Alveolar Fricative Voicing in Appalachia: Preliminary Investigation

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STAT 695

April 18, 2015

Contents

Background

The goal of this study is to identify which sociolinguistic variables are most associated with how speakers of the Appalachian Dialect voice alveolar fricatives. Fricatives are consonants that are produced by forcing air between two articulators, in this case the tongue and alveolar ridge (which is the ridge in your mouth between your upper teeth and the hard palate at the top of your mouth). A sibilant is a consonant where the tongue is curled so that the air also flows under the edge of the teeth; alveolar fricatives are a subset of this class. Like most consonant classes, alveolar fricatives can be voiced or voiceless. Voiced alveolar fricatives are [z] sounds, and voiceless alveolar fricatives are [s] sounds.

The simplest explanation of voicing is whether or not the vocal chords vibrate (referred to as glottal pulsing) as a sound is produced. However, recent studies in psycholinguistics have revealed that the perception of voicing is actually a very complicated phenomenon, and whether a listener perceives a sound as voiced or voiceless depends on several variables. A change in any one of these variables can change this perception. Because of this, studying voicing cannot simply be done by categorizing a sound a "voiced" or "voiceless," as convenient as that might be. In this study, the four main variables that are being considered as indicative of voicing are the Duration of the Sibilant, Center of Gravity, Percent Voicelessness of the sibilant, and the Duration of the Preceding Segment[1,2]

Simply put, this study is concerned with whether speakers pronounce the "s" in a word like "brothers" with an [s] sound like in "bus" (voiceless), or a [z] sound as in "buzz" (voiced), and, perhaps more importantly, it is about how we quantify that difference.

Data Collection

Sixty-seven interviews were conducted with life-long residents of the Appalachian Region of the United States, including West Virginia, Southwestern Pennsylvania, and Southeastern Ohio. Demographic information was recorded for each speaker. Tokens, which are the unique speech acts that make up the observations in the data, containing alveolar fricatives were identified in audio recordings of the interviews and analyzed using Praat[3]. There are an average of forty-six tokens per speaker, with as few as twenty-seven and as many as fifty-six (Figure 1).

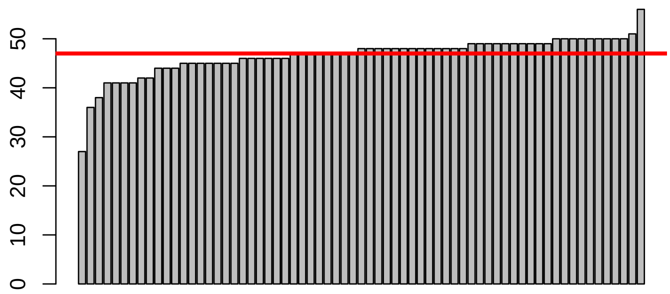


Figure 1: Token Count by Speaker

Independent Variables

Social Variables

For each interviewee (speaker), researchers recorded their ethnicity, education level, region, age, sex, social class, and rurality. Most of these variables are factors with two or three levels, but age is recorded both as a numeric age in years and as a factor with four levels based on age group. While effort was made to find at least one token for every combination of factor levels, there is substantial unbalance both the number of tokens for each factor (Figure 2) and number of speakers for each factor (Figure 3), especially for `ethnicity`, `college`, `rurality`, and `class`.

[1] For a full listing of variables and their definitions, see Appendix A.1
[2] I'll try to get references for these studies from Dr. Hazen at some point.
[3] Praat is a software suite purpose built for analyzing phonetic data.
`http://www.fon.hum.uva.nl/praat/`

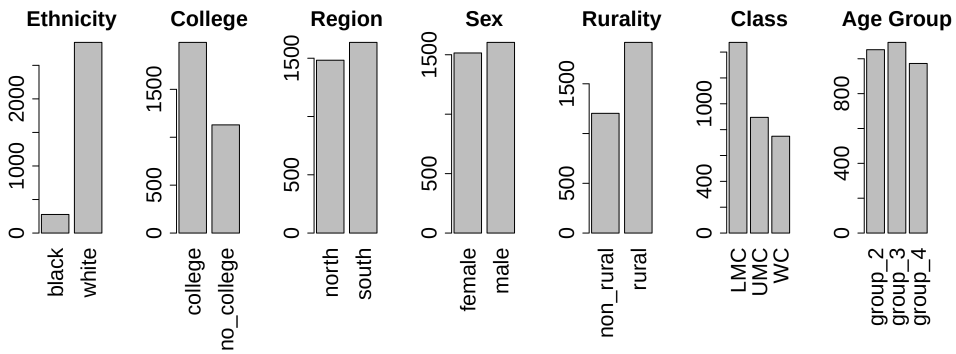


Figure 2: Token Counts by Social Variable

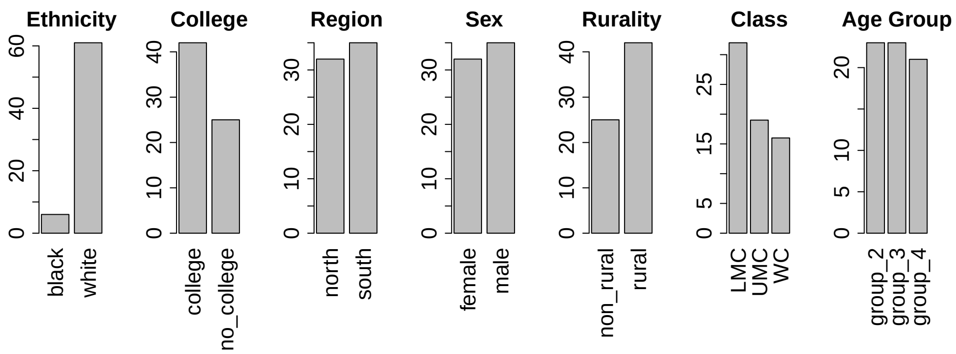


Figure 3: Speaker Counts by Social Variable

While the age groups are fairly evenly represented, this is because the age groups are not defined with even age ranges (see Appendex A.1). When numeric ages are considered, it is obvious that people between the ages of twenty and twenty-five far outnumber any other similarly sized age range in the data (Figure 4). Because of this, and the fact that both age variables are collected at the speaker level and not at the token level, it will probably be better to use `age_group` as a factor than `age` as a numeric predictor.

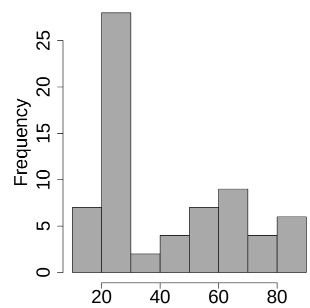


Figure 4: Histogram of Speaker Ages

Linguistic Variables

The linguistic variables were collected at the word or token level, and describe the sibilant of interest and its linguistic environment.

Morphological Variables

The morphological variables are both categorical variables. Morphological Standing specifies how the word containing the sibilant is stressed, and Sibilant Location describes where in that word the sibilant occurs. Almost all of the sibilants are part of words that with primary or secondary stress in the sentence, and there are many more word-final sibilants than internal sibilants.

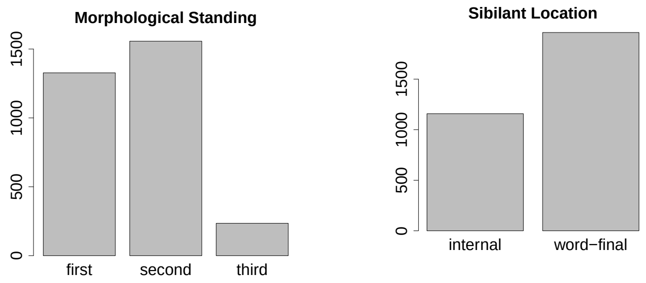


Figure 5: Token Count by Morphological Variable

Phonological Variables

The phonological variables describe the types of sounds that precede and follow the sibilant, as well as its standard pronunciation. These variables are more closely associated with the word than the token, but in the case where a pause follows a word-final sibilant this line is blurred.

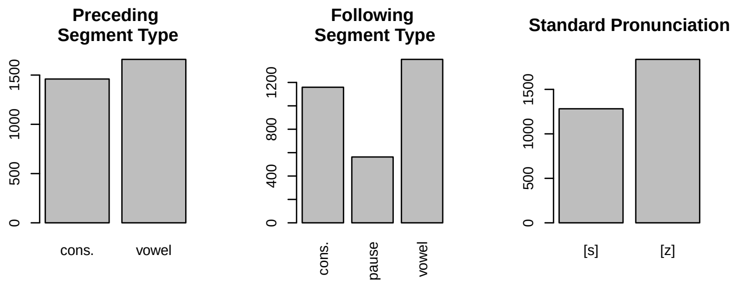


Figure 6: Token Count by Phonological Variable

Phonetic Variables

The phonetic variables are physical characteristics of the sibilant and the preceding segment, and they are collected at the token level. Pitch and intensity were measured at three points in both the preceding segment and sibilant: at 5%, 25%, and 50% through the duration of the sounds.

