Glide affiliation - Supplementary materials

6.1 Bayesian Data Analysis

The present work uses Bayesian Data Analysis (BDA) for statistical inferences. This implies that we do not focus on a single point estimate for a given parameter β, but rather we use Bayes Theorem to derive a posterior distribution of plausible estimates of β. Importantly, we do not use p-values or any other decision rules for determining the importance of an effect. BDA allows us to quantify our uncertainty in a more straightforward way with regard to our statistical models and focus on estimation.

6.2 Syllable division task

The first model analyzed the syllabification task data using multinomial logistic regression. The participants responses (triphthong, hiatus, simplification) were modeled in a simple, intecept-only model, and as a function of the post-consonantal glide ([j], [w]). Table 6.1 below provides the complete output summary of the model.

Table 6.1: Model summary for the syllabification task. The table reports posterior medians, 95% credible intervals, and probability of direction to assess estimates, along with Rhat and Effective sample size to assess model fit.

Model	Parameter	Estimate	P(direction)	Rhat	ESS	Prior
Main	μ Simplification: Intercept	−0.30 [−0.96, 0.29]	0.84	1.00	1724.03	Normal(0, 20)
Main	μ Triphthong: Intercept	0.12 [−0.45, 0.66]	0.66	1.00	1974.05	Normal(0, 20)
[j]	μ Simplification: Intercept	−0.29 [−1.00, 0.47]	0.78	1.00	1576.48	Normal(0, 20)
[j]	μ Triphthong: Intercept	−0.14 [−0.89, 0.52]	0.65	1.00	1604.93	Normal(0, 20)
[w]	μ Simplification: Intercept	−0.37 [−1.61, 0.76]	0.73	1.00	1480.26	Normal(0, 20)
[w]	μ Triphthong: Intercept	0.54 [−0.42, 1.55]	0.88	1.00	1238.82	Normal(0, 20)

6.3 Phrase reading task

6.3.1 GAMMs

GAMMs represent an extension to the linear model framework that allow non-linear functions called factor smooths to be applied to predictors. In this sense, the predictors can be classified into two types: parametric terms (equivalent to fixed effects in hierarchical model terminology) and smooth terms. Random smooths are conceptually similar to random slopes and intercepts in the mixed-effects regression framework (Winter & Wieling, 2016). Thus, they allow the by-subject trajectory shapes to vary as a function of a parametric effect and are essential in avoiding anti-conservative models.

6.3.2 F1

The model summary output of the duration model is available in Table 6.2 here:

Table 6.2: Model summary for the duration analysis. The table reports posterior medians, 95% credible intervals, and probability of direction to assess estimates, along with Rhat and Effective sample size to assess model fit.

Parameter	Estimate	P(direction)	Rhat	ESS	Prior
Intercept	−0.07 [−0.41, 0.27]	0.65	1.00	2540.31	Normal(0, 0.2)
Palatal	0.22 [−0.20, 0.62]	0.86	1.00	2091.63	Normal(0, 0.5)

The full model specification used to fit the F1 GAMM is provided below, followed by the full output of the model summary in Table 6.3.

```
# Set priors
priors <- c(
  prior(normal(0, 0.5), class = Intercept),
  prior(normal(0, 0.5), class = b),
  prior(
    student_t(3, 0, 1),
    class = sds,
    coef = s(time_course_segment, bs = "cr", k = 3)),
  prior(
    student_t(3, 0, 2.5),
    class = sds,
    coef = s(time_course_segment, by = is_palatal_ord, bs = "cr", k = 4)),
  prior(
    student_t(3, 0, 2.5),
    class = sds,
    coef = s(time_course_segment, participant, bs = "fs", m = 1, k = 3)),
  prior(cauchy(0, 2), class = sigma)
  )

# Model formula
mode_formula <- bf(
 f1norm ~ is_palatal_ord +
  s(time_course_segment, bs = "cr", k = 3) + # ref smooth
  s(time_course_segment, by = is_palatal_ord, bs = "cr", k = 4) + # diff
  s(time_course_segment, participant, bs = "fs", m = 1, k = 3), # random
)

# F1 GAM
b_gam_f1 <- brm(
  formula = model_formula
  family = gaussian(),
  prior = priors,
  backend = "cmdstanr", iter = 2000, warmup = 1000, cores = 4,
  control = list(adapt_delta = 0.999999, max_treedepth = 20),
  data = carrier_tc_final_gamm,
  )
```

Table 6.3: Model summary for the F1 GAMM. The table reports posterior medians, 95% credible intervals, and probability of direction to assess estimates, along with Rhat and Effective sample size to assess model fit.

