thin = 1;
##          total post-warmup draws = 10000
##
## Multilevel Hyperparameters:
## ~exp_subject_id (Number of levels: 49)
##                Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
```

```
## sd(Intercept)   0.0167    0.0124   0.0007   0.0458 1.0010     6435     5210
##
## Regression Coefficients:
##             Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## Intercept     0.6123    0.0316   0.5509   0.6735 1.0004    17550     7165
## yrs_mus_exp   0.0007    0.0029  -0.0051   0.0064 1.0005    17923     6999
##
## Further Distributional Parameters:
##       Estimate Est.Error l-95% CI u-95% CI   Rhat Bulk_ESS Tail_ESS
## sigma   0.1671    0.0100   0.1489   0.1874 1.0012    17877     7495
##
## 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) |  0.7154 | 0.0323 | [ 0.65,  0.78] | 2.60e+22 | 1.000 | 15954.0000
## scramble2   | -0.1290 | 0.0280 | [-0.18, -0.07] |   757.55 | 1.000 | 15174.0000
## scramble3   | -0.1814 | 0.0284 | [-0.24, -0.13] | 2.60e+04 | 1.000 | 14437.0000
## yrs_mus_exp |  0.0007 | 0.0026 | [ 0.00,  0.01] |    0.026 | 1.000 | 15626.0000
```

```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)
```

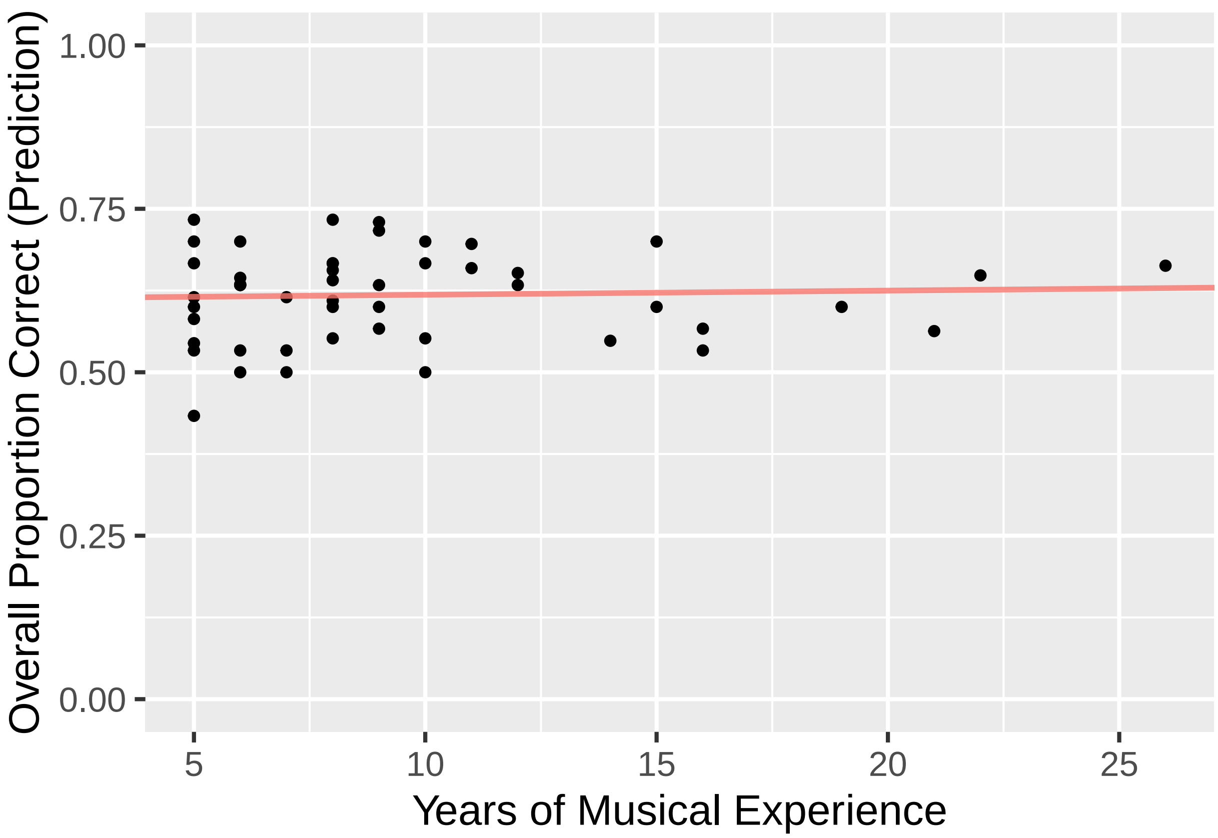
```
## Summary of Posterior Distribution
##
## Parameter   | Median |    MAD |        95% CI |       BF |  Rhat |        ESS
## ----------------------------------------------------------------------------
## (Intercept) | 0.6122 | 0.0321 | [ 0.55, 0.67] | 4.75e+20 | 1.000 | 17648.0000
## yrs_mus_exp | 0.0006 | 0.0029 | [ 0.00, 0.01] |    0.030 | 1.000 | 17847.0000
```

Strong evidence against an effect of years of musical experience.

Figure S1B

```
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 (Prediction)') +
  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/FigS1B_prediction.png', width = 5, height = 5)
```