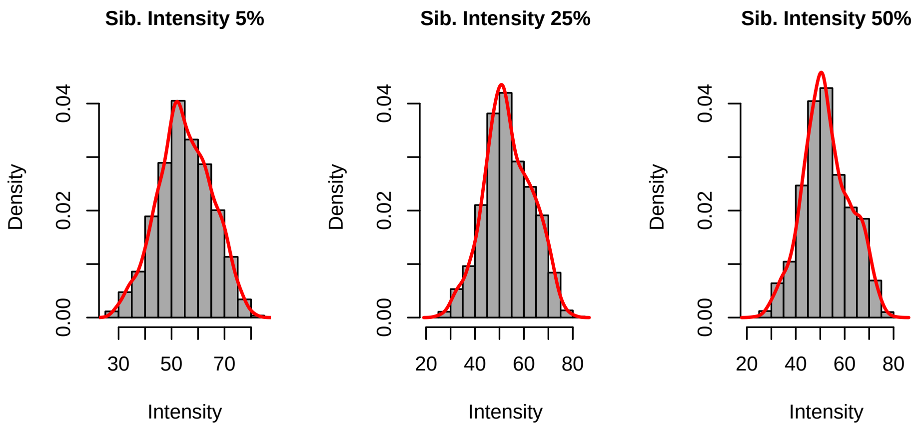


Figure 7: Density Histograms of Sibilant Intensities

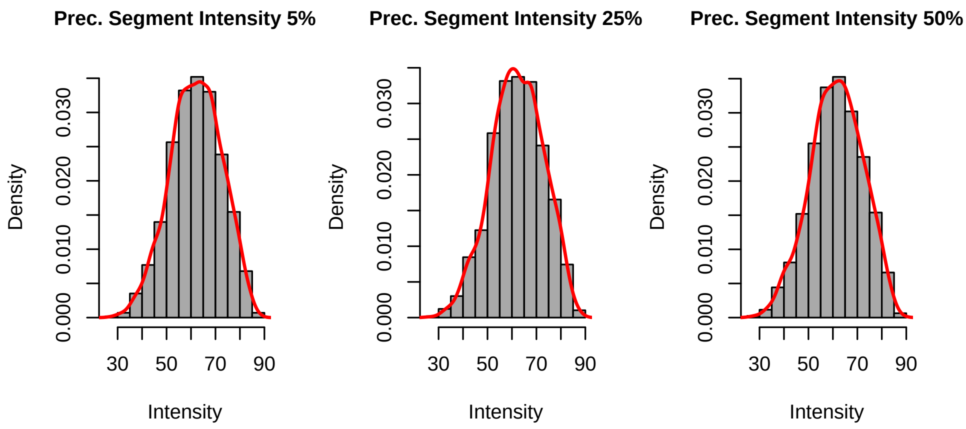


Figure 8: Density Histograms of Preceding Segment Intensities

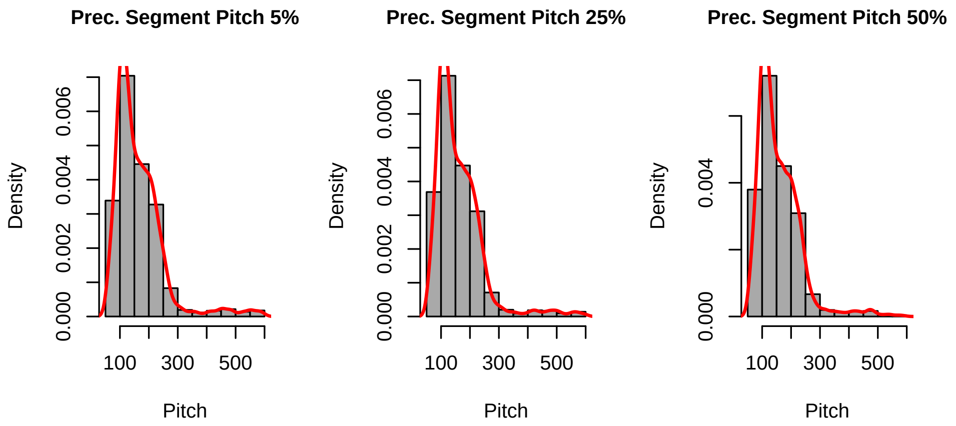


Figure 9: Density Histograms of Preceding Segment Pitches

Random Effects

There are two random effects in this data: speaker and word. How the relationship between speaker, word, and token is defined could potentially make a huge impact on the results and warrants careful consideration. Out of 3,119 tokens, there are 1,295 unique words among the sixty-seven speakers; 790 of those occur in just one token[4]. Speakers used as few as twenty-one and as many as forty-nine unique words, with a median count of forty (see Appendix A.2.e).

The simpler model is to consider word and speaker as separate (crossed) effects. Word-to-word variability and speaker-to-speaker variablity are considered separately, and like words are grouped together regardless of the speaker. If the speaker has no bearing on the word this model will fit well.

The other approach would be to nest words inside of speaker. Here, words are only grouped together if they are spoken by the same individual. This model would consider the variability among the 2,617 unique word:speaker combinations instead of the 1,295 unique words. This model is the best choice if certain speakers prefer certain words (or types of words).

Conceptually, either structure makes sense, and, given the large number of unique words relative to both the number of speakers and the number of tokens, there is not a clearly defined better choice. To determine the nature of the relationship, it will come down to modeling the responses both ways and comparing the results. If one method consistently outperforms the other, that will point to the true

[4] This makes sense. According to Zipf's Law, the frequencies of words in any given corpus are inversely proportional to their rank. Even though this data is a sample of specific types of words from within a corpus, it should still follow a power law distribution (at least approximately).
`http://en.wikipedia.org/wiki/Zipf%27s_law`

underlying structure of the data.

Dependent Variables

The responses are all phonetic variables and, taken as a whole, paint the picture of the sounds that were recorded in the token, particularly the sibilant and its preceding segment. The model used for each response is determined by its distributionality. Responses that follow Normal Distributions (or can be easily transformed to) can be modeled with Linear Mixed Models (LMMs), while responses that follow other well-defined distributions (such as Binomial or Gamma Distributions) can be modeled using Generalized Linear Mixed Models (GLMMs). If any response does not follow a well-behaved distribution an appropriate non-parametric model can be used.

Sibilant Duration

Sibilant Duration is the time, in seconds, it took the speaker to create that particular sibilant sound.

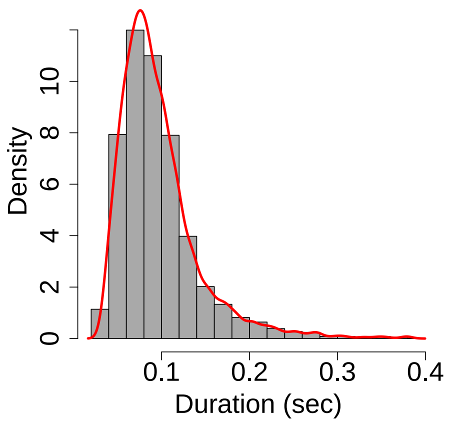


Figure 10: Density Histogram of Sibilant Duration

The distribution is strictly positive and has significant right-skew, which is not unexpected. Time measurements, by nature, have a lower bound of zero, and, given the relatively short amount of time it takes to produce a consonant sound, it is not surprising that the density is highest closer to zero and tapers off as duration increases.

This shape resembles either a Lognormal Distribution (i.e., the logarithm of the variable has a Normal Distribution) or a Gamma Distribution. How closely it follows these distributions can be evaluated using Quantile–Quantile Plots (Figure 11). In these plots, the points following an approximately straight line indicate that the distribution of the variable closely follows the named distribution.

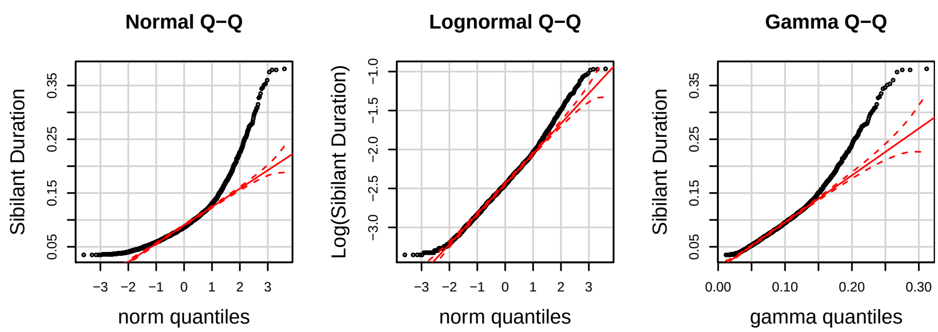


Figure 11: Sibilant Duration Quantile–Quantile Plots

Since Sibilant Duration most closely follows a Lognormal Distribution, an LMM will be fit using the logarithm of Sibilant Duration as the response.

Preceding Segment Duration

Similar to Sibilant Duration, Preceding Segment Duration is a measurement of the time it took to produce the sound preceding the sibilant.

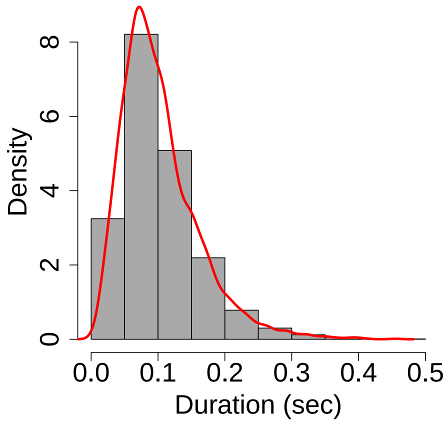


Figure 12: Density Histogram of Preceding Segment Duration

Again, the distribution is strictly positive and right-skewed. The increased variability in Preceding Segment Duration compared to Sibilant Duration likely comes from the fact that the preceding segments can be a variety of consonants and vowels, whereas the sibilant is restricted to only alveolar fricatives. The same process of examining Quantile–Quantile Plots is used to select an appropriate model for Preceding Segment Duration.

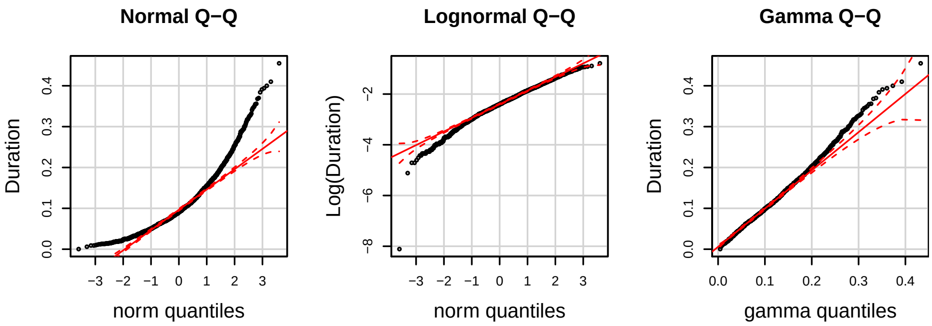


Figure 13: Preceding Segment Duration Quantile–Quantile Plots

For Preceding Segment Duration, a Gamma GLMM is the best fit.

Center of Gravity

The Center of Gravity (CoG) is the average frequency over the sibilant's sound spectrum. Since the tokens were recorded in interviews, two methods were used to "clean up the signal" and filter out any interference that may distort the Center of Gravity. One method is to only consider the middle sixty percent of the signal, which makes sure only the sibilant itself is being considered and no noise from the preceding or following segments is bleeding over into the sibilant spectrum. In addition to this, the token spectrums were filtered using the Hann Function, which is a bell-shaped window function, to help eliminate extraneous noise.

Center of Gravity, then, exists in four different versions: the Full (raw) CoG, the Middle 60% CoG, the Filtered CoG, and the Filtered Middle 60% CoG. Obviously, these four variables will be highly collinear. To avoid any of the issues that arise from multicollinearity, it makes the most sense to only select the version with the smoothest curve, which is the Filtered Middle 60% CoG (Figure 14).

