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

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### 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**

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 ui X11   
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 tz America/New\_York   
 date 2021-11-02

loadedversion date  
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bookdown 0.24 2021-09-02  
brms 2.16.1 2021-08-23  
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lubridate 1.8.0 2021-10-07  
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posterior 1.1.0 2021-09-09  
purrr 0.3.4 2020-04-17  
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RcppParallel 5.1.4 2021-05-04  
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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  
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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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