Parameter	Function	Estimate	P(direction)	Rhat	ESS	Prior
Intercept		0.04 [−0.30, 0.37]	0.62	1.00	1241.48	Normal(0, 0.5)
Not palatal		−0.15 [−0.31, 0.00]	0.98	1.00	5632.28	Normal(0, 0.5)
Time course	Smooth	0.40 [−0.15, 0.86]	0.93	1.00	1617.80	student_t(3, 0, 1)
Time course: Not palatal	Smooth	0.05 [−0.17, 0.24]	0.67	1.00	5176.51	student_t(3, 0, 1)

An exploratory model not reported on the time course of the intensity measurements is provided below in Table 6.4.

Table 6.4: Model summary for the F1 GAMM. The table reports posterior medians, 95% credible intervals, and probability of direction to assess estimates, along with Rhat and Effective sample size to assess model fit.

Parameter	Function	Estimate	P(direction)	Rhat	ESS	Prior
Intercept		−0.10 [−0.48, 0.29]	0.72	1.00	1178.24	Normal(0, 0.5)
Not palatal		0.23 [0.10, 0.36]	1.00	1.00	5471.15	Normal(0, 0.5)
Time course	Smooth	0.69 [0.32, 1.02]	1.00	1.00	1761.32	student_t(3, 0, 1)
Time course: Not palatal	Smooth	0.37 [0.20, 0.56]	1.00	1.00	4063.34	student_t(3, 0, 1)

6.4 Reproducibility information

About this document

This document was written in RMarkdown using `papaja` (Aust & Barth, 2020).

Session info

```
 setting  value
 version  R version 4.1.0 (2021-05-18)
 os       macOS Big Sur 10.16
 system   x86_64, darwin17.0
 ui       X11
 language (EN)
 collate  en_US.UTF-8
 ctype    en_US.UTF-8
 tz       America/New_York
 date     2021-11-02

               loadedversion       date
assertthat             0.2.1 2019-03-21
bayesplot              1.8.1 2021-06-14
bookdown                0.24 2021-09-02
brms                  2.16.1 2021-08-23
broom.mixed            0.2.7 2021-07-07
```

```
cmdstanr                 0.4.0 2021-07-22
coda                    0.19-4 2020-09-30
devtools                 2.4.2 2021-06-07
dplyr                    1.0.7 2021-06-18
emmeans                  1.7.0 2021-09-29
forcats                  0.5.1 2021-01-27
fs                       1.5.0 2020-07-31
gamm4                    0.2-6 2020-04-03
ggdist                   3.0.0 2021-07-19
ggplot2                  3.3.5 2021-06-25
ggridges                 0.5.3 2021-01-08
glue                     1.4.2 2020-08-27
haven                    2.4.3 2021-08-04
here                     1.0.1 2020-12-13
kableExtra               1.3.4 2021-02-20
knitr                     1.36 2021-09-29
lme4                  1.1-27.1 2021-06-22
loo                      2.4.1 2020-12-09
lubridate                1.8.0 2021-10-07
magrittr                 2.0.1 2020-11-17
markdown                   1.1 2019-08-07
mgcv                    1.8-38 2021-10-06
modelr                   0.1.8 2020-05-19
mvtnorm                  1.1-3 2021-10-08
patchwork                1.1.1 2020-12-17
posterior                1.1.0 2021-09-09
purrr                    0.3.4 2020-04-17
Rcpp                     1.0.7 2021-07-07
RcppParallel             5.1.4 2021-05-04
readr                    2.0.2 2021-09-27
readxl                   1.3.1 2019-03-13
remotes                  2.4.1 2021-09-29
reprex                   2.0.1 2021-08-05
rlang                   0.4.11 2021-04-30
rmarkdown                 2.11 2021-09-14
rprojroot                2.0.2 2020-11-15
rstan                   2.21.2 2020-07-27
rstantools               2.1.1 2020-07-06
rvest                    1.0.1 2021-07-26
scales                   1.1.1 2020-05-11
sessioninfo              1.1.1 2018-11-05
stringr                  1.4.0 2019-02-10
tibble                   3.1.5 2021-09-30
tidybayes                3.0.1 2021-08-22
tidyr                    1.1.4 2021-09-27
tidyselect               1.1.1 2021-04-30
viridisLite              0.4.0 2021-04-13
```

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