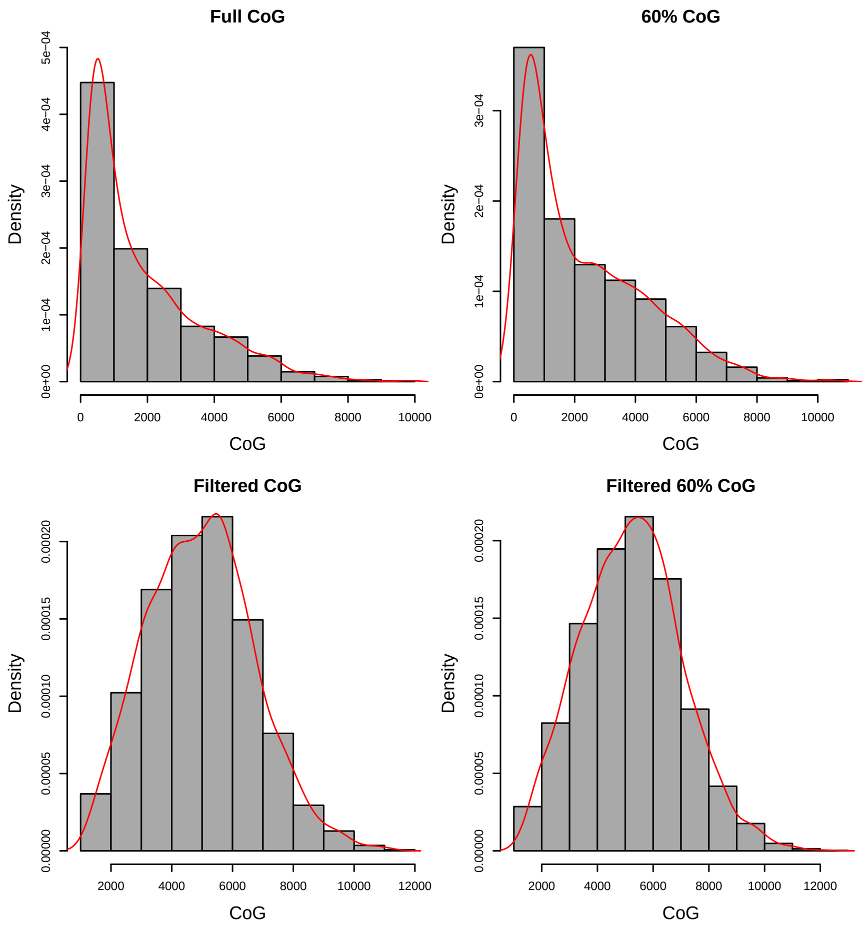


Figure 14: Density Histograms of Centers of Gravity

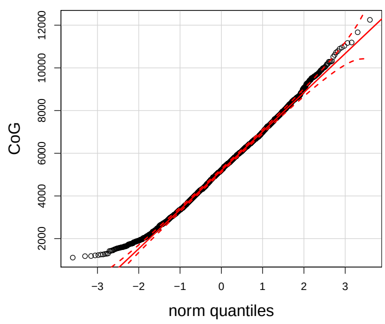


Figure 15: Normal Quantile–Quantile Plot for Filtered 60% CoG

While the distribution isn't perfectly Normal (Figure 15), a straightforward LMM should be sufficient for modeling the Center of Gravity.

Percent Voicelessness

Percent Voicelessness as a variable name is slightly misleading. This variable is a measure of the percent of the sibilant's duration that lacks glottal pulsing, and, as discussed previously, this is only one part of what determines whether a sound is voiced or voiceless. As Figure 16 shows, Percent Voicelessness is continuous, bimodal, and bounded by zero and one. As such, it most likely follows a Beta Distribution with shape parameters less than one.

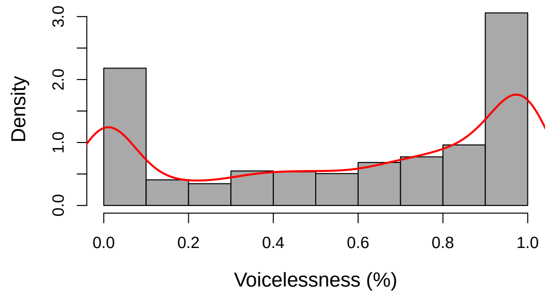


Figure 16: Density Histogram of Percent Voicelessness

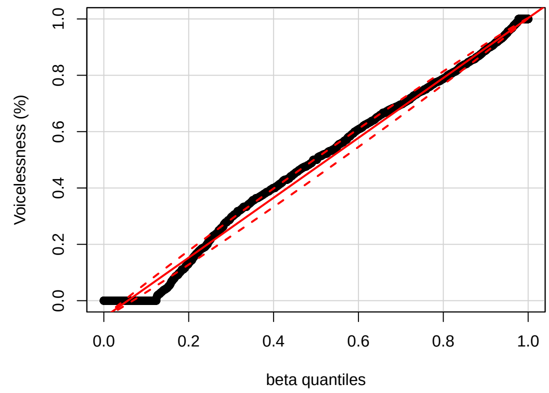


Figure 17: Beta Quantile–Quantile Plot of Percent Voicelessness
($\alpha = 0.5, \beta = 0.35$)

Beta Distributions, by their restricted nature, present unique challenges for modeling. This could possibily be modeled as a GLMM with a logit link function, but it may be best to use Beta Regression[5] or some kind of non-parametric regression. This will be explored later.

[5] `http://cran.r-project.org/web/packages/betareg/vignettes/betareg-ext.pdf`

Analysis

For each response there are seven social variables, fourteen linguistic variables, and three covariates, for a total of twenty-four predictors that need to be evaluated. Even if models are restricted to only those with two-factor interactions, that adds another 276 potential terms. Given this complex nature, backward variable selection techniques will be avoided in favor of forward selection. As this analysis is continued, the approach to variable selection will be refined.

Unfortunately, the functionality is not yet included in any R package to automatically apply forward selection techniques to mixed effects models. Rense Nieuwenhuis, a sociologist from Swedish Institute for Social Research (SOFI) of Stockholm University, publicly released his code for a function that implements a basic stepwise function for forward selection with mixed effects models. It works by iteratively fitting models with added terms and comparing them using a (ML) likelihood ratio test[6].

Hox outlines a step-up procedure for variable selection in mixed effects models which will be (mostly) followed here[7].

1. Fit a model with only the random intercepts. Instead of an intercept only model, selection will start with the other responses as covariates.
2. Determine significant fixed effects at the observation level (low level effects).
3. Determine significant fixed effects at the group level. In this study, these are the social variables (which describe the speaker) and the morphological/phonological variables (which describe the word).
4. Explore the random effects structure.

In addition to using a log transformation for Sibilant Duration, several variables should be scaled. Center of Gravity ranges from 1,112–12,250 Hz, durations range from 0.035–0.445 sec., the intensities range from 23.11–89.47 dB, and Percent Voicelessness is in the unit interval (0–1). Scaling CoG, the pitches, and the intensities will lead to coefficients that are easier to compare (with the added benefit of reducing collinearity).

For the time being interactions will only be considered between variables of the same type (e.g., interactions among social variables and among morphological variables, but not between them) and a few other interactions of interest (such as sibilant location and standard pronunciation). Also worth noting is that model comparisons are only meaningful if the models are based on the same data. Because of this, any row that contains a missing value will have to be omitted.

Sibilant Duration

Base Model

```
Linear mixed model fit by REML
Formula:
lme4::lmer(formula = log(sib_dur)   prec_segment_dur + sib.cog + vls_percent + (1 | word)
+ (1 | speaker), data = dat2)

REML at convergence:  1717.105
```

Random Effects:

Groups	Name	Variance	St.Dev.
word	(Intercept)	0.01	0.11
speaker	(Intercept)	0.02	0.15
Residual		0.10	0.32

```
Number of obs:  2437, groups:  word, 1074; speaker, 67
```

Fixed Effects:

[6] As this is an unpublished package that has never been formally peer-reviewed, its methodology and results need to be verified before we run with them.
http://www.rensenieuwenhuis.nl/r-sessions-32/

[7] Hox, J. J. (2002). Multilevel analysis techniques and applications. Mahwah, N.J.: Lawrence Erlbaum Associates. (45-50).

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-2.812	0.026	197.529	-107.354	0.000
prec_segment_dur	1.836	0.129	1915.706	14.180	0.000
sib.cog	0.096	0.010	1386.651	9.432	0.000
vls_percent	0.318	0.021	2398.252	14.965	0.000

Selecting Low Level Fixed Effects

Now the low level effects (those collected at the token level) can be added to the model using forward selection.

```
   Linear mixed model fit by REML
Formula:
lme4::lmer(formula = log(sib_dur)   prec_segment_dur + sib.cog + vls_percent + (1 | word)
+ (1 | speaker) + prec.int25 + prec.pitch50 + prec.pitch05:prec.pitch50, data = dat2)

REML at convergence:  1722.39

Random Effects:
```

Groups	Name	Variance	St.Dev.
word	(Intercept)	0.01	0.11
speaker	(Intercept)	0.02	0.15
Residual		0.10	0.32

```
Number of obs:  2437, groups:  word, 1074; speaker, 67

Fixed Effects:
```

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-2.819	0.026	194.067	-106.875	0.000
prec_segment_dur	1.927	0.131	1974.257	14.681	0.000
sib.cog	0.097	0.010	1540.440	9.477	0.000
vls_percent	0.304	0.021	2385.997	14.185	0.000
prec.int25	-0.033	0.013	625.374	-2.641	0.008
prec.pitch50	-0.025	0.012	1741.743	-2.192	0.029
prec.pitch50:prec.pitch05	0.013	0.004	2209.404	2.952	0.003

```
Selection completed in 6.8 minutes.
```

This model has an interaction that includes `prec.pitch05`, which was not left in the model on its own.

```
> sib.dur.1.1 <- update(sib.dur.1, . ~ . + prec.pitch05)
```

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
sib.dur.1	10	1696.94	1754.92	-838.47	1676.94			
sib.dur.1.1	11	1698.83	1762.61	-838.41	1676.83	0.11	1	0.7442

While there is no real difference in the fit of the models, first-order terms always need to be included if their interactions are.

```
   Linear mixed model fit by REML
Formula:
lme4::lmer(formula = log(sib_dur)   prec_segment_dur + sib.cog + vls_percent + (1 | word)
+ (1 | speaker) + prec.int25 + prec.pitch50 + prec.pitch05 + prec.pitch50:prec.pitch05,
data = dat2)

REML at convergence:  1729.261

Random Effects:
```

Groups	Name	Variance	St.Dev.
word	(Intercept)	0.01	0.11
speaker	(Intercept)	0.02	0.14
Residual		0.10	0.32

Number of obs: 2437, groups: word, 1074; speaker, 67

Fixed Effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-2.819	0.026	195.420	-106.757	0.000
prec_segment_dur	1.928	0.131	1971.419	14.681	0.000
sib.cog	0.097	0.010	1538.381	9.474	0.000
vls_percent	0.305	0.021	2384.629	14.187	0.000
prec.int25	-0.033	0.013	618.644	-2.615	0.009
prec.pitch50	-0.023	0.014	2267.101	-1.617	0.106
prec.pitch05	-0.004	0.012	2356.820	-0.323	0.747
prec.pitch50:prec.pitch05	0.013	0.004	2194.657	2.969	0.003

Selecting High Level Fixed Effects

Fixed effects collected at the group level can now be considered.

```
   Linear mixed model fit by REML
Formula:
lme4::lmer(formula = log(sib_dur)   prec_segment_dur + sib.cog + vls_percent + (1 | word)
+ (1 | speaker) + prec.int25 + prec.pitch50 + prec.pitch05 + age_group + prec.pitch50:prec.pitch05
+ sib.combined:following.type, data = dat2)

REML at convergence:  1303.739
```

Random Effects:

Groups	Name	Variance	St.Dev.
word	(Intercept)	0.00	0.06
speaker	(Intercept)	0.01	0.12
Residual		0.09	0.30

Number of obs: 2437, groups: word, 1074; speaker, 67

Fixed Effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-2.758	0.033	135.396	-82.922	0.000
prec_segment_dur	1.436	0.120	1370.917	11.938	0.000
sib.cog	0.085	0.009	1393.879	9.122	0.000
vls_percent	0.191	0.021	2345.222	9.078	0.000
prec.int25	-0.017	0.011	499.649	-1.476	0.141
prec.pitch50	-0.015	0.013	2261.748	-1.192	0.233
prec.pitch05	-0.000	0.011	2392.557	-0.045	0.964
age_groupgroup_3	-0.126	0.038	60.488	-3.303	0.002
age_groupgroup_4	-0.144	0.039	59.642	-3.695	0.000
prec.pitch50:prec.pitch05	0.007	0.004	2191.216	1.791	0.073
sib.combined[s]:following.typecons.	0.190	0.024	807.619	7.876	0.000
sib.combined[z]:following.typecons.	0.014	0.018	1485.596	0.741	0.459
sib.combined[s]:following.typepause	0.510	0.035	1553.364	14.595	0.000
sib.combined[z]:following.typepause	0.418	0.025	2067.947	17.007	0.000
sib.combined[s]:following.typevowel	0.213	0.021	878.092	10.320	0.000

```
Selection completed in 7.47 minutes.
```

By adding in the high level effects, the word-to-word variability has been reduced substantially, and the speaker-to-speaker and token-to-token variability marginally. At the same time, `prec.int25` is no longer significant, and its removal can be evaluated. Like with the low level variable selection, there are interactions included in this model that are missing first-order terms (`following.type` and `sib.combined`), and this needs to be corrected first.

```
> sib.dur.2.0 <- update(sib.dur.2, .~. + following.type + sib.combined)
```

```
Linear mixed model fit by REML
Formula:
lme4::lmer(formula = log(sib_dur)   prec_segment_dur + sib.cog + vls_percent + (1 | word)
+ (1 | speaker) + prec.int25 + prec.pitch50 + prec.pitch05 + age_group + following.type
+ sib.combined + prec.pitch50:prec.pitch05 + sib.combined:following.type, data = dat2)

REML at convergence:  1303.739
```

Random Effects:

Groups	Name	Variance	St.Dev.
word	(Intercept)	0.00	0.06
speaker	(Intercept)	0.01	0.12
Residual		0.09	0.30

Number of obs: 2437, groups: word, 1074; speaker, 67

Fixed Effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-2.568	0.037	197.418	-69.655	0.000
prec_segment_dur	1.436	0.120	1370.918	11.938	0.000
sib.cog	0.085	0.009	1393.879	9.122	0.000
vls_percent	0.191	0.021	2345.222	9.078	0.000
prec.int25	-0.017	0.011	499.649	-1.476	0.141
prec.pitch50	-0.015	0.013	2261.748	-1.192	0.233
prec.pitch05	-0.000	0.011	2392.557	-0.045	0.964
age_groupgroup_3	-0.126	0.038	60.488	-3.303	0.002
age_groupgroup_4	-0.144	0.039	59.642	-3.695	0.000
following.typepause	0.320	0.035	2359.026	9.023	0.000
following.typevowel	0.023	0.023	1631.346	1.034	0.301
sib.combined[z]	-0.176	0.023	882.451	-7.569	0.000
prec.pitch50:prec.pitch05	0.007	0.004	2191.216	1.791	0.073
following.typepause:sib.combined[z]	0.084	0.042	2381.074	1.992	0.046
following.typevowel:sib.combined[z]	-0.037	0.029	1629.832	-1.272	0.203

Interestingly, despite these terms not being selected by the step function, they are highly significant.

```
> sib.dur.2.1 <- update(sib.dur.2.0, . ~ . - prec.int25)
```

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
sib.dur.2.1	17	1246.64	1345.22	-606.32	1212.64			
sib.dur.2.0	18	1246.43	1350.81	-605.22	1210.43	2.21	1	0.1372

Having `prec.int25` is no better than not having it in the model, so it is safe to drop the term.

```
Linear mixed model fit by REML
Formula:
lme4::lmer(formula = log(sib_dur)   prec_segment_dur + sib.cog + vls_percent + (1 | word)
+ (1 | speaker) + prec.pitch50 + prec.pitch05 + age_group + following.type + sib.combined
+ prec.pitch50:prec.pitch05 + following.type:sib.combined, data = dat2)

REML at convergence:  1298.8
```

Random Effects:

Groups	Name	Variance	St.Dev.
word	(Intercept)	0.00	0.06
speaker	(Intercept)	0.01	0.12
Residual		0.09	0.30

```
Number of obs:  2437, groups:  word, 1074; speaker, 67
```

Fixed Effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-2.573	0.037	199.384	-70.042	0.000
prec_segment_dur	1.400	0.118	1285.856	11.881	0.000
sib.cog	0.086	0.009	1311.384	9.307	0.000
vls_percent	0.196	0.021	2364.551	9.422	0.000
prec.pitch50	-0.017	0.013	2346.514	-1.345	0.179
prec.pitch05	-0.001	0.011	2390.419	-0.122	0.903
age_groupgroup_3	-0.126	0.038	61.411	-3.306	0.002
age_groupgroup_4	-0.140	0.039	60.411	-3.613	0.001
following.typepause	0.325	0.035	2354.153	9.183	0.000
following.typevowel	0.023	0.023	1622.177	1.028	0.304
sib.combined[z]	-0.173	0.023	850.412	-7.473	0.000
prec.pitch50:prec.pitch05	0.008	0.004	2310.532	1.991	0.047
following.typepause:sib.combined[z]	0.083	0.042	2383.381	1.961	0.050
following.typevowel:sib.combined[z]	-0.037	0.029	1621.454	-1.265	0.206

Comparing Grouping Structures

Now that the fixed effects that most contribute to the optimal model have been identified, the best random effects structure can be explored. Up to now, the usual interpretation of word crossed with speaker has been used. If, for example, there are speakers who tend to use more [s]'s than [z]'s, a nested structure where unique word:speaker combinations are considered instead of unique words may be better.

```
   Linear mixed model fit by REML
Formula:
lme4::lmer(formula = log(sib_dur)   prec_segment_dur + sib.cog + vls_percent + prec.pitch50
+ prec.pitch05 + age_group + following.type + sib.combined + (1 | speaker/word) +
prec.pitch50:prec.pitch05 + following.type:sib.combined, data = dat2)

REML at convergence:  1291.545
```

Random Effects:

Groups	Name	Variance	St.Dev.
word:speaker	(Intercept)	0.02	0.13
speaker	(Intercept)	0.01	0.12
Residual		0.08	0.28

```
Number of obs:  2437, groups:  word, 2108; speaker, 67
```

Fixed Effects:

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-2.572	0.037	187.767	-70.191	0.000
prec_segment_dur	1.352	0.116	2306.424	11.676	0.000
sib.cog	0.089	0.009	1360.144	9.593	0.000
vls_percent	0.197	0.021	2371.304	9.495	0.000
prec.pitch50	-0.016	0.013	2350.853	-1.252	0.211
prec.pitch05	-0.002	0.011	2390.327	-0.216	0.829
age_groupgroup_3	-0.126	0.039	61.662	-3.271	0.002
age_groupgroup_4	-0.141	0.039	60.710	-3.588	0.001
following.typepause	0.328	0.035	2301.399	9.329	0.000
following.typevowel	0.023	0.022	2376.263	1.045	0.296
sib.combined[z]	-0.174	0.022	2352.309	-7.779	0.000
prec.pitch50:prec.pitch05	0.007	0.004	2335.284	1.883	0.060
following.typepause:sib.combined[z]	0.081	0.042	2356.043	1.936	0.053
following.typevowel:sib.combined[z]	-0.036	0.029	2373.186	-1.249	0.212

The significance of the coefficients did not change very much, but the nested model has more word-to-word variability and less residual token-to-token variability when compared to the crossed model.

	Df	AIC	BIC	logLik	deviance	Chisq	Chi Df	Pr(>Chisq)
Crossed	17	1246.64	1345.22	-606.32	1212.64			
Nested	17	1239.18	1337.76	-602.59	1205.18	7.46	0	0.0000

The fit of the model with the nested structure is significantly better than the fit of the model with the crossed structure.

Model Diagnostics

To verify that this model is appropriate, we need to check that the residuals are independent of each other and Normally distributed with a mean of zero (residuals being the difference between the predicted response and the actual response for every token).

The assumption of Normality can be verified with a Quantile–Quantile Plot and independence and mean by plotting the residuals against their index (Figure 18). The residuals should form a straight line in the Normal Q–Q Plot, and they should be randomly scattered about zero (on the y-axis) in the Residual by Index Plot.

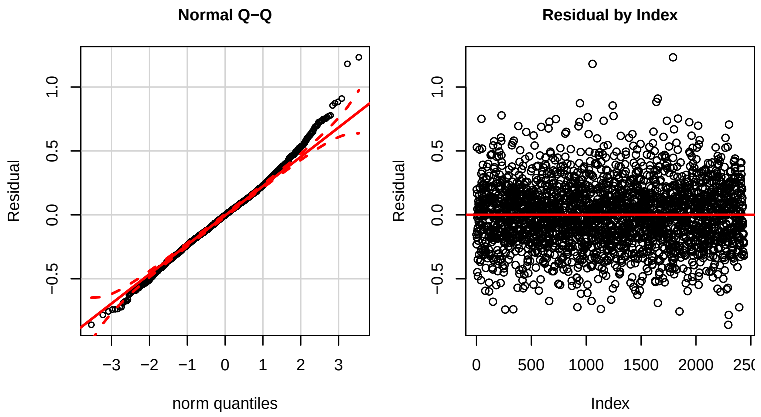


Figure 18: Diagnostic Plots

The slight curvature at the top of the Q–Q Plot, along with the slightly higher number of positive residuals at the top of the Residual by Index Plot show that there may be a slight right-skew in the residuals, but this is not enough to be troubling.

Interpretation

This first caveat with interpreting this model is dealing with transformations that were used. Several variables were centered and scaled (standardized), and the response was the natural logarithm of Sibilant Duration, not Sibilant Duration itself. These transformations would be a complication if the model was intended for prediction. Fortunately, this study only concerned with identifying relationships between these variables, and neither scaling the predictors nor log-transforming the response affect these interpretations.

An increase or decrease in the logarithm of Sibilant Duration would also be an change of the same direction in Sibilant Duration, and the same holds true for scaling the independent variables. A simple interpretation of variable coefficients for log-transformed responses is that a one-unit change in the independent variable (with all others held constant) will result in a change in the dependent variable of $100 \cdot (\text{coefficient})\%$. Positive coefficients represent an increase in the response, and negative coefficients represent a decrease[8].

For the scaled variables, a one-unit change is one standard deviation of that variable. For the categorical variables, R chooses one level to be the base value, and the coefficients represent the change in the response when changing the level.

It is also important to keep in mind with mixed effects models that the coefficients are the estimated average effect among all of the groups, so the p-values should not be treated as gospel. A coefficient with

[8] More accurately, for a coefficient $\hat{\beta}$, a one-unit change in the independent variable x multiplies the expected value of the response by $e^{\hat{\beta}}$. For small values of $\hat{\beta}$ like we have here, the percent change is a useful approximation.

a p-value of 0.06 may be important to the model, and one with a coefficient of 0.04 may not be all that important to the practical interpretation. For now, the decision about whether to focus on coefficients that are close (on either side) to 0.05 will be based on weighing how significant they are against their effect size. For example, the interaction `prec.pitch50:prec.pitch05` is marginally significant, but its coefficient is only 0.007, which represents a change in expected Sibilant Duration of only 0.7%. This change may or may not be statistically significant, but, practically, that is not much of a difference. The `following.typepause:sib.combined[z]` interaction could also go either way, but it represents a change of 8.1% in Sibilant Duration and is probably worth following up on.

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-2.572	0.037	187.767	-70.191	0.000
prec_segment_dur	1.352	0.116	2306.424	11.676	0.000
sib.cog	0.089	0.009	1360.144	9.593	0.000
vls_percent	0.197	0.021	2371.304	9.495	0.000
prec.pitch50	-0.016	0.013	2350.853	-1.252	0.211
prec.pitch05	-0.002	0.011	2390.327	-0.216	0.829
age_groupgroup_3	-0.126	0.039	61.662	-3.271	0.002
age_groupgroup_4	-0.141	0.039	60.710	-3.588	0.001
following.typepause	0.328	0.035	2301.399	9.329	0.000
following.typevowel	0.023	0.022	2376.263	1.045	0.296
sib.combined[z]	-0.174	0.022	2352.309	-7.779	0.000
prec.pitch50:prec.pitch05	0.007	0.004	2335.284	1.883	0.060
following.typepause:sib.combined[z]	0.081	0.042	2356.043	1.936	0.053
following.typevowel:sib.combined[z]	-0.036	0.029	2373.186	-1.249	0.212

Table 1: Coefficients of Final Sibilant Duration Model

Several conclusions can be drawn by examining the coefficients in this model (Table 1):

1. Increases in the covariates (the other responses) all result in an increase in Sibilant Duration, particularly the duration of the preceding segment.
2. As the age of the speaker increases, the Sibilant Duration tends to decrease.
3. Duration is generally decreased for sibilants that are traditionally pronounced as a [z] when compared to those that are traditionally pronounced as an [s].
4. Sibilants that precede a pause are longer, on average, than those that precede a consonant, but there is no significant difference between sibilants that precede consonants when compared to vowels.
5. If the sibilant precedes a pause but is traditionally pronounced as a [z], the following pause mitigates the decrease in duration that is expected from the traditional pronunciation.

These relationships can be easily visualized with parallel box plots:

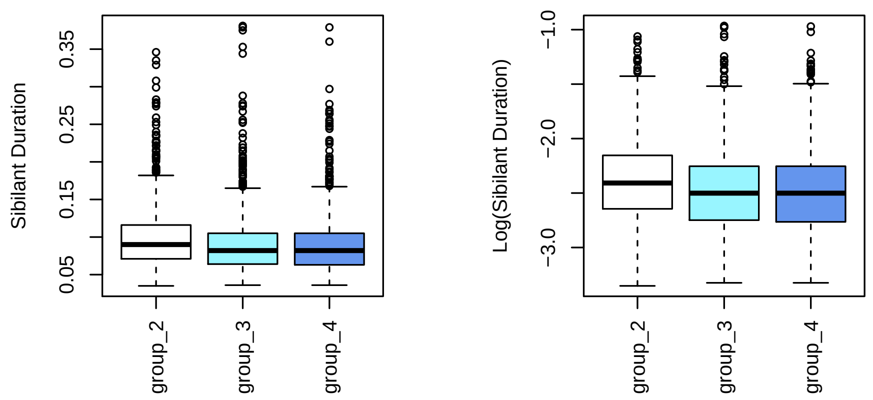


Figure 19: Sibilant Duration by Age Group

While the difference between age groups is harder to see with the significant right skew in Sibilant Duration, it becomes more distinct with the log-transformation (Figure 19).

In Figure 20, The interaction between following segments and standard pronunciations is explored. For each type of following segment, [s]'s have longer durations than [z]'s. Regardless of standard pronunciation, sibilants that precede pauses are longer than sibilants that precede vowels and consonants, and there is a lot more variability for these sibilants. There is less of a difference (and more variability) between the standard pronunciations that precede pauses than for segments that precede consonants or vowels, which is a good visualization of the interaction.

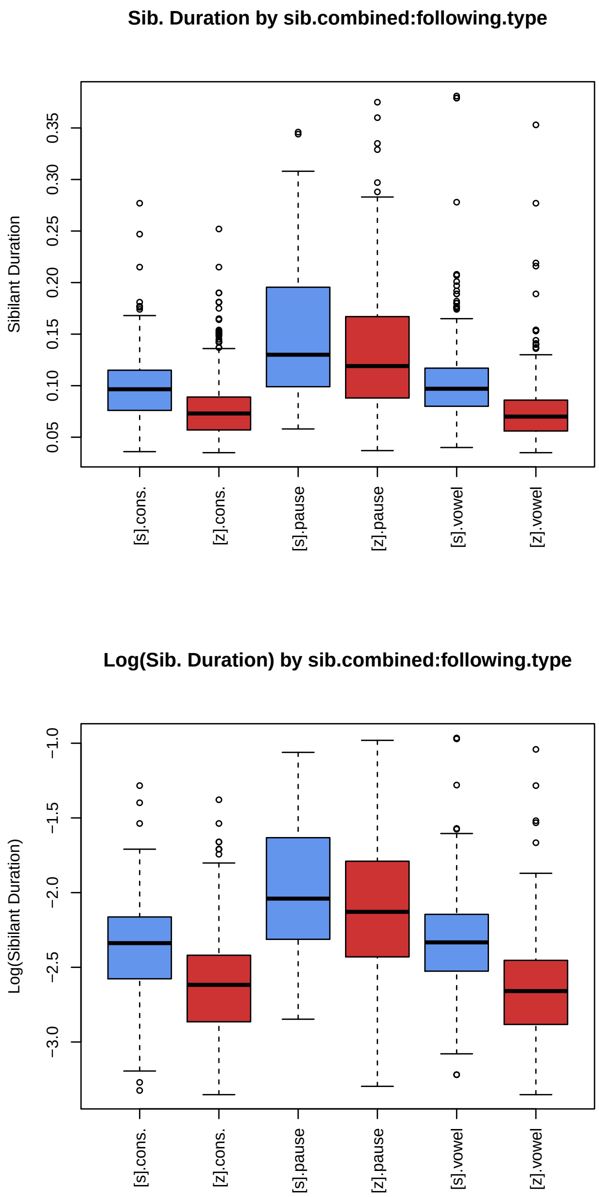


Figure 20: Sibilant Duration by Standard Pronunciation and Following Segment

Another visual representation of the interaction is, as its name would suggest, the Interaction Profile Plot (Figure 21). Here, each line represents the drop in the mean of Sibilant Duration from [s] to [z] for each of the following segment types. Since Sibilant Duration is not significantly different for following consonants and vowels, the lines overlap, and for following pauses the line is much higher. The interactions are evident by the different slopes of the lines, with the slope for following pauses being shallower than the slope for following consonants (while there is an interaction for vowels, it is insignificant in the model).

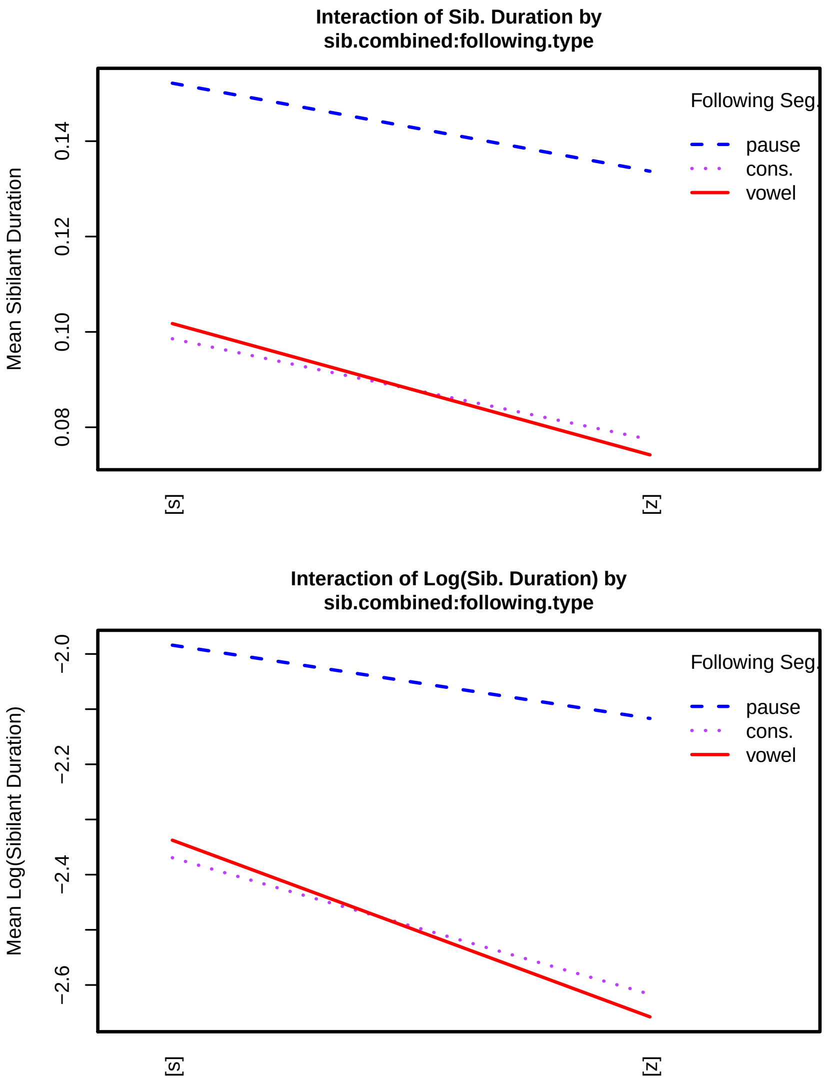


Figure 21: Interaction Profiles of Sibilant Duration by
Standard Pronunciation and Following Segment

For all of these plots, the differences between groups, while they exist in the untransformed data, become more distinct when the log-transformation is used. This is a good demonstration of the transformation's utility when working with highly skewed data.

Preceding Segment Duration

Preceding Segment Duration will be modeled using a Gamma Generalized Linear Mixed Model.

Center of Gravity

Center of Gravity will be modeled using a Linear Mixed Model with no transformation. Again, the filtered middle 60% is the best measure to use.

Percent Voicelessness

The best model for Percent Voicelessness still needs to be explored further. There are packages that implement Multilevel Beta Regression in CRAN which are worth looking at.

Appendices

A.1 Variable Definitions

Variable	Type	Role	Description
`speaker`	Categorical	Random Effect	Label of interviewee.
`ethnicity`	Categorical	Fixed Effect	Black or White.
`college`	Categorical	Fixed Effect	Whether or not the interviewee has had any higher education. Considered indicative of speakers' socioeconomic aspirations
`region`	Categorical	Fixed Effect	North or South.
`age_group`	Categorical (Ordered)	Fixed Effect	Age group, ordered by birth year. group_1: Pre-1919 group_2: 1919-1947 group_3: 1950-1970 group_4: 1980-1989
`age`	Numeric	Fixed Effect	2005 - `birth_year`
`birth_year`	—	—	Used to find age.
`sex`	Categorical	Fixed Effect	Male or Female.
`class`	Categorical	Fixed Effect	Lower Middle, Upper Middle, or Working Class.
`rurality`	Categorical	Fixed Effect	Rural or Non-Rural
`interval`	—	—	Praat variable.
`word`	Categorical	Random Effect	The word of interest in the token
`morphological_standing`	Categorical	Fixed Effect	Three levels determined by how the word is stressed in a sentence. See How to Guide, pages 12-14.
`sibilant`	Categorical	—	Whether the word is pronounced with an [s] or [z] in *standard pronunciation.* `s` and `z` are for word-final sibilants, while `p` and `w` represent [s] and [z], respectively, for word-internal sibilants.
`sib.combined`	Categorical	Fixed Effect	[s] and [z] according to *standard phonological pronunciation*, determined by `sibilant`.
`sib.location`	Categorical	Fixed Effect	word-final or internal, determined by `sibilant`
`sib_start`	—	—	Time code for start of sibilant in interview.
`sib_end`	—	—	Time code for end of sibilant in interview.
`sib_dur`	Numeric	Response	Duration of sibilant. `sib.end - sib.start`
`vls_percent`	Numeric (Ratio)	Response	Percent Voicelessness: Percent of `sib.dur` without glottal pulsing.

`sib_COG_full`	Numeric	Response	Center of Gravity: mean height of sibilant spectrum[9]
`sib_COG_filtered`	Numeric	Response	Mean of sibilant spectrum filtered with the Hann Function[10]
`sib_COG_60`	Numeric	Response	Center of Gravity of the middle 60% of the sibilant spectrum.
`sib_COG_60_filtered`	Numeric	Response	Mean height of the middle 60% of the sibilant spectrum filtered by the Hann Function.
`sib_intensity05`	Numeric	Fixed Effect	Intensity (dB) of sibilant at 5% of duration.
`sib_intensity25`	Numeric	Fixed Effect	Intensity (dB) of sibilant at 25% of duration.
`sib_intensity50`	Numeric	Fixed Effect	Intensity (dB) of sibilant at 50% of duration.
`prec_segment`	—	—	Sound that precedes sibilant.
`prec_segment.type`	Categorical	Fixed Effect	Vowel or Consonant.
`prec_segment_start`	—	—	Time code for start of `prec_segment` in interview.
`prec_segment_end`	—	—	Time code for end of `prec_segment` in interview.
`prec_segment_dur`	Numeric	Response	Length of preceding segment. `prec_segment_end - prec_segment_start`
`prec_segment_intensity05`	Numeric	Fixed Effect	Intensity (dB) of preceding segment at 5% of duration.
`prec_segment_intensity25`	Numeric	Fixed Effect	Intensity (dB) of preceding segment at 25% of duration.
`prec_segment_intensity50`	Numeric	Fixed Effect	Intensity (dB) of preceding segment at 50% of duration.
`prec_segment_pitch05`	Numeric	Fixed Effect	Pitch of preceding segment at 5% of duration.
`prec_segment_pitch25`	Numeric	Fixed Effect	Pitch of preceding segment at 25% of duration.
`prec_segment_pitch50`	Numeric	Fixed Effect	Pitch of preceding segment at 50% of duration.
`following_segment`	—	—	Sound that follows sibilant.
`following_segment.type`	Categorical	Fixed Effect	Vowel, Consonant, or Pause.

[9] `http://www.fon.hum.uva.nl/praat/manual/Spectrum__Get_centre_of_gravity___.html`
[10] `http://en.wikipedia.org/wiki/Hann_function`

A.2 Code

A.2.a Data Shaping

```
> ## read in main data file
> dat <- read.csv("./data/s_z_final.csv", header=T, na.strings=c("--undefined--", ""))

> ## read in the subsets
> csv.files <- list.files("./data")

> csv.files <- csv.files[!grepl("^[s_z|G234]", csv.files)]

> csv.names <- unlist(strsplit(csv.files, ".csv"))  ##just to have for reference.

> for(file in csv.files){
+     f.name <- strsplit(file, ".csv")[[1]]
+     assign(f.name, read.csv(paste("./data/", file, sep=""), header=T,
+                             na.strings=c("--undefined--", "")))
+ }

> ## Verify that dimensions of subsets match with dimensions of
> ## full data set, just to be safe.
> dim.mat <- t(sapply(csv.names, FUN=function(X) dim(eval(parse(text=X)))))

> sum(dim.mat[,1])/2 == nrow(dat)
[1] TRUE

> table(dim.mat[,2] == ncol(dat))[1]
TRUE
  12

> ## get approx. ages
> dat$age_group <- dat$age

> dat$age <- 2005 - dat$birth_year

> #### Investigate outlier in prec_segment_dur
> (max.dur <- max(dat$prec_segment_dur))
[1] 23.927

> max.ind <- which.max(dat$prec_segment_dur)

> dat$prec_segment_end[max.ind] - dat$prec_segment_start[max.ind]
[1] 23.926

> dat$prec_segment[max.ind]
[1] e
Levels: ^ ! ) @ a A b d e E f g i I j k l m n N o p P r t th u U v w W Y

> ## A 24sec 'e' doesn't make sense and not an obvious arithmetic error. NA it.
> dat$prec_segment_dur[which.max(dat$prec_segment_dur)] <- NA

> #### create a new column for if a token is internal or external
> dat$sib.location <- factor(ifelse(grepl("p|w", dat$sibilant),
+                                   "internal", "word-final"))

> #### create a new column for if sibilant is [s] or [z], regardless of location
> dat$sib.combined <- factor(ifelse(grepl("s|p", dat$sibilant), "[s]", "[z]"))

> #### create look-up tables to find _seg.types
```

```
> seg.cons <- c(unique(unlist(lapply(csv.names[grep("PreCon$",csv.names)],
+                      FUN=function(X) levels(eval(parse(text=X))$prec_segment)))),
+                      "ch", "d3", "h", "H", "s", "TH")

> seg.vowels <- unique(unlist(lapply(csv.names[grep("PreVowel$", csv.names)],
+                      FUN=function(X) levels(eval(parse(text=X))$prec_segment))))

> seg.type <- as.list(c(rep("vowel", length(seg.vowels)),
+                     rep("cons.", length(seg.cons)),
+                     "pause"))

> names(seg.type) <- as.list(c(seg.vowels, seg.cons, "#"))

> ## create cols for _segment.types, ignoring NA rows
> dat$prec_segment.type <- as.factor(sapply(dat$prec_segment,
+                                    FUN=function(X) seg.type[[X]]))

> inds.foll <- !is.na(dat$following_segment)

> dat$following_segment.type[inds.foll] <- sapply(as.character(
+        dat$following_segment[inds.foll]), FUN=function(X) seg.type[[X]])

> dat$following_segment.type <- as.factor(dat$following_segment.type)

> #### NA weird data in morphological_standing for now
> summary(dat$morphological_standing)
  first  first   second second    third
   1326       1    1556       1     235

> ## nuke whitespaces
> morpho <- as.character(dat$morphological_standing)

> morpho <- sapply(dat$morphological_standing,
+                 FUN = function(X) sub("[[:blank:]]*$", "", X))

> ## fix obvious typo
> #morpho[which(morpho=="secong")] <- "second"  ##fixed in data
> ## get rid of anything not first, second, or third
> dat$morphological_standing <- factor(ifelse(grepl("first|second|third", morpho),
+                                             morpho, NA))

> summary(dat$morphological_standing)
 first second  third
  1327   1557    235
```

A.2.b Independant Variable Plots

Figure 1 (page 1):

```
> barplot(sort(as.vector(table(dat$speaker))))
> abline(h=round(mean(table(dat$speaker))), col="red", lwd=3)
```

Figure 2 (page 2):

```
> social <- dat[,c(1:5, 7:9, 36)]
> par(mfrow=c(1,7), cex.axis=2, las=3, cex.main=2, mai=c(1.5, .5, .5, .25))
> barplot(table(social$ethnicity), main="Ethnicity")
> barplot(table(social$college), main="College")
> barplot(table(social$region), main="Region")
> barplot(table(social$sex), main="Sex")
> barplot(table(social$rurality), main="Rurality")
```

```
> barplot(table(social$class), main="Class")
> barplot(table(social$age_group), main="Age Group")
```

Figure 3 (page 2):

```
> library(plyr)
> social.speaker <- ddply(social, ~ speaker, count)[,-10]
> par(mfrow=c(1,7), cex.axis=2, las=3, cex.main=2, mai=c(1.5, .5, .5, .25))
> barplot(table(social.speaker$ethnicity), main="Ethnicity")
> barplot(table(social.speaker$college), main="College")
> barplot(table(social.speaker$region), main="Region")
> barplot(table(social.speaker$sex), main="Sex")
> barplot(table(social.speaker$rurality), main="Rurality")
> barplot(table(social.speaker$class), main="Class")
> barplot(table(social.speaker$age_group), main="Age Group")
```

Figure 4 (page 2):

```
> par(mfrow=c(1,1), mai=c(.5, 1, .5, .5))
> hist(social.speaker$age, col="darkgrey", xlab="Age",
+      main="", cex.axis=2, cex.lab=2)
```

Figure 5 (page 3):

```
> par(cex.axis=2, cex.lab=2, cex.main=2, mai=c(.5, .5, 1, 0))
> barplot(summary(dat$morphological_standing),  main="Morphological Standing")
> par(cex.axis=2, cex.lab=2, cex.main=2)
> barplot(summary(dat$sib.location), main="Sibilant Location")
```

Figure 6 (page 3):

```
> par(mfrow=c(1,3))
> barplot(summary(dat$prec_segment.type), main="Preceding\n Segment Type")
> barplot(summary(dat$following_segment.type), main="Following\n Segment Type", las=3)
> barplot(summary(dat$sib.combined), main="Standard Pronunciation")
```

Figure 7 (page 3):

```
> par(mfrow=c(1, 3), cex=.75, cex.main=1)
> hist(dat$sib_intensity05, main="Sib. Intensity 5%",
+      xlab="Intensity", col="darkgrey", freq=FALSE, ylim=c(0, 0.045))
> lines(density(dat$sib_intensity05), col="red", lwd=2)
> hist(dat$sib_intensity25, main="Sib. Intensity 25%",
+      xlab="Intensity", col="darkgrey", freq=FALSE, ylim=c(0, 0.045))
> lines(density(dat$sib_intensity25), col="red", lwd=2)
> hist(dat$sib_intensity50, main="Sib. Intensity 50%",
+      xlab="Intensity", col="darkgrey", freq=FALSE, ylim=c(0, 0.045))
> lines(density(dat$sib_intensity50), col="red", lwd=2)
```

Figure 8 (page 4):

```
> par(mfrow=c(1, 3), cex=.75, cex.main=1)
> hist(dat$prec_segment_intensity05, main="Prec. Segment Intensity 5%",
+      xlab="Intensity", col="darkgrey", freq=FALSE)
> lines(density(dat$prec_segment_intensity05), col="red", lwd=2)
> hist(dat$prec_segment_intensity25, main="Prec. Segment Intensity 25%",
+      xlab="Intensity", col="darkgrey", freq=FALSE)
> lines(density(dat$prec_segment_intensity25), col="red", lwd=2)
> hist(dat$prec_segment_intensity50, main="Prec. Segment Intensity 50%",
+      xlab="Intensity", col="darkgrey", freq=FALSE)
> lines(density(dat$prec_segment_intensity50), col="red", lwd=2)
```

A.2.c Dependant Variable Plots

Figure 10 (page 5):

```
> par(cex=1, cex.lab=2, cex.main=2, cex.axis=2, mai=c(1, 1, 0, .5))
> hist(dat$sib_dur, freq=FALSE, xlab="Duration (sec)", main="",
+      ylim=c(0, 13), col="darkgrey")
> lines(density(dat$sib_dur), col="red", lwd=3)
```

Figure 11 (page 5):

```
> library(MASS); library(car)
> par(mfrow=c(1, 3), cex=.5, cex.main=1.5, cex.lab= 1.5, cex.axis=1,
+     mai=c(.5, .65, .5, 0))
> qqPlot(dat$sib_dur, main="Normal Q-Q", ylab="Sibilant Duration", lwd=1)
> qqPlot(log(dat$sib_dur), main="Lognormal Q-Q", ylab="Log(Sibilant Duration)", lwd=1)
> gamma.coef <- round(fitdistr(dat$sib_dur, "gamma")[[1]], 3)
> qqPlot(dat$sib_dur, "gamma", shape=gamma.coef[1], rate=gamma.coef[2],
+        main="Gamma Q-Q", ylab="Sibilant Duration", lwd=1)
```

Figure 12 (page 6):

```
> par(cex=1, cex.lab=2, cex.main=2, cex.axis=2, mai=c(1, 1, 0, .5))
> hist(dat$prec_segment_dur, freq=FALSE, xlab="Duration (sec)", main="",
+      ylim=c(0, 9), col="darkgrey")
> lines(density(dat$prec_segment_dur[!is.na(dat$prec_segment_dur)]),
+       col="red", lwd=3)
```

Figure 13 (page 6):

```
> par(mfrow=c(1, 3), cex=.5, cex.main=1.5, cex.lab= 1.5, cex.axis=1,
+     mai=c(.5, .65, .5, 0))
> qqPlot(dat$prec_segment_dur, main="Normal Q-Q", ylab="Duration", lwd=1)
> qqPlot(log(dat$prec_segment_dur), main="Lognormal Q-Q", ylab="Log(Duration)", lwd=1)
> gamma.coef <- round(fitdistr(dat$prec_segment_dur[!is.na(dat$prec_segment_dur)],
+                              "gamma")[[1]], 3)
> qqPlot(dat$prec_segment_dur, "gamma", shape=gamma.coef[1], rate=gamma.coef[2],
+        main="Gamma Q-Q", ylab="Duration", lwd=1)
```

Figure 14 (page 7):

```
> par(mfrow=c(2,2), cex=.5, cex.main=1.5, cex.lab= 1.5, cex.axis=1,
+     mai=c(.5, .5, .25, 0))
> hist(dat$sib_COG_full, xlab="CoG", main="Full CoG", freq=FALSE, col="darkgrey",
+      ylim=c(0, 5e-4))
> lines(density(dat$sib_COG_full), col="red")
> hist(dat$sib_COG_60, xlab="CoG", main="60% CoG", freq=FALSE, col="darkgrey")
> lines(density(dat$sib_COG_60), col="red")
> hist(dat$sib_COG_filtered, xlab="CoG", main="Filtered CoG", freq=FALSE,
+      col="darkgrey")
> lines(density(dat$sib_COG_filtered), col="red")
> hist(dat$sib_COG_60_filtered, xlab="CoG", main="Filtered 60% CoG", freq=FALSE,
+      col="darkgrey")
> lines(density(dat$sib_COG_60_filtered), col="red")
```

Figure 15 (page 7):

```
> par(mfrow=c(1,1), cex=1, cex.lab=1.5, cex.main=1.5, cex.axis=1,
+     mai=c(1, 1, 0, 0))
> qqPlot(dat$sib_COG_60_filtered, ylab="CoG")
```

Figure 16 (page 8):

```
> par(cex=1, cex.lab=1.25, cex.main=1.5)
> hist(dat$vls_percent, freq=FALSE, xlab="Voicelessness (%)",
+      col="darkgrey", main="")
> lines(density(dat$vls_percent), col="red", lwd=2)
```

Figure 17 (page 8):

```
> qqPlot(dat$vls_percent, "beta", shape1=0.5, shape2=0.35,
+        ylab="Voicelessness (%)")
```

A.2.d Analysis

A.2.d.i Sibilant Duration

```
> ######### Define a print function for model summaries that
> ######### typesets things better
> pretty.summary.print <- function(mod.sum){
+     cat("\\begingroup
+         \\catcode\`_=\\active
+         \\gdef\\works{
+            \\catcode\`_=\\active
+            \\def_{\\textunderscore\\-}%
+         }")
+     cat("\\texttt{")
+     cat(mod.sum$methTitle, "\\newline ")
+     cat("Formula:\\newline ")
+     print(mod.sum$call)
+     cat("\\newline\\newline REML at convergence: ", mod.sum$AICtab, "\\newline ")
+     cat("\\newline\ Random Effects:\\newline ")
+     retab <- data.frame(mod.sum$varcor, stringsAsFactors=FALSE)[,-3]
+     colnames(retab) <- c("Groups", "Name", "Variance", "St.Dev.")
+     retab$Name[3] <- ""
+     retab <- xtable(retab)
+     print(retab, floating=FALSE, include.rownames=FALSE)
+     cat("\\newline Number of obs: ", length(residuals(mod.sum)),
+         ", groups: ", "word, ", mod.sum$ngrps[1], "; speaker, ",
+         mod.sum$ngrps[2], "\\newline ", sep="")
+     cat("\\newline Fixed Effects:\\newline ")
+     coefs <- xtable(mod.sum$coef, digits=3)
+     print(coefs, floating=FALSE)
+     cat("}\\endgroup\\newline")
+ }
> ######### Rename and subset data better for analysis
> ######### & create the basis model
> library(xtable)
> library(lme4, quietly=TRUE)
> library(lmerTest, quietly=TRUE, warn.conflicts=FALSE)
> #### Get a data frame with only the variables under consideration
> dat2 <- dat[,c(1:4, 7:9, 11:12, 16:17, 21:24, 28, 29:34, 36:40)]
> colnames(dat2)[6] <- "social.class" #to avoid confusion with function class()
> #### Shorten names for narrower printing
> colnames(dat2)[9] <- "morph.standing"
> colnames(dat2)[12] <- "sib.cog"
> colnames(dat2)[17:19] <- paste(rep("prec.int", 3),
+                                c("05", "25", "50"), sep="")
> colnames(dat2)[20:22] <- paste(rep("prec.pitch", 3),
+                                c("05", "25", "50"), sep="")
> colnames(dat2)[26:27] <- c("prec.type", "following.type")
> #### scale COG & intensities
> dat2$sib.cog <- scale(dat2$sib.cog)
> dat2[,17:19] <- scale(dat2[,17:19])
> dat2[,20:22] <- scale(dat2[,20:22])
> ## omit rows w/ NAs so all models have same number of observations
> dat2 <- na.omit(dat2)
> #### get base model
> sib.dur.0 <- lmer(log(sib_dur) ~ prec_segment_dur + sib.cog
```

```
+                  + vls_percent + (1|word) + (1|speaker), dat2)
> s0 <- summary(sib.dur.0)
> pretty.summary.print(s0)
> ######### Get things prepped for step function & use it for low level vars.
> source("forward.lmer.R")
> #### forward.lmer only takes variable names, not a formula for upper, which is
> #### rather inconvenient.  Create vectors of variable names & interactions:
> terms <- list(
+     soc = colnames(dat2)[c(2:7, 23)],
+     morpho = colnames(dat2)[c(9,24)],
+     phonol = colnames(dat2)[25:27],
+     phonetic = colnames(dat2)[c(13:15, 17:22)]
+ )
> #### get interactions
> interact <- function(vars){
+     interact <- vars
+     for(i in 1:(length(vars)-1)){
+         for(j in (i+1):length(vars)){
+             interact <- append(interact, paste(vars[i], vars[j], sep=":"))
+         }
+     }
+     interact
+ }
> terms <- lapply(terms, interact)
> #### start modeling.  huzzah.  may take a while.
> ## time <- system.time(sib.dur.1 <- forward.lmer(sib.dur.0,
> ##                                   blocks=terms$phonetic,
> ##                                   max.iter = length(terms$phonetic),
> ##                                   sig.level=0.05, print.log=FALSE))
> s1 <- summary(sib.dur.1)
> #### re-run model w/ lmerTest to we can can p-vals
> s1 <- summary(sib.dur.1 <- lmerTest::lmer(s1$call$formula, dat2))
> pretty.summary.print(s1)
> cat("\\newline\\newline\\texttt{Selection completed in",
+     round(time[3]/60, 1), "minutes.}\\newline\\newline")
> ######### add pitch05, check fit, & print new coef tab
> sib.dur.1.1 <- update(sib.dur.1, . ~ . + prec.pitch05)
> print(xtable(anova(sib.dur.1.1, sib.dur.1)), table.placement="h!")
> sib.dur.1.1 <- lmer(summary(sib.dur.1.1)$call$formula, dat2)
> pretty.summary.print(summary(sib.dur.1.1))
> ######### Start selecting high level terms
> ## time2 <- system.time(sib.dur.2 <- forward.lmer(sib.dur.1.1,
> ##                                     blocks=c(terms$morpho, terms$soc, terms$phono,
> ##                                              "sib.combined:sib.location"),
> ##                                     max.iter = length(c(terms$morpho, terms$soc,
> ##                                                         terms$phono)) + 1,
> ##                                     sig.level=0.05, print.log=FALSE))
> s2 <- summary(sib.dur.2)
> #### re-run model w/ lmerTest to we can get can p-vals
> s2 <- summary(sib.dur.2 <- lmerTest::lmer(s2$call$formula, dat2))
> pretty.summary.print(s2)
> cat("\\newline\\newline\\texttt{Selection completed in",
+     round(time2[3]/60, 2), "minutes.}\\newline\\newline")
> #### Manually add following.type
> sib.dur.2.0 <- update(sib.dur.2, .~. + following.type + sib.combined)
> #### Manually drop prec.int25, verify, & print new coef tab
> sib.dur.2.0 <- lmer(summary(sib.dur.2.0)$call$formula, dat2)
> pretty.summary.print(summary(sib.dur.2.0))
> cat("\\newline\\newline")
> sib.dur.2.1 <- lmer(summary(sib.dur.2.1)$call$formula, dat2)
```

```
> pretty.summary.print(summary(sib.dur.2.1))
> ######## Compare grouping strategies
> sib.dur.3 <- update(sib.dur.2.1, . ~ . - (1|word) - (1|speaker) + (1|speaker/word))
> sib.dur.3 <- lmerTest::lmer(summary(sib.dur.3)$call$formula, dat2)
> pretty.summary.print(summary(sib.dur.3))
> cat("\\newline\\newline")
> a <- anova(sib.dur.2.1, sib.dur.3)
> rownames(a) <- c("Crossed", "Nested")
> print(xtable(a), table.position="h!")
> ######## Get a pretty coefficient table for reference
> print(xtable(summary(sib.dur.3)$coef,
+              caption="Coefficients of Final Sibilant Duration Model",
+              label="tab:sib.dur", digits=3), table.placement="h!")
```

Exploratory Plots
Figure 18 (page 14):

```
> par(mfrow=c(1,2), mai=c(.75, .75, .5, 0), cex=.75, cex.main=1, cex.lab=1)
> qqPlot(residuals(sib.dur.3), main="Normal Q-Q", ylab="Residual")
> plot(1:length(residuals(sib.dur.3)), residuals(sib.dur.3),
+      xlab="Index", ylab="Residual", main="Residual by Index")
> abline(h=0, col="red", lwd=2)
```

Figure 19 (page 15):

```
> par(mfrow=c(1,2), las=3, mai=c(1, 1, .25, .25), cex=.75, cex.main=1, cex.lab=1)
> with(dat2, boxplot(sib_dur ~ age_group,
+      ylab="Sibilant Duration", xlab="",
+      col=c("white", "cadetblue1", "cornflowerblue",
+      main="Sib. Duration by Age Group")))
> with(dat2, boxplot(log(sib_dur) ~ age_group,
+      ylab="Log(Sibilant Duration)", xlab="",
+      col=c("white", "cadetblue1", "cornflowerblue",
+      main="Log(Sib. Duration) by Age Group")))
```

Figure 20 (page 16):

```
> par(mfrow=c(2,1), las=3, cex=.75, cex.main=1.25, cex.lab=1,
+     mai=c(1, 1, 1, 1))
> with(dat2, boxplot(sib_dur ~ sib.combined*following.type,
+                    ylab="Sibilant Duration",
+                    col=c("cornflowerblue", "brown3"),
+                    main="Sib. Duration by sib.combined:following.type"))
> with(dat2, boxplot(log(sib_dur) ~ sib.combined*following.type,
+                    ylab="Log(Sibilant Duration)",
+                    main="Log(Sib. Duration) by sib.combined:following.type",
+                    col=c("cornflowerblue", "brown3")))
```

Figure 21 (page 17):

```
> par(mfrow=c(2,1), las=3, cex=.75, cex.main=1, cex.lab=1,
+     mai=c(.5, 1, .5, .5), lwd=2)
> interaction.plot(dat2$sib.combined, dat2$following.type, dat2$sib_dur,
+                  lwd=2, col=c("darkorchid1", "blue", "red"),
+                  xlab="",
+                  ylab="Mean Sibilant Duration",
+                  main="Interaction of Sib. Duration by\nsib.combined:following.type",
+                  trace.label="Following Seg.", xpd=TRUE)
> interaction.plot(dat2$sib.combined, dat2$following.type, log(dat2$sib_dur),
+                  lwd=2, col=c("darkorchid1", "blue", "red"),
+                  xlab="",
+                  ylab="Mean Log(Sibilant Duration)",
+                  main="Interaction of Log(Sib. Duration) by\nsib.combined:following.type",
+                  trace.label="Following Seg.", xpd=TRUE)
```

A.2.e Word Frequencies

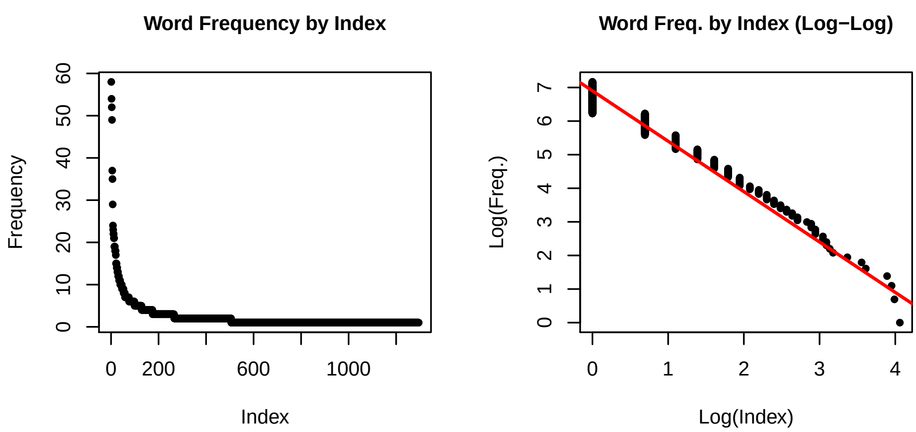
```
> library(lme4)
> (n.unique.words <- length(table(dat$word)))

[1] 1295

> (n.hapax <- length(table(dat$word)[table(dat$word) == 1]))

[1] 790


> par(mfrow=c(1,2), cex=.75, cex.main=1, cex.lab=1)
> #### Zipf's Law:
> plot(sort(table(dat$word), decreasing=TRUE),
+      main="Word Frequency by Index",
+      ylab="Frequency", pch=20)
> ## Log-Log should be roughly linear:
> plot(log(sort(table(dat$word), decreasing=TRUE)), log(1:n.unique.words),
+      main="Word Freq. by Index (Log-Log)",
+      xlab="Log(Index)", ylab="Log(Freq.)", pch=20)
> abline(a=6.9, b=-1.5,
+             col="red", lwd=2)
```




```
> #### Look at words within speaker:
> speaker.word.count <- by(dat$word, dat$speaker, count)
> speaker.word.table <- sapply(speaker.word.count, nrow)
> summary(speaker.word.table)

   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  21.00   36.00   40.00   39.06   42.00   49.00

> barplot(sort(speaker.word.table), main="Number of Unique Words by Speaker")
> abline(h=mean(speaker.word.table), col="red")
> #### Double check that lmer() gets the same number of unique words and
> #### figure out the number of groups in nested structure
> summary(lmer(sib_dur ~ (1|speaker) + (1|word), dat))$ngrps  #crossed

   word speaker
   1295      67

> summary(lmer(sib_dur ~ (1|speaker/word), dat))$ngrps  #nested

word:speaker      speaker
        2617           